Methods to Measure and Enhance the Circularity of Wastewater Resources

A thesis submitted for the degree of Doctor of Philosophy

by

David C. Renfrew

Department of Civil and Environmental Engineering

College of Engineering Design and Physical Sciences

Brunel University London

Uxbridge, UB8 3PH, United Kingdom

October 2023

Dedicated to John Harris

– I would’ve loved your feedback

Acknowledgements

I would like to extend my dearest thanks to the following people, who directly and indirectly helped with the completion of my research journey, as without their emotional and intellectual support it would not have been possible.

Firstly, I would like to express my deepest gratitude to my supervisor Prof. Evina Katsou. The trust she has had in me since the beginning and the opportunities she provided me with have not only grown my confidence as a researcher, but also as a person. The level of enthusiasm and creativity she brings instilled an environment that meant everyday was exciting and filled with new possibilities. Her kindness, knowledge, patience, and work ethic are an inspiration and meant that during the last 3 years there were more times of enjoyment than not.

I would also like to thank members of the H2020 DEEP PURPLE consortia, as their collaboration throughout my research was invaluable. I am especially grateful the project co-ordinator Patricia Zamora, scientific manager Dr. Daniel Puyol, and Eugenio Marin for their support. Additionally, I would like to extend thanks to Amanda Lake, Prof. Simos Malamis, and Dr. Eliza Harris for their interesting discussions and contributions to this work.

Next, I would like to thank my friends and colleagues from Brunel University London Eliza, João, Daniel, George, Nilay, and Morad, for creating such a fruitful and successful environment, as well as collaboration. I must also extend a special thanks to Vasileia, who was always there when I needed help or advice, and whose breadth of knowledge is truly something to aspire to.

Without a doubt, the support of friends in London, Bath, and back home have eased the difficult times with both reassurance and laughter. I would like to especially thank Becky and Adam for their enduring sense of humour when cooped up together during COVID-19 lockdowns.

I am eternally grateful for the love and support of my family. To my parents, your success and endeavour, especially seeing what you have dealt with and achieved over the last few years, is a true inspiration. To Ewan and Maya, thank you for providing light relief and a sense of perspective when I needed it most. And to my grandparents, Vera, John, Betty, and Bill, your guidance has helped me far beyond just completing this work, and I will forever hold it dear.

Finally, I would like to express how grateful I am to Emma, for her love and being at my side throughout this shared journey. The passion you have and ability to express it is something I constantly strive for. Your continued empathy and support have helped me through the difficult times, and your reassurance has instilled confidence when needed most, so without you this would not have been possible.

David C. Renfrew

Brunel University London

Uxbridge, United Kingdom

October 2023

Abstract

The need for an alternative to the linear economy and a practical method to operationalise sustainable development has led to a surge in popularity of the circular economy (CE) concept. Europe's CE Action Plan establishes the importance of circular wastewater treatment and resource utilisation, however, a lack of standardised CE definitions and assessment methods are hindering this transition. Therefore, the first step of this research reviewed the indicator-based decision support systems (DSS) developed for wastewater treatment plant (WWTPs). It found that technology selection DSS aims are ill-defined and the scope of indicators used for process optimisation is narrow, meaning the sector is far from standardised assessments and decision making. This led to the development of a structured approach that generates shared CE strategies at a regional level, by adapting a multi-criteria analysis tool to select resource recovery technologies. A UK wastewater sector example demonstrated the approach's decision-making capabilities, identifying five priority resources and quantifying the expected benefits in terms of nutrient recovery. However, it was concluded that a holistic assessment is required for further analysis of impacts to circularity and sustainability when implementing the selected technologies. Reviewing circularity assessments, and definitions of waste, showed a paradox exists when applied to WWTPs, as wastewater, regardless of its production, is non-virgin so is currently considered a circular input. To overcome this, the CE principle of resource traceability was combined with their degree of environmental harm, to define the circularity of water, carbon, nitrogen, and phosphorus. This method showed how actions of water users impact upstream and downstream circularity of a conventional WWTP. Following this, it was seen that material circularity is commonly used as a proxy for environmental performance, revealing a large disconnect between circularity and sustainability during assessments. Therefore, the assessment method was expanded to investigate how changes to physical resource circularity directly impacts value creation. By defining several principles from sustainability science literature, a method that systematically selects resource, action, and sustainability indicators using participatory approaches was developed. Additionally, it showed how appropriate benchmarks are defined for direct quantification of impacts to resource circularity and sustainable value creation. This was validated by comparing extended aeration and novel photobioreactor (PBR) WWTPs, highlighting multi-dimensional benefits of the PBR compared with the conventional process. Lastly, it is believed the developed method can act as the basis for standardising the holistic circularity assessment of wastewater resources.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

AAD	Advanced Anaerobic Digestion
AAT	Advanced Thermal Treatment
AD	Anaerobic Digestion
AGS	Aerobic Granular Sludge
AHP	Analytical Hierarchy Process
AnMBR	Anaerobic Membrane Bioreactors
ANP	Analytical Network Process
ASM	Activated Sludge Model
BAS	Biosolids Assurance Scheme
BNR	Biological Nutrient Removal
BOD	Biological Oxygen demand
BSM	Benchmark Simulation Model
BWM	Best-Worst Method
CAPEX	Capital Costs
CAS	Conventional Activated Sludge
CBA	Choosing-by-advantages
CE	Circular Economy
CEAP	Circular Economy Action Plan
CHP	Combined Heat and Power
COD	Chemical Oxygen Demand
CREW	Centre of Expertise for Waters
DALY	Disability-adjusted Life Years
DNSH	Do No Significant Harm
DO	Dissolved Oxygen
DS	Dry Solids
DSS	Decision Support System
EC	Energy Consumption
ELECTRE	Elimination and Choice Expressing the Reality
EMF	Ellen MacArthur Foundation
EPS	Extracellular Polymeric Substances
EQI	Effluent Quality Index
EU	European Union
FOG	Fats, Oils, Grease
GHG	Greenhouse Gas
GSA	Global Sensitivity Analysis
HGV	Heavy Goods Vehicle
IAE	Integral of Absolute Error
IPCC	Intergovernmental Panel on Climate Change
ISE	Integral of Squared Error
ISO	International Standards Organisation

KPI	Key Performance Indicator
LAM	Linear Assignment Method
LCA	Life Cycle Assessment
LCC	Life Cycle Costing
MBR	Membrane Bioreactor
MC	Monte Carlo
MCA	Multi-criteria Analysis
MCDM	Multi-criteria Decision-making
MF	Micro Filtration
MFA	Material Flow Analysis
MJ	Mega Joules
MVM	Million Vehicle Miles
N	Nitrogen
NO_3^-	Nitrate
NP	Nitrogen and Phosphorus
NSGA	Non-dominated Sorting Genetic Algorithm
OC	Organic Carbon
OCI	Overall Cost Index
ODIs	Outcome Delivery Incentives
OECD	Organisation for Economic Co-operation and Development
OPEX	Operating Cost
P	Phosphorus
PBR	Photobioreactor
PE	Population equivalent
PHA	Polyhydroxyalkanoate
PI	Proportional-Integral
PPB	Purple Phototrophic Bacteria
PROMETHEE	Preference Ranking Organization Method for Enrichment Evaluation
RMSE	Root Mean Square Error
RO	Reverse Osmosis
RR	Resource Recovery
SCADA	Supervisory Control and Data Acquisition
SCP	Single Cell Proteins
SDGs	Sustainable Development Goals
SFA	Substance Flow Analysis
SOI	System of Interest
SPPD-WRF	Strategic Planning and Process Design of Water Resource Factories
SRT	Solids Retention Time
SST	Sewage Sludge Treatment
TBL	Triple Bottom Line
TF	Trickling Filter
TH	Thermal Hydrolysis
TKN	Total Kjeldahl Nitrogen

TN	Total Nitrogen
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
TRL	Technology Readiness Level
TSS	Total Suspended Solids
UF	Ultrafiltration
UKWIR	UK Water Industry Research
UWWTD	Urban Wastewater Treatment Directive
VFAs	Volatile Fatty Acids
VPC	Value Proposition Canvas
VRE	Value-based Resource Efficiency
VSS	Volatile Suspended Solids
WAS	Waste Activated Sludge
WR	Water Reuse
WW	Wastewater
WWT	Wastewater Treatment
WWTP	Wastewater Treatment Plant

1 Introduction

1.1 Research motivation

Throughout the 20th century, economic growth has led to prosperity and a greater standard of living for many people across the globe (Didenko et al., 2018; Jørgensen and Pedersen, 2018). The traditional linear economic model that achieved these unprecedented levels of growth is founded upon the principles of unrestrained extraction and consumption of natural resources, and impudent disposal of the resultant waste (Ellen MacArthur Foundation, 2015). This treacherous path has resulted in the immense production of negative externalities, accelerating anthropogenic impacts on the environment including climate change, biodiversity loss, and water scarcity (Corvellec and Paulsson, 2023; Geissdoerfer et al., 2017; Voulvoulis, 2018). In response to these concerns, several initiatives have evolved that offer a compromise between boundless economic growth and environmental protection with the hope of evading catastrophe, the most successful being sustainable development (Velenturf and Purnell, 2021).

The seminal Brundtland report, published in 1987, defined the basis for sustainable development and called for the creation of routes to initiate its progress (Saidani et al., 2019), resulting in the definition of the United Nation's Sustainable Development Goals (SDGs) (Schroeder et al., 2019) and the planetary boundary framework (Steffen et al., 2015) in 2015. However, their effectiveness was called into question, as the ambiguity of sustainable development means it is often too vague to implement (V Superti et al., 2021), whilst six of the nine planetary boundaries have already been exceeded (Persson et al., 2022; Wang-Erlandsson et al., 2022). Unfortunately, the patterns of urbanisation and population growth have only exacerbated finite resource pressures and unwanted impacts of the linear economy (Dagilienė et al., 2021; Ellen MacArthur Foundation, 2015). This meant industrial and political decision makers needed a practical alternative to the unsustainable and linear 'take-make-dispose' economy, leading to the emergence of the circular economy (CE) concept (Papageorgiou et al., 2021; V Superti et al., 2021).

Although the premise of the CE concept is not entirely new (CE related waste legislation implemented since 1970s (Moraga et al., 2019)), its popularity has surged in recent years since its inclusion within national policy, endorsement from industry, and appraisal by academia (Geissdoerfer et al., 2017). As a result, a plethora of definitions have been developed that capture the CE's principles, actions, and values. Most notably, the Ellen MacArthur Foundation (EMF) define CE principles as enhancing natural capital, designing out negative externalities, and keeping materials at their highest utility, with the ultimate aim of decoupling economic growth from finite material consumption (Ellen MacArthur Foundation, 2015). The CE is an umbrella concept that brings together many emerging fields in sustainability science, including industrial symbiosis, eco-efficiency, natural capitalism, biomimicry, and eco-design (Korhonen et al., 2018), which through the implementation of specific actions provides a route to operationalise the sustainable development of economic systems (Kirchherr et al., 2017), such as those of the 10R framework (Reike et al., 2018). Concurrently, the ability of the CE to directly facilitate many SDGs (and indirectly support all) (Morseletto et al., 2022; Schroeder et al., 2019) has cemented its pertinence in achieving the shared goal of sustainable economic development.

Validation of the relationship between the practical nature of the CE and achieving SDGs somewhat justifies the concepts popularity. The first country to directly implement national CE policy was China in 2008 with the Circular Economy Promotion Law (Harris et al., 2021), achieving success at local government levels (Su et al., 2013). The European Union (EU) then following with its first Circular Economy Action Plan (CEAP) in 2015, detailing 54 actions that were to be completed by 2019, in areas such as waste management, plastics, food waste, innovation, and monitoring (European Commission, 2015). Following this, a new CEAP was published (European Commission, 2020a), which is labelled as one of the main building blocks of making Europe the first climate neutral continent as part of the European Green Deal (European Commission, 2021a). Again, the new CEAP provides specific actions that should be taken to improve the circularity of key product value chains, whilst establishing circularity as a prerequisite to climate neutrality (European Commission, 2020a), undoubtably intertwining circularity and sustainability objectives even further. The CEAP has led to the subsequent development of numerous initiatives, such as the Zero Pollution Action Plan (European Commission, 2021b) and Critical Raw Materials Communication (European Commission, 2020b), which has manifested the EU as a global CE leader, explaining the exponential increase of academic interest and publications during this period (Alcalde-Calonge et al., 2022). However, the success of the EU's CE policies are yet to be fully confirmed, which can only be achieved by meeting set targets such as the 55% reduction in carbon emissions by 2030, as defined by the European Climate Law (Council of the European Union, 2021) .

The broad endorsement of the CE concept coupled with limited implementation and evidence of success leaves it open to criticism. In fact, it is argued that the CE concept is not new, and just a reconstituted version of sustainable growth and development to reconcile economic and environmental issues (Corvellec et al., 2022). Furthermore, support for the CE may only come from its uncontroversial nature, as its promises many benefits with few burdens, often mitigating problems or conflicts that could emerge by leaving the linear economy (Corvellec et al., 2022). The proposed issues are evidenced by the current lack of agreement on defining a CE (Kirchherr et al., 2017; V Superti et al., 2021), resulting in opposed theoretical interpretations of circularity. This has led to inconsistent and misleading CE assessments, as there is no standardised way to distinguish between circular strategies (Blomsma and Brennan, 2017). More worryingly, assessments have aligned material recirculation with environmental impact (Harris et al., 2021), risking decisions being made based solely on resource circularity without considering direct impacts to sustainability dimensions. From a technical perspective, thermodynamics (entropy) prevents complete material circularity as recirculation will always generate some waste and require energy consumption (Korhonen et al., 2018). Lastly, on a practical level the CE assumes that a new consumption culture will emerge (Corvellec et al., 2022), where there is actually a possibility of greater impacts from more frequent production and distribution, quality degradation, and rebound effects boosting consumption (Figge et al., 2022; Korhonen et al., 2018). Therefore, there is a need for more in depth academic inspection of CE science to create a more standardised conceptual understanding, or else the concept is at risk of perpetual contention and may fail altogether (Kirchherr et al., 2017).

To achieve this, it is logical that scientific developments must prioritise sectors and resources that will expedite CE evolution and resultant benefits. Water is the only resource for which there is no alternative for sustaining life and maintaining a prosperous economy (Morseletto et al., 2022; Sauvé et al., 2021). Linear treatment of water resources has disrupted its natural hydrogeochemical cycle through intensive agricultural, industrial, and municipal activities, degrading water quality and resource availability, now resulting in widespread water scarcity (Morseletto et al., 2022; Voulvoulis, 2018). Fortunately, the CE aligns well with water resource management, as they both rely on the cyclical flow of resources and intersect multiple scales, levels of governance, and industrial sectors (Morseletto et al., 2022). The importance and interconnectivity of water for societal and environmental function mean that enhancing water resource circularity is key to unlocking a CE (Nika et al., 2020). Transformation of waste management systems is a cornerstone of the CE, to eliminate resource inputs and waste production (Ellen MacArthur Foundation, 2015; Geissdoerfer et al., 2017). Therefore, the most obvious route to a circular water sector is targeting the treatment, use, and recovery of wastewater, facilitating better environmental and human protection, enhanced process efficiency, and resource valorisation. (Nika et al., 2020).

Enhancing the circularity of wastewater treatment plants (WWTPs) is linked with many sustainable actions, such as process intensification, waste valorisation, energy efficiency, emissions mitigation (water and air), and reduction of costs. WWTPs have two main methods for improving their circularity performance; namely enhancing efficiency and resource recovery (Mo and Zhang, 2013). Efficiency improvements require strategies to optimise process performance, whether this be supporting decision making to select sets points that boost effluent quality and reduce energy consumption, or replace aging infrastructure with more intensive, lower impact technology (Mannina et al., 2019). Alternatively, there are many avenues for resource recovery from wastewater, including water itself, which has been implemented in many countries using membrane technology to supplement water demand (Kehrein et al., 2020a). Wastewater also carries large amounts of chemical and thermal energy, and anaerobic digestion (AD) is already widely used to generate biogas as a source of renewable energy for WWTPs (Gherghel et al., 2019). Of the mineral fertilisers used for food production, 30 % of nitrogen and 20 % of phosphorus are excreted to wastewater, making them available for recovery using crystallisation and stripping technology (Kehrein et al., 2020a). Lastly, a range of other materials can be captured, such as cellulose (Ruiken et al., 2013), or generated using advanced processes including biopolymers and volatile fatty acids (Atasoy et al., 2018).

The potential to transform the wastewater sector by implementing these strategies to replace aging infrastructure and outdated operating procedures has been recognised by the EU. Since 1991, the Urban Wastewater Treatment Directive (UWWTD) (91/271/EEC) dictated the actions of the sector by setting pollutant limits on WWTP discharge and requirements for effluent monitoring. However, a recent proposal has been produced to bring the wastewater sector in line with the European Green Deal and new CEAP, by setting targets for the recovery of phosphorus, energy neutrality, and polluter payments (European Commission, 2022). Subsequently, as part of the CEAP, additional regulation has been developed that directly relates to the use of wastewater resources; namely Integrated Nutrient Management Plans (Radini et al., 2023), Water Reuse Regulation (2020/741) (European Parliament, 2020), and the European Hydrogen Strategy (European Commission, 2020c). Notwithstanding, there is still no consensus on how optimal technologies and strategies should be selected, and consequently assessed, to ensure they achieve defined circularity and sustainability targets (Ahmed et al., 2022; Åkerman et al., 2020).

Circularity indicators and assessments have been developed to the extent there is now thought to be an overabundance, creating confusion and hindering standardisation (Corona et al., 2019). This lack of clarity, combined with no agreed CE definition, stops the development of bottom-up approaches needed for the appraisal and certification of new circular value chains. Therefore, the certification landscape is fragmented, for a few specific products such as biopolymers (Rosenboom et al., 2022), and based on voluntary schemes so there is little legal basis to enforce circularity, facilitating malpractice (Kazancoglu et al., 2021). This encourages the creation of assessments that rely on predefined lists or cherry picking of indicators, resulting in either patchy or biased assessments (Harris et al., 2021; V Superti et al., 2021). Additionally, the indicators that have been developed are criticised for mitigating the multi-dimensional impacts and benefits of circularity (Corona et al., 2019), instead solely focusing on material circulation (Harris et al., 2021; Saidani et al., 2019). Without consideration of the wider aspects it is difficult to build business cases that encourage investment in circular alternatives (Nika et al., 2021), meaning their competitive advantage in terms of enhanced sustainability cannot be measured (Lahti et al., 2018). This is particularly important when dealing with the water sector as it is historically risk adverse and slow to adopt new technologies (Mihelcic et al., 2017).

Specific issues also exist for the circularity assessment of wastewater processes and resources, as currently most literature and subsequently indicators have been developed for technical manufacturing systems (Kirchherr et al., 2017), meaning they require either adjustment or displacement with a new discourse (Sauvé et al., 2021). This is evidenced by the mismatch of the popular 10R framework, as some of the actions included are not compatible for enhancing wastewater resource circularity (Morseletto et al., 2022). The circular use of wastewater relies on cascading of resources until they degrade in quality and require safe regeneration within the natural environment (Stegmann et al., 2020). In the case of technical systems, this is not seen as a circular method of waste management, as they are reliant on reverse logistics of technical resources (Chojnacka et al., 2020). Although, this relationship between wastewater resource management and the environment inevitably adds to the complexity of circularity assessments. Furthermore, wastewater production is dictated by upstream water users, who are unaware of the impacts they have on downstream processes, leading to asymmetry and hindering the ability to assign responsibility for linear water usage (Savenije and van der Zaag, 2020). On top of this, the current definitions of waste rely on functionality- or value-based approaches (Iacovidou et al., 2017), or if an input is non-virgin (wbcsd, 2022). This creates a paradox during the circularity assessment of waste treatment facilities, as regardless of how waste is produced all waste inputs can be considered non-virgin and therefore circular. As a result, wastewater resources produced in a linear manner can be treated as circular if they reach a WWTP, meaning it is easy for WWTPs to have 100 % circularity, as meeting discharge permit limits enables their outlets to be considered circular. This results in WWTP circularity assessments of little value for decision making, that are unable to deter linear practices by investigating wastewater inflow and outflow characteristics.

This highlights a significant gap in the development of CE science, as wastewater resources are currently inaccessible to circularity assessments. The critical nature of this resource means its mitigation has the potential disrupt the symbiotic relationships necessary to achieve a CE. Therefore, the aim of this thesis is to understand how indicator-based assessments are used by WWTP decision makers to select circular technologies and optimise performance, and develop methodologies for the selection and optimisation of WWTP technology, through the assessment of wastewater resources considering material circularity and wider impacts to sustainability. This will result in several beneficial outcomes including how to define assessment baselines to set realistic targets against a suitable benchmark, methods to select, prioritise, and optimise wastewater strategies at operational and strategic levels, and development of a more standardised methodology for the assessment of wastewater resource circularity.

1.2 Overview of research programme

1.2.1 Research questions addressed

The primary research questions addressed in this thesis are:

1. What is the current landscape of indicator-based decision making at WWTPs? Specifically, how are indicators selected and utilised in decision support tools for technology selection and process optimisation at WWTPs, and how are decisions aligned with the sustainability and circularity aims? Lastly, what progress has been made towards standardising these assessments and can recommendations be provided to expedite this process? (Chapter 2)

2. How can decision support tools developed for technology selection be applied to provide a consensus for CE strategies to enhance wastewater sector circularity? Can they be used as part of a structured approach to establish which resources have the greatest resource recovery potential at a regional level and quantify the potential benefits in terms of resource recovery? (Chapter 3)
3. Can the circularity of wastewater be defined beyond just having no value or as 'non-virgin' and be used to overcome the current assessment paradox for characterising the circularity of wastewater resources? Does tracing the source and destination of wastewater and its constituent resources enable responsibility to be assigned for linear water use? (Chapter 4)
4. Can a methodology be developed that facilitates the standardisation of wastewater circularity assessments by systematically selecting indicators to quantify the sustainable value created by circular practices? How does altering the circularity of physical resource flows impact the sustainability of wastewater systems? (Chapter 5)

1.2.2 Aims and objectives

Research hypothesis: *The current definitions, indicators, and methods used for circularity assessments are not applicable to wastewater technologies and resources. There is a significant gap when it comes to defining the circularity of waste streams that if not corrected will lead to wastewater system assessments of little value. Additionally, the use of material-based indicators as a proxy for the assessment of sustainability dimensions is not correct, and instead a method is needed to bridge the gap that exists between circularity and sustainability impacts. Combining these aspects will enable a holistic assessment of how the CE can create value for stakeholders from wastewater.*

The aim of the presented research is to develop methodologies that facilitate wastewater technology selection for resource recovery and a more standardised circularity assessment of wastewater resources for multiple levels of decision-making including technology selection and process optimisation. The method for resource recovery technology selection will examine how a multi-criteria decision-making (MCDM) tool is integrated within a structured approach for identifying resources with the greatest potential benefits for a region. In order to validate the technology selection approach, it should be applied to a regional wastewater scenario and used evaluate which resources must be prioritised for recovery, exploring how shared CE strategies can be developed at a macro level. Following technology selection, a method is needed to directly assess and quantify potential impacts of their implementation on wastewater resource circularity, to validate performance and facilitate optimisation. This requires investigation of the currently accepted methods of circularity assessments and combination with novel approaches to overcome the gaps identified when dealing with wastewater resources. The developed methodology must be able to flexibly and systematically select indicators depending on the specific scenario of application, and be able to link how circular actions that alter the physical wastewater resources in a system impact sustainability dimensions. To examine the developed circularity assessment methodology, it must be applied to a WWTP example, highlighting the advantages of the method by revealing the direct impacts to circularity and sustainability when implementing circular strategies.

To test the research hypothesis and achieve the defined aims, the specific objectives of this thesis are to:

1. Review the existing literature on the topic of how decision support systems (DSS) are used for technology selection and process optimisation in WWTPs. Investigate how indicators are chosen and utilised in the DSSs to achieve outcomes that align with defined goals of water sector decision makers, whether this is to improve operational, circularity, or sustainability performance. Enhance understanding of indicator selection processes for WWTP decision making by summarising practices that should be avoided and providing a set of recommendations to improve practices as the water sectors goes through a period of transformation to meet regulatory and sustainability targets.
2. Adapt and apply a MCDM tool for the selection of technologies that enhance the circularity of wastewater resources, considering wider impacts. Evaluate the approach by applying it to a case study, showing how DSSs can be used to build a shared CE strategy for wastewater at a macro level. Scrutinise which resources and technologies that should be prioritised for resource recovery and evaluate the expected returns in terms of quantities captured and market potential.
3. Create definitions for the circularity of wastewater and the important resources carried that go beyond the fact it is ‘non-virgin’ to overcome the current assessment paradox. Investigate how the CE principle of resource traceability can be used to define circularity by understanding the source and destination of wastewater resources and combining it with the degree of harm they cause when interacting with the natural

environment. Use the approach to examine how changing upstream and downstream practices impacts the circularity of wastewater resources, enabling responsibility to be assigned for linear water use.

4. Develop a method with an indicator taxonomy that is able to harmonise circularity and sustainability assessments using principles from relevant sustainability and CE literature. Evaluate how stakeholder inputs can be utilised during the indicator selection process to understand how circular actions implemented in wastewater systems create value for them. Scrutinise assessment decision-making capabilities by applying it to an example comparing a novel circular and conventional wastewater treatment technology, validating that it can directly quantify how changes in resource circularity impact sustainability dimensions.

1.2.3 Methodological approach

In the first phase of this thesis, a review of indicator selection and utilisation by WWTP DSSs is completed (Chapter 2) and combined with the application of a MCDM tool to support wastewater resource recovery technology selection (Chapter 3). A thorough review is completed on the available knowledge of WWTP DSS i) typology, ii) sector goals, iii) prioritised aims, iv) indicator categorisation, v) indicator selection procedures, vi) indicator weighting methods, vii) indicator scoring systems, viii) technology ranking, and ix) technology selection. The review focuses on DSSs for technology selection and process optimisation at WWTPs, concluding with the issues identified from current procedures and a set of recommendations for improving future indicator-based decision-making protocols. The next step utilises a multi-criteria (indicator) tool as part of a methodology for the selection of technologies for wastewater treatment plants that improve circularity performance through resource recovery. A MCDM tool is selected and integrated as part of a method for planning consensus strategies for resource recovery at a regional scale. This includes i) modelling of the current baseline scenario, ii) market potential calculations, iii) multi-criteria technology selection, iv) identification of priority technologies, v) developing resource recovery scenarios, and vi) quantifying expected benefits. The DSS chosen is adapted from one developed by UK Water Industry Research (UKWIR) for multi-criteria analysis (MCA) as it utilises six capitals indicators to consider wider impacts to sustainability. The approach is applied to an example of the UK wastewater sector as the necessary data is available as part of OFWAT's PR19 reports.

It is identified that a method to assess the potential impacts to circularity and sustainability is required once technology selection is completed, to ensure desired benefits are produced and unwanted impacts are mitigated.

Once the need for a holistic circularity assessment of wastewater is established, the second phase of work is to define a framework for classification of wastewater resource circularity. The basis of this work combines the CE principle of resource traceability with environmental science theory, enabling the disentanglement and circularity definition of wastewater water, carbon, nitrogen, and phosphorus resources. A wastewater resource assessment methodology is then formed combining the use of circularity indicators (including inflows and outflows, water, energy, and economic dimensions) and material flow analysis (MFA). To highlight the advantages of this novel classification approach it is applied to an example, with different scenarios tested to investigate their impacts on inflow and outflow resource circularity.

Following validation of wastewater circularity definitions, a systematic and holistic circularity assessment method is developed. The methodology is created by defining several principles from relevant circularity and sustainability science literature, establishing the need to link circularity and sustainability using value creating actions of wastewater processes. The steps include i) wastewater system definition and modelling, iii) circular solution selection, modelling, action indicator selection, iii) resource classification, indicator calculation, circularity performance assessment, and iv) sustainability indicator selection and value creation analysis. This results in the necessary indicator taxonomy that combines resource flow, action, and sustainability analysis to link changes in physical resource circularity with sustainability impacts. The relevant indicators are identified using the perspectives of stakeholders to understand how the actions of circular wastewater systems create value. The methodology is trialled by applying it to a novel photobioreactor wastewater treatment technology and comparing it with a conventional process that acts as a benchmark.

1.2.4 Thesis outline

Chapter 2: Literature Review – Indicator based multi-criteria decision support systems for wastewater treatment plants

In this chapter, a review of WWTP DSSs was conducted, to define how indicator based-decision making is currently conducted and provide a list of recommendations to improve practices that will facilitate more standardised development of future protocols. It was established that the main function of MCDM tools are technology selection and the optimisation of process operation. The European Commission revealed their ambition for greater levels of sustainability, circularity, and environmental and human health protection in recent publications, which DSS application must align with to meet the defined targets in the water sector. Many differences in DSS procedures were found, including a large contrast regarding aims, as process optimisation tools clearly define their goals and indicators used, whilst technology selection procedures tend to use vague language, making it hard for decision makers to connect the selected indicators with their desired sustainability and circularity outcomes. Recommendations are made to improve DSS usage, including more rigorous indicator selection protocols, such as participatory approaches, and expansion of indicators sets as it was common to focus on economic aspects.

Chapter 3: Where is the greatest potential for resource recovery in wastewater treatment plants?

This chapter highlights how a MCDM can be adapted and integrated as part of a structured approach for prioritising resources and selecting recovery technologies to build shared CE wastewater strategies at a regional scale, and quantify the potential benefits of this in terms of nutrient recovery. It was identified that the water sector is poised to benefit from the CE transition, due to its intrinsic circularity and the critical resources handled by wastewater. Currently, the range of options for resource recovery married with few examples from industry hinders strategic decision making and technology uptake. Resource recovery on a regional scale improves market share and mitigates investment risk, therefore, a structured approach was developed for the selection of priority technologies to act as a guide for strategic planning. A representative UK wastewater model acted as the baseline, with MCA used to select resources and create an enhanced resource recovery scenario. It revealed the five 'priority resources' for this region and quantified the potential of the sector to increase nitrogen and phosphorus recovery by implementing the relevant technology. Lastly, the need for a cross-cutting approach for the holistic assessment of wastewater system circularity was discussed.

Chapter 4: Tracing wastewater resources: unravelling the circularity of waste using source, destination, and quality analysis

In this chapter, the principle of resource traceability was used to disentangle wastewater resources to define their circularity and investigate how wastewater producer actions impact upstream and downstream circularity. Initially it was found that the current definitions of wastewater circularity lead to paradoxical assessments that generate results of little value for evidence-based decision-making. This led to the development of a classification approach which combines resource traceability with their ability to cause harm when released to the environment, adopting the attitude that not all waste is created equally. It revealed how upstream agricultural, industrial, and human practices impact downstream treatment and the effectiveness of resource cycling within the natural environment. The framework was validated by applying it to a WWTP and investigating scenarios that influence resource circularity, showing how it can educate and assign responsibility to water users for development of robust circular economy policy.

Chapter 5: Systematic assessment of wastewater resource circularity and sustainable value creation

The last chapter defines five principles from literature to create a circularity assessment methodology that uses participatory approaches as part of the systematic selection of indicators to determine how changes to physical resource circularity impact sustainable value creation. Firstly, a lack of universal definitions and measurement tools that are required to achieve the CE's full potential was highlighted. Building on the work of Chapter 4, a holistic circularity assessment methodology was created that uses three indicator typologies, namely resource flow, action, and sustainability indicators. Stakeholder inputs were used to generate value propositions, which are used to systematically investigate the impacts of changing resource circularity on sustainable value creation. The assessment was exhibited by applying it to a small-scale WWTP, comparing conventional extended aeration and novel photobioreactor technologies. Resource flow indicator results highlight improved outflow circularity, renewable energy usage, and economic efficiency of the novel system. Action indicators revealed that the photobioreactor technology was successful at achieving its defined value creating goals. Lastly, sustainability indicators enabled the direct quantification of environmental, economic, and social value creation, confirming that stakeholder benefits result from the photobioreactor wastewater treatment technology.

Figure 1.1 summarises the development of thesis logic which is separated into three phases of work. It shows how each phase and chapter are connected to one another (along with the main objectives), to create a collection of methods that can help facilitate the circular transition of the wastewater sector by selecting technologies and assessing their impact on resource circularity and sustainability. The expected outcome of this research is to generate the indicator taxonomy required for a truly holistic circularity assessment, using stakeholder perspectives are used as part of the indicator selection process to understand how value is created for them by circular practices in the wastewater sector. It is hoped these methods will accelerate the CE transition of the water sector, by providing tools to implement circular practices across multiple levels of decision making from technology selection to implementation and monitoring.

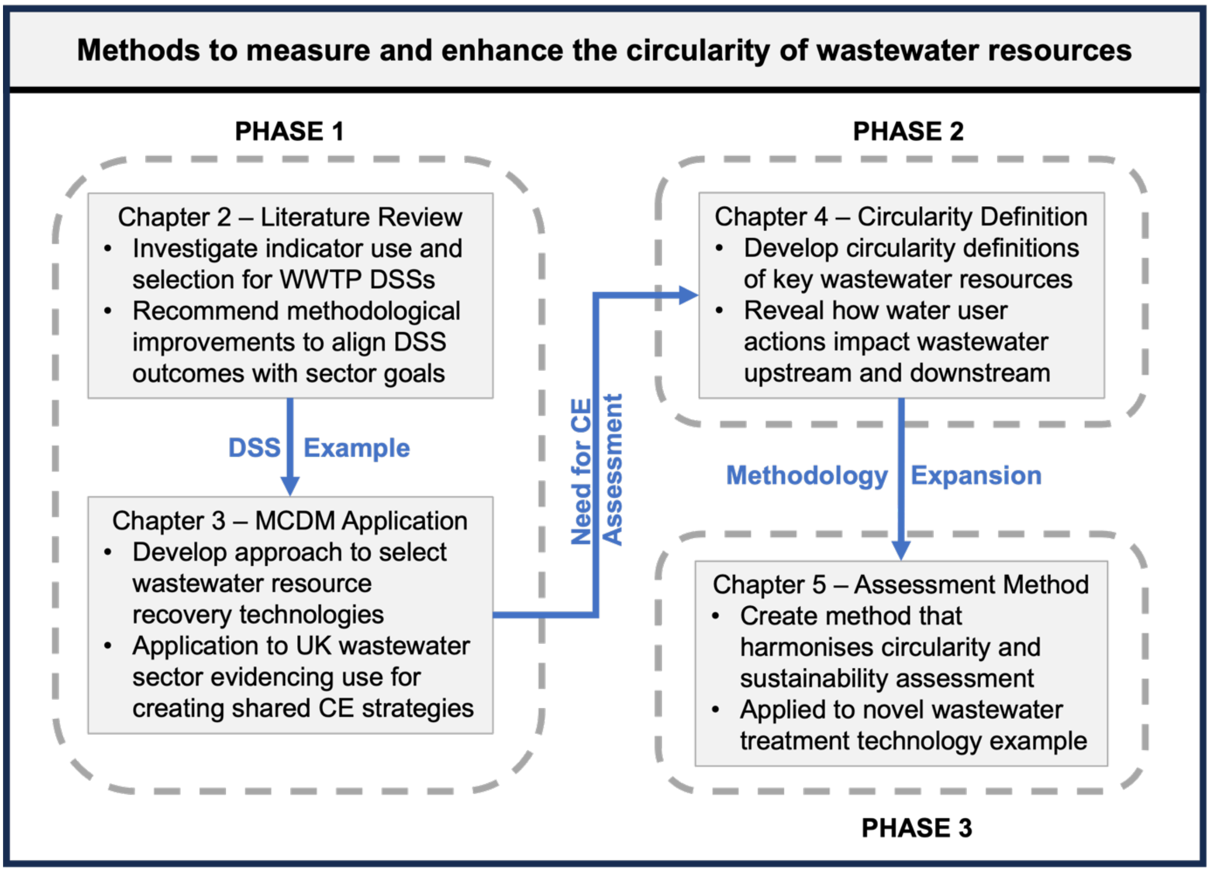


Figure 1.1. Connections between chapters and main objectives of each chapter in the thesis.

2 Literature Review

2.1 Introduction

The wastewater sector is faced with many challenges that result from ageing and inefficient processes, including substantial carbon emissions, high energy consumption, regulatory compliance failures, and loss of public trust (Borzooei et al., 2019). Unfortunately they are only being worsened by the impacts of climate change, urbanisation, and population growth (Haldar et al., 2022). Although a plethora of technologies have been developed in recent years to combat these issues at a wastewater treatment plant (WWTP) level by academia and industry (Kehrein et al., 2020a), water utilities are unable to make the required investment decisions to shift towards sustainable wastewater treatment. Decision support systems (DSSs) have been used to support complex decision making in the water sector, including WWTPs with the aim of optimising technology selection procedures or process control to improve operational performance (Wardropper and Brookfield, 2022).

Wastewater decision makers have additional considerations compared with other industries, as on top of conventional technical, economic, and environmental issues, the social and regulatory implications of their actions must be considered (Ullah et al., 2020). Commonly public perception and social acceptance problems arise when utilising and recycling wastewater streams to generate resources (Kehrein et al., 2020a). Water provision and sanitation services are also highly regulated and must be protected due to their importance for society, industry, and the environment (Preisner et al., 2022). Additionally, it is proving difficult to create markets for new products recovered from wastewater, such as tackling the end-of-waste status for their use in the European Union (Palmeros Parada et al., 2022). Therefore, water utility and WWTP decision makers are facing stricter regulations to improve operation regarding human health protection, environmental preservation, and emissions reduction (Mannina et al., 2019), whilst simultaneously pursuing greater circularity and revenue generation through resource recovery strategies to improve business performance. This creates complex multi-objective problems when operating and selecting technologies for improving WWTPs, which are traditionally labour intensive, trial-and-error experiments that rely on the judgement of operators (Ntalaperas et al., 2022; Sucu et al., 2021). To ensure that all relevant information, performance trade-offs, and cause and effect relationships are taken into consideration when dealing with complex problems, DSSs must be utilised by the water sector for more robust decision making (Ullah et al., 2020).

A DSS is a computational system that assists the user in choosing an optimal or consistent solution to a particular problem in a reduced timeframe, particularly when the solution is unclear, by aggregating often conflicting values or preferences to examine the trade-offs between solution objectives (Giupponi and Sgobbi, 2013; Mannina et al., 2019; Wardropper and Brookfield, 2022). A review by Mannina et al. (2019) classified wastewater DSS intentions as; design, energy consumption, operational optimisation, improvement of effluent quality, or environmental sustainability. Of course, decision makers may want to investigate a combination of or all of these goals at once, which can often be contradictory (Eseoglu et al., 2022). For example, WWTP direct emissions and electricity consumption typically increase when improving effluent quality, however, this action negatively impacts any net zero targets. Therefore, when using DSSs to solve multi-objective problems the goal of the study must be defined with clear constraints for optimisation, and an adequate number of relevant key performance indicators (KPIs) chosen, to ensure the resulting decision is a true reflection of the defined goals.

Multi-criteria decision-making (MCDM) tools for selecting the optimal technology for a specific scenario have been developed in literature (Eseoglu et al., 2022; Južnič-Zonta et al., 2022; Sucu et al., 2021). Depending on MCDM application, the goals of the assessment will impact the KPIs used to constrain the decision-making process and final outcome. Conventional WWTP operation is monitored using effluent quality and consequently controlled with a few key parameters, meaning process control is often intuitive with operators unable to understand the real time impacts of their decisions (Ntalaperas et al., 2022). Another key area for DSS use in the water sector is online process optimisation, however, it has not been widely applied in WWTPs as improvements to sensors, mathematical models (soft sensors), and data visualisation are needed for precise operational monitoring and control. However, a combination of data-driven models and artificial intelligence enables performance prediction that can be used to reduce energy demand, decrease costs, improve effluent quality, and lower emissions (Matheri et al., 2022).

Considering the transformation that WWTPs face to improve performance by reducing emissions, energy consumption, and operating costs whilst meeting stricter regulatory targets, water utilities are expected to become ever more reliant on DSSs to solve multi-objective problems for optimal selection and operation of sustainable technology. This study focuses on the use of multi-criteria DSSs to support these two functions for WWTP decision makers. Rather than focussing solely on their typology, analysis of the correct selection and utilisation of relevant KPIs during DSS application is prioritised, to ensure that outcomes fulfil decision maker requirements. This is a pertinent aspect of complex multi-objective decision-making and one which is often overlooked or undervalued by the methodologies in the literature.

2.2 Methodology

2.2.1 Wastewater sector goals

Currently, there is a mismatch in terms of the decision maker goals and the KPIs selected when utilising DSSs at a WWTP level. Therefore, this section maps the wastewater ambitions of the European Commission which can be used to direct the utilisation of DSSs to meet water sector targets.

The European Commission has directives which act as the framework for adequate wastewater treatment in the EU and are critical sources for understanding high-level water sector goals. However, in many cases they are decades old and do not reflect the regions recent sustainability ambitions (European Commission, 2022). The Urban Wastewater Treatment Directive (UWWTD) (91/271/EEC) published in 1991, acted as the basis for transforming European water systems by limiting pollutant levels in WWTP discharge. The Sewage Sludge Directive (86/278/EEC) was introduced for the correct use of sewage sludge in agriculture. It details the requirements in terms of heavy metal concentration, quantities of sludge applied per hectare, and the crops prohibited from application (Council of the European Union, 1986). Although the UWWTD and Sewage Sludge Directive have been successful in improving environmental and human health, as 92 % of wastewater is now treated satisfactorily (European Commission, 2022), the next generation of wastewater treatment must go beyond this to achieve the EU's sustainability goals, whilst ensuring this fundamental objective is still maintained.

To instigate further change to WWTPs, a proposal to update the UWWTD was published in October 2022 with the aim of introducing new rules up to the year 2040 (European Commission, 2022). This update will be key for delivering the European Green Deal's zero pollution target and highlights many water sector goals that decision makers will need to adopt in Europe. It expands regulatory compliance to smaller plants and introduces binding energy neutrality targets for the sector, polluter pays for the treatment of toxic micropollutants, and minimum recovery rates for phosphorus. Additionally, improved data monitoring and usage are required for measuring and mitigating greenhouse gas (GHG) emissions and micropollutants, and making KPIs public to improve benchmarking and transparency (European Commission, 2022).

The European Commission is pursuing a CE to facilitate many of its sustainability targets, therefore, it published the CE Action Plan in 2020 (European Commission, 2020d). As part of this, the European Commission aims to intensify nutrient recovery from wastewater by establishing Integrated Nutrient Management Plans (Radini et al., 2023). Another key element is the development of Water Reuse Regulation (2020/741) to facilitate the circular use of wastewater effluents. The document provides a classification system regarding the technology required to achieve the contaminant levels for application to specific crop grades (European Parliament, 2020), relying on the use of Water Reuse Risk Management plans to ensure public and environmental health (Radini et al., 2023). WWTPs should improve effluent quality for the circular use of water, also reducing the quantity of raw water abstracted. Therefore, it is clear that for a sustainable and circular transition, WWTPs must focus on emissions reduction, resource recovery, and water reuse, and acknowledge the importance of proper data usage, to align with water sector goals at a European level.

Analysis of regional government wastewater strategies is vital for creating useful DSSs. However, their it remains challenging to implement tangible decisions at WWTP level, as individual utilities have their own priorities based on local facets. Considering legislative constraints, sector-wide ambitions, and local factors can make the identification of priorities at a WWTP-scale challenging for decision makers. Therefore, rigorous indicator selection and usage is needed to ensure DSS KPIs align with stakeholder goals at every level of decision making, or else WWTPs are at risk of undesirable future impacts and events.

2.2.2 Article collection

2.2.2.1 Research question

There have been recent publications which discuss multi-criteria analysis (MCA) DSSs for the wastewater sector (Ddiba et al., 2023; Mannina et al., 2019), however they allude to issues that exist for the assessment and selection of technologies. Mannina et al. (2019) states that '*sustainable aspects are incorporated in accordance to DSS developers, as there is no standard* *that can be applied while developing the systems*', whilst Ddiba et al. (2023) concludes that some sustainability implications are not adequately covered by decision support tools. This shows that a lack of standardisation has resulted in the development of indicator-based methodologies that do not fully consider the sector's sustainability goals. However, the wastewater sector must meet the requirements set out in Section 2.1 in the coming years, therefore, this review systematically analyses the specific indicators selected, and how they are used by DSSs, to understand the impact on WWTP outcomes. This results in the research question of *how are indicators selected and utilised in decision support tools for technology selection and process optimisation at WWTPs, and to what extent are sustainability and circularity pillars harmonised to meet decision maker goals?* Additionally, the need to construct standardised DSS procedures to facilitate sustainability outcomes is highlighted, thus following literature review recommendations are provided to act as the starting point for this. The types of MCA used to facilitate complex decision making have already been the subject of systematic reviews (Kozłowska, 2022), meaning the methods available in literature have already established. Therefore, they do not require further generalised study and is why the focus of this review is on DSSs implemented for wastewater technology assessment to understand current practices and provide recommendations for improvement.

2.2.2.2 Search strategy

The evaluation of WWTP DSSs was completed using systematic review, following the guidelines of the Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA) method (Page et al., 2021). Articles describing multi-criteria, indicator-based DSSs for WWTP technology selection and process optimisation were collected from Scopus (www.scopus.com) and Web of Science (www.webofscience.com) databases. The configuration of this review required two independent searches to collect data using a combination of Boolean connectors, and a previous review in the area by Mannina et al. (2019) established the time series of 2018-2022. MCDM technology selection DSSs were found using the search term ("wastewater treatment" OR WWT OR WWTP OR sludge) AND (DSS OR "decision support system" OR MCA OR "multi criteria" OR MCDM OR "multi-criteria") AND (selection OR identification OR KPI). Whilst the multi-objective optimisation DSS search used (WWTP OR "wastewater treatment plant" OR "wastewater treatment process") AND (control OR operation OR monitoring OR optimisation OR optimization) AND multi AND (criteria OR objective) terms.

2.2.2.3 Selection of studies

Figure 2.1 shows the steps taken to screen initial search results and collect articles used for review (Page et al., 2021). Results were exported to Mendeley reference management software for processing, and after removing duplicates 127 articles and 144 articles related to technology selection and process optimisation DSSs were identified respectively. They were then analysed to ensure the inclusion of only high-quality, peer-reviewed, original articles, thereby removing non-English, conference proceedings, book chapter, and review paper sources. Next, sources were primarily screened based on their title, and subsequently using the abstract and content in full, to establish the final list of articles. Technology selection DSSs were excluded if used for geographic location planning, source selection, resource allocation, performance assessment, or operation monitoring, and did not utilise multiple indicators for decision making. Process optimisation DSSs were excluded if only used for performance monitoring, fault-detection, visualisation tasks, load prediction, or sensor utilisation, and did not use multiple indicators to optimise control parameters. An additional six relevant articles were collected from a review paper by Mannina et al. (2019) investigating DSSs for WWTPs, to incorporate appropriate literature from outside the search time series.

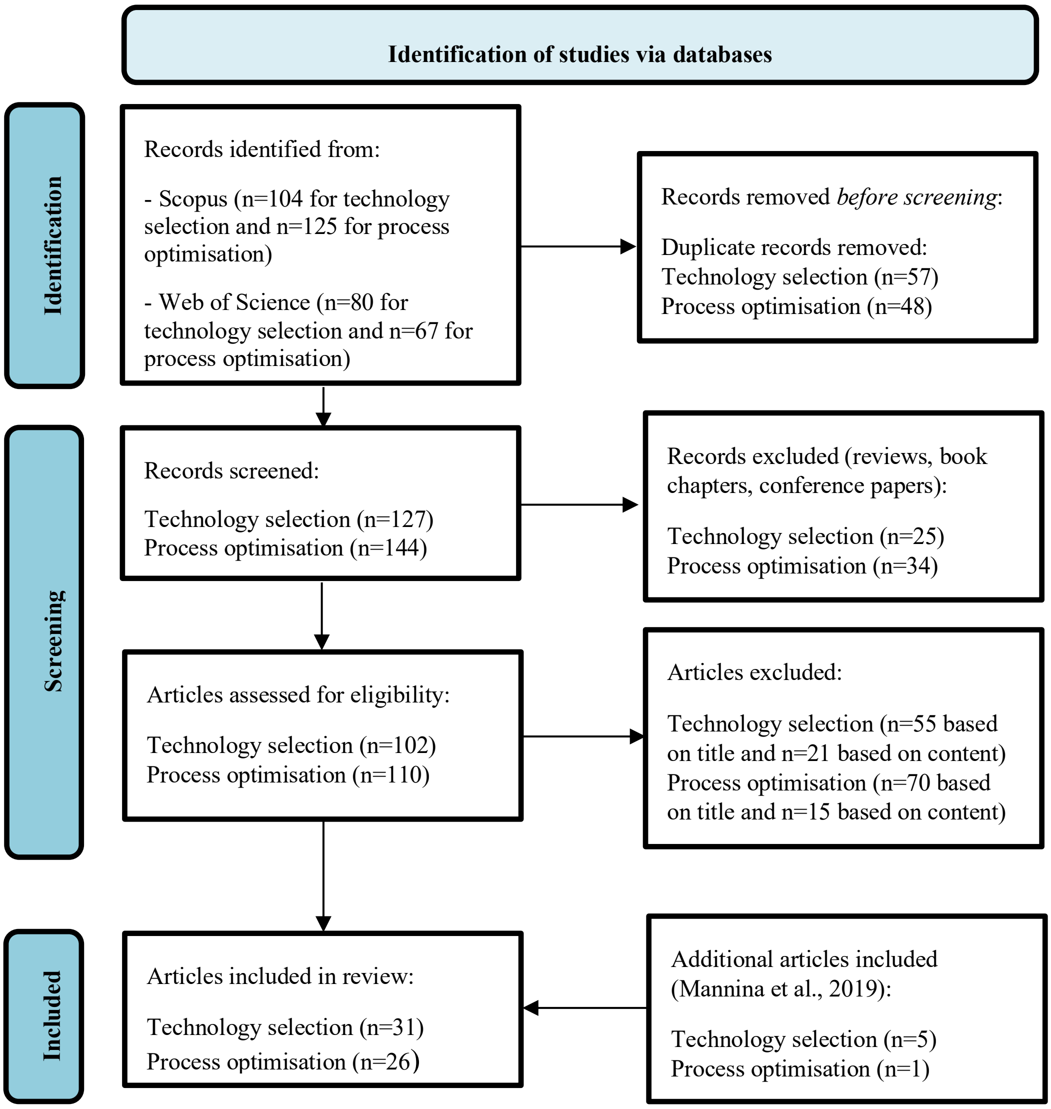


Figure 2.1. Flowchart of the steps taken during the article selection procedure (Page et al., 2021).

2.3 Technology selection DSSs

The decision to invest in new technology at a WWTP is a complex and multi-faceted decision to fulfil business, sustainability, and regulatory targets. MCDM tools have been developed for this purpose, however, there is often little emphasis on linking the goals of the assessment with indicator selection, weighting, and scoring methods. This potentially leads to outcomes that do not truly satisfy all stakeholder and decision maker goals at regional, national, utility, community, or WWTP scales. The relevant literature collected in Section 2.2.2 is reviewed to understand conventional methods and highlight good practices regarding alignment of MCDM KPIs with defined goals. Table 2.1 summarises the MCDM technology selection DSS tools for WWTPs collected from literature, resulting in a total of thirty-one articles.

Table 2.1. Summary of wastewater treatment MCDM technology selection DSSs.

Author	Year	Group	Aim	Case Study	Assessment Categories	Weighting Method	KPIs Selected
Molinos-Senante et al.	2014	WWT	*Assess the sustainability of WWT technologies*	1,500 PE WWTP	Economic, Environmental, Social	AHP	CAPEX, OPEX, removal efficiency, energy consumption, land use, sludge production, potential for RR and WR, reliability, odours, noise, visual impact, public acceptance, complexity
Garrido-Baserba et al.	2015	SST	*Identification and assessment of the most appropriate sludge treatment technologies*	1,000,000 PE WWTP	Economic, Environmental	Fixed	Annual cash flow, annual income, total annual equivalent costs, GWP
Castillo et al.	2016	WWT	*Analysis of the alternatives through a multi-criteria approach, considering operational, economic, and environmental criteria*	Retrofit vs construction of WWTP in Italy	Economic, Environmental, Operational	User Defined	Nitrogen removal, CAPEX, OPEX, CBA, LCA, noise, visual impact, need for specialised staff, flexibility
Chhipi-Shrestha et al.	2017	WR	*Evaluating the potentiality of fit-for-purpose wastewater treatment and specific reuse for a community*	Comparing non-potable water uses for 10,000 PE community	Economic, Environmental	User Defined	Microbial concentration, quantitative microbial risk assessment, development of alternative treatment trains, estimation of reclaimed water quantity and its distribution, LCC, energy use, carbon emissions
An et al.	2018	SST	*Helping the decision- makers/stakeholders to select the most sustainable technology among multiple scenarios*	Three sludge management strategies	Economic, Environmental, Social, Technical	AHP	CAPEX, OPEX, land use, environmental risk, resource utilisation efficiency, operability, site selection, applicability, and management level requirement
Arroyo and Molinos-Senante	2018	WWT	*Choice of the most sustainable WWT alternative*	Seven small-scale WWT technologies	Economic, Environmental, Social	CBA	CAPEX, OPEX, removal efficiency, energy consumption, land use, sludge production, potential for RR and WR, reliability, odours, noise, visual impact, public acceptance, complexity
Sadr et al.	2018	WR	*Selection of WWT technologies for non-potable water reuse applications in different contexts*	Large WWTPs in Brazil and Greece	Economic, Environmental, Social, Technical	AHP	CAPEX, OPEX, energy consumption, environmental impact, community acceptance, adaptability, ease of construction and deployment, land requirement, complexity, water quality

Oertlé et al.	2019	WR	*Promote water reuse in regions where it is still an emerging concept*	Thirteen treatment trains in different locations	Economic, Technical, Requirements and Impacts	User Defined	CAPEX, OPEX, distribution costs, energy demand, chemical demand, odour generation, sludge production, land required, groundwater impact, reliability, ease of upgrade, adaptability, ease of operation/ construction/ demonstration
Đurđević et al.	2020	SST/RR	*Technology selection for sewage sludge energy recovery*	WWTP planned for Rijeka, Croatia	Socio-economic, Environmental, Technical	AHP	Material stabilisation, energy reuse, nutrient recovery, commercial acceptance, product transport/storage, GHG reduction, pre-treatment requirements, hazardous by-products, heavy metal content, public acceptance, OPEX, CAPEX, labour requirements, energy savings, societal contribution
Ali et al.	2020	WWT	*Evaluate and prioritize different wastewater treatment technologies used in Pakistan*	Five WWT alternatives in Pakistan	Undefined	VIKOR	Cost, land requirement, processing time, manpower requirement, efficiency, environmental impact, energy consumption, sludge production, safety, chemical requirement
Gherghel et al.	2020	WWT/SST	*Identify the most suitable treatment scheme for the management of wastewater and sludge*	Large WWTP of 720,000 PE in Italy	Economic, Environmental, Energy, Land Use	AHP	GHG emissions, running costs, service landfill surface, electricity consumption, planimetric size, biorefinery capabilities, landfill requirements
Chrispim et al.	2020	RR	*Support decision-making on resource recovery strategies; to recommend operational and technological strategies*	WWTP in Sao Paulo serving 1.4 million PE	Economic, Social, Environmental and Technical, Political	N/A	Recovery potential, maturity, resource utilisation, skilled labour requirements, product quality, positive environmental impact, CAPEX, OPEX, revenue, logistics, acceptance, accordance with policy and legislation
Liu et al.	2020	WWT	*Optimize the sewage treatment technologies and their combination technologies*	Town in Liao River Basin, China	Economic, Environmental, Social	AHP	Construction cost, land cost, OPEX, removal rate, life expectancy, stability, resource recovery, simplicity, ecological values, risk assessment
Ullah et al.	2020	WWT	*Assist decision-makers to select suitable WWTTs from a set of alternatives*	Two sources of wastewater in Islamabad, Pakistan	Undefined	N/A	Odour, removal efficiency, land use, manpower, financial resources, time availability, chemical availability,

							oxygen requirement, sludge management and disposal
Palma-Heredia et al.	2020	SST/RR	*Selection of the best-fitting sewage sludge valorisation strategies*	WWTP in Spain	Regional Level, Plant Level, Process Level	Fixed	Viability, material circularity, self-sufficiency, risk assessment, NPV, removal efficiency, sludge production, biogas production, efficiency, CAPEX, OPEX
Ling et al.	2021	WWT	*Assess and compare the sustainability of different wastewater treatment options*	Seven WWT options in UK	Economic, Environmental, Social, Resilience	AHP	Energy requirement, land use, pollutant removal, sludge production, RR potential, GHG emissions, public acceptance, odour, noise, visual impact, reliability, complexity, CAPEX, OPEX
Fetanat et al.	2021	WWT/RR	*Prioritize energy recovery from wastewater treatment technologies*	WW management in Behbahan City, Iran	Water Security, Energy Security, Food Security	LAM	Water security (access, safety, and affordability), energy security (availability, accessibility, affordability, acceptability, applicability, and adaptability), food security (availability, access, utilisation, and stability)
Büyüközkan and Tüfekçi	2021	WWT	*Evaluate the most suitable WWT decision system*	WWT selection for a company in Istanbul, Turkey	Economic, Environmental, Technical, Administrative, Management	AHP	Water/energy/discharge/chemical costs, monitoring, waste production, environmental benefits, facility management, NPV, volumetric capacity, water quality, applicability and performance, reliability and sustainability
Lizot et al.	2021	WWT	*Evaluation of WWT systems considering relevant economic, social, technical, and environmental criteria*	Twenty WWT options for a sanitation company in Brazil	Economic, Environmental, Social, Technical	AHP	CAPEX, OPEX, NPV, Land, manpower, reliability, replicability, complexity, removal efficiency, sludge production, GWP, acceptance
Sucu et al.	2021	RR	*Find the optimum treatment train consisting of compatible unit processes which can recover water, energy and/or nutrients*	Large and small WWTP recovering irrigation water	Economic, Environmental, Social, Technical	User Defined	Annual cost, potential income, acceptability, affordability, land area, odour, noise, flexibility
de Almeida et al.	2021	WWT	*Develop and apply a methodology for sewage treatment systems selection*	Benevente River watershed in Brazil	Operational, Technical, Environmental, Social	Multi Attribute Utility Theory	Removal efficiency, energy demand, land use, CAPEX, OPEX, sludge treated, sludge disposed, reliability, simplicity, resistance, odour, noise, aerosol generation, insect attraction

Eseoglu et al.	2022	WWT	*Technology selection problem for wastewater treatment that integrates all aspects of sustainability with the behavioural characteristics of decision makers*	Four WWTPs greater than 100,000 m^3/d Istanbul, Turkey	Economic, Environmental, Social, Technical	AHP	Energy consumption, sludge production, reuse of treated water, capital cost, land required, OM cost, energy saving, sludge disposal cost, removal eff, maturity, simplicity, applicability, replicability, flexibility, reliability, odour, manpower needed, social acceptance, social benefit, aesthetic
Leoneti et al.	2022	WWT	*Choosing a WWTP for a municipality*	Six 40,000 PE WWTP alternatives in Brazil	Economic, Social, Environmental	Game Theory (rank order centroid)	Cost, effluent quality, land area, sludge production
Liu and Ren	2022	SST/RR	*Promote the sustainable decision-making process of sludge management*	Four sludge-to-energy options	Economic, Environmental, Social, Technical	BWM	Climate change, acidification, eutrophication, net cost, social acceptance, governmental support, educational significance, odour, complexity, maturity, accessibility
Attri et al.	2022	WWT	*Sustainability assessment of wastewater treatment technologies*	Six alternatives for secondary WWT	Economic, Environmental, Social, Functional	Fuzzy Stepwise Weighted Assignment Ratio Analysis	Removal efficiency, effluent DO and coliform, NP removal capabilities, area, power requirement, OPEX, CPAEX, odour, noise, visual impact, flexibility, reliability, ease of operation, FOG tolerance, waste sludge production
Renfrew et al.	2022	RR	*Identification of strategies for resource recovery from wastewater*	Priority resource identification for UK water sector	Recovery, Market, Cost, Carbon, Treatment Impacts, 6 Capitals	User Defined	RR potential, market, treatment, cost, carbon, 6 capitals
Nkuna et al.	2022	SST/RR	*Selection of the most viable thermochemical technology to handle municipal WWS for energy recovery*	Three technologies converting WW sludge to energy	Economic, Technical	AHP	Dependability, maturity, sludge use, energy production, energy consumption, CAPEX, OPEX
Južnič-Zonta et al.	2022	RR	*Given a set of resource recovery and wastewater treatment process units, quickly determine the best plant configuration*	Medium size WWTP in Manresa, Spain	Economic, Environmental, Technical	User Defined	Effluent quality, costs, maturity, GHG emissions, area
Silva Junior et al.	2022	WWT	*Select the most appropriate technologies for wastewater treatment*	WWT in urban and rural municipalities in Brazil	Economic, Socio-Environmental, Technical	User Defined	Area demand, quality performance, mechanisation rates, electric power consumption, CAPEX, OPEX, operational complexity, BOD removal

Srivastava and Singh	2022	WR	*Selection of an appropriate wastewater treatment chain that produces effluent suitable for the defined reuse*	WWT technologies for water reuse in Kanpur, India	Economic, Environmental, Technical	Full Consistency Method	CAPEX, OPEX, land use, energy consumption
Salamirad et al.	2023	WWT	*Select the most appropriate municipal WWT technology*	Seven WWTP alternatives in Iran	Economic, Social, Environmental	BWM	Investment cost, reliability, efficiency, volume dependency, requirement for additional treatment, energy consumption, sludge production, odour, workforce requirement, law and regulation compliance, salinity removal, bacteria removal

Table 2.1 summarises DSS properties namely the technologies selected, aim, case study of application, and categories used to group assessment indicators. The four main technology groups selected using MCDM DSSs are; wastewater treatment (WWT), sewage sludge treatment (SST), water reuse (WR) and resource recovery (RR), or a combination thereof. Since 2018, the development of DSSs for the selection of RR technologies has emerged as a priority for decision makers. The aim of each DSS has been directly quoted from the source, as this is key to understanding specific goals of the DSS when selecting appropriate indicators to facilitate desired outcomes. Lastly, the categories as defined by authors when selecting indicators are provided, as this is the first step DSS users and/or developers take when relating their goals to selected KPIs for technology assessment. The assessment category column in Table 2.1 highlights the popularity of using the sustainability dimensions of economic, environmental, social, and technical categories to group indicators. Steps of the reviewed MCDM DSSs are summarised in Figure 2.2, including examples at each stage from the reviewed literature.

