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# Cost-Energy Optimum Pathway for the UK Food Manufacturing Industry to Meet the UK National Emission Targets

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**Abstract:** This paper investigates and outlines a cost-energy optimised pathway for the UK food manufacturing industry to attain the national Greenhouse Gas (GHG) emission reduction target of 80%, relative to 1990 levels, by 2050. The paper employs the linear programming platform TIMES, and it models the current and future technology mix of the UK food manufacturing industry. The model considers parameters such as capital costs, operating costs, efficiency and the lifetime of technologies to determine the cheapest pathway to achieve the GHG emission constraints. The model also enables future parametric analyses and can predict the influence of different economic, trade and dietary preferences and the impact of technological investments and policies on emissions. The study showed that for the food manufacturing industry to meet the emission reduction targets by 2050 the use of natural gas as the dominant source of energy in the industry at present, will have to be replaced by decarbonised grid electricity and biogas. This will require investments in Anaerobic Digestion (AD), Combined Heat and Power (CHP) plants driven by biogas and heat pumps powered by decarbonised electricity.

**Keywords:** UK food manufacturing; energy efficiency; emission reduction; combined heat and power

## 1. Introduction

### *1.1. Context*

By 2050, the global population is predicted to reach 9.7 billion [1]. Driven by many factors, including population growth, the global primary energy consumption has maintained a consistent rise over the years (an average of 1.7% growth in the last 10 years, [2]). It therefore becomes necessary to decarbonise energy systems and improve energy efficiency across all sectors of various economies. The industrial sector (including the non-combusted use of fuels) currently consumes about 50% of all global energy and feedstock fuels [3], which is projected to increase by an average of 1.2%/year, up until 2040. The quantity and type of fuels consumed in the industrial sector vary across countries, depending on the quantity and quality of the output of the economy, and on their technological development. Three distinct industry categories are identified: energy-intensive manufacturing, non-energy-intensive manufacturing, and nonmanufacturing. The food and drink industry is categorised as energy-intensive [4]. World over, the food sector is a major energy consumer and emissions producer. In the US for instance, the sector accounted for about 15.7% of the national energy consumption in 2007 [5], with some processing aspects such as cooking, cooling, and freezing contributing an average share of 15–20% of the total US food system energy use [6]. In the EU, the amount of energy necessary to cultivate, process, pack and distribute food accounted for 17%

of the gross energy and 26% of the overall final energy consumption in 2013 [7]. Processing alone, accounted for 28% of this energy. Even more significant proportions are reported in some developing countries such as Brazil, China and India, each of which has massive food industries. In Brazil for instance, the food industry is the largest energy consumer in the entire industrial sector [8]. The UK food and drink industry is one of the largest emitters of $CO_2$ in the UK [9], it consumed as much as 24.6 TWh of energy and emitted approximately 9.1 MtCO2e, or just over 1% of the total UK $CO_2$ emissions in 2014 [10] and is the fourth-highest industrial energy user in the country [11]. In view of the resolutions of the United Nations Framework on Climate Change, and the subsequent Kyoto Protocol and Paris Agreement on emission reduction targets of the various countries of the world, improving energy-efficiency and decarbonising food manufacturing operations become critical. The UK is already working towards delivering these agreements through the UK Climate Change Act which targets at least, an 80% reduction in greenhouse gas emissions by 2050, relative to the 1990 levels [12,13]. The UK food and drink manufacturing sector has reduced its emissions from energy use by 42% between 1990 and 2015 [10]. However, to meet the required overall targets in the long-term, further reductions are required across the board, and in the food industry in particular. The Climate Change Committee has assessed that an annual reduction rate of 3% is required to enable the UK to meet the national target of 80% emission reduction by 2050 [14]. The analysis performed in this paper will further reinforce the pathway for the food processing sector in view of what technologies will aid the sector to successfully contribute to the national emission reduction.

### *1.2. UK Food Processing Industry*

In its entirety, the UK Food industry is a complex and interactive chain involving different stages as illustrated in Figure 1. It comprises of many actors within the chain, but is also reliant on third party sectors such as the energy generation sector and the materials producing/ disposal sector.

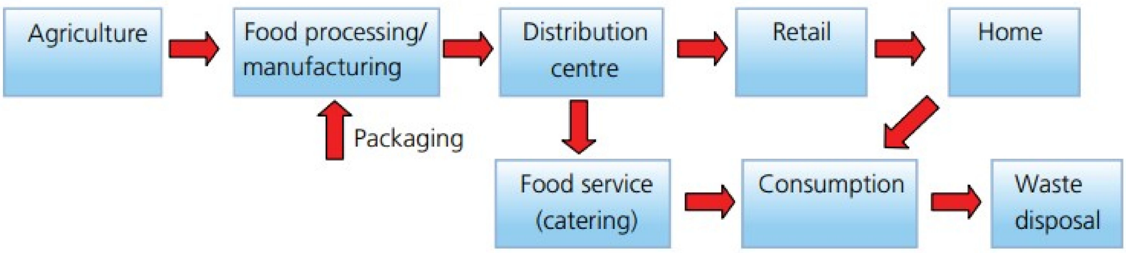



**Figure 1.** Schematic of main stages in the food chain [15].

The UK food and drink processing industry is also quite diverse with many subsectors such as dairy, brewery, distilling, sugar, confectionery, bakery, rendering, meat processing, fish and seafood, poultry, malting, soft drinks, animal feed, oil and fat, glucose, canned food, ice cream, and pet food. Each of these subsectors has very specific processing technologies, which can be aggregated.

The main processing operations applied all through the entire food and drink sector include materials reception and treatment; size reduction, mixing and forming; separation techniques; product processing techniques; heat processing; and post-processing operations. The biggest sub-sectors are cereals, bakery, meat, dairy, seafood and "other groceries" [11]. The most widespread technologies for the sector and their share in energy consumption can be divided as follows: Boilers: 54%; Direct heating: 27%; Motors: 12%; Refrigeration: 5%; and Compressed air: 2%. The sector mainly consumes natural gas (about 67%), followed by electricity, and a small amount of oil and coal. The high heat demand of several processes, together with the emissions from electricity consumption mainly make up the food and drink manufacturing sector $CO_2$ emissions [11]. From the aforementioned, the majority of energy goes into heating activities (refer to natural gas, boiler & direct heating data mentioned before). The concurrent decarbonisation of the UK electricity grid creates opportunities to reduce emissions and non-renewable energy consumption by the electrification of heat. Pasteurisation and sterilisation activities could well be served by microwaves, ohmic heating (for conductive foods), pulsed electric fields, high pressure processing (with high volume fill ratios), and similar technologies, which in addition, impart superior nutritional and sensory attributes. Microwave-combination techniques e.g., microwave-infrared and microwave-hot air impingement techniques could be effective for baking operations. High coefficient of performance heat pumps could be useful in utilising waste heat for drying activities, while microwave combination systems could also be deployed. Membrane processes such as reverse osmosis and ultra-filtration could be promising alternatives for conventional thermal evaporation. Traditional pinch technology and mathematical programming-based heat recovery remain relevant in these systems. Improved automation would be helpful in all cases to steer individual processes and systems within the narrow limits of optimal operation. For motors and motor-operated systems the use of variable frequency drives is desirable. Waste generated during processing operations could be valorised and/or converted to energy using anaerobic digestion, fermentation, torrefaction and similar technologies. Combined heat and power systems could also be developed.