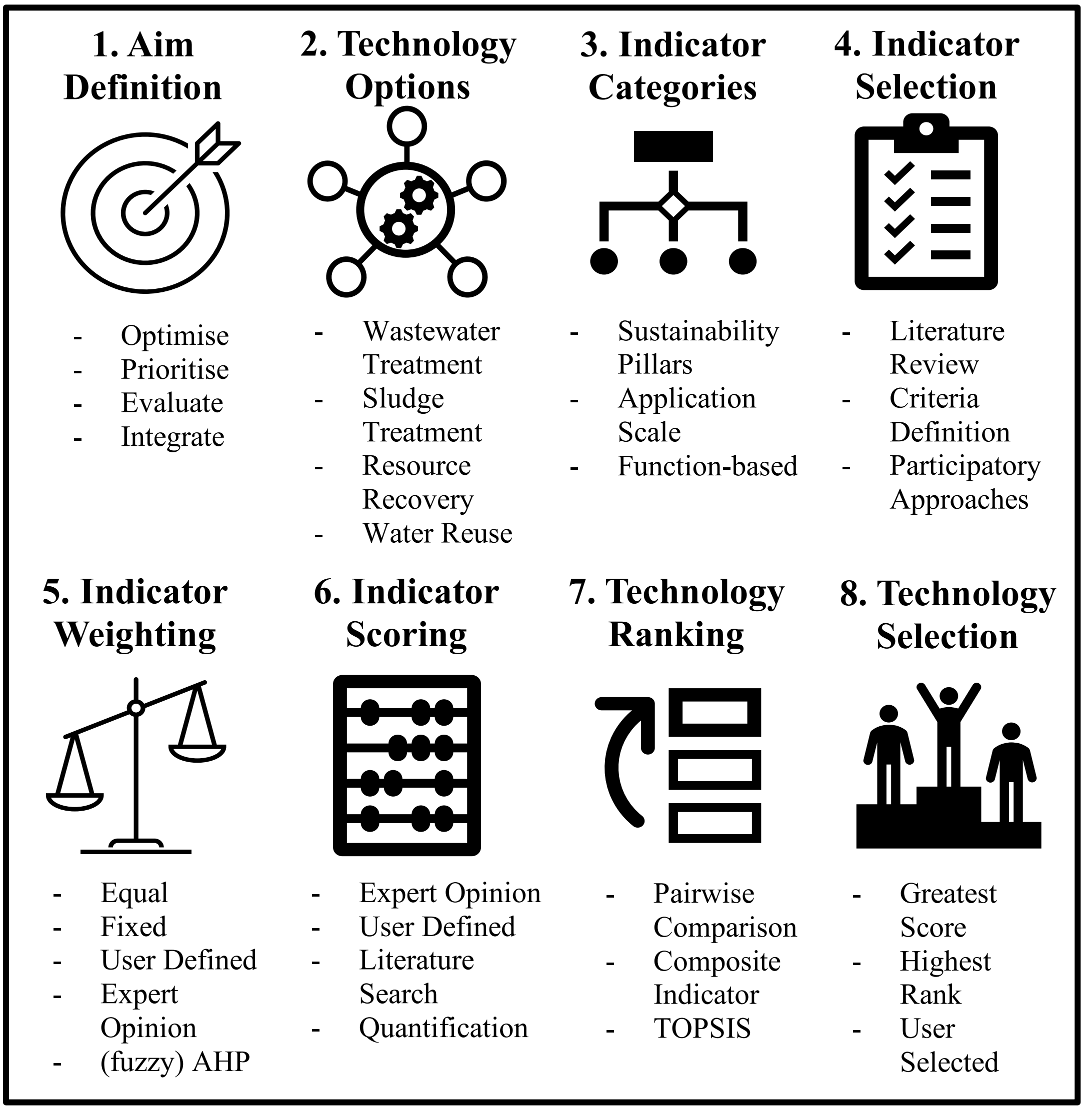


Figure 2.2. Generic steps of MCDM technology selection DSSs, including examples and techniques available for use at each stage.

The thirty-one papers developing MCDM technology selection DSSs were categorised in Table 2.1 based on the type of technology being assessed. Selection of WWT technologies is the most common with fifteen DSSs, as WWT decision making is complex so enhanced and efficient treatment methods are required to meet sector goals. RR is the second most common focus, which can be attributed to the emphasis placed on RR by many DSSs selecting sludge treatment technologies, usually for energy recovery. This highlights the desire of decision makers to make use of a resource that was previously considered a waste during WWT, reflecting modern objectives at a utility and government level to enhance the circularity of their practices. Four DSSs for WR technology selection have been developed, acknowledging that due to global warming, water stress is being exacerbated for many people, requiring water to be utilised in a more efficient way by decision makers. Lastly, two DSSs focused solely on the selection of technologies for sewage sludge treatment, whilst only one was developed that combined technology selection for wastewater treatment and sewage sludge treatment. It is critical to list the type of technologies being selected by a DSS so that the correct assessment criteria or indicators can be integrated. This is reflected by the low number of WWT/SST DSSs, as it is difficult to find a list of selection criteria that are suitable for the assessment of both treatment technologies since their goals and expected outcomes differ.

2.3.1 DSS goals

To ensure that selected technologies will result in the benefits expected by stakeholders and decision makers, the aim of DSS application must be clearly defined. As shown in Table 2.1, the most common aims used vague and generic language for the selection of the most *suitable/appropriate/viable/best-fitting* technology in ten DSSs. Although this reveals the intention of the DSS, rarely are these terms explained in a way that enables the user to understand what these 'suitable' technologies may look like considering the scenario of application. This lack of direction limits wider utilisation of developed DSSs and could explain why most MCDM tools have not been used across multiple case studies. Next, nine DSSs aim for the *identification/selection/prioritisation/recommendation* of technologies for a specific function, including non-potable water reuse or resource recovery strategies. Although this instructs the user with regards to the expected function of selected technologies, it does not provide any justification as to the reasoning for their selection. Third, the aim of seven DSSs is to select sustainable or assess the sustainability of alternatives. This is not useful unless a vision of sustainable wastewater treatment is defined by the DSS developers, as users cannot fully understand how to assess and compare the sustainability of alternatives. *Evaluation/analysis* of technologies utilising specified criteria such as environmental or economic aspects is another common DSS aim, with three identified from the collated list. These highlight the assessment criteria used to select technologies but does not provide the user with adequate reasoning of why they should implement the technologies. Finally, two DSSs aim to *optimise* or *find the optimum* solution, which is difficult to comprehend unless the objectives being optimised are explicitly defined. Without a clear definition of DSS aims, there is a disconnect in user knowledge, as the aim is key for understanding why a DSS is implemented and selecting the correct indicators to facilitate desired outcomes. Therefore, vague language must be mitigated, and complete definition of aims is encouraged from DSS developers to help users implement technology selection tools correctly.

2.3.2 Indicator selection

As discussed, selection of assessment indicators or criteria when using any WWTP DSS is crucial to ensure that the chosen technology fulfils decision maker and stakeholder goals. Therefore, the methodologies implemented for indicator selection by the reviewed MCDM tools are scrutinised and summarised in Figure 2.3.

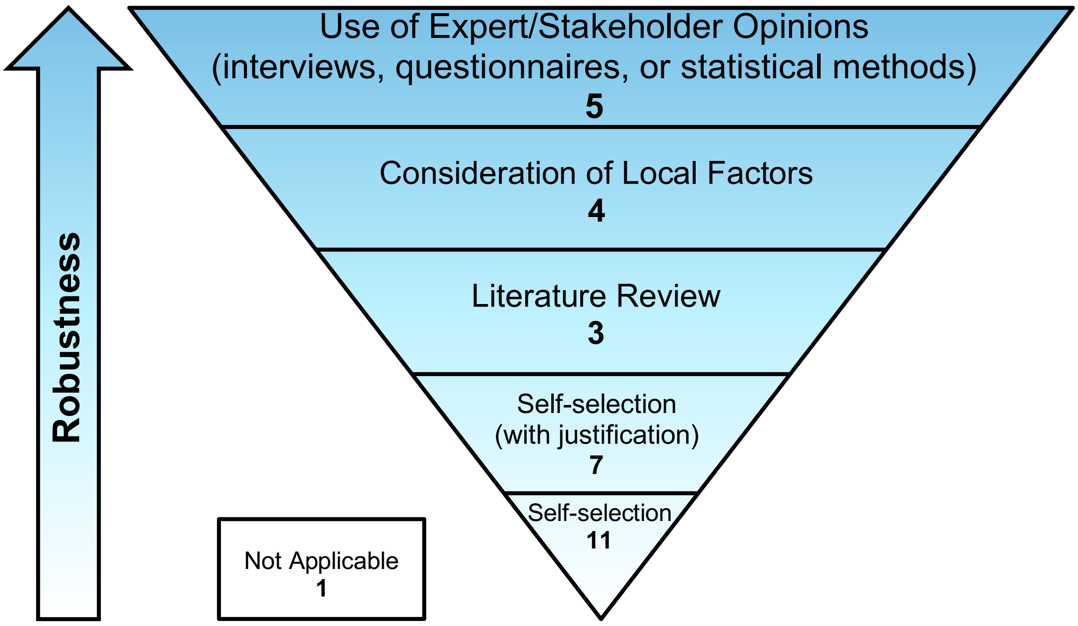


Figure 2.3. Methods of indicator selection used by MCDM technology selection DSSs, with the number DSSs using each method in bold.

Figure 2.3 shows that it is common for DSS developers to self-select indicators or provide a list to users from which they can choose indicators, with little methodological explanation given (An et al., 2018; Castillo et al., 2016; Chhipi-Shrestha et al., 2017; Chrispim et al., 2020; Fetanat et al., 2021; Garrido-Baserba et al., 2015; Gherghel et al., 2020; Južnič-Zonta et al., 2022; Renfrew et al., 2022; Srivastava and Singh, 2022; Sucu et al., 2021). This results in a significant gap in DSS user knowledge, as they are unable to reason whether the selected indicators are relevant to their scenario of application. In these cases, data availability can be used to guide indicator selection, as users should rely on primary data where possible or secondary data that can be acquired through reasonable effort, such as modelling, whilst meeting data quality requirements. To improve the robustness of indictor selection, some authors define criteria or provide additional justifications that can be used to choose appropriate indicators from literature (Arroyo and Molinos-Senante, 2018; Attri et al., 2022; Liu and Ren, 2022; Molinos-Senante et al., 2014; Nkuna et al., 2022; Palma-Heredia et al., 2020; Sadr et al., 2018). For example, Molinos-Senante et al. (2014) reasons indicators selection using *transparent, representative, relevant and quantifiable* evaluation criteria, however, definitions of these terms are not provided potentially resulting in ambiguity for the user.

More complete approaches conducted structured literature reviews for indicator selection (da Silva Junior et al., 2022; Leoneti et al., 2022; Lizot et al., 2021). Lizot et al. (2021) describes the terms entered into literature search engines to collect assessment criteria utilised by other WWT MCDM tools, and then lists specific information and data availability requirements applied to create indicator shortlists. However, only a short description of shortlisting steps is given which focuses on technical aspects (such as plant load, location, or size), rather than sustainability goals. Alternatively authors used knowledge of local factors to select appropriate DSS indicators from literature (de Almeida et al., 2022; Oertlé et al., 2019). Đurđević et al. (2020) utilised their own judgement to select DSS indicators considering the state of wastewater and sewage sludge management, socio-economic standards, and available data (from national databases) in the local area. Liu et al. (2020) provides an explanation of the local context for each indicator provided, such as using economic costs as the project may *need some financial support from the community* or process simplicity *due to the lack of professionals* for operation. This strategy encourages the DSS user to consider local factors during decision making, however, a more robust approach is to use local stakeholder perspectives as well.

Some DSS developers recognise the importance of rigorous indicator selection to achieve desired outcomes by utilising external expert or stakeholder opinions, for example to screen assessment criteria from a longlist identified during literature review (Ali et al., 2020; Salamirad et al., 2023). Ling et al. (2021) developed a method starting with a round of literature review to collate indicators previously used to evaluate WWT performance. The list is then refined based on key terminology mentioned during interviews (thematic analysis using Nviva software) with water company employees utilising the DSS. Eseoglu et al. (2022) employs the use of a questionnaire study by experts from across many roles in WWTPs from design to operation, and combines this with other information including effluent discharge regulation, environmental impacts, and design parameters. These DSSs acknowledge that indicator selection is an important part of strategic MCDM, and the combination of stakeholder views with technical appraisal of local factors enables the user to select indicators which adequately reflect their goals. Figure 2.3 highlights that these more robust indicator selection methods are less popular, helping to answer the research question by reporting a lack of robust methods for indicator selection in most of the DSSs developed for WWTPs.

The specific indictors selected showed that only two DSSs did not utilise economic indicators (Chrispim et al., 2020; Fetanat et al., 2021), with most the common being capital and operating expenditure, whilst others chose life cycle costing (LCC) (Chhipi-Shrestha et al., 2017) and net present value analysis (Lizot et al., 2021). Removal efficiencies of regulated wastewater constituents, including total suspended solids (TSS), chemical oxygen demand (COD), biological oxygen demand (BOD), nitrogen, and phosphorus, were commonly selected to determine treatment performance (Arroyo and Molinos-Senante, 2018; Eseoglu et al., 2022; J Ling et al., 2021; Liu et al., 2020; Molinos-Senante et al., 2015; Silva Junior et al., 2022). Indicators of environmental performance covered GHG emission (Gherghel et al., 2020; Južnič-Zonta et al., 2022; Jiean Ling et al., 2021), carbon footprint (Chhipi-Shrestha et al., 2017; Renfrew et al., 2022), and life cycle assessment (LCA) (usually eutrophication, climate change, and acidification) impacts (Castillo et al., 2016; Lizot et al., 2021). Effort was made to consider the social impacts of technologies, commonly their odour and noise aspects (Eseoglu et al., 2022; Oertlé et al., 2019; Sucu et al., 2021), whilst some quantified microbial (Chhipi-Shrestha et al., 2017) and ecological risks (Liu et al., 2020). In most cases, circularity indicators were combined with environmental KPI sets, including water reuse (Eseoglu et al., 2022; Lizot et al., 2021), resource or product recovery potential (Chrispim et al., 2020; Renfrew et al., 2022), and material circularity (Palma-Heredia et al., 2020). Lastly, technology energy consumption was one of the most commonly selected indicators, however, only a few DSSs consider renewable energy (Lizot et al., 2021), energy reduction (Durdević et al., 2020), or self-sufficiency (Palma-Heredia et al., 2020) dimensions.

From this it is clear that DSS developers select indicators from across the triple bottom line to support sustainable performance, but there is a gap in terms of facilitating sustainability targets and circularity assessments. Few KPIs are explicitly selected to quantify progress towards the high-level water sector targets of Section 2.2.1 by failing to link indicator selection with targets such as GHG reduction, phosphorus recovery, or energy neutrality. This even includes those DSSs with the aim of selecting technologies for sustainable and circular actions, such as water reuse or energy recovery.

2.3.3 Indicator categorisation

Often criteria or indicators are categorised to show user assessment priorities and indicate potential benefits or impacts of selected technologies. Table 2.1 defines the DSSs categories employed to separate indicators and shows that twenty of the thirty-one DSSs utilise discrete sustainability pillars. The most popular combination uses four environmental, economic, social, and technical (assumed interchangeable with *functional, operational,* or *resilience*) categories. Nine DSSs used a combination of other categories defined by the developers, and some did use sustainability pillars, however, they were combined to create hybrid socio-economic or -environmental categories. Many DSSs also utilise circularity KPIs, however, as mentioned in Section 2.3.2 they are categorised as environmental indicators. This is worrying as enhancing the circularity of wastewater resources does not directly correspond to improved environmental performance. This leads to a significant gap in decision maker knowledge as circularity indicators are being used to as a substitute for sustainability impacts. Therefore, DSSs with circularity objectives, such as resource recovery, need standardised assessments that use CE indicators to evidence enhanced resource circularity, supported by sustainability analysis to quantify wider benefits. This will facilitate technology selection that simultaneously meet the water sector sustainability and circularity targets detailed in the European Green Deal and CEAP.

Some DSS developers created hybrid categories including socio-economic (Đurđević et al. 2020) and socio-environmental (Silva Junior et al., 2022), or combined environmental and technical categories together (Chrispim et al., 2020). This suggests authors may be unsure as to which categories some indicators belong. This is further perpetuated by authors placing the same indicators in different sustainability pillar categories. For example, WWT technology removal efficiencies have been placed in environmental sustainability (Liu et al., 2020; Lizot et al., 2021; Molinos-Senante et al., 2014) and technical categories (Eseoglu et al., 2022; Silva Junior et al., 2022). This may explain the increase in popularity of using the four pillars of sustainability for categorisation in recent years, as it enables delineation of operational and environmental KPIs, highlighting the desire of decision makers to understand the environmental impacts of potential technologies more clearly. However, this seems to result in some confusion regarding the objectives of certain indicators, such as GHG/carbon footprint, as Đurđević et al. (2020) defines this as a technical indicator, whereas Lizot et al. (2021) utilises it as an indicator of environmental performance. Similarly, odour and noise indicators are placed in both environmental (Sucu et al., 2021) and more commonly social categories (Eseoglu et al., 2022; Lizot et al., 2021; Molinos-Senante et al., 2014). These differences evidence the need to enhance sustainability/circularity assessment knowledge and develop standardised methods for KPI selection and categorisation.

The popularity of indicator categorisation using sustainability pillars has led to some DSS developers using this method even when their defined aims do not refer to sustainable technology selection. To combat this, some authors generated their own indicator categorisation strategies. Fetanat et al. (2021) developed indicator categories using the water-energy-food nexus framework to view wastewater as a renewable energy source, which aligns with the DSS goal to prioritise energy recovery from WWT. Palma-Heredia et al. (2020) created an indicator hierarchy depending on the scale of the application, therefore allowing decision makers at regional, WWTP, and operational levels to prioritise certain indicators. Although these categorisation methods are not as established in literature as sustainability pillars, developing indicator categories which consider DSS goals may be a more effective way for users to understand the indicators required to achieve their aims, especially whenever sustainable technology selection is not the objective. However, it can be concluded there is confusion when categorising selected indicators and how this activity aligns DSS outcomes with decision maker goals.

2.3.4 Indicator weighting

Weighting of MCDM indicators is a critical stage for DSS users, as it enables them to prioritise or mitigate specific criteria that may align or conflict with their objectives. Therefore, the frequency of each technique implemented by DSS developers for indicator weighting is provided in Figure 2.4. The MCA discussed are those currently employed by water sector DSSs and does not reflect best practices for multi-attribute decision making.

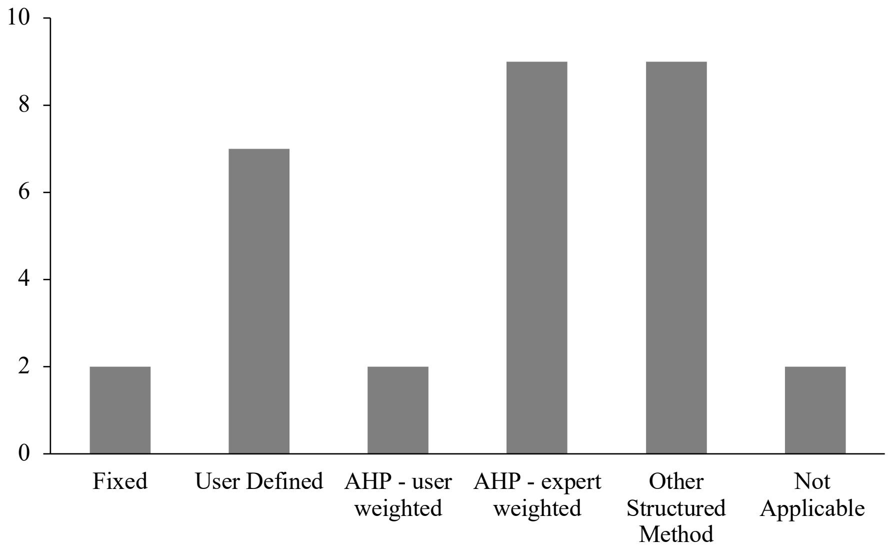


Figure 2.4. Methods used to weight indicators for MCDM technology selection DSSs.

It is common for indicators to be weighted according to the DSS user, and then a weighted summation is simply calculated to create a composite indicator used to analyse technologies. Garrido-Baserba et al. (2015) and Palma-Heredia et al. (2020) develop DSS weights for indicators that are predetermined and fixed, and given equal weighting respectively. Although this simplifies DSS usage, this weighting system is not recommended as it does not provide users with the ability to tailor KPI impacts to reflect their goals, which can be viewed as undermining the principles of MCDM. Another method commonly employed by DSS developers is to allow users to define weights themselves, (Castillo et al., 2016; Chhipi-Shrestha et al., 2017; Južnič-Zonta et al., 2022; Oertlé et al., 2019; Renfrew et al., 2022; Silva Junior et al., 2022; Sucu et al., 2021), however, DSS users can be faced with more than 20 indicators so assigning weights without a structured methodology of comparing indicators can lead to inconsistencies during analysis. This can result in indicator weightings that do not align adequately with aims and lead to bias in the assessment. Therefore, techniques are employed by DSS developers enabling structured analysis of indicators using opinions of experts and stakeholders.

The analytical hierarchy process (AHP) is the most common weighting method used by reviewed DSSs with eleven. AHP was proposed by Saaty (1987) for decision making influenced by multiple independent factors (Liu et al., 2020). It investigates the relationship between criteria to create a hierarchy from which they can be prioritised (Eseoglu et al., 2022), often utilising external experts and stakeholders to create pair-wise comparisons. Therefore, many DSSs reviewed use standard AHP for weighting indicators (Đurđević et al., 2020; Gherghel et al., 2020; Jiean Ling et al., 2021; Lizot et al., 2021; Molinos-Senante et al., 2014; Nkuna et al., 2022). However, Ling et al. (2021) reported rarely seeing extreme scores on the judgement scale, and when the full scale was used the threshold consistency ratio (compares the weighting matrix against a random matrix, acceptable value of ≤0.1) is often not achieved. To overcome the uncertainty due to imprecise human judgements or ambiguity, fuzzy logic is implemented (Eseoglu et al., 2022). Many DSSs employ fuzzy-AHP weighting (An et al., 2018; Büyüközkan and Tüfekçi, 2021; Eseoglu et al., 2022; Liu et al., 2020; Sadr et al., 2018), providing a structured method of indicator weighting whilst mitigating inconsistencies of human thinking.

Apart from AHP, DSS developers integrated a variety of weighting methods (Ali et al., 2020; Attri et al., 2022; de Almeida et al., 2022; Fetanat et al., 2021; Leoneti et al., 2022). Arroyo and Molinos-Senante (2018) implement Choosing-By-Advantages (CBA), citing several improvements over AHP including that it does not assume linear trade-offs between criteria. CBA encourages DSS users to understand the differences between criteria and assesses the importance of these differences, as supposed to AHP which can create conflicting questions. The Best-Worst Method (BWM) used by Liu and Ren (2022) and Salamirad et al. (2023) provides a simpler weighting step for decision makers as the number of comparisons is reduced, improving the consistency ratio of results and removing much of the uncertainty during pairwise comparisons. Srivastava and Singh (2022) simplify weighting even further by employing the Full Consistency Method, minimising the number of comparisons to achieve consistent results.

Lastly, some DSS developers recommend the use of 'experts' without actually defining whom this might include (Attri et al., 2022; Liu et al., 2020), collecting opinions from stakeholders with little knowledge of the investigated system or local area, leading to inconsistent results. Whereas Eseoglu et al. (2022) utilises expert opinions from every stage of WWT including design, construction and operation engineers, and Gherghel et al. (2020) acknowledges the viewpoints of stakeholders from six different specialities, such as political, environmental, and plant operator stakeholders to ensure the holistic collection of viewpoints. Therefore, stakeholders with a range of expertise that understand local factors for indicator weighting should be used to reduce bias and inconsistency.

Generally, the majority of DSSs in this study rely on AHP to weight criteria, which is corroborated by other reviews in the area (Kozłowska, 2022; Zolghadr-Asli et al., 2021), potentially incorporating high levels of uncertainty. Therefore, to ensure better indicator utilisation fuzzification and consultation of relevant experts can be used to reduce uncertainty. Additionally, methods recommended in literature, not utilised by the water sector DSSs reviewed, to mitigate weighting procedure errors are the entropy method for objective weight assignment or analytical network process (ANP) to account for correlations between criteria (Zolghadr-Asli et al., 2021).

2.3.5 Indicator scoring

A range of methods to score assessment indicators have been utilised due to the variety of scales and units of indicator results, and often the mix of quantitative and qualitative indicators selected. Linguistic (such as very bad to very good) or numerical (can be from 0 up to 10) series are commonly integrated to normalise results enabling their combination. Several DSSs rely on the experts used for indicator weighting to assign numerical ratings directly based on their opinion (Đurđević et al., 2020; Jiean Ling et al., 2021; Renfrew et al., 2022), usually when there is lack of empirical data (Jiean Ling et al., 2021). Alternatively, Fetanat et al. (2021) relied on linguistic terms to rate technology alternatives as the indicators selected were immeasurable (such as energy security availability).

Literature searches were used to establish numeric ranges of indicator results for each technology assessed (Attri et al., 2022). Silva Junior et al. (2022) collected data from technical-scientific literature relevant to case study location and assigned the final result by calculating the mean of the data range found. Before combination of indicator results, they were normalised to a value between 0-1 using the lowest and highest value observed for each parameter. Rather than quantitatively normalising values collected from literature, Liu and Ren (2022) utilised a linguistic scale of five from *very good to very poor*, whilst Lizot et al. (2021) created ranges for each indicator to assign a numeric value to normalise quantitative indicator scores.

Lastly, a common method for assigning scores to indicators is to directly quantify results (except for the indicators which are inherently qualitative). It was observed that most environmental and economic indicators were quantifiable, whilst technical and social indicators were qualitatively scored (Castillo et al., 2016; Leoneti et al., 2022; Liu and Ren, 2022; Molinos-Senante et al., 2014). Quantitative calculation of each indicator investigating technology performance is recommended, as it incorporates specific details and local factors of the case study. Relying on the judgement of DSS users or external experts enables uncertainty through the ambiguity or bias of human decision making to incorrectly score technologies. Furthermore, the use of values extracted from literature can mitigate the influence of local factors which can be pertinent for economic and technical indicators. Of course, when using qualitative indicators to investigate social aspects, local stakeholder views should be used to score technologies, due to their greater understanding of potential impacts in a given region.

2.3.6 Ranking

The final step is to rank technologies for selecting the technology which supposedly best meets user requirements. Palma-Heredia et al. (2020) presents KPI results and recommends the DSS user to complete pairwise comparisons for technology selection. Although this is a simple method of completing the final ranking, extensive indicator lists create complexity and inconsistencies in user judgement. Therefore, the most common method of technology ranking employed by DSS developers is to create a composite indicator using the weighted sum method (Castillo et al., 2016; de Almeida et al., 2022; Garrido-Baserba et al., 2015; Gherghel et al., 2020; Liu and Ren, 2022; Molinos-Senante et al., 2014). This synthesises indicator scores and their corresponding weights into a single performance index used to rank and select technologies (Jiean Ling et al., 2021).

In the cases where multiple experts or stakeholders are used to weight or score assessment indicators, systematic analysis of results is needed to rank and select technologies. The technique for order of preference by similarity to ideal solution (TOPSIS) is commonly coupled with AHP. TOPSIS selects the best alternative based on the shortest distance to the ideal solution and the farthest distance from the negative-ideal solution in geometric terms (Južnič-Zonta et al., 2022), to intensify the correctness and validate selection of the most appropriate technology (Nkuna et al., 2022). When fuzzification of data has occurred during indicator weighting, to improve the robustness of outcomes, this can be continued to complete fuzzy-TOPSIS (Attri et al., 2022; Büyüközkan and Tüfekçi, 2021; Eseoglu et al., 2022; Liu et al., 2020; Sadr et al., 2018). Another method employed to overcome the uncertainty of comparative analysis, is fuzzy-VIKOR as used by Ali et al. (2020), which utilises positive and negative characteristics to define compromises when conflicting views cause issues with decision making. This is achieved by calculating three variables to establish the summation and maximum distance from the best value, which are then combined to calculate an overall score.

Alternatively, Leoneti et al. (2022) implements game theory to determine the preferred option from the list of acceptable outcomes, selecting the technology that maximises the Nash equilibria social welfare function. Lastly, Fetanat et al. (2021) utilised the linear assignment method (LAM) to rank technologies for energy recovery from WWTs. This method is chosen as it ranks alternatives according to conflicting criteria, by analysing the trade-offs between the ranking of each indicator for each technology. Therefore, LAM may be beneficial as wastewater and sewage sludge treatment shifts to prioritise other functions, such as resource recovery or water reuse. Studies in this area agree that TOPSIS is the most common ranking procedure (Štilić and Puška, 2023), however, best practice depends on the scenario of application. Methods such as the preference ranking organization method for enrichment evaluation (PROMETHEE) and elimination and choice expressing the reality (ELECTRE) methods are suited to handle conflicting stakeholder priorities (Štilić and Puška, 2023), whereas fuzzy logic and use of experts from as many specialities as possible should be used to tackle subjective ranking issues (Garcia-Garcia, 2022).

2.3.7 Uncertainty

There are various types of uncertainty that exist in MCDM that can arise at each step of DSS utilisation resulting from: variation, ambiguity, and incomplete preferences of human inputs; lack of system, parameter, data, external factor, or model knowledge; and prediction of outcomes or future events (climatic or socio-economic changes) (Walling and Vaneeckhaute, 2020). There are many methods to deal with MCDM uncertainty, one being fuzzification of scoring, weighting, and ranking procedures reliant on human judgement, as previously discussed in Section 2.3.4, 2.3.5, and 2.3.6. Alternatively, sensitivity analysis is able to provide decision makers with insights into the uncertainty resulting from erroneous modelling of the assessed system or potential/future scenarios.

Scenario investigation is a widely applied method of sensitivity analysis, in which MCDM indicator weighting is altered to reflect different viewpoints or future situations. For example, Molinos-Senante et al. (2014) and Salamirad et al. (2023) conducted scenario analysis by favourably weighting environmental, economic, and social KPIs in turn, validating the selected technology (constructed wetlands and integrated fixed-film activated sludge respectively) still ranked highest under alternative weighting schemes. Alternatively, Renfrew et al. (2022) improved the robustness of technology selection by weighting KPIs based on potential future scenarios, including legislative changes for emissions compliance and carbon footprint reduction, and selecting technologies based on their average performance across the scenarios. Furthermore, global sensitivity analysis (GSA) was utilised to verify that technology ranking is robust to fluctuating inputs over a +/-10 % range and investigate which parameter's uncertainty have the largest impact on MCDM outcomes, educating future assessments (Renfrew et al., 2022). Lastly, Južnič-Zonta et al. (2022) aimed to use Monte-Carlo (MC) simulations to overcome probabilistic uncertainty of bio-chemical modelling processes to configure design parameters, before technology ranking is calculated and verified over each iteration (however this was not included in case study). Therefore, if potential errors are likely to be introduced by MCDM structure or case study that impact outcomes, then sensitivity analysis (scenario or global) should be used to validate the robustness of DSS results.

2.3.8 Recommendations

As discussed, there are already many reviews of DSS typologies in the literature, therefore, the review focuses on how indicator usage can be improved based on the methods currently implemented for WWTP technology selection. Therefore, following the review of thirty-one MCDM DSSs final recommendations and comments are provided in Table 2.2. Unfortunately, Sections 2.3.2 and 2.3.3 highlight the significant gap related to the utilisation of circularity and sustainability indicators, mainly that circularity aspects are used to investigate environmental performance and the lack of alignment with water sector goals reported as part of European Green Deal and CEAP. Additionally, WWTP DSSs still rely on user defined weighting, scoring, and ranking procedures, or structured methods, such as AHP and TOPSIS, which have issues with introducing uncertainty to the assessment. Generally, decision making in the water sector is still some distance from standardisation and harmonisation of sustainability and circularity assessments.

Table 2.2. Summary of issues, recommendations, and beneficial outcomes related to the reviewed wastewater treatment MCDM technology selection DSSs.

Issue	Recommendation	Outcome
Few DSSs provide a clear definition of aims or goals	Defining the goal and scope of the assessment should become common practice, as the first step of DSS development or application	Help decision makers understand the desired outcome of DSS utilisation
Rigorous indicator selection is often overlooked by DSS developers and do not consider high level water sector goals	Utilise participatory methods to incorporate local stakeholder, business (water utility), and regional/governmental objectives	Technology selection using KPIs that adequately reflects desired results and facilitate sector transformation
Indicator categorisation is often unclear resulting in inconsistencies across DSSs, mitigating circularity objectives	Use categorises that reflect the intentions of the DSS, helping to create more robust weighting strategies and consider CE targets of the water sector	Help to select and group relevant indicators, such as using sustainability pillars when selecting sustainable technologies, and mitigate the alignment of CE metrics with sustainability impacts
Expert or user defined weighting schemes can lead to a lack of local factor consideration	Stakeholders with an understanding of the local area from a range of job roles should be used for indicator weighting	Ensures that DSSs select technology that will meet the local demands in each scenario of application and reduce uncertainty of results
Unstructured or subjective weighting and ranking methods can lead to uncertain outcomes	Consider the specific issues of each DSS application to decide which method should be used to reduce uncertainty, such as entropy methods to enhance the objectivity of weighting, and either fuzzy logic to reduce human error or PROMETHEE/ELECTRE to overcome conflicting priorities during ranking	Remove the inconsistency and reduce uncertainty that can arise when human inputs are used to weight and rank indicators
There is little critical analysis of final technology selection in relation to decision maker goals	Techniques such as sensitivity analysis should be applied to investigate DSS outcomes	Ensure that the method is consistent across alternative scenarios, enhancing robustness of final technology selection

It is worth noting that analysis of DSS case studies showed that economic indicators were commonly prioritised during the weighting stages (Eseoglu et al., 2022; Liu et al., 2020; Lizot et al., 2021; Sadr et al., 2018). The CBA method employed by Arroyo and Molinos-Senante (2018) excluded economic indicators during the initial assessment, prioritising environmental and social factors, as monetary resources available are usually the constraint for any project. Environmental and social indicator results are then plotted against cost to facilitate the selection of the best technology option. Authors highlight the impacts of this by comparing AHP with CBA and showed that by considering economic factors alongside environmental and social indicators, unfavourable impacts were offset by low capital and operating costs. Therefore, as governments demand improved environmental and social performance of WWT in the coming years, to achieve targets such as net zero, the exclusion of economic indicators from initial assessment may be favoured.

2.4 Multi-objective optimisation control

Following the selection of technologies, another type of DSS is needed for multi-objective optimisation of WWTP process operation and control. It is necessary to conduct distinct analysis of these DSS types as they are utilised differently by decision makers. Therefore, alternative methods and indicators are required, as it was seen that technology selection DSSs focus on sustainability KPIs whereas operational optimisation DSSs target cost and regulatory (effluent quality) aspects. Table 2.3 summarises the multi-objective process optimisation WWTP DSSs collected from literature, resulting in the review of twenty-six articles.

Table 2.3. Summary of multi-objective control DSSs for optimisation of WWTP operation.

Author	Year	Control	Aim	Application	Objective Function
Qiao et al.	2018	Dynamic	*Achieving the effluent quality (EQ) requirements and minimizing the EC*	BSM1	Energy consumption (EC) and EQI
Díaz-Madroñero et al.	2018	Static	*Develop more sustainable water systems*	2,500 PE WWTP in Alicante, Spain	Total connections costs, total freshwater use, and total regenerated freshwater use
Han et al.	2018	Dynamic	*Optimal control operation with EC reduction while retaining standard EQ*	BSM1	EC and EQI
Qiao and Zhou	2018	Dynamic	*Acquire the balance between EC and EQ with the usage of the best set points*	BSM1	EC and EQI
Qiao et al.	2019	Dynamic	*Suitable set-points to balance the treatment performance and the operational costs*	BSM1	EQI and EC
Zhou and Qiao	2019	Dynamic	*Optimal control strategy is designed to reduce EC without violating effluent standards*	BSM1	EQI and OCI
Pisa et al.	2019	Dynamic	*Reduction of the number of violations as well as the improvement of WWTP's EQI and OCI metrics*	BSM2	EQI and OCI
Dai et al.	2019	Dynamic	*Optimal modification of an anaerobic–anoxic/nitrifying/ induced crystallization (A2N-IC) process*	ASM-2D	EQ, operating cost, and total volume
Borzooei et al.	2019	Static	*Evaluate and improve existing process performance in addition to optimize the production of renewable energy*	2 million PE Castiglione Torinese WWTP, Italy	EQI and ECI
Mannina et al.	2020	Static	*Optimization ... in terms of operational costs and direct greenhouse gases emissions.*	Pilot plant MBR	Effluent Fine, EQI (liquid and gas), oxygen-to-total-Kjeldahl-nitrogen ratio, ratio nitrate-ammonia, CO_2 and N_2O emissions, and direct and indirect GHG emissions.
Revollar et al.	2021	Static	*Improving the eco-efficiency of WWTPs*	BSM2	EQI, OCI, Net energy, Excess heating energy, Electricity consumption, Energy/Pollution removed, Energy net/Pollution removed, Violations of the permit limits of effluent N, NH_4 and COD
Heo et al.	2021	Dynamic	*Operate at cost-efficient and sustainable WWTP*	BSM2	EQI, OCI, CH_4 reutilised as energy source
Ortiz-Martínez et al.	2021	Dynamic	*Optimize an economic cost term and an effluent quality index*	BSM1	EQI and economic cost
Han et al.	2021	Dynamic	*Achieve excellent treatment performance for a WWTP*	BSM1 and 10,000 m^3/d WWTP Beijing, China	EC and EQI
Tejaswini et al.	2021	Dynamic	*Enhance the performance of the WWTP by optimizing the parameters of the default control strategy*	BSM1	EQI and OCI

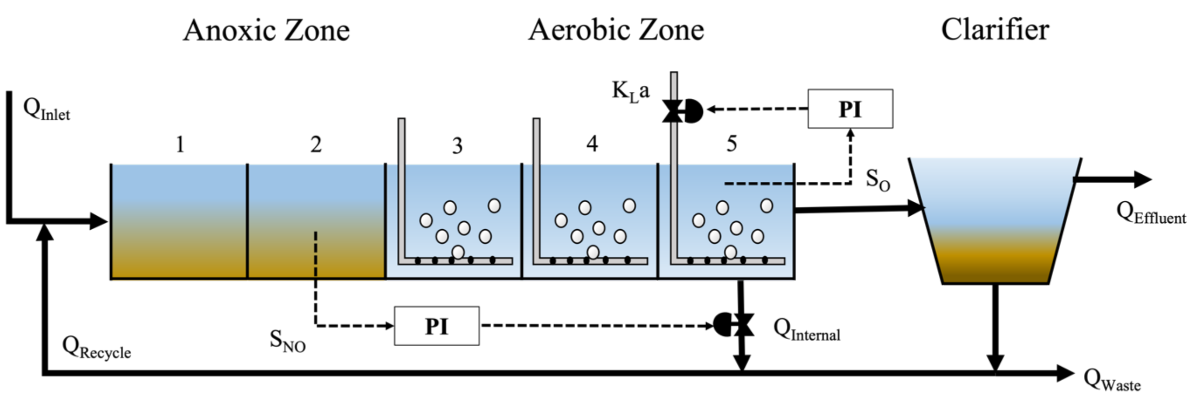
Chen et al.	2021	Static	*Obtain sustainable control strategies*	10,000 PE WWTP Jiangsu Province, China	LCC and three LCA impact indicators (energy consumption, eutrophication, GHGs)
Campana et al.	2021	Dynamic	*Reduce WWTP operating costs, improving at the same time treated effluent quality*	86,400 PE WWTP, Italy	Self-sufficiency ratio and net present cost
Li et al.	2021	Dynamic	*Meet the requirements of effluent quality and maintain sustainable operation with the lowest energy cost*	BSM1	EC and EQI
Fox et al.	2022	Dynamic	*Best setup that can enable optimal operational, environmental and energy performance*	Residential development SBR	NH_4 removal, prediction error, treatment time reduction
Xie et al.	2022	Dynamic	*Achieve tracking control of the main operating variables of the WWTP*	BSM1	EC and EQI
Niu et al.	2022	Dynamic	*Optimize EQ and EC in wastewater treatment process*	BSM1	EC and EQI
Han et al.	2022	Dynamic	*Optimal control strategy is proposed to improve the performance of WWTP*	BSM1	EQI, pumping energy, aeration energy
Caligan et al.	2022	Static	*Minimize the system's overall economic costs and environmental greenhouse gas emissions*	Wastewater sludge to bioenergy park	Cost and GHG emissions
F. Li et al.	2022	Dynamic	*Optimize the control of WWTPs*	BSM1	EC and EQI
Han et al.	2022	Dynamic	*Guarantee satisfactory EQ and EC with the excellent control accuracy of WWTP*	BSM1	EC and EQI
Du and Peng	2023	Dynamic	*Optimal control of wastewater treatment process*	BSM1	EC and EQI

Table 2.3 shows that there has been an increase in the number of publications in this area, growing from four in 2018 to seven in 2022 which coincides with the availability of Benchmark Simulation Model (BSM) 1 and BSM2 (IWA, 2018) for testing WWTP control strategies. It was noted that some authors have published multiple papers in this area in recent years, testing different algorithms to find the optimal control strategy on the same simulation platform. DSSs were then categorised depending on their ability to optimise the control of process operation dynamically or statically. They were classified as dynamic if they could respond to changes in real-time to find the optimal control parameters, whereas static systems relied on user defined values and then calculated KPIs utilising model results. Most DSSs were dynamic, which corresponds with use of BSMs as time series data across three weather conditions is available for simulation testing (IWA, 2018). Generally, DSS aims were stated in clearer terms than those for MCDM technology selection, often stating which performance parameters or KPIs are being targeted for optimisation. Most DSSs were not applied to real case studies and applied to BSMs

instead due to the complexity and non-linearity of WWTP modelling. This reliance results in little variation of the type or number of KPIs selected to optimise systems, as BSMs have predefined KPIs related to effluent quality and energy consumption/cost.

As shown in Figure 2.5, the BSM1 plant is a 5-compartment activated sludge reactor modelled using Activated Sludge Model (ASM) 1, with configuration facilitating nitrification-denitrification for biological nitrogen removal. The model utilises proportional-integral (PI) controllers to control the dissolved oxygen (DO) level by manipulating the oxygen transfer coefficient, and nitrate level setpoints by changing the internal recycle rate in the fifth and second compartments respectively (IWA, 2018). The performance assessment of the plant is based on two main KPIs; the effluent quality index (EQI) and overall cost index (OCI). The EQI is the weighted sum (weightings from literature) of effluent contaminant TSS, COD, BOD, Kjeldahl nitrogen (TKN), and nitrate (NO_3^-). The other indicator is the OCI which combines cost factors of sludge production, aeration energy, pumping energy, mixing energy, and external carbon consumption (Alex et al., 2018). BSM2 utilises the same wastewater treatment process, with the addition of sludge anaerobic digestion. Therefore, the OCI is updated to balance heat energy required and energy generated from methane production. It is also stated that the number of effluent limit violations and amount of time limits are not met must be reported, meaning operation is constrained by discharge limits of $NH_4 \leq 4$ mg/l; total nitrogen (TN) ≤ 18 mg/l; TSS ≤ 30 mg/l; BOD≤ 10 mg/l; COD ≤ 100 mg/l (Alex et al., 2018).

Figure 2.5. BSM1 process flow diagram and control systems based on figure from IWA (2018) where Q is the



flowrate, S is the set point, PI is the controller, and K_La is the transfer coefficient.

2.4.1 DSS goals

In Section 2.3 it was revealed that MCDM technology selection DSS aims are too generic, meaning it is difficult to relate indicator selection to desired outcomes. Many of the multi-objective process optimisation DSSs reviewed in Table 2.3 take the opposite approach, as twelve stated the KPIs targeted for optimisation in their aims. This definition enables users to clearly understand the outcomes that can be expected when implementing this optimisation technique, however, many of these DSSs relied on BSMs meaning there is little flexibility in the indicators utilised. Another helpful method of defining DSS aims for the user is to identify its specific function. For example, Borzooei et al., (2019) and Revollar et al. (2021) aimed to *optimise the production of renewable energy* and improve the eco-efficiency of WWTPs respectively, making it clear to users the reasons for implementing this DSS and selecting indicators for optimisation. Still, a significant number of multi-objective optimisation DSS developers use vague language when stating their aims. Eight DSSs aim to either *optimise* or *improve performance* of WWTPs, whilst three DSSs aim for *sustainable* operation or control of WWTPs, without explicitly stating which areas are targeted. Therefore, DSSs clearly define their aims, but few explicitly relate this to sustainability or circularity objectives, aiming to generally 'optimise WWTP performance' or improve conventional operation KPIs.

2.4.2 Static vs dynamic control

Of the twenty-six DSSs reviewed in Table 2.3, six provided users with static control strategies for improving the operation of WWTPs, meaning the results are used by operators to make decisions rather than the DSS dynamically altering operation. Borzooei et al., (2019) created a simulation of a large-scale WWTP and altered the SRT between 10-40 days, then plots the EQI and EC results to establish the optimal SRT for process operation. Mannina et al. (2020) goes a step further by using TOPSIS to optimise five operational parameters using ten KPIs and combining this with E-FAST sensitivity analysis to understand the influence of operating parameters on performance. These static DSSs allow users to observe and understand what an optimised system may look like, enabling them to derive and implement the WWTP control strategy. The remaining twenty DSSs are able to dynamically alter operation parameters without user interference. For example, Heo et al. (2021) uses the fuzzy c-mean algorithm to process and cluster influent data to predict initial BSM2 setpoints, a deep neural network then completes the multi-objective optimisation calculation for EQI, OCI, and biogas generation performance indicators, and finally the NSGA-II algorithm searches for the optimal setpoint of each controller. Therefore, the WWTP can maintain optimal performance and respond to fluctuations in influent composition. The use of DSSs for dynamic optimisation means that indicator selection must focus on KPIs that are calculated from data that is easily and reliably monitored over a given period.

2.4.3 Modelling platform

Of the nineteen DSSs that dynamically control WWTP operation, fourteen are implemented in BSM1 without being tested on real processes. In most cases these DSSs are made up of two algorithms, one responsible for the multi-objective optimisation of KPIs (commonly a neural network) and another for determining the set point of controllers (such as a NSGA-II or AMODE algorithm (Heo et al., 2021; Ortiz-Martínez et al., 2021; Qiao et al., 2019, 2018; Tejaswini et al., 2021)). The repeated investigation of different algorithm combinations is necessary to which results in the best EQI and OCI outcomes, and lowest controller error (Du and Peng, 2023). Two DSSs are used to control the operation of BSM2, enabling users to optimise operation considering biogas production as part of the OCI. Two DSSs are utilised for the dynamic control of actual processes including the work of Han et al. (2021) which runs initial tests on BSM1 then uses data extracted from the SCADA system of a 10,000 m^3/d plant in Beijing, China to run experimental tests. Lastly, Dai et al. (2019) developed their own optimisation models, using ASM-2D to optimise a WWTP for inducing crystallisation. Therefore, few DSSs have been tested on real systems so may not perform as expected when applied at different scales or locations, especially under unexpected influent loadings. It is recommended that users test DSSs in real systems or on models that represent the specific process it will be applied to, ensuring optimisation reflects the operational expectations of decision makers.

In the cases of static control, the DSSs developed usually rely on simulation software or the development of process models. Four DSSs used their own models which facilitated the selection and utilisation of less conventional KPIs, including regenerated water usage (Díaz-Madroñero et al., 2018), energetic self-sufficiency (Campana et al., 2021), and environmental impact (kg CO_2eq) (Caligan et al., 2022). Two DSSs simulated WWTPs in Hydromantis's GPS-X software, with configurations based on real-world processes (Chen et al., 2021) and fed with historic data taken from plant SCADA systems (Borzooei et al., 2019). Lastly, Revollar et al. (2021) specify four scenarios (fluctuating DO, NH_4, and internal recycle setpoints) in BSM2, which enables the calculation of eco-efficiency indicators for comparing control strategies. Therefore, static control systems are able to optimise a greater variety of KPIs, like the EQI and OCI, and operational parameters, including solids retention time (Borzooei et al., 2019; Mannina et al., 2020) or process flowrates (Caligan et al., 2022; Revollar et al., 2021).

2.4.4 Indicators selected

The reliance of DSS developers on BSM platforms results in little variability of selected indicators. In fact, Table 2.3 shows eighteen reviewed DSSs used only the inbuilt indicators of BSMs, including EQI, OCI, or its sub indicators (pumping, aeration, and total energy consumption). Although indicators are fixed in the platform, little justification or reasoning for selecting these indicators is given by DSS or BSM sources, except that they cover both economic and environmental impacts (Li et al., 2021), reflect the operational state of the WWTP, and can evaluate process performance (Han et al., 2022a). EQI and OCI indicators reflect the traditional goals of water related literature and regulations, such as for human health protection and cost functions, that will always be important to maintain WWTP performance. However, modern water sector targets relate to areas such as GHG emissions and resource recovery, therefore, expansion to include KPIs that reflect these goals is recommended for further development of BSMs. This is needed as inclusion of sustainability and circularity dimensions would enable users to optimise WWTP operation considering the wider impacts to stakeholders and achieve targets defined in Section 2.2.1, such as those defined in the CEAP.

Subsequently, the eight remaining DSSs developed integrated other indicators to optimise process operation considering impacts other than cost and effluent quality. Three DSSs calculate process GHGs, including Mannina et al. (2020) that consider a combination of CO_2 and N_2O emissions, direct and indirect GHGs, and air-EQI to understand how MBR operational parameters impact emissions. Caligan et al. (2022) also considered GHGs emissions and compared this with cost functions, whilst Chen et al. (2021) conducted full LCC and LCA to investigate the impact of indicator prioritisation on a 10,000 PE WWTP. Other DSSs selected indicators to investigate a specific function of a WWTP, namely freshwater and regenerated water use (Díaz-Madroñero et al., 2018), eco-efficiency (Revollar et al., 2021), treatment time reduction (Fox et al., 2022), and energetic self-sufficiency (Campana et al., 2021). These indicators align better with modern water sector sustainability goals compared with EQI and OCI indicators. However, they all employed self-selection methods and generally circularity indicators were mitigated from optimisation DSSs, showing this is yet to become a priority of WWTP operators.

2.4.5 Indicator prioritisation

Again, there is a difference between static and dynamic DSS indicators in how they are analysed to produce the optimal solution. The majority of dynamic calculations aim to minimise the performance indicators selected, including BSMs trying to minimise both EQI and OCI (or energy consumption). This results in an optimisation problem (Heo et al., 2021) since decreasing one of these KPIs increases the other, for example greater removal efficiency requires additional energy consumption from aeration and recirculation pumping. Therefore, DSS algorithms must cope with KPI trade-offs, known Pareto sets, which derives a sub-optimal solution for the chosen KPIs but establishes that both results are better than the rest of the potential outcomes in the search space (Qiao et al., 2018). Fox et al. (2022) developed one of the only dynamic optimisation DSSs to employ a weighting method, with the hope of considering site-specific requirements. Local plant operators assigned weights, which were combined with KPI result rankings to decide on the soft sensors that produces the best control strategy. In previous years it was common to weight KPIs to create a single objective optimisation (Niu et al., 2022), however, this necessitates real-time supervision by plant operators to achieve optimal control (Han et al., 2014).

Of the static DSSs, three utilise KPI weighting to achieve the optimal solution. Díaz-Madroñero et al. (2018) used fuzzy goal programming to incorporate decision maker preferences and trade-offs between objective functions. Alternatively, Chen et al. (2021) normalises LCA impact indicator results and uses weights defined in literature, whilst Mannina et al. (2020) weights all ten objective functions selected equally. The use of decision maker weighting strategies is recommended, as it enables the goals of local stakeholders to be integrated within optimisation outcomes. Lastly, some DSS developers did not provide a method for selecting the optimal strategy, leaving it to the interpretation of the user to compare KPI results (Revollar et al., 2021), such as Borzooei et al. (2019) which relies on optimisation curves showing EQI vs OCI to select the best operational SRT parameter. Although weighting strategies are useful, the dynamic optimisation of KPIs is now accepted as best practice to enable automatic, supervisory control of plants, placing greater emphasis on proper selection of KPIs to reflect decision maker needs during WWTP operation.

2.4.6 Error and uncertainty

These DSSs aim to provide an optimised control strategy for the operation of WWTPs, however, alternative controllers, KPIs, or conditions may result in differing performance. Therefore, it is critical to test the sensitivity of DSS performance on results. One of the main strategies employed was to compare the optimised KPI results with alternative controller algorithms, to ensure the adopted method achieves the best performance. Controller performance metrics including the Integral of Absolute Error (IAE) (no error weighting), Integral of Squared Error (ISE) (penalises larger errors), and Root Mean Square Error (RMSE) were utilised. In fact, six DSSs compare the controller algorithm deployed using the IAE with other algorithms (Han et al., 2022a, 2021; Li et al., 2022; Qiao et al., 2019, 2018; Xie et al., 2022), one utilised both ISE and IAE for comparison (Han et al., 2018), and another implemented RSME (Qiao and Zhou, 2018) to investigate whether the method used results in the lowest error. Additionally, six DSSs compared controller algorithms using KPI results only (Han et al., 2022b; Li et al., 2021; Mannina et al., 2020; Niu et al., 2022; Pisa et al., 2019; Zhou and Qiao, 2019), which is a useful exercise to reassure the user their DSS will produce the best outcomes. However, investigating errors is important as it indicates the size and longevity of potential disruptions to system performance.

Multi-objective optimisation DSSs utilise similar approaches to those discussed in Section 2.3.7 for MCDM for uncertainty analysis. For example, the DSS developed by Caligan et al. (2022) formulated scenarios to investigate the impacts of events that WWTP operators may face, including how the fluctuation of biofuel prices, inlet wastewater quality, and requirements for wastewater and sludge disposal, impact on cost and GHG emission KPIs. Ortiz-Martínez et al. (2021) created scenarios simulating lack of aeration due to process error and mitigation of flow recirculation due to maintenance, to investigate the effect on process optimisation. Alternatively, some authors investigated optimisation strategies through prioritisation of certain indicators to see how the system responds. DSSs were tested by optimising either the environmental (i.e. EQI) or economic (i.e. OCI) KPI, and comparing this with when both are optimised (Chen et al., 2021; Tejaswini et al., 2021).

Mult-objective optimisation DSSs have other inherent uncertainties to deal with when modelling WWTP systems, such as climatic changes and fluctuating wastewater concentration (Chen et al., 2018). DSS developers tackled this uncertainty by investigating the effects of the wastewater influent on performance using fluctuation of the TKN/COD inlet ratio (Heo et al., 2021) and fuzzification of inlet composition (Díaz-Madroñero et al., 2018). However, further uncertainty analysis is recommended to test how WWTP optimisation models respond to external factors. MC simulations are commonly used for modelling input uncertainty as different probability distributions (normal, parametric etc.) can be selected depending on error attributes and case study characteristics (Haag et al., 2019). Testing the uncertainty of DSS performance is critical and for a complete study it is recommended to make comparisons in KPI performance and controller error with other systems, and investigate fluctuations to influent load and process operation to ensure the DSS will meet all user expectations when deployed at a real WWTP.

2.4.7 Recommendations

Following the review of twenty-six multi-objective DSSs for optimisation of WWTP process operation, some final recommendations and comments are provided in Table 2.4. However, it can again be concluded that although these DSSs aim to optimise WWTP performance there is little attention given to how this results in the indicators selected for optimisation, nor an explanation of how subsequent operation aligns with sustainability aims, and mitigate circularity dimensions entirely.

Table 2.4. Summary of issues, recommendations, and beneficial outcomes related to the reviewed wastewater treatment multi-objective process optimisation DSSs.

Issue	Recommendation	Outcome
Few DSSs are applied to real WWTP systems, mitigating the impacts of local climate and influent composition	Test DSSs in realistic process models or trial them in real-world systems	User achieves the expected performance when DSS is applied to their system
Although KPI selection is fixed for many of the DSSs reviewed, rigorous indicator selection is often overlooked	Develop process models that utilise KPIs considering local stakeholder and business objectives for WWTP optimisation, rather than depending on those integrated within BSMs	DSS will optimise WWTP in a way that generates desired benefits for stakeholders
Focussing on EQI and OCI (or energy consumption) KPIs provides a narrow view of 'optimal' or 'sustainable' WWTP performance	Expansion of indicators to include environmental, social, circularity, and technical aspects	Align WWTP operation with modern sustainability and circularity aims of the water sector
Dynamic control and optimisation of WWTPs aligns better with the water sector's digitisation goals, mitigating plant operator decision making capabilities	Implement robust indicator selection to ensure optimal performance facilitates decision maker goals at a plant level	Responsive systems that optimise performance in terms of selected KPIs, rather than relying on intuitive decision making of operators
Many DSSs did not investigate the performance of controller algorithms using appropriate metrics	IAE and ISE are recommended for understanding the response of the selected algorithm to process alterations, especially as dynamic operation of WWTPs evolves	Better understanding of how the investigated WWTP will respond to external stressors

2.5 Summary of main findings

- The European Commission is pursuing a CE to facilitate many of its sustainability targets and according to publications, such as the CEAP in 2020, WWTPs must focus on emissions reduction, resource recovery, and water reuse, and acknowledge the importance of proper data usage, to align with water sector goals at a European level.

- For MCDM technology selection DSSs, selection of WWT technologies is the most common and RR is the second most common focus to improve the efficiency and circularity of WWTP performance.

- Generally, MCDM technology selection aims are vague or use generic language, meaning there is a disconnect in user knowledge which hinders selecting the correct indicators to facilitate desired outcomes. Additionally, common methods of indicator selection and weighting were user defined with little explanation, meaning they are unable to reason whether indicator sets consider the scenario of application.

- To overcome this, it is recommended to clearly define DSS aims before the assessment, and use structured, participatory approaches for indicator selection and utilisation, such as fuzzy-AHP and -TOPSIS, that consider stakeholder inputs.

- For multi-objective optimisation control DSSs aims were defined much more clearly, usually improving cost and effluent quality indices. However, most DSSs relied on the use of BSM platforms, meaning indicators were fixed and of limited scope (effluent quality and cost), and were not usually tested on real WWTPs.

- Therefore, it is recommended to undertake more rigorous indicator selection procedures to expand the scope of the assessment and test the resultant DSSs in operational processes. Additionally, the systematic use of controller performance investigation (IAE and ISE) is advised to understand the dynamic response of the system to different situations.

- Lastly, considering the issues with both DSS typologies it is clear that the wastewater sector is still some distance from standardised decision-making processes. However, it is hoped the recommendations provided can act as a basis to expedite this for indicator-based DSSs.

3 Where is the Greatest Potential for Resource Recovery in Wastewater Treatment Plants?

3.1 Introduction

As governments implement ambitious targets to curb the anthropogenic impact of climate change, industrial practices must change in tandem. It has been recognised that further action is needed to ensure planetary health, which has led to the rapid growth of the circular economy (CE) concept over the past decade (Kirchherr et al., 2017). The Ellen MacArthur Foundation define the CE as "*one that is restorative and regenerative by design and aims to keep products, components, and materials at their highest utility and value at all times, distinguishing between technical and biological cycles"* (Ellen MacArthur Foundation, 2015). CE practices are linked with achieving many Sustainable Development Goals (SDGs), facilitating sustainable development (Panchal et al., 2021) and beyond, by actively restoring and regenerating material and energy cycles (Jazbec et al., 2020). The water sector is uniquely poised for this transition, due to its intrinsic circularity and the environmental, economic and social value of capturing the resources it handles (Mihelcic et al., 2017).

The water sector handles an array of resources, predominantly found in wastewater, that are valuable and critical, bestowing opportunities for revenue generation and diversification. Resources recovered from wastewater fall into many categories such as water, energy, biofuels, fertilisers, and biopolymers (Kehrein et al., 2020a), some of which are becoming increasingly scarce due to growing global population and urbanisation (Dagilienė et al., 2021). Investment in resource recovery infrastructure enables water utilities to realise benefits that reach far beyond revenue generation. Resource recovery is intrinsically linked to sustainable and circular practices such as process intensification, resource circularity, and waste valorisation, which can reduce plant footprint, improve operating costs, increase energy efficiency, reduce negative externalities, and offset the carbon footprint of wastewater treatment facilities (Coma et al., 2017; Gherghel et al., 2019; Kehrein et al., 2020a; Ruiken et al., 2013).

These prospective benefits have resulted in extensive work in recent decades, by both academia and industry, to develop technologies that shift the focus of wastewater treatment plants (WWTPs) from pollutant removal to resource recovery facilities (Kehrein et al., 2020a). This has resulted in a multitude of technological options for the extraction of resources from wastewater, providing water utilities with ample choice along the entire treatment pathway for plant design and process retrofitting (Kehrein et al., 2020c). However, decision makers must consider trade-offs between the benefits of selected technologies and the potential impacts when identifying which resources to target for recovery. Furthermore, on a practical level plant operators have limited experience in innovative resource recovery technologies, with few full-scale examples of evidence-based assessments for process optimisation. The latter, creates challenges for selection of priority resource recovery technologies and strategic planning, especially whenever necessary factors such as cost, risk, and market potential need to be incorporated into decision making.

With the current emphasis placed on resource recovery and circularity, there seems to be disproportionately few methods, or examples of evaluating the resource recovery alternatives in WWTPs to support decision making (Chrispim et al., 2020). Efforts to systematically investigate the resource recovery potential of WWTPs focus on site-specific assessments. For instance, Kehrein et al. (2020c) developed a framework for strategic planning and process design of water resource factories (SPPD-WRF). The SPPD-WRF aims to integrate resource recovery metrics in the site-specific design of treatment processes, thereby making resource recovery a measurable process design objective on a plant scale (Kehrein et al., 2020c). Similarly, the framework developed and implemented by Chrispim et al. (2020) at a large WWTP in Sao Paulo, focused on site-specific evaluation of resource recovery technologies through energy, water and nutrient recovery analysis, whilst considering the broader influences of market demand, legislation, technological options, and stakeholders.

The identification of resource recovery alternatives on a regional/sectoral level gives water utilities the ability to improve market share, mitigating some investment risk, and enables strategic planning of circular solutions by the water sector. A study in Scotland aimed to quantify available resources and estimate their commercial value in wastewater (CREW, 2018). The authors achieved this valuation, alongside estimations of potential carbon savings, but provided no methodology to support decision making for optimising resource recovery strategies on this scale, whilst considering wider impacts. There are studies which advocate for the wider assessment of resource recovery scenarios; however, poor data availability, costs, and design complexity is restricting the use of integrated approaches for effective decision making (Kehrein et al., 2020a, 2020c; van der Hoek et al., 2018). Therefore, there is a need for a structured approach to support decision-making by assessing resource recovery potential from wastewater on a regional scale, to select appropriate technologies for a given scenario.

Given that water utilities monitor material and energy flows, there is data available for measuring their current position within the CE, and monitoring and/or estimating the potential of the water sector's transition as circular strategies are adopted, such as resource recovery. This work aims to detail an approach for supporting water utility companies through planning and identification of strategies for resource recovery from wastewater on a regional scale.

3.2 Methodology

The structured approach proposed for the identification of resource recovery strategies on a regional scale is detailed in Figure 3.1. It starts with understanding the baseline scenario through construction of a system model, which is crucial as it enables performance improvements to be benchmarked. This is achieved through material flow analysis (MFA) and substance flow analysis (SFA). Next, a combination of market analysis and multi-criteria analysis (MCA) are used to rank and select resource recovery options. A long list of resources (with associated technology pathways) has been developed based on previous studies in literature UK Water Industry Research (UKWIR) (Aunon et al., 2015) and Centre of Expertise for Waters (CREW) (CREW, 2018)), and shortlisted using technology readiness level (TRL). The 'priority resources' are identified by scoring shortlisted resources using a range of criteria such as cost, carbon, and treatment impacts. Altering criteria weighting, permits the investigation of how future scenarios (i.e. prioritising carbon impacts) can affect the priority resources. The selected resource recovery options are implemented within the model to create an updated 'resource recovery scenario' to understand the improvements achieved by retrofitting the technologies. Lastly, a six capitals approach is discussed as part of the need for a holistic value assessment, for strategic planning of resource recovery technologies.

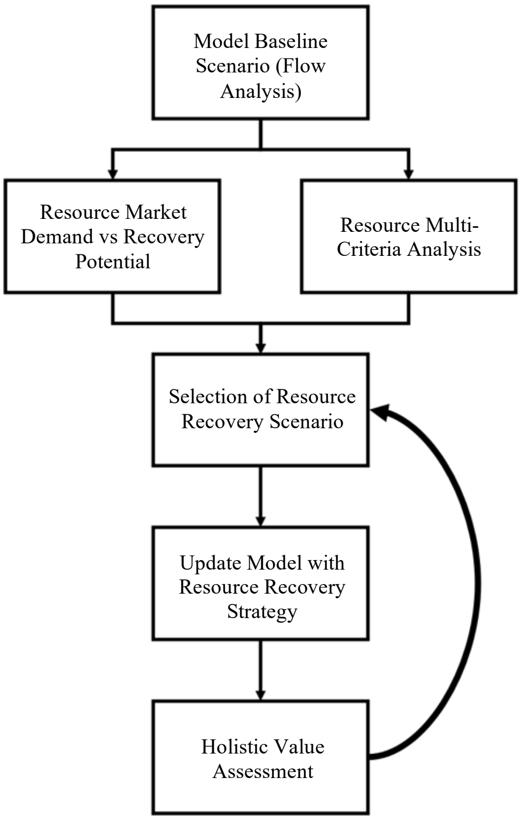


Figure 3.1. Steps of the structured approach developed for selecting regional resource recovery strategies.

3.2.1 *Baseline scenario model*

The first step is to establish a baseline scenario model for benchmarking purposes, to allow the gains made by implementation of resource recovery technologies to be investigated. MFA and SFA are conducted to identify unnecessary waste of natural resources, energy, and materials along process chains as suggested by the Organisation for Economic Co-operation and Development (OECD) (2008). This information is used for the investigation of resource recovery strategies.

To improve understanding of the approach presented in this work, the UK wastewater sector was used as an example. A mass balance to represent the UK wastewater sector was constructed together with MFA (chemical oxygen demand (COD), biological oxygen demand (BOD), total suspended solids (TSS), volatile suspended solids (VSS), water) and SFA (nitrogen (N), phosphorus (P), organic carbon (OC)). Input data for the mass balance model was taken from publicly available databases and literature for the year 2018/19 for England and Wales including: population equivalent (PE) served, flow handled (facilities PE > 25,000), sludge composition, type of wastewater treatment and sludge management processes (European Environmental Agency, 2018; OFWAT, 2019; Smyth et al., 2021) (Northern Irish and Scottish flows were calculated from reported PE and typical wastewater production per capita from literature). The 2018/19 operating year was chosen as this is the most recent price reporting year for OFWAT (PR19). Standard wastewater loadings were used, with removal efficiencies and kinetic parameters taken from literature (Tchobanoglous et al., 2014).

This information was combined to produce a representation of the UK wastewater sector, which is visualised in Figure 3.2 and displays system boundaries. The UK wastewater treatment sector was represented using eight wastewater treatment methods, six sludge treatment options and three types of solids disposal. The wastewater pathways are as follows: conventional activated sludge (CAS) with preanoxic zone (A), trickling filter (TF) (B), phosphorus removal (assumed to be chemical) (C), disinfection (D), postanoxic denitrification (E) and phosphorus removal and postanoxic denitrification (F). The fraction of influent wastewater handled by each treatment pathway is: A 44 %, B 4 %, A+C 31 %, A+D 13 %, B+C 3 %, B+D 3%, B+E 1 %, and B+F 1 %. Finally, 99.2 % of influent wastewater is discharged from the process. The sludge treatment and disposal pathways are as follows: primary sludge (1), waste activated sludge (2), advanced anaerobic digestion (AAD) (assumed thermal hydrolysis (TH) pretreatment) (3), anaerobic digestion (AD) (4), liming (5), incineration (ash landfilled) (6), composting (7), land reclamation (8), farmland application (9) and landfill (10). Sludge production is split: 61 % primary and 39 % waste activated sludge. The fractions of sludge sent to each treatment system are: 52 % AAD, 34 % AD, 3 % liming, 7 % incineration, and 0.1 % composting (the remaining 4 % is untreated). Finally, sludge disposal fractions for each method are: 3 % land reclamation, 95 % farmland application, and 2 % landfill. The values and parameters used for the construction of the mass balance model are summarised in Tables A.1-A.3 of Appendix A.

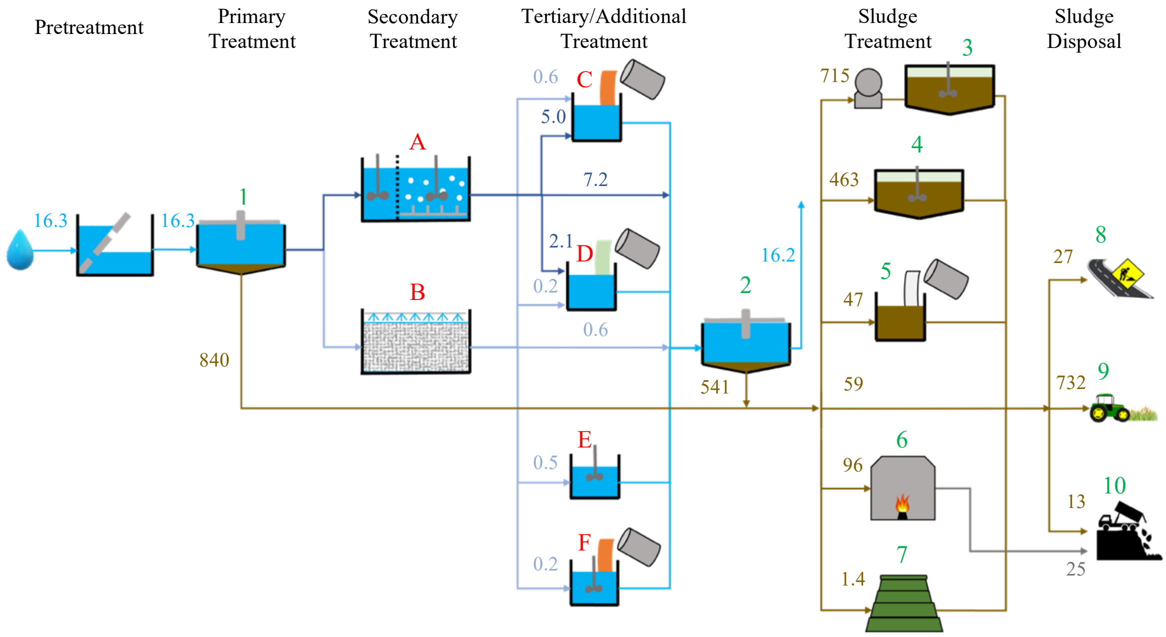


Figure 3.2. Representation of the UK wastewater system mass balance model. The wastewater line is coloured blue and treatment systems are labelled A-F with flowrates in Mm^3/d. The sludge line is coloured brown, and treatment and disposal systems labelled 1-10 with sludge flowrates in ktDS/a.

3.2.2 *Market potential analysis*

This section describes the methodology followed for the estimation of the market potential of recovered resources for the UK market. The market potential of a product reveals the extent to which it can fulfil the current market needs. It therefore indicates the potential demand for recovered resources, and in the context of this work, highlights the position of wastewater resources within the circular economy on a regional scale. If the potential market penetration is low, then the potential uptake of a new product or feedstock is less likely. Thereby, it is important to understand the market potential of resources available in wastewater before significant investments are made. Kehrein et al. (2020a) published a critical review of technologies available to recover resources from municipal WWTPs and calculated the market potentials for the Netherlands and Flanders (Belgium). Each resource was considered independently, so the market potential represents the maximum resource recovery that could be achieved under ideal circumstances using appropriate technologies. This includes the calculation of the absolute market potentials, meaning additional aspects such as market viability, incentives, and regulations were not considered. The market potential calculation by Kehrein et al. (2020a) was performed, alongside a review of recovery technologies and bottlenecks, to inform decision makers on the resources in wastewater. Here it is used as the basis to analyse the attractiveness of UK wastewater resources in terms of their potential market demand and goes further by integrating the results in a category of the MCA for the selection of priority resources.

The market potential is found by calculating the total amount of a product that can be recovered from wastewater compared to the total market demand for that product. The market demand for each resource was taken from relevant governmental and industrial reports, with values chosen as close to the modelled time period as possible (2018/19) (Agricultural Industries Confederation, 2021; AHDB, 2019; Alberici et al., 2017; Baumann and Westermann, 2016; Department for Business Energy and Industrial Strategy, 2020; Department for Environment Food and Rural Affairs, 2018; Department for Transport, 2020; Eurostat, 2019; Grand View Research, 2021; Mineral Products Association, 2018). The resources chosen for this analysis were a combination of those shortlisted for MCA (based on TRL) and those from the assessment by Kehrein et al. (2020a) to enable comparisons between the UK and Netherlands/Belgium for validation of results. The next stage was to establish the amount of recoverable resources from UK wastewater streams. The total resources handled were calculated utilising the wastewater loads from the mass balance model and reported sludge production (OFWAT, 2019). Removal efficiencies from literature were applied to calculate the fraction of each resource that could potentially be recovered (Kehrein et al., 2020a; Mills, 2016; Organics Group, 2020; Palmieri et al., 2019; Soares et al., 2021; Tchobanoglous et al., 2014) and are summarised in Table A.5 of Appendix A.

3.2.3 Multi-criteria technology selection

This section explains the approach followed in the MCA for the identification of the ‘priority resources’ considering different scenarios. The MCA methodology was developed as part of a project commissioned by UKWIR to understand the greatest sustainable economic benefit for resource recovery from the water cycle (UKWIR, 2021). The MCA was used to assess the resource recovery opportunities in the UK wastewater sector.

Initially the selected categories for the MCA were recovery potential, market potential, treatment impacts, cost, and carbon impacts. The criteria were chosen to establish how technologies would impact business goals of water utility companies. Additional criteria were also included in the MCA to align with UK water utilities who are increasingly adopting the capitals concept for holistic value assessment of their systems to maximise stakeholder benefits, as evidenced by their inclusion in the total value and impact assessment by Yorkshire Water (2018). Capitals are used to broaden the scope of assessments for decision making, by recognising the effects businesses have on a system and monetising their impacts. Environmental, human, social, natural, intellectual, financial, and relationship capitals have been linked with, and can be seen as an extension of sustainability pillars by water utilities. To reflect this, and provide a holistic assessment of recovered resources, the MCA incorporates the 6 capitals listed, alongside the initial assessment categories.

3.2.3.1 Scoring

A long list of resources was drawn from previous work by UKWIR (Aunon et al., 2015) and CREW (CREW, 2018). A discussion on the resource recovery technologies analysed in this study is provided in Section 3 of Appendix A. The resource recovery technologies were shortlisted by assessing the TRL. The in-house experience and industrial knowledge of Jacobs Engineering Group Inc. was used to evaluate resource recovery technologies and determine a near term resources shortlist (and technology pathway), by screening opportunities with TRL > 7 (*system prototype demonstration in operational environment)* (UKWIR, 2021). Some longlisted resources were considered unlikely to be near term despite their associated processes attaining TRL 7 or above, and not included in the shortlisted resources. This resulted in a shortlist of 13 relevant resource recovery opportunities and associated technology pathways which are provided in Table 3.1.

Once shortlisted, a semi-quantitative scoring system between 1 (lowest) and 5 (highest) was applied to the chosen criteria which evaluate aspects of economically sustainable resource recovery (scoring criteria guidance provided in Table A.6 of Appendix A. Scores for each technology were decided using in-house expertise of Jacobs Engineering Group Inc. (UKWIR, 2021) with exception of the market potential, which utilises the results calculated using the method of Section 3.2.2.

Table 3.1. Shortlisted resources and associated recovery technologies.

Shortlisted Resource	Recovery Technology
Biochar	Advanced Thermal Treatment (AAT) – pyrolysis or gasification
Biogas	AAD – enzymatic or thermal hydrolysis
Biogas	Co-digestion
Biosolids	AAD, Advanced Dewatering, Biodrying
Biomethane	Membrane/Water Scrubbing
Biopolymers	Aerobic Granular Sludge (AGS) Extracellular Polymeric Substances (EPS)
Fats, Oils, Grease (FOG)	Dissolved Air Flotation
Grit	Pretreatment Removal
Heat	Effluent Heat Pumps
Hydrogen	Reverse Osmosis (RO) and Effluent Electrolysis
Nitrogen	Air/Thermal Stripping of Sludge Liquors
Phosphorus	Struvite Precipitation
Syngas	AAT – pyrolysis or gasification

3.2.3.2 Scenario analysis

To investigate the sensitivity of the recovery options to future scenarios, criteria weightings were applied to reflect the possibility of short-term changes to the status quo in areas of compliance, carbon, and resource efficiency legislation (UKWIR, 2021). The results were used to calculate a final average score (and ranking) for resource recovery strategies by considering sensitivity to the following scenarios:

- **Status quo** – business as usual which focuses on viable markets for recovered resources, cost of implementation, impacts on treatment capacity, and resulting compliance.

- **Emissions compliance** – focuses on water and air emissions which drives treatment of final effluent and intermittent discharges to more stringent standards and improved environmental/social outcomes.

- **Carbon reduction** – assumes companies have carbon related targets for operational and embodied carbon which mandate reduction in carbon sources and creation of carbon sinks (increased sequestration).

- **Resource max** – assumes numerical targets and metrics aligned with resource recovery; resource efficiency and principles of the waste hierarchy and circular economy are applied with focus on sustainable resource recovery, minimisation of waste and keeping resources in use at maximum value.

The scenarios and weightings presented have been constructed by industrial experts. Full explanation of technology scoring and scenario weighting can be found in Tables A.7-A.9 of Appendix A.

3.2.3.3 Global sensitivity analysis

Global sensitivity analysis (GSA) is needed to improve the understanding of which criteria and scenario weights have the most significant influence on the final scores achieved, and therefore the final resource ranking. GSA assesses the impact that varying model inputs, within a specified range, has on output results. For GSA the range of variable inputs are all considered simultaneously (Sarrazin et al., 2016). Sobol' sensitivity analysis was applied; the Sobol sequence is a quasi-random, low-discrepancy sequence used to generate uniform samples of parameter space (Sobol′, 2001). The Sobol' scheme is extended with Saltelli's sampling scheme (Saltelli, 2002) from SAlib Python package (Herman and Usher, 2017) to reduce error in the resulting sensitivities. Sobol (variance based) GSA was run for 414,000 iterations on each resource, with bounds allowing input fluctuations of ±10 % to calculate the sensitivity of input parameters (MCA criteria scores and scenario weightings) on MCA output results (Sobol′, 2001). The sensitivity of resources to each criterion is presented as the sensitivity index, with the sum of indices equalling 1. The greater the sensitivity index of a given criterion, the greater influence it has on the final score of each resource and therefore ranking.

3.2.3.4 Priority resource selection

The average score achieved across the 4 investigated scenarios was used to create a final ranking, with the top 5 identified as 'priority resources'. An interaction matrix was constructed to show how each of the priority resources can be combined with the other shortlisted technologies to create integrated resource recovery strategies (example given in Table 3.3). Case studies focusing on the recovery of priority resources were used to understand additional resource recovery opportunities that could be exploited. These were divided into technologies which are required as part of the process for priority resource capture (x), as well as other strategies with the potential to enhance system performance (xx). This produces integrated resource recovery schemes that focus on the best performing resources for a given scenario, additional resources that can be captured, and potential process enhancements. To decide the final strategy, treatment methods from the original mass balance model are compared with resource recovery schemes to evaluate potential performance.

3.2.4 Evaluation of resource recovery scenario

Following the provision of five priority resources (and their associated technology pathway) to target within the studied UK example, the baseline scenario was updated accordingly to estimate the potential gains in nutrient recovery. MFA and SFA of the updated resource recovery scenario model show how nutrients flow around the new system, enabling comparisons to be drawn in terms of nutrient recovery and revealing the enhancements of implementing resource recovery technologies. When creating the resource recovery scenario, it is important to remain realistic in terms of application of the priority resources and technologies. For example, even though AGS systems may improve resource recovery (EPS and struvite recovery), it is not reasonable to consider that all WWTPs will utilise this technology. Therefore, a more pragmatic and representative approach is to target systems that already have P removal, due to the phosphorus accumulating properties of AGS systems.

3.3 Results and discussion

3.3.1 Baseline scenario material and substance flow analysis

This section shows the results of the baseline UK model. In the UK, 5,946 Mm^3/a of wastewater is handled, 1.38 Mt Dry Solids(DS)/a of sludge is produced, and 0.77 MtDS/a of treated solids are disposed. The results of the MFA and SFA were used to construct Sankey diagrams, which are shown in Figure 3.3. Sankey diagrams are commonly utilised to summarise flow analysis as they enable the viewer to be exposed to not only how materials flow around a system but also the magnitude of these flows, as the width of the flow is proportional to its magnitude. Sankey diagrams were generated using Microsoft Power BI software (Microsoft Corporation, 2014).

Secondary/tertiary treatment nutrient assimilation and effluent discharge are significant hotspots of the system, where large fractions of nutrients are lost. Of the total influent N and P, it was calculated that 8 % and 25 % are currently recycled through farmland application respectively, as 95 % of biosolids were recycled to farmland during the year studied. This high fraction is due to the fact that all of the reported sludge treatment methods comply with the Biosolids Assurance Scheme (BAS). The BAS aligns practices with government strategies for beneficial use of sludge (Biosolids Assurance Scheme 2020). Although, low nutrient recovery rates suggest that using biosolids in this way might not be the optimal method for recovery in the current scenario. Of influent OC, 26 % was recovered through farmland application and biogas production. It should be noted that the percentages quoted, are the total quantity of nutrients applied to farmland, as the availability of N and P to the next crop yield are 15 % and 50 % respectively for biosolids application (AHDB, 2019). This means that not all nutrients will be usefully recycled during the year of application. The modelling of N recovery in Amsterdam-West WWTP (1,014,000 PE) estimates that 11 % is recovered when 100 % of digested sludge is applied to land (van der Hoek et al., 2018). This is comparable with the model’s estimate, considering that not all sludge is digested or applied to land. MFA and SFA of the UK example reveal that a large fraction of nutrients in wastewater nutrients are not recovered; this does mean there is significant scope for improvement through implementation of resource recovery technologies.

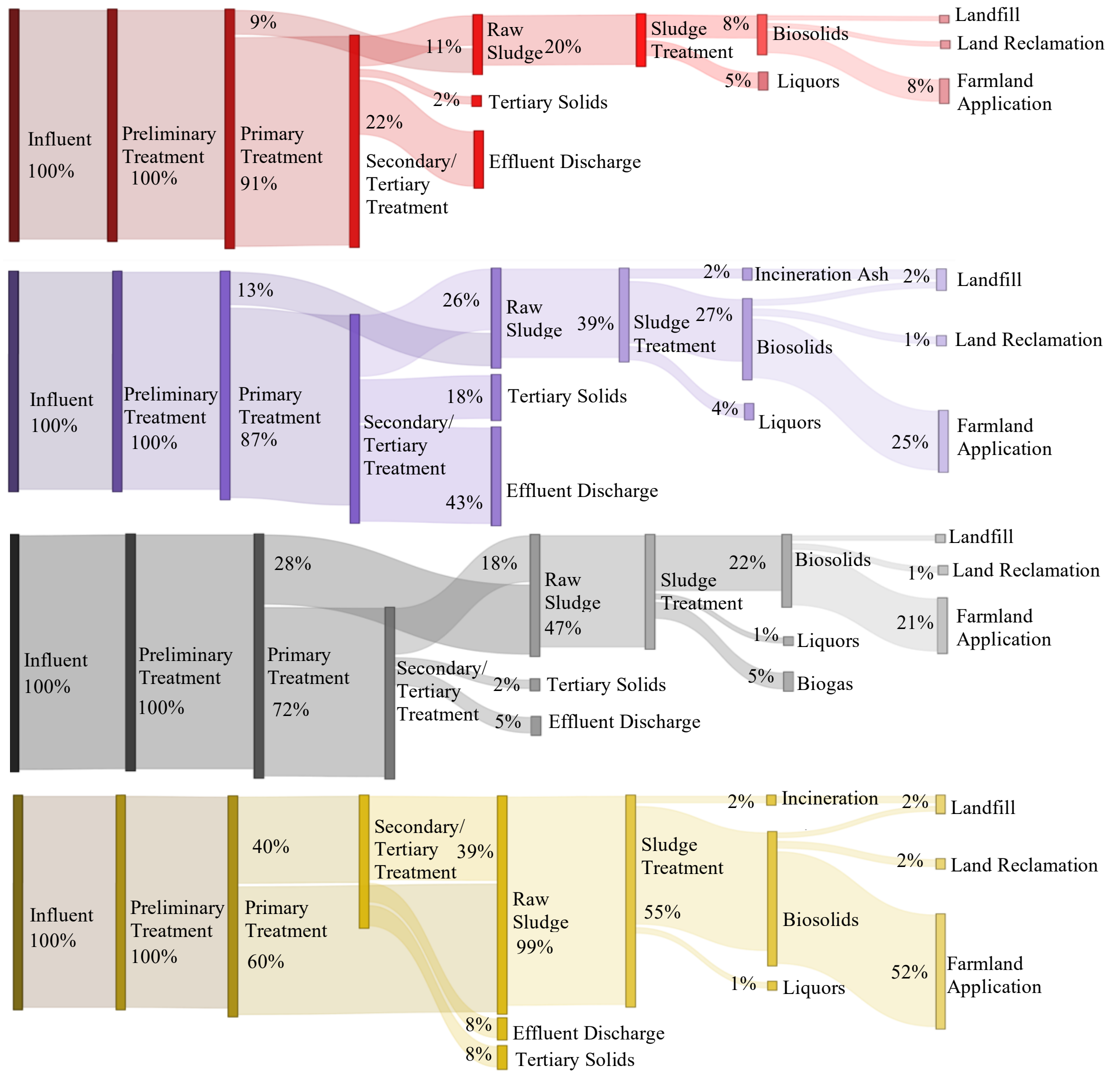


Figure 3.3. Sankey diagrams representing the flow of substances through a model of the UK wastewater system. The results of SFA are shown here for nitrogen (red), phosphorus (purple), organic carbon (grey) and total suspended solids (yellow). The percentage of influent nutrients present in each flow are given, any flows with <1 % are not labelled.

3.3.2 Market potential analysis

Market potentials for UK wastewater resources are summarised in Table 3.2. The market potential reveals the UK market demand for the resources studied, the quantity of resources that are potentially recoverable, and the ratio of these values.

Table 3.2. Summary of UK resource market demand, recoverable quantity of resources and resource market potential.

UK Market Potential of UK Water Resources						
Resource Demand	Demand	Unit	Resource Recovered	Recovery	Unit	Market Potential
Water (total abstraction)	12,341.9	M m^3/a	Water (total content)	5,887.0	M m^3/a	47.7%
			Water (MF-UF)	5,004.0	M m^3/a	40.5%
			Water (MF-UF/RO)	3,753.0	M m^3/a	30.4%
Water (public supply)	5,639.1	M m^3/a	Water (total content)	5,887.0	M m^3/a	104.4%
			Water (MF-UF)	5,004.0	M m^3/a	88.7%
			Water (MF-UF/RO)	3,753.0	M m^3/a	66.6%
Energy (Natural Gas)	3,158.0	PJ/a	CH_4 (from COD AD)	32.5	PJ/a	1.0%
Electricity Consumption	1,244.1	PJ/a	Electricity CH_4 (CHP)	12.3	PJ/a	1.0%
			Electricity (sludge co-combustion)	3.9	PJ/a	0.3%
Derived Heat Consumption	150.1	PJ/a	Heat CH_4 (CHP)	13.0	PJ/a	8.7%
			Effluent Heat (heat pump)	123.0	PJ/a	82.0%
Cellulose (paper production)	3,851.0	kt/a	Influent Cellulose	567.5	kt/a	14.7%
			Co-combustion Energy	7.8	PJ/a	0.2%
			Electricity (cellulose co-combustion)	2.3	PJ/a	0.2%
			Heat (cellulose co-combustion)	3.9	PJ/a	2.6%
CO2 consumption	450.0	kt/a	CO_2 from Biogas (sludge AD)	178.1	kt/a	39.6%

			CO_2 from Biogas (influent COD)	964.5	kt/a	214.3%
Nitrogen (Mineral Fertiliser - farm application)	1,038.0	kt/a	Influent N	236.9	kt/a	22.8%
			Raw Sludge N	53.2	kt/a	5.1%
			Raw Sludge Biodrying	37.3	kt/a	3.6%
			Biosolids N	42.1	kt/a	4.1%
Ammonia			N Fertiliser	10.9	kt/a	1.1%
Phosphorus (Mineral Fertiliser - farm application)	81.3	kt/a	Influent P	45.2	kt/a	55.6%
			Struvite P	15.8	kt/a	19.5%
			Raw Sludge P	26.2	kt/a	32.2%
			Recoverable P (Wet Chem)	23.6	kt/a	29.0%
			Biosolids P	18.4	kt/a	22.6%
AnMBR			CH_4 (AnMBR + AAD)	16.2	PJ/a	0.5%
			Electricity from CH_4 (CHP)	6.1	PJ/a	0.5%
			Heat from CH_4 (CHP)	6.5	PJ/a	4.3%
Gasification (Syngas)			Energy (Syngas)	24.5	PJ/a	0.8%
			Electricity (CHP)	9.3	PJ/a	0.7%
			Heat (CHP)	9.8	PJ/a	6.5%
Soil Conditioner	1,805.0	kt/a	Biochar (pyrolysis)	319.1	kt/a	17.7%
Grit	61,700.0	kt/a	Grit Removal	307.3	kt/a	0.5%
UK HGV Transport	17.4	bvm	Electrolysis of 0.32 % Effluent	17.4	bvm	100%
UK HGV Sludge Transport	5.9	mvm	Electrolysis of 0.00011% Effluent	5.9	mvm	100%
Animal Feed N	222.1	kt/a	Influent N	236.9	kt/a	106.7%

			SCP (AD digestate)	53.2	kt/a	24.0%
Global Market Potential of UK Water Resources						
Resource Demand	Demand	Unit	Resource Recovered	Recovery	Unit	Market Potential
VFA (Acetate)	16,000.0	kt/a	Acetate Recovery	483.8	kt/a	3.0%
VFA (Propionate)	380.0	kt/a	Propionate Recovery	219.9	kt/a	57.9%
VFA (Butyrate)	500.0	kt/a	Butyrate Recovery	100.0	kt/a	20.0%
PHA	35.9	kt/a	PHA Recovery	319.8	kt/a	891.3%
Alginate	43.0	kt/a	EPS (from sludge)	226.2	kt/a	525.6%

Table 3.2 shows that technology for the production of fuels and subsequent energy and electricity generation (whether gasification, AAD or anaerobic membrane bioreactors (AnMBR) and the use of combined heat and power (CHP) systems) can substitute little more than 1 % of UK demand. However, the water sector consumes approximately 3 % of UK energy so there is potential to move towards improved sector self-sufficiency (Majid et al., 2020). Grit recovery has limited market potential, meaning sustainable disposal (e.g. land reclamation) may be more appropriate rather than marketing it as a valuable product.

Cellulose, single cell proteins (SCP), biochar, volatile fatty acids (VFAs), struvite and biosolids (NP) have theoretical market potentials between 4 % and 24 %. Therefore, it has been shown that these resources can substitute a significant fraction of the current market, meaning there should be a demand from businesses to utilise them as feedstocks.

Water reuse (ultrafiltration (UF), micro filtration (MF) and RO), CO_2 generation, heat recovery, phosphorus recovery (sludge), propionate and hydrogen production have market potentials greater than 25 %. This shows that wastewater can provide a significant fraction of the current market demand, creating attractive opportunities to improve the sustainability of some industrially useful feedstocks. It was shown that large scale polyhydroxyalkanoates (PHA) and EPS production may in fact saturate markets, however, demand for these biopolymers is growing (Grand View Research, 2021). Due to its energy density the market potential of hydrogen was studied by calculating the fraction of wastewater effluent that must be electrolysed to fulfil fuel demands of heavy goods vehicles (HGV). It was shown that only

0.0001% of effluent should undergo electrolysis to supply all HGV miles, 5.9 mvm (million vehicle miles), required for sludge transportation.

The market potentials calculated in Table 3.2 are in agreement with those calculated by Kehrein et al. (2020a), as the trends and magnitudes are similar to those seen for the Netherlands and Belgium. The calculation of UK market potentials in this study gives an example of how to provide quantitative results to feed the MCA scoring whenever data is readily available, rather than relying exclusively on qualitative criteria. The results can also be used as a validation of selected priority resources as they have been calculated considering data that is specific to the UK scenario.

3.3.3 Multi-criteria analysis

3.3.3.1 Scoring and investigation of future scenarios

This section discusses the results from the MCA considering both the unweighted scores and the weighted scores for the investigation of potential future scenarios. The unweighted scores for each resource are highlighted in Figure 3.4, revealing the individual scoring for each category. When each category is given equal weighting, the total scores range from the lowest of 19 (FOG) to the highest of 32 (heat from heat pumps), out of a maximum of 40.

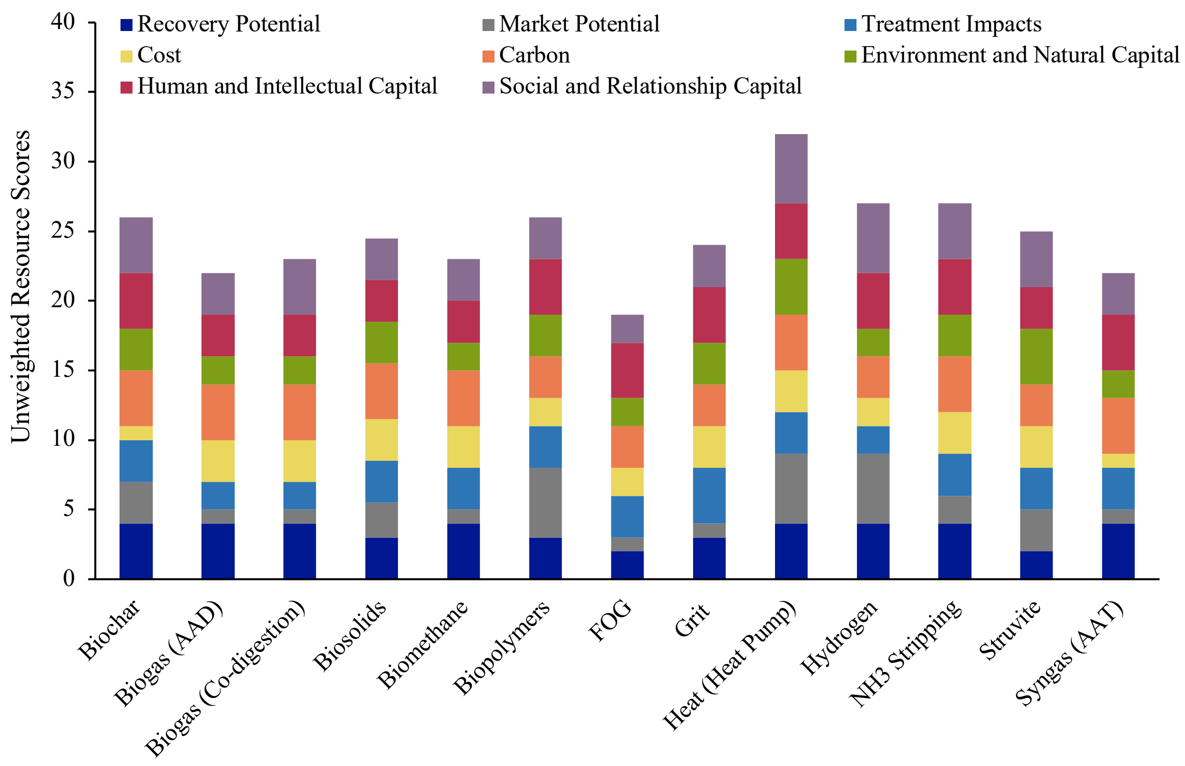


Figure 3.4. Unweighted assessment criteria scores for shortlisted, near-term resource recovery opportunities from UK wastewater.

Results from the application of criteria weightings to study the impact of potential future scenarios to the ranking of technologies are summarised in Figure 3.5. The final scores were calculated by averaging the weighted scores for each resource across the four scenarios. This revealed after weighting, that again heat recovery through utilisation of heat pumps was ranked highest, and FOG recovery the lowest. The resources that experienced the greatest range over the scenarios were hydrogen, syngas (AAT), and biogas (co-digestion). Currently hydrogen generation requires large inputs of electrical energy so may be limited if strict emissions limits were implemented, but it performs strongly in terms of recovery and market potential. Although the carbon benefits and recovery potential for syngas are high, undesirable cost and market potential (for energy generation) results in large fluctuations between scenarios. At present co-digestion is not a viable recovery option in the UK due to regulatory limits, however, any updates to facilitate its implementation would result in enhanced generation of biogas, meaning its use is uncertain.

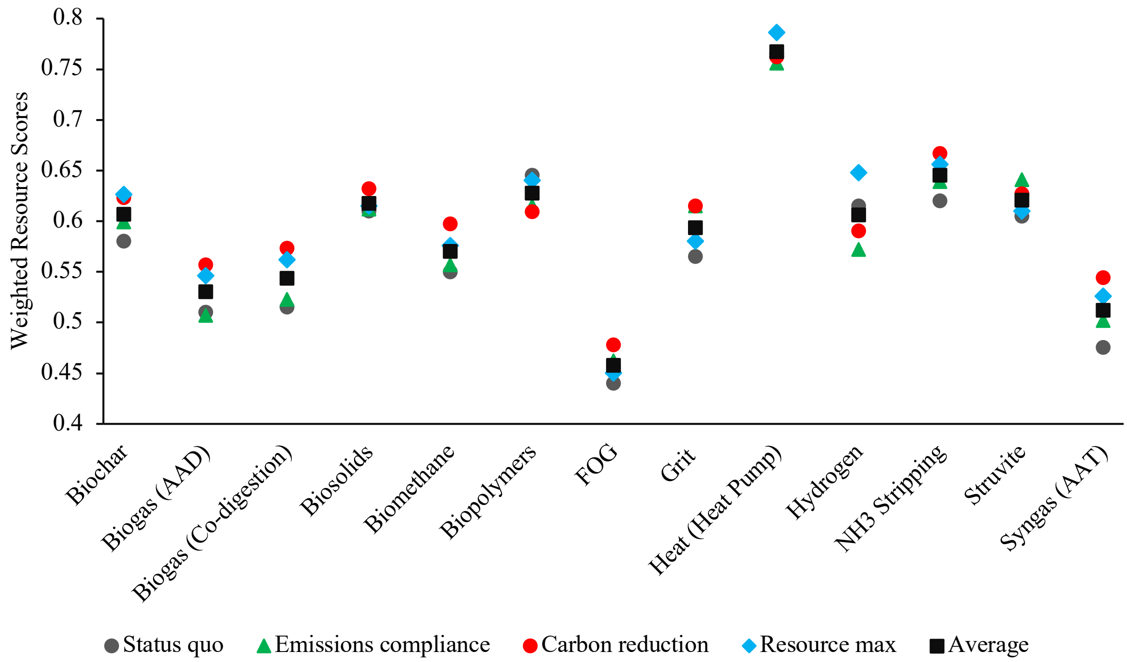


Figure 3.5. Sensitivity analysis results from the application of 4 potential future scenarios through assessment criteria weighting: status quo, emissions reduction, resource max and carbon reduction (based on the figure in report by UKWIR (2021)).

3.3.3.2 Global sensitivity analysis

This section summarises the results of the GSA completed for the scoring of shortlisted resources, to investigate the impact of uncertainties in the scenario weightings and criteria scores. Figure 3.6A shows the results of the GSA conducted on MCA scores. The greater the sensitivity index, the greater the influence that a specific MCA criterion score or the weighting of a potential future scenario has on the final score of a technology. Regarding the MCA categories, carbon has the largest influence on seven out of the thirteen shortlisted resources, followed by market potential and treatment impacts with the largest influence on three resources each. When considering only the potential future scenarios, scoring was most sensitive to carbon reduction measures, which may be due to the fact that circular solutions are seen as an important route to carbon neutrality for the water sector. The final score of the technologies had the lowest sensitivity to human and intellectual capital, shown to have the lowest influence for ten of the thirteen shortlisted resources. This criterion had the lowest weighting for all four scenarios investigated and there was little variation in awarded scores. As more emphasis is placed on maximising the 6 capitals, it is likely that greater focus will be placed on these criteria by businesses in the future.

Box plots have been drawn in Figure 3.6B to reveal the variance exhibited by each resource and its associated technology across all iterations of the GSA. The resources are ordered in terms of median scores, and heat recovery is the top performer, as even the minimum score recorded for heat is higher than the median score of any other. After heat recovery, the scores plateau somewhat, until biomethane where there is a decline which reveals that selection of methods for the recovery of chemical energy may not be favourable. Comparing resources by applying this method helps to ensure robust selection of resources, as it confirms the top ranked options perform well over a range of conditions and should be resilient to system changes and scoring uncertainty.

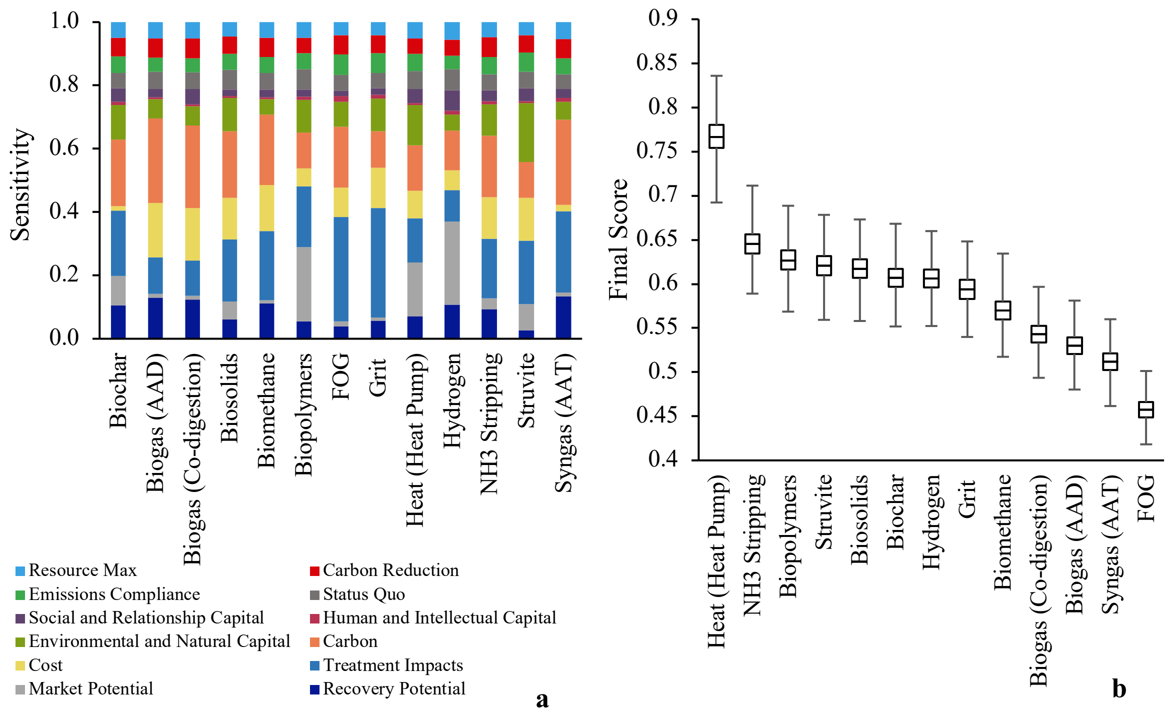


Figure 3.6. **a**: Results of the global sensitivity analysis conducted on MCA inputs (criteria scoring and scenario weightings) showing their influence on resource ranking scores. **b**: Box plots of the final scores over the 414,000 iterations completed during GSA.

3.3.3.3 Priority resource selection

The investigation of different scenarios and GSA enabled the ranking of the different technologies. The final average values were used to rank wastewater resources and the top 5 are highlighted as 'priority resources', which are heat (heat pumps), ammonia (stripping), biopolymers (EPS), struvite, and biosolids. These are deemed priority resources as they have performed best across the multiple objectives of the MCA, as well as showing resilience and consistency to potential future influences, and are summarised in Figure 3.7. Three of the priority resources align with the five resources with the greatest market potentials calculated by Kehrein et al. (2020), which are EPS, heat and biosolids (Kehrein et al., 2020a). A report for Scotland also names heat recovery via heat pumps as a resource with significant potential and concludes that biopolymer resources are promising in terms of recovery and market value (CREW, 2018). The comparison in Figure 3.5 provides confidence that even if the analysed system experiences changes, then selected resources should still perform effectively, therefore, supporting the robustness of priority resource selection. Figure 3.6B further supports this selection by revealing the extent to which uncertainty in scoring influences technology ranking, as priority resources still outperform the others over the range investigated during GSA.

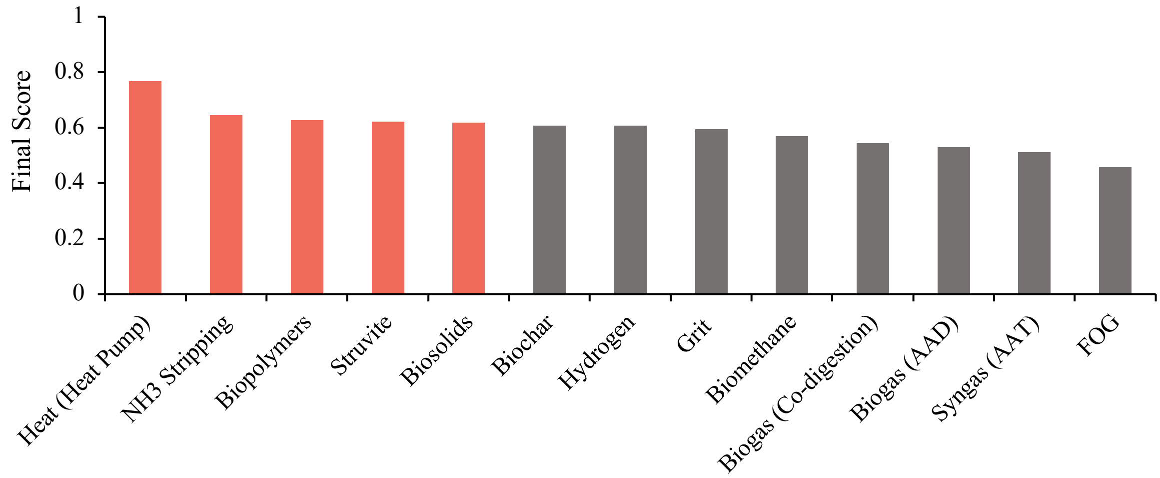


Figure 3.7. Wastewater resources score ranking with the 5 top performing resources highlighted in red.

3.3.4 Resource recovery scenario results

This section discusses the results from the implementation of the integrated resource recovery scenario within the UK wastewater example. The resource recovery scenario is developed from the selected priority resources and the results of MFA indicate the gains in terms of nutrient recovery compared with the baseline scenario.

3.3.4.1 Resource recovery scenario development

Potential integrated resource recovery scenarios are discussed in this section and shown in the interaction matrix (Table 3.3). Realistic scenarios for integration of resource recovery solutions were identified based on the results of the MCA, revealing how recovering priority resources can be coupled with technologies for co-production of other shortlisted resources (maximizing resource recovery efficiency) based on case studies (Biosys, 2021a; CENTRISYS-CNP, 2021; Kehrein et al., 2020b; Severn Trent, 2021; The Royal Borough of Kingston Upon Thames, 2021) and literature (Gherghel et al., 2019; Kehrein et al., 2020a).

The combination of priority resource recovery with additional technologies for the creation of an integrated scenario is discussed in the following paragraphs. This part of the assessment is necessary as it enables the construction of an appropriate integrated system of technologies that is representative of specific cases.

Table 3.3. Matrix identifying which resources are currently integrated in case studies of priority resource recovery (x), and others that enhance recovery in terms of yield or energy efficiency (xx).

	Priority Resource Recovery Schemes				
Resources	Heat (Heat Pump)	NH_3 Stripping	Biopolymers	Struvite	Biosolids
Heat (Heat Pump)	x	xx	xx	xx	xx
Hydrogen					
NH_3 (Stripping)		x			
Biopolymers			x		
Biochar					
Biosolids	xx	x	x	x	x
Struvite			x	x	
Grit					
Biogas (Co-digestion)		xx		xx	xx
Biomethane					
Syngas (AAT)					
Biogas (AAD)	xx	x	x	x	x
FOG					xx

Heat pumps that capture heat from effluent streams have highly generic applications, so could be potentially integrated with most shortlisted resources. Processes for biogas and biosolids have been highlighted to potentially enhance heat recovery efficiency as they can be exploited for on-site heating. This is due to barriers such as heat losses encountered by exporting heat and the infrastructure costs associated, so usage on site is preferred to maximise recovery (Nagpal et al., 2021). On-site recovery could be used for heating process units (biological treatment, AD processes for biogas generation) or applied for advanced biosolids treatment, including biodrying and dewatering applications (Kehrein et al., 2020a).

Ammonia stripping has been shown to be more efficient (in terms of energy and recovery) when conducted on digestate or digester reject liquors, as they are highly concentrated with nitrogen (van der Hoek et al., 2018). Therefore, systems that employ this ammonia recovery strategy will have anaerobic digestion on site, producing biogas and biosolids. Additionally, to enhance performance of the ammonia recovery system, co-digestion could be considered to increase the nutrient concentration of digester streams (Montusiewicz and Lebiocka, 2011) (although co-digestion is currently prohibited in UK). Ammonia can be directly combusted to generate energy or used to produce fertiliser and although processes that utilise it for energy recovery tend to consume more energy than is recovered, and barriers such as low production rates and high cost compared with industrial fertilisers limit uptake (Kehrein et al., 2020a).

Biopolymers (EPS) are present in the solid fraction produced from AGS systems. Enhanced biological nutrient removal occurs due to the presence of phosphate accumulating organisms in AGS systems, therefore, after EPS extraction phosphorus can be recovered as struvite (Kehrein et al., 2020b). Controlled release of the accumulated phosphorus requires subjecting sludge to anaerobic conditions, so AD can be used to simultaneously produce biogas and biosolids. TH may help disrupt the large flocs/granules produced during AGS treatment enhancing yields. Establishing an integrated scenario will improve the viability of this resource recovery scheme as currently the EPS market still needs to be fully established due to the high cost of production (Tavares Ferreira et al., 2021).

Struvite recovery, via controlled precipitation, captures phosphorus and nitrogen from concentrated streams after sludge digestion where nutrients have been solubilised. Therefore, biogas and biosolids production is a prerequisite of this recovery scheme. Struvite production is limited compared with industrial fertilisers due to the scale of viable plants, maintenance costs, and issues with product quality (Ghosh et al., 2019). To enhance the degree of struvite recovery, co-digestion could be utilised to increase nutrient load of digester streams, and renewable heat recovered via heat pumps employed for various on-site applications.

Biosolids are produced from AD systems and this resource is currently widely adopted by the UK water sector. However in the UK, The Sludge (Use in Agriculture) Regulations must be adhered to before application of sewage sludge to land, which specifies the of type of activity and contaminant limits that must be met (Public Health England and Wales and Public Health Scotland, 1989). Additionally, the introduction of new legislation may impact the practicalities of spreading biosolids produced from sewage sludge (Severn Trent, 2021). There are many ways to integrate other resource recovery practices to enhance biosolids generation, such as using heat pumps to generate renewable energy to support heating required for sludge digestion.

Co-digestion of sewage sludge and municipal solid waste has been successfully exploited across Europe, in countries including Denmark, Germany, and Switzerland, to improve biosolids nutrient loading and biogas yields (Cavinato et al., 2013). Regulatory issues prohibit co-digestion in the UK as it makes the process complex and expensive, specifically around the use of food waste where Animal By-Product Regulations mitigate the digestates scope within The Sludge (Use in Agriculture) Regulations (CIWEM, 2011). In Europe there are no such issues, with slaughtered animals that were fit for consumption requiring only a simple, thermal sanitation step before AD (Holm-Nielsen et al., 2009).

Based on this analysis, an integrated system for the recovery of priority resources, and co-production of additional resources, can be created using appropriate technologies for the specific case analysed. Treatment trains representative of the existing UK asset base from the baseline model were compared with technologies required for the recovery of priority resources to decide on the final integrated resource recovery scenario. It was shown that the priority resource recovery pathways require, and are even enhanced by, the integration of AAD for the production of biosolids and biogas, therefore the scenario integrated within the baseline model is as follows:

- Treatment trains with P removal are replaced with AGS processes for EPS and struvite recovery
- Addition of NH_3 stripping to remaining (non-AGS sludge treatment) AD systems
- Addition of TH pretreatment to remaining (non-AGS sludge treatment) AD systems
- Resultant biosolids utilised for farmland application
- Thermal energy generation from heat pumps on effluent streams is compared with chemical energy from biogas

3.3.4.2 Resource recovery material and substance flow analysis

In this section, the resultant scenario provided in Section 3.3.4.1 is implemented within the baseline model to quantify the impacts of the implementing resource recovery technologies. The CAS and TF treatment schemes with P removal (34 % of total flow) were replaced by AGS systems, which produce additional EPS and struvite resources. Reported data from a full scale Nereda® granular sludge plant in Garmerwolde, Netherlands (Pronk et al., 2015) was used to model the AGS process. Sludge, struvite, EPS, and biogas production rates were taken from literature (Guo et al., 2020; Kehrein et al., 2020b). TH units were integrated with AD processes used to treat the sludge produced by the remaining system to enhance biogas production and bioavailability of nutrients (Morgan-Sagastume et al., 2011). Thermally driven ammonia stripping was implemented on the concentrated liquor streams of the AAD systems to enhance nitrogen recovery (Organics Group, 2020). The quantity of energy from biogas production is compared with the potential of heat pumps on effluent streams for energy recovery. The parameters used for these calculations are summarised in Table A.4 of Appendix A.

The reconfigured model favouring resource recovery practices was used to conduct MFA and SFA to investigate the degree to which nutrient recovery is improved. This resulted in decreased sludge (1.13 MtDS/a) and biosolids (0.66 MtDS/a) production, which is influenced by the relatively low generation by AGS systems. Figure 3.8 shows the results of the MFA and SFA for the updated resource recovery scenario. The influence of focussing on resource recovery is shown in Figure 3.8 by the greater variety of product streams generated, such as EPS, struvite, and ammonia.

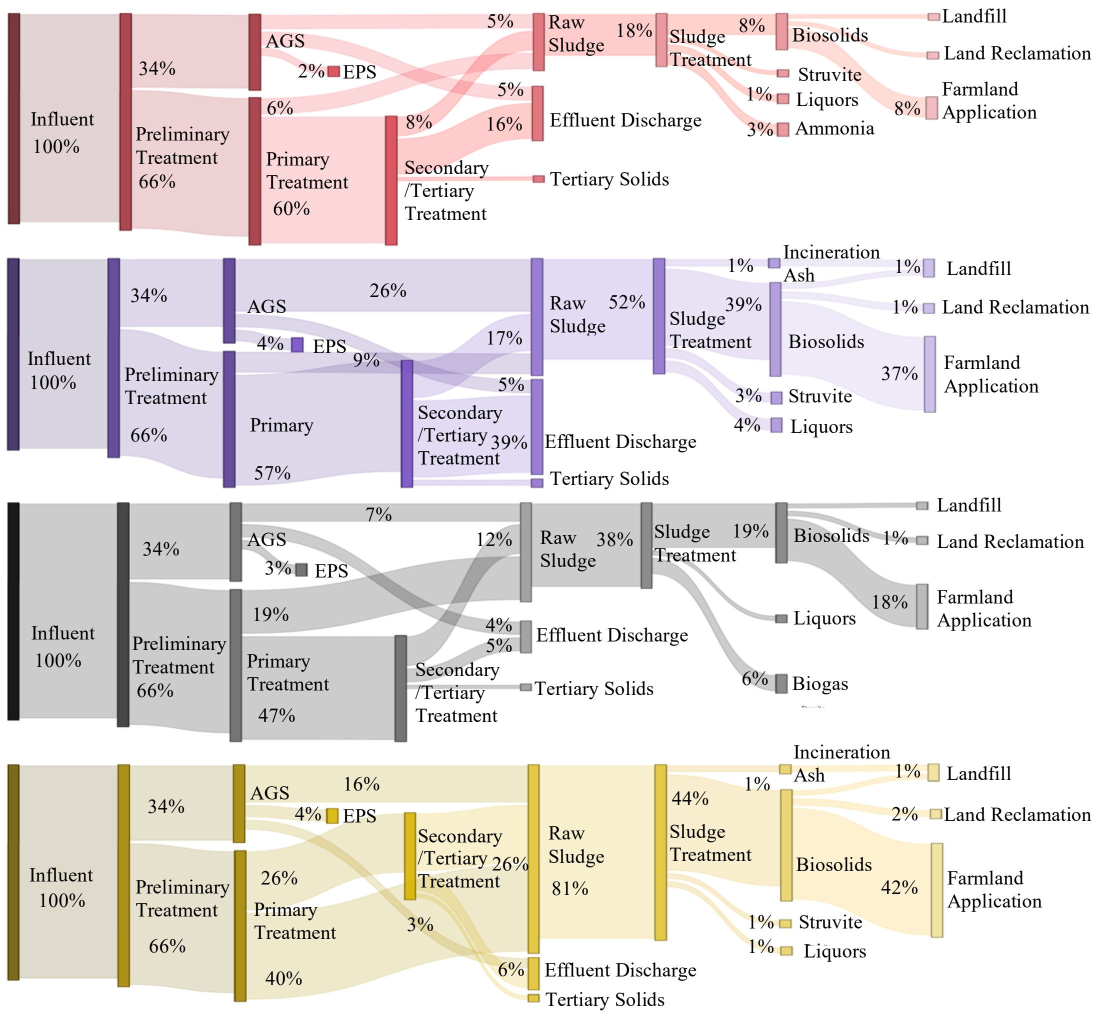


Figure 3.8. Sankey diagrams representing the flow of substances for the updated resource recovery scenario. The results of SFA are shown here for nitrogen (red), phosphorus (purple), organic carbon (grey) and total suspended solids (yellow). The percentage of influent nutrients present in each flow are given, any flows with <1 % are not labelled.

The results from Figure 3.8 were used to calculate the nutrients recovered in the resource recovery scenario and then compared with the baseline values to calculate gains achieved, which are summarised in Figure 3.9. Although biosolids production decreased by approximately 0.1 MtDS/a, the effect of TH meant that the nitrogen content was consistent between scenarios (50.5 tN/d and 50.2 tN/d in baseline and resource recovery scenarios respectively). Thermal stripping of digestion liquors recovered 21.2 tN/d, and additionally 12.1 tN/d and 1.5 tN/d was captured in EPS and struvite respectively. This increased the recovery of nitrogen by 68 % compared with the baseline. Enhanced P recovery was mainly influenced by the phosphorus accumulating properties of AGS systems, which resulted in a greater fraction being applied as biosolids (46.0 tP/d). Struvite and EPS further supplemented this by recovering 3.4 tP/d and 4.5 tP/d respectively, resulting in an increase of 71 % compared with the baseline scenario for P recovery through the existing mix of biological and physio-chemical treatment processes. There was minimal impact on the recovery of OC, due to the balance of reduced sludge production of AGS systems, increased biogas generation of AAD processes, and the recovery of EPS. These results demonstrate the potential to achieve significant advances in recovery of N and P from UK wastewater. Energy recovery yields were compared for biogas generation and effluent heat pump strategies. The energy stored in biogas generated by the system is equivalent to 4.6 PJ/a; however, 6.4 MJ/m^3 of energy can be captured from effluent wastewater. Therefore, it was calculated that heat pumps are required on approximately 12 % of the total flow to match energy recovery from biogas.

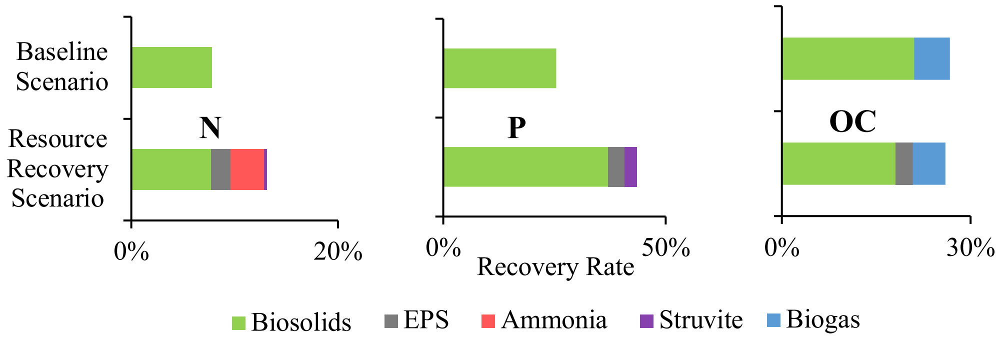


Figure 3.9. The recovery rate of N, P, and OC as a percentage of the influent comparing the resource recovery scenario with the baseline scenario.

Even in the updated resource recovery scenario, large quantities of nitrogen are assimilated during wastewater treatment, but the low N concentration of wastewater influent limits efficiency of pretreatment recovery. However, 80 % of influent N (van der Hoek et al., 2018) (and 50 % of influent P (Mo and Zhang, 2013)) is in the form of urine; thus, potentially warranting an investigation into investment in separate collection infrastructure to enhance nutrient recovery in this scenario. For example, it was shown that adding urine to the stripper inlet stream equivalent to 10 % of sludge liquor volume translates to approximately 40 %

increase in ammonia concentration (Morales et al., 2013). When assessing the use of heat pumps for the recovery of thermal energy, it was shown to be approximately 8 times greater than the chemical energy from biogas, which is in agreement with the values of Hao et al. (2019).

The recommended technologies provided by the regional assessment are required to act as the foundation for further analysis by individual water utilities or treatment sites. For the UK example, it was recommended that heat, ammonia, biopolymers, struvite and biosolids should be priority resources. However, it is beneficial for local factors to be considered during selection in these specific cases as there are many alternative methods, technologies, drivers, and barriers to consider at this scale, which could be accounted for in a quantitative capitals assessment. Therefore, there is a need for the development of a holistic value assessment to enable the conclusive appraisal of implementing circular solutions.

3.4 Summary of main findings

- It was seen there are disproportionately few methods, or examples of evaluating the resource recovery alternatives in WWTPs to support decision making. Efforts to systematically investigate their resource recovery potential tend to focus on site-specific assessments, whilst the identification of resource recovery alternatives on a regional/sectoral level has the advantage of improved market share, mitigating some investment risk

- To enable strategic planning of circular solutions by the water sector, an MCA tool developed by UKWIR for technology selection was integrated within a framework to create resource recovery strategies at a regional level. The approach was validated by applying it to an example of the UK wastewater sector using data taken from PR19 reports.

- Market potential analysis showed that technology produces fuels, and subsequent energy and electricity generation, can substitute little more than 1 % of UK demand. Whilst water reuse, CO_2 generation, heat recovery, phosphorus recovery (sludge), propionate and hydrogen production have market potentials greater than 25 %, and PHA and EPS production may even saturate markets.

- By applying the MCA tool and testing performance across four potential future scenarios, the UK's 'priority resources' were found to be heat (heat pumps), ammonia (stripping), biopolymers (EPS), struvite, and biosolids.

- By selecting technologies to facilitate the capture of priority resources, recovery of nitrogen and phosphorus increased by 68 % and 71 % respectively compared with the baseline recovery using the existing mix of biological and physio-chemical treatment processes.

- Large quantities of nitrogen are assimilated still during wastewater treatment in the 'resource recovery scenario' potentially warranting an investigation into investment in separate collection infrastructure to enhance nutrient recovery in this scenario.

4 Tracing Wastewater Resources: Unravelling the Circularity of Waste using Source, Destination, and Quality Analysis

4.1 Introduction

Transitioning towards a circular economy (CE) means decoupling economic growth from the consumption of finite resources (Kjaer et al., 2019), providing a pathway to operationalise the sustainability of economic systems through specific activities that close and extend resource loops (Kirchherr et al., 2017). The attention given to the CE concept by industry in recent years has generated such momentum that it is becoming integrated within environmental policy (EU, China, US) (Moraga et al., 2019). However, it is argued the vagueness and uncontroversial nature of a CE has resulted in its popularity, by promising multiple benefits with few burdens (Corvellec et al., 2022). This ambiguity is signified by the lack of universal definitions (Moraga et al., 2019) and standardised metrics required for evidence-based decision making (Åkerman et al., 2020), meaning this trait now hinders the CE transition.

Currently, the most commonly exhibited circular strategies are more appropriate for technical processes (Kirchherr et al., 2017), which correlates to a lack of assessment methodologies for biological systems, as the terminology used and indicators selected cannot be directly utilised across both paradigms (Navare et al., 2021). This also applies to water systems as many technical CE strategies are not appropriate, including repairing, refurbishing, and remanufacturing actions (Morseletto et al., 2022), due to the nature of resources carried and biological treatment processes utilised. Subsequently, the assessment of biotic and water resource circularity must acknowledge the differences with technical materials, such as investigating the sustainability of their extraction (harvesting or abstraction) to validate resource circularity, as circular technical processes aim to mitigate natural resource extraction entirely (Navare et al., 2021). Additionally, these resources must be cascaded as they degrade in quality, until they are regenerated to their original state by the environment (Stegmann et al., 2020), whilst technical systems focus on reverse logistics to maintain resource value (Morseletto et al., 2022).

The recovery of value from wastewater is pertinent for realising a fully CE (Smol et al., 2020), however, in wastewater treatment plants (WWTP) the provision of service is dictated by upstream water user habits and the local climate, whereas most other production processes have choice of upstream materials and feedstocks. This leads to water asymmetry, where downstream users are dependent on upstream water use, whilst upstream users are mostly unaware or unimpacted by their own usage (Savenije and van der Zaag, 2020). Currently, it is difficult to pass responsibility on to water users to alter wastewater composition or production volumes, as this is a very sensitive area in terms of regulation and human rights protection (Gleick, 1998). Therefore, this is a pertinent area of development as it is currently difficult to define physical water resources as sustainable or unsustainable (Sauvé et al., 2021); it is how they are used along with the resultant impacts of usage. In technical systems, similar problems have been overcome by using the CE principle of traceability to enhance the sustainability of consumer practices. However, the technology is reliant on physically tagging products (Hoosain et al., 2023), thus this method is inappropriate for wastewater resources and requires an alternative strategy.

Wastewater production rate and composition is highly complex and case specific but it is ultimately dictated by water users (Sauvé et al., 2021), so generation that goes against CE principles should be penalised during circularity assessments. To address the resource imbalance caused by linear consumption, several methods have been trialled to facilitate the enhancement of circularity, including footprint calculators, material flow analysis (MFA), and life cycle assessments (LCA) (Metson et al., 2020). However, footprint calculations mitigate the spaciotemporal aspect needed to fully appreciate resource circularity (Metson et al., 2020; Sauvé et al., 2021), MFA neglects the resultant impacts of resources interacting with the natural environment, and LCA commonly assumes zero burden of waste streams utilised as feedstocks, ignoring the effect of upstream decision making on circularity (Pradel et al., 2016). Therefore, no currently available methodology can provide a holistic approach to mend water and nutrient balances, hindering evidence-based decision making for the CE.

To realise this, traceability principles are needed to develop assessments that go beyond the current blanket definitions of waste, to show how water usage impacts circularity. However, understanding and standardising waste circularity becomes challenging when reviewing the definitions currently available in literature. Strategy- (Moraga et al., 2019), functionality-, and value-based (Iacovidou et al., 2017) classifications have been developed, but these consider technical manufacturing systems, meaning they cannot be applied to wastewater resources as wastes are deemed to have no value to the holder. More worryingly, a prominent industrial CE advocate defines an incoming waste stream as being non-virgin and therefore circular (wbcsd, 2022). This creates a paradox during the assessment of waste and wastewater treatment facilities, as intentional or preventable generation of waste is against many CE principles, yet it would be considered a circular inflow within these system boundaries, leading to errors during quantitative circularity assessments.