Many of the technologies may apply to niche industries within the food processing sector, whilst other technologies can have a broader impact on the sector as a whole. This study aims at identifying the technologies as well as the source of energy used by the technologies to lower energy consumption and $CO_2$ emissions, as similarly performed by Griffin et al. [13] for the pulp and paper sector in the UK. The technologies are aggregated based on their end-uses, as opposed to being product-specific, mainly due to any unavailability of data to perform such product-specific investigations.

### *1.3. Analytical Approaches Used in the Literature*

Mistry and Smith [16] researched, on behalf of the UK Department of Environment, Food and Rural Affairs (DEFRA), the techno-economics of CHP plants in the UK using livestock and other wastes as feedstock. Their model employed the internal rate of return (IRR) as a gauge of the efficiency of the investment. The model used a simple capital-cost relationship based on limited available data and different subsidy rate scenarios, to conclude that currently only 3.5% of UK dairy livestock would benefit from using on-farm integrated Anaerobic Digester (AD) and Combined Heat-Power (CHP) system, where the biogas generated from the AD is fed to the CHP on site. Similarly, Dolan et al. [17] employed an IRR approach to quantify the techno-economic feasibility of CHP plants in the UK using source isolated organic wastes, whereby the conclusion was that under the government's energy incentives, selling excess heat and electricity from CHP plants would double the IRR. Zglobisz et al. [18] used the IRR method to examine the impact of UK policies on the deployment of AD plants using food wastes as the feedstock. The major drawback of using IRR is that it considers the investment related to the technology as a stand-alone investment, which is not the case when analysing the energy performance of different economic sectors.

Other modelling approaches include the use of Life Cycle Analysis (LCA) and Life Cycle Cost (LCC), with examples such as Mohamad et al. [19], Brandao et al. [20], Schmidt Rivera et al. [21], Willersinn et al. [22], amongst others. The main benefit of the LCA and LCC modelling approaches is that they study the particular sector or product in a very detailed manner, but at the expense of extensive time consumption and the possibility of conducting parametric analyses at such detailed level. Furthermore, the lack of standardisation in LCA and LCC analyses prevents or complicates comparison studies [23].

Other studies have employed the Input-Output modelling approach. Canning et al. [5] employed the input-output analysis of the National US food system to trace the energy flow of roughly 400 industries, using data obtained from two federal sources. Zhang et al. [24] employed multi-regional input-output model to track the embodied energy for various sectors in China in 2007. Bekhet and Abdullah [25] studied the agricultural energy chain in Malaysia, in an attempt to reduce food imports, minimise energy consumption and increase the yield of the agricultural industry. The observations from these previous studies, and from others [26] have shown that input-output models provide an aggregate overview of the energy flow of the sectors in question, allowing the user to analyse inter-industry relationships, with data usually obtained from the same sources (improving data consistency) and providing weights of the individual inputs to the final results allowing the user to determine the most consequential input. However, the main drawbacks are that input-output models tend to stop at demand along the chain, and generally ignore wastes. The aggregation of data at high level obtained from input-output tables prevents the determination of process-specific energy hotspots along the chain, and the low frequency of national input-output tables from the government statistics office further introduces uncertainty into the models [26]. The latter drawback increases the difficulty in the creation of trends and model validation.

In summary, therefore, previous studies have focused mainly on using IRR, LCA, LCC and Input-Output models to determine the economic viability of food systems, considering the system as a stand-alone investment or aggregated system. However, the food industry is a complex system, and many factors such as the technologies, food demand, food diet, energy costs, food wastes and food trade, all interact with each other to create the food system. Therefore, in order to adequately study the system, a comprehensive model encompassing these various factors should be employed. This study employs the linear programming technique to analyse the energy performance of technologies used in the food manufacturing sector. Linear programming techniques have been widely used in modelling food, bioenergy and farming management decisions such as: Jones and Salter [27]; Kassier [28]; Ballarin et al. [29]; Jablonski et al. [30], where the objective function—total costs or net profit margins—can either be minimised or maximised, respectively, subject to technical, economic, environmental and resource constraints. The IEA-ETSAP TIMES (The Integrated MARKAL-EFOM System) model generator is used here to link the technologies, energy and cost parameters of the food processing sector in a partial equilibrium model, and together with a technology-rich foundation, this allows the quantification of energy mix over a multi-period time horizon [31]. TIMES uses a linear optimisation objective function which determines the least-cost pathway by minimising the total discounted system costs (or maximising the total discounted consumer and producer surplus) in order to satisfy the sector's exogenous energy demands, subject to technical, economic, environmental and resource constraints. Adopting a partial equilibrium solution strategy, the TIMES model assumes a perfect foresight as decisions are made with full knowledge of future policy, technical, economic developments and available resources [32]. A full description of the sets, attributes, variables, and equations of the TIMES model is available in Reference [32].

The simultaneous consideration of the various technologies in this TIMES model allows the determination of the real performance of the emission reduction constraints, as it accounts for the price competitiveness and the net present value (NPV) of all technologies simultaneously. This is preferred as opposed to using more isolationist methods of discounted cash flow, such as the ordinary Internal Rate of Return (IRR) method, which considers the capital and operating (including electricity/ fuel) costs of different technologies on their own, and later allowing the comparison of these technologies based on their IRR. The TIMES model provides a solution with the absolute monetary and energy quantities (i.e., NPV) of technologies, as opposed to ratios (such as the IRR), which is particularly crucial in cases where project/technology/sector sizes vary.

As mentioned in Section 1.2 and as alluded to in this section, the UK food processing industry is a highly interactive sector with both the sectors in the food chain, as well as third party sectors, particularly with the UK energy sector. In this regards, the model to be used should be able to capture this interactivity and adapt the overall model with regards to the different demands of the food sector.