To overcome this, traceability principles should be applied to adopt the attitude that not all waste is created equally (Girard, 2022). The actions of wastewater producers across different sectors must be used to assign responsibility for linear utilisation of resources, shifting the current paradigm of policy instruments that only promote circularity to actively discourage linear practices (Corvellec et al., 2022). This is needed as it is currently difficult to construct economically feasible circular business models as disposal of materials to environmental sinks is relatively cheap (Åkerman et al., 2020). This means an approach is needed to assign responsibility for unsustainable water usage and wastewater production. Therefore, the aim of this work is to develop a method that measures and assesses the circularity of the main inflow and outflow wastewater resources (i.e. water, carbon, nitrogen, and phosphorus) based on CE principles for biobased systems (specifically traceability), to understand the consequences of upstream actions on downstream treatment processes. This characterisation will act as the foundation for developing holistic circularity assessments, enabling the incorporation of wider impacts such as environmental and human health dimensions.

4.2 Methodology

4.2.1 Overview

The framework developed by Harder et al. (2021b, 2021a) is one of the only examples in literature analysing the traceability of nutrients in biological systems, aiming for nutrient circularity '*disentanglement*'. However, it presents a simplified nutrient end-of-life scenario, ignoring nutrient interactions with the atmosphere and water bodies for resource cycling. Therefore, this work builds upon the Harder et al. (2021b, 2021a) framework by considering nutrient and water resources, to understand how they are cycled to supplement air, water, and soil in biological systems or as materials in technical systems, and lost to the environment in a harmful, dissipative manner during wastewater treatment. This model is illustrated in Figure 4.1, highlighting the interconnectivity of wastewater resources with other sectors and how they disrupt natural water cycles through unsustainable water usage. This is needed as the economic and environmental burden of treatment is usually shared by stakeholders regardless of their individual consumption, making it challenging to develop policy that discourages unsustainable water use. Traceability of wastewater resources using this model enables assessors to understand the purpose behind water use, its alignment with CE principles, and the subsequent impact on water quality. Therefore, the approach can be used to assign responsibility to water users, helping to guide policy and regulatory frameworks that address sector-specific goals.

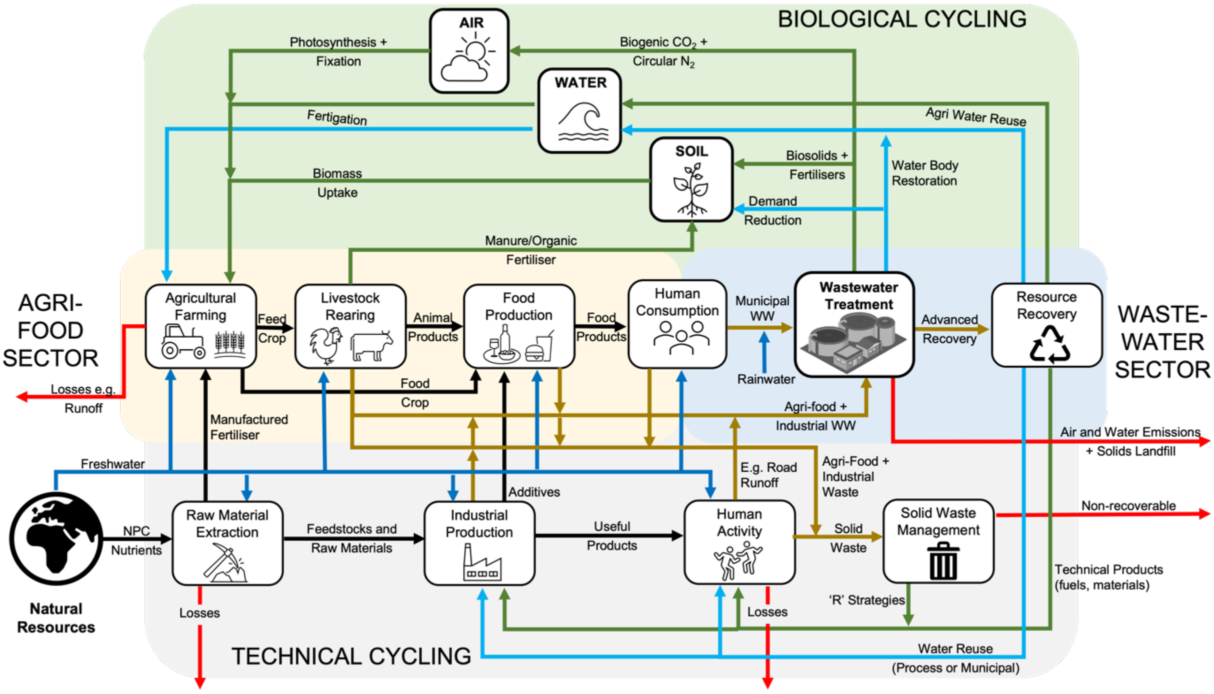


Figure 4.1. Expansion of a figure from Harder et al. (2021b) to show resource flows related to wastewater treatment through the human system. Flows are divided into technical (black), virgin water (dark blue), circular nutrient (green), circular water (light blue), losses (red), and waste treatment (brown) resources.

Utilising resource disentanglement, the current work aims to detail the origin and nature of wastewater resources to ensure they are not mistakenly labelled as circular during assessments. Firstly, influent water is classified based on source and recoverability from Kakwani and Kalbar

(2022), whilst outflow circularity is defined by water quality and intended use to supplement fresh water abstraction. Nitrogen and phosphorus inflow circularity is based on nutrient sources from the work of Comber et al. (2013), whereas outflows must contribute to natural nutrient cycling or substitute virgin nutrient consumption to be classed as circular. Lastly, properties of biogenic or fossil carbon are used to differentiate circularity according to Law et al. (2013), as the former is part of natural cycling and release of the latter has detrimental impacts on the environment. Adding the interactions of wastewater treatment with environmental and human systems in this way will shed light on the previously neglected elements of waste resource circularity, by establishing which practices facilitate resource renewability, restoration, and substitution, as well as those that impede natural cycling.

4.2.2 Resource flow classification

The characteristics of waste streams cause confusion when defining and assigning circular properties. Terms such as raw material, virgin, biogenic, by-product, and renewable are often used in CE literature to describe resources, some of which reveal intrinsic circular properties whilst others require further investigation of resource characteristics. Korhonen et al. (2018) discusses the problem of distinguishing between wastes and by-products, concluding that without proper definition of materials it is *difficult to intentionally support their utilisation*. Using the principle of traceability, it is possible to assume that a waste feedstock may not be circular or contains non-circular components. This may not align with the common 'zero burden' burden assumption but without this classification it is easy to assume that as long as a WWTP operates as expected (meeting discharge permit limits), 100 % of wastewater inflows and 100 % of wastewater outflows are circular, meaning the assessment is of little value to decision makers.

The developed method utilises the principles of the Do No Significant Harm (DNSH) framework (Italia Domani, 2021), to reason whether resource flows that interact with environmental (soil, water, and air) and human systems should be considered linear, and combines it with an understanding of resource source and destination. By applying this method to critically analyse wastewater, the different resources that make up this complex stream can be disentangled. Therefore, not only can all resource inputs and outputs be characterised, but also the different fractions and components of each nutrient considering their individual properties using the selected criteria and developed definitions from Sections 4.2.2.1 to 4.2.2.3. This is necessary due to the complexity of wastewater so definitions for the circularity classification of water, carbon, nitrogen, and phosphorus resources are provided, along with common wastewater treatment examples in Tables 4.1-4.7 to facilitate indicator calculation.

4.2.2.1 Water

According to Kakwani and Kalbar (2022) improving water circularity should focus on distinct water collection for water restoration, recycling, reuse, and reclamation. Whereas the definition of outflow circularity requires understanding of the quality of the water flow and its destination.

Inflow circularity

This starts by defining a WWTP's primary aim, which is to collect wastewater and treat contaminants so that it can be discharged to restore a water body, recognising the potential of WWTPs to possess advanced technologies for water recycling, reuse, or reclamation. Next, the circular inflow fraction is defined as the *recoverable water that flows into a WWTP which has the potential to be upgraded for restoration of a water body or other recycling, reuse, and reclamation purposes*. Then the non-circular inflow requires an estimation of the quantity of water that is lost upstream, which is defined as the *unrecoverable water that is lost between water provision and WWTP, such as human consumption losses, distribution losses, spillages, or evaporation*, all of which reduce the amount of water a facility can treat. Lastly, a final category of water inflows is defined, for the water fraction in materials required for WWTP operation, such as ferric chloride ($FeCl_3$) solution. These fractions are usually recoverable but from virgin sources, so are considered linear (although the scale of wastewater treatment means they can usually be neglected). The values used in this study are summarised in Table 4.1 and are taken from Kakwani and Kalbar (2022).

Table 4.1. Circularity fractionation of water inflows.

Stream	Input Fractions	Status
WWTP inlet	80%	Circular (recoverable)
Losses (Consumption - WWTP Inlet)	20%	Linear (unrecoverable)
$FeCl_3$ (40 % solution)	<1 % (negligible)	Linear (virgin)

Outflow circularity

Firstly, an outflow is defined as circular if *it is discharged at the required regulatory quality used for restoration of a freshwater body (in the same catchment) or upgraded for purposes that reduce virgin water abstraction (recycling, reuse, reclamation) by supplementing the needs of other processes*. This step requires regulatory limits to be established that confirm the restorative abilities of wastewater discharges, such as the DSNH criteria (2021/C58/01) for 'the sustainable use and protection of water and marine resources'. This is appropriate for assessing European WWTPs and states to follow requirements of the Water Framework Directive (WFD) (2000/60/EC) to assess environmental degradation risks (European Commission, 2021c). The WFD uses the Urban Wastewater Treatment Directive (UWWTD) (91/271/EEC) for classifying discharges to water bodies (European Parliament, 2000) and can be used to guide quality requirements (Council of the European Union, 1991). However, an additional action is needed when the receiving water body is reaching its allowable limit of pollution (according to the WFD). In these cases the grey-water footprint is used to calculate the critical load of discharges, to ensure the freshwater flow sufficiently dilutes contaminants, according to the method of Aldaya et al. (2011). If not, then the discharge of treated wastewater by a WWTP cannot be seen as a regenerative action and will receive a linear classification until water body quality or effluent concentrations are improved to satisfy the critical load. Lastly, the linear outflows are defined as water that is *discharged at a level of contamination that does not meet regulatory limits and is therefore harmful to environmental and human health, not returned in a controlled manner for freshwater body restoration, or is used in a way that does not result in the reduction of virgin water abstraction.* Table 4.2 summarises common outflows and destinations, with the expected fraction of water in each stream taken from literature (Tchobanoglous et al., 2014), showing how this influences the circularity classification.

Table 4.2. Circularity fractionation of water outflows.

Stream	Water Content	Destination	Status
Screenings	50-90%	Landfill	Linear
Fats, Oils, Grease (FOG)	15-95%	Landfill	Linear
Grit	13-65%	Landfill	Linear
Effluent	>99.9%	Restoration (groundwater, lake, river)	Circular
		Recycling (irrigation or further upgrading)	Circular
		Sea Water	Linear
		Discharge Fails to Meet Permit Limits	Linear
		Overflow Discharge	Linear
Biosolids	65-85%	Landfill	Linear
		Incineration	Linear
		Land Application	Circular/Linear

Additional considerations - biosolids

In the case of biosolids application to land, their moisture must be compared with that of the receiving soil. Data is collected from appropriate literature, as European soil moisture can fluctuate between 5 % and 44 % in arid and cold climates respectively (Almendra-Martín et al., 2022), whereas biosolids solids content can be approximately 25 % when dewatered, 50 % when composted, and >75 % when dried (Tchobanoglous et al., 2014). Therefore, it is possible for soil to have greater moisture content than the applied solids, meaning application will not improve soil water deficit. Finally, the water fraction is considered circular when high water content biosolids or sludge is applied to dry soils that *reduce the water deficit, resulting in the reduction of raw water abstraction*.

4.2.2.2 Phosphorus and Nitrogen

Comber et al. (2013) completed substance flow analysis (SFA) of domestic wastewater nutrients entering sewage treatment works and is used to divide nutrient fractions based on their origin, and categorised by whether they originate from human waste or unnatural sources. MFA and SFA allow the inflows to be tracked through the system, and outflow streams quantified, which enables the degree of harm to be established.

Inflow circularity

The objective of defining nitrogen and phosphorus (NP) nutrient circularity relies on understanding their renewability within biological systems. Firstly, NP inflows are defined as circular if *it is from a source that contributed to the natural human diet and cycling of nitrogen or phosphorus*, such as human excreta. Next, any farming or animal wastes entering the system are classified as linear, as these nutrients should be kept within the farming/food system and applied to crops. Then NP is considered to have non-circular properties when sourced *from preventable or non-natural sources and is part of the non-natural and unnecessary use of nitrogen or phosphorus*. Table 4.3 provides a summary of the fractions of domestic wastewater, with the data for the fractionation of inflows taken from studies by Comber et al. (2013) and van der Hoek et al. (2018).

Table 4.3. Circularity fractionation of NP inflows.

<table>
<tr><th colspan="3">Phosphorus</th><th colspan="3">Nitrogen</th></tr>
<tr><th>Stream</th><th>Input Fraction</th><th>Status</th><th>Stream</th><th>Input Fraction</th><th>Status</th></tr>
<tr><td>Urine</td><td>30%</td><td rowspan="2">Circular</td><td>Urine</td><td>80%</td><td rowspan="2">Circular</td></tr>
<tr><td>Faeces</td><td>10%</td><td>Faeces</td><td>14%</td></tr>
<tr><td>Food Scraps</td><td>1%</td><td rowspan="6">Linear</td><td rowspan="6">Greywater (kitchen, laundry, or bathroom)</td><td rowspan="6">6%</td><td rowspan="6">Linear</td></tr>
<tr><td>Food Additives</td><td>29%</td></tr>
<tr><td>Automatic Dishwashing</td><td>9%</td></tr>
<tr><td>Laundry Detergents</td><td>14%</td></tr>
<tr><td>Tap Water Dosing</td><td>6%</td></tr>
<tr><td>Personal Care product</td><td>1%</td></tr>
</table>

Outflow circularity

The first step is to define circular outflows as being *effectively recovered for controlled release to soil (for fertilisation or conditioning) or safe return to the atmosphere*, or are utilised in *products to extend the life of nutrients in the human system, substituting the use of virgin resources.* Then linear flows are the opposite as they *are not recovered effectively and are released to the environment (atmosphere, water, and soil) in a way that is harmful to the natural functioning of ecosystems*. During classification of linear flows, it is critical to consider atmospheric emissions, especially N_2O as it is a reactive form of nitrogen produced during nitrification-denitrification processes and is a powerful greenhouse gas (GHG) making it harmful to the environment. Additionally, the eutrophic properties of NP mean that any release of these nutrients in wastewater discharge is assumed to be potentially harmful following the DNSH principles, as well as being a loss of useful resources from the human system, so are deemed linear.

Table 4.4 provides a summary of the properties of WWTP NP resource outflows, with typical concentrations taken from Tchobanoglous et al. (2014). It is worth noting that some streams have the potential to be linear or circular depending on their destination, for example if water is recycled to be used in agriculture, then NP nutrients are used in a circular manner in cases such as fertigation. The phosphorus in incineration ash can be leached and collected before landfill to be used in a circular manner, and the circularity of 'Other' uses of biosolids depends on the scenario, including composting or land reclamation processes. Therefore, the circular properties of nutrient outflows are dependent on the specific scenario and how resource outflows are used.

Table 4.4. Circularity fractionation of NP outflows.

Phosphorus				**Nitrogen**			
Stream	**Nutrient fraction**	**Destination**	**Status**	**Stream**	**Nutrient fraction**	**Destination**	**Status**
Effluent	1-2 mg/L	Sea Water	Linear	Effluent	5-15 mg/L	Sea Water	Linear
		Freshwater Body	Linear			Freshwater Body	Linear
		Water Upgrading/ Recycling e.g. fertigation	Circular / Linear			Water Upgrading/ Recycling e.g. fertigation	Circular / Linear
	>2 mg/L	Discharge Fails to Meet Permit Limits	Linear		>15 mg/L	Discharge Fails to Meet Permit Limits	Linear
	3.7-11 mg/L	Overflow Discharge	Linear		23-69 mg/L	Overflow Discharge	Linear
Biosolids	approx. 1.9 % Dry Solids (DS)	Landfill	Linear	Biosolids	approx. 4.4 %DS	Landfill	Linear
		Incineration	Circular / Linear			Incineration	Linear
		Land Application	Circular / Linear			Land Application	Circular / Linear
		Other	Circular / Linear			Other	Circular / Linear
				Gas Emissions *in the case of nitrification-denitrification	1.6 % Influent N (0.016 - 4.5 %) (Doorn et al., 2019)	N_2O	Linear
					29 % of Total N removed minus N_2O	N_2 (from organic fertilisers and biological fixation)	Circular
					65 % of Total N removed minus N_2O	N_2 (from synthetic fertilisers and atmospheric deposition)	Neutral
					6 % of Total N removed minus N_2O	N_2 (from greywater)	Neutral

Additional considerations – N_2 emissions

For nitrogen gas (N_2) emissions, a unique classification of 'neutral' is defined and used in combination with circular fractions. Initially, the circular allowance of N_2 is calculated as the fraction of nitrogen in human excreta (94 % of inlet) from organic fertilisers (manure) and nitrogen fixation, as this facilitates the extended life of nutrients in the human system and natural cycling. Then the remaining fraction is calculated from synthetic fertiliser application and atmospheric deposition of nitrogen, and whilst the N_2 gas generated from this does not cause environmental harm, it is not part of natural nitrogen cycling, nor does it contribute to the replenishment of atmospheric nitrogen sinks, so it is considered neutral. The other neutral fraction is calculated from the greywater inlet (6 %), as this is not part of natural nitrogen cycling. The N_2 fractions in Table 4.4 are collected from values in the Food and Agriculture Organization database (Food and Agriculture Organization of the United Nations, 2020) for nitrogen applied to cropland in EU-27 countries (year 2020) and are provided in Table 4.5. Lastly, in the cases of nitrification-denitrification it is recommended to calculate an additional indicator for the fraction of 'non-harmful' nitrogen outflow, so that linear, neutral, and circular resource flows are compared. This ensures that true nitrogen cycling is rewarded whilst good practices of biological nutrient removal (BNR) are not penalised by the assessment.

Table 4.5. Nitrogen applied to cropland in EU-27 countries in 2020.

Total Mass to Crops				**Status**
14,241,375		tonnes		Neutral/Circular
Total fractions		**Mass**		
Synthetic Fertilisers	62%	8,796,622	tonnes	Neutral
Manure Applied to Soils	28%	3,979,757	tonnes	Circular
Atmospheric Deposition	7%	1,031,166	tonnes	Neutral
Biological Fixation	3%	433,829	tonnes	Circular

Additional considerations – NP release

The mechanism of release is important for NP classification, which is why land application has been defined as potentially circular or linear. The first step is to consider the efficiency of NP application to farmland, as the particularities of each case, the amount applied, the time of year, and the method used can impact the utilisation of nutrients by cropland. For example, nutrients returned to an ecosystem at a rate higher than it is able absorb them can negatively impact nutrient cycling (Navare et al., 2021). Poor practice has the potential for serious environmental and health risks, such as the downstream generation of ammonia emissions from biosolids, which poses a threat to air quality and can cause respiratory issues, as well as contributing to nitrogen deposition. Therefore, land application can be classified as circular if *applied to croplands in an efficient manner considering the NP needs of crops, such that crop growth is enhanced and synthetic NP fertiliser requirements are reduced*. For example, WWTPs that use $FeCl_3$ dosing to enhance phosphorus removal produces a fraction of biosolids nutrients that are unavailable to the soil and are considered linear.

4.2.2.3 Carbon

Organic carbon (OC) plays a key role in wastewater treatment performance but is also critical in many resource recovery strategies. When completing GHG accounting of WWTPs, there is already an emphasis placed on understanding the emissions that occur due to fossil OC in the influent (Tseng et al., 2016). Therefore, a similar approach is followed when assigning circularity to OC flows. It is important to distinguish that biogenic carbon is absorbed and emitted by organic matter as part of the natural carbon cycle, whilst fossil carbon is created over very long timescales from dead organic matter, meaning its release disturbs the natural equilibrium which increases atmospheric concentrations. Thus, fossil carbon release causes environmental harm, substantiating its inclusion in GHG accounting protocols and classification as a linear action in this work.

Inflow Circularity

OC classification is different to the NP definitions of circularity but aligns the methodology with GHG accounting principles, as this is a priority of many sustainability targets. Therefore, OC is defined as circular if it *contributes to the natural cycling of biogenic carbon*, whereas it is considered linear if it *contributes to the unnatural use of avoidable fossil carbon*. For domestic wastewater, approximately 94.5 % of influent OC is biogenic, and therefore circular, whilst the remaining 5.5 % is fossil and linear (Law et al., 2013). When applying the classification framework to define OC circularity, it is recommended to start by understanding influent carbon composition of the WWTP in question as fossil and biogenic fractions are variable, especially if the plant is treating a proportion of wastewater from industrial sources, before SFA is completed.

Outflow Circularity

Determining the circular fraction of OC outflows requires SFA of this resource through WWTPs, to determine the quantity in each outflow as well as the fraction that is fossil carbon. Therefore, the first step is to collect data for quantifying the fraction of fossil carbon in each outflow stream, for example Table 4.6 summarises those for activated sludge plants (Law et al., 2013).

Table 4.6. Fractionation of fossil carbon in wastewater system outflows.

Outputs		Notes
Effluent	5.0 %	
Sludge (no anaerobic digestion (AD))	64.5 %	
Sludge (post AD)	56.8 %	88% of fossil carbon to sludge and 12% to biogas
Biogas (from AD)	7.7 %	
Direct Gas Emissions	30.5 %	

Then OC outflows are considered circular if there is *controlled release of biogenic carbon dioxide to the atmosphere or biogenic carbon to soil (for fertilisation or conditioning), or is utilised in products to extend the life of carbon in the human system, substituting the use of fossil resources*. This step requires the important distinction types of carbon emissions, as only biogenic CO_2 released to the atmosphere can be considered circular as this contributes to natural carbon cycling, whereas fossil CO_2 or other GHGs do not. The difference in timescales of fossil and present-day biogenic carbon cycling must be considered to assess the circularity of biosolids application to land. Fossil fuel CO_2 emissions release carbon that has been stored for millions of years, whereas biogenic feedstock consumption and CO_2 production is balanced by uptake during growth of new biomass on a timescale of years to decades. Therefore, biogenic carbon output as biosolids is considered circular. In contrast, the fossil carbon fraction in biosolids is considered linear, as it has been shown that only 35-60 % of carbon is retained in soils over 20 years (McLeod and Lake, 2021), with the rest lost to the atmosphere before fossil carbon stocks are replenished. Lastly, linear organic carbon outflows are defined as being *not effectively recovered for controlled release back to natural cycles, including fossil carbon dioxide or other powerful GHGs released to the atmosphere or fossil carbon to soil, with the potential to harm the environment*. This classification aligns with the wastewater sector's current carbon accounting rules (U.S. Environmental Protection Agency, 2011) and Table 4.7 summaries the characteristics of OC outflows of interest.

Table 4.7. Circularity fractionation of OC outflows.

Stream	OC fraction	Destination	Status
FOG	77 % TS	Landfill	Linear
Screenings	41.3 % TS	Landfill	Linear
Effluent	approx. 10 mg/L	Sea Water	Linear
		Fresh Water Body	Linear
		Water Upgrading/Recycling	Circular/Linear
	109-328 mg/L	Overflow Discharge	Linear
Biosolids	19-35 %DS	Landfill	Linear
		Incineration	
		Fossil Emissions	Linear
		Biogenic Emissions	Circular (CO_2)/Linear (CO and CH_4)
		Ash (landfill)	Linear
		Land Application	
		Fossil	Linear
		Biogenic	Circular
		Other	Circular/Linear
Direct Gas Emissions *in the case centralised aerobic processes	Total carbon removal minus CH_4 emissions	**CO_2**	
		Fossil	Linear
		Biogenic	Circular
	Emission factor of 0.0075 $kgCH_4/kgCOD$ (Doorn et al., 2019)	CH_4	Linear
Biogas	approx. 65 % CH_4 (remainder assumed CO_2)	**Biogas Combustion**	
		Fossil CO_2 and Fugitive CH_4	Linear
		Biogenic CO_2	Circular

Additional considerations - outflows

Carbon emissions in effluent discharge do not have the same harmful eutrophic properties as nitrogen and phosphorus, but this represents a useful resource that is lost to the environment, has potential to be released as GHGs downstream, and the ability to negatively alter river carbon dynamics (Lee et al., 2023), meaning it is classified as linear. Additionally, a caveat is needed when biochar is generated and applied to soil, as this carbon has a turnover time of hundreds to thousands of years making both biogenic and fossil carbon fractions circular, as OC is adequately sequestered compared with conventional biosolids (McLeod and Lake, 2021). Lastly, for the case of advanced resource recovery, fossil carbon that is stored usefully within a product for the human system, replacing the need for fossil carbon extraction (such as paint production) would be considered circular using the definition of outflow circularity provided.

To conclude, it is not possible for all flows to be classified as fully linear or circular, for example there are losses during many circular recovery processes. Therefore, to collect data with a sufficient level of detail when applying the framework to real-world WWTPs it is critical to engage with local process operators and environmental scientists to understand downstream processing steps and environmental interactions.

4.2.3 Assessment

The development of process models is required for SFA and MFA of resources to complete the circularity characterisation approach described in Section 4.2.2, enabling the calculation of indicators for assessment of WWTP resource circularity. The circularity indicators selected cover the key areas of material inflows and outflows, water, energy, and economics, following a similar structure to the Circular Transition Indicator framework (wbcsd, 2022). Using the classification of Section 4.2.2 to assign circularity facilitates more standardised and robust analysis of key resources during the assessment, enabling the comparison of results across different wastewater systems (plant location, technology, or size). The selected resource flow indicators are summarised in Table 4.8.

Table 4.8. Indicators selected for resource flow analysis.

Category	Indicator	Equation
Materials	Circular Inflow (as defined by classification approach) (%)	$\frac{Mass\ Circular\ Inflow}{Total\ Mass\ of\ Inflow}$
	Renewable Recirculation Outflow (%)	$\frac{Mass\ Renewable\ Ouflow}{Total\ Mass\ of\ Outflow}$
	Circular Outflow (as defined by classification approach) (%)	$\frac{Mass\ Circular\ Outflow}{Total\ Mass\ of\ Outflow}$
	Circular Flow (%)	$\frac{Circular\ Inflow + Circular\ Outflow}{2}$
	Wastewater Nutrient Removal Efficiency (%)	$1 - \frac{Output\ Concentration}{Input\ Concentration}$
Water	Water Discharged in Accordance with CE Principles (%)	$\frac{Volume\ of\ Circular\ Discharge}{Volume\ of\ Water\ Withdrawal}$
	Water Use from Circular Sources (%)	$\frac{Volume\ Water\ Used\ from\ Circular\ Sources}{Volume\ of\ Water\ Required\ by\ the\ Process}$
Energy	Energy Consumed from Renewable Sources (%)	$\frac{Renewable\ Energy\ Consumption}{Total\ Energy\ Consumption}$
Value	Circular Material Productivity (€/kg)	$\frac{Total\ Revenue}{Mass\ of\ Linear\ Inflow}$
	Value-based Resource Efficiency (€/€)	$\frac{Gross\ Output - Personnel\ and\ Service\ Costs}{Input\ Energy\ and\ Material\ Value} - 1$
	Product Value per Mass (€/kg)	$\frac{Product\ Revenue}{Mass\ of\ Virgin\ Resources}$

Table 4.8 includes the circular inflow and outflow indicators, calculated using the scheme developed in Section 4.2.2, and the fraction of renewable resources as useful insights are provided when comparing results of these indicators. The removal efficiency of the treatment process is a common indicator of WWTP operational performance (von Sperling et al., 2020), as the most important result is the treatment of wastewater to a satisfactory standard. The Value-based Resource Efficiency (VRE) shows the economic efficiency of the WWTP (Di Maio et al., 2017), revealing how the gross output (revenue) compares to the cost of energy and materials. The product value per mass indicator is included as the recovery of high value products from wastewater will become more popular, enabling the impacts to revenue streams to be understood and analysis of product revenue separately from service fees. However, in conventional WWTPs this will often be zero as there is little market for the low value resources

recovered, such as biosolids. This indicator is useful in cases when comparing alternate resource recovery technologies or strategies to determine the economic efficiency of value-added product generation.

To interpret assessment outcomes, a combination of Sankey diagrams and indicator results from Table 4.8 are then used to complete hotspot analysis of the WWTP. Sankey diagrams visualise the results of MFA, showing the viewer both the pathway and magnitude of resource flows in the system, as the width of each stream is proportional to its magnitude (Renfrew et al., 2022). Indicator results build upon this, showing how the size and destination of these streams impact the circularity of resource flows in the WWTP. The same analysis must then be applied for the investigation of potential scenarios that alter the circularity of WWTP resource flows, validating how any decision maker actions will impact the upstream and downstream, or for comparing alternate systems to identify better practices in terms of circularity (Section 4.3).

4.3 Results

This section demonstrates implementation of the classification approach developed in Section 4.2 to assess a conventional WWTP. Potential scenarios impacting process upstream and downstream are utilised to elucidate how the approach can be used for evidence-based decision making considering the actions of water users.

4.3.1 System definition

A centralised, conventional, activated sludge WWTP at a scale of 270,000 population equivalents, with an average load of 12,000 m^3/d in Estiviel, Spain was selected for the assessment (Rodríguez-Chueca et al., 2019). This is a common treatment process across Europe so is an interesting case to test the capabilities of the resource classification approach.

4.3.2 System boundaries

The WWTP is assumed to operate with conventional pretreatment to remove grit, screenings, and FOG, followed by primary clarification. From the effluent quality quoted in literature (Rodríguez-Chueca et al., 2019), it was assumed secondary treatment consists of aerobic and anoxic zones to facilitate nitrification-denitrification, with ferric dosing to chemically remove phosphorus. Primary and waste activated sludge (WAS) are stabilised using anaerobic digestion (AD) with the generated biogas utilised for energy recovery to heat digesters and supply electricity to the plant. System boundaries are drawn from when wastewater leaves the water user and flows into the WWTP (meaning the impacts of leakages are considered), until wastewater effluent is discharged from the plant and biosolids are applied to land as shown in Figure 4.2.

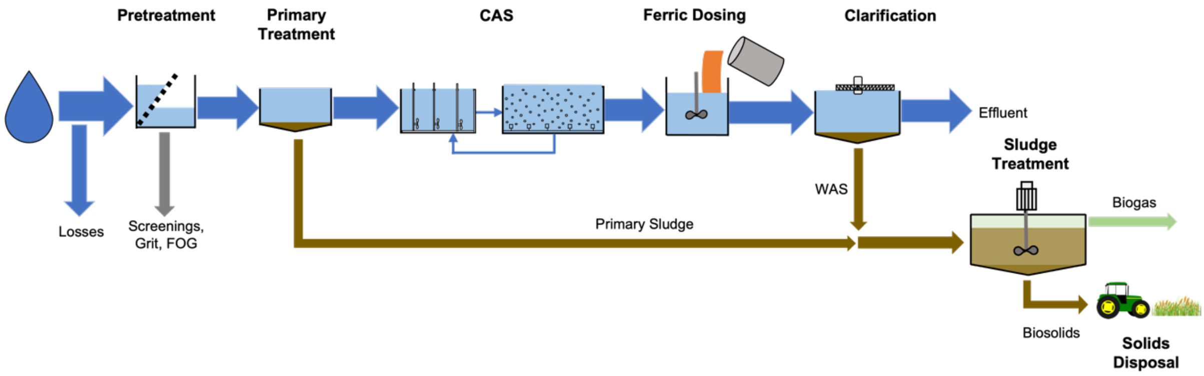


Figure 4.2. Process stages of the assessed WWTP.

4.3.3 *System modelling*

A model of the WWTP was constructed for the physical, chemical, and biological treatment units using parameters taken from literature provided in Tables B1-B4 of Appendix B, enabling MFA for each wastewater resource to be completed. The wastewater influent and effluent loadings were taken from literature describing a WWTP of this size in Estiviel, Spain (Rodríguez-Chueca et al., 2019).

4.3.4 *Resource flow characterisation*

The circularity assessment was completed using the tables and definitions from Section 4.2.2 to characterise the water, nitrogen, phosphorus, and carbon resource flows, and a summary is provided in Tables B5-B8 of Appendix B. Combining MFA results with the assigned circular properties enables the calculation of assessment indicators in Table 4.8.

4.3.5 *Scenario investigation*

As stated previously, one of the main goals of this approach is to support CE policy by investigating the impacts of water user behaviour and upstream decisions on WWTP circularity and the downstream environment. Therefore, once MFA and resource classification has been completed, assessors should use this information combined with water related policy (UWWTD) or regional goals (CE Action Plan) to create alternate scenarios for quantifying potential changes to WWTP circularity. To reveal the value of the resource classification approach, targeted scenarios impacting WWTP inlet and outlet have been generated reflecting plausible real-world changes to the system that influence process upstream and downstream circularity:

1. A company starts operating in the municipality, producing an additional 400 m^3/d of wastewater for treatment containing 1000 mgC/l of fossil carbon.
2. Due to local farmers changing fertiliser application practices and more intensive rainfall due to climate change, runoff from local farmland entering the sewage system increases NP concentration by an average of 5 %.
3. A local campaign in the region has raised consumer awareness regarding the negative environmental impacts of dishwashing and washing machine detergents, reducing consumption by 50 %.
4. The local water utility decides to invest in biogas upgrading for biomethane production to directly inject it into the grid, generating additional revenue and excess CO_2 as a by-product.
5. Improved nutrient management plans from European Commission regulation result in a 50 % reduction of synthetic fertiliser use by local farmers, with demand matched by an increase in organic fertilisers application.

4.3.6 Assessment

4.3.6.1 Material flow analysis

Figure 4.3 provides the Sankey diagrams for water (3A) and nutrients (3B) flowing through the WWTP, revealing the circular and linear resources in the system.

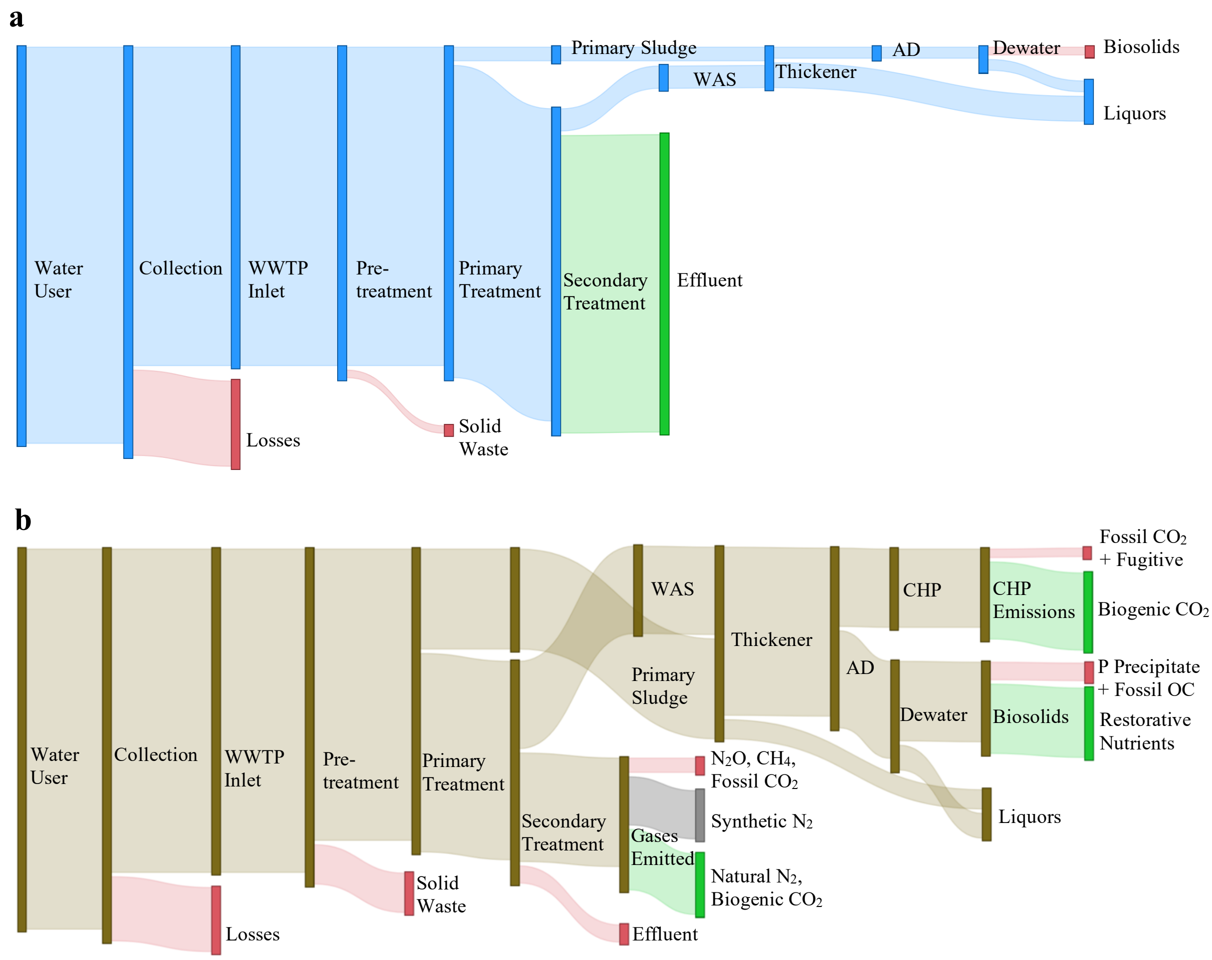


Figure 4.3. MFA of the WWTP system with circular flows in green and linear flows in red, and other flows that stay within the system boundaries. **b**; water resources **a**; nutrient resources.

The MFA is usually applied for identifying hotspots in terms of material losses, but further insights can be found by integrating the classification approach for use as a tool to highlight which resource flows must be targeted to improve WWTP circularity. Figure 4.3A shows that the majority of water resources are lost to the environment as effluent discharge, however, UWWTD requirements are met and effluent is below the critical load of the receiving water body, so this can be considered a regenerative and therefore circular action. Still a significant proportion of influent water is lost during collection (from user to WWTP), warranting further investigation into leakage reduction measures as this would result in the greatest benefits to water circularity. The water in biosolids is seen as a loss of resources, as in its current form the water balance of the soil is not improved. By diluting biosolids this could be reversed to reduce water abstraction for irrigation and be seen as a circular water flow, however, this must be considered against potential impacts such as additional transportation.

The impacts of losses during wastewater collection are also shown for nutrient resources in Figure 4.3B, therefore, investments in leakage reduction would be of benefit for improving overall process circularity. There is also a large loss of carbon from FOG removal during pretreatment, which could be overcome by adding this resource to AD units to improve WWTP circularity. Additionally, there are losses of nitrogen and carbon gaseous emissions to the atmosphere in a harmful manner, meaning better WWTP control is needed to reduce N_2O production, as well as strategies to reduce inlet fossil carbon and investments in technology to sequester these emissions. There is also a significant fraction of N_2 emissions from secondary treatment (41.6 % of total resources directly emitted) that have a ‘neutral’ classification, evidencing that a high proportion of nutrient inflow comes from synthetic nitrogen sources. Lastly, it is shown that a fraction of biosolids nutrients are linear as they are unavailable to the soil due to the use of chemical phosphorus removal, meaning a biological treatment process that removes phosphorus is needed improve resource circularity.

Ultimately, MFA quantified that only approximately 75 % and 50 % of water and nutrients resource outflows are circular in the assessed WWTP respectively, showing there is still significant scope for improvement. It also highlights the importance of boundary selection during the assessment, as here the collection losses are considered before WWTP inlet, limiting outflow circularity indicators, as 20 % of all resources are lost from the system, emphasising the impacts of leakage on circularity. However, decision makers may wish to define boundaries of the WWTP itself to investigate the circularity of process operation only.

4.3.6.2 Resource flow indicators

Figure 4.4 provides the resource flow indicator results for material inflows and outflows. Using the classification framework, indicator results provide more detailed resource analysis than MFA alone or using the alterative definitions of circularity from literature.

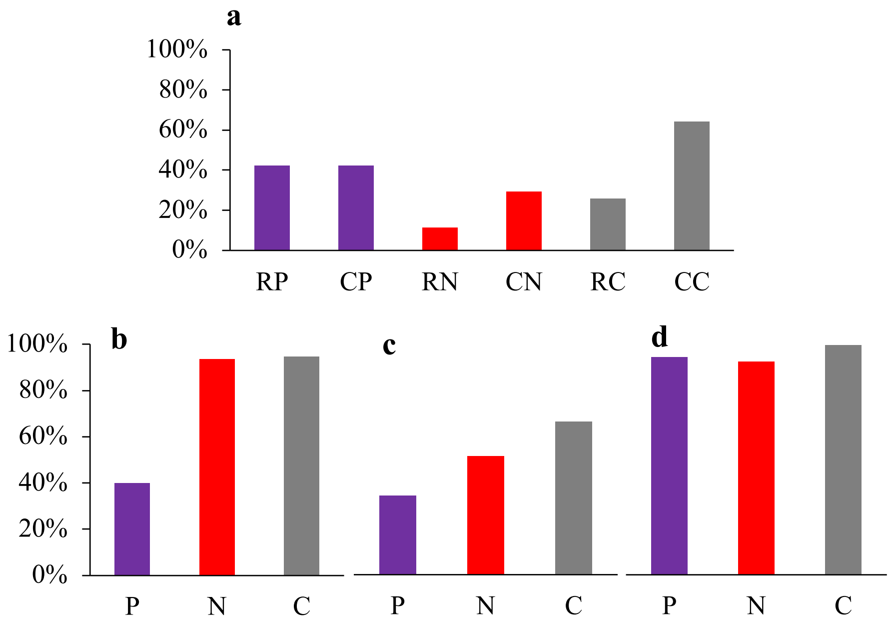


Figure 4.4. **a**; renewable (R) and circular (C) outflow, **b**; circular inflow, **c**; total circularity, and **d**; WWTP removal efficiency indicator results for carbon, nitrogen, and phosphorus nutrients.

Figure 4.4A shows outflow renewability and circularity are equal for phosphorus (42.2 %), as renewability is taken to be the material safely returned to soil for nutrient cycling. As biosolids are the only product containing phosphorus generated by the process (only other outflow is the effluent), renewability is also equal to the quantity circular resource outflows. This poor performance is related to the phosphate compound generated during chemical phosphorus removal, meaning that 43.8 % of biosolids phosphorus is unavailable to the soil. The production of N_2 emissions sourced from natural nitrogen cycling during secondary treatment is a circular outflow, thus it can be added to biosolids nitrogen, so outflow circularity reaches 29.3 % compared with renewability of 11.4 %. Outflow circularity is low for nitrogen, as 53.8 % of resources leaving the system is N_2 produced during nitrification-denitrification, which is neutral in terms of circularity and should be targeted by decision-makers. For carbon outflows, there is a large difference between renewability (25.8 %) and circularity (64.2 %), as the biogenic CO_2 produced during secondary treatment and biogas combustion are considered circular outflows, whilst the remining linear fraction is from fossil CO_2 and methane emissions generated during secondary treatment, AD, and biogas combustion. Therefore, biogenic gaseous emissions make up a larger proportion of circular carbon outflows than those applied as biosolids to land for soil restoration.

Figure 4.4B highlights that phosphorus is the resource with the lowest inlet circularity (40.0 %), meaning it should be prioritised for enhancement by changing water user habits, especially as it is the most finite and critical resource of those analysed. This is also evidenced in Figure 4.4C, as phosphorus is the lowest performing resource for overall circularity (41.1 %). However, nitrogen's total circularity of 61.5 % shows inconsistency between its inflow and outflow performance, as it achieves the lowest outflow renewability and circularity ratings of the nutrients analysed, so these resource flows have the largest potential for improvement. Lastly, WWTP operational performance is assessed in Figure 4.4D, which confirms that it performs well at removing all nutrient resources from wastewater (>90 %). Therefore, gaseous and solid outflows should be prioritised to see the most significant improvements to outflow circularity.

Table 4.9 summarises the results for water, energy, and economic resource flow indicators. The circular discharge indicator shows the fraction of wastewater effluent that is discharged within permit limits and recharges water sources, with the remaining water fraction coming from wastewater collection losses and solids production (pretreatment and biosolids), again highlighting the need to reduce leakages to improve circularity. The renewable energy fraction shows the WWTP performs well, however this comes from energy recovery from biogas combustion and the fact that 67 % of Spain's electricity is already generated from renewable sources (IEA, 2021). Therefore, the energy recovery system only results in a 20 % gain of renewables consumption, meaning higher value recovery strategies should be investigated. Material productivity reveals WWTP economic efficiency in terms of linear resource consumption, as gate fees (revenues) are relatively fixed so the linear fractions of wastewater inlets or virgin material consumption (polyelectrolyte or ferric chloride) should be mitigated to see the largest benefit to this indicator. Similarly, the VRE shows the WWTP operates in an economically favourable manner, but revenue is stationary so OPEX must be targeted by reducing material or energy consumption to leverage significant improvements. Lastly, circular water use and value per mass are zero, as it is assumed this municipality utilises water abstracted from virgin sources and the WWTP does not generate revenue from product sales respectively, emphasising aspects that are easily exploitable to see circularity enhancements.

Table 4.9. Water, energy, and economic resource flow indicator results.

Water	
Circular Discharge	78.8 %
Water Use from Circular Sources	0 %
Energy	
Renewable Fraction	86.8 %
Economic	
Material Productivity (€/kg)	4.8
Value-based Resource Efficiency (€/€)	2.7
Value per Mass (€/kg)	0

4.3.6.3 Scenario analysis

Now considering the scenarios posed in Section 4.3.5 and outcomes in Table 4.10, the value of the classification framework is clear as it enables impacts of changing water user habits (at regulatory, regional, or human scales) to be quantified in terms of circularity, by connecting upstream and downstream impacts. A summary of the material indicator results for all scenarios investigated is provided in Table B9 of Appendix B.

Table 4.10. Impacts to resource circularity when WWTP is subjected to potential scenarios.

Scenario	Circularity Impacts	
	Description	Quantitative Change
1	Linear inflow of carbon increases	5.5 % to 21.5 %
	Circular outflow of carbon decreases	64.2 % to 53.6 %
	Fossil CO_2 emissions increase	by 370 %
	Total effluent carbon increases	by 33 %
2	Linear inflow of N increases	6.4 % to 10.9 %
	Linear inflow of P increases	60 % to 62 %
	Circular outflow of P decreases	42.2 % to 40.9 %
	Unavailable biosolids P increases	by 10.6 %
3	Circular inflow of P increases	40 % to 45.2 %
	Circular outflow of P decreases	42.2 % to 41.0 %
	Biosolids P decreases	by 13.5 %
4	Circular outflow of carbon increases	64.2 % to 64.6 %
5	Circular outflow of N increases	29.3 % to 49.4 %
	Total circular flow of N increases	61.5 % to 71.5 %

Scenario 1

An additional 400 kg/d of non-renewable, fossil carbon discharged to wastewater from upstream production not only increases the linear influent by 16.0 % but also reduces outflow circularity by 10.6 %. The reduction in outflow circularity is due to the significant increase of fossil CO_2 emissions production during secondary treatment and biogas combustion, and large quantities of fossil carbon in biosolids (four times greater). However, the additional fossil carbon inlet also increases nitrogen outflow circularity by 0.4 %, due to enhanced biomass production, reducing the emissions generated during secondary treatment required to achieve the same effluent quality. This quantifies both the direct impacts of the company on municipal wastewater and indirect impacts of their practices on the environment downstream, providing decision makers with the knowledge to lobby them to reduce wastewater production, pay greater fees for remediation, or utilise biogenic carbon sources.

Scenario 2

The effects of poor farming practice that results in greater runoff are quantified in terms of reducing inflow circularity of nitrogen and phosphorus by 4.5 % and 2 % respectively. Although the WWTP is modelled so that effluent quality remains the same, the principle of traceability is used to directly show the impacts on to the wider process. Outflow phosphorus circularity reduces by 1.3 % as a greater quantity of ferric chloride is needed to maintain the desired effluent quality, meaning that the proportion of biologically unavailable phosphorus in biosolids increases by 10.6 %. These results are useful to educate both local governments and farmers to highlight the negative impacts of their choices, and change either regulation or behaviour through incentivising good or penalising poor practice.

Scenario 3

As the public become more environmentally conscientious, it could lead to changes in water use habits such as reduction in washing detergent use. These stakeholders will be aware that reducing material consumption has benefits, but now they can be educated upon the downstream consequences of this on wastewater circularity. It was shown that a reduction of 50 % improves the circularity of influent phosphorus by 5.2 %. However, phosphorus outflow circularity decreases by 1.2 % as the same effluent quality is maintained using chemical removal processes, reducing the quantity of biosolids phosphorus by 13.5 %. This emphasises the potential benefits of biological removal to simultaneously improve the circularity of wastewater effluent and biosolids, as in this case reducing ferric chloride dosage would have no impact on circularity as this action would only increase the quantity of effluent phosphorus.

Scenario 4

Upgrading biogas to biomethane generates a higher value product and useful by-product, which are positive actions when viewed through a CE lens. However, this scenario actually produced few benefits in terms of resource circularity, only increasing carbon outflow circularity by 0.4 % as biogas created from fossil carbon was not combusted and released to the atmosphere, and fugitive emissions are still generated. Therefore, in cases such as these, wider assessments of the process are needed to justify investment decisions, including economic analysis as biomethane prices range from 26-78 €/MWh (Legrand et al., 2022) and environmental assessments to investigate changes to air quality and emissions production in the local area.

Scenario 5

Improving the management of wastewater nutrients is a priority of the proposal to update the UWWTD and CEAP (European Commission, 2022), meaning it is important that assessment methods can account for these changes. Subsequently, reducing synthetic fertiliser usage by 50 % resulted in an increase of nitrogen outflow circularity by 20.1% as these N_2 emissions, previously considered neutral, now receive a circular classification. Emitting this form of N_2 is seen as a regenerative action for the natural cycling of nitrogen, which increases from 29 % to 61.5 % of N_2 in this scenario. This increases nitrogen total circularity by 10 %, highlighting the benefits in terms of WWTP circularity resulting from regenerative emissions production. Therefore, the classification approach is able to investigate how nutrient utilisation in a specific geographical area meets new regulatory goals and targets, by monitoring the circularity performance of its WWTPs.

It is worth noting that although these results are useful for decision makers to understand the circularity of resource flows, wider assessments are needed to prioritise actions that will result in the greatest benefits or mitigation of impacts to sustainability. For example, Figure 4A highlights that nitrogen outflows are a large hotspot that should be improved, however, this could result in other impacts such as increased energy consumption, meaning it is economically or environmentally unfavourable. Therefore, the classification approach should act as the basis for the holistic assessment of WWTP systems, linking how physical changes to resource flow circularity impacts the sustainable value generated for stakeholders.

4.4 Discussion

4.4.1 Resource flow characterisation

Using the definitions of waste circularity described in Section 4.1 results in the overinflation of waste treatment process circularity performance, with little variation between systems, meaning the utility of CE assessments is limited for decision making. For example, a treatment plant that accepts mishandled, preventable, or contaminated waste, and sends it to landfill, would achieve an overall circularity of 50 %. When compared to an economic system that minimises waste production and applies circular principles to cascade resource use and extend its life, and sends 50 % to both landfill and recycling, only to gain 25 % in overall circularity, even though it is applying CE principles in the upstream and downstream, it emphasises current circularity assessment issues. The classification framework presented in this work enables the circularity of each wastewater resource to be scrutinised, resulting in more robust and detailed circularity analysis to enhance decision making capabilities from WWTP circularity assessments.

4.4.2 Carbon emissions

The decision to award particular resources a circular status may be subject to debate, one of those being biogenic CO_2. A circular classification was given as this is in line with the EPA's current carbon accounting protocol, as it is reasoned that biogenic CO_2 emissions have no net atmospheric impact, so biogenic processes sequester CO_2 during feedstock production equivalent to the direct biogenic CO_2 emissions from a stationary source such as waste management. Therefore, the chosen classification aligns with the common assumption that biogenic carbon emissions are carbon neutral (Navare et al., 2021). However, the European Chemical Industry Council (Cefic, 2022) argues that this justification does not incentivise the use of bio-based materials and suggests that carbon removal credits should be assigned when biomass is produced and penalise all CO_2 emissions, whether biogenic or fossil when released back to the atmosphere. Therefore, the classification of biogenic carbon developed here is not able to explicitly conclude whether climate neutrality is achieved, as this must consider time-dependent fluxes of carbon to verify that the production rate is lower than sequestration (Navare et al., 2021). Development of this approach for carbon accounting would enable more transparent analysis, remove the issues with assessment timelines, and avoid double counting of carbon credits.

This also highlights a larger issue with the current carbon accounting procedures of WWTPs, as influent carbon is usually assumed to be biogenic and ignores fossil carbon during assessments (Maktabifard et al., 2023). This is corroborated by the 2019 IPCC refinement, which encourages countries to evaluate these emissions during GHG inventory development and stating that 4-14 % of WWTP influent carbon is fossil (Doorn et al., 2019). However, this has not been followed as there is no standardised method for quantifying fossil carbon in WWTP outflows (IWA, 2023). The WWTP assessment example in this work showed the large impact that fossil carbon can have on circularity using this classification. Therefore, a similar approach, utilising resource traceability, could be implemented as the omission of potentially significant fossil carbon WWTP emissions puts the net-zero and carbon neutrality ambitions of the water sector at risk.

4.4.3 Local considerations

Another issue with the resource classification examples provided is that the fractionation was completed using values from literature. The composition of wastewater will change with geography depending on the local water users, whereas leakage and amount of water lost is impacted by local water infrastructure. Similarly, regulatory limits and the preferred method of wastewater treatment of a region will impact resource outflow concentration, production rates, and destination. Therefore, when a technology is being investigated for implementation in a real-world process, it is recommended to conduct a study to quantify missing information, such as the sources of wastewater nutrients and fraction of water loss. For better understanding of resource outflows, wastewater process operators should be consulted to validate the concentration and production rates of gaseous emissions, effluents, and waste streams. There are also several sources that detail how to test the fossil fraction of OC along each stage of a WWTP (Law et al., 2013; Tseng et al., 2016). This ensures that local factors are incorporated to accurately calculate circularity indicators when investigating the selection of technologies for integration within real-world processes.

4.4.4 Resource recovery prioritisation

This framework aims to enhance the circularity of wastewater processes, with a key aspect of this transition being resource recovery. Examples could not be provided for all potential resource recovery scenarios, so in the cases where certain resources or destinations are not covered in Tables 4.1-4.7, the definitions provided should be used for classification. Authors are aware that the definitions taken for some nutrient classifications may induce favourable resource flow indicator results for activities that may be perceived as 'less circular'. For example, in the framework provided, certain N_2 fractions and biogenic CO_2 emissions are classified as circular, which could result in greater circular outflows for a process employing nitrification-denitrification, than one investigating advanced nutrient recovery (due to process inefficiency losses). However, prioritisation of different wastewater solutions is case specific, for instance in many areas upgrading WWTPs with BNR secondary treatment will result in a more sustainable process, compared to some traditional or conventional processes. On the other hand, employing resource recovery technologies might result in additional wider benefits for stakeholders and therefore greater added value. To quantify the benefits of these value creating actions, alternative sustainability indicators are required, for example, eco-efficiency and LCA impact indicators can be selected to quantify changes in economic and environmental performance (Smol and Koneczna, 2021).

4.5 Summary of main findings

- Current definitions of waste create a paradox during the circularity assessment of wastewater treatment facilities, as intentional or preventable generation of waste is against many CE principles, yet it would be considered a circular inflow within these system boundaries due to its non-virgin status.

- To overcome this, the CE principle of resource traceability is used understand wastewater resource source and destination, and is combined with their ability to cause harm when interacting with various parts of the natural environment to disentangle WWTP input and output circularity

- This led to the creation of a framework of definitions to assign circularity to wastewater water, nitrogen, carbon, and phosphorus resources, as well as some examples for common WWTPs.

- The methodology was validated by using it to assess the circularity of a Spanish WWTP, using MFA and a taxonomy of resource flow indicators divided into the key areas of materials (inflows and outflows), water, economics, and energy analysis. This enabled a more detailed assessment of wastewater resource circularity than if current definitions had been used, also showing how the actions of wastewater producers impact resource circularity.

- Five scenarios were investigated to show the value of the classification framework as it enables the effect of changing water user habits (at regulatory, regional, or human scales) to be quantified in terms of circularity, by connecting upstream and downstream impacts.

- Industrial action increasing fossil carbon concentration (400 m^3/d effluent at 1000 mgC/l) reduced inflow and outflow circularity by 16 % and 10.6 % respectively, as secondary and sludge treatment fossil emissions increase significantly. Additionally, changes to human habits reducing detergent use by 50 % improved phosphorus inflow circularity by 5.2 % and better agricultural practices reducing synthetic fertiliser usage by 50 % increased nitrogen outflow circularity by 20.1 %.

- The classification approach facilitates robust circularity indicator calculation, acting as the basis for standardising the circularity assessment of wastewater systems to assign responsibility to different wastewater producers. This approach should be used to develop common and consistent policy and regulatory frameworks, not only rewarding circularity but impeding or penalising linear practices.

5 Systematic Assessment of Wastewater Resource Circularity and Sustainable Value Creation

5.1 Introduction

The water sector is key to the circular economy (CE) transition due to the direct reliance industry and society has on clean water supply and adequate wastewater management (Smol et al., 2020). Recent efforts to develop specialised tools to facilitate circularity, such as KWR's dashboard for a circular water sector (KWR, 2021) and The World Bank's Water in Circular Economy and Resilience framework (The World Bank, 2021), highlights the CE's potential to improve water sector practices. Although this shows water utilities have a desire to enhance their circularity, it has not translated into the universal definitions and standardised measurement tools required for ubiquitous understanding of CE benefits for stakeholders (Ahmed et al., 2022).

It has been shown that engineering and technological aspects are no longer barriers that inhibit the circular transition, in fact it is a lack of planning and performance analysis (Smol and Koneczna, 2021), and hesitant company culture viewing circular investments as economically unfavourable in the short term (Kirchherr et al., 2018). Without a dedicated methodology for measuring the value creation of wastewater processes, it is difficult to build business cases and convince companies to invest in circular solutions (product, technology, process, service, or strategy) (Nika et al., 2021).This is compounded by the fact that there is limited research on how the CE provides this competitive advantage (Lahti et al., 2018), emphasising the need for assessments that can prove economic feasibility of circular solutions and quantify their multi-dimensional benefits.

CE monitoring frameworks focus on measuring material flows, where aligning resource focused indicators with triple bottom line (TBL) dimensions has been used as evidence for the assessment of sustainability (Harris et al., 2021). This results in patchy assessments, rebound effects, and impact leakage (Chen, 2021), leading to insufficient consideration of wider sustainability impacts and the attitude of *circularity for circularity's sake* (Harris et al., 2021). Concurrently, environmental impact indicators, including life cycle assessment (LCA) impacts, have been used to assess the circularity of products and services (Corona et al., 2019). Although these indicators validate CE effectiveness, they cannot quantify changes to resource circularity, even though this is needed to differentiate the CE from the vague goal of sustainable development. Therefore, a significant gap exists in CE assessments to systematically understand how changes in physical resource flows impact sustainability dimensions.

This is pertinent for the assessment of water systems as water utilities' strategic circular aims focus on societal-level sustainability issues such as carbon neutrality, water provision, and energy security, the majority of which are realised by exploiting the value of wastewater. Tapaninaho and Heikkinen (2022) found that sustainability value is created when societal-level sustainability aims are addressed by circular business models, and that the traditional focus of value creation on profitability is insufficient to capture the breath of CE benefits. Therefore, sustainable value creation should be used as a holistic indicator of circular performance for wastewater systems, which uses stakeholder collaboration to understand value creation across the TBL (Tapaninaho and Heikkinen, 2022). This is critical to showcase the validity and societal relevance of the CE, or else the concept is at risk of being thought of as unachievable or discredited as a new form of greenwashing (Calisto Friant et al., 2020).

In this work, an assessment method is constructed which combines a detailed understanding of wastewater process circularity with the support of explicit sustainability analysis. It shows how the actions of decision makers alter physical wastewater resource flows and the resultant impacts of this on sustainable value creation. Therefore, the method is able to distinguish between and assess intrinsic circularity, following the three CE principles of designing out negative externalities, regeneration of natural capital, and keeping products and materials in use (using resource flow and action indicator sets) (Ellen MacArthur Foundation, 2015), and consequential circularity impacting sustainability dimensions (using complementary analysis techniques). This requires systematic indicator selection and calculation, and it is hoped the methodology provided implements this to act as the basis for standardising holistic wastewater resource circularity assessments.

5.2 Methodology

The CE concept serves as a key facilitator of sustainable development, therefore, the assessment method is based on five principles developed from relevant sustainability science, sustainability assessment, and CE literature (Sala et al., 2015; Valeria Superti et al., 2021; Tapaninaho and

Heikkinen, 2022; Troullaki et al., 2021). The methodology developed provides solutions to the gaps identified in current circularity assessments (Section 5.1).

5.2.1 Methodological principles

Principle 1: Circularity performance assessments should consider both intrinsic circularity and consequential circularity in line with the definitions provided by Saidani et al. (2019). As a result, the developed method is concept specific (assessment of circular performance without excessively opening scope), yet multi-dimensional (simultaneously highlights impacts of circularity on sustainability dimensions). This is achieved by selecting a taxonomy of indicators which demand a detailed assessment of resource circularity and efficiency, and are then used to identify relevant sustainability impacts. Thereby, circularity and sustainability indicators are used to support each other, validating outcomes to strengthen decision making capabilities, facilitating circularity assessments that are normative and valid. This mitigates the current approach of excessively opening the scope of indicator sets, in which circularity and sustainability assessments are used as fragmented pillars or as a substitute for the other (Troullaki et al., 2021), diluting analysis of both dimensions (Valeria Superti et al., 2021).

Principle 2: Circular actions are used as a foundation for the selection of relevant circularity performance indicators and to guide complementary sustainability analysis. Therefore, systematic selection of indicators considering the scenario of application has been integrated in the assessment methodology, using project specific data and models. This means indicator selection is flexible and dynamic, depending on individual project targets, directed by the proposed 'circular actions' of the investigated system (Coenen et al., 2020; Moraga et al., 2019). This facilitates a pertinent aspect of sustainability science, linking science to actions through solution-oriented assessments (Sala et al., 2015; Troullaki et al., 2021).

Principle 3: It is necessary to understand and quantify the impacts the investigated system has on sustainable value creation considering environmental, social, and economic dimensions. This enables users to holistically understand how the consequential circularity impacts of the investigated system contribute to sustainable development. For the assessment of wastewater processes this is particularly important, as in the CE, waste valorisation must be prioritised to transform these streams, previously considered as burdens in the linear economy, into valuable resources and products (Leder et al., 2020).

Principle 4*:* Resource traceability is a key element of circularity measurement and assessment as it provides an enhanced understanding of circularity by tracking the source and destinations of flows. Resource traceability of biotic/water resources is not commonly employed (Harder et al., 2021b), but the developed methodology evidences its utility using characterisation from Chapter 4 to trace key wastewater resources, enabling robust circularity indicator calculation.

Principle 5: Stakeholder participation is vital for the assessment to increase CE acceptance and credibility by providing context specific insights. In the method developed, stakeholder perspectives are key for understanding the goals of circular actions, to select relevant performance indicators and assess sustainable value creation.