## 2. Methodology

### 2.1. Modelling Approach

The UKTM (UK TIMES MODEL) is used in this paper. UKTM is a National UK energy model which comprises of various sectors, including power generation, transport, processing, residential, service and agricultural sectors. The TIMES model is a least-cost optimisation model based on life cycle costs of different technologies. It is a partial equilibrium demand-driven model assuming perfect foresight and information, and fully competitive markets, representing the entire UK energy system [33]. A more detailed explanation can be found in Reference [34].

UKTM has been used in various energy systems analyses by the UK's Department for Business, Energy and Industrial Strategy and the Committee for Climate Change [33]. Furthermore, UKTM has been used for various research outputs, including Daly et al. [35] who looked at the non-domestic upstream GHG emissions of the UK; Fais et al. [36] who studied the role of the overall UK industrial sector; Fais et al. [37] who studied the impact of technology uncertainty on future low carbon pathways; and Nerini et al. [33] who investigated the influence of myopic decision making on the model.

The UKTM in its original form studies the energy usage of its sectors at relatively high levels, which does not provide improvements to specific industries within each sector. Hence in this study, the processing sector of UKTM was further disaggregated, as shown in Figure 2, to include the food processing sector in Table 1, as well as all the technologies found in Table 2. Figure 2 shows that the Energy inputs obtained from the original UKTM are fed to the technologies used in the modified food processing sector, based on the food demand constrained to the model. The model also accounts for the use of Anaerobic Digesters and Combined-Heat Power (CHP) systems to generate onsite electricity and heat. Any excess electricity or biogas is assumed to be released to the grid, although priority is given to onsite usage.

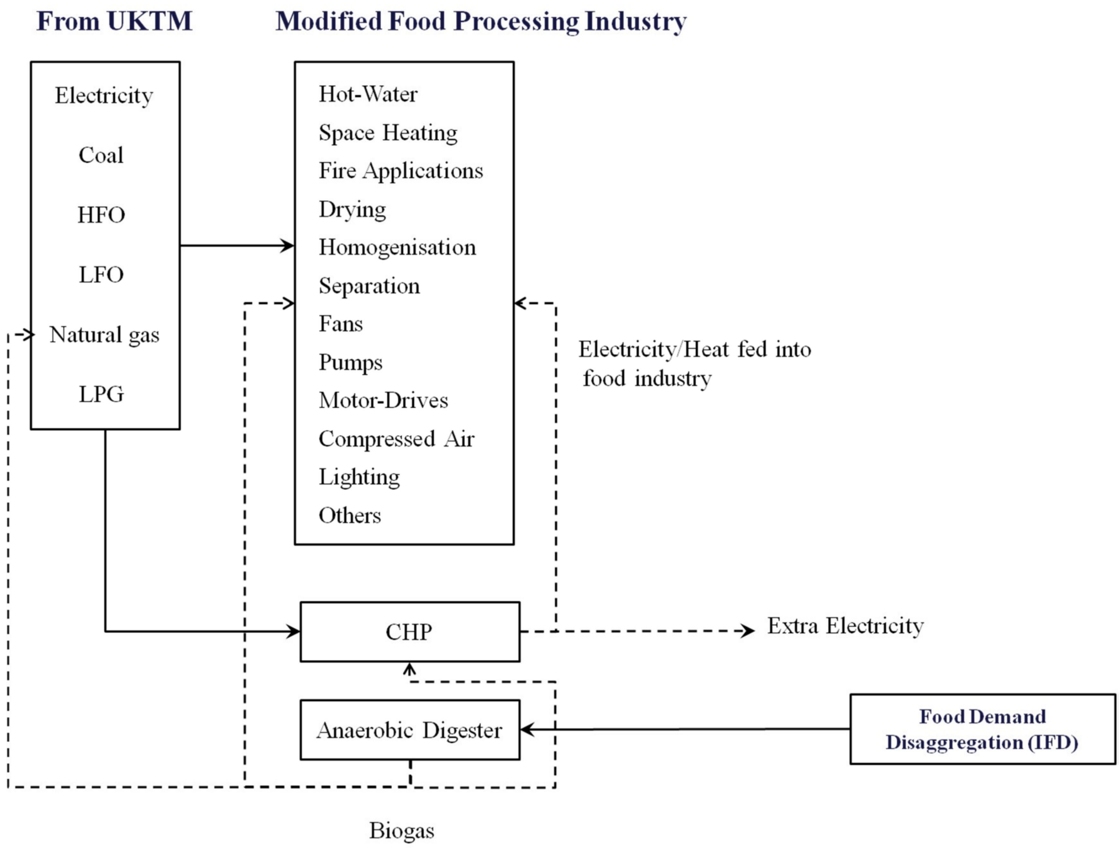



**Figure 2.** Schematic of UKTM Modified Food Processing Industry.

The simulations were divided into a 'Business As Usual' (BAU) case where there are no GHG emission constraints, and the 'Low Greenhouse' case (LGH) where the 80% GHG emission reduction target is constrained into the model. The simulation horizon is defined from 2010–2050, where 2010 is the base year. One of the crucial aspects for using this model is that it enables the performance of the sector to be analysed with the interaction of other industries, particularly the power generation industry, which is crucial in determining the embedded emissions in the energy used.

## 2.2. Model Disaggregation

### 2.2.1. Industry Disaggregation

The food manufacturing industry was disaggregated with respect to the Standard Industry Classification (SIC) codes employed by the UK Office of National Statistics (ONS). This was done in order to facilitate the corroboration of data used in the study and national statistics from the ONS. The SIC classification is as per Table 1. The main source of data for the UK is the Office of National Statistics (ONS), which publishes environmental accounts data (which include energy use and GHG emissions) and the annual business inquiry (ABI) data for specific industries.

**Table 1.** SIC2007 breakdown of food manufacturing industry [38].

| SIC2007 Reference | Class Name | Description | Energy Consumed (2015)—MToe | kT of $CO_2e$—2015 |
|---|---|---|---|---|
| SIC 10.1 | Processing and preserving of meat and production of meat products | - Processing/preserving meat and poultry meat<br>- Production of meat and poultry meat products | 0.72 | 1135 |
| SIC 10.2–3 | Processing and preserving of fish, crustaceans, molluscs, fruit and vegetables | - Processing and preserving of fish, crustaceans, molluscs, fruit and vegetables<br>- Processing and preserving of potatoes<br>- Manufacture of fruit and vegetable juice<br>- Other processing and preserving of fruit and vegetables | 0.51 | 998 |
| SIC 10.4 | Manufacture of vegetable and animal oils and fats | - Manufacture of oils and fats<br>- Manufacture of margarine and similar edible fats | 0.04 | 81 |
| SIC 10.5 | Manufacture of dairy products | - Operation of dairies and cheese making<br>- Liquid milk and cream production<br>- Butter and cheese production<br>- Manufacture of milk products (other than liquid milk and cream, butter, cheese)<br>- Manufacture of ice cream | 0.48 | 859 |
| SIC 10.6 | Manufacture of grain mill products, starches and starch products | - Grain milling<br>- Manufacture of breakfast cereals and cereals-based foods<br>- Manufacture of starches and starch products | 0.38 | 642 |
| SIC 10.7 | Manufacture of bakery and farinaceous products | - Manufacture of bread, fresh pastries/cakes, rusks and biscuits, preserved pastries/cakes, pastas, couscous, and similar farinaceous products | 0.69 | 1209 |
| SIC 10.8 | Manufacture of other food products | - Manufacture of sugar, cocoa, chocolate, sugar confectionery, condiments, seasonings, prepared meals, homogenised food preparations<br>- Processing of tea and coffee | 0.72 | 1506 |
| SIC 11.01-06 | Manufacture of alcoholic beverages | - Distilling, rectifying and blending of spirits<br>- Manufacture of wine, cider, non-distilled fermented beverages, beer and malt. | 0.72 | 1316 |
| SIC 11.07 | Manufacture of soft drinks | - Manufacture of soft drinks<br>- Production of mineral waters and other bottled waters | 0.17 | 182 |

A survey of the UK food manufacturing industry by the Food and Drink Federation (FDF) reveals the energy consumption distribution to be as shown in Figure 3. We observe that heat generation from gas boilers represents a significant proportion (56%) of the energy used in the industry, followed by direct gas heating (22%), natural gas Combined Heat and Power CHP (14%), grid electricity (7%) and biomass direct heating (1%). These data have been integrated into the model to represent the base year technologies, and enable the model to build on this database to predict future technology mix in the industry, based on the linear optimisation model described in Section 2.1.

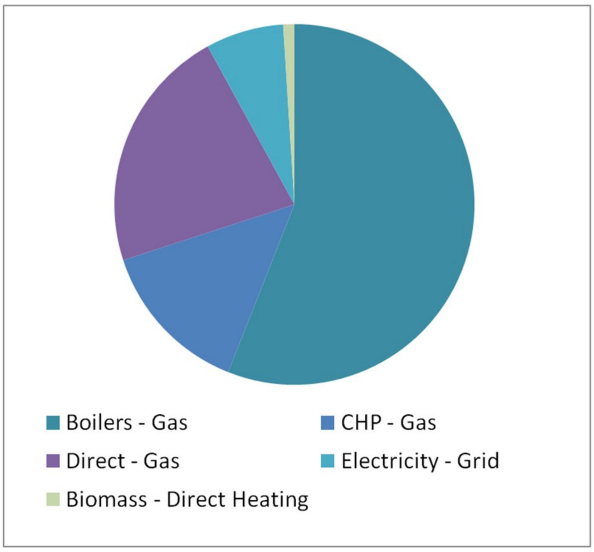



**Figure 3.** Energy consumption (2010–2015) ratio in the UK food manufacturing industry [39].

#### 2.2.2. Technology Disaggregation

The UKTM power generation sector consists of electricity generated from fossil fuels (coal, natural gas and oil), renewable energy sources (wind, solar, hydro, biogas and biomass) and nuclear energy. These resources are fed into various types of technologies including combustion, gas turbines, onshore/ offshore wind turbines and small/large scale PV plants. UKTM consists of a large database of technologies which includes the efficiencies, capital costs, operating costs and lifetimes of these technologies. The database has been developed in collaboration with the UK Department for Business, Energy and Industrial Strategy (BEIS) [40], to enable an accurate representation of the energy generation sector of the UK. Refer to the schematic in Figure 2 for more information.

The UK food manufacturing module, developed in this study and incorporated in UKTM, consists of a variety of technologies associated with different food types and SIC Classifications, as shown in Table 2. The technologies include both current and novel technologies with potential application in the future.