5.2.2 Methodological explanation

By combining the principles summarised in Section 5.2.1 a method was developed for the systematic assessment of wastewater resource circularity, as shown in Figure 5.1. The steps in Figure 5.1 result in a taxonomy of indicators that, when calculated using the resource classification approach of Renfrew et al. (2023), can act as the basis for standardising the circularity assessment of wastewater resources. The method provides i) a detailed analysis of inflow and outflow (materials/nutrients), energy, water, and economic resource circularity, ii) a performance evaluation of the circular actions implemented, as well as iii) analysis of the sustainability impacts and sustainable value generated by the targeted system of interest (SOI).

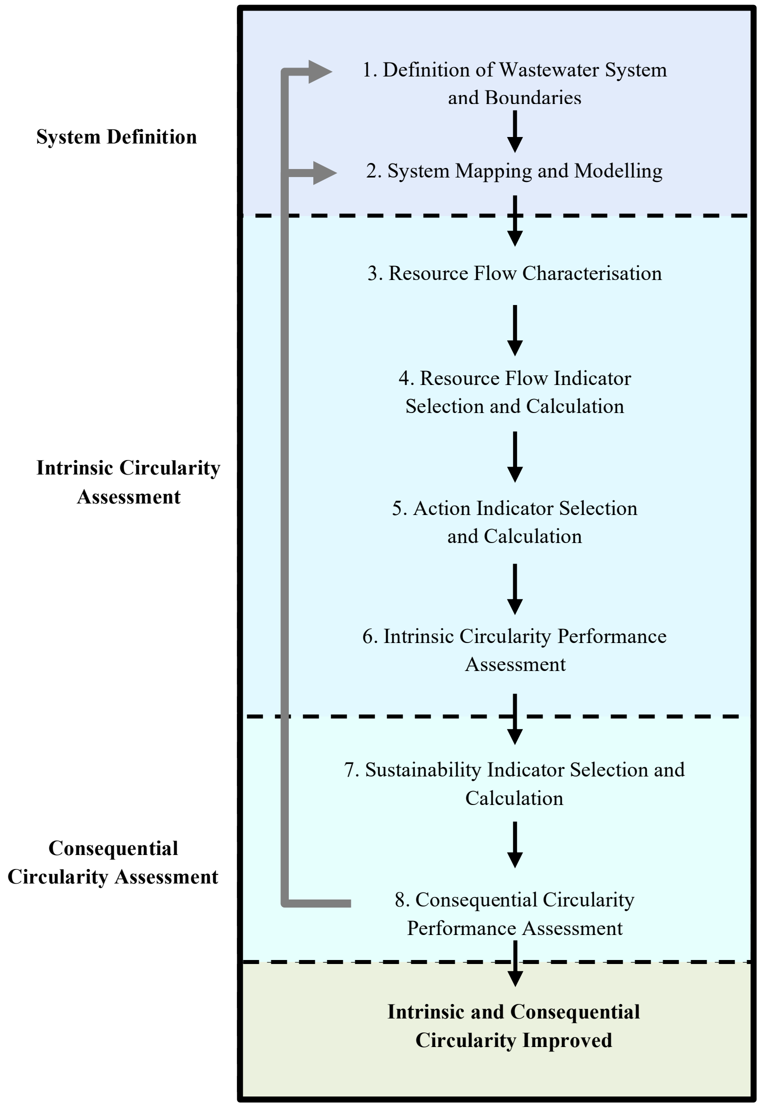


Figure 5.1. Framework for the circularity assessment of wastewater systems.

5.2.2.1 Definition of wastewater system and boundaries

The first phase of the methodology involves defining assessment goal and scope. Overall it is recommended to align the goal and scope definition with both the intrinsic and consequential circularity following the requirements of standardised performance assessments such as ISO 14040 guidelines (British Standards Institute, 2020). In line with ISO 14040, the goal includes explaining the reason, intended application, and interested audience of the assessment, whilst assessment scope illustrates the system being studied, boundaries, and assumptions. This may also include the functional unit, allocation methods, limitations, and data requirements if necessary.

This phase of the methodology also includes the definition of SOI circularity goals. Strategic goals are commonly defined as quantitative targets that are calculated using key performance indicators (KPIs) which guides the selection of relevant circular action indicators and facilitates the assessment of sustainable value creation impacts and trade-offs. There are many sources in the literature defining the strategic goals of the CE transition for wastewater, such as the work of Smol et al. (2020) that developed a framework based on the six actions of reduction, reclamation, reuse, recycling, recovery, and rethink. Furthermore, the strategic goals of the European wastewater sector are mapped out in the proposed update to the Urban Wastewater Treatment Directive, including net zero and resource recovery targets (European Commission, 2022). Additionally, it is recommended to use project publications (such as websites, deliverables, or industrial reports) to consider the specific goals for each targeted SOI and scenario of application.

Comprehensive understanding of the goal and scope facilitates the definition of the benchmark system, which acts as a baseline with which the targeted SOI can be compared against during the assessment. Establishing a representative benchmark is required for robust performance assessment and is dependent on the scenario of application. To develop a suitable benchmark, it is recommended to use either a real-world case study (such as the technology the SOI is replacing) or a model of a conventional industrial technology developed with process experts.

System boundaries are pertinent when assessing circular systems as they must be able to account for resource loops and the multiple life cycles of resources or products that can be recovered (Çapa et al., 2022). Furthermore, the temporal boundaries of circular systems may also require definition. An appropriate temporal scale is needed to account for the cascading uses of secondary resources captured from wastewater. Therefore, it is important to understand and define spatial and temporal boundaries in detail.

5.2.2.2 System mapping and modelling

Detailed description of the process(es) being investigated is required for modelling and data collection. Important aspects to describe are the location, loading, treatment process units, or operational constraints to establish necessary information about the wastewater system (Zawartka et al., 2020). Additionally, if temporal boundaries are established, the process data needs to be updated accordingly for each different resource cycle, including the variations of all flows described when prospective or forecast data is utilised (Beloin-Saint-Pierre et al., 2020).

The effectiveness of the circularity assessment is dependent on the accuracy of process modelling, for both the SOI and benchmark system. Creation of the process inventories requires modelling or simulation of wastewater treatment units of varying complexity, which can be physical, chemical, or biological processes (Zawartka et al., 2020). It is recommended to use primary data when available, and whilst secondary data or modelling can be used, the impact on result reliability must be considered.

The development of process models enables MFA and substance flow analysis (SFA) to understand how resources flow around the benchmark system and targeted SOI. These models are combined with the resource classification approach from Chapter 4 (Renfrew et al., 2023) that defines their source and destination, which improves resource traceability. This helps to assign circular characteristics to resource flows, which is required for robust calculation of assessment indicators.

5.2.2.3 Resource flow classification

To facilitate indicator calculation, circular properties must be assigned to all resource flows in the modelled systems. Defining the circularity of resource inputs and outputs enhances the traceability and transparency of indicator calculation, facilitating principle 4 of the methodology and more robust assessment of wastewater resources. This information enables the calculation of the resource flow and selected action indicators to complete the intrinsic circularity assessment.

However, according to Renfrew et al. (2023), current definitions of waste circularity are inadequate, resulting in errors during quantitative assessments. Therefore, it is recommended to use the framework presented in Chapter 4 and by Renfrew et al. (2023) for wastewater resource classification. The approach uses an environmental science perspective to simply define a resource's circularity by considering a combination of its source and destination, and its ability to cause harm, to reason whether outflows to the environment (soil, water, and air) should be considered linear, utilising the principles of the Do No Significant Harm (DNSH) framework (Italia Domani, 2021). This facilitates the calculation of circularity indicators for key wastewater resources.

5.2.2.4 Resource flow indicator selection and calculation

Resource flow circularity indicators are the first indicator taxonomy which assess the intrinsic circularity performance of the SOI. They should cover the key areas of material inflow and outflow, water, energy, and economic resource circularity, following a similar structure to those utilised by the wbcsd (2022). This aims to provide a more standardised analysis of key resources during the assessment and is useful for activities such as hotspot analysis. It should also enable comparison of results across different wastewater systems (plant location, technology, or size) as the indicators are sourced and calculated using similar methods. The indicators recommended for resource circularity assessment are summarised in Table 4.8 and are taken from the framework proposed by Renfrew et al. (2023) in Chapter 4.

5.2.2.5 Action indicator selection and calculation

In order to identify the indicators required for the second intrinsic circularity indicator taxonomy, circular actions need to be defined. Circular actions are the measures implemented which contribute to CE goals, thereby facilitating the three CE principles. Utilising these indicators ensures that the performance of the SOI's circular actions can be assessed and verify that they achieve CE goals, as defined in principle 2. To do this stakeholder inputs are crucial for understanding how the SOI circular actions satisfy expectations compared with the benchmark system (facilitating principle 5) and meet strategic circularity goals. The strategic goals defined by the goal and scope are used to align stakeholder and project targets before indicators are selected, ensuring they are able to assess necessary aspects of circularity for decision making.

The development of VPCs with project stakeholders is recommended for this step, and the method of da Luz Peralta et al. (2020) is employed for the example in Section 5.3. This requires the views of stakeholders to understand the desires and obstacles for implementation, and linking them with 'gain creators' and 'pain relievers' to show how a technology aims achieve stakeholder expectations i.e., identifying SOI circular goals. To create the VPC, workshops with relevant stakeholders are required to create a Lean Canvas, revealing SOI circular actions that satisfy expectations, and an Empathy Map of what stakeholders wish to accomplish (da Luz Peralta et al., 2020).

To link the goals identified from VPCs with appropriate indicators, the first step is to group them based on strategic goals of the SOI. These are used to create generic CE actions that are initiated in the SOI, for example recycling or renewable energy generation. Simultaneously, VPC development recognises how the SOI aims to meet stakeholder expectations, by using ‘gain creators’ to highlight the technology goals. These are combined with the generic CE actions to develop circular actions of the specific SOI being assessed, in terms of stakeholder requirements. Lastly, the specific circular actions are used to select appropriate indicators from literature for the assessment of circular action performance, to understand if the defined goals are achieved. These steps are illustrated in Figure 5.2 and an example is provided in Section 5.3.5.

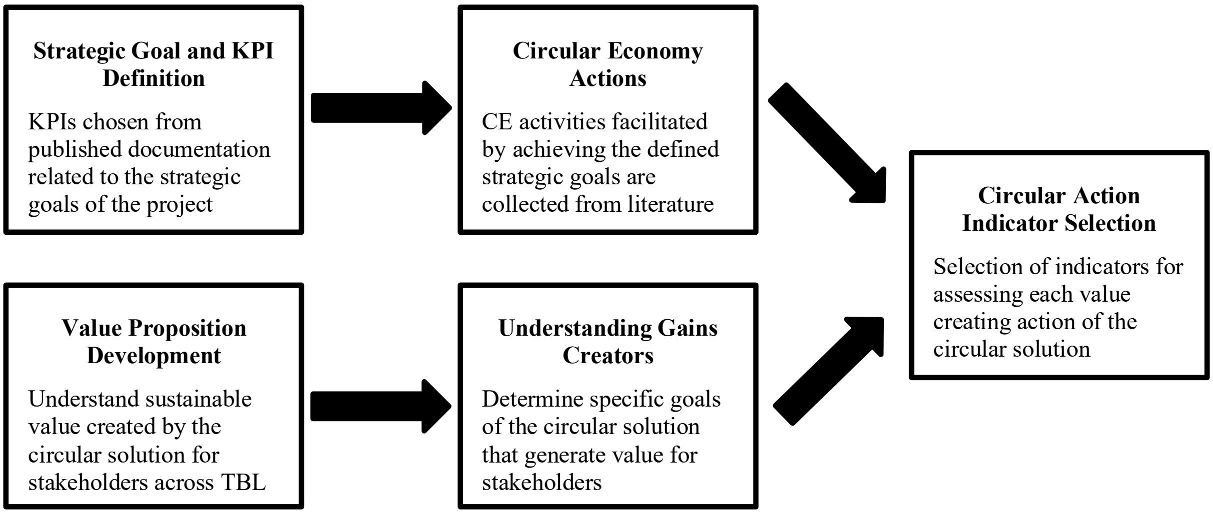


Figure 5.2. Steps for selecting indicators to assess the value creating actions of circular solutions.

These indicators reveal the success of SOI actions, as they will be tailored to each scenario considering technological, stakeholder, and local context aspects. The action indicators differ from those analysing resource flows, as they can communicate how the relationships between sustainability pillars and CE principles are impacted by the SOI using the VPC developed, instead of just reporting information on resource properties. For example, improving the renewability of resource flows only reveals information about physical materials, whereas an indicator such as the eco-efficiency shows how circular actions affect greenhouse gas (GHG) emissions and revenue. The identification of circular actions to select indicators follows a similar approach to that of Nika et al. (2022), however, this method goes a step further by using

VPCs to understand the performance of the SOI's circular actions for more systematic and targeted indicator selection.

Circular action indicator calculation may require a combination of resource flow characterisation with additional analysis or modelling to quantify wider impacts, such as environmental and economic dimensions for eco-efficiency indicators. However, this is dependent on the indicators selected to assess circular actions. Thereby, the action indicator taxonomy can be combined with the resource flow indicator taxonomy to provide a complete assessment of intrinsic circularity performance.

5.2.2.6 Intrinsic circularity performance assessment

The results provided by the resource flow and circular action indicator taxonomies show whether the SOI has been successful at improving the circularity of physical resource loops in the defined system and whether the performance of SOI circular actions meets stakeholder expectations and CE goals. Improvements can be directly quantified by comparing SOI results with those of the benchmark system. This step of the methodology fulfils principle 1, facilitating decision making based on intrinsic system circularity, ensuring assessment validity.

5.2.2.7 Sustainability indicator selection and calculation

To investigate the impacts that result from the implementing SOI's intrinsic circularity (both resource flows alterations and circular actions), a third complementary sustainability indicator taxonomy must be selected to quantify the value created for stakeholders and understand the SOI's consequential circularity. If indicators have been selected with adequate scope, then all dimensions of the TBL should be represented; if not, then at least one indicator should be selected and calculated for the missing dimension(s) to ensure a holistic assessment of sustainable value. Strategic goals highlighted during goal and scope definition can be used to guide indicator selection for any missing TBL dimensions.

To understand the impacts of consequential circularity, it is recommended to use the data requirements of the circular action indicators for identification of the required areas for sustainability analysis. This avoids pre-selection of complementary analysis techniques, enhancing assessment flexibility, mitigating the omission of sustainability impacts which are pertinent to the assessment. For example, eco-efficiency indicator calculation requires both environmental and economic inputs, highlighting that more detailed LCA or life cycle costing would be suitable as complementary analysis. Process inventories derived from benchmark and SOI models can be used to complete the required complementary assessment techniques. This indicator taxonomy reveals wider impacts of SOI implementation not captured during the intrinsic circularity analysis. Once sustainability indicators have been calculated, the results are utilised to quantify the sustainable value creation that results from SOI implementation, to see if it is able to satisfy the value proposition for stakeholders.

5.2.2.8 Consequential circularity performance assessment

The final step of the method requires examination of the SOI sustainability indicator taxonomy results against the benchmark process. This facilitates direct measurement of the environmental, economic, and social sustainable value generated by the SOI, as required in principle 3, and shows whether the SOI satisfies the value proposition developed with stakeholders. Therefore, sustainable value creation is used to determine SOI consequential circularity performance. If the SOI improves both intrinsic and consequential circularity of the investigated wastewater system, then it can move to the next phase of design as it is able to generate value for stakeholders by improving system circularity. If not then the project goals, technology, or design can be iterated to update models and indicators until a suitable SOI is selected.

To enhance decision making capabilities and result communication, interpretation of results should consistent with the goal and scope of the assessment to make appropriate conclusions, explain limitations, and provide recommendations for wastewater system circularity performance (British Standards Institute, 2020). Results should be readily understandable and easily communicated to the intended audience, therefore, it is recommended that sustainable value creation is used to verify whether the defined circular goals of the system have been successfully achieved (as shown in Section 5.3).

5.3 Results

This section demonstrates implementation of the method developed in Section 5.2 for the assessment of a novel technology integrated within a WWTP. In this case, the SOI is an anaerobic purple phototrophic bacteria (PPB) photobioreactor (PBR) technology for wastewater treatment, known commercially as ANPHORA® (includes clarifiers, PBRs, sludge treatment), and was selected as it claims many benefits over conventional treatment processes.

5.3.1 Define wastewater system and boundaries

The goal of the assessment is to quantify circularity improvements and the sustainable value created by implementing ANPHORA® technology for wastewater treatment. It will be used to evidence the advantages of this system compared with conventional technology and results will be shared with water sector stakeholders to expedite technology uptake.

Strategic goals of the project are mapped using publications and communications to define the expected advantages of the system (Deep Purple, 2019):

1. Produce high value products from waste streams of sewage sludge
2. Recover resources contaminated in wastewater
3. Minimise waste
4. Minimise energy demand of the plant trending towards self-sufficiency or energy positivity
5. Reduce GHG emissions of value chains by 20%
6. Generate revenue from the recovery of waste resources
7. Establish economic feasibility
8. Evaluate environmental impacts

These statements clearly show that considered technologies wish to enhance value recovery from waste streams to facilitate the CE. From the statements, generic CE actions are identified and will be used as themes to categorise the technology gains creators. The terminology of minimising, maximising, and reducing several operational constraints such as economics, waste, GHG emissions, and energy demand are facilitated by developing disruptive technologies to *optimise process performance*. The emphasis on generating economic value from bioproducts and recovering energy from waste streams means that the technology must have the ability to *cascade biomaterials*. Lastly, recovering the organic and nutrient contaminants in wastewater and reducing waste production is achieved through the action of *recycling and waste minimisation* for wastewater resources.

As the SOI being assessed is known, a benchmark technology must be chosen to establish a baseline for results comparison. By consulting industrial experts, it was decided to use a conventional extended aeration system as a benchmark, which is an activated sludge process with high solid retention times between 20 and 40 days. Primary clarifiers are not required, therefore, the conventional process was assumed to operate with pretreatment of screenings and grit removal, aeration tank (nitrification) with clarifiers, and sludge is stabilised by liming. System boundaries are drawn from when wastewater leaves the water user and flows into the WWTP (meaning losses are accounted for), until wastewater effluent is discharged from the plant and biosolids are applied to land, as shown in Figure 5.3. The ANPHORA® technology demonstration site is located in Spain, so processes were modelled considering local factors.

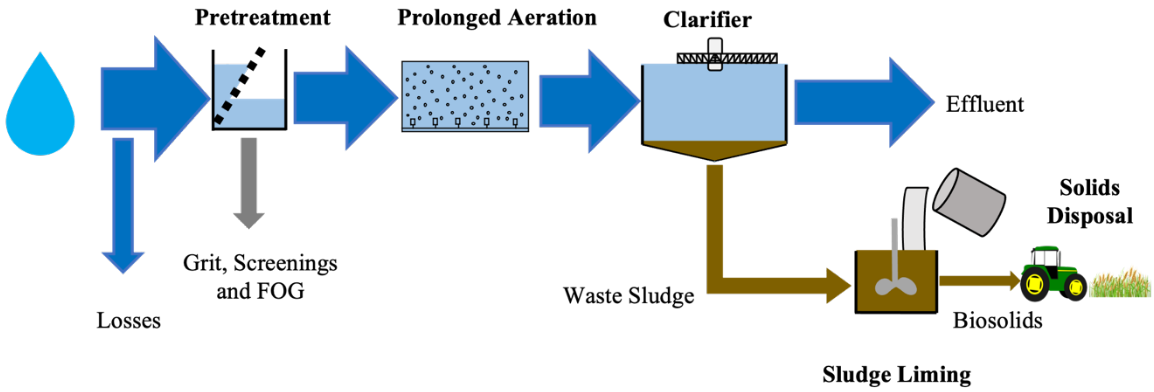


Figure 5.3. Process stages of the conventional extended aeration WWTP.

5.3.2 *System mapping and modelling*

Advantages of the ANPHORA® technology are highlighted when used to treat wastewater for small, rural populations; thus a scale of 10,000 population equivalents (PE) (design load of 3,000 m^3/d) was selected. Wastewater treatment on this scale in Spain regulates chemical oxygen demand (COD) removal and discharge limits. Due to limitations in data availability for a 10,000 PE WWTP case study, a model for the conventional process of prolonged aeration was constructed using parameters taken from literature for the physical and biological treatment units. The influent loadings were taken from literature for a wastewater treatment plant in the same area as the ANPHORA® demonstration facility (Rodríguez-Chueca et al., 2019). The data utilised to construct process models is provided in Tables C.1-C.4 of Appendix C.

The PBR was chosen for assessment as it operates anaerobically resulting in significant energy demand and emissions generation reduction compared with conventional aerobic treatment. The nutrient content of the PPB biomass means it can be used as a biofertiliser and sold to generate revenue. The biomass also has greater biomethane potential compared with conventional activated sludge, therefore it is economically viable to anaerobically digest sludge and produce biogas for energy recovery. The project is currently at the demonstration phase; however, these real-world scenarios have been agreed with experts for application of the circularity assessment method to a full-scale system.

Figure 5.4 summarises the PBR process boundaries, which operates with screenings, grit, and fats, oils, grease (FOG) removal pretreatment, primary settling, anaerobic raceway PBRs, and clarifiers before wastewater discharge. Sludge is thickened, anaerobically digested, and dewatered before it can be sold as a high-quality biomass fertiliser for land application.

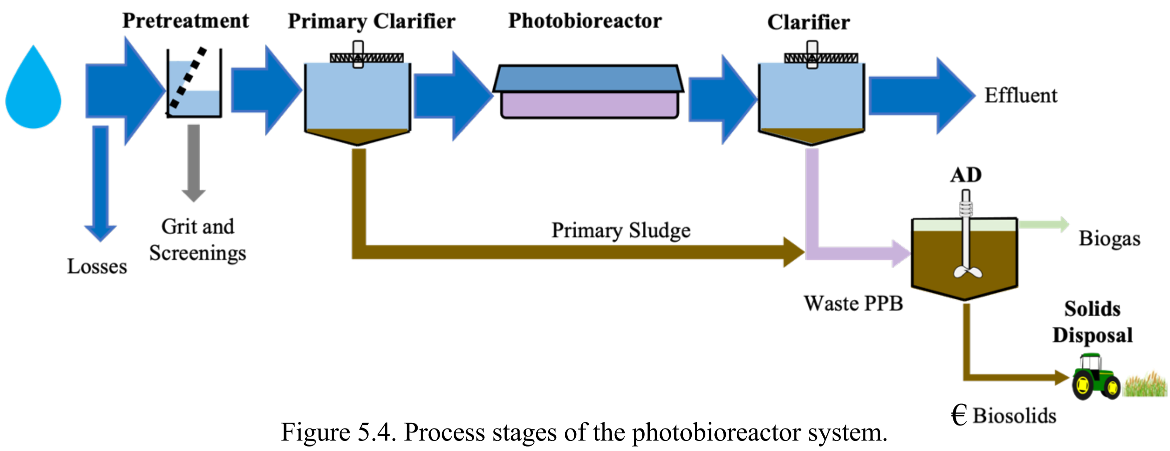


Figure 5.4. Process stages of the photobioreactor system.

The PBR has only operated at a demo scale, and therefore required scale up calculations to ensure accuracy for the energy consumption and cost parameters. It was assumed that the removal efficiencies and nutrient content of the PPB biomass would be unaffected by scale up of the system. The circular PBR system was modelled using data provided in Tables C.5-C.8 of Appendix C.

5.3.3 Resource flow characterisation

The circularity assessment was completed using the approach developed in Section 4.2 to characterise the water, nitrogen, phosphorus, and carbon resources from the benchmark and SOI process models. Tables C.9-C.16 in Appendix C provide the circularity classifications of resource inflows and outflows.

5.3.4 Resource flow indicator selection and calculation

The taxonomy of resource flow indicators selected is provided in Table 4.8. Results of the outflow, nutrient extraction, and renewable energy indicators are provided in Figure 5.5. WWTP removal efficiency was assessed and showed there was a reduction in carbon removal of 9.2 %, however, COD discharge limits are still met. This results in lower carbon outflow circularity for the PBR process, but due to the composition of PPB biomass greater renewability is achieved. Nitrogen and phosphorus removal are improved by 148 % and 32 % respectively, due to the accumulation of nutrients by the PPB biomass meaning greater outflow circularity and renewability are achieved for NP by ANPHORA®. Whilst there are no NP consent limits for this type of small-scale treatment, performance is better in terms of both environmental protection and circularity. However, if this process was applied in an area with NP discharge limits, then tertiary treatment or polishing of the effluent would be required. Lastly, renewable energy usage grows from 67 % to 85 % due to the recovery of energy from biogas, which increases the renewable fraction above that of the Spanish electricity grid mix (including nuclear and biofuels) (IEA, 2021).

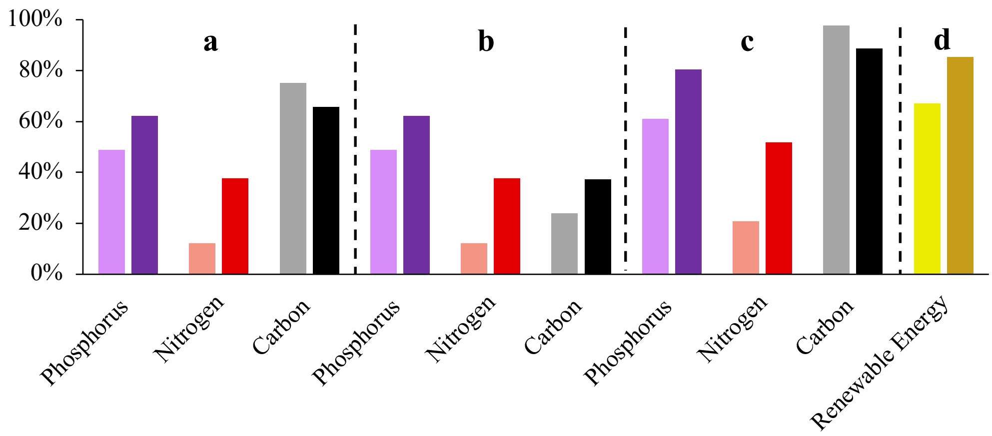


Figure 5.5. Resource flow indicator results, where the lighter colour is the conventional process and darker colour indicates the PBR process. **a**: outflow circularity, **b**: outflow renewability, **c**: wastewater nutrient extraction, and **d**: renewable energy usage.

There was negligible change between conventional and PBR scenario influent resources, and therefore inflow and water indicators, when comparing systems so these results are not presented. Additionally, material productivity increased by approximately 300 % as greater revenue from the sale of PPB biofertiliser is coupled with a reduction of linear inputs, namely lime for sludge treatment. Value per mass of the systems increased from 0 €/kg for the conventional system to 40.8 €/kg for the PBR, and this high value is achieved as the only virgin or primary material input is the polymer required for sludge thickening. The value of zero for the benchmark system occurs as only revenue from product sales is included in the calculation, excluding the service fee of wastewater treatment.

5.3.5 Action indicator selection and calculation

To ensure appropriate indicators are selected for evaluating the performance of PBR circular actions, the strategic goals must be understood and combined with the outcomes from sustainable VPC development. As explained in Section 5.2.2, the participatory method is utilised to link the generic, high level CE actions identified from the strategic goals of the project with the unique circular actions of the SOI for indicator selection. In this case study, the technology developers were used to generate the VPC, and the resultant Lean Canvas is presented in Figure 5.6.

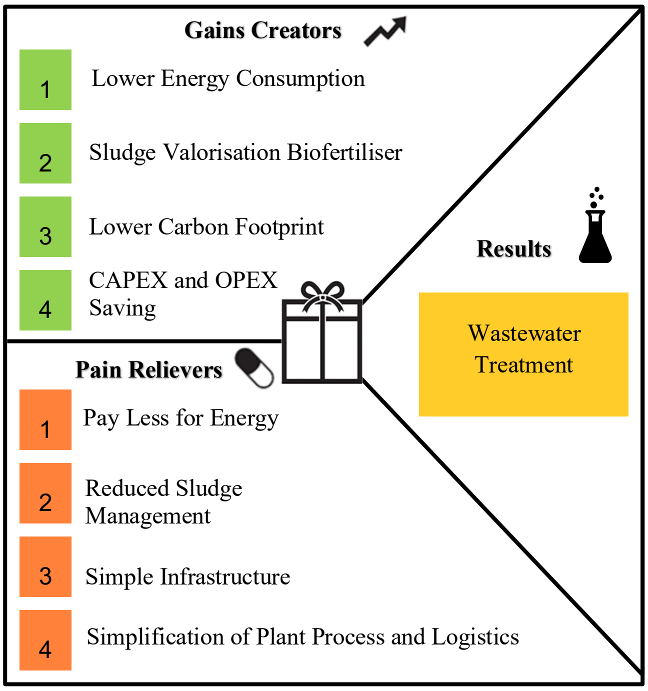


Figure 5.6. Lean Canvas developed for the PBR technology based on that of da Luz Peralta et al. (2020).

The ‘gain creators’ category identifies how the ANPHORA® technology is expected meet stakeholder expectations and the four gains creators were combined with CE actions identified in Section 5.3.1 to generate specific circular actions of the PBR process. The steps to select indicators for evaluating the circular actions are summarised in Table 5.1, starting with the gains creators in the left hand column. Indicator results show the performance of ANPHORA’s® circular actions at meeting stakeholder expectations and project CE strategic goals, compared with the conventional extended aeration process. Table 5.1 summarises the second indicator taxonomy selected for the assessment of intrinsic circularity.

Table 5.1. Steps to select indicators for assessing actions of the PBR technology.

Gains Creators	CE Action	Value Creating Action of Circular Solution	Indicators Associated	Equation
Lower Energy Consumption	Development of New Processes for Value Chain Optimisation	Reduction of Energy Intensity	Circular Process Energy Intensity (Lokesh et al., 2020)	$\frac{Energy\ Demand - Internally\ Derived\ Energy}{Mass\ of\ Products\ (incl.co\ and\ recovered)}$
			Self-sufficiency (Agudelo-Vera et al., 2012)	$\frac{Total\ Energy\ Produced}{Total\ Energy\ Demand}$
			Electricity Grid Demand Minimisation (Agudelo-Vera et al., 2012)	$\frac{Baseline\ Demand - Minimised\ Demand}{Baseline\ Demand}$
Lower Carbon Footprint		Achieving Decarbonisation	Carbon footprint	
			Emissions Eco-efficiency (Walker et al., 2009)	$\frac{Value\ Gained\ (Revneue)}{Mass\ of\ Emissions\ (Air\ and\ Water)}$
Savings on Logistics and Infrastructure		Reducing Capital Costs (CAPEX) and Operating Costs (OPEX)	Yearly Reduction in Cost vs Conventional Treatment	
Valorisation of Sludge	Cascading of Biomaterials	Extraction/Generation of Value Added Bioproducts	Waste Eco-efficiency (Walker et al., 2009)	$\frac{Value\ Gained\ (Revneue)}{Mass\ of\ Waste\ (Solid)}$
			Value Added per Functional Unit (Medina-Mijangos and Seguí-Amórtegui, 2021)	$\frac{Total\ Value\ Created}{Volume\ Wastewater\ Treated}$
		Renewable Resource Use (nutrients from fertilisation)	Substitution Factor of Virgin Materials (Jander and Grundmann, 2019) – Biosolids N	$\frac{Function\ per\ kg\ of\ Recovered\ Material}{Function\ per\ kg\ of\ Conventional\ Material}$
	Recycling	Retain Nutrients in Wastewater for Fertiliser Production and Safe Return to Soil	Recovery Rate of WWTP - Nutrients NPC (Institut de la statistique du Québec, 2020)	$\frac{Mass\ of\ Nutrient\ (NPC)\ in\ Recovered\ Products}{Total\ Mass\ of\ Nutrient\ Inflow\ to\ WWTP}$

Results from the circularity assessment of project actions are summarised in Table 5.2 and are presented as the percentage change against the benchmark conventional process measurement, to reveal the performance of SOI circular actions.

Table 5.2. Results from circularity action indicators shown as the percentage change between conventional and PBR processes.

Action	Indicator	% Change
Reduce Energy Intensity	Circular Energy Intensity (kWh/kg Carbon)	- 67.6 %
	Self-Sufficiency	58.5 % (vs 0)
	Electricity Grid Demand Minimisation (kWh/d)	+ 13.4 %
Achieving Decarbonisation	Carbon Footprint (kgCO_2 eq)	- 66.3 %
	Emissions Eco-efficiency (€/kg)	+ 97.7 %
Reduce CAPEX/OPEX	Yearly Cost (€)	- 44.6 %
Extraction/Generation of Value-Added Products	Waste Eco-efficiency (€/kg)	- 34.5 %
	Value added per m^3 Wastewater Treated (€/ m^3)	+ 1152.6 %
Renewable Resource Use	Substitution Factor N fertiliser (kg/kg)	+ 345.0 %
Retain Nutrients	Carbon Recovery Rate	+ 165.3 %
	Nitrogen Recovery Rate	+ 195.0 %
	Phosphorus Recovery Rate	+ 15.5 %

The energy reduction indicators show that not only is the demand for electricity from the grid reduced, but self-sufficiency increases to almost 60 % (from a baseline of 0) and circular energy intensity is more than halved. This trend can be attributed to the reduced energy requirement from mitigation of aeration processes, the amount of carbon available in waste sludge increasing, and energy recovery from combustion of biogas produced by AD. Carbon footprint reduction is achieved mostly through the mitigation of direct process emissions from anaerobic operation of ANPHORA®. Carbon footprint is a proxy for emissions to air and water, therefore, the emissions eco-efficiency result is almost doubled due to the decrease in the mass of emissions to air and nutrient concentration in the effluent, and increased revenue from biofertiliser sales. The yearly costs of the process, amortised CAPEX and OPEX, are also reduced due to the mitigation of aeration and chemicals required for sludge treatment.

Waste eco-efficiency is shown to decrease for the PBR process, as even though revenue is increased, there is greater removal of pretreatment solids that are landfilled. However, this has potential to be improved through addition of captured FOG to AD reactors. The largest increase is the value added per m^3 of wastewater treated, which can be attributed to a reduction in total costs and increased revenue from biofertiliser sales. The substitution factor of conventional biosolids compared with PPB biomass shows why this can be marketed as a higher quality fertiliser. Lastly, there was an increase in recovery for all nutrients analysed by the process, due the recovery of biogas and the high nutrient content of PPB biomass compared with conventional biosolids.

5.3.6 Intrinsic circularity performance assessment

Resource flow indicators showed that the PBR system had negligible impact on resource inflow circularity, but was successful as improving the outflow circularity and removal efficiency of nitrogen and phosphorous. Action indicator results highlighted an improvement in performance of the PBR process versus conventional treatment (except waste eco-efficiency), ranging from 13 % to greater than 1,000 %. Therefore, the ANPHORA® technology improves intrinsic circularity of the WWTP system as it achieves the circular action performance requirements and enhances the circularity of wastewater resource loops.

5.3.7 Sustainability indicator selection and calculation

One of the key outcomes of this assessment is to understand the sustainable value generated by, or consequential circularity of, SOI circular actions. The indicators selected to evaluate circular actions are used as a guide for directing sustainability indicator taxonomy selection. The circular action indicators utilised, including eco-efficiency, carbon footprint, and value added per mass, highlight the expected environmental and economic impacts of the SOI. Therefore, LCA and more detailed analysis of carbon footprint are required to understand environmental value creation, as well as total value-added inspection for economic impact investigation. Although the circular action indicators do not directly reveal which social indicators are needed to investigate the PBR process impacts, it is important that all TBL dimensions are considered.

Due to the ANPHORA’s® potential to reduce emissions and pollution, and generate revenue from waste streams, social indicators were selected to reflect these impacts. Those chosen were endpoint impacts, including disability-adjusted life years (DALY), employment, and economic contribution to the local community indicators.

Carbon Footprint

Carbon footprint analysis was completed following the method defined by the IPCC for wastewater treatment facilities (Doorn et al., 2019). Emission factors for wastewater treatment were taken from the IPCC method, whilst those for other resources such as electricity and chemicals were extracted from ecoinvent databases. A description of the method and parameters used is found in Section C.4.1 of Appendix C.

Life Cycle Assessment

The LCA was completed using the same boundaries as the MFA and a functional unit of 1 m^3 of wastewater treated, following ISO 14040 and 14044 (British Standards Institute, 2020). The inventory used to complete the analysis is the same as that constructed for MFA and indicator calculation. SimaPro v9.4 was used to conduct the calculation of seven Environmental Product Declaration (2018) impact indicators; acidification, eutrophication, photochemical oxidation, abiotic depletion (elements), abiotic depletion (fossil fuels), water consumption, and ozone layer depletion.

Economic Value Added

Determining the operational and economic profitability of the investment in ANPHORA® was achieved by assessing the economic value added of the system. Figure 5.7 explains the economic relationship between the water user and wastewater utility (Faragò et al., 2021). The water user pays an expected fee for the provision of the wastewater treatment services by the wastewater utility, however, investment in technologies can disrupt this flow by creating a surplus (revenue greater than expenditure) or deficit of value (revenue lower than expenditure), resulting in savings or increasing fees. Therefore, to understand the economic value generated by the water utility, the expected difference between WWTP operator revenue and costs were calculated for the conventional and biorefinery processes.

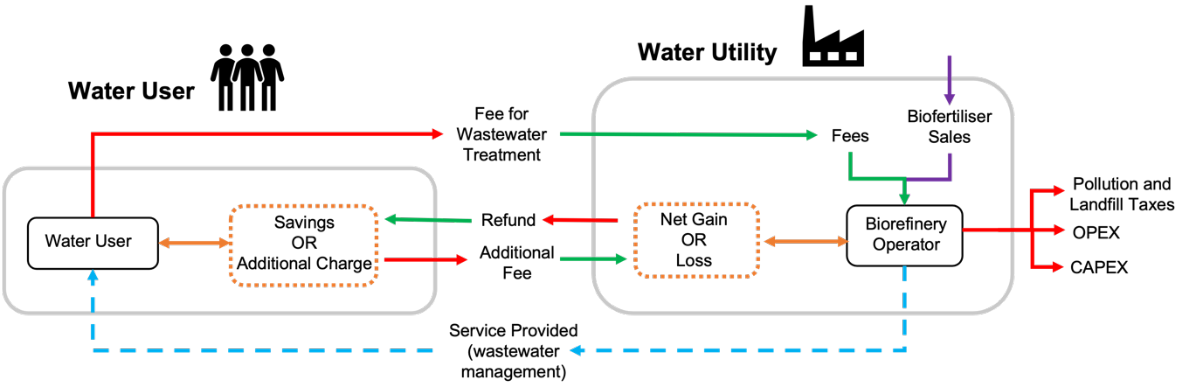


Figure 5.7. Economic relationship between stakeholders in wastewater systems (adapted from Faragò et al. (2021))

A method was followed similar to that of Medina-Mijangos and Seguí-Amórtegui (2021) for the assessment and is calculated using Equation 5.1:

$$VC = (WWT_V \times GF) - (CAPEX + OPEX + ST) + In \qquad (5.1)$$

Where, WWT_V is the volume of wastewater treated (m^3), GF are the gate fees of the WWTP (€/m^3), ST are state taxes for landfill and discharge (€), In is income from sales of products (€), and CAPEX is amortised. The steps and data used for economic value-added analysis are summarised Section C.4.2.

Social Value Analysis

The social assessment comprises of three indicator groups targeting endpoint impacts, employment, and economic development of the local community. The damage to human health, ecosystems, and resources indicators were calculated using the ReCiPe Endpoint (H) model (Huijbregts et al., 2017), and included the production of chemicals and electricity consumed, direct emissions, and emissions from application of generated sludge to soil as fertiliser (European Commission, 2018). The inventory of material and energy flows, as well as environmental releases, can be found in Tables C.21 and C.22 of Appendix C.

Employment and economic development indicators were calculated using information for the municipality of Soria. This area has a population of 10,445, which is similar to the 10,000 PE

WWTP example, therefore it was used to investigate the social impacts that a WWTP of this size can have on a community (INE, 2022). Employment growth resulting from investment in PBR technology was calculated based on discussions with local experts regarding expectations compared to conventional technologies. Employment of the conventional plant was estimated based on the total employees that work in the wastewater treatment sector in the autonomous community Castile and León (where Soria is located), to calculate an employment factor of workers per population (Santos et al., 2021). Then the population of Soria was used to calculate the number of workers in an urban WWTP of a similar size. Lastly, the effect on the economic development of the local community was calculated according to the expected economic value generated by both WWTPs. The impact on economic development was calculated based on the economic value added relative to the gross domestic product of the municipality (INE, 2022). Revenues and costs of suppliers were excluded because consumables were assumed to not be locally sourced.

5.3.8 Consequential circularity performance assessment

Figure 5.8 summarises the results of the complementary sustainability analysis required to quantify the sustainable value creation of the PBR process. LCA results in Figure 5.8B show that PBR operation performs better in six out of the seven impact categories investigated, ranging from 15 % to 41 % reduction. Eutrophication sees the largest decrease of 41 %, attributed to the reduction of NP emissions in wastewater effluents. Ozone depletion, photochemical oxidation and acidification decrease by 34 %, 20 % and 15 % respectively which occurs due to the reduction of emissions to air during wastewater and sludge treatment. The cost-benefit analysis of Figure 5.8C shows that as the gate fees are constant the increase in revenue for the PBR system is a result of biofertiliser sales, adding approximately 0.1 M€/y. There is also reduction in OPEX due to the lower energy demand associated with the mitigation of aeration during biological treatment and energy recovery from biogas, as well as the removal of lime requirements for sludge treatment. Combining this results in an economic value added of almost M€ 0.5 per year for water the utility. Therefore, the PBR system facilitates better environmental and economic performance which are key for establishing project viability (a more detailed description of results is provided in Section C.5 of Appendix C).

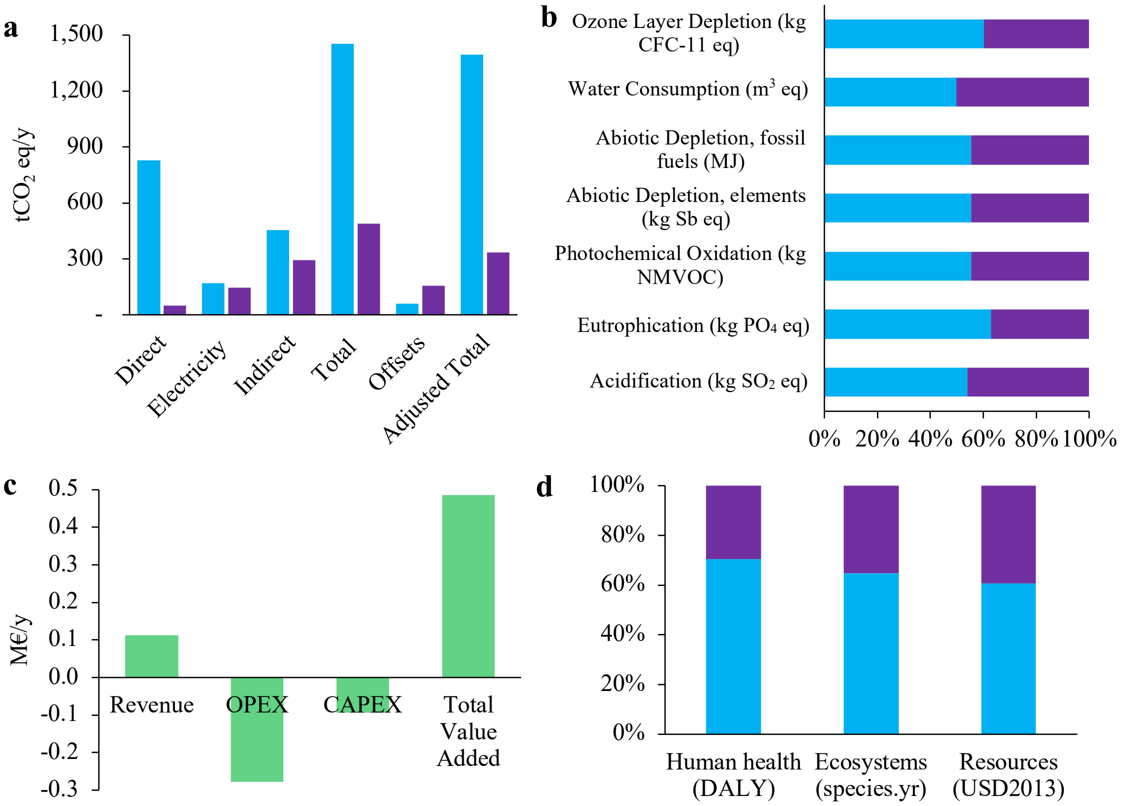


Figure 5.8. Conventional extended aeration process results in blue, and PBR process results in purple. **a**: Carbon footprint results divided into direct, electricity, and indirect emissions, and offsets, **b**: LCA impact indicator results, **c**: economic value added visualised as the difference between revenue and costs of the PBR and conventional systems, and **d**: social endpoint (H) impact indicator results.

This methodology aims to quantify the sustainable value creation that is generated from circular actions implemented by the SOI that change physical resource flows. Therefore, once analysis is complete it is important to relate the sustainability analysis results with the gains creators identified during VPC construction. Lowering energy consumption creates value across all TBL dimensions as it reduces the harmful emissions produced during electricity generation, reducing electricity emissions by 13.4 % and other related LCA impacts categories, such as acidification and abiotic depletion of fossil fuels by 15 % and 19 % respectively, to create value for the environment. Reducing harmful emissions also provides social value by decreasing DALY by 58 % and lower electricity demand contributes to the reduction in OPEX, creating economic value for utilities. Lowering the carbon footprint creates significant environmental value by mitigating two thirds of emissions, increasing to 75 % when considering offsets of chemical fertilisers. Economic value added is the main indicator of the value created from savings on logistics and infrastructure, shown by the reduction of OPEX and CAPEX of 0.28 M€/y and 0.09 M€/y respectively which results in savings for the water utility. Valorisation of sludge creates economic value as shown by the increase in revenue of 0.11 M€/y, but also impacts social value by increasing the contribution to the local economy by almost 12 times. Lastly, the result of improved wastewater treatment performance has a strong influence on carbon footprint and other LCA categories by decreasing direct emissions by more than 90 %, and related LCA impacts such as eutrophication by 41 %, to generate significant value for the environment. Additionally, greater reduction of emissions to air, water, and soil as a result of wastewater treatment reflects the lessening of DALY (by 58 %), thereby generating social value through enhanced WWTP performance from the ANPHORA® technology. Therefore, the SOI results in consequential circularity improvements for stakeholders across economic, environmental, and social TBL dimensions.

This example highlights the main benefit of the developed method, namely the systematic selection and calculation of indicators to determine how changes in the circularity of physical resources impact sustainability dimensions. This development is critical to the success of the CE transition as recent policy relies on enhanced resource circularity to meet many sustainability targets. For example, the new CE Action Plan is one of the main building blocks of the European Green Deal, which targets a 55 % reduction of GHG emissions by 2030 (compared with 1990) (European Commission, 2021a). However, it has been shown that the water sector is unable to implement circular strategies as decision makers cannot assess how their investments will facilitate sustainability objectives (Renfrew et al., 2022). Therefore, this method provides an integrated approach to support decision making by using pertinent, well-established metrics, including LCA and cost benefit analysis, to validate that investments which improve resource circularity also enhance sustainability performance. Assessment of the PBR provides a detailed example of how impacts can be directly quantified across the TBL including carbon footprint reduction to satisfy Green Deal targets, economic prosperity to justify the investment to businesses, and societal health and wealth benefits to reassure citizens about changes to the local area. Therefore, this method presents an important step in CE science, enabling industry decision makers to quantify how their circular actions leads to progress towards sustainability targets and business objectives, accelerating CE progress.

5.4 Discussion

Current assessment methodologies mainly rely on providing a list of preselected indicators from which users can choose, however, this runs the risk of facilitating cherry-picking to highlight specific interests of decision makers (Harris et al., 2021; V Superti et al., 2021). Here a participatory approach to select a tailored set of indicators in a flexible yet replicable way, to ensure holistic assessment of the impacts that circular actions have on sustainable development. Papageorgiou et al. (2021) showed that CE assessment frameworks lack indicators which measure reduction of emissions, value creation, and social dimensions. Therefore, these aspects which are heavily relied upon for policy related decisions and industrial investment are often neglected during assessments. Here, an emphasis is placed on understanding the value added by circular interventions compared with conventional technologies, as this is one of the key metrics for evidencing business investment

This methodology provides decision makers with the information to satisfy a range of activities including performance comparison of their process with other WWTPs, selecting circular technologies that fulfil desired circularity and sustainability goals, and selecting indicators for optimising of process operation and sustainability. Selecting technologies can be a challenge for wastewater decision makers, due to trade-offs that must be considered for each technological option. Many multi-criteria decision making (MCDM) tools have been developed specifically for wastewater systems, that can rationalise options according to the user's priorities (Renfrew et al., 2022; Sucu et al., 2021). This assessment methodology can investigate and validate the outcomes from MCDM analysis for selecting circular technologies, as evidence for investment by water utility companies. Alternatively, the resource flow and circular action indicators selected could facilitate WWTP optimisation, whether it be hotspot analysis of a static system or integration of indicators within the control strategy of a process, to ensure more sustainable and circular operational performance. Therefore, this method can be used for multiple levels of decision making from plant optimisation to strategic planning.

5.5 Summary of main findings

- Current CE monitoring frameworks focus on measuring material flows, and align resource focussed circularity indicators with TBL dimensions to evidence that sustainability is adequately measured, therefore, there is a significant gap in CE assessments to systematically understand how changes in physical resource flows impacts sustainability of wastewater systems.

- The societal level aims of the wastewater sector make sustainable value creation suitable for use as a holistic indicator of circular performance for wastewater systems, which incorporates stakeholder collaboration to understand value creation across the TBL, meaning an assessment methodology was constructed from five principles developed from relevant sustainability and circularity literature.
- This resulted in a taxonomy of indicators that provide a detailed analysis of materials/nutrients, energy, water, and economic resource circularity, the success of value generating circular actions, and the resultant sustainable value created for stakeholders.
- An important aspect of the methodology is to create and utilise suitable benchmarks for the assessment, so the method was validated by implementing it for the assessment of a PBR wastewater treatment system and comparing this against a conventional extended aeration process, to directly quantify benefits in terms of circularity and sustainability.
- Using the resource classification approach developed in Chapter 4 and inputs from technology developers to generate a VPC for indicator selection, the assessment showed that the PBR system is able to improve resource outflow circularity, achieve its desired value creating goals, and create value across the TBL for stakeholders.
- Therefore, the developed method is able to facilitate robust indicator calculation and systematically assess how changes to a physical system in terms of resource circularity alter sustainability dimensions, and it is hoped this can be used as the basis for standardising the holistic assessment of wastewater systems.

6 Conclusions and Recommendations for Future Research

6.1 Conclusions

The importance of water provision and wastewater management for societal, environmental, and industrial prosperity has established the water sector as a priority area to facilitate a circular economy (CE). Unfortunately, the sector is risk averse and there is an absence of the expertise needed to select appropriate circular technologies, hindering CE adoption. Additionally, a lack of coherence in defining and assessing wastewater resource circularity means potential benefits cannot be fully quantified or monitored. This led to creating the research hypothesis: *The current definitions, indicators, and methods used for circularity assessments are not applicable to wastewater technologies and resources. There is a significant gap when it comes to defining the circularity of waste streams that if not corrected will lead to wastewater system assessments of little value. Additionally, the use of material-based indicators as a proxy for the assessment of sustainability dimensions is not correct, and instead a method is needed to bridge the gap that exists between circularity and sustainability impacts. Combining these aspects will enable a holistic assessment of how the CE can create value for stakeholders from wastewater.*

This thesis demonstrates the specificities that must be considered when dealing with wastewater circularity, and provides methods for the systematic selection and assessment of circular wastewater solutions, whilst ensuring the holistic impacts on sustainability dimensions are included. The research follows a logical path, starting with a detailed understanding of indicator-based decision making at a wastewater treatment plant (WWTP) level, and developing a framework for integrating a decision support system (DSS) to define shared resource recovery strategies to improve sector circularity. This review highlighted the need for a more rigorous wastewater circularity assessment, starting with the creation of new definitions and a classification system for wastewater resource circularity. This enables the disentanglement and tracing of wastewater resources to facilitate the assessment of previously hidden and inaccessible resources, overcoming the assessment paradox that currently exists. The wastewater circularity classification then formed the basis of a holistic assessment methodology, that uses systematic indicator selection to combine resource circularity and sustainable value creation analysis. Importantly, participatory methods are used for indicator selection to logically integrate circularity and sustainability dimensions within the assessment.

The method was validated by applying it to an example of a novel wastewater treatment technology, showing how a benchmark can be defined to directly quantify changes to circularity and sustainability indicators. This provides a robust scientific foundation for practitioners to use the methods developed for a range of decision-making purposes to enhance the circular transformation of the water sector.

6.1.1 Research question 1

What is the current landscape of indicator-based decision making at WWTPs?

In Chapter 2, the reviewed literature established the complex nature of decision making at WWTPs, highlighting the need for indicator-based DSS tools, and the importance of this in achieving national level (European Union and UK) CE and sustainability objectives. The review emphasised a division in WWTP DSS utilisation, which is primarily split into two groups, namely multi-criteria decision-making (MCDM) for technology selection and multi-objective process optimisation tools. For MCDM technology selection, eight commons steps were identified as being aim definition, technology identification, indicator categorisation, indicator selection, indicator weighting, indicator scoring, technology ranking, and technology selection. For multi-objective process optimisation, there was a reliance on Benchmark Simulation Models (BSMs) to conduct decision making meaning that goals, key performance indicators (KPIs), and outcomes are similar across these types of DSSs. Therefore, critical analysis of WWTP DSSs followed a similar structure.

Specifically, how are indicators selected and utilised in decision support tools for technology selection and process optimisation at WWTPs, and how are decisions aligned with the sustainability and circularity aims?

The primary focus of each DSS typology was to select technology that enhances wastewater treatment performance and optimisation of set points to improve costs and effluent quality. The review details the lack of consensus regarding the selection and utilisation of indicators for decision making in the wastewater sector. Unfortunately, it is clear that many MCDM technology selection DSSs still rely on user defined weighting, scoring, and ranking procedures which introduces high degrees of uncertainty into the assessment. These DSSs often rely on predetermined list of indicators that do not reflect the desired goals or ignore wider benefits of innovative technologies. Alternatively, multi-objective optimisation DSSs are over reliant on

BSM models, meaning decision makers are not able to select KPIs altogether, and their sustainability and circularity aims are ignored. DSS issues are highlighted by the focus on economic performance for both technology selection and process optimisation DSSs, meaning decision making does not consider the modern goals of the wastewater sector to improve circularity and sustainability.

Lastly, what progress has been made towards standardising these assessments and can recommendations be provided to expedite this process?

Following critical review, problems with DSS methodologies in terms of indicator selection and utilisation were highlighted and recommendations provided. The main issues with MCDM technology selection DSSs are i) a lack of clear goal definition, ii) mitigation of rigorous indicator selection procedures, iii) unclear definitions for indicator categorisation, iv) users deciding indicator weighting (excluding local expert inputs), v) unstructured ranking methods leading to uncertain outcomes, and vi) rarely are selected technologies critically analysed against defined goals. These were used to develop a list of recommendations including the use of participatory methods to include local stakeholder perspectives, structured approaches (such as fuzzy-Analytical Hierarchy Process and -Technique for Order of Preference by Similarity to Ideal Solution) for robust indicator weighting and ranking, and sensitivity analysis to validate DSS outcomes. Similarly for multi-objective optimisation DSSs, the identified issues are i) a lack of DSS application to real WWTP systems (focus on BSM control), ii) often indicators are fixed within the model and more rigorous selection procedures are overlooked, iii) focus on Overall Cost Index and Effluent Quality Index indicators which provides a narrow view of what 'optimal' performance is, iv) dynamic control mitigates plant operator decision making capabilities, and v) many DSSs mitigated performance analysis. Therefore, recommendations are provided including testing of DSSs on real WWTPs, expansion of indicator sets to include wider impacts (triple bottom line dimensions), and use of Integral of Absolute Error and Integral of Squared Error calculations to investigate DSS error and response. Therefore, many recommendations could be provided for future DSS development that is more standardised for aligning aims with outcomes that facilitate water sector decision maker goals.

6.1.2 Research question 2

How can decision support tools developed for technology selection be applied to provide a consensus for CE strategies to enhance wastewater sector circularity?

The problems identified in Chapter 2 emphasise the need for structured approaches to facilitate practical decision making in the wastewater sector to its transition towards a CE. This is addressed in Chapter 3 by developing an approach that integrates a DSS for wastewater technology selection to create a collective resource recovery strategy for improving nutrient circularity at a regional scale. The framework starts with development of the baseline scenario, and then uses a combination of market potential analysis and a semi-quantitative DSS developed by UK Water Industry Research for technology selection. This DSS was selected as it incorporates the 6 capitals for a wider benefits assessment, as well as a range of more conventional criteria such as cost, carbon, and treatment impacts, which were scored using expert inputs. This was used to identify 'priority' resources for a given region, with corresponding recovery technologies integrated within a baseline model of the specified region, to generate a 'resource recovery scenario'. An important step was to alter criteria weighting, to investigate how future scenarios (such as prioritising carbon impacts) impacts resource scores, with the average across the scenarios used to decide the final resource ranking. Material flow analysis (MFA) and the quantity of key wastewater resources recovered (nitrogen and phosphorus) were used to analyse both scenarios, identify hotspots, and directly quantify improvements.

Can they be used as part of a structured approach to establish which resources have the greatest resource recovery potential at a regional level and quantify the potential benefits in terms of resource recovery?

To corroborate the effectiveness and understanding of the approach, it was applied to the UK wastewater sector as the necessary data was available as part of the OFWAT's PR19 reports. MFA and recovery rate indicators revealed that in the baseline scenario a large fraction of nutrients is currently lost through assimilation during secondary/tertiary treatment, showing there is significant scope for improvement. Market potential analysis highlighted the resource with the lowest demand would be chemical electricity generation, demonstrating that investment in higher value resources may provide greater benefits. In fact, water reuse, CO_2, hydrogen, and phosphorus resources had market potentials above 25 %, whilst polyhydroxyalkanoates and extracellular polymeric substances (EPS) recovery even had potential to saturate the market. The average score across the four potential scenarios established the top five 'priority resources' as heat (heat pumps), ammonia (stripping), biopolymers (EPS), struvite, and biosolids. A resource recovery scenario that integrated technologies for recovery of these resources, such as aerobic granular sludge, advanced anaerobic digestion (AD), and struvite precipitation, quantified that nitrogen and phosphorus recovery could both be increased by approximately 70 %. However, a large proportion of nitrogen is still assimilated during wastewater treatment, potentially warranting an investigation into investment for separate collection infrastructure to enhance nutrient recovery. However, it was discussed that the recommended technologies provided by the regional assessment must act as the foundation for further analysis by individual water utilities or treatment sites. Therefore, there is a need for the development of a holistic assessment that enables conclusive appraisal of implementing circular solutions.

6.1.3 Research question 3

Can the circularity of wastewater be defined beyond just having no value or as 'non-virgin' and be used to overcome the current assessment paradox for characterising the circularity of wastewater resources?

To facilitate the construction of a wastewater assessment methodology, Chapter 4 focuses on redefining waste resource circularity to ensure assessment outcomes are of value for evidence-based decision making. Currently, it is difficult to define physical water resources as sustainable or unsustainable, as it is how water resources are used and the resultant impacts that defines its sustainability and circularity, by understanding the source, destination, and how quality changes on the journey between them. Therefore, the actions and intent of wastewater producers across different sectors must be used to assign responsibility for linear utilisation of resources, shifting the current paradigm of policy instruments that are only used to promote circularity. To realise this, traceability principles were combined with an understanding of wastewater resources' potential to cause harm when released to the environment, to go beyond the blanket definition of waste and show how water usage impacts its circularity. This was challenging considering current definitions of circularity but through disentanglement of resource flows, all wastewater system inputs and outputs can be characterised, and used for assigning circular properties prior to indicator calculation. An explanation and definitions for the circularity classification of wastewater water, carbon, nitrogen, and phosphorus resources were developed, along with examples for some of the most common wastewater treatment scenarios. This unlocked the circularity of previous hidden wastewater resources to overcome the current assessment paradox for waste streams.

Does tracing the source and destination of wastewater and its constituent resources enable responsibility to be assigned for linear water use?

To show the advantages of the methodology, an assessment of wastewater resource flows that combines the classification framework, MFA, and circularity indicators was developed and applied to a WWTP example (12,000 m^3/d). The indicators selected to assess WWTP resource flows covered the key areas of material inflows and outflows, water, energy, and economics, and were used to investigate how potential water user actions impact circularity in WWTP upstream and downstream. For example, it was shown that industrial action increasing fossil carbon concentration (400 m^3/d effluent at 1000 mgC/l) reduced inflow and outflow circularity by 16 % and 10.6 % respectively, as secondary and sludge treatment fossil emissions increase significantly. Additionally, changes to water user habits that reduce detergent use by 50 % improved phosphorus inflow circularity by 5.2 % and better agricultural practices reducing synthetic fertiliser usage by 50 % increased nitrogen outflow circularity by 20.1 %. This analysis provides an answer to RQ3 but the issue of changing geography, local water user habits, local regulatory limits, and the preferred method of treatment of a region impacting wastewater composition, production rates, and destination was raised. Therefore, additional studies may be needed to quantify missing information for a specific WWTP system requiring local wastewater process operators to validate assumptions. Lastly, the need to expand the scope of the assessment beyond just resource flow analysis, by incorporating wider sustainability analysis to quantify the sustainable environmental, social, and economic stakeholder value was discussed.

6.1.4 Research question 4

Can a methodology be developed that facilitates the standardisation of wastewater circularity assessments by systematically selecting indicators to quantify the sustainable value created by circular practices?

The need for a holistic wastewater circularity assessment is met by the work of Chapter 5. Initially, the significant gap between current circularity and sustainability assessments which must be overcome to build business cases and convince companies to invest in circular solutions was highlighted. However, current CE monitoring frameworks focus on measuring material flows and align resource focussed circularity indicators with triple bottom line resulting in patchy assessments and consequences such as rebound effects and impact leakage. Therefore, a methodology was developed to systematically link changes in physical resource circularity with resultant sustainable value creation, to harmonise the assessment of wastewater processes and resources. The method was based on several principles defined from relevant sustainability science and CE literature such as using circular actions, quantifying value creation, and stakeholder participation. This resulted in an eleven-step framework, which utilises a taxonomy of indicators with three indicator typologies, namely resource flow, circular action, and sustainability indicators. The resource classification approach of Chapter 4 is used for robust indicator calculation, with stakeholder inputs utilised to develop value propositions which enables indicators to be systematically selected. This facilitates flexible indicator selection considering specific aspects of each scenario of application, meaning it can be applied across multiple levels of decision making, including static assessments for comparing technologies, hotspot identification for improving circularity, or performance monitoring for process optimisation.

How does altering the circularity of physical resource flows impact the sustainability of wastewater systems?

The assessment relies on the establishment of a benchmark conventional process so that direct changes to resource circularity and sustainability impacts can be quantified. Therefore, to show assessment method capabilities, and enhance understanding of its application, it was implemented to assess an example comparing novel photobioreactor (PBR) and conventional extended aeration technologies at a scale of 10,000 population equivalents. It was shown how strategic project goals are combined with value creating goals of the circular technology to select relevant action indicators, with the data requirements feeding complementary sustainability indicator selection. Resource flow indicators were calculated using the resource classification approach and results highlighted improved outflow circularity (specifically for nitrogen and phosphorus nutrients), renewable energy usage, and economic performance for the PBR system. Action indicators revealed that the PBR technology was successful at achieving the defined value creating goals as all indicators revealed improvements, except for waste eco-efficiency, however this highlights how addition of captured solids to anaerobic digesters would enhance circularity. Lastly, sustainability indicators (carbon footprint, life cycle assessment (LCA), economic value added, and social LCA) enabled the direct quantification of environmental, economic, and social value creation, confirming the benefits of PBR wastewater treatment technology for stakeholders. The results of this assessment should be used to expedite uptake of the PBR technology at this scale, by providing evidence of its holistic benefits in terms of circularity and sustainability.