**Table 2.** List of Food Manufacturing technologies investigated.

| Technologies | Attributes | Fuel Source | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Coal | Fuel Oil | Gas Oil | Natural Gas | Burning Oil | LPG | Electricity | Biomass |
| Boilers | Efficiency | 78.8% | 85.9% | 78.8% | 80.0% | 78.8% | 78.8% | 95.0% | 80.0% |
| | CAPEX | 737 | 123 | 134 | 104 | 134 | 134 | 187.2 | 737 |
| | OPEX | 18 | 6 | 7 | 3.5 | 7 | 7 | 6.3 | 18 |
| Direct-fired Ovens | Efficiency | 31.5% | 34.4% | 31.5% | 32.0% | 31.5% | 31.5% | 41.2% | 31.5% |
| | CAPEX | 2858 | 627 | 684 | 510 | 683 | 683 | 3060 | 2858 |
| | OPEX | 70 | 31 | 34 | 17 | 34 | 34 | 30.6 | 70 |
| Indirect-fired Ovens | Efficiency | 14.8% | 16.1% | 14.8% | 15.0% | 14.8% | 14.8% | - | 15.0% |
| | CAPEX | 1340 | 294 | 321 | 239 | 320 | 320 | - | 1361 |
| | OPEX | 149 | 66 | 73 | 36 | 73 | 73 | - | 147 |
| CHP | Overall Efficiency | 67% | 73% | 67% | 68% | 67% | - | - | 67% |
| | Heat Power Ratio (CHPR) | 2.9 | 2.6 | 2.5 | 1.6 | 2.5 | - | - | 2.9 |
| | CAPEX | 1700 | 404 | 382 | 5035 | 382 | - | - | 1700 |
| | OPEX | 15 | 4 | 3 | 46 | 3 | - | - | 15 |
| Conventional Air Drying | Efficiency | 69% | 75% | 69% | 70% | 69% | 69% | 57% | 69% |
| | CAPEX | 893 | 160 | 166 | 140 | 166 | 167 | 248 | 134 |
| | OPEX | 22 | 8 | 8 | 4 | 8 | 8 | 1.2 | 21 |
| Motor-Drives Application | Efficiency | - | - | - | - | - | - | 93% | - |
| | CAPEX | - | - | - | - | - | - | 56 | - |
| | OPEX | - | - | - | - | - | - | 3 | - |
| Pumps | Efficiency | - | - | - | - | - | - | 79% | - |
| | CAPEX | - | - | - | - | - | - | 220 | - |
| | OPEX | - | - | - | - | - | - | 12 | - |
| Compressed Air | Efficiency | - | - | - | - | - | - | 79% | - |
| | CAPEX | - | - | - | - | - | - | 590 | - |
| | OPEX | - | - | - | - | - | - | 30 | - |
| Walk-in Chilling | Efficiency | - | - | - | - | - | - | 345% (COP) | - |
| | CAPEX | - | - | - | - | - | - | 59 | - |
| | OPEX | - | - | - | - | - | - | 3 | - |
| Walk-in Freezing | Efficiency | - | - | - | - | - | - | 172% (COP) | - |
| | CAPEX | - | - | - | - | - | - | 95 | - |
| | OPEX | - | - | - | - | - | - | 10 | - |
| Homogenisation/ Centrifugal Separation | Efficiency | - | - | - | - | - | - | 81% | - |
| | CAPEX | - | - | - | - | - | - | 278 | - |
| | OPEX | - | - | - | - | - | - | 13.84 | - |
| Fans | Efficiency | - | - | - | - | - | - | 79% | - |
| | CAPEX | - | - | - | - | - | - | 270 | - |
| | OPEX | - | - | - | - | - | - | 15 | - |
| Anaerobic Digester (AD) | Efficiency-Energy | - | - | - | - | - | - | - | 60% (biogas generated/energy content of feedstock) |
| | CAPEX | - | - | - | - | - | - | - | 17.13 |
| | OPEX | - | - | - | - | - | - | - | 1.2 |
| Lighting-Metal Halide | Efficiency (Lm/W) | - | - | - | - | - | - | 95 | - |
| | CAPEX | - | - | - | - | - | - | 13 | - |
| | OPEX | - | - | - | - | - | - | 0.64 | - |
| Lighting-Sodium | Efficiency (Lm/W) | - | - | - | - | - | - | 105 | - |
| | CAPEX | - | - | - | - | - | - | 11 | - |
| | OPEX | - | - | - | - | - | - | 0.54 | - |
| Lighting-Fluorescent | Efficiency (Lm/W) | - | - | - | - | - | - | 100 | - |
| | CAPEX | - | - | - | - | - | - | 87 | - |
| | OPEX | - | - | - | - | - | - | 4 | - |
| Lighting-LED | Efficiency (Lm/W) | - | - | - | - | - | - | 125 | - |
| | CAPEX | - | - | - | - | - | - | 65 | - |
| | OPEX | - | - | - | - | - | - | 0.64 | - |
| Freezing-Batch Air | Efficiency | - | - | - | - | - | - | 154% (COP) | - |
| | CAPEX | - | - | - | - | - | - | 144 | - |
| | OPEX | - | - | - | - | - | - | 38 | - |
| Freezing-Continuous | Efficiency | - | - | - | - | - | - | 122% (COP) | - |
| | CAPEX | - | - | - | - | - | - | 225 | - |
| | OPEX | - | - | - | - | - | - | 59 | - |

**Table 2.** *Cont.*

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Freezing-Vertical Plates** | Efficiency | - | - | - | - | - | - | 167% (COP) | - |
| | CAPEX | - | - | - | - | - | - | 104 | - |
| | OPEX | - | - | - | - | - | - | 10 | - |
| **Heat Pumps (Air-Source)** | Efficiency | - | - | - | - | - | - | 220% | - |
| | CAPEX | - | - | - | - | - | - | 113 | - |
| | OPEX | - | - | - | - | - | - | 12 | - |
| **Heat Pumps (Ground Source)** | Efficiency | - | - | - | - | - | - | 250% (COP) | - |
| | CAPEX | - | - | - | - | - | - | 141.25 | - |
| | OPEX | - | - | - | - | - | - | 15 | - |
| **Heat Pumps (Water Source)** | Efficiency | - | - | - | - | - | - | 500% (COP) | - |
| | CAPEX | - | - | - | - | - | - | 282.5 | - |
| | OPEX | - | - | - | - | - | - | 30 | - |

Note: 1. CAPEX are given in £m/GW_output, or £m/GWe_output for CHP systems, and OPEX are given in £m/PJ_output, or £m/PJe_output. 2. The refrigerant leakage rate from refrigeration equipments was assumed to be 10% annually, as per industry average. 3. The efficiencies of heat pumps are obtained from studies and surveys conducted by the Carbon Trust [41]. 4. Drying efficiencies refers to the PJ of moisture removed per PJ of energy input, and was obtained by multiplying the efficiency of the boilers with the fan for Conventional air drying.

The list of technologies detailed in Table 2 comprise the main technologies used as inputs to the Food Manufacturing model. The list is a working database, whereby, as information is obtained on new technologies, they can be added to ensure an updated list of technologies in the model. The model then employs these technologies to determine the cheapest combination of technologies which can satisfy the demand and emission reduction targets. The technology discount rate was set at the UK technology average rate of 3% [42], and the degression rate at 5% as per the UK Historical average.

**Table 3.** Amount of Waste generated by the sector and respective biogas production.

| | Mt of Wastes (Food, Effluents, Sludge) per Mt of Food Demand | | | Biogas PJ/Mt of Waste |
|---|---|---|---|---|
| | **2010** | **2015** | **>2025** | |
| **Meat sector** | 0.381 | 0.349 | 0.319 | 14.20 |
| **Fish, Fruits and Vegs** | 0.157 | 0.123 | 0.096 | 4.12 |
| **Grains and starch products** | 1.00 | 0.976 | 0.952 | 5 |
| **Animal and vegetable oil Products** | 0.4 | 0.383 | 0.369 | 14.20 |
| **Bakery products** | 0.4 | 0.323 | 0.261 | 7.391 |
| **Dairy products** | 0.4 | 0.384 | 0.370 | 14.20 |
| **Other food items** | 0.5 | 0.365 | 0.267 | 7.391 |
| **Alcoholic drinks** | 0.017 | 0.0169 | 0.016 | 0.00112 |
| **Soft drinks and water** | 0.050 | 0.0472 | 0.0443 | $6.124 \times 10^{-5}$ |
| **Animal feed** | 0.381 | 0.3653 | 0.352 | 7.391 |
| **Tobacco** | 0.029 | 0.0279 | 0.0269 | 7.391 |

Note: referring to Table 3, the energy content of the biogas is based on the average calorific content of representative products in the sector. For the cases of bakery, other food, animal feed and tobacco, the values PJ/Mt of waste have been assumed similar to the average of the other food items. The effects of reduction in food wastes in food manufacturing have been accounted for with respect to the Courtauld commitment trends as set out by WRAP [43].

In UKTM, if a technology capacity investment rate is unconstrained, the model can decide to invest any capacity of the technology at any time period. This does not necessarily represent reality as technology investment depends on the availability, the perception of the benefits associated with the technology and the anticipated investment rate of a technology. Hence, in order to make the model more accurately represent reality in new technology adoption in specific industries, annual capacity growth constraints have been applied to limit the rate of adoption of technologies. This specifically refers to the rate of growth of a technology's capacity (Mt in the case of AD) in year 'y', with respect to the previous year '$y-1$', i.e., $\text{Cap}_y = \text{Cap}_{y-1} \times$ growth-rate.

For instance, the average growth rate of AD in food industries was estimated from the surveys and workshop conducted by Parson Brinckerhoff, DECC and BIS as part of the 2050 Industrial roadmaps (GOV.UK roadmaps, 2017). This report does not explicitly refer to AD but to bioenergy, and due to lack of information, the bioenergy data was also employed for AD. The maximum applicability rate of bioenergy is 50% of all food industry. However, only a maximum of 33% of applicable industries has surveyed to be prone to adopt bioenergy. Hence, the share of industries prone to AD is 16.5%, producing a growth rate of 1 + (16.5/36) = 1.005 (where 36 is the number of years simulated by the group of consultants). The growth rate is used in UKTM to limit the adoption of AD in the chain, to represent real-world penetration of a technology. It should be noted that this study explicitly models scenarios which are not influenced by external government incentives. The results obtained are thus obtained by natural market and technological forces influencing the overall discounted costs of the linear UKTM model employed in this paper.

#### 2.2.3. Demand Disaggregation

The demand for the food manufacturing sector was also divided according to the SIC classifications used throughout this study. Demand is assumed to increase with the expected growth rate of the UK population, based on ONS estimates as shown in Figure 4 [44].

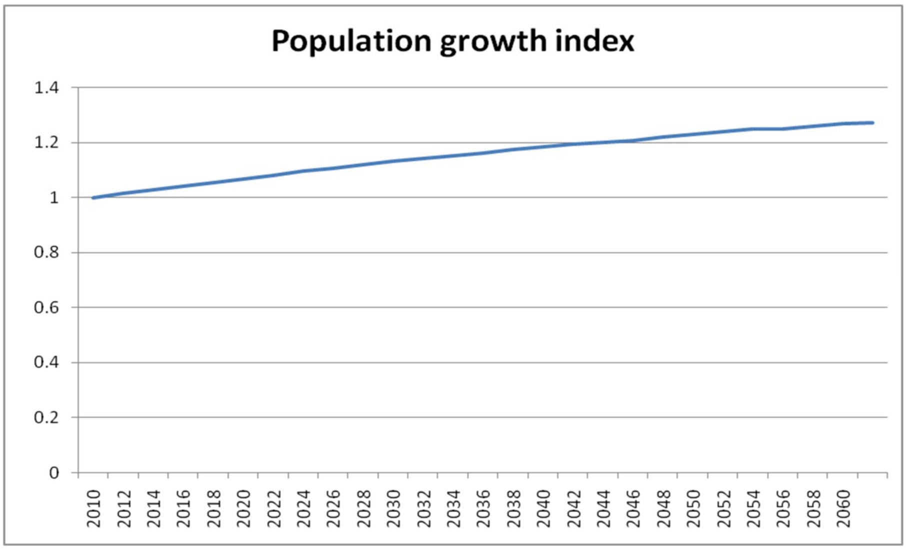



**Figure 4.** Population growth index [44].

The analysis assumed that the food mix and dietary preferences of the population remain similar to that of the base year through the simulation horizon. This assumption may not remain entirely valid for the modelling horizon but provides a starting point in investigating and understanding the factors that influence the choice of technologies in the UK food manufacturing sector and their potential impact. However, any shift from processed to no or minimally processed foods in the future will have an impact, and this will be considered through scenario analysis studies that will be carried out and reported later in the project.

Another assumption made in the study is that food Import/Export ratios will remain the same over the simulation horizon as those of the base year. Again, international market forces and policies that may be adopted by the UK government as a result of Brexit will have an impact on this. The influence of any changes in the import/export ratios on the impact of technologies that may be adopted in the future will be considered in future work in this project.

## 3. Simulation Results and Analysis

### 3.1. Overview of Simulation Results

Figure 5 shows the variation of the energy consumption and emissions of the food manufacturing sector in 2050 based on the Business As Usual (BAU) scenario where the projections do not include any constraints on GHG emissions, but rather, the food industry uses the lower-cost technologies and energy vectors for food production to satisfy demand. The shaded areas represent the energy consumption in PJ, whilst the dotted line represents the reduction in GHG emissions, relative to 1990 levels. It should be noted that the CO2e emissions rate at the start of the modelling period in 2010 is 60% that of 1990, based on estimates of reductions achieved by the industry between 1990 and 2010, provided by the Food and Drink Federation [45]. It can be seen from Figure 5 that in the BAU scenario, reduction in $CO_2$ emissions will reach 28% of 1990 levels, a reduction of 32% over the simulation period. This demonstrates that even without the imposition of GHG emission constraints on the food industry, it will be economically more beneficial for the industry to migrate from fossil to low carbon fuel and technologies. It can be observed from Figure 5 that this migration will take place through the replacement of LPG, LFO, Kerosene, HFO, Coal and Natural gas by biogas and biomass. Biogas is then primarily used to produce electricity through CHP technologies as shown in Section 3.3. In this case, the benefits arise from the use of biogas and biomass which are produced from wastes, as shown in Table 3, generated in the food factories, as opposed to having to purchase energy feedstock from the market.

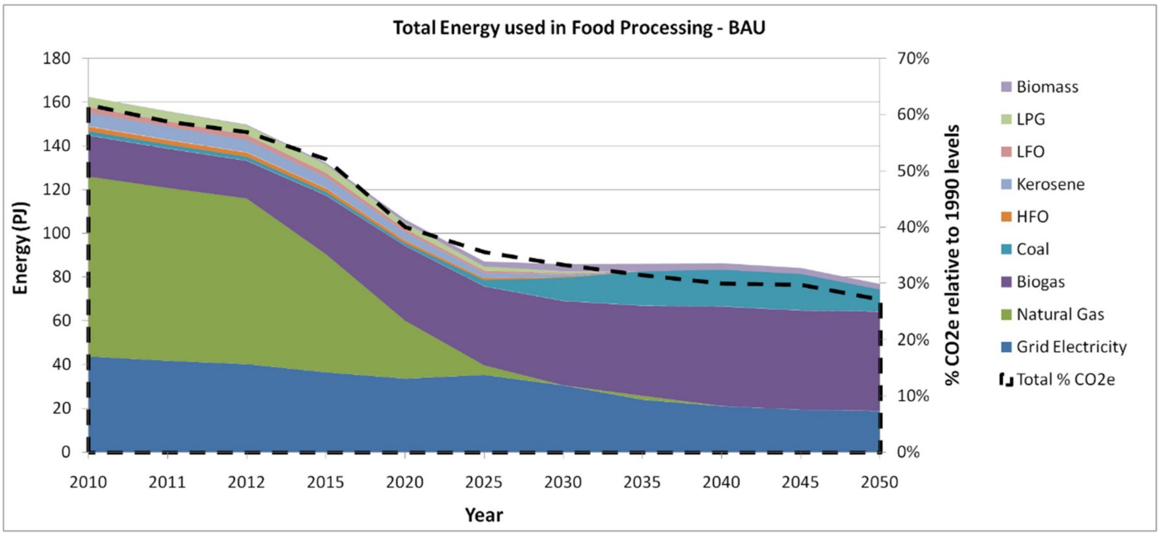



**Figure 5.** Energy consumption and emissions for the Business As Usual (BAU) scenario Consumption.

Figure 6 shows the predicted variation of energy consumption and emissions for the period to 2050 for the 80% GHG reduction target, relative to 1990 levels. It can be observed that the overall reduction in energy consumption will be similar to the BAU case, partly because the energy requirements of the food industry are the same for both the BAU and 80%-GHG cases (due to same food demand), and also because the BAU case already achieves a least overall cost (capital and operation costs) solution from sourcing energy and adopting efficient technologies, mainly through the adoption of AD technology. The reduction in GHG emissions in 2050 relative to 2010 will, however, be higher than the BAU case, at 49%, compared to the 32%. This reduction shows that although the UK reduction is mandated at 80%, relative to 1990 levels, the food industry has the potential to exceed this reduction to a value of 89%, mainly because of the emissions associated with the consumption of grid electricity is reduced (see Figure 7) and the availability of onsite feedstocks to generate biogas. Also (to a lesser extent), the improvement relative to the BAU case lies in the elimination of coal and biomass feedstock (with their respective combustion-related emissions) and replacement with mainly biogas, and grid electricity. (Note that the feedstock considered for AD in UKTM includes all organic wastes such as food, sludge, and effluents, and excludes the feedstock that goes to animal feed. The next sections therefore focus on the impact of electrifying the food manufacturing industry, and the use of Biogas generated from wastes from the UK food manufacturing sector.

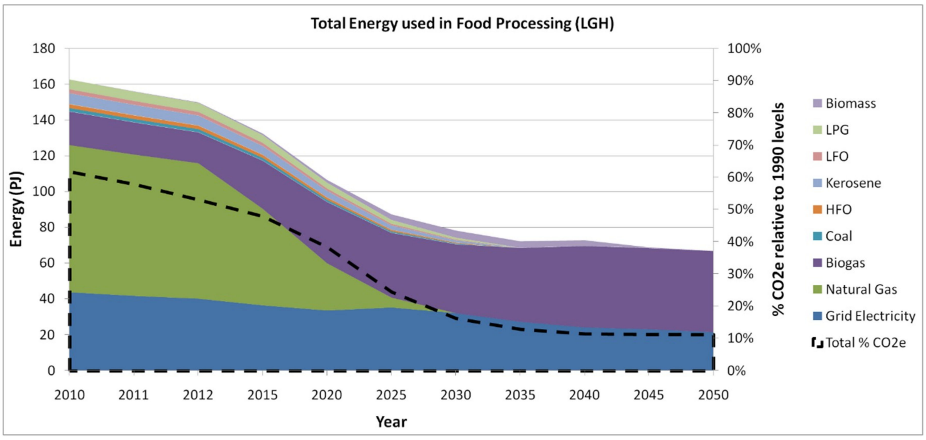



**Figure 6.** Energy consumption and emissions for the 80% GHG reduction scenario. (Note that legends and colours in Figures 5 and 6 are aligned in sequential order for ease of interpretation).

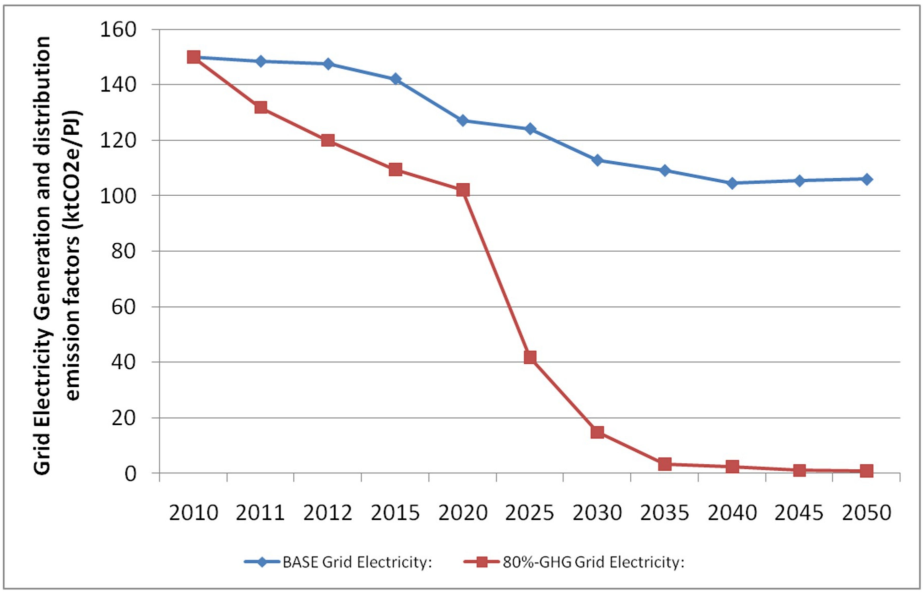
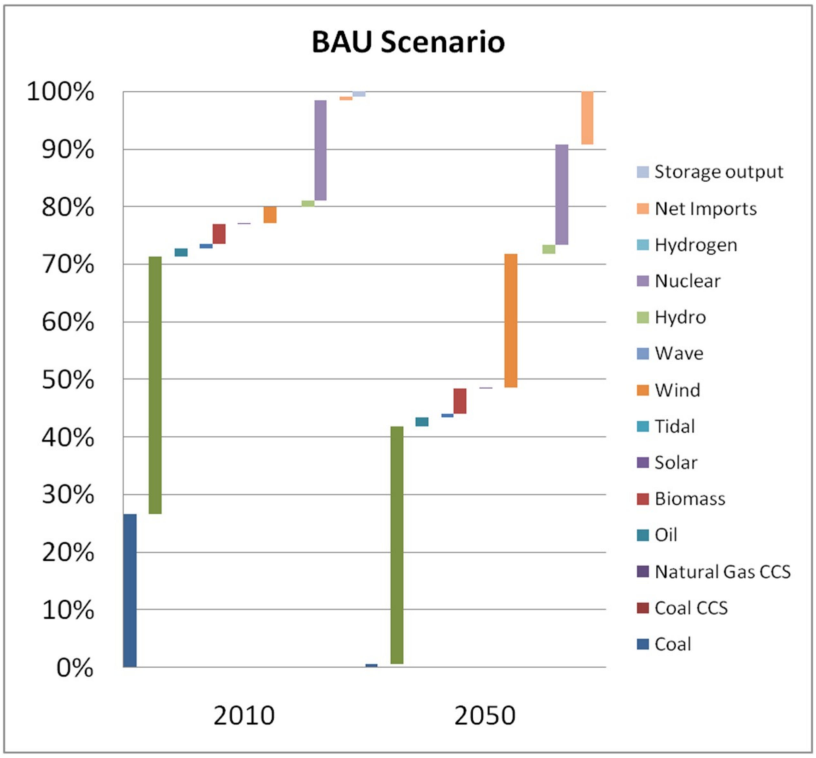