Evolution of the work throughout this thesis adds a valuable contribution to the current paradigm of CE science by providing a scientific basis for measuring, assessing, and implementing circular wastewater solutions. By understanding the current landscape of indicator-based decision making in the wastewater sector, and combining this with the necessary redefinition of wastewater circularity, this investigation was able to unlock a new area of circularity assessment, by tracing wastewater resources that were previously hidden using the current definition of waste streams. Following this development of CE theory, this body of work culminated in the creation of a logical and holistic assessment of wastewater circularity and sustainability. By using stakeholder participation to understand the value creating actions of circular technologies, the relationship between circularity and sustainability can be fully appreciated and quantified. Proper utilisation of the method will enable it to be implemented for decision making at an operational and strategic level, facilitating the circular transition of the water sector. It is also hoped that by integrating the resource classification approach within the holistic assessment it will help to strengthen its symbiotic relationships for achieving a CE by highlighting the importance of wastewater treatment. In fact, this approach could be expanded and used as a tool for assigning responsibility for linear production of waste, acting as a foundation to move away from current policy which mostly acts to encourage circular practice rather than hindering linear actions.

6.2 Recommendations for future research

Although this thesis is structured in a way that the main questions raised by a chapter are answered by the subsequent one, there are aspects of WWTP DSSs and circularity assessments that could not be covered in the current body of work but require further exploration and development. The first, follows the review of WWTP DSSs and how the digitisation of the water sector will facilitate more structured and detailed data usage to provide greater insights for decision making. Inefficient use of data is one of the main problems in plant management which many WWTPs currently struggle to solve. The wastewater treatment (WWT) process is complicated and decentralised, so data is scattered, and managers can struggle to supervise the whole plant leading to poor performance. The water industry is still developing data collection, management, analytics, and controls to more effectively use data to inform decision making across all operational functions (Corominas et al., 2018). As a result, most data are relatively untapped to support decisions that would enable higher levels of performance and control. Subsequently, online optimisation of WWTP control has not been widely applied to real-world systems, due to the complex, non-linear behaviour of biological WWT (increasing the computational requirements), lack of visualisation techniques, and low-quality sensor measurements (Matheri et al., 2022). Types of advanced control known as model predictive controllers, use data-driven techniques for early correction of process operation to reduce process faults and therefore costly downtime, effluent violations, and resource consumption (Ntalaperas et al., 2022). The combination of this with effectively constructed multi-objective optimisation DSSs results in powerful and desirable tools for the water sector to achieve its environmental targets and sustainability goals. Finally, the use of data-driven techniques can also be extended to improve the selection of indicators, including the use of techniques combined with expert knowledge, to find precise KPIs for monitoring specific strategic goals. This would enable the differentiation between performance (lead) and result (lag) indicators, and create numeric thresholds and benchmarks (del Mar Roldán-García et al., 2021), providing more knowledge for decision making purposes. This provides direction for the next phase of automatic WWTP control, therefore DSSs can be used to remove human judgement from decision making, minimising errors for performance optimisation.

The next development is required after the inclusion of the 6 capitals in the multi-criteria technology selection approach of Chapter 3. Using the 6 capitals enables the assessment to go further than the typical focus on financial and manufactured capital, resulting in a more holistic selection process. The use of a capitals assessment is seen as a way to maximise value creation in a more inclusive way, which is evidenced by their incorporation within national water strategic plans, including the *UK 2050 Water Innovation Strategy* (2020) and Water Services Association of Australia circular economy transition (Jazbec et al., 2020). Their inclusion in the developed approach aims to identify technologies that generate greater net sustainability of the entire system. However, the assessment of capitals relied on expert judgement scoring (UKWIR, 2021), so to fully understand the value of capturing resources, the next phase of the assessment should be to quantify the capitals to act as the final validation of selected technologies. The method developed by Yorkshire Water (2018) could act as a starting point for this, as it places value on circular resource flows and a cost on negative externalities. This will require more detailed analysis of the studied system to expand the assessment for incorporation of other sustainability aspects (environmental, social, economic dimensions).

The main requirement for further study realised by Chapter 4 was expansion of the work to harmonise the assessment of resource circularity and sustainability impacts, thereby being answered by Chapter 5. However, utility of the developed holistic assessment methodology could be increased by evolving certain aspects. Firstly, it was defined that the flexibility of the assessment method would enable multiple levels of decision making, but currently it has only been applied to the static assessment of a WWTP to quantify the benefits of a novel technology. Therefore, to justify this statement, work must be put into showcasing a variety of decision-making capabilities and be tested in a range of different environments to also prove its value at an operational level. This would be achieved by using the methodology to select indicators, then integrating them within the DSS of a WWTP to optimise performance based not only on conventional parameters (such as effluent quality) but also circularity and sustainability KPIs. This would require enhancement of current data monitoring and analysis procedures, as described in the first paragraph of this section, for dynamic indicator calculation and assessment. There are currently few examples of performance optimisation DSSs considering wider impacts in the literature, however, Chen et al. (2021) dynamically optimises dissolved oxygen and chemical dosage at a 10,000 PE WWTP in China, using life cycle costing and LCA impact indicators as a reward function, showing this is possible.

As many circular intervention technologies are still being developed at low technology readiness level (TRL), their assessment requires additional consideration to expedite development and uptake. To elucidate the advantages of these technologies, circularity assessments, and other sustainability analysis techniques (LCA, technoeconomic assessment, or social LCA) need to be completed. However, low TRL technologies (pilot and demo scale) cannot compete in terms of economics, often due to higher energy and material consumption, with industrial scale processes. Therefore, technologies should be modelled at the full scale of implementation, requiring scale up calculations to build the models necessary for circularity assessments. Although, caution must be taken when building models and inventories of scaled up or future systems, as this introduces possibilities for high levels of uncertainty during the assessment. To overcome the issues of uncertainty when modelling scaled-up technologies, the principles of prospective LCAs can be utilised. van der Giesen et al. (2020) recommends the use of responsive evaluations by technology designers and other relevant stakeholders to provide insights on the design choices and contextual factors which have larger influences on the outcomes of assessments, and therefore require greater attention when being modelled. The insights from technology designers can be combined with learning curves and upscaling analysis from experts in the fields of chemical and process engineering to create representative and realistic models of full-scale technologies. For example, Tecchio et al. (2016) provides a systematic method for the scale up of biorefinery processes, utilising primary data from pilot scale systems and combining it with knowledge of thermo-chemical processes, to estimate the environmental impact at an industrial scale. Ex-ante and prospective LCA approaches provide many insights required for developing accurate models for full scale processes. This is pertinent, as to elucidate the advantages of circular technologies they must be modelled and compared at an industrial scale, even though many are still at low TRL. Therefore, an additional development to the proposed circularity assessment method should focus on the integration of a systematic process for constructing full scale models for low TRL circular technologies, and investigation of uncertainty to mitigate calculation errors and improve assessment transparency.

In response to the demand for a standardised way to measure circularity, the International Standards Organisation (ISO) is currently drafting a family of documents related to the circular economy (International Standards Organization, 2022). However, they are horizontal standards that can be used by all sectors following a principles-based approach to act as a guidance for circularity assessments; so understandably it is impossible to cover the individual barriers of application to all potential scenarios and sectors. Therefore, work must be done to translate the guidance into application for each sector. Current terminology and definitions will lead to inconsistencies when utilising the ISO to assess the circularity of WWTPs, specifically during the calculation of indicators. The classification approach and method of indicator selection would enable users of the ISO to systematically characterise resource circularity, select indicators, and quantify value creation, ending the ambiguity that currently surrounds these areas and facilitating standardisation of indicator calculation. Standardisation is needed to facilitate the comparison of assessment results across different case studies, enabling decision makers to compare the impacts of alternate WWTP operation, technology, and location with their own in a robust manner. Therefore, it is hoped this work can provide tools to act as starting point for translating ISO 59020 to standardise the assessment of wastewater systems.

Lastly, application of the current example to a static assessment of a WWTP resulted in the selection and utilisation of more than 30 indicators. This number of indicators is required to holistically assess circularity and sustainability, however, the variety of indicators across multiple dimensions adds to the complexity when interpreting results for decision making. To provide more simplistic outcomes, indicators can be aggregated into a single output that is able to demonstrate overall circularity. Without this it may be difficult for inexperienced decision makers to extract the required information from assessment results, hindering acceptance and uptake of the methodology. There are several methods for indicator aggregation including structured approaches requiring the inputs of experts, such as Choosing-By-Advantages (Arroyo and Molinos-Senante, 2018), Analytical Hierarchy Process (Gherghel et al., 2020), Best-Worst Method (Liu and Ren, 2022), Full-Consistency Method (Srivastava and Singh, 2022), and Interpretive Structural Modelling (Nika et al., 2021). Statistical approaches are also able to objectively rank and assign weights to indicators using methods including Principal Component Analysis (Teixeira de Souza et al., 2021), Correlation Analysis (Pearson's, Hierarchical Clustering, and Random Forests) (Pacheco-Romero et al., 2022), and MICMAC Analysis (Nika et al., 2021). Utilising these methods would enhance communication of results by summarising assessment outcomes into a form that is simple for stakeholders to understand. A single circularity score could even form the basis of a rating scale, facilitating comparison across different technologies in terms of circularity performance.

References

Agricultural Industries Confederation, 2021. Fertiliser consumption in the UK (Annual Summary) [WWW Document]. URL https://www.agindustries.org.uk/resource/fertiliser-consumption-in-the-uk.html (accessed 4.13.22).

Agudelo-Vera, C.M., Mels, A., Keesman, K., Rijnaarts, H., 2012. The Urban Harvest Approach as an Aid for Sustainable Urban Resource Planning. J. Ind. Ecol. 16, 839–850. https://doi.org/https://doi.org/10.1111/j.1530-9290.2012.00561.x

AHDB, 2019. Nutrient Management Guide (RB209) [WWW Document]. URL https://ahdb.org.uk/nutrient-management-guide-rb209 (accessed 4.13.22).

Ahmed, A.A., Nazzal, M.A., Darras, B.M., Deiab, I.M., 2022. A comprehensive multi-level circular economy assessment framework. Sustain. Prod. Consum. 32, 700–717. https://doi.org/https://doi.org/10.1016/j.spc.2022.05.025

Åkerman, M., Humalisto, N., Pitzen, S., 2020. Material politics in the circular economy: The complicated journey from manure surplus to resource. Geoforum 116, 73–80. https://doi.org/https://doi.org/10.1016/j.geoforum.2020.07.013

Alberici, S., Noothout, P., Mir, G.U.R., Stork, M., Wiersma, F., 2017. ASSESSING THE POTENTIAL OF CO2 UTILISATION IN THE UK [WWW Document]. URL https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/799293/SISUK17099AssessingCO2_utilisationUK_ReportFinal_260517v2__1_.pdf

Alcalde-Calonge, A., Sáez-Martínez, F.J., Ruiz-Palomino, P., 2022. Evolution of research on circular economy and related trends and topics. A thirteen-year review. Ecol. Inform. 70, 101716. https://doi.org/https://doi.org/10.1016/j.ecoinf.2022.101716

Aldaya, M.M., Chapagain, A.K., Hoekstra, A.Y., Mekonnen, M.M., 2011. The Water Footprint Assessment Manual: Setting the Global Standard, 1st ed. Routledge. https://doi.org/https://doi.org/10.4324/9781849775526

Alex, J., Benedetti, L., Copp, J., Gernaey, K.V., Jeppsson, U., Nopens, I., Pons, M.N., Steyer, J.P., Vanrolleghem, P., 2018. Benchmark Simulation Model no. 1 (BSM1).http://iwa-mia.org/wp-content/uploads/2019/04/BSM_TG_Tech_Report_no_1_BSM1_General_Description.pdf

Ali, Y., Pervez, H., Khan, J., 2020. Selection of the Most Feasible Wastewater Treatment Technology in Pakistan Using Multi-Criteria Decision-Making (MCDM). WATER Conserv. Sci. Eng. 5, 199–213. https://doi.org/10.1007/s41101-020-00094-6

Almendra-Martín, L., Martínez-Fernández, J., Piles, M., González-Zamora, Á., Benito-Verdugo, P., Gaona, J., 2022. Analysis of soil moisture trends in Europe using rank-based and empirical decomposition approaches. Glob. Planet. Change 215, 103868.

https://doi.org/https://doi.org/10.1016/j.gloplacha.2022.103868

Alvarado, V.I., Hsu, S.-C., Wu, Z., Lam, C.-M., Leng, L., Zhuang, H., Lee, P.-H., 2019. A Standardized Stoichiometric Life-Cycle Inventory for Enhanced Specificity in Environmental Assessment of Sewage Treatment. Environ. Sci. Technol. 53, 5111–5123. https://doi.org/10.1021/acs.est.9b01409

An, D., Xi, B.D., Ren, J.Z., Ren, X.S., Zhang, W.S., Wang, Y., Dong, L.C., 2018. Multi-criteria sustainability assessment of urban sludge treatment technologies: Method and case study. Resour. Conserv. Recycl. 128, 546–554. https://doi.org/10.1016/j.resconrec.2016.08.018

Ardolino, F., Cardamone, G.F., Parrillo, F., Arena, U., 2021. Biogas-to-biomethane upgrading: A comparative review and assessment in a life cycle perspective. Renew. Sustain. Energy Rev. 139, 110588. https://doi.org/https://doi.org/10.1016/j.rser.2020.110588

Arroyo, P., Molinos-Senante, M., 2018. Selecting appropriate wastewater treatment technologies using a choosing-by-advantages approach. Sci. Total Environ. 625, 819–827. https://doi.org/https://doi.org/10.1016/j.scitotenv.2017.12.331

Atasoy, M., Owusu-Agyeman, I., Plaza, E., Cetecioglu, Z., 2018. Bio-based volatile fatty acid production and recovery from waste streams: Current status and future challenges. Bioresour. Technol. https://doi.org/10.1016/j.biortech.2018.07.042

Attri, S.D., Singh, S., Dhar, A., Powar, S., 2022. Multi-attribute sustainability assessment of wastewater treatment technologies using combined fuzzy multi-criteria decision-making techniques. J. Clean. Prod. 357, 131849. https://doi.org/https://doi.org/10.1016/j.jclepro.2022.131849

Aunon, E., Ryan, S., Sawyer, R., 2015. Municipal Sewage: One Man's Waste, Another Man's Treasure! London [WWW Document]. URL https://ukwir.org/eng/reports/15-PM-03-5/145974/Municipal-Sewage-One-Mans-Waste-Another-Mans-Treasure (accessed 4.13.22).

Batstone, D.J., Hülsen, T., Mehta, C.M., Keller, J., 2015. Platforms for energy and nutrient recovery from domestic wastewater: A review. Chemosphere 140, 2–11. https://doi.org/https://doi-org.ezproxy.brunel.ac.uk/10.1016/j.chemosphere.2014.10.021

Baumann, I., Westermann, P., 2016. Microbial Production of Short Chain Fatty Acids from Lignocellulosic Biomass: Current Processes and Market. Biomed Res. Int. 2016, 8469357. https://doi.org/10.1155/2016/8469357

Beloin-Saint-Pierre, D., Albers, A., Hélias, A., Tiruta-Barna, L., Fantke, P., Levasseur, A., Benetto, E., Benoist, A., Collet, P., 2020. Addressing temporal considerations in life cycle assessment. Sci. Total Environ. 743, 140700. https://doi.org/https://doi.org/10.1016/j.scitotenv.2020.140700

Biosolids Assurance Scheme, 2020. Standard Guidance Notes [WWW Document]. URL https://assuredbiosolids.co.uk/scheme-documents/

Biosys, 2021a. Tully AD plant Ballymena [WWW Document]. URL https://www.byosis.com/case-studies/ballymena-plant (accessed 7.1.21).

Biosys, 2021b. Experts in N-stripping & recovery [WWW Document]. URL https://www.byosis.com/ (accessed 6.9.21).

Blomsma, F., Brennan, G., 2017. The Emergence of Circular Economy: A New Framing Around Prolonging Resource Productivity. J. Ind. Ecol. 21, 603–614. https://doi.org/https://doi.org/10.1111/jiec.12603

Borzooei, S., Campo, G., Cerutti, A., Meucci, L., Panepinto, D., Ravina, M., Riggio, V., Ruffino, B., Scibilia, G., Zanetti, M., 2019. Optimization of the wastewater treatment plant: From energy saving to environmental impact mitigation. Sci. Total Environ. 691, 1182–1189. https://doi.org/https://doi.org/10.1016/j.scitotenv.2019.07.241

British Standards Institute, 2020. Environmental management. Life cycle assessment. Principles and framework. (BS EN ISO 14040:2006+A1:2020). https://doi.org/https://doi.org/10.3403/30154435U

Burgos, A.J., López, J.S., Rodríguez, P.U., 2015. TRICKLING FILTERS SERIES: SECONDARY TREATMENTS. https://www.wateractionplan.com/documents/177327/558166/Trickling+filters.pdf/1c2ef2b5-6f3b-326a-c33b-bea411572184

Büyüközkan, G., Tüfekçi, G., 2021. A multi-stage fuzzy decision-making framework to evaluate the appropriate wastewater treatment system: a case study. Environ. Sci. Pollut. Res. 28, 53507–53519. https://doi.org/10.1007/s11356-021-14116-w

Caligan, C.J.A., Garcia, M.M.S., Mitra, J.L., San Juan, J.L.G., 2022. Multi-objective optimization for a wastewater treatment plant and sludge-to-energy network. J. Clean. Prod. 368, 133047. https://doi.org/https://doi.org/10.1016/j.jclepro.2022.133047

Calisto Friant, M., Vermeulen, W.J. V, Salomone, R., 2020. A typology of circular economy discourses: Navigating the diverse visions of a contested paradigm. Resour. Conserv. Recycl. 161, 104917. https://doi.org/https://doi.org/10.1016/j.resconrec.2020.104917

Campana, P.E., Mainardis, M., Moretti, A., Cottes, M., 2021. 100% renewable wastewater treatment plants: Techno-economic assessment using a modelling and optimization approach. Energy Convers. Manag. 239. https://doi.org/10.1016/j.enconman.2021.114214

Çapa, S., Özdemir, A., Günkaya, Z., Özkan, A., Banar, M., 2022. An environmental and economic assessment based on life cycle approaches for industrial wastewater treatment and water recovery. J. Water Process Eng. 49, 103002. https://doi.org/https://doi.org/10.1016/j.jwpe.2022.103002

Castillo, A., Porro, J., Garrido-Baserba, M., Rosso, D., Renzi, D., Fatone, F., Gómez, V., Comas, J., Poch, M., 2016. Validation of a decision support tool for wastewater treatment selection. J. Environ. Manage. 184, 409–418. https://doi.org/https://doi.org/10.1016/j.jenvman.2016.09.087

Cavinato, C., Bolzonella, D., Pavan, P., Fatone, F., Cecchi, F., 2013. Mesophilic and thermophilic anaerobic co-digestion of waste activated sludge and source sorted biowaste in pilot- and full-scale reactors. Renew. Energy 55, 260–265. https://doi.org/https://doi.org/10.1016/j.renene.2012.12.044

Cefic, 2022. Towards an accurate accounting for carbon from biomass in the Product Environmental Footprint (PEF).https://cefic.org/app/uploads/2022/09/Cefic-position-on-PEF-Product-Environmental-Footprint-Towards-an-accurate-accounting-for-carbon-from-biomass-in-the-Product-Environmental-Footprint-PEF.pdf

CENTRISYS-CNP, 2021. Water Reclamation Facility Upgrades System for Struvite Recovery [WWW Document]. Munic. CASE Stud. URL https://www.centrisys-cnp.com/municipal-case-studies/water-reclamation-facility-upgrades-system-for-struvite-recovery (accessed 7.1.21).

Chen, C.-W., 2021. Clarifying rebound effects of the circular economy in the context of sustainable cities. Sustain. Cities Soc. 66, 102622. https://doi.org/https://doi.org/10.1016/j.scs.2020.102622

Chen, K., Wang, H., Valverde-Pérez, B., Zhai, S., Vezzaro, L., Wang, A., 2021. Optimal control towards sustainable wastewater treatment plants based on multi-agent reinforcement learning. Chemosphere 279, 130498. https://doi.org/https://doi.org/10.1016/j.chemosphere.2021.130498

Chen, X., Xu, Z., Yao, L., Ma, N., 2018. Processing Technology Selection for Municipal Sewage Treatment Based on a Multi-Objective Decision Model under Uncertainty. Int. J. Environ. Res. Public Health. https://doi.org/10.3390/ijerph15030448

Chhipi-Shrestha, G., Hewage, K., Sadiq, R., 2017. Fit-for-purpose wastewater treatment: Conceptualization to development of decision support tool (I). Sci. Total Environ. 607–608, 600–612. https://doi.org/https://doi.org/10.1016/j.scitotenv.2017.06.269

Chojnacka, K., Moustakas, K., Witek-Krowiak, A., 2020. Bio-based fertilizers: A practical approach towards circular economy. Bioresour. Technol. 295, 122223. https://doi.org/https://doi.org/10.1016/j.biortech.2019.122223

Chrispim, M.C., de M. de Souza, F., Scholz, M., Nolasco, M.A., 2020. A Framework for Sustainable Planning and Decision-Making on Resource Recovery from Wastewater: Showcase for São Paulo Megacity. Water 12. https://doi.org/10.3390/w12123466

Cieślik, B., Konieczka, P., 2017. A review of phosphorus recovery methods at various steps of wastewater treatment and sewage sludge management. The concept of "no solid waste generation" and analytical methods. J. Clean. Prod. 142, 1728–1740. https://doi.org/https://doi-org.ezproxy.brunel.ac.uk/10.1016/j.jclepro.2016.11.116

CIWEM, 2011. Co-digestion of sewage sludge and waste [WWW Document]. URL https://www.ciwem.org/assets/pdf/Policy/Policy Position Statement/Co-digestion-of-sewage-sludge-and-waste.pdf

Coenen, T.B.J., Haanstra, W., Jan Braaksma, A.J.J., Santos, J., 2020. CEIMA: A framework for identifying critical interfaces between the Circular Economy and stakeholders in the lifecycle of infrastructure assets. Resour. Conserv. Recycl. 155, 104552. https://doi.org/https://doi.org/10.1016/j.resconrec.2019.104552

Collin, T.D., Cunningham, R., Asghar, M.Q., Villa, R., MacAdam, J., Jefferson, B., 2020. Assessing the potential of enhanced primary clarification to manage fats, oils and grease (FOG) at wastewater treatment works. Sci. Total Environ. 728, 138415. https://doi.org/https://doi.org/10.1016/j.scitotenv.2020.138415

Collivignarelli, M.C., Canato, M., Abbà, A., Miino, M.C., 2019. Biosolids: What are the different types of reuse? J. Clean. Prod. 238, 117844. https://doi.org/https://doi-org.ezproxy.brunel.ac.uk/10.1016/j.jclepro.2019.117844

Coma, M., Martinez-Hernandez, E., Abeln, F., Raikova, S., Donnelly, J., Arnot, T.C., Allen, M.J., Hong, D.D., Chuck, C.J., 2017. Organic waste as a sustainable feedstock for platform chemicals. Faraday Discuss. https://doi.org/10.1039/c7fd00070g

Comber, S., Gardner, M., Georges, K., Blackwood, D., Gilmour, D., 2013. Domestic source of phosphorus to sewage treatment works. Environ. Technol. 34, 1349–1358. https://doi.org/10.1080/09593330.2012.747003

Conca, V., da Ros, C., Valentino, F., Eusebi, A.L., Frison, N., Fatone, F., 2020. Long-term validation of polyhydroxyalkanoates production potential from the sidestream of municipal wastewater treatment plant at pilot scale. Chem. Eng. J. 390, 124627. https://doi.org/https://doi-org.ezproxy.brunel.ac.uk/10.1016/j.cej.2020.124627

Corominas, L., Garrido-Baserba, M., Villez, K., Olsson, G., Cortés, U., Poch, M., 2018. Transforming data into knowledge for improved wastewater treatment operation: A critical review of techniques. Environ. Model. Softw. 106, 89–103. https://doi.org/https://doi.org/10.1016/j.envsoft.2017.11.023

Corona, B., Shen, L., Reike, D., Rosales Carreón, J., Worrell, E., 2019. Towards sustainable development through the circular economy—A review and critical assessment on current circularity metrics. Resour. Conserv. Recycl. https://doi.org/10.1016/j.resconrec.2019.104498

Corvellec, H., Paulsson, A., 2023. Resource shifting: Resourcification and de-resourcification for degrowth. Ecol. Econ. 205, 107703. https://doi.org/https://doi.org/10.1016/j.ecolecon.2022.107703

Corvellec, H., Stowell, A.F., Johansson, N., 2022. Critiques of the circular economy. J. Ind. Ecol. 26, 421–432. https://doi.org/https://doi.org/10.1111/jiec.13187

Council of the European Union, 2021. Establishing the framework for achieving climate neutrality and amending Regulations (EC) No 401/2009 and (EU) 2018/1999 (‘European Climate Law’). https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32021R1119

Council of the European Union, 1991. Council Directive of 21 May 1991 concerning urban wastewater treatment. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex%3A31991L0271

Council of the European Union, 1986. COUNCIL DIRECTIVE of 12 June 1986 on the protection of the environment, and in particular of the soil, when sewage sludge is used in agriculture (86/278/EEC). https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex%3A31986L0278

CREW, 2018. Water and the circular economy - where is the greatest sustainable economic benefit for resource recovery in the water cycle? [WWW Document]. URL https://www.crew.ac.uk/publication/circular-economy

da Luz Peralta, C.B., Echeveste, M.E., Martins, V.L.M., Lermen, F.H., 2020. Applying the framework to identify customer value: A case of sustainable product in agriculture. J. Clean. Prod. 270, 122384. https://doi.org/https://doi.org/10.1016/j.jclepro.2020.122384

da Silva Junior, L.C.S., de Sá Salomão, A.L., Pereira Santos, A.S., 2022. MATTI - a multi-criteria decision analysis framework for assessing wastewater treatment technologies. Water Sci. Technol. 86, 2764–2776. https://doi.org/10.2166/wst.2022.374

Dagilienė, L., Varaniūtė, V., Bruneckienė, J., 2021. Local governments' perspective on implementing the circular economy: A framework for future solutions. J. Clean. Prod. 310, 127340. https://doi.org/https://doi.org/10.1016/j.jclepro.2021.127340

Dai, H.L., Chen, W.L., Peng, L.H., Wang, X.G., Lu, X.W., 2019. Modeling and performance improvement of an anaerobic-anoxic/nitrifying-induced crystallization process via the multi-objective optimization method. Environ. Sci. Pollut. Res. 26, 5083–5093. https://doi.org/10.1007/s11356-018-3971-1

Ddiba, D., Andersson, K., Dickin, S., Ekener, E., Finnveden, G., 2023. A review of how decision support tools address resource recovery in sanitation systems. J. Environ. Manage. 342, 118365. https://doi.org/https://doi.org/10.1016/j.jenvman.2023.118365

de Almeida, K.N., dos Reis, J.A.T., Mendonça, A.S.F., Silva, F.G.B., 2022. Methodology to support the planning of sewage treatment systems within river basins. Int. J. Environ. Sci. Technol. 19, 3741–3756. https://doi.org/10.1007/s13762-021-03387-y

de Azevedo Basto, P., Savastano Junior, H., de Melo Neto, A.A., 2019. Characterization and pozzolanic properties of sewage sludge ashes (SSA) by electrical conductivity. Cem. Concr. Compos. 104, 103410. https://doi.org/https://doi.org/10.1016/j.cemconcomp.2019.103410

Deep Purple, 2019. Recover Energy & Valuable Resources from urban waste streams in Photobiorefineries with the help of purple phototropic bacteria [WWW Document]. URL https://deep-purple.eu/ (accessed 9.28.20).

del Mar Roldán-García, M., García-Nieto, J., Maté, A., Trujillo, J., Aldana-Montes, J.F., 2021. Ontology-driven approach for KPI meta-modelling, selection and reasoning. Int. J. Inf. Manage. 58, 102018. https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2019.10.003

Department for Business Energy and Industrial Strategy, 2020. UK ENERGY IN BRIEF 2020 [WWW Document]. URL https://www.gov.uk/government/statistics/uk-energy-in-brief-2020 (accessed 4.13.22).

Department for Environment Food and Rural Affairs, 2019. Water abstraction statistics: England, 2000 to 2017 [WWW Document]. URL https://www.gov.uk/government/statistics/water-abstraction-estimates

Department for Environment Food and Rural Affairs, 2018. Animal Feed Statistics for Great Britain – December 2017 [WWW Document]. URL https://www.gov.uk/government/statistics/animal-feed-production (accessed 3.14.22).

Department for Transport, 2020. Road traffic statistics [WWW Document]. URL https://roadtraffic.dft.gov.uk/summary (accessed 6.26.21).

Di Maio, F., Rem, P.C., Baldé, K., Polder, M., 2017. Measuring resource efficiency and circular economy: A market value approach. Resour. Conserv. Recycl. 122, 163–171. https://doi.org/https://doi.org/10.1016/j.resconrec.2017.02.009

Díaz-Madroñero, M., Pérez-Sánchez, M., Satorre-Aznar, J.R., Mula, J., López-Jiménez, P.A., 2018. Analysis of a wastewater treatment plant using fuzzy goal programming as a management tool: A case study. J. Clean. Prod. 180, 20–33. https://doi.org/https://doi.org/10.1016/j.jclepro.2018.01.129

Didenko, N.I., Klochkov, Y.S., Skripnuk, D.F., 2018. Ecological Criteria for Comparing Linear and Circular Economies. Resources. https://doi.org/10.3390/resources7030048

do Amaral, K.C., Aisse, M.M., Possetti, G.R.C., Prado, M.R., 2018. Use of life cycle assessment to evaluate environmental impacts associated with the management of sludge and biogas. Water Sci. Technol. 77, 2292–2300. https://doi.org/10.2166/wst.2018.146

Doorn, M.R.J., Towprayoon, S., Vieira, S.M.M., Irving, W., Palmer, C., Pipatti, R., Wang, C., 2019. 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories Wastewater Treatment and Discharge. https://www.ipcc.ch/report/2019-refinement-to-the-2006-ipcc-guidelines-for-national-greenhouse-gas-inventories/

Du, X., Peng, Y., 2023. Multi-objective pity beetle algorithm based optimal control of wastewater treatment process. Process Saf. Environ. Prot. 170, 188–206. https://doi.org/https://doi.org/10.1016/j.psep.2022.12.005

Durdević, D., Trstenjak, M., Hulenić, I., 2020. Sewage sludge thermal treatment technology selection by utilizing the analytical hierarchy process. Water (Switzerland) 12. https://doi.org/10.3390/W12051255

Đurđević, D., Trstenjak, M., Hulenić, I., 2020. Sewage Sludge Thermal Treatment Technology Selection by Utilizing the Analytical Hierarchy Process. Water 12. https://doi.org/10.3390/w12051255

Ellen MacArthur Foundation, 2015. Towards a Circular Economy: Business Rationale for an Accelerated Transition [WWW Document]. URL https://ellenmacarthurfoundation.org/towards-a-circular-economy-business-rationale-for-an-accelerated-transition (accessed 4.13.22).

Eseoglu, G., Yapsakli, K., Tozan, H., Vayvay, O., 2022. A novel fuzzy framework for technology selection of sustainable wastewater treatment plants based on TODIM methodology in developing urban areas. Sci. Rep. 12, 8800. https://doi.org/10.1038/s41598-022-12643-1

European Commission, 2022. Questions and Answers on the new EU rules on treating urban wastewater [WWW Document]. URL https://ec.europa.eu/commission/presscorner/detail/en/QANDA_22_6281 (accessed 1.16.23).

European Commission, 2021a. COMMUNICATION FROM THE COMMISSION TO THE EUROPEAN PARLIAMENT, THE COUNCIL, THE EUROPEAN ECONOMIC AND SOCIAL COMMITTEE AND THE COMMITTEE OF THE REGIONS EMPTY “Fit for 55”: delivering the EU’s 2030 Climate Target on the way to climate neutrality. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52021DC0550

European Commission, 2021b. EU Action Plan: “Towards Zero Pollution for Air, Water and Soil.” https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:52021DC0400

European Commission, 2021c. Technical guidance on the application of ‘do no significant harm’ under the Recovery and Resilience Facility Regulation. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52021XC0218%2801%29

European Commission, 2020a. A new Circular Economy Action Plan For a cleaner and more competitive Europe. https://eur-lex.europa.eu/legal-content/EN/TXT/?qid=1583933814386&uri=COM:2020:98:FIN

European Commission, 2020b. Critical Raw Materials Resilience: Charting a Path towards greater Security and Sustainability. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52020DC0474

European Commission, 2020c. A hydrogen strategy for a climate-neutral Europe. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52020DC0301

European Commission, 2020d. A new Circular Economy Action Plan For a cleaner and more competitive Europe. https://eur-lex.europa.eu/legal-content/EN/TXT/?qid=1583933814386&uri=COM:2020:98:FIN

European Commission, 2018. Product Environmental Footprint Category Rules (PEFCR) for still and sparkling wine. https://eplca.jrc.ec.europa.eu/permalink/PEFCR_guidance_v6.3-2.pdf

European Commission, 2015. Closing the loop - An EU action plan for the Circular Economy. https://eur-lex.europa.eu/resource.html?uri=cellar:8a8ef5e8-99a0-11e5-b3b7-01aa75ed71a1.0012.02/DOC_1&format=PDF

European Environmental Agency, 2018. Urban waste water treatment viewer 2018 (provisional data) [WWW Document]. Urban Waste Water Treat. Dir. URL https://eea.maps.arcgis.com/apps/MapJournal/index.html?appid=a4b0695edb6645a2a74e35887cf7a974&embed=true (accessed 6.16.21).

European Parliament, 2020. REGULATION (EU) 2020/741 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 25 May 2020 on minimum requirements for water reuse. https://www.legislation.gov.uk/eur/2020/741/body/adopted/data.pdf

European Parliament, 2000. Establishing a framework for Community action in the field of water policy. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex%3A32000L0060

Eurostat, 2019. Total paper and paperboard production [WWW Document]. URL https://data.europa.eu/data/datasets/zep5cpgfhgsgfhwxspr6zg?locale=en (accessed 6.16.21).

Eurostat, 2005. Construction producer price and construction cost indices overview [WWW Document]. URL https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Construction_producer_price_and_construction_cost_indices_overview (accessed 1.3.23).

Faragò, M., Damgaard, A., Madsen, J.A., Andersen, J.K., Thornberg, D., Andersen, M.H., Rygaard, M., 2021. From wastewater treatment to water resource recovery: Environmental and economic impacts of full-scale implementation. Water Res. 204, 117554. https://doi.org/https://doi.org/10.1016/j.watres.2021.117554

Fetanat, A., Tayebi, M., Mofid, H., 2021. Water-energy-food security nexus based selection of energy recovery from wastewater treatment technologies: An extended decision making framework under intuitionistic fuzzy environment. Sustain. Energy Technol. Assessments 43, 100937. https://doi.org/https://doi.org/10.1016/j.seta.2020.100937

Figge, F., Dimitrov, S., Schlosser, R., Chenavaz, R., 2022. Does the circular economy fuel the throwaway society? The role of opportunity costs for products that lose value over time. J. Clean. Prod. 368, 133207. https://doi.org/https://doi.org/10.1016/j.jclepro.2022.133207

Food and Agriculture Organization of the United Nations, 2020. Fertilizers by Nutrient [WWW Document]. URL https://www.fao.org/faostat/en/#data/ESB (accessed 3.22.23).

Fox, S., McDermott, J., Doherty, E., Cooney, R., Clifford, E., 2022. Application of Neural Networks and Regression Modelling to Enable Environmental Regulatory Compliance and

Energy Optimisation in a Sequencing Batch Reactor. Sustainability 14. https://doi.org/10.3390/su14074098

FuelCellsWorks, 2020. Worlds First Fuel Cell Heavy-Duty Truck, Hyundai XCIENT Fuel Cell, Heads to Europe for Commerical Use [WWW Document]. URL https://fuelcellsworks.com/news/worlds-first-fuel-cell-heavy-duty-truck-hyundai-xcient-fuel-cell-heads-to-europe-for-commercial-use/ (accessed 8.25.21).

Garcia-Garcia, G., 2022. Using Multi-Criteria Decision-Making to optimise solid waste management. Curr. Opin. Green Sustain. Chem. 37, 100650. https://doi.org/https://doi.org/10.1016/j.cogsc.2022.100650

Garrido-Baserba, M., Molinos-Senante, M., Abelleira-Pereira, J.M., Fdez-Güelfo, L.A., Poch, M., Hernández-Sancho, F., 2015. Selecting sewage sludge treatment alternatives in modern wastewater treatment plants using environmental decision support systems. J. Clean. Prod. 107, 410–419. https://doi.org/https://doi.org/10.1016/j.jclepro.2014.11.021

Geissdoerfer, M., Savaget, P., Bocken, N.M.P., Hultink, E.J., 2017. The Circular Economy – A new sustainability paradigm? J. Clean. Prod. 143, 757–768. https://doi.org/https://doi.org/10.1016/j.jclepro.2016.12.048

Geissler, B., Mew, M.C., Steiner, G., 2019. Phosphate supply security for importing countries: Developments and the current situation. Sci. Total Environ. 677, 511–523. https://doi.org/https://doi.org/10.1016/j.scitotenv.2019.04.356

Gherghel, A., Teodosiu, C., De Gisi, S., 2019. A review on wastewater sludge valorisation and its challenges in the context of circular economy. J. Clean. Prod. 228, 244–263. https://doi.org/https://doi.org/10.1016/j.jclepro.2019.04.240

Gherghel, A., Teodosiu, C., Notarnicola, M., De Gisi, S., 2020. Sustainable design of large wastewater treatment plants considering multi-criteria decision analysis and stakeholders' involvement. J. Environ. Manage. 261, 110158. https://doi.org/https://doi.org/10.1016/j.jenvman.2020.110158

Ghosh, S., Lobanov, S., Lo, V.K., 2019. An overview of technologies to recover phosphorus as struvite from wastewater: advantages and shortcomings. Environ. Sci. Pollut. Res. 26, 19063–19077. https://doi.org/10.1007/s11356-019-05378-6

Girard, G., 2022. Does circular bioeconomy contain singular social science research questions, especially regarding agriculture – industry nexus? Clean. Circ. Bioeconomy 3, 100030. https://doi.org/https://doi.org/10.1016/j.clcb.2022.100030

Giupponi, C., Sgobbi, A., 2013. Decision Support Systems for Water Resources Management in Developing Countries: Learning from Experiences in Africa. Water 5, 798–818. https://doi.org/10.3390/w5020798

Gleick, P.H., 1998. The human right to water. Water Policy 1, 487–503. https://doi.org/https://doi.org/10.1016/S1366-7017(99)00008-2

Grand View Research, 2021. Alginate Market Size, Share & Trends Analysis [WWW Document]. URL https://www.grandviewresearch.com/industry-analysis/alginate-market (accessed 6.16.21).

Guo, H., Felz, S., Lin, Y., van Lier, J.B., de Kreuk, M., 2020. Structural extracellular polymeric substances determine the difference in digestibility between waste activated sludge and aerobic granules. Water Res. 181, 115924. https://doi.org/https://doi.org/10.1016/j.watres.2020.115924

Haag, F., Reichert, P., Maurer, M., Lienert, J., 2019. Integrating uncertainty of preferences and predictions in decision models: An application to regional wastewater planning. J. Environ. Manage. 252, 109652. https://doi.org/https://doi.org/10.1016/j.jenvman.2019.109652

Haldar, K., Kujawa-Roeleveld, K., Acharjee, T.K., Datta, D.K., Rijnaarts, H., 2022. Urban water as an alternative freshwater resource for matching irrigation demand in the Bengal delta. Sci. Total Environ. 835, 155475. https://doi.org/https://doi.org/10.1016/j.scitotenv.2022.155475

Han, H.-G., Chen, C., Sun, H.-Y., Qiao, J.-F., 2022a. Multi-objective integrated optimal control for a wastewater treatment process. Control Eng. Pract. 128, 105296. https://doi.org/https://doi.org/10.1016/j.conengprac.2022.105296

Han, H.-G., Liu, Z., Lu, W., Hou, Y., Qiao, J.-F., 2021. Dynamic MOPSO-Based Optimal Control for Wastewater Treatment Process. IEEE Trans. Cybern. 51, 2518–2528. https://doi.org/10.1109/TCYB.2019.2925534

Han, H.-G., Qian, H.-H., Qiao, J.-F., 2014. Nonlinear multiobjective model-predictive control scheme for wastewater treatment process. J. Process Control 24, 47–59. https://doi.org/https://doi.org/10.1016/j.jprocont.2013.12.010

Han, H.-G., Zhang, L., Liu, H.-X., Qiao, J.-F., 2018. Multiobjective design of fuzzy neural network controller for wastewater treatment process. Appl. Soft Comput. 67, 467–478. https://doi.org/https://doi.org/10.1016/j.asoc.2018.03.020

Han, H.-G., Zhang, L., Qiao, J., 2022b. Dynamic Optimal Control for Wastewater Treatment Process Under Multiple Operating Conditions. IEEE Trans. Autom. Sci. Eng. 1–13. https://doi.org/10.1109/TASE.2022.3189048

Hao, X., Li, J., van Loosdrecht, M.C.M., Jiang, H., Liu, R., 2019. Energy recovery from wastewater: Heat over organics. Water Res. 161, 74–77. https://doi.org/https://doi.org/10.1016/j.watres.2019.05.106

Harder, R., Giampietro, M., Mullinix, K., Smukler, S., 2021a. Assessing the circularity of nutrient flows related to the food system in the Okanagan bioregion, BC Canada. Resour. Conserv. Recycl. 174, 105842. https://doi.org/https://doi.org/10.1016/j.resconrec.2021.105842

Harder, R., Giampietro, M., Smukler, S., 2021b. Towards a circular nutrient economy. A novel way to analyze the circularity of nutrient flows in food systems. Resour. Conserv. Recycl. 172, 105693. https://doi.org/https://doi.org/10.1016/j.resconrec.2021.105693

Harris, S., Martin, M., Diener, D., 2021. Circularity for circularity's sake? Scoping review of assessment methods for environmental performance in the circular economy. Sustain. Prod. Consum. 26, 172–186. https://doi.org/https://doi.org/10.1016/j.spc.2020.09.018

Heimersson, S., Svanström, M., Cederberg, C., Peters, G., 2017. Improved life cycle modelling of benefits from sewage sludge anaerobic digestion and land application. Resour. Conserv. Recycl. 122, 126–134. https://doi.org/https://doi.org/10.1016/j.resconrec.2017.01.016

Heo, S., Nam, K., Tariq, S., Lim, J.Y., Park, J., Yoo, C., 2021. A hybrid machine learning–based multi-objective supervisory control strategy of a full-scale wastewater treatment for cost-effective and sustainable operation under varying influent conditions. J. Clean. Prod. 291, 125853. https://doi.org/https://doi.org/10.1016/j.jclepro.2021.125853

Herman, J., Usher, W., 2017. SALib: An open-source Python library for Sensitivity Analysis. J. Open Source Softw. 2, 97. https://doi.org/10.21105/joss.00097

Holm-Nielsen, J.B., Al Seadi, T., Oleskowicz-Popiel, P., 2009. The future of anaerobic digestion and biogas utilization. Bioresour. Technol. 100, 5478–5484. https://doi.org/https://doi.org/10.1016/j.biortech.2008.12.046

Hoosain, M.S., Paul, B.S., Doorsamy, W., Ramakrishna, S., 2023. The Influence of Circular Economy and 4IR Technologies on the Climate–Water–Energy–Food Nexus and the SDGs. Water. https://doi.org/10.3390/w15040787

Hrbek, J., 2019. Status report on thermal gasification of biomass and waste 2019 IEA Bioenergy Task 33 special report [WWW Document]. URL https://www.ieabioenergy.com/blog/publications/new-publication-2019-status-report-on-thermal-gasification-of-biomass-and-waste/

Huijbregts, M.A.J., Steinmann, Z.J.N., Elshout, P.M.F., Stam, G., Verones, F., Vieira, M., Zijp, M., Hollander, A., van Zelm, R., 2017. ReCiPe2016: a harmonised life cycle impact assessment method at midpoint and endpoint level. Int. J. Life Cycle Assess. 22, 138–147. https://doi.org/10.1007/s11367-016-1246-y

Iacovidou, E., Velis, C.A., Purnell, P., Zwirner, O., Brown, A., Hahladakis, J., Millward-Hopkins, J., Williams, P.T., 2017. Metrics for optimising the multi-dimensional value of resources recovered from waste in a circular economy: A critical review. J. Clean. Prod. 166, 910–938. https://doi.org/https://doi.org/10.1016/j.jclepro.2017.07.100

IEA, 2021. Electricity [WWW Document]. URL https://www.iea.org/fuels-and-technologies/electricity (accessed 1.20.23).

INE, 2022. Results by Autonomous Communities and Autonomous Cities. 2019 Benchmark Revision Series (ESA 2010) [WWW Document]. URL https://www.ine.es/dyngs/INEbase/en/operacion.htm?c=Estadistica_C&cid=1254736167

628&menu=resultados&idp=1254735576581 (accessed 1.18.23).

Institut de la statistique du Québec, 2020. Cadre conceptuel et indicateurs pour la mesure de l'économie verte. https://statistique.quebec.ca/fr/document/cadre-conceptuel-et-indicateurs-mesure-economie-verte

International Standards Organization, 2022. ISO/CD 59020 Circular Economy — Measuring and assessing circularity [WWW Document]. URL https://www.iso.org/standard/80650.html (accessed 1.3.23).

Italia Domani, 2021. The DNSH principle (Do No Significant Harm) in the NRRP [WWW Document]. URL https://www.italiadomani.gov.it/en/Interventi/dnsh.html#:~:text=The Do No Significant Harm,accessing funding from the RRF (accessed 1.17.23).

IWA, 2023. Greenhouse Gas Emissions and Water Resource Recovery Facilities. https://iwa-network.org/publications/greenhouse-gas-emissions-and-wwrfs/

IWA, 2018. Benchmarking [WWW Document]. Model. Integr. Assess. URL http://iwa-mia.org/benchmarking/#BSM1 (accessed 3.2.22).

Jander, W., Grundmann, P., 2019. Monitoring the transition towards a bioeconomy: A general framework and a specific indicator. J. Clean. Prod. 236, 117564. https://doi.org/https://doi.org/10.1016/j.jclepro.2019.07.039

Jazbec, M., Mukheibir, P., Turner, A., 2020. Transitioning the Water Industry with the Circular Economy [WWW Document]. URL https://www.wsaa.asn.au/publication/transitioning-water-industry-circular-economy (accessed 4.13.22).

Jørgensen, S., Pedersen, L.J.T., 2018. The Circular Rather than the Linear Economy BT - RESTART Sustainable Business Model Innovation, in: Jørgensen, S., Pedersen, L.J.T. (Eds.), . Springer International Publishing, Cham, pp. 103–120. https://doi.org/10.1007/978-3-319-91971-3_8

Južnič-Zonta, Ž., Guisasola, A., Baeza, J.A., 2022. Smart-Plant Decision Support System (SP-DSS): Defining a multi-criteria decision-making framework for the selection of WWTP configurations with resource recovery. J. Clean. Prod. 367, 132873. https://doi.org/https://doi.org/10.1016/j.jclepro.2022.132873

Kakwani, N.S., Kalbar, P.P., 2022. Measuring urban water circularity: Development and implementation of a Water Circularity Indicator. Sustain. Prod. Consum. 31, 723–735. https://doi.org/https://doi.org/10.1016/j.spc.2022.03.029

Kazancoglu, I., Sagnak, M., Kumar Mangla, S., Kazancoglu, Y., 2021. Circular economy and the policy: A framework for improving the corporate environmental management in supply chains. Bus. Strateg. Environ. 30, 590–608. https://doi.org/https://doi.org/10.1002/bse.2641

Kehrein, P., van Loosdrecht, M., Osseweijer, P., Garfí, M., Dewulf, J., Posada, J., 2020a. A critical review of resource recovery from municipal wastewater treatment plants – market supply potentials{,} technologies and bottlenecks. Environ. Sci. Water Res. Technol. 6, 877–910. https://doi.org/10.1039/C9EW00905A

Kehrein, P., van Loosdrecht, M., Osseweijer, P., Posada, J., 2020b. Exploring resource recovery potentials for the aerobic granular sludge process by mass and energy balances – energy{,} biopolymer and phosphorous recovery from municipal wastewater. Environ. Sci. Water Res. Technol. 6, 2164–2179. https://doi.org/10.1039/D0EW00310G

Kehrein, P., van Loosdrecht, M., Osseweijer, P., Posada, J., Dewulf, J., 2020c. The SPPD-WRF Framework: A Novel and Holistic Methodology for Strategical Planning and Process Design of Water Resource Factories. Sustainability 12. https://doi.org/10.3390/su12104168

Kirchherr, J., Piscicelli, L., Bour, R., Kostense-Smit, E., Muller, J., Huibrechtse-Truijens, A., Hekkert, M., 2018. Barriers to the Circular Economy: Evidence From the European Union (EU). Ecol. Econ. 150, 264–272. https://doi.org/https://doi.org/10.1016/j.ecolecon.2018.04.028

Kirchherr, J., Reike, D., Hekkert, M., 2017. Conceptualizing the circular economy: An analysis of 114 definitions. Resour. Conserv. Recycl. 127, 221–232. https://doi.org/https://doi.org/10.1016/j.resconrec.2017.09.005

Kjaer, L.L., Pigosso, D.C.A., Niero, M., Bech, N.M., McAloone, T.C., 2019. Product/Service-Systems for a Circular Economy: The Route to Decoupling Economic Growth from Resource Consumption? J. Ind. Ecol. 23, 22–35. https://doi.org/https://doi.org/10.1111/jiec.12747

Kong, Z., Wu, J., Rong, C., Wang, T., Li, L., Luo, Z., Ji, J., Hanaoka, T., Sakemi, S., Ito, M., Kobayashi, S., Kobayashi, M., Qin, Y., Li, Y.-Y., 2021. Large pilot-scale submerged anaerobic membrane bioreactor for the treatment of municipal wastewater and biogas production at 25 °C. Bioresour. Technol. 319, 124123. https://doi.org/https://doi-org.ezproxy.brunel.ac.uk/10.1016/j.biortech.2020.124123

Korhonen, J., Honkasalo, A., Seppälä, J., 2018. Circular Economy: The Concept and its Limitations. Ecol. Econ. 143, 37–46. https://doi.org/https://doi.org/10.1016/j.ecolecon.2017.06.041

Kozłowska, J., 2022. Methods of Multi-Criteria Analysis in Technology Selection and Technology Assessment: A Systematic Literature Review. Eng. Manag. Prod. Serv. 14, 116–137. https://doi.org/doi:10.2478/emj-2022-0021

KWR, 2021. Meaning of circularity for the water sector [WWW Document]. URL https://www.kwrwater.nl/en/actueel/meaning-of-circularity-for-the-water-sector/ (accessed 1.3.23).

Lahti, T., Wincent, J., Parida, V., 2018. A Definition and Theoretical Review of the Circular Economy, Value Creation, and Sustainable Business Models: Where Are We Now and Where Should Research Move in the Future? Sustainability 10. https://doi.org/10.3390/su10082799

Lan, R., Tao, S., 2014. Ammonia as a Suitable Fuel for Fuel Cells. Front. Energy Res. 2, 35. https://doi.org/10.3389/fenrg.2014.00035

Law, Y., Jacobsen, G.E., Smith, A.M., Yuan, Z., Lant, P., 2013. Fossil organic carbon in wastewater and its fate in treatment plants. Water Res. 47, 5270–5281. https://doi.org/https://doi.org/10.1016/j.watres.2013.06.002

Leder, N., Kumar, M., Rodrigues, V.S., 2020. Influential factors for value creation within the Circular Economy: Framework for Waste Valorisation. Resour. Conserv. Recycl. 158, 104804. https://doi.org/https://doi.org/10.1016/j.resconrec.2020.104804

Lee, E.-J., Lee, S.-C., Lee, K., Cha, J.-Y., Han, Y.-N., Kim, S.G., Oh, N.-H., 2023. Properties of river organic carbon affected by wastewater treatment plants. Sci. Total Environ. 858, 159761. https://doi.org/https://doi.org/10.1016/j.scitotenv.2022.159761

Legrand, M., Labajo-Hurtado, R., Rodríguez-Antón, L.M., Doce, Y., 2022. Price arbitrage optimization of a photovoltaic power plant with liquid air energy storage. Implementation to the Spanish case. Energy 239, 121957. https://doi.org/https://doi.org/10.1016/j.energy.2021.121957

Leoneti, A.B., Banares-Alcantara, R., Pires, E.C., de Oliveira, S., 2022. A Multi-Criteria and Multi-Agent Framework for supporting complex decision-making processes. Gr. Decis. Negot. 31, 1025–1050. https://doi.org/10.1007/s10726-022-09785-y

Li, F., Su, Z., Wang, G., 2022. An effective dynamic immune optimization control for the wastewater treatment process. Environ. Sci. Pollut. Res. 29, 79718–79733. https://doi.org/10.1007/s11356-021-17505-3

Li, F., Su, Z., Wang, G., 2021. An effective integrated control with intelligent optimization for wastewater treatment process. J. Ind. Inf. Integr. 24, 100237. https://doi.org/https://doi.org/10.1016/j.jii.2021.100237

Ling, Jiean, Germain, E., Murphy, R., Saroj, D., 2021. Designing a Sustainability Assessment Framework for Selecting Sustainable Wastewater Treatment Technologies in Corporate Asset Decisions. Sustainability 13. https://doi.org/10.3390/su13073831

Ling, J, Germain, E., Murphy, R., Saroj, D., 2021. Designing a sustainability assessment tool for selecting sustainable wastewater treatment technologies in corporate asset decisions. Sustain. 13. https://doi.org/10.3390/su13073831

Liu, B., Tang, J., Li, Z., Yan, Y., Chen, J., 2020. Optimal Selection of Sewage Treatment Technologies in Town Areas: A Coupled Multi-Criteria Decision-Making Model. Environ. Manage. 66, 709–721. https://doi.org/10.1007/s00267-020-01338-w

Liu, Y., Ren, J., 2022. Developing a sustainability-oriented multi-criteria game theoretical decision analysis framework: A case study of sludge management. J. Clean. Prod. 354, 131807. https://doi.org/https://doi.org/10.1016/j.jclepro.2022.131807

Lizot, M., Goffi, A.S., Thesari, S.S., Trojan, F., Afonso, P.S.L.P., Ferreira, P.F. V, 2021. Multi-criteria methodology for selection of wastewater treatment systems with economic, social, technical and environmental aspects. Environ. Dev. Sustain. 23, 9827–9851. https://doi.org/10.1007/s10668-020-00906-8

Llácer-Iglesias, R.M., López-Jiménez, P.A., Pérez-Sánchez, M., 2021. Energy Self-Sufficiency Aiming for Sustainable Wastewater Systems: Are All Options Being Explored? Sustainability 13. https://doi.org/10.3390/su13105537

Lokesh, K., Matharu, A.S., Kookos, I.K., Ladakis, D., Koutinas, A., Morone, P., Clark, J., 2020. Hybridised sustainability metrics for use in life cycle assessment of bio-based products: resource efficiency and circularity. Green Chem. 22, 803–813. https://doi.org/10.1039/C9GC02992C

Longo, S., d'Antoni, B.M., Bongards, M., Chaparro, A., Cronrath, A., Fatone, F., Lema, J.M., Mauricio-Iglesias, M., Soares, A., Hospido, A., 2016. Monitoring and diagnosis of energy consumption in wastewater treatment plants. A state of the art and proposals for improvement. Appl. Energy 179, 1251–1268. https://doi.org/https://doi.org/10.1016/j.apenergy.2016.07.043

Lorenzo-Toja, Y., Alfonsín, C., Amores, M.J., Aldea, X., Marin, D., Moreira, M.T., Feijoo, G., 2016. Beyond the conventional life cycle inventory in wastewater treatment plants. Sci. Total Environ. 553, 71–82. https://doi.org/https://doi.org/10.1016/j.scitotenv.2016.02.073

Ma, P., Rosen, C., 2021. Land application of sewage sludge incinerator ash for phosphorus recovery: A review. Chemosphere 274, 129609. https://doi.org/https://doi-org.ezproxy.brunel.ac.uk/10.1016/j.chemosphere.2021.129609

Majid, A., Cardenes, I., Zorn, C., Russell, T., Colquhoun, K., Bañares-Alcantara, R., Hall, J.W., 2020. An Analysis of Electricity Consumption Patterns in the Water and Wastewater Sectors in South East England, UK. Water 12. https://doi.org/10.3390/w12010225

Maktabifard, M., Al-Hazmi, H.E., Szulc, P., Mousavizadegan, M., Xu, X., Zaborowska, E., Li, X., Mąkinia, J., 2023. Net-zero carbon condition in wastewater treatment plants: A systematic review of mitigation strategies and challenges. Renew. Sustain. Energy Rev. 185, 113638. https://doi.org/https://doi.org/10.1016/j.rser.2023.113638

Mannina, G., Ni, B.-J., Ferreira Rebouças, T., Cosenza, A., Olsson, G., 2020. Minimizing membrane bioreactor environmental footprint by multiple objective optimization. Bioresour. Technol. 302, 122824. https://doi.org/https://doi.org/10.1016/j.biortech.2020.122824

Mannina, G., Rebouças, T.F., Cosenza, A., Sànchez-Marrè, M., Gibert, K., 2019. Decision support systems (DSS) for wastewater treatment plants – A review of the state of the art. Bioresour. Technol. 290, 121814. https://doi.org/https://doi.org/10.1016/j.biortech.2019.121814

Matheri, A.N., Mohamed, B., Ntuli, F., Nabadda, E., Ngila, J.C., 2022. Sustainable circularity and intelligent data-driven operations and control of the wastewater treatment plant. Phys. Chem. Earth, Parts A/B/C 126, 103152.

https://doi.org/https://doi.org/10.1016/j.pce.2022.103152

McLeod, A., Lake, A., 2021. UK Water Net Zero Carbon - Quantifying the benefits of biosolids to land. https://www.jacobs.com/newsroom/news/uk-water-net-zero-carbon-quantifying-benefits-biosolids-land

Medina-Mijangos, R., Seguí-Amórtegui, L., 2021. Technical-economic analysis of a municipal solid waste energy recovery facility in Spain: A case study. Waste Manag. 119, 254–266. https://doi.org/https://doi.org/10.1016/j.wasman.2020.09.035

Metson, G., MacDonald, G., Leach, A., Compton, J., Harrison, J., Galloway, J., 2020. The U.S. consumer phosphorus footprint: where do nitrogen and phosphorus diverge? Env. Res Lett. 15, 1–15. https://doi.org/10.1088/1748-9326/aba781

Microsoft Corporation, 2014. Power BI: Interactive Data Visualization BI Tools. https://powerbi.microsoft.com/en-gb/

Mihelcic, J.R., Ren, Z.J., Cornejo, P.K., Fisher, A., Simon, A.J., Snyder, S.W., Zhang, Q., Rosso, D., Huggins, T.M., Cooper, W., Moeller, J., Rose, B., Schottel, B.L., Turgeon, J., 2017. Accelerating Innovation that Enhances Resource Recovery in the Wastewater Sector: Advancing a National Testbed Network. Environ. Sci. Technol. 51, 7749–7758. https://doi.org/10.1021/acs.est.6b05917

Mills, N., 2016. Unlocking the full energy potential of sewage sludge. https://openresearch.surrey.ac.uk/esploro/outputs/doctoral/Unlocking-the-full-energy-potential-of-sewage-sludge/99515301502346

Mineral Products Association, 2018. Profile of the UK Mineral Products Industry [WWW Document]. URL https://www.mineralproducts.org/Homepage-Promotions/Profile-of-the-UK-Mineral-Products-Industry.aspx (accessed 4.13.22).

Mo, W., Zhang, Q., 2013. Energy–nutrients–water nexus: Integrated resource recovery in municipal wastewater treatment plants. J. Environ. Manage. 127, 255–267. https://doi.org/https://doi-org.ezproxy.brunel.ac.uk/10.1016/j.jenvman.2013.05.007

Molinos-Senante, M., Gomez, T., Caballero, R., Hernandez-Sancho, F., Sala-Garrido, R., 2015. Assessment of wastewater treatment alternatives for small communities: An analytic network process approach. Sci. Total Environ. 532, 676–687. https://doi.org/10.1016/j.scitotenv.2015.06.059

Molinos-Senante, M., Gómez, T., Garrido-Baserba, M., Caballero, R., Sala-Garrido, R., 2014. Assessing the sustainability of small wastewater treatment systems: A composite indicator approach. Sci. Total Environ. 497–498, 607–617. https://doi.org/https://doi.org/10.1016/j.scitotenv.2014.08.026

Montusiewicz, A., Lebiocka, M., 2011. Co-digestion of intermediate landfill leachate and sewage sludge as a method of leachate utilization. Bioresour. Technol. 102, 2563–2571. https://doi.org/https://doi.org/10.1016/j.biortech.2010.11.105

Moraga, G., Huysveld, S., Mathieux, F., Blengini, G.A., Alaerts, L., Acker, K. Van, de Meester, S., Dewulf, J., 2019. Circular economy indicators: What do they measure? Resour. Conserv. Recycl. 146, 452–461. https://doi.org/https://doi.org/10.1016/j.resconrec.2019.03.045

Morales, N., Boehler, M.A., Buettner, S., Liebi, C., Siegrist, H., 2013. Recovery of N and P from Urine by Struvite Precipitation Followed by Combined Stripping with Digester Sludge Liquid at Full Scale. Water 5, 1262–1278. https://doi.org/10.3390/w5031262

Morgan-Sagastume, F., Pratt, S., Karlsson, A., Cirne, D., Lant, P., Werker, A., 2011. Production of volatile fatty acids by fermentation of waste activated sludge pre-treated in full-scale thermal hydrolysis plants. Bioresour. Technol. 102, 3089–3097. https://doi.org/https://doi.org/10.1016/j.biortech.2010.10.054

Morseletto, P., Mooren, C.E., Munaretto, S., 2022. Circular Economy of Water: Definition, Strategies and Challenges. Circ. Econ. Sustain. 2, 1463–1477. https://doi.org/10.1007/s43615-022-00165-x

Nagpal, H., Spriet, J., Murali, M.K., McNabola, A., 2021. Heat Recovery from Wastewater—A Review of Available Resource. Water 13. https://doi.org/10.3390/w13091274

Nancharaiah, Y. V, Mohan, S.V., Lens, P.N.L., 2016. Recent advances in nutrient removal and recovery in biological and bioelectrochemical systems. Bioresour. Technol. 215, 173–185. https://doi.org/https://doi-org.ezproxy.brunel.ac.uk/10.1016/j.biortech.2016.03.129

Navare, K., Muys, B., Vrancken, K.C., Van Acker, K., 2021. Circular economy monitoring – How to make it apt for biological cycles? Resour. Conserv. Recycl. 170, 105563. https://doi.org/https://doi.org/10.1016/j.resconrec.2021.105563

NextGen, 2020. SPERNAL UNITED KINGDOM [WWW Document]. URL https://nextgenwater.eu/demonstration-cases/spernal/ (accessed 6.9.21).

Nika, C.-E., Expósito, A., Kisser, J., Bertino, G., Oral, H.V., Dehghanian, K., Vasilaki, V., Iacovidou, E., Fatone, F., Atanasova, N., Katsou, E., 2021. Validating Circular Performance Indicators: The Interface between Circular Economy and Stakeholders. Water 13. https://doi.org/10.3390/w13162198

Nika, C.E., Vasilaki, V., Expósito, A., Katsou, E., 2020. Water Cycle and Circular Economy: Developing a Circularity Assessment Framework for Complex Water Systems. Water Res. 187, 116423. https://doi.org/https://doi.org/10.1016/j.watres.2020.116423

Nika, C.E., Vasilaki, V., Renfrew, D., Danishvar, M., Echchelh, A., Katsou, E., 2022. Assessing circularity of multi-sectoral systems under the Water-Energy-Food-Ecosystems (WEFE) nexus. Water Res. 221, 118842. https://doi.org/https://doi.org/10.1016/j.watres.2022.118842

Niu, G., Li, X., Wan, X., He, X., Zhao, Y., Yi, X., Chen, C., Xujun, L., Ying, G., Huang, M., 2022. Dynamic optimization of wastewater treatment process based on novel multi-objective ant lion optimization and deep learning algorithm. J. Clean. Prod. 345, 131140.

https://doi.org/https://doi.org/10.1016/j.jclepro.2022.131140

Nkuna, S.G., Olwal, T.O., Chowdhury, S.P.D., 2022. Assessment of thermochemical technologies for wastewater sludge-to-energy: An advance MCDM model. Clean. Eng. Technol. 9, 100519. https://doi.org/https://doi.org/10.1016/j.clet.2022.100519

Ntalaperas, D., Christophoridis, C., Angelidis, I., Iossifidis, D., Touloupi, M.-F., Vergeti, D., Politi, E., 2022. Intelligent Tools to Monitor, Control and Predict Wastewater Reclamation and Reuse. Sensors 22. https://doi.org/10.3390/s22083068

OECD, 2008. MEASURING MATERIAL FLOWS AND RESOURCE PRODUCTIVITY Volume I. The OECD Guide [WWW Document]. Vol. 1. URL https://www.oecd.org/environment/indicators-modelling-outlooks/MFA-Guide.pdf

OECD, 2004. The FEASIBLE Model, Version 2 User Manual and Documentation, Appendix 3. https://www.oecd.org/env/outreach/36229036.pdf

Oertlé, E., Hugi, C., Wintgens, T., Karavitis, C.A., 2019. Poseidon—Decision Support Tool for Water Reuse. Water 11. https://doi.org/10.3390/w11010153

OFWAT, 2019. Data tables and models, Price Reviews. https://www.ofwat.gov.uk/regulated-companies/price-review/2019-price-review/data-tables-models/

Organics Group, 2020. Thermally-Driven Ammonia Strippers: Ammonia stripping with waste heat [WWW Document]. URL https://organics.uk/about-us/ (accessed 4.13.22).

Ortiz-Martínez, V.M., Martínez-Frutos, J., Hontoria, E., Hernández-Fernández, F.J., Egea, J.A., 2021. Multiplicity of solutions in model-based multiobjective optimization of wastewater treatment plants. Optim. Eng. 22, 1–16. https://doi.org/10.1007/s11081-020-09500-3

Pacheco-Romero, M., Vallejos, M., Paruelo, J.M., Alcaraz-Segura, D., Torres-García, M.T., Salinas-Bonillo, M.J., Cabello, J., 2022. A data-driven methodological routine to identify key indicators for social-ecological system archetype mapping. Environ. Res. Lett. 17, 45019. https://doi.org/10.1088/1748-9326/ac5ded

Page, M.J., McKenzie, J.E., Bossuyt, P.M., Boutron, I., Hoffmann, T.C., Mulrow, C.D., Shamseer, L., Tetzlaff, J.M., Akl, E.A., Brennan, S.E., Chou, R., Glanville, J., Grimshaw, J.M., Hróbjartsson, A., Lalu, M.M., Li, T., Loder, E.W., Mayo-Wilson, E., McDonald, S., McGuinness, L.A., Stewart, L.A., Thomas, J., Tricco, A.C., Welch, V.A., Whiting, P., Moher, D., 2021. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. Syst. Rev. 10, 89. https://doi.org/10.1186/s13643-021-01626-4

Palma-Heredia, D., Poch, M., Cugueró-Escofet, M.À., 2020. Implementation of a Decision Support System for Sewage Sludge Management. Sustainability 12. https://doi.org/10.3390/su12219089

Palmeros Parada, M., Kehrein, P., Xevgenos, D., Asveld, L., Osseweijer, P., 2022. Societal values, tensions and uncertainties in resource recovery from wastewaters. J. Environ. Manage. 319, 115759. https://doi.org/https://doi.org/10.1016/j.jenvman.2022.115759

Palmieri, S., Cipolletta, G., Pastore, C., Giosuè, C., Akyol, Ç., Eusebi, A.L., Frison, N., Tittarelli, F., Fatone, F., 2019. Pilot scale cellulose recovery from sewage sludge and reuse in building and construction material. Waste Manag. 100, 208–218. https://doi.org/https://doi.org/10.1016/j.wasman.2019.09.015

Panchal, R., Singh, A., Diwan, H., 2021. Does circular economy performance lead to sustainable development? – A systematic literature review. J. Environ. Manage. 293, 112811. https://doi.org/https://doi.org/10.1016/j.jenvman.2021.112811

Papageorgiou, A., Henrysson, M., Nuur, C., Sinha, R., Sundberg, C., Vanhuyse, F., 2021. Mapping and assessing indicator-based frameworks for monitoring circular economy development at the city-level. Sustain. Cities Soc. 75, 103378. https://doi.org/https://doi.org/10.1016/j.scs.2021.103378

Parliamentary Office of Science and Technology, 2014. Phosphate Resources [WWW Document]. URL https://post.parliament.uk/research-briefings/post-pn-477/

Persson, L., Carney Almroth, B.M., Collins, C.D., Cornell, S., de Wit, C.A., Diamond, M.L., Fantke, P., Hassellöv, M., MacLeod, M., Ryberg, M.W., Søgaard Jørgensen, P., Villarrubia-Gómez, P., Wang, Z., Hauschild, M.Z., 2022. Outside the Safe Operating Space of the Planetary Boundary for Novel Entities. Environ. Sci. Technol. 56, 1510–1521. https://doi.org/10.1021/acs.est.1c04158

Pilli, S., Yan, S., Tyagi, R.D., Surampalli, R.Y., 2015. Thermal Pretreatment of Sewage Sludge to Enhance Anaerobic Digestion: A Review. Crit. Rev. Environ. Sci. Technol. 45, 669–702. https://doi.org/10.1080/10643389.2013.876527

Pisa, I., Santín, I., Morell, A., Vicario, J.L., Vilanova, R., 2019. LSTM-Based Wastewater Treatment Plants Operation Strategies for Effluent Quality Improvement. IEEE Access 7, 159773–159786. https://doi.org/10.1109/ACCESS.2019.2950852

Poulsen, T.G., Hansen, J.A., 2003. Strategic environmental assessment of alternative sewage sludge management scenarios. Waste Manag. \& Res. 21, 19–28. https://doi.org/10.1177/0734242X0302100103

Pradel, M., Aissani, L., Villot, J., Baudez, J.-C., Laforest, V., 2016. From waste to added value product: towards a paradigm shift in life cycle assessment applied to wastewater sludge – a review. J. Clean. Prod. 131, 60–75. https://doi.org/https://doi.org/10.1016/j.jclepro.2016.05.076

Preisner, M., Smol, M., Horttanainen, M., Deviatkin, I., Havukainen, J., Klavins, M., Ozola-Davidane, R., Kruopienė, J., Szatkowska, B., Appels, L., Houtmeyers, S., Roosalu, K., 2022. Indicators for resource recovery monitoring within the circular economy model implementation in the wastewater sector. J. Environ. Manage. 304, 114261. https://doi.org/https://doi.org/10.1016/j.jenvman.2021.114261

Pronk, M., de Kreuk, M.K., de Bruin, B., Kamminga, P., Kleerebezem, R., van Loosdrecht, M.C.M., 2015. Full scale performance of the aerobic granular sludge process for sewage treatment. Water Res. 84, 207–217.

https://doi.org/https://doi.org/10.1016/j.watres.2015.07.011

Public Health England and Wales, Public Health Scotland, 1989. The Sludge (Use in Agriculture) Regulations 1989. https://www.legislation.gov.uk/uksi/1989/1263/made

Qiao, J.-F., Hou, Y., Han, H.-G., 2019. Optimal control for wastewater treatment process based on an adaptive multi-objective differential evolution algorithm. Neural Comput. Appl. 31, 2537–2550. https://doi.org/10.1007/s00521-017-3212-4

Qiao, J.-F., Hou, Y., Zhang, L., Han, H.-G., 2018. Adaptive fuzzy neural network control of wastewater treatment process with multiobjective operation. Neurocomputing 275, 383–393. https://doi.org/https://doi.org/10.1016/j.neucom.2017.08.059

Qiao, J., Zhou, H., 2018. Modeling of energy consumption and effluent quality using density peaks-based adaptive fuzzy neural network. IEEE/CAA J. Autom. Sin. 5, 968–976. https://doi.org/10.1109/JAS.2018.7511168

Radini, S., González-Camejo, J., Andreola, C., Eusebi, A.L., Fatone, F., 2023. Risk management and digitalisation to overcome barriers for safe reuse of urban wastewater for irrigation – A review based on European practice. J. Water Process Eng. 53, 103690. https://doi.org/https://doi.org/10.1016/j.jwpe.2023.103690

Reike, D., Vermeulen, W.J. V, Witjes, S., 2018. The circular economy: New or Refurbished as CE 3.0? — Exploring Controversies in the Conceptualization of the Circular Economy through a Focus on History and Resource Value Retention Options. Resour. Conserv. Recycl. 135, 246–264. https://doi.org/https://doi.org/10.1016/j.resconrec.2017.08.027

Renfrew, D., Vasilaki, V., McLeod, A., Lake, A., Danishvar, S., Katsou, E., 2022. Where is the greatest potential for resource recovery in wastewater treatment plants? Water Res. 220, 118673. https://doi.org/https://doi.org/10.1016/j.watres.2022.118673

Renfrew, D., Vasilaki, V., Nika, E., Harris, E., Katsou, E., 2023. Tracing wastewater resources: unravelling the circularity of waste using source, destination, and quality analysis. Water Res. 120901. https://doi.org/https://doi.org/10.1016/j.watres.2023.120901

Revollar, S., Meneses, M., Vilanova, R., Vega, P., Francisco, M., 2021. Eco-Efficiency Assessment of Control Actions in Wastewater Treatment Plants. Water 13. https://doi.org/10.3390/w13050612

Robles, Á., Durán, F., Giménez, J.B., Jiménez, E., Ribes, J., Serralta, J., Seco, A., Ferrer, J., Rogalla, F., 2020. Anaerobic membrane bioreactors (AnMBR) treating urban wastewater in mild climates. Bioresour. Technol. 314, 123763. https://doi.org/https://doi.org/10.1016/j.biortech.2020.123763

Rodríguez-Chueca, J., Varella della Giustina, S., Rocha, J., Fernandes, T., Pablos, C., Encinas, Á., Barceló, D., Rodríguez-Mozaz, S., Manaia, C.M., Marugán, J., 2019. Assessment of full-scale tertiary wastewater treatment by UV-C based-AOPs: Removal or persistence of antibiotics and antibiotic resistance genes? Sci. Total Environ. 652, 1051–1061. https://doi.org/https://doi.org/10.1016/j.scitotenv.2018.10.223

Ros, C. Da, Conca, V., Eusebi, A.L., Frison, N., Fatone, F., 2020. Sieving of municipal wastewater and recovery of bio-based volatile fatty acids at pilot scale. Water Res. 174, 115633. https://doi.org/https://doi-org.ezproxy.brunel.ac.uk/10.1016/j.watres.2020.115633

Rosenboom, J.-G., Langer, R., Traverso, G., 2022. Bioplastics for a circular economy. Nat. Rev. Mater. 7, 117–137. https://doi.org/10.1038/s41578-021-00407-8

Ruiken, C.J., Breuer, G., Klaversma, E., Santiago, T., van Loosdrecht, M.C.M., 2013. Sieving wastewater – Cellulose recovery, economic and energy evaluation. Water Res. 47, 43–48. https://doi.org/https://doi.org/10.1016/j.watres.2012.08.023

Saaty, R.W., 1987. The analytic hierarchy process—what it is and how it is used. Math. Model. 9, 161–176. https://doi.org/https://doi.org/10.1016/0270-0255(87)90473-8

Sadr, S.M.K., Saroj, D.P., Mierzwa, J.C., McGrane, S.J., Skouteris, G., Farmani, R., Kazos, X., Aumeier, B., Kouchaki, S., Ouki, S.K., 2018. A multi expert decision support tool for the evaluation of advanced wastewater treatment trains: A novel approach to improve urban sustainability. Environ. Sci. Policy 90, 1–10. https://doi.org/https://doi.org/10.1016/j.envsci.2018.09.006

Saidani, M., Yannou, B., Leroy, Y., Cluzel, F., Kendall, A., 2019. A taxonomy of circular economy indicators. J. Clean. Prod. 207, 542–559. https://doi.org/https://doi.org/10.1016/j.jclepro.2018.10.014

Sala, S., Ciuffo, B., Nijkamp, P., 2015. A systemic framework for sustainability assessment. Ecol. Econ. 119, 314–325. https://doi.org/https://doi.org/10.1016/j.ecolecon.2015.09.015

Salamirad, A., Kheybari, S., Ishizaka, A., Farazmand, H., 2023. Wastewater treatment technology selection using a hybrid multicriteria decision-making method. Int. Trans. Oper. Res. 30, 1479–1504. https://doi.org/10.1111/itor.12979

Saltelli, A., 2002. Making best use of model evaluations to compute sensitivity indices. Comput. Phys. Commun. 145, 280–297. https://doi.org/https://doi.org/10.1016/S0010-4655(02)00280-1

Santos, E., Lisboa, I., Eugénio, T., 2021. Economic Sustainability in Wastewater Treatment Companies: A Regional Analysis for the Iberian Peninsula. Appl. Sci. 11. https://doi.org/10.3390/app11219876

Sarrazin, F., Pianosi, F., Wagener, T., 2016. Global Sensitivity Analysis of environmental models: Convergence and validation. Environ. Model. Softw. 79, 135–152. https://doi.org/https://doi.org/10.1016/j.envsoft.2016.02.005

Sauvé, S., Lamontagne, S., Dupras, J., Stahel, W., 2021. Circular economy of water: Tackling quantity, quality and footprint of water. Environ. Dev. 39, 100651. https://doi.org/https://doi.org/10.1016/j.envdev.2021.100651

Savenije, H.H.G., van der Zaag, P., 2020. Water Value Flows Upstream. Water.

https://doi.org/10.3390/w12092642

Schroeder, P., Anggraeni, K., Weber, U., 2019. The Relevance of Circular Economy Practices to the Sustainable Development Goals. J. Ind. Ecol. 23, 77–95. https://doi.org/https://doi.org/10.1111/jiec.12732

Severn Trent, 2021. Biosolids recycling [WWW Document]. Biosolids. URL https://www.severntrent.com/sustainability-strategy/environment/bioresources/biosolids/ (accessed 7.5.21).

Silva Junior, L.C.S. da, Salomão, A.L. de S., Santos, A.S.P., 2022. MATTI – a multi-criteria decision analysis framework for assessing wastewater treatment technologies. Water Sci. Technol. 86, 2764–2776. https://doi.org/10.2166/wst.2022.374

Smith, C., Hill, A.K., Torrente-Murciano, L., 2020. Current and future role of Haber–Bosch ammonia in a carbon-free energy landscape. Energy Environ. Sci. 13, 331–344. https://doi.org/10.1039/C9EE02873K

Smol, M., Adam, C., Preisner, M., 2020. Circular economy model framework in the European water and wastewater sector. J. Mater. Cycles Waste Manag. 22, 682–697. https://doi.org/10.1007/s10163-019-00960-z

Smol, M., Koneczna, R., 2021. Economic Indicators in Water and Wastewater Sector Contributing to a Circular Economy (CE). Resources 10. https://doi.org/10.3390/resources10120129

Smyth, M., Brookes, A., Riches, S., Bungay, S., 2021. A PREDICTIVE MODEL TO DETERMINE AMMONIUM LEVELS IN DIGESTATE LIQUORS, in: European Biosolids and Organic Resources Conference. https://www.aquaenviro.co.uk/wp-content/uploads/2017/03/A-predictive-model-to-determine-ammonium-levels-in-digestate-liquors-final.docx

Soares, A., Vale, P., Kim, J.E., Hofman, J., 2021. Factsheet – Anaerobic Membrane Bioreactor (AnMBR). https://mp.uwmh.eu/media/factsheets/Factsheet1_AnMBRDegassing_unit_JvkOXFZ.pdf

Sobol′, I.M., 2001. Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates. Math. Comput. Simul. 55, 271–280. https://doi.org/https://doi.org/10.1016/S0378-4754(00)00270-6

Spring, 2020. UK 2050 Water Innovation Strategy [WWW Document]. URL https://spring-innovation.co.uk/app/uploads/2021/12/UK-2050-Water-Innovation-Strategy.pdf

Srivastava, R.R., Singh, P.K., 2022. Reuse-focused selection of appropriate technologies for municipal wastewater treatment: a multi-criteria approach. Int. J. Environ. Sci. Technol. 19, 12505–12522. https://doi.org/10.1007/s13762-021-03803-3

Staff, J., Phetmanh, G., 2016. Compost Certification Scheme Annual Report 2016 [WWW Document]. URL https://www.qualitycompost.org.uk/

Steffen, W., Richardson, K., Rockström, J., Cornell, S.E., Fetzer, I., Bennett, E.M., Biggs, R., Carpenter, S.R., de Vries, W., de Wit, C.A., Folke, C., Gerten, D., Heinke, J., Mace, G.M., Persson, L.M., Ramanathan, V., Reyers, B., Sörlin, S., 2015. Planetary boundaries: Guiding human development on a changing planet. Science (80-.). 347, 1259855. https://doi.org/10.1126/science.1259855

Stegmann, P., Londo, M., Junginger, M., 2020. The circular bioeconomy: Its elements and role in European bioeconomy clusters. Resour. Conserv. Recycl. X 6, 100029. https://doi.org/https://doi.org/10.1016/j.rcrx.2019.100029

Štilić, A., Puška, A., 2023. Integrating Multi-Criteria Decision-Making Methods with Sustainable Engineering: A Comprehensive Review of Current Practices. Eng. https://doi.org/10.3390/eng4020088

Su, B., Heshmati, A., Geng, Y., Yu, X., 2013. A review of the circular economy in China: moving from rhetoric to implementation. J. Clean. Prod. 42, 215–227. https://doi.org/https://doi.org/10.1016/j.jclepro.2012.11.020

Sucu, S., van Schaik, M.O., Esmeli, R., Ouelhadj, D., Holloway, T., Williams, J.B., Cruddas, P., Martinson, D.B., Chen, W.-S., Cappon, H.J., 2021. A conceptual framework for a multi-criteria decision support tool to select technologies for resource recovery from urban wastewater. J. Environ. Manage. 300, 113608. https://doi.org/https://doi.org/10.1016/j.jenvman.2021.113608

Superti, Valeria, Houmani, C., Binder, C.R., 2021. A systemic framework to categorize Circular Economy interventions: An application to the construction and demolition sector. Resour. Conserv. Recycl. 173, 105711. https://doi.org/https://doi.org/10.1016/j.resconrec.2021.105711

Superti, V, Merino-Saum, A., Baur, I., Binder, C.R., 2021. Unraveling how the concept of circularity relates to sustainability: An indicator-based meta-analysis applied at the urban scale. J. Clean. Prod. 315, 128070. https://doi.org/https://doi.org/10.1016/j.jclepro.2021.128070

Tapaninaho, R., Heikkinen, A., 2022. Value creation in circular economy business for sustainability: A stakeholder relationship perspective. Bus. Strateg. Environ. 31, 2728–2740. https://doi.org/https://doi.org/10.1002/bse.3002

Tavares Ferreira, T.J., Luiz de Sousa Rollemberg, S., Nascimento de Barros, A., Machado de Lima, J.P., Bezerra dos Santos, A., 2021. Integrated review of resource recovery on aerobic granular sludge systems: Possibilities and challenges for the application of the biorefinery concept. J. Environ. Manage. 291, 112718. https://doi.org/https://doi.org/10.1016/j.jenvman.2021.112718

Tchobanoglous, G., Stensel, H.D., Tsuchihashi, R., Burton, F., 2014. Wastewater Engineering Treatment and Resource Recovery, 5th ed. McGraw-Hill Education, New York.

Tecchio, P., Freni, P., De Benedetti, B., Fenouillot, F., 2016. Ex-ante Life Cycle Assessment approach developed for a case study on bio-based polybutylene succinate. J. Clean. Prod.

112, 316–325. https://doi.org/https://doi.org/10.1016/j.jclepro.2015.07.090

Teixeira de Souza, A., Carneiro, L.A.T.X., da Silva Junior, O.P., de Carvalho, S.L., Américo-Pinheiro, J.H.P., 2021. Assessment of water quality using principal component analysis: a case study of the Marrecas stream basin in Brazil. Environ. Technol. 42, 4286–4295. https://doi.org/10.1080/09593330.2020.1754922

Tejaswini, E.S.S., Panjwani, S., Gara, U.B.B., Ambati, S.R., 2021. Multi-objective optimization based controller design for improved wastewater treatment plant operation. Environ. Technol. Innov. 23, 101591. https://doi.org/https://doi.org/10.1016/j.eti.2021.101591

The Royal Borough of Kingston Upon Thames, 2021. England's first sewage-powered heating scheme planned for Kingston [WWW Document]. URL https://www.kingston.gov.uk/news/article/80/england-s-first-sewage-powered-heating-scheme-planned-for-kingston (accessed 7.1.21).

The World Bank, 2021. Water in Circular Economy and Resilience (WICER). https://www.worldbank.org/en/topic/water/publication/wicer#:~:text=The%20main%20report%20of%20the,preserve%20and%20regenerate%20natural%20systems.

Tortajada, C., Nambiar, S., 2019. Communications on Technological Innovations: Potable Water Reuse. Water 11. https://doi.org/10.3390/w11020251

Troullaki, K., Rozakis, S., Kostakis, V., 2021. Bridging barriers in sustainability research: A review from sustainability science to life cycle sustainability assessment. Ecol. Econ. 184, 107007. https://doi.org/https://doi.org/10.1016/j.ecolecon.2021.107007

Tseng, L.Y., Robinson, A.K., Zhang, X., Xu, X., Southon, J., Hamilton, A.J., Sobhani, R., Stenstrom, M.K., Rosso, D., 2016. Identification of Preferential Paths of Fossil Carbon within Water Resource Recovery Facilities via Radiocarbon Analysis. Environ. Sci. Technol. 50, 12166–12178. https://doi.org/10.1021/acs.est.6b02731

U.S. Environmental Protection Agency, 2011. ACCOUNTING FRAMEWORK FOR BIOGENIC CO2 EMISSIONS FROM STATIONARY SOURCES. https://www.epa.gov/sites/default/files/2016-08/documents/biogenic-co2-accounting-framework-report-sept-2011.pdf

UKWIR, 2021. Where is the Greatest Sustinable Economic Benefit for Resource Recovery in the Water Cycle? [WWW Document]. URL https://ukwir.org/final-report-for-where-is-the-greatest-sustainable-economic-benefit-for-resource-recovery-in-the-water-cycle (accessed 4.13.22).

Ullah, A., Hussain, S., Wasim, A., Jahanzaib, M., 2020. Development of a decision support system for the selection of wastewater treatment technologies. Sci. Total Environ. 731, 139158. https://doi.org/https://doi.org/10.1016/j.scitotenv.2020.139158

Valentino, F., Morgan-Sagastume, F., Campanari, S., Villano, M., Werker, A., Majone, M., 2017. Carbon recovery from wastewater through bioconversion into biodegradable polymers. N. Biotechnol. 37, 9–23.

https://doi.org/https://doi.org/10.1016/j.nbt.2016.05.007

van der Giesen, C., Cucurachi, S., Guinée, J., Kramer, G.J., Tukker, A., 2020. A critical view on the current application of LCA for new technologies and recommendations for improved practice. J. Clean. Prod. 259, 120904. https://doi.org/https://doi.org/10.1016/j.jclepro.2020.120904

van der Hoek, J.P., Duijff, R., Reinstra, O., 2018. Nitrogen Recovery from Wastewater: Possibilities, Competition with Other Resources, and Adaptation Pathways. Sustainability 10. https://doi.org/10.3390/su10124605

van Loosdrecht, M.C., Brdjanovic, D., 2014. Water treatment. Anticipating the next century of wastewater treatment. Science 344, 1452–1453. https://doi.org/10.1126/science.1255183 [doi]

Velenturf, A.P.M., Purnell, P., 2021. Principles for a sustainable circular economy. Sustain. Prod. Consum. 27, 1437–1457. https://doi.org/https://doi.org/10.1016/j.spc.2021.02.018

Verstraete, W., de Caveye, P. Van, Diamantis, V., 2009. Maximum use of resources present in domestic "used water." Bioresour. Technol. 100, 5537–5545. https://doi.org/https://doi-org.ezproxy.brunel.ac.uk/10.1016/j.biortech.2009.05.047

von Sperling, M., Verbyla, M.E., Oliveira, S.M.A.C., 2020. Assessment of Treatment Plant Performance and Water Quality Data. IWA Publishing.

Voulvoulis, N., 2018. Water reuse from a circular economy perspective and potential risks from an unregulated approach. Curr. Opin. Environ. Sci. Heal. 2, 32–45. https://doi.org/https://doi.org/10.1016/j.coesh.2018.01.005

Walker, R.V., Jiang, F., Osidele, O.O., Beck, M.B., 2009. Eco-effectiveness, eco-efficiency, and the metabolism of a city: A multi-sectoral analysis, in: 2009 IEEE International Conference on Systems, Man and Cybernetics. pp. 1470–1475. https://doi.org/10.1109/ICSMC.2009.5346300

Walling, E., Vaneeckhaute, C., 2020. Developing successful environmental decision support systems: Challenges and best practices. J. Environ. Manage. 264. https://doi.org/10.1016/j.jenvman.2020.110513

Wang-Erlandsson, L., Tobian, A., van der Ent, R.J., Fetzer, I., te Wierik, S., Porkka, M., Staal, A., Jaramillo, F., Dahlmann, H., Singh, C., Greve, P., Gerten, D., Keys, P.W., Gleeson, T., Cornell, S.E., Steffen, W., Bai, X., Rockström, J., 2022. A planetary boundary for green water. Nat. Rev. Earth Environ. 3, 380–392. https://doi.org/10.1038/s43017-022-00287-8

Wang, J., Wang, S., 2019. Preparation, modification and environmental application of biochar: A review. J. Clean. Prod. 227, 1002–1022. https://doi.org/https://doi-org.ezproxy.brunel.ac.uk/10.1016/j.jclepro.2019.04.282

Wardropper, C., Brookfield, A., 2022. Decision-support systems for water management. J. Hydrol. 610, 127928. https://doi.org/https://doi.org/10.1016/j.jhydrol.2022.127928 wbcsd, 2022. Circular Transition Indicators v3.0 - Metrics for business, by business.

Williams, J.B., Clarkson, C., Mant, C., Drinkwater, A., May, E., 2012. Fat, oil and grease deposits in sewers: Characterisation of deposits and formation mechanisms. Water Res. 46, 6319–6328. https://doi.org/https://doi.org/10.1016/j.watres.2012.09.002

Xie, Y.B., Wang, D., Qiao, J.F., 2022. Dynamic multi-objective intelligent optimal control toward wastewater treatment processes. Sci. China Technol. Sci. 65, 569–580. https://doi.org/10.1007/s11431-021-1960-7

Yang, J., Monnot, M., Ercolei, L., Moulin, P., 2020. Membrane-Based Processes Used in Municipal Wastewater Treatment for Water Reuse: State-Of-The-Art and Performance Analysis. Membranes (Basel). 10. https://doi.org/10.3390/membranes10060131

Yorkshire Water, 2018. Total Impact and Value Assessment - Methodology Report [WWW Document]. URL https://www.yorkshirewater.com/media/hm2dfl0b/tiva-methodology-report.pdf

Zawartka, P., Burchart-Korol, D., Blaut, A., 2020. Model of Carbon Footprint Assessment for the Life Cycle of the System of Wastewater Collection, Transport and Treatment. Sci. Rep. 10, 5799. https://doi.org/10.1038/s41598-020-62798-y

Zhou, H., Qiao, J., 2019. Multiobjective optimal control for wastewater treatment process using adaptive MOEA/D. Appl. Intell. 49, 1098–1126. https://doi.org/10.1007/s10489-018-1319-7

Zolghadr-Asli, B., Bozorg-Haddad, O., Enayati, M., Chu, X., 2021. A review of 20-year applications of multi-attribute decision-making in environmental and water resources planning and management. Environ. Dev. Sustain. 23, 14379–14404. https://doi.org/10.1007/s10668-021-01278-3

List of Publications

The thesis is based on the following publications and conference presentations:

Publications

- **Renfrew, D.**, Vasilaki, V., McLeod, A., Lake, A., Danishvar, S., Katsou, E., 2022. Where is the greatest potential for resource recovery in wastewater treatment plants? Water Res. 220, 118673. https://doi.org/https://doi.org/10.1016/j.watres.2022.118673

- UKWIR. What does a circular economy water industry look like? Published by UK Water Industry Research Limited, 3rd Floor, 36 Broadway, Westminster, London, SW1H 0BH. (**co-author**)

- Nika, C.E., Vasilaki, V., **Renfrew, D.**, Danishvar, M., Echchelh, A., Katsou, E., 2022. Assessing circularity of multi-sectoral systems under the Water-Energy-Food-Ecosystems (WEFE) nexus. Water Res. 221, 118842. https://doi.org/https://doi.org/10.1016/j.watres.2022.118842

- **Renfrew, D.**, Vasilaki, V., Nika, E., Harris, E., Katsou, E., 2023. Tracing wastewater resources: unravelling the circularity of waste using source, destination, and quality analysis. Accepted to Water Research Journal for publication.

- **Renfrew, D.**, Vasilaki, V., Katsou, E., 2023. Indicator based-multi-criteria decision support systems for wastewater treatment plants. Accepted to Science of the Total Environment Journal for publication.

- **Renfrew, D.**, Vasilaki, V., Nika, E., Tsalidis, G.A., Marin, E., Katsou, E., 2023. Systematic assessment of wastewater resource circularity and sustainable value creation. Accepted to Water Research Journal for publication.

Conference presentations

- **Renfrew, D.**, Vasilaki, V., Katsou, E., 2021. Measuring and assessing circularity and sustainability in the UK water sector. Oral presentation at the AQUA 360 conference, 31st August – 2nd September 2021, Exeter, United Kingdom.

- **Renfrew, D.**, Vasilaki, V., Katsou, E., 2022. Holistic circularity assessments utilising an action-oriented approach. Oral presentation at IWA World Water Congress and Exhibition, 11th – 15th September 2022, Copenhagen, Denmark.

- **Renfrew, D.**, Vasilaki, V., Nika, E., Tsalidis, G.A., Marin, E., Katsou, E., 2023. Circularity and sustainable value creation assessment of a photobiorefinery process. Oral presentation at Water Innovation and Circularity Conference, 7th – 9th June 2023, Athens, Greece.

- **Renfrew, D.**, Vasilaki, V., Nika, E., Tsalidis, G.A., Marin, E., Katsou, E., 2023. Utilising sustainable value propositions to understand the value creation of circular actions in wastewater systems. Oral presentation at the IWA International Conference of eco-Technologies for Wastewater Treatment, 26th – 29th June 2023, Girona, Spain.

Appendix A

A.1 Model description and parameters

The flow of nutrient components in wastewater, from influent to sludge disposal, were analysed as these are the important fractions when investigating resource recovery. MFA describes and quantifies the material flows through a system, making it an important tool for understanding industrial ecology and metabolism. Therefore, it was chosen as a starting point for the identification of resource recovery opportunities as it encourages understanding and visualisation of the current landscape. A mass balance model was created to represent the main flows in UK wastewater treatment.

Input data for the mass balance model was collected from PR19 databases for England and Wales for the latest reporting period. This provides data for WWTP with PE > 25,000, including the PE served, flow passed to full treatment, sewage sludge treatment and disposal pathways (data for Northern Ireland and Scotland was calculated from reported PE and standard assumption of 200 L wastewater per capita per day produced). Wastewater composition was calculated using reported water PE loadings (grams per capita per day), which were divided into soluble and suspended fractions. The model was constrained using untreated primary and waste activated sludge compositions reported in literature for the UK. Model input data is summarised in Table A.1.

Table A.1. Input data used to model baseline scenario for UK wastewater sector.

PE (OFWAT, 2019)	59,009,151		**Primary Sludge** (Smyth et al., 2021)		**Sludge Treatment** (OFWAT, 2019)		**Sludge Disposal** (OFWAT, 2019)	
Total Flow (OFWAT, 2019)	16,291,689.1	m^3/d	Dry Solids	6 %	Untreated	1.8 %	Land Reclamation	3.5 %
Total load (Tchobanoglous et al., 2014)			Volatile Fraction	70 %	Raw Sludge Liming	3.4 %	Farmland Application	94.8 %
COD	8,851.4	t/d	Nitrogen	2.50 %	AD	33.5 %	Other	1.7 %
BOD	3,540.5	t/d	Phosphorus	0.70 %	Advanced AD	51.7 %		
N	649.1	t/d	**WAS** (Smyth et al., 2021)		Incineration	7.0 %		
P	123.9	t/d	Dry Solids	1.50 %	Composting	0.1 %		
TSS	3,835.6	t/d	Volatile Fraction	80 %	Other	2.4 %		
VSS	2,876.7	t/d	Nitrogen	5 %				
OC	2,671.8	t/d	Phosphorus	2.20 %				

To make the model more realistic, it was aligned with current UK wastewater network practices by incorporating multiple treatment pathways. These were chosen using the European Environmental Agency's Urban Wastewater Treatment database which records the PE served by WWTPs equipped with secondary and tertiary (P, N, NP, disinfection) treatment (European Environmental Agency, 2018). This was coupled with additional PR19 data that indicates whether UK WWTPs implement activated sludge (AS) or TF biological treatment processes. This resulted in eight different treatment pathways for UK wastewater and are summarised in Table A.2. The activated sludge process was modelled with pre-anoxic zones, for denitrification-nitrification, therefore it was assumed that only trickling filter processes required tertiary N removal. Tertiary P removal was achieved using ferric dosing (with additional solids production calculated) followed by tertiary solids removal. One assumption that must be noted is that chemical P sludge is not combined with raw sludge streams, due to the fact that P salts have limited bioavailability what applied to land (Parliamentary Office of Science and Technology, 2014). Since the databases used for constructing the model do not provide information, such as the compound used or the dosage rate for precipitation, the P in this stream was modelled to be collected during tertiary solids removal to account for the phosphorus in the system. This ensured that the total P in the conventional system was accounted for (in terms of total mass in WW and current bioavailability for land application of P) and that there was potential to recover better quality P in the updated resource recovery scenario.

Table A.2. Fraction of wastewater sent to each secondary/tertiary treatment train after primary treatment.

Treatment Pathway	AS	TF
Secondary Only	44.0%	3.7%
Tertiary/Additional		
P removal	30.6%	3.4%
N Removal	0	1.3%
NP removal	0	2.8%
Other (disinfection)	12.6%	1.4%

The primary and waste activated sludge (WAS) raw sludge streams were combined before undergoing the sludge treatment pathways described in Table 1. AD and advanced AD were modelled using standard kinetic parameters, with the AAD process assumed to operate a thermal hydrolysis system to enhance volatile destruction and biogas yield. Biogas generated by AD was assumed to have a methane content of 65 % (Tchobanoglous et al., 2014). Dewatering systems employing polymer addition were assumed to achieve solids recovery rates of 98 % and cake DS of 25 % before sludge disposal (Tchobanoglous et al., 2014) (AHDB, 2019). Treatment parameters are summarised in Table A.3.

Table A.3. Parameters used to model wastewater and sludge treatment for baseline UK scenario.

Baseline Model Parameters					
Screening – 6 mm bar screen (Tchobanoglous et al., 2014)					
Removal	67	L/1000 m^3	Moisture	75 %	
Density	750	kg/ m^3	Volatiles	75 %	
Grit (Tchobanoglous et al., 2014)					
Removal	0.3	m^3/1000 m^3	Moisture	60 %	
Density	1660	kg/ m^3	Volatiles	28.5 %	
Primary Clarifier (Tchobanoglous et al., 2014)					
Solids Removal	60 %				
Activated Sludge (Tchobanoglous et al., 2014)					
bCOD:BOD	1.6	TSS:VSS	0.85	VSS:BOD	0.85
Y_h	0.45	gVSS/gCOD	SRT	17	days
b_{aob}	0.135	g/g d	Y_n	0.15	gVSS/gNO_X
b_h	0.12	gVSS/gVSS d	f_d	0.15	
NO_X effluent	6.0	g/m^3	P removal	25 %	
Trickling Filter (Tchobanoglous et al., 2014) (Burgos et al., 2015)					
BOD removal	85 %		NH_4-N effluent	5	g/m^3
Nitrification	80 %		Sludge production	0.5	kg/kgBOD
TSS removal	50 %		P removal	20 %	
Post anoxic N removal (Tchobanoglous et al., 2014)					
Nitrate removal	90 %		Methanol	1.5	gCOD/g
Yield	0.15	gVSS/gCOD			
P removal (Tchobanoglous et al., 2014)					
Soluble effluent achieved	0.1	g/m^3	Solids Removal	85 %	
Anaerobic Digestion (Tchobanoglous et al., 2014)					
Y	0.08	gVSS/gCOD	μ_m	0.35	g/g day

b_H	0.03	g/g day	K_s	120	mgCOD/L
f_d	0.1		SRT	15	days
VSS removal	44%		Biogas generation	370	m^3/tDS
Advanced AD					
VSS removal	60 %		Biogas generation	410	m^3/tDS
Thermal Hydrolysis (Morgan-Sagastume et al., 2011)					
Soluble COD	817 %	Increase	VSS	55 %	Decrease
Soluble N	167 %	Increase	TSS	52 %	Decrease
Soluble P	17 %	Increase			
Composting (Tchobanoglous et al., 2014) (Poulsen and Hansen, 2003)					
VSS removal	25 %		P removal	6 %	
N removal	33 %				
Incineration (de Azevedo Basto et al., 2019)					
P_2O_5 ash fraction	8 %		Volatile Removal	100 %	

After the application of MCA, a scenario that focused on resource recovery was decided. This involved the integration of aerobic granular sludge treatment systems, which produce struvite and EPS. Thermal ammonia stripping from AAD liquors streams was also implemented and the energy recovery from heat pumps investigated. The parameters used to model the updated resource recovery scenario are presented in Table A.4.

Table A.4. Parameters used to model updated resource recovery scenario with selected technologies from MCA.

Resource Recovery Model Updates					
AGS Removal Efficiency (Pronk et al., 2015)					
COD	87 %	PO_4 removal	91 %	TP removal	87 %
BOD	96 %	TN removal	86 %		
TSS	92 %	NH_4-N removal	97 %		
AGS Production (Kehrein et al., 2020b) (Guo et al., 2020)					
Sludge	0.14	kg/m^3 influent	Sludge COD	71.3	g/L
Sludge DS	6 %		Sludge VS	5 %	
EPS to sludge	20 %		EPS N fraction	8 wt%	
EPS C fraction	47 wt%		EPS P fraction	3 wt%	
COD to biogas	50 %		VS AD removal	25.4 %	
Influent P in digestate	85 %		Struvite crystallisation	80 %	
Ammonia Stripping (Organics Group, 2020)					
N recovery	98.5 %				
Heat Pump (Hao et al., 2019)					
c	4.18	kJ/kg	CoP	3.5	
dT	4	℃	Q	1.77	kWh/m^3

When it came to the collection of information to construct models for MFA, parameters were taken from the Wastewater Engineering textbook of Tchobanoglous et al. (2014) as a basis for the calculations. This textbook is regarded the gold standard for wastewater design, therefore, where possible typical parameter values were extracted from this source. When ranges were given, the average value within the range was used. In cases where no data was provided for specific technologies, other literature sources were utilised (as referenced in Tables A.3 and A.4), and care was taken to ensure they were representative of the system analysed in this work. For example, the work of Morgan-Sagastume et al. (2014) shows the performance efficiency of a full-scale CAMBI™ process for a mixture of primary sludge and WAS from domestic wastewater in Denmark, meaning it is similar to this study in terms of process operation, feedstock and climate conditions. Furthermore, the example of AGS operation by Pronk et al. (2015) was used as the example for removal efficiencies as it operates at full scale in a similar climate (Netherlands) to this system, for the treatment of domestic sewage.

A.2 Market potential vs market demand

The interest in resource recovery from wastewater has led to the development of an extensive list of potential products and technological options for their extraction. Figure A.1 provides a simplified diagram of the water flowing through an urban system, summarising attractive opportunities when focus is shifted from wastewater treatment to resource recovery.

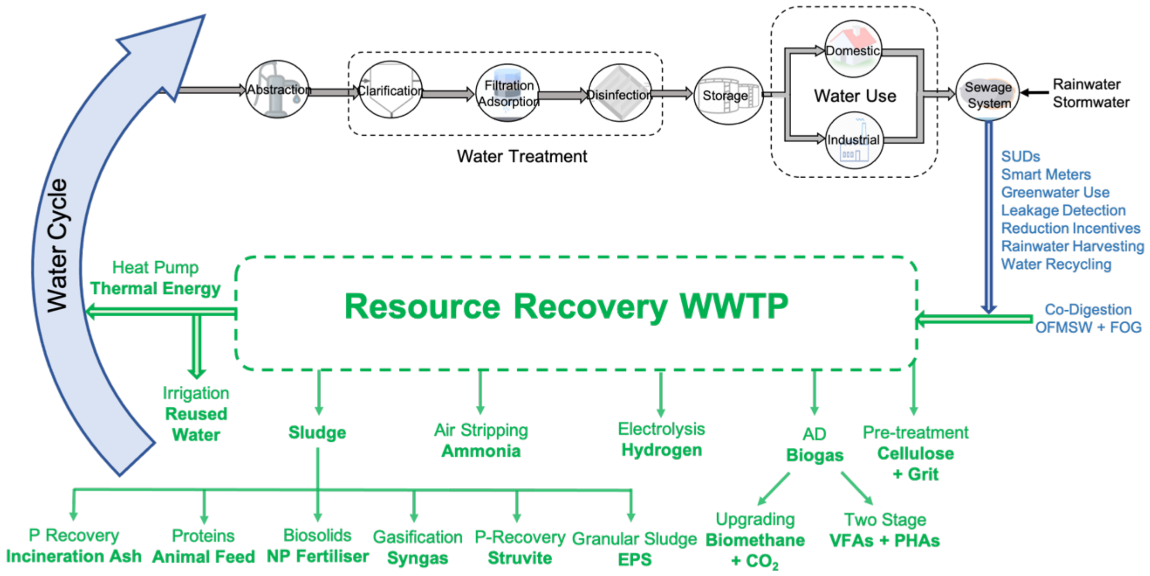


Figure A.1. Simplified version of the urban water cycle, highlighting potential opportunities for resource recovery from wastewater (green), along with other sustainable activities that should be implemented by water companies (blue).

One of the first chances to capture resources is during WW influent pre-treatment. Grit from screening can supplement virgin feedstocks for construction aggregates with a circular alternative and sieving processes with certain mesh size (<0.35 mm) capture cellulose fibres (Ruiken et al., 2013). Primary and secondary treatment yield sewage sludge that has the potential to generate a range of valuable resources. AD is the current method of sludge treatment implemented by water utilities to generate biogas for energy recovery, however, a two-stage process isolates VFAs which have inherent value or can be used to synthesis PHAs (Coma et al., 2017). Upgrading biogas will yield a higher-grade fuel and valuable by-product stream of CO_2. AnMBRs have the potential to generate biogas whilst simultaneously treating WW, resulting in reduction of facility capital and operating expenditures (Soares et al., 2021). Co-digestion practices incorporate other solid municipal waste streams to amplify the concentration of nutrients in AD processes, resulting in greater product yields (Cavinato et al., 2013).

The sewage sludge is the concentrated solid stream removed from wastewater which is has a high nutrient content and is very versatile in terms of the resource recovery opportunities it presents. Incineration of raw sludge provides a method of energy recovery, resulting in ash which rich in phosphorus that be extracted using acid and base leaching (Gherghel et al., 2019). Gasification of sewage sludge yields a hydrogen rich fuel (syngas), which can be used to recover energy or as a feedstock for chemical production (Gherghel et al., 2019). Treated biosolids (AD, liming etc.) produces a nutritious matrix that can be applied to farmland, substituting the need for mineral fertilisers with a sustainable and circular alternative. Solubilisation of the nitrogen in sludge occurs during AD treatment, application of air or thermal stripping will remove ammonia from dewatering liquors (Kehrein et al., 2020a). Nitrogen in sludge can be used to generate single cell proteins which replace animal fodder, such as soybeans, that have a high carbon footprint. EPSs are used by microorganisms for cell adhesion during granular sludge processes, employing chemical extraction methods produces alginate-like gels (Kehrein et al., 2020b).

The treated effluent stream leaving a WWTP contains residual soluble fractions of nutrients, making it attractive for reuse for agricultural irrigation purposes. Electrolysis of wastewater effluents yields hydrogen to hopefully power vehicles in the future, due to its clean burning and high energy density. Lastly, integrating heat pumps on effluent streams result in the recovery of thermal energy, which is preferred due to the risk of fouling with influent streams (Kehrein et al., 2020b). It is worth noting that as well as resource recovery there is significant effort required to implement other sustainable practices such as leakage detection/reduction, water recycling, sustainable urban drainage, N_2O monitoring and rainwater harvesting. All of which are required for the sustainable development of the water industry (Jazbec et al., 2020).

The product recovery calculations utilised the flow handled, raw sludge produced, biosolids disposed and transportation requirements reported from PR19 data tables, with wastewater load concentration taken from literature. Each resource was considered independently, so the market potential represents the maximum resource recovery that could be achieved under ideal circumstances using correct technologies. The resource availability and recovery efficiencies were taken from the review paper by Kehrein et al. (2020a), and literature reported for UK case studies and pilot plants. Market demands were taken from UK centric sources, namely government and industrial reports. Some additional resources were considered to reflect those shortlisted by the implementation of the MCA framework including, grit, ammonia, syngas, hydrogen and AnMBR biogas.

Table A.5. Market potential calculation parameters given as UK market demand and recovery efficiencies.

Market Demands			Recovery Potential		
Water					
Total Water Abstraction (Department for Environment Food and Rural Affairs, 2019)	10,400	Mm^3/a	UF/MF Efficiency (Verstraete et al., 2009)	85 %	
			RO Efficiency (Verstraete et al., 2009)	75 %	
Energy					
Natural Gas Demand (Department for Business Energy and Industrial Strategy, 2020)	3,158	PJ/a	COD Capture (Kehrein et al., 2020a)	80 %	
Electricity Demand (Department for Business Energy and Industrial Strategy, 2020)	1,244	PJ/a	Methane Generation (Kehrein et al., 2020a)	0.35	m^3/kgCOD
Heat Demand (Department for Business Energy and Industrial Strategy, 2020)	150	PJ/a	Methane Energy Density (Kehrein et al., 2020a)	35.9	MJ/m^3
			CHP efficiency (Verstraete et al., 2009)	38 %	Electricity
			CHP efficiency (Verstraete et al., 2009)	40 %	Heat
			Co-combustion energy (Kehrein et al., 2020a)	0.4	TJ/t
Hydrogen					
HGV Demand (Department for Transport, 2020)	17.4	bvm	Hydrogen generation (CREW, 2018)	0.119	tH_2/m^3
Sludge Transport Demand (OFWAT, 2019)	5.9	mvm	H_2 requirement (FuelCellsWorks, 2020)	12.5	HGVkm/kg
AnMBR					
			COD removal (Soares et al., 2021)	65 %	
			Methane biogas content (Soares et al., 2021)	80 %	
			Methane generation (Soares et al., 2021)	0.26	m^3/kgCOD
Syngas					

			Energy generation (Mills, 2016)	4,028	kWh/tDS
Cellulose					
Paper Production (Eurostat, 2019)	3,815,000	t/a	Availability (Palmieri et al., 2019)	31	g/d.PE
			Removal Efficiency (Palmieri et al., 2019)	85 %	
			COD fraction of inlet (Kehrein et al., 2020a)	31 %	
			Pellet Energy Density (Kehrein et al., 2020a)	13.8	MJ/kg
CO_2					
CO_2 Demand (Alberici et al., 2017)	450,000	t/a			
VFAs					
Acetate Demand (Kehrein et al., 2020a)	16,000,000	t/a	COD up-concentration (Kehrein et al., 2020a)	75 %	
Propionate Demand (Kehrein et al., 2020a)	380,000	t/a	VFA yield (Kehrein et al., 2020a)	33 %	
Butyrate Demand (Kehrein et al., 2020a)	500,000	t/a	PHA yield 19	40 %	
EPS					
Alginate Market (Grand View Research, 2021)	43,028	t/a	Sludge production (Kehrein et al., 2020a)	0.4	kg/kgCOD
			EPS content (Kehrein et al., 2020a)	17.5 %	
Nitrogen					
Mineral Fertiliser Demand (Agricultural Industries Confederation, 2021)	1,038,000	t/a	Sludge Content (AHDB, 2019)	3.15 %	
			Biodrying Efficiency (Kehrein et al., 2020a)	70 %	
Biochar					
Soil Conditioner Demand (Staff and Phetmanh, 2016)	1,805,000	t/a			
Ammonia					

			Stripping Efficiency (Organics Group, 2020)	98.5 %	
			Energy Density (Lan and Tao, 2014)	22.5	MJ/kg
Phosphorus					
Mineral Fertiliser Demand (Agricultural Industries Confederation, 2021)	81,282	t/a	Sludge P_2O_5 Content (AHDB, 2019)	3.55 %	
			Struvite P Recovery (Kehrein et al., 2020a)	35 %	
Grit					
Sand and Gravel Demand (Mineral Products Association, 2018)	61.7	Mt/a	Removal (Kehrein et al., 2020a)	0.3	$m^3/1000\ m^3$
SCP					
Animal Feed Demand (Department for Environment Food and Rural Affairs, 2018	222,128	t/a	Protein Conversion	100 %	Assumed

A.3 Review of wastewater resource recovery technologies

Wastewater that has undergone secondary treatment and then subjected to further contaminant removal permits its consideration for reuse applications. These tertiary treatment steps are commonly membrane filtration or advanced oxidation processes. Reused water is either potable (directly or indirectly) or non-potable, where it is more commonly applied for irrigation or industrial cooling (Yang et al., 2020). MF and UF are used to remove suspended particles and pathogens, while NF and RO are able to remove dissolved substances, such as di- and monovalent ions. A combination of membrane filtration and ultraviolet (UV) treatment or ozonation can produce potable water, with one of the most successful water reuse case studies being the NEWater process in Singapore. NEWater utilises a combination of MF/UF, RO and UV disinfection to produce both potable and non-potable water, accounting for approximately 40 % of the country’s water demand (Tortajada and Nambiar, 2019). Although these water reuse technologies have been widely implemented, application is usually driven by necessity in water stressed countries including the USA, Australia and South Africa (Tortajada and Nambiar, 2019).

The emergence of AnMBR enables effective implementation of water reuse strategies in more variable climates (Robles et al., 2020). It has been demonstrated that AnMBRs simultaneously produce high quality effluent (> 90 % chemical oxygen demand (COD) removal) and biogas (> 75 % methane) from wastewater (Kong et al., 2021). This facilitates the reduction of energy consumption, water reuse and renewable energy production. The Spernal WWTP (UK) demonstrates this system, which aims to produce pathogen and solid free effluent, whilst reducing sludge generation, improving energy efficiency, and producing biogas (NextGen, 2020). This combination of benefits makes AnMBRs an attractive, cost-effective opportunity for enhancing water security as water stress becomes a more pertinent issue for regions such as the UK.

There are numerous methods to convert the volatile fraction of wastewater sludge into gaseous fuels through biological and physio-chemical processes (Gherghel et al., 2019). AD of sludge is currently employed by many facilities to recover energy in the form of biogas, which is typically combusted within CHP units to generate electricity and heat (van Loosdrecht and Brdjanovic, 2014). Frequently AD systems are improved using advanced processes, such as thermal hydrolysis TH which utilises heat and pressure to rupture cell walls, enhancing nutrient bioavailability. In turn, TH results in greater volatile destruction, biogas production and pathogen removal, whilst reducing sludge production, transportation and dewatering (Pilli et al., 2015). Membrane filtration and water/chemical scrubbing are utilised to clean biogas which is then upgraded to produce biomethane, permitting its injection into national energy infrastructure (Ardolino et al., 2021).

Gasification and pyrolysis of sewage sludge yields valuable syngas, and biochar as a by-product that can be applied as a soil conditioner. Biochar has a range of benefits including soil pollutant remediation, carbon sequestration and enhanced microorganism activity (Wang and Wang, 2019). There are several examples across Europe where this has been implemented (Hrbek, 2019). In the UK, Yorkshire Water have demonstrated this on a commercial scale as a route towards energetic self-sufficiency. The consistent and reliable flow of water through WWTPs provides opportunities for further renewable energy generation. Hydropower can be harnessed from process effluents, while significant quantities of thermal energy are available for recovery throughout the wastewater network using heat pumps (Llácer-Iglesias et al., 2021).

Raw wastewater and sludge streams are sources of nutrients that can be recycled to replace the demand of fossil-fuel derived fertilisers (Mo and Zhang, 2013), including nitrogen, phosphorus, potassium and magnesium (Nancharaiah et al., 2016). Presently, strict discharge limits are placed on effluent NP concentrations, due to their eutrophic properties, meaning practices are focussed on contaminant removal. Artificial fertiliser production is responsible for a significant fraction of global GHGs (ammonia production emits 1.2 % of anthropogenic CO_2 emissions (Smith et al., 2020)) and the finite reserves of phosphate rock have been well documented in recent times (Geissler et al., 2019). Of the mineral fertiliser utilised for food production it is estimated that 30 % of nitrogen (Verstraete et al., 2009) and 20 % of phosphorus (Batstone et al., 2015) are excreted, meaning that wastewater represents a significant fraction of global nutrient stocks. Therefore, it is counter intuitive to assimilate these critical resources during wastewater treatment, so maximising their recovery is paramount.

Current practice utilises NP remaining after treatment through direct application of sewage sludge/biosolids to farmland. Uptake of this practice is limited in some regions due to low nutrient concentration compared to artificial fertilisers, high transportation cost, potential for contamination (pathogens, heavy metals, organics), and social acceptance (Collivignarelli et al., 2019; Ma and Rosen, 2021). Struvite crystallisation is a method of recovering NP from wastewater sludge and reject streams, requiring stoichiometric amounts of ammonium, phosphorus and magnesium (Cieślik and Konieczka, 2017). This produces a high-grade, slow-release fertiliser and mitigates the problem of pipe clogging caused by spontaneous struvite precipitation (Nancharaiah et al., 2016). Many companies, including Ostara Pearl® and AirPrex®, have developed technology for the controlled precipitation of struvite. Although recovery rates of greater than 90 % of phosphorus from sludge processing streams are reported, this translates to only approximately 20 % recovery of influent phosphorus (Ghosh et al., 2019). It was estimated that 24 % of wastewater nitrogen could be recovered by utilising air stripping technology on digester reject streams of the Amsterdam-West WWTP (van der Hoek et al., 2018). Air stripping is a promising method of nutrient recovery, that has been successfully exploited in the UK using Biosys systems to treat ammonia rich AD streams. Nitrogen is then recovered through scrubbing of the ammonia gas and utilised as green fertiliser (Biosys, 2021b).

A variety of alternative products have been harnessed from other components in wastewater. Cellulose represents a large fraction of wastewater COD (35 %) and is easily recovered during primary treatment, enabling the intensification of downstream processes (Ruiken et al., 2013). The Cellvation® system, developed by SMART-Plant, recovers cellulose from influent wastewater streams by implementing Salnes fine mesh sieves achieving >40 % suspended solids removal (Ros et al., 2020). The recovered fibres present a range of options including paper pulp feedstock, composite manufacture and 2G sugar generation. Volatile fatty acids (VFAs) are favourably synthesised by isolating acidogenic biomass populations during AD, which are used to derive further valuable products. One such product are PHA biopolyesters, which accumulate intracellularly in biomass. PHA is promising as it shows similar properties to fossil-based thermosets, but mitigates many environmental burdens due to their biodegradability and derivation from renewable feedstocks (Valentino et al., 2017). There are several European projects demonstrating these processes on a commercial scale, which achieve recovery rates that represent up to 17.5 % of influent COD (Conca et al., 2020).

A.4 Multi-criteria analysis

The MCA methodology utilised was developed as part of a project commissioned by UK Water Industry Research (UKWIR) to understand the greatest sustainable economic benefit for resource recovery from the water cycle (UKWIR, 2021). In this work, the MCA method has been used as part of the approach to assess the resource recovery opportunities in the UK wastewater sector.

A.4.1 Scoring criteria guidance

Table A.6. Scoring criteria guidance on how scores are assigned for each of the MCA categories taken from UKWIR (2021).

	Score guidance				
Category	1	2	3	4	5
Recovery potential	Less than 20% of material likely recoverable and in limiting circumstances. Recovery is inefficient and would be better achieved through other means of waste management hierarchy – e.g. reduced inputs.	Less than 50% may be recoverable. Recovery is unlikely to be efficient relative to other means of waste management hierarchy – e.g. reduced inputs.	About half of material may be recoverable in a moderate number of cases. Recovery efficiency is neutral relative to other management measures within waste management hierarchy.	About half of material may be recoverable in most circumstances. Resource recovery of this nature is likely to be efficient within waste management hierarchy.	Greater than 80% of material may be recoverable in most circumstances. Recovery location is extremely efficient with respect to waste management hierarchy.
Market potential (UK)	Recovered product can substitute <1% of established products.	Recovered product can substitute <10% of established products.	Recovered product can substitute 10-25 % of established products.	Recovered product can substitute 25-50% established products.	Recovered product can substitute >50% of established products.
Treatment	Recovery offers no material benefit to established treatments or introduces new treatment challenges Major adaptation of established treatment trains	Recovery has neutral impact on established treatments Moderate adaption of established treatment trains	Recovery removes modest load (e.g. <50%) from established treatments or provides other treatment benefits (e.g. operational benefits). Some adaption of established treatment trains.	Recovery removes significant load (e.g. >50%) from established treatments Minor adaption of established treatment trains	Recovery can completely replace established treatments Minor adaption of established treatment trains

Cost	Total cost anticipated to be much higher versus established equivalent processes Exacerbates existing costs elsewhere	Total cost likely to be much higher versus established equivalent processes.	Cost likely to be neutral – neither higher nor lower for the resource recovery.	Similar or lower cost to established comparable treatments.	Similar or lower cost to established comparable treatments May offset significant existing cost elsewhere
Carbon	Greater net emissions versus established equivalent processes No potential to reduce emissions elsewhere on or off site (e.g. Scopes 1, 2 and 3). Greater net emissions from recovered product versus established equivalent products.	Greater emissions likely versus established processes. Limited potential to reduce emissions elsewhere on or off site (e.g. Scopes 1, 2 and 3).	Carbon impact likely to be no different to existing product/technology pathway.	Lower emissions likely versus established processes. Opportunity to reduce emissions on or off site as a result of resource recovery. Some potential to sequester carbon.	Significantly lower net emissions versus established processes. Likely to reduce emissions elsewhere from established equivalent processes. Opportunity to sequester carbon. Net negative emissions from recovered product versus established equivalent products
Environment and Natural capital	Evidence of detriment to natural capital assets across the catchment. Likely to be less sustainable alternative. Evidence of high risk arising from emerging contaminants above that of established equivalent products	No evidence of improved nature-based systems and processes including contribution to natural capital, ecosystem services and biodiversity. There are no opportunities identified for the restoration of the natural environment and/or opportunities to limit extraction and use of natural capital assets.	Limited/some evidence of improved nature-based systems and processes including contribution to natural capital, ecosystem services and biodiversity. Opportunities for the restoration of the natural environment are limited. Opportunities to limit extraction and use of natural capital assets is limited.	Evidence of improved nature-based systems and processes including contribution to natural capital, ecosystem services and biodiversity. Opportunities for the restoration of the natural environment are present. Limits extraction and use of natural capital assets.	Evidence of significantly improved nature-based systems and processes including contribution to natural capital, ecosystem services and biodiversity. Significant opportunities for the restoration of the natural environment are present. Significantly limits extraction and use of natural capital assets.

		Evidence of less-sustainable option. Evidence of some risk arising from emerging contaminants above that of established equivalent products	No clear sustainability benefit from high level consideration. Limited evidence of some risk arising from emerging contaminants but limited relative to established equivalent products As to be expected, many resource recovery options have associated benefits and disbenefits (trade-offs) in relation to natural capital and environmental considerations. This requires to be considered in the analysis.	Sustainability benefit from high level consideration. Limited evidence of some risk arising from emerging contaminants but limited relative to established equivalent products.	Clear sustainability benefit from high level consideration. No evidence of risk arising from emerging contaminants.
Human and intellectual capital	Negative impact on employee knowledge and wellbeing. Potential for higher H&S risks which are likely to require to be managed. May have detrimental impact on intellectual capital of organisation.	Potential for negative impact on human capital through enhanced wellbeing and learning opportunity. Potential for some increased H&S risks. Potential for detrimental impact on intellectual capital of organisation.	No positive or impact on human or intellectual capital. No expected change to H&S risks.	Positive impact on human capital through enhanced wellbeing and/or learning opportunity. Potential for neutral or reduced H&S risks.	Positive impact on human capital through enhanced wellbeing and/or learning opportunity. Reduced H&S risks.
Social and Relationship capital	Considered to contribute detrimentally to customer relationships and trust. Reduces existing societal and stakeholder relationships.	May provide detrimental impact on existing customer relationships and trust. May decrease/constrain existing societal and stakeholder relationships.	Does not provide opportunity to strengthen nor weaken existing relationships and trust with customers. Does not provide opportunity to build relationships with stakeholders beyond present.	Offers some opportunity to strengthen relationships and build trust with customers. Provides opportunity to build relationships with existing and multiple new stakeholders including	Offers opportunity to strengthen relationships and build trust with customers. Provides significant opportunity to build relationships with existing and multiple new stakeholders including

				supply chain, academia and wider society.	supply chain, academia and wider society.

A.4.2 Resource recovery technology scoring

Table A.7. Scores achieved by each of the shortlisted resource recovery technologies. All were assigned by experts at Jacobs Engineering Ltd. (taken from UKWIR (2021)) except the market potential which utilised calculated values (justification for each score given is provided below). These scores were used as inputs to the MCA to rank the technologies for the given scenario.