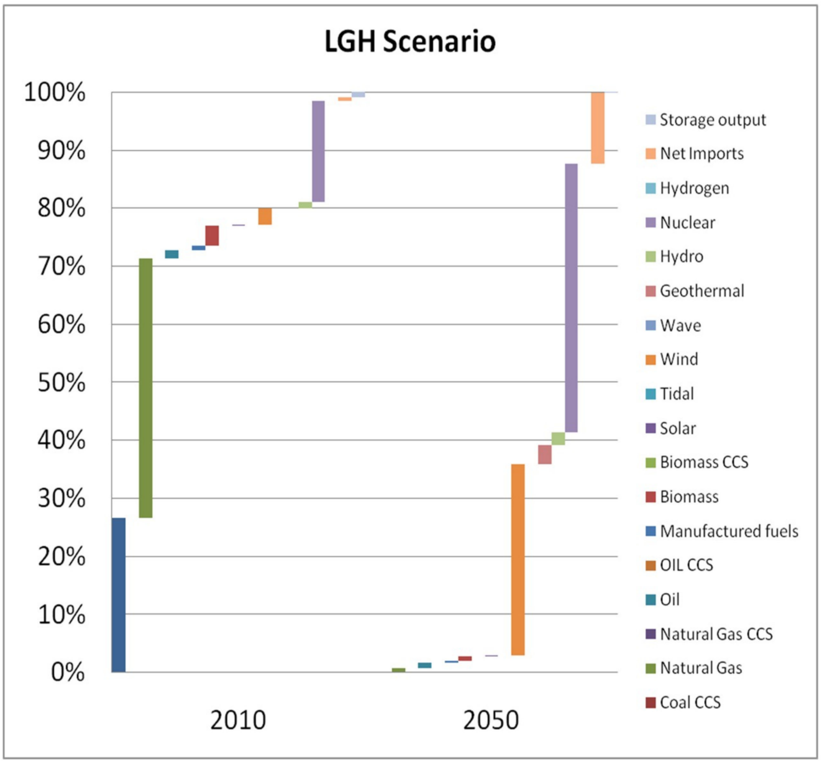

**Figure 7.** Changes in emission factors from Grid Electricity.

### 3.2. Impact of Electrifying the Food Manufacturing Sector

The main difference between the BAU and the LGH cases arises from the fact that the emissions associated with grid electricity are lower in the LGH scenario, as obtained from UKTM. In the UK, power generation produces the highest amount of emissions (36% of all emissions) [11] and also has a high potential of emissions reduction due to the current dominance of fossil fuels. In this regard, the UKTM model has shown that with the imposition of the 80% GHG reductions, associated carbon emission factors with power generation and grid electricity will also change as shown in Figure 7. This results from a drastic change in the fuel sources used to generate electricity, i.e., a drastic shift from fossil fuel to renewable and nuclear sources of energy, as shown in Figure 8.




(**a**)




(**b**)

**Figure 8.** (**a**) Fuel source for generating electricity in the BAU case; (**b**) fuel source for generating electricity in the LGH case. (Note that legends and colours in Figure 8 are aligned in sequential order for ease of interpretation).

### 3.3. Impact of Using Biogas Generated from Waste

The use of organic wastes (food, sludge, effluents) in the food industry is observed to contribute significantly to energy production. These refer to wastes that exclude the current ratio and are re-used, such as in animal feedstocks.

Of all organic wastes produced in the industry, 92% of all waste feedstocks go to AD and are consumed through CHPs, whilst the remaining 8% are dried and processed to be burned in biomass boilers. The trend in the use of Biogas is shown in Figure 9. However, towards the end of the simulation horizon, biogas produced is solely used for the purpose of CHP. We note that the other technologies primarily produce heat as the secondary energy, and hence are valid only for heat requiring processes. The fact that the CHP technology can produce both heat and electricity makes it a very versatile technology, and by using biogas makes it an even more overall energy-to-cost-efficient technology. In this regards, CHP technology is the preferred method to employ biogas in the model as the simulation progresses. The performance of CHPs is further explained in Section 3.4.

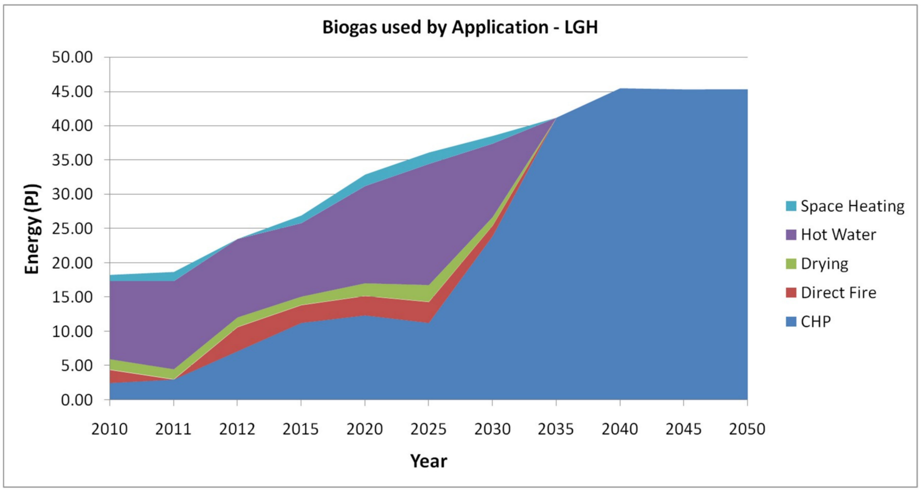