WW Resource	**Recovery Potential**	**Market Potential**	**Treatment Impacts**	**Cost**	**Carbon**	**Environment and Natural Capital**	**Human and Intellectual Capital**	**Social and Relationship Capital**	**Total**
Biochar	4	3	3	1	4	3	4	4	**26**
	Maximum energy generation from sludge but significant energy required for sludge drying	Market potential of 18 %	Emerging contaminant destruction in biosolids	High capital investment required for AAT technology	Carbon sequestration benefits. Reduced carbon emissions vs incineration.	Considerable new infrastructure required for significant resource impact	Learning opportunity due to technology novelty in sector	Customers perceived benefit from end of biosolids for land application	
Biogas (AAD)	4	1	2	3	4	2	3	3	**22**
	Increased biogas production but additional energy input required	Market potential of <1 %	Increased nutrient load to AD liquor	Neutral due to balanced biogas production and energy demand/ infrastructure	Increased yield of renewable energy source	Limited impact on food and water	Already established, so BAU	Already established, so BAU	
	4	1	2	3	4	2	3	4	**23**

Biogas (Co-digestion)	High potential for recovery of energy but source reduction of waste preferable	Market potential of <1 %	Generation of additional AD liquors and will require site intervention for food waste supplements	Neutral due to enhanced biogas yield with increased liquors treatment	Carbon benefit from avoided landfilling of food waste		Opportunity to increased knowledge base of co-digestion AD process	Can strengthen customer and local community relationship through treatment of food waste	
Biosolids	3	2.5	3	3	4	3	3	3	**24.5**
	BAU	Market potential of 4 % (N) and 23 % (P)	BAU	BAU	Soil carbon sequestration and substitution of artificial fertilisers	Low-cost nutrient cycling balanced by risk of contaminants	BAU	BAU	
Biomethane	4	1	3	3	4	2	3	3	**23**
	High potential for energy generation but additional process steps and energy required for biogas upgrading	Market potential of <1 %	BAU in many places	Added cost is balanced by economic subsidies	Substitution of fossil-based fuels in national grid	Limited impact of water and food	BAU in many places	BAU in many places	
Biopolymers	3	5	3	2	3	3	4	3	**26**
	Requirement of Nereda facility for EPS recovery	Market potential of >100 %	Removes approx. 1/3 of sludge treatment load	Requires installation of AGS infrastructure but balanced by process intensification	Little impact compared to existing product	Potential to limit production of fossil-based plastics	Learning opportunity with new processes and products	Potential to benefit local supply chain	

FOG	2	1	3	2	3	2	4	2	**19**
	Marginal additional recovery vs existing practice	Market potential of <1 %	Minimal downstream capacity improve1ment	Additional infrastructure or chemicals required	Additional biogas yield balanced by additional energy/ chemical requirement	May reduce leaching to water sources from landfill	Potential for increased wellbeing due to preventative maintenance approach	May risk customer confusion around FOG use at home	
Grit	3	1	4	3	3	3	4	3	**24**
	Existing grit removal removes moderate quantities	Market potential of <1 %	Enhanced grit recovery would result in downstream process benefits	Balance between investment and reduced downstream maintenance cost	Evidence of carbon benefits vs landfill disposal	Virgin sand or aggregate replacement	Potential for increased wellbeing due to preventative maintenance approach reducing high pressure environments	Potential for company to upcycle and reuse locally	
Heat (Heat Pump)	4	5	3	3	4	4	4	5	**32**
	Needs alignment for better use in community, onsite heat can be used for building heating	Market potential of 82 %	Use on final effluent should not have adverse effects	Balance of cost of infrastructure with grid energy saving	Substitution with fossil-based fuels from grid	Cooler effluent returned to surface water	Knowledge and skills development for heat pumps	Opportunity to provide renewable source of heating to local communities	
Hydrogen	4	5	2	2	3	2	4	5	**27**
	Feedstock is abundant but limited by	Market potential of >100 %	New infrastructure required (RO	Capital and operating costs of RO and	Potential to decarbonise transport but currently	Reduced volume to surface water	Knowledge and skills development for	Use of hydrogen that is visible and beneficial to local	

	renewable energy requirement		and electrolyser)	electrolyser systems	significant energy needed for generation		hydrogen generation	community, such as bus services	
NH3 Stripping	4	2	3	3	4	3	4	4	**27**
	Limited to liquor stream but enhances recovery vs biosolids use only	Market potential of 1 %	Added process complexity but balanced by reduced treatment load	Infrastructure required but balanced by load reduction/ increased capacity	N_2O reduction of secondary treatment	Potential to improve effluent quality/reduce liquor loads and substitute artificial fertiliser	New learning and potential skills through technology adoption	Fertiliser and/or energy substitution likely build value with supply chains and across sectors	
Struvite	2	3	3	3	3	4	3	4	**25**
	Limited to liquor stream, also low flow to biological P works	Market potential of 19 %	Increased process complexity balanced by reduced maintenance	Value of fertiliser and reduced maintenance balanced by chemical requirement and additional infrastructure	Chemical requirement balanced through substitution of mined P	Extend infrastructure lifetime and substitute mined fertiliser	New learning and potential skills through technology adoption, although sites have already adopted	Potential use of sustainable fertiliser in local community	
Syngas (AAT)	4	1	3	1	4	2	4	3	**22**
	High energy production but energy required for drying	Market potential of <1 %	Required scale of AAT facility would mean this would take place off site	Very high cost of large-scale facility	High potential to substitute fossil fuels but significant capital carbon from infrastructure	Potential to substitute fossil fuels but high energy requirement for operation and materials for construction	New learning and potential skills through AAT technology adoption		

A.4.3 Weighting for sensitivity to future scenarios

Table A.8. These are the weighting criteria assigned to categories used to score RR technologies which were decided using Jacobs Engineering Group Inc. inhouse expertise, taken from UKWIR (2021).

Scenario	Recovery potential	Market	Treatment	Cost	Carbon	Environment & Natural Capital	Human & Intellectual Capital	Social & Relationship Capital	Maximum
Status quo	10%	20%	20%	20%	15%	10%	3%	3%	5
Emissions compliance	8%	10%	25%	15%	11%	21%	3%	8%	5
Carbon reduction	10%	8%	20%	15%	20%	16%	4%	8%	5
Resource max	15%	15%	15%	15%	15%	12%	5%	8%	5

A.4.4 Scenario and consensus scores

Table A.9. Final scores achieved after scoring and weighting for each scenario investigated. The final score was used to create the final rank order of RR technologies to create the updated RR scenario.

WW Resource	Unweighted	Status quo	Emissions compliance	Carbon reduction	Resource max	Consensus
Heat (Heat Pump)	0.8	0.765	0.756	0.762	0.786	0.76725
NH3 Stripping	0.675	0.62	0.639	0.667	0.656	0.6455
Biopolymers	0.65	0.645	0.615	0.609	0.64	0.62725
Struvite	0.625	0.605	0.641	0.627	0.61	0.62075
Biosolids	0.6125	0.61	0.612	0.632	0.615	0.61725
Biochar	0.65	0.58	0.599	0.623	0.626	0.607
Hydrogen	0.675	0.615	0.572	0.59	0.648	0.60625
Grit	0.6	0.565	0.615	0.615	0.58	0.59375
Biomethane	0.575	0.55	0.557	0.597	0.576	0.57
Biogas (Co-digestion)	0.575	0.515	0.523	0.573	0.562	0.54325
Biogas (AAD)	0.55	0.51	0.507	0.557	0.546	0.53
Syngas (AAT)	0.55	0.475	0.502	0.544	0.526	0.51175

FOG	0.475	0.44	0.462	0.478	0.45	0.4575

References

Agricultural Industries Confederation, 2021. Fertiliser consumption in the UK (Annual Summary). https://www.agindustries.org.uk/resource/fertiliser-consumption-in-the-uk.html

AHDB, 2019. Nutrient Management Guide (RB209). https://ahdb.org.uk/nutrient-management-guide-rb209

Alberici, S., Noothout, P., Mir, G.U.R., Stork, M., Wiersma, F., 2017. ASSESSING THE POTENTIAL OF CO2 UTILISATION IN THE UK. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/799293/SISUK17099AssessingCO2_utilisationUK_ReportFinal_260517v2__1_.pdf

Ardolino, F., Cardamone, G.F., Parrillo, F., Arena, U., 2021. Biogas-to-biomethane upgrading: A comparative review and assessment in a life cycle perspective. Renew. Sustain. Energy Rev. 139, 110588. https://doi.org/https://doi.org/10.1016/j.rser.2020.110588

Batstone, D.J., Hülsen, T., Mehta, C.M., Keller, J., 2015. Platforms for energy and nutrient recovery from domestic wastewater: A review. Chemosphere 140, 2–11. https://doi.org/https://doi-org.ezproxy.brunel.ac.uk/10.1016/j.chemosphere.2014.10.021

Biosys, 2021. Experts in N-stripping & recovery. https://www.byosis.com/

Burgos, A.J., López, J.S., Rodríguez, P.U., 2015. TRICKLING FILTERS SERIES: SECONDARY TREATMENTS. https://www.wateractionplan.com/documents/177327/558166/Trickling+filters.pdf/1c2ef2b5-6f3b-326a-c33b-bea411572184

Cavinato, C., Bolzonella, D., Pavan, P., Fatone, F., Cecchi, F., 2013. Mesophilic and thermophilic anaerobic co-digestion of waste activated sludge and source sorted biowaste in pilot- and full-scale reactors. Renew. Energy 55, 260–265. https://doi.org/https://doi.org/10.1016/j.renene.2012.12.044

Cieślik, B., Konieczka, P., 2017. A review of phosphorus recovery methods at various steps of wastewater treatment and sewage sludge management. The concept of “no solid waste generation” and analytical methods. J. Clean. Prod. 142, 1728–1740. https://doi.org/https://doi-org.ezproxy.brunel.ac.uk/10.1016/j.jclepro.2016.11.116

Collivignarelli, M.C., Canato, M., Abbà, A., Miino, M.C., 2019. Biosolids: What are the different types of reuse? J. Clean. Prod. 238, 117844. https://doi.org/https://doi-org.ezproxy.brunel.ac.uk/10.1016/j.jclepro.2019.117844

Coma, M., Martinez-Hernandez, E., Abeln, F., Raikova, S., Donnelly, J., Arnot, T.C., Allen, M.J., Hong, D.D., Chuck, C.J., 2017. Organic waste as a sustainable feedstock for platform chemicals. Faraday Discuss. https://doi.org/10.1039/c7fd00070g

Conca, V., da Ros, C., Valentino, F., Eusebi, A.L., Frison, N., Fatone, F., 2020. Long-term validation of polyhydroxyalkanoates production potential from the sidestream of municipal wastewater treatment plant at pilot scale. Chem. Eng. J. 390, 124627. https://doi.org/https://doi-org.ezproxy.brunel.ac.uk/10.1016/j.cej.2020.124627

CREW, 2018. Water and the circular economy - where is the greatest sustainable economic benefit for resource recovery in the water cycle?. https://www.crew.ac.uk/publication/circular-economy

de Azevedo Basto, P., Savastano Junior, H., de Melo Neto, A.A., 2019. Characterization and pozzolanic properties of sewage sludge ashes (SSA) by electrical conductivity. Cem. Concr. Compos. 104, 103410. https://doi.org/https://doi.org/10.1016/j.cemconcomp.2019.103410

Department for Business Energy and Industrial Strategy, 2020. UK ENERGY IN BRIEF 2020. https://www.gov.uk/government/statistics/uk-energy-in-brief-2020

Department for Environment Food and Rural Affairs, 2019. Water abstraction statistics: England, 2000 to 2017. https://www.gov.uk/government/statistics/water-abstraction-estimates

Department for Transport, 2020. Road traffic statistics. https://roadtraffic.dft.gov.uk/summary

European Environmental Agency, 2018. Urban waste water treatment viewer 2018 (provisional data). https://eea.maps.arcgis.com/apps/MapJournal/index.html?appid=a4b0695edb6645a2a74e35887cf7a974&embed=true

Eurostat, 2019. Total paper and paperboard production. https://data.europa.eu/data/datasets/zep5cpgfhgsgfhwxspr6zg?locale=en

FuelCellsWorks, 2020. Worlds First Fuel Cell Heavy-Duty Truck, Hyundai XCIENT Fuel Cell, Heads to Europe for Commerical Use. https://fuelcellsworks.com/news/worlds-first-fuel-cell-heavy-duty-truck-hyundai-xcient-fuel-cell-heads-to-europe-for-commercial-use/

Geissler, B., Mew, M.C., Steiner, G., 2019. Phosphate supply security for importing countries: Developments and the current situation. Sci. Total Environ. 677, 511–523. https://doi.org/https://doi.org/10.1016/j.scitotenv.2019.04.356

Gherghel, A., Teodosiu, C., De Gisi, S., 2019. A review on wastewater sludge valorisation and its challenges in the context of circular economy. J. Clean. Prod. 228, 244–263. https://doi.org/https://doi.org/10.1016/j.jclepro.2019.04.240

Ghosh, S., Lobanov, S., Lo, V.K., 2019. An overview of technologies to recover phosphorus as struvite from wastewater: advantages and shortcomings. Environ. Sci. Pollut. Res. 26, 19063–19077. https://doi.org/10.1007/s11356-019-05378-6

Grand View Research, 2021. Alginate Market Size, Share & Trends Analysis. https://www.grandviewresearch.com/industry-analysis/alginate-market

Guo, H., Felz, S., Lin, Y., van Lier, J.B., de Kreuk, M., 2020. Structural extracellular polymeric substances determine the difference in digestibility between waste activated sludge and aerobic granules. Water Res. 181, 115924. https://doi.org/https://doi.org/10.1016/j.watres.2020.115924

Hao, X., Li, J., van Loosdrecht, M.C.M., Jiang, H., Liu, R., 2019. Energy recovery from wastewater: Heat over organics. Water Res. 161, 74–77. https://doi.org/https://doi.org/10.1016/j.watres.2019.05.106

Hrbek, J., 2019. Status report on thermal gasification of biomass and waste 2019 IEA Bioenergy Task 33 special report. https://www.ieabioenergy.com/blog/publications/new-publication-2019-status-report-on-thermal-gasification-of-biomass-and-waste/

Jazbec, M., Mukheibir, P., Turner, A., 2020. Transitioning the Water Industry with the Circular Economy. https://www.wsaa.asn.au/publication/transitioning-water-industry-circular-economy

Kehrein, P., van Loosdrecht, M., Osseweijer, P., Garfí, M., Dewulf, J., Posada, J., 2020a. A critical review of resource recovery from municipal wastewater treatment plants – market supply potentials{,} technologies and bottlenecks. Environ. Sci. Water Res. Technol. 6, 877–910. https://doi.org/10.1039/C9EW00905A

Kehrein, P., van Loosdrecht, M., Osseweijer, P., Posada, J., 2020b. Exploring resource recovery potentials for the aerobic granular sludge process by mass and energy balances – energy{,} biopolymer and phosphorous recovery from municipal wastewater. Environ. Sci. Water Res. Technol. 6, 2164–2179. https://doi.org/10.1039/D0EW00310G

Kong, Z., Wu, J., Rong, C., Wang, T., Li, L., Luo, Z., Ji, J., Hanaoka, T., Sakemi, S., Ito, M., Kobayashi, S., Kobayashi, M., Qin, Y., Li, Y.-Y., 2021. Large pilot-scale submerged anaerobic membrane bioreactor for the treatment of municipal wastewater and biogas production at 25 °C. Bioresour. Technol. 319, 124123. https://doi.org/https://doi-org.ezproxy.brunel.ac.uk/10.1016/j.biortech.2020.124123

Lan, R., Tao, S., 2014. Ammonia as a Suitable Fuel for Fuel Cells. Front. Energy Res. 2, 35. https://doi.org/10.3389/fenrg.2014.00035

Llácer-Iglesias, R.M., López-Jiménez, P.A., Pérez-Sánchez, M., 2021. Energy Self-Sufficiency Aiming for Sustainable Wastewater Systems: Are All Options Being Explored? Sustainability 13. https://doi.org/10.3390/su13105537

Ma, P., Rosen, C., 2021. Land application of sewage sludge incinerator ash for phosphorus recovery: A review. Chemosphere 274, 129609. https://doi.org/https://doi-org.ezproxy.brunel.ac.uk/10.1016/j.chemosphere.2021.129609

Mills, N., 2016. Unlocking the full energy potential of sewage sludge. https://openresearch.surrey.ac.uk/esploro/outputs/doctoral/Unlocking-the-full-energy-potential-of-sewage-sludge/99515301502346

Mineral Products Association, 2018. Profile of the UK Mineral Products Industry. https://www.mineralproducts.org/Homepage-Promotions/Profile-of-the-UK-Mineral-Products-Industry.aspx

Mo, W., Zhang, Q., 2013. Energy–nutrients–water nexus: Integrated resource recovery in municipal wastewater treatment plants. J. Environ. Manage. 127, 255–267. https://doi.org/https://doi-org.ezproxy.brunel.ac.uk/10.1016/j.jenvman.2013.05.007

Morgan-Sagastume, F., Pratt, S., Karlsson, A., Cirne, D., Lant, P., Werker, A., 2011. Production of volatile fatty acids by fermentation of waste activated sludge pre-treated in full-scale thermal hydrolysis plants. Bioresour. Technol. 102, 3089–3097. https://doi.org/https://doi.org/10.1016/j.biortech.2010.10.054

Nancharaiah, Y. V, Mohan, S.V., Lens, P.N.L., 2016. Recent advances in nutrient removal and recovery in biological and bioelectrochemical systems. Bioresour. Technol. 215, 173–

185. https://doi.org/https://doi-org.ezproxy.brunel.ac.uk/10.1016/j.biortech.2016.03.129

NextGen, 2020. SPERNAL UNITED KINGDOM. https://nextgenwater.eu/demonstration-cases/spernal/

OFWAT, 2019. Data tables and models. https://www.ofwat.gov.uk/regulated-companies/price-review/2019-price-review/data-tables-models/

Organics Group, 2020. Thermally-Driven Ammonia Strippers: Ammonia stripping with waste heat. https://organics.uk/about-us/

Palmieri, S., Cipolletta, G., Pastore, C., Giosuè, C., Akyol, Ç., Eusebi, A.L., Frison, N., Tittarelli, F., Fatone, F., 2019. Pilot scale cellulose recovery from sewage sludge and reuse in building and construction material. Waste Manag. 100, 208–218. https://doi.org/https://doi.org/10.1016/j.wasman.2019.09.015

Parliamentary Office of Science and Technology, 2014. Phosphate Resources. https://post.parliament.uk/research-briefings/post-pn-477/

Pilli, S., Yan, S., Tyagi, R.D., Surampalli, R.Y., 2015. Thermal Pretreatment of Sewage Sludge to Enhance Anaerobic Digestion: A Review. Crit. Rev. Environ. Sci. Technol. 45, 669–702. https://doi.org/10.1080/10643389.2013.876527

Poulsen, T.G., Hansen, J.A., 2003. Strategic environmental assessment of alternative sewage sludge management scenarios. Waste Manag. \& Res. 21, 19–28. https://doi.org/10.1177/0734242X0302100103

Pronk, M., de Kreuk, M.K., de Bruin, B., Kamminga, P., Kleerebezem, R., van Loosdrecht, M.C.M., 2015. Full scale performance of the aerobic granular sludge process for sewage treatment. Water Res. 84, 207–217. https://doi.org/https://doi.org/10.1016/j.watres.2015.07.011

Robles, Á., Durán, F., Giménez, J.B., Jiménez, E., Ribes, J., Serralta, J., Seco, A., Ferrer, J., Rogalla, F., 2020. Anaerobic membrane bioreactors (AnMBR) treating urban wastewater in mild climates. Bioresour. Technol. 314, 123763. https://doi.org/https://doi.org/10.1016/j.biortech.2020.123763

Ros, C. Da, Conca, V., Eusebi, A.L., Frison, N., Fatone, F., 2020. Sieving of municipal wastewater and recovery of bio-based volatile fatty acids at pilot scale. Water Res. 174, 115633. https://doi.org/https://doi-org.ezproxy.brunel.ac.uk/10.1016/j.watres.2020.115633

Ruiken, C.J., Breuer, G., Klaversma, E., Santiago, T., van Loosdrecht, M.C.M., 2013. Sieving wastewater – Cellulose recovery, economic and energy evaluation. Water Res. 47, 43–48. https://doi.org/https://doi.org/10.1016/j.watres.2012.08.023

Smith, C., Hill, A.K., Torrente-Murciano, L., 2020. Current and future role of Haber–Bosch ammonia in a carbon-free energy landscape. Energy Environ. Sci. 13, 331–344. https://doi.org/10.1039/C9EE02873K

Smyth, M., Brookes, A., Riches, S., Bungay, S., 2021. A PREDICTIVE MODEL TO DETERMINE AMMONIUM LEVELS IN DIGESTATE LIQUORS, in: European Biosolids and Organic Resources Conference. https://conferences.aquaenviro.co.uk/proceedings/predictive-model-determine-ammonium-levels-digestate-liquors/

Soares, A., Vale, P., Kim, J.E., Hofman, J., 2021. Factsheet – Anaerobic Membrane Bioreactor (AnMBR). https://mp.uwmh.eu/media/factsheets/Factsheet1_AnMBRDegassing_unit_JvkOXFZ.pdf

Staff, J., Phetmanh, G., 2016. Compost Certification Scheme Annual Report 2016. https://www.qualitycompost.org.uk/

Tchobanoglous, G., Stensel, H.D., Tsuchihashi, R., Burton, F., 2014. Wastewater Engineering Treatment and Resource Recovery, 5th ed. McGraw-Hill Education, New York.

Tortajada, C., Nambiar, S., 2019. Communications on Technological Innovations: Potable Water Reuse. Water 11. https://doi.org/10.3390/w11020251

UKWIR, 2021. Where is the Greatest Sustinable Economic Benefit for Resource Recovery in the Water Cycle?. https://ukwir.org/final-report-for-where-is-the-greatest-sustainable-economic-benefit-for-resource-recovery-in-the-water-cycle

Valentino, F., Morgan-Sagastume, F., Campanari, S., Villano, M., Werker, A., Majone, M., 2017. Carbon recovery from wastewater through bioconversion into biodegradable polymers. N. Biotechnol. 37, 9–23. https://doi.org/https://doi.org/10.1016/j.nbt.2016.05.007

van der Hoek, J.P., Duijff, R., Reinstra, O., 2018. Nitrogen Recovery from Wastewater: Possibilities, Competition with Other Resources, and Adaptation Pathways. Sustainability 10. https://doi.org/10.3390/su10124605

van Loosdrecht, M.C., Brdjanovic, D., 2014. Water treatment. Anticipating the next century of wastewater treatment. Science 344, 1452–1453. https://doi.org/10.1126/science.1255183

Verstraete, W., de Caveye, P. Van, Diamantis, V., 2009. Maximum use of resources present in domestic "used water." Bioresour. Technol. 100, 5537–5545. https://doi.org/https://doi-org.ezproxy.brunel.ac.uk/10.1016/j.biortech.2009.05.047

Wang, J., Wang, S., 2019. Preparation, modification and environmental application of biochar: A review. J. Clean. Prod. 227, 1002–1022. https://doi.org/https://doi-org.ezproxy.brunel.ac.uk/10.1016/j.jclepro.2019.04.282

Yang, J., Monnot, M., Ercolei, L., Moulin, P., 2020. Membrane-Based Processes Used in Municipal Wastewater Treatment for Water Reuse: State-Of-The-Art and Performance Analysis. Membranes (Basel). 10. https://doi.org/10.3390/membranes10060131

Appendix B

B.1 Conventional process model

In this section, the data provided was used to create the mass balance model enabling MFA of the conventional 270,000 PE WWTP process. The wastewater influent and effluent loadings were taken from literature and are provide in Table B.1 (Rodríguez-Chueca et al., 2019).

Table B.1. Influent loading reported for the WWTP.

Parameter	Value	Unit
COD	640	g/m^3
BOD	340	g/m^3
TN	80	g/m^3
NH_3	63	g/m^3
NO_3^-	0.99	g/m^3
TP	12	g/m^3
TSS	320	g/m^3

Quantities of solids removed during pretreatment stages were calculated using parameters in Table B.2 taken from literature, and mass balancing across process units was used to calculate resultant effluent quality (Tchobanoglous et al., 2014). Primary clarifier performance was taken from literature for a WWTP in Estiviel for each component listed in Table B.1 (Rodríguez-Chueca et al., 2019).

Table B.2. Pretreatment process solids removal parameters.

Screening – 6 mm bar screen					
Removal	90	L/1000 m^3	Moisture	75 %	
Density	750	kg/ m^3	Volatiles	75 %	
Grit					
Removal	0.01	m^3/1000 m^3	Moisture	40 %	
Bulk Density	1,660	kg/ m^3	Volatiles	28.5 %	
FOG					
Concentration	57	mg/l	Removal	50 %	
Moisture	55 %				

Kinetic parameters used to calculate removal efficiencies and biomass production during secondary treatment are shown in Table B.3 (Tchobanoglous et al., 2014).

Table B.3. Kinetic and removal parameters for secondary treatment.

Activated Sludge (Tchobanoglous et al., 2014)					
bCOD:BOD	1.6	TSS:VSS	0.85	VSS:BOD	0.85
Y_h	0.45	gVSS/gCOD	SRT	18	days
b_{aob}	0.135	g/g d	Y_n	0.15	gVSS/gNO_X
b_h	0.12	gVSS/gVSS d	f_d	0.15	
NO_X effluent	6.0	g/m^3	P removal	25 %	
Nutrient Removal (Tchobanoglous et al., 2014)					
Nitrate removal	90 %		Methanol	1.5	gCOD/g
Yield	0.15	gVSS/gCOD			
P removal (Tchobanoglous et al., 2014)					
Soluble effluent achieved	0.1	g/m^3	Solids Removal	85 %	

Sludge is thickened, stabilised with anaerobic digestion AD, then the resultant biosolids are dewatered before land application and biogas is combusted in a CHP unit for energy generation. The parameters used are shown in Table B.4 for the stoichiometric method used for AD modelling (Alvarado et al., 2019) and then subsequent dewatering and energy balance (do Amaral et al., 2018; Tchobanoglous et al., 2014).

Table B.4. Parameters required for sludge treatment model.

<table>
<tr><td colspan="6">Anaerobic Digestion (Alvarado et al., 2019)</td></tr>
<tr><td colspan="2">Primary Sludge Composition</td><td colspan="2">WAS Composition</td><td colspan="2">Kinetic Parameters</td></tr>
<tr><td>C</td><td>29.8 %</td><td>C</td><td>40.1 %</td><td>fso</td><td>0.11</td></tr>
<tr><td>H</td><td>5.4 %</td><td>H</td><td>6.6 %</td><td>fd</td><td>0.8</td></tr>
<tr><td>N</td><td>20.9 %</td><td>N</td><td>26.4 %</td><td>b</td><td>0.05 d^{-1}</td></tr>
<tr><td>O</td><td>2.2 %</td><td>O</td><td>8.3 %</td><td>fe</td><td>0.934</td></tr>
<tr><td colspan="6">Sludge Thickening (Tchobanoglous et al., 2014)</td></tr>
<tr><td colspan="2">Primary Sludge</td><td colspan="2">WAS</td><td colspan="2">Dewatering</td></tr>
<tr><td rowspan="3">DS</td><td rowspan="3">2.7 %</td><td>DS</td><td>3.7 %</td><td>DS</td><td>22 %</td></tr>
<tr><td rowspan="2">Polyelectrolyte Requirement</td><td rowspan="2">22 kg/t</td><td>Dewatering Efficiency</td><td>98 %</td></tr>
<tr><td>Polyelectrolyte Requirement</td><td>7.3 kg/t</td></tr>
<tr><td colspan="6">AD Heat Transfer (Tchobanoglous et al., 2014)</td></tr>
<tr><td>Wall (above round)</td><td>1</td><td>W/m^2 C</td><td>Roof (not insulated)</td><td>4.5</td><td>W/m^2 C</td></tr>
<tr><td>Floor (dry)</td><td>1.25</td><td>W/m^2 C</td><td>Wall (below ground)</td><td>0.625</td><td>W/m^2 C</td></tr>
<tr><td colspan="6">CHP Performance</td></tr>
<tr><td>Electric Efficiency</td><td colspan="2">30 %</td><td>Heat Efficiency</td><td colspan="2">35 %</td></tr>
</table>

Lastly, the energy requirement for the process was calculated using values taken from literature, based on kWh/m^3 for a range of wastewater treatment plant sizes (Longo et al., 2016).

B.2 Resource flow characterisation of the process

The resource flow characterisation of the WWTP is presented in Tables B.5-B.8.

Table B.5. Water resource flow characterisation for the assessed WWTP.

Influent			
Stream	**Fraction**	**Status**	
WWTP inlet	80 %	Circular	
Losses (Consumed - WWT Inlet)	20 %	Linear	
$FeCl_3$ (40 % solution)	negligible	Linear	
Outlets			
Stream	**Water Fraction of the Stream**	**Destination**	**Status**
Screenings	75 %	Landfill	Linear
Grit	40 %	Landfill	Linear
FOG	55 %	Landfill	Linear
Effluent	>99.9 %	Restoration (river)	Circular
Biosolids	78 %	Land application	Linear *assumed not to reduce water abstraction

Table B.6. Phosphorus resource flow characterisation for the assessed WWTP.

<table>
<tr><th colspan="4">Influent</th></tr>
<tr><th>Stream</th><th>Fraction</th><th colspan="2">Status</th></tr>
<tr><td>Urine</td><td>30 %</td><td colspan="2" rowspan="2">Circular</td></tr>
<tr><td>Faeces</td><td>10 %</td></tr>
<tr><td>Food scraps</td><td>1 %</td><td colspan="2" rowspan="6">Linear</td></tr>
<tr><td>Food additives</td><td>29 %</td></tr>
<tr><td>Auto dishwashing</td><td>9 %</td></tr>
<tr><td>Laundry Detergents</td><td>14 %</td></tr>
<tr><td>Tap water dosing</td><td>6 %</td></tr>
<tr><td>Personal Care product</td><td>1 %</td></tr>
<tr><th colspan="4">Outlets</th></tr>
<tr><th>Stream</th><th>P fraction</th><th>Destination</th><th>Status</th></tr>
<tr><td>Effluent</td><td>0.79 mg/L</td><td>Fresh water body</td><td>Linear</td></tr>
<tr><td rowspan="2">Biosolids</td><td rowspan="2">3.9 %DS</td><td>Land application</td><td>Circular</td></tr>
<tr><td>Land application</td><td>Linear (low bioavailability)</td></tr>
</table>

Table B.7. Nitrogen resource flow characterisation for the assessed WWTP.

<table>
<tr><th colspan="4">Influent</th></tr>
<tr><th>Stream</th><th>Fraction</th><th colspan="2">Status</th></tr>
<tr><td>Urine</td><td>80 %</td><td colspan="2" rowspan="2">Circular</td></tr>
<tr><td>Faeces</td><td>14 %</td></tr>
<tr><td>Greywater (kitchen/laundry/bathroom)</td><td>6 %</td><td colspan="2">Linear</td></tr>
<tr><th colspan="4">Outlets</th></tr>
<tr><th>Stream</th><th>N fraction</th><th>Destination</th><th>Status</th></tr>
<tr><td>Effluent</td><td>7.03 mg/L</td><td>Fresh water body</td><td>Linear</td></tr>
<tr><td>Biosolids</td><td>4.2 %DS</td><td>Land application</td><td>Circular</td></tr>
<tr><td rowspan="3">N Emissions</td><td>N_2O (1.6 % of inlet N)</td><td>Atmosphere</td><td>Linear</td></tr>
<tr><td>N_2 (71 %)</td><td>Atmosphere</td><td>Neutral</td></tr>
<tr><td>N_2 (29 %)</td><td>Atmosphere</td><td>Circular</td></tr>
</table>

Table B.8. Carbon resource flow characterisation for the assessed WWTP.

Influent			
Stream	**Fraction**	**Status**	
Fossil	5.5 %	Linear	
Biogenic	94.5 %	Circular	
Outlets			
Stream	**OC fraction**	**Destination**	**Status**
Screenings	41.3 % of TS	Landfill	Linear
FOG	77 % of TS		Linear
Effluent	3.16 mg/L	Fresh water body	Linear (biogenic)
	5 % of total fossil OC		Linear (fossil)
Biosolids	20 % of TS	Land application	Circular (biogenic)
	56.76 % of total fossil OC		Linear (fossil)
CAS Emissions	30.5 % of total fossil OC	Atmosphere	Linear (fossil)
	Remaining CO_2		Circular (biogenic)
	CH_4 (0.0075 $kgCH_4/kgCOD$)		Linear
Biogas Emissions (7.74 % of total fossil OC)	Fugitive CH_4	Atmosphere	Linear
	Fugitive fossil CO_2 (approx. 1 %)		Linear (fossil)
	Fugitive CO_2 remaining		Circular (biogenic)
	Fossil combustion emissions (approx. 1 %)		Linear (fossil)
	Combustion emissions remaining		Circular (biogenic)

B.3 Scenario analysis

Table B.9 summarises outcomes of scenario analysis, providing the indicators results for those utilised in Figure 4.4. Therefore, all changes to resource circularity can be compared for the conventional WWTP and each scenario investigated.

Table B.9. Summary of indictor results for each scenario analysed.

Scenario	Indicator	P	N	OC
Original	Circular Inflow	40.0 %	93.6 %	94.5 %
	Renewable Outflow	42.2 %	11.4 %	25.8 %
	Circular Outflow	42.2 %	29.3 %	64.2 %
	Total Circularity	41.1 %	61.5 %	79.4 %
	Removal Efficiency	93.9 %	91.8 %	99.0 %
1	Circular Inflow	40.0 %	93.6 %	78.5 %
	Renewable Outflow	41.9 %	12.2 %	28.7 %
	Circular Outflow	41.9 %	29.7 %	53.6 %
	Total Circularity	40.9 %	61.7 %	66.1 %
	Removal Efficiency	93.7 %	91.5 %	98.9 %
2	Circular Inflow	38.0 %	89.1 %	94.5 %
	Renewable Outflow	40.9 %	11.3 %	25.9 %
	Circular Outflow	40.9 %	29.3 %	64.3 %
	Total Circularity	39.4 %	59.2 %	79.4 %
	Removal Efficiency	94.2 %	92.2 %	99.0 %
3	Circular Inflow	45.2 %	93.6 %	94.5 %

	Renewable Outflow	41.0 %	11.4 %	25.8 %
	Circular Outflow	41.0 %	29.3 %	64.2 %
	Total Circularity	43.1 %	61.5 %	79.4 %
	Removal Efficiency	93.1 %	91.8 %	99.0 %
4	Circular Inflow	40.0 %	93.6 %	94.5 %
	Renewable Outflow	42.2 %	11.4 %	25.8 %
	Circular Outflow	42.2 %	29.3 %	64.6 %
	Total Circularity	41.1 %	61.5 %	79.5 %
	Removal Efficiency	93.9 %	91.8 %	99.0 %
5	Circular Inflow	40.0 %	93.6 %	94.5 %
	Renewable Outflow	42.2 %	11.4 %	25.8 %
	Circular Outflow	42.2 %	49.4 %	64.2 %
	Total Circularity	41.1 %	71.5 %	79.4 %
	Removal Efficiency	93.9 %	91.8 %	99.0 %

References

Alvarado, V.I., Hsu, S.-C., Wu, Z., Lam, C.-M., Leng, L., Zhuang, H., Lee, P.-H., 2019. A Standardized Stoichiometric Life-Cycle Inventory for Enhanced Specificity in Environmental Assessment of Sewage Treatment. Environ. Sci. Technol. 53, 5111–5123. https://doi.org/10.1021/acs.est.9b01409

do Amaral, K.C., Aisse, M.M., Possetti, G.R.C., Prado, M.R., 2018. Use of life cycle assessment to evaluate environmental impacts associated with the management of sludge and biogas. Water Sci. Technol. 77, 2292–2300. https://doi.org/10.2166/wst.2018.146

Longo, S., d'Antoni, B.M., Bongards, M., Chaparro, A., Cronrath, A., Fatone, F., Lema, J.M., Mauricio-Iglesias, M., Soares, A., Hospido, A., 2016. Monitoring and diagnosis of energy consumption in wastewater treatment plants. A state of the art and proposals for improvement. Appl. Energy 179, 1251–1268. https://doi.org/https://doi.org/10.1016/j.apenergy.2016.07.043

Rodríguez-Chueca, J., Varella della Giustina, S., Rocha, J., Fernandes, T., Pablos, C., Encinas, Á., Barceló, D., Rodríguez-Mozaz, S., Manaia, C.M., Marugán, J., 2019. Assessment of full-scale tertiary wastewater treatment by UV-C based-AOPs: Removal or persistence of antibiotics and antibiotic resistance genes? Sci. Total Environ. 652, 1051–1061. https://doi.org/https://doi.org/10.1016/j.scitotenv.2018.10.223

Tchobanoglous, G., Stensel, H.D., Tsuchihashi, R., Burton, F., 2014. Wastewater Engineering Treatment and Resource Recovery, 5th ed. McGraw-Hill Education, New York.

Appendix C

C.1 Convention extended aeration model

In this section, the data provided was used to create the mass balance model enabling MFA of the conventional 10,000 PE WWTP process. The wastewater influent loadings were taken from literature and are provided in Table C.1 (Rodríguez-Chueca et al., 2019). The wastewater loading is assumed to have the same loading as the example from Chapter 4.

Table C.1. Influent loading for the PBR WWTP.

Parameter	Value	Unit
COD	640	g/m^3
BOD	340	g/m^3
TN	80	g/m^3
NH_3	63	g/m^3
NO_3^-	0.99	g/m^3
TP	12	g/m^3
TSS	320	g/m^3

Quantities of solids removed during pretreatment stages were calculated using parameters in Table C.2 taken from literature, and mass balancing across process units was used to calculate resultant effluent quality (Tchobanoglous et al., 2014).

Table C.2. Pretreatment process solids removal parameters.

Screening – 6 mm bar screen					
Removal	90	L/1000 m^3	Moisture	75 %	
Density	750	kg/ m^3	Volatiles	75 %	
Grit					
Removal	0.01	m^3/1000 m^3	Moisture	40 %	
Bulk Density	1,660	kg/ m^3	Volatiles	28.5 %	

Extended aeration is an activated sludge process, with kinetic parameters used to calculate removal efficiencies and biomass production shown in Table C.3 (Tchobanoglous et al., 2014). Only nitrification occurs and there is no enhanced chemical or biological phosphorus removal, meaning soluble nutrient concentrations in the effluent are high, however, chemical COD limits are met before discharge.

Table C.3. Kinetic parameters for extended aeration.

Extended Aeration					
bCOD:BOD	1.6		b_h	0.12	gVSS/gVSS d
TSS:VSS	0.85		b_{aob}	0.135	g/g d
VSS: BOD	0.85		Y_n	0.15	gVSS/gNO_X
Y_h	0.45	gVSS/gCOD	f_d	0.15	

Sludge is thickened, stabilised with liming, then dewatered and the parameters used are shown in Table C.4 (do Amaral et al., 2018; Tchobanoglous et al., 2014).

Table C.4. Parameters required for liming sludge treatment calculations.

Sludge Treatment					
Thickened WAS	3.7 %	DS	Dewatered Cake	22 %	DS
Thickener Efficiency	98 %		Dewatering Efficiency	98 %	
Polyelectrolyte Requirement	22	kg/t	Polyelectrolyte Requirement	7.3	kg/t
Liming Carbon Loss	15%	As CO_2 emissions	Sludge Lime Dose	300	$kgCa(OH)_2/tDS$
Liming Nitrogen Loss	2.8%	As NH_3 emissions			

Lastly, the energy requirement for the process was calculated using values taken from literature, based on kWh/m^3 for a range of wastewater treatment plant sizes (Longo et al., 2016).

C.2 Circular solution model

In this section, the data provided was used to update the conventional process mass balance model enabling MFA of the circular intervention technology. Table C.5 provides the parameters for the updated pretreatment process that includes FOG removal (Collin et al., 2020; Tchobanoglous et al., 2014; Williams et al., 2012).

Table C.5. FOG removal pretreatment operation parameters.

FOG Removal					
Concentration	57	mg/L	Removal	50%	
DS	45 %				

The effluent quality of the primary settler was taken from literature (Rodríguez-Chueca et al., 2019) and used to calculate the removal efficiencies of wastewater components shown in Table C.6.

Table C.6. Removal efficiencies of primary settler.

Component	Primary Clarifier Removal Efficiency
Suspended Solids (SS)	63 %
Biological Oxygen Demand (BOD)	18 %
COD	20 %
Nitrogen	11 %
Phosphorus	25 %

The PBR operation was modelled using parameters reported by project partners, which are summarised in Table C.7.

Table C.7. PBR and clarifier operation parameters.

Soluble COD removal	80 %		Nitrogen removal	40 %	
COD removal	80 %		Phosphorus removal	70 %	
BOD removal	90 %		TSS removal	80 %	
Biomass Yield	0.21	gVSS/gCOD	Recycle Ratio	0.1	
Settler Efficiency	97 %		Sludge DS	0.40 %	

For sludge treatment, thickeners were assumed to operate as reported for the conventional process. A stoichiometric method was used to complete the mass balance for the AD and biogas production calculations (Alvarado et al., 2019). A heat balance was completed across the digester, showing the heat requirements could be covered by biogas combustion in a boiler (with the excess sent to a generator for electricity production). The digestate is then dewatered before being sold for land application. The parameters required for these calculations are provided in Table C.8 (Tchobanoglous et al., 2014).

Table C.8. Sludge treatment and energy balance parameters.

AD Kinetic Parameters					
f_{s0}	0.11		b	0.05	d^{-1}
f_d	0.8		SRT	20	D
Heat Balance					
Generator Efficiency	30 %	Electricity	Methane Energy Density	38.8	MJ/m^3
Boiler Efficiency	86 %	Heat			
Heat Transfer Coefficients of Digester (Tchobanoglous et al., 2014)					
Wall	1	W/ m^2 C	Roof	4.5	W/ m^2 C
Floor	1.25	W/ m^2 C	Air Temperature	15.2	℃
Inlet Temperature	15	℃	Digester Temperature	37	℃
Dewatering					
Cake	22 %	Dry solids	Polyelectrolyte Dose	0.05	L/m^3
Efficiency	98 %				

The thermal hydrolysis is assumed to perform as reported (Morgan-Sagastume et al., 2011). Lastly, the energy balance was completed using the values reported for conventional equipment (Longo et al., 2016), whilst energy consumption by the PBR at this scale was provided by project partners.

C.3 Resource flow characterisation of the analysed processes

Here the resource flow characterisation tables used for conventional extended aeration WWTP indicator calculation are presented in Tables C.9-C.12.

Table C.9. Water resource flow characterisation for conventional process.

Influent			
Stream	**Fraction**	**Status**	
WWTP inlet	80 %	Circular	
Losses (Consumption - WWT Inlet)	20 %	Linear	
Outlets			
Stream	**Water Fraction of the Stream**	**Destination**	**Status**
Screenings	75 %	Landfill	Linear
Grit	40 %	Landfill	Linear
Effluent	>99.9 %	Restoration (groundwater, lake, river)	Circular
Biosolids	78 %	Land application	Linear *assumed it does not reduce the raw water abstraction

Table C.10. Phosphorus resource flow characterisation for conventional process.

<table>
<tr><th colspan="4">Influent</th></tr>
<tr><th>Stream</th><th>Fraction</th><th colspan="2">Status</th></tr>
<tr><td>Urine</td><td>30 %</td><td colspan="2" rowspan="2">Circular</td></tr>
<tr><td>Faeces</td><td>10 %</td></tr>
<tr><td>Food scraps</td><td>1 %</td><td colspan="2" rowspan="6">Linear</td></tr>
<tr><td>Food additives</td><td>29 %</td></tr>
<tr><td>Auto dishwashing</td><td>9 %</td></tr>
<tr><td>Laundry Detergents</td><td>14 %</td></tr>
<tr><td>Tap water dosing</td><td>6 %</td></tr>
<tr><td>Personal Care product</td><td>1 %</td></tr>
<tr><th colspan="4">Outlets</th></tr>
<tr><th>Stream</th><th>P fraction</th><th>Destination</th><th>Status</th></tr>
<tr><td>Effluent</td><td>4.98 mg/L</td><td>Fresh water body</td><td>Linear</td></tr>
<tr><td>Biosolids</td><td>2.96 %DS</td><td>Land application</td><td>Circular</td></tr>
</table>

Table C.11. Nitrogen resource flow characterisation for conventional process.

<table>
<tr><th colspan="4">Influent</th></tr>
<tr><th>Stream</th><th>Fraction</th><th colspan="2">Status</th></tr>
<tr><td>Urine</td><td>80 %</td><td colspan="2" rowspan="2">Circular</td></tr>
<tr><td>Faeces</td><td>14 %</td></tr>
<tr><td>Greywater (kitchen/laundry/bathroom)</td><td>6 %</td><td colspan="2">Linear</td></tr>
<tr><th colspan="4">Outlets</th></tr>
<tr><th>Stream</th><th>N fraction</th><th>Destination</th><th>Status</th></tr>
<tr><td>Effluent</td><td>67.31 mg/L</td><td>Fresh water body</td><td>Linear</td></tr>
<tr><td>Biosolids</td><td>5 %DS</td><td>Land application</td><td>Circular</td></tr>
<tr><td rowspan="2">Emissions</td><td>NH_3</td><td>Atmosphere</td><td>Linear</td></tr>
<tr><td>N_2O</td><td>Atmosphere</td><td>Linear</td></tr>
</table>

Table C.12. Carbon resource flow characterisation for conventional process.

Influent		
Stream	**Fraction**	**Status**
Fossil	5.5 %	Linear
Biogenic	94.5 %	Circular

Outlets			
Stream	**OC fraction**	**Destination**	**Status**
Screenings	41.3 % TS	Landfill	Linear
Effluent	3.87 mg/L	Fresh water body	Linear (biogenic)
	5 % of total fossil OC		Linear (fossil)
Biosolids	20 %	Land application	Circular (biogenic)
	56.76 % of total fossil OC		Linear (fossil)
Gas Emissions	>99% CO_2	Atmosphere	Circular (Biogenic)
	30.5 % of total fossil OC	Atmosphere	Linear (Fossil)
	CH_4 (0.0075 $kgCH_4/kgCOD$)	Atmosphere	Linear
Liming Emissions	CO_2	Atmosphere	Circular (biogenic)
	7.74 % of total fossil OC	Atmosphere	Linear fossil

Here the resource flow characterisation tables used for the PBR WWTP with circular interventions indicator calculations are presented in Tables C.13-C.16.

Table C.13. Water resource flow characterisation for the circular process.

Influent			
Stream	**Fraction**	**Status**	
WWTP inlet	80 %	Circular	
Losses (Consumption - WWT Inlet)	20 %	Linear	
Outlets			
Stream	**Water Fraction of the stream**	**Destination**	**Status**
Screenings	75 %	Landfill	Linear
FOG	55 %	Landfill	Linear
Grit	40 %	Landfill	Linear
Effluent	>99.9 %	Restoration (groundwater, lake, river)	Circular
Biosolids	78 %	Land application	Linear *assumed it does not reduce the raw water abstraction

Table C.14. Phosphorus resource flow characterisation for the circular process.

<table>
<tr><th colspan="4">Influent</th></tr>
<tr><th>Stream</th><th>Fraction</th><th colspan="2">Status</th></tr>
<tr><td>Urine</td><td>30 %</td><td colspan="2" rowspan="2">Circular</td></tr>
<tr><td>Faeces</td><td>10 %</td></tr>
<tr><td>Food scraps</td><td>1 %</td><td colspan="2" rowspan="6">Linear</td></tr>
<tr><td>Food additives</td><td>29 %</td></tr>
<tr><td>Auto dishwashing</td><td>9 %</td></tr>
<tr><td>Laundry Detergents</td><td>14 %</td></tr>
<tr><td>Tap water dosing</td><td>6 %</td></tr>
<tr><td>Personal Care product</td><td>1 %</td></tr>
<tr><th colspan="4">Outlets</th></tr>
<tr><th>Stream</th><th>P fraction</th><th>Destination</th><th>Status</th></tr>
<tr><td>Effluent</td><td>2.49 mg/L</td><td>Fresh water body</td><td>Linear</td></tr>
<tr><td>Biosolids</td><td>5 %DS</td><td>Land application</td><td>Circular</td></tr>
</table>

Table C.15. Nitrogen resource flow characterisation for the circular process.

<table>
<tr><th colspan="4">Influent</th></tr>
<tr><th>Stream</th><th>Fraction</th><th colspan="2">Status</th></tr>
<tr><td>Urine</td><td>80 %</td><td colspan="2" rowspan="2">Circular</td></tr>
<tr><td>Faeces</td><td>14 %</td></tr>
<tr><td>Greywater (kitchen/ laundry bathroom)</td><td>6 %</td><td colspan="2">Linear</td></tr>
<tr><th colspan="4">Outlets</th></tr>
<tr><th>Stream</th><th>N fraction</th><th>Destination</th><th>Status</th></tr>
<tr><td>Effluent</td><td>40.9 mg/L</td><td>Fresh Water</td><td>Linear</td></tr>
<tr><td>Biosolids</td><td>22 %DS</td><td>Land application</td><td>Circular</td></tr>
</table>

Table C.16. Carbon resource flow characterisation for the circular process.

<table>
<tr><th colspan="4">Influent</th></tr>
<tr><th>Stream</th><th>Fraction</th><th colspan="2">Status</th></tr>
<tr><td>Fossil</td><td>5.5 %</td><td colspan="2">Linear</td></tr>
<tr><td>Biogenic</td><td>94.5 %</td><td colspan="2">Circular</td></tr>
<tr><th colspan="4">Outlets</th></tr>
<tr><th>Stream</th><th>C fraction</th><th>Destination</th><th>Status</th></tr>
<tr><td>FOG</td><td>77 % TS</td><td>Landfill</td><td>Linear</td></tr>
<tr><td>Screenings</td><td>41.3 % TS</td><td>Landfill</td><td>Linear</td></tr>
<tr><td rowspan="2">Effluent</td><td>19.6 mg/L</td><td rowspan="2">Fresh water body</td><td>Linear (biogenic)</td></tr>
<tr><td>7.1 % of total fossil OC</td><td>Linear (fossil)</td></tr>
<tr><td rowspan="2">Biosolids</td><td>43 %</td><td rowspan="2">Land application</td><td>Circular (biogenic)</td></tr>
<tr><td>81.7 % of total fossil OC</td><td>Linear (fossil)</td></tr>
<tr><td rowspan="3">Biogas</td><td>45 wt% C</td><td>Used Biogas</td><td>Circular (biogenic)</td></tr>
<tr><td>11.1 % of total fossil OC</td><td>Used Biogas</td><td>Linear (Fossil)</td></tr>
<tr><td>1.4 % of biogas</td><td>Biogas fugitive</td><td>Linear</td></tr>
</table>

C.4 Methods of sustainability analysis

C.4.1 Carbon footprint

Scope 1 emissions consider direct emissions from the system including, gases produced during wastewater treatment, transportation, and sludge treatment (fugitive emissions). These emission factors were taken from the IPCC report and ecoinvent 3 database, with transport factors taken from literature (Lorenzo-Toja et al., 2016). Scope 2 emissions are those indirectly produced by the production of energy and parameters are summarised in Table C.17.

Table C.17. Parameters required to calculate scope 1 and 2 emissions from processes.

Transportation					
Grit	0.195	kgkm/m^3	Chemicals	0.755	kgkm/m^3
Grease	0.009405	kgkm/m^3	Sludge	156.515	kgkm/m^3
Emission factors					
N_2O Direct Emissions (conventional process)	0.016	kgN_2O/kgN	Transport	0.168	kgCO_2/tkm
CH_4 Direct Emissions (conventional process)	0.0075	kgCH_4/kg/COD	Fugitive AD Emissions	1.40%	
Scope 2					
Grid Electricity	0.403	kgCO_2/kWh			

Scope 3 emissions are indirect emissions resulting from effluent discharge, sludge application to land and chemical consumption. Emission factors were taken from IPCC documentation for effluent and sludge application, whilst chemical emission factors were taken from the ecoinvent 3 database and are summarised in Table C.18.

Table C.18. Parameters required to calculate scope 3 emissions from processes.

N_2O Effluent	0.005	kgN_2O/kgN	CH_4 Effluent	0.028	kgCH_4/kgCOD
Limed sludge to land	20	kgCH_4/tDS	Polyelectrolyte	2.83	kgCO_2/kg
AD sludge to land	5	kgCH_4/tDS	Lime	0.95	kgCO_2eq/kg
Sludge to land	0.01	kgN/kgN			

Additionally, the offsets from application of biofertiliser and biosolids were calculated by mitigating the production and application of industrial fertilisers. The information was collected from the ecoinvent 3 database and literature (Heimersson et al., 2017), and is summarised in Table C.19.

Table C.19. Parameters required to calculate carbon offsets from biosolids application to land.

Ammonium Nitrate (as nitrogen)	7.97	$kgCO_2$ eq/kg	Phosphate Fertiliser P_2O_5 (as phosphorus)	1.84	$kgCO_2$ eq/kg
Replacement ratio	0.5		Replacement Ratio	0.7	

C.4.2 Economic value

The value added method of Medina-Mijango et al. (Medina-Mijangos and Seguí-Amórtegui, 2021) was followed and is calculated using Equation C1:

$$VC = (WWT_V \times GF) - (CAPEX + OPEX + ST) + In \quad \text{(C1)}$$

Where, WWT_V is the volume of wastewater treated (m^3), GF are the gate fees of the WWTP (€/m^3), ST are state taxes for landfill and discharge (€), and In is income from sales of products (€). For economic calculations, it was assumed that both the conventional and biorefinery facilitates were constructed in Spain in the year 2021. The CAPEX for the construction of a conventional wastewater treatment plant of this size and type was calculated using a method provided by the OCED (OECD, 2004). The expenditure in EUR/PE for a Mechanical-Biological-Nitrification process between 2,000-10,000 PE is given by Equation C2:

$$CAPEX = \frac{10}{7.44}^{-0.2612\log(PE)+4.26} \quad \text{(C2)}$$

Equation S2 provides the CAPEX for the year 1990, therefore, Construction Cost Indices (CCI) were used to scale the results accordingly (Eurostat, 2005). The construction costs for the biorefinery facility were provided by the project consortium partners, based on scale up of the demonstration site CAPEX (load 3,000 m^3/d). Amortisation was calculated using Equation C3:

$$Investment_{EUR/Year} = CAPEX \times \frac{r(1+r)^{n}}{(1+r)^{n}-1} \qquad (C3)$$

Where r is the discount rate (4 %) and n is the time horizon (15 years as recommended by project engineers). OPEX, revenue, and tax data for conventional and biorefinery plants were provided by wastewater operators for plants of this size: reported for conventional plant of this size and estimated from demonstration photobioreactor system scale up. Economic data used for the value-added calculations is summarised in Table C.20.

Table C.20. Parameters required for economic value added calculations.

Parameter	Unit	Conventional Plant	Biorefinery
CAPEX	€	Estimated	3,200,000
OPEX	€/m^3	0.4	0.135
Landfill Cost	€/t	42	
Discharge Cost	€/m^3	0.01751	
Gate Fee	€/m^3	0.8	
Fertiliser Sale	€/t	N/A	150

C.4.3 Social assessment

Parameters required for the calculation of social indicators are presented in Tables C.21 and C.22.

Table C.21. Material and electricity inflows of urban WWTP systems.

Consumables	Unit	Conventional Plant	Novel Plant
Lime	kg/m^3 wastewater	0.0701	0
Polyelectrolyte	kg/m^3 wastewater	0.00693	0.00253
Electricity	kWh/m^3 wastewater	0.382	0.331

Table C.22. Environmental releases of urban WWTP systems to soil, water, and air.

Substance	Unit	Conventional Plant	PBR Plant
Emissions to Soil			
Phosphorus	kg/m^3 wastewater	0.00677	0.00782
Emissions to Water			
COD	kg/m^3 wastewater	0.0192	0.0774
Nitrogen	kg/m^3 wastewater	0.0633	0.0386
Phosphorus	kg/m^3 wastewater	0.00468	0.00236
Nitrate (includes fertiliser application to soil)	kg/m^3 wastewater	0.0149	0.0439
Emissions to Air			
N_2O	kg/m^3 wastewater	0.00268	0.000633
CO_2 (Fossil)	kg/m^3 wastewater	0.00974	0.00491
CH_4	kg/m^3 wastewater	0.00991	0.00349

C.5 Sustainability analysis results

Carbon footprint

Results of carbon footprint analysis are summarised in Figure 5.8A of the manuscript. Scope 1 (direct) emissions have the greatest reduction between systems, as even though fugitive emissions from sludge treatment are approximately 10 times greater for the PBR system, direct emissions from wastewater treatment can be assumed negligible. Therefore, Scope 1 emissions are only 6 % of the conventional system. Scope 2 (electricity consumption) emissions decreased by more than 10 % due to the reduction in demand of grid electricity. Scope 3 (indirect) emissions account for indirect process emissions and the PBR system achieves a reduction of a third, attributed to higher removal of nitrogen from the wastewater effluent and decreased emissions generation from digested biosolids when applied to land compared with limed sludge. Lastly, carbon offsets were measured by calculating emissions avoided by the process. Offsets of the PBR process are four times greater than for the conventional treatment process, as the higher nutrient content of PPB biosolids means it is able to substitute a greater amount of industrial NP fertiliser applied to land than conventional biosolids. To summarise, the PBR process is much more efficient in terms of emissions release to air. Total emissions for the PBR system are almost a third of the emissions from conventional treatment. Additionally, whenever this is adjusted to incorporate offsets from application of biosolids to land this drops even further to approximately a quarter.

LCA

Results from LCA comparing each impact category for the conventional and PBR WWTPs are presented in Figure 5.8B of the manuscript. PBR operation performs better in six out of the seven impact categories investigated, ranging from 15 % to 41 % reduction. Eutrophication sees the largest decrease of 41 %, attributed to the reduction of NP emissions in wastewater effluents. Ozone depletion, photochemical oxidation and acidification decrease by 34 %, 20 % and 15 % respectively which occurs due to the reduction of emissions to air during wastewater and sludge treatment. Lastly, abiotic depletion of elements and fossil fuels decrease by 20 % and 19 % respectively, which is correlated with reductions in chemical and energy consumption from the grid for the PBR system. Lastly, water consumption undergoes a small increase of 0.4 %, however a change of this size is considered negligible. Combining this analysis with the carbon footprint results it can be concluded that the operation of the PBR system improves the environmental performance of wastewater treatment at this scale.

Economic value added

In the manuscript Figure 5.8C provides the economic value added results, showing the change in revenue and costs between PBR and conventional processes. The same volume of wastewater is treated by both systems, therefore, the gate fees are constant meaning the increase in revenue for the PBR system is a result of biofertiliser sales, adding approximately 0.1 M€/y. There is a reduction in OPEX due to the lower energy demand associated with the mitigation of aeration during biological treatment and energy recovery from biogas, as well as the removal of lime requirements for sludge treatment. The economic value generated by the PBR system is the increase in revenue added to the reduction in CAPEX and OPEX, which is almost M€ 0.5 per year for water the utility. This shows that the PBR technology system for the treatment of wastewater is a more economically sustainable process compared with the conventional prolonged aeration system at this scale.

Social impacts

In the manuscript Figure 5.8D provides impact results for human health, ecosystems, and resources indicators. The PBR system results in a reduction to all impact indicators compared to the conventional system, with the largest reduction being to the human health indicator which decreases DALY by 58 %. This trend occurs due to similar reasons explained for the favourable LCA and carbon footprint results. Smaller grid energy and material consumption, coupled with the mitigation of significant proportions of direct and indirect emissions results in the reduction of endpoint impacts. Employment was also used to quantify the social impacts of the system. Based on the employment data for local wastewater workers, it is estimated that 3 employees would be required to operate a WWTP of this size. Project partners responsible for plant operation estimate that over the course of the project employment growth of 1-5 people is expected. Therefore, for projects that implement PBR technologies, employment is expected to rise by an average of 100 % over a time frame of approximately 5 years. Lastly, contribution to the local economy of the WWTP was calculated by dividing the economic value added of the systems by the expected GDP of the local area (Soria). PBR system increased this to 0.0018%, compared with 0.00014% for the conventional system. Therefore, these 5 indicators confirm that the PBR system results in greater social value.

References

Alvarado, V.I., Hsu, S.-C., Wu, Z., Lam, C.-M., Leng, L., Zhuang, H., Lee, P.-H., 2019. A Standardized Stoichiometric Life-Cycle Inventory for Enhanced Specificity in Environmental Assessment of Sewage Treatment. Environ. Sci. Technol. 53, 5111–5123. https://doi.org/10.1021/acs.est.9b01409

Collin, T.D., Cunningham, R., Asghar, M.Q., Villa, R., MacAdam, J., Jefferson, B., 2020. Assessing the potential of enhanced primary clarification to manage fats, oils and grease (FOG) at wastewater treatment works. Sci. Total Environ. 728, 138415. https://doi.org/https://doi.org/10.1016/j.scitotenv.2020.138415

do Amaral, K.C., Aisse, M.M., Possetti, G.R.C., Prado, M.R., 2018. Use of life cycle assessment to evaluate environmental impacts associated with the management of sludge and biogas. Water Sci. Technol. 77, 2292–2300. https://doi.org/10.2166/wst.2018.146

Eurostat, 2005. Construction producer price and construction cost indices overview [WWW Document]. URL https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Construction_producer_price_and_construction_cost_indices_overview (accessed 1.3.23).

Heimersson, S., Svanström, M., Cederberg, C., Peters, G., 2017. Improved life cycle modelling of benefits from sewage sludge anaerobic digestion and land application. Resour. Conserv. Recycl. 122, 126–134. https://doi.org/https://doi.org/10.1016/j.resconrec.2017.01.016

Longo, S., d'Antoni, B.M., Bongards, M., Chaparro, A., Cronrath, A., Fatone, F., Lema, J.M., Mauricio-Iglesias, M., Soares, A., Hospido, A., 2016. Monitoring and diagnosis of energy consumption in wastewater treatment plants. A state of the art and proposals for improvement. Appl. Energy 179, 1251–1268. https://doi.org/https://doi.org/10.1016/j.apenergy.2016.07.043

Lorenzo-Toja, Y., Alfonsín, C., Amores, M.J., Aldea, X., Marin, D., Moreira, M.T., Feijoo, G., 2016. Beyond the conventional life cycle inventory in wastewater treatment plants. Sci. Total Environ. 553, 71–82. https://doi.org/https://doi.org/10.1016/j.scitotenv.2016.02.073

Medina-Mijangos, R., Seguí-Amórtegui, L., 2021. Technical-economic analysis of a municipal solid waste energy recovery facility in Spain: A case study. Waste Manag. 119, 254–266. https://doi.org/https://doi.org/10.1016/j.wasman.2020.09.035

Morgan-Sagastume, F., Pratt, S., Karlsson, A., Cirne, D., Lant, P., Werker, A., 2011. Production of volatile fatty acids by fermentation of waste activated sludge pre-treated in full-scale thermal hydrolysis plants. Bioresour. Technol. 102, 3089–3097. https://doi.org/https://doi.org/10.1016/j.biortech.2010.10.054

OECD, 2004. The FEASIBLE Model, Version 2 User Manual and Documentation, Appendix 3.

Rodríguez-Chueca, J., Varella della Giustina, S., Rocha, J., Fernandes, T., Pablos, C., Encinas, Á., Barceló, D., Rodríguez-Mozaz, S., Manaia, C.M., Marugán, J., 2019. Assessment of full-scale tertiary wastewater treatment by UV-C based-AOPs: Removal or persistence of antibiotics and antibiotic resistance genes? Sci. Total Environ. 652, 1051–1061. https://doi.org/https://doi.org/10.1016/j.scitotenv.2018.10.223

Tchobanoglous, G., Stensel, H.D., Tsuchihashi, R., Burton, F., 2014. Wastewater Engineering Treatment and Resource Recovery, 5th ed. McGraw-Hill Education, New York.

Williams, J.B., Clarkson, C., Mant, C., Drinkwater, A., May, E., 2012. Fat, oil and grease deposits in sewers: Characterisation of deposits and formation mechanisms. Water Res. 46, 6319–6328. https://doi.org/https://doi.org/10.1016/j.watres.2012.09.002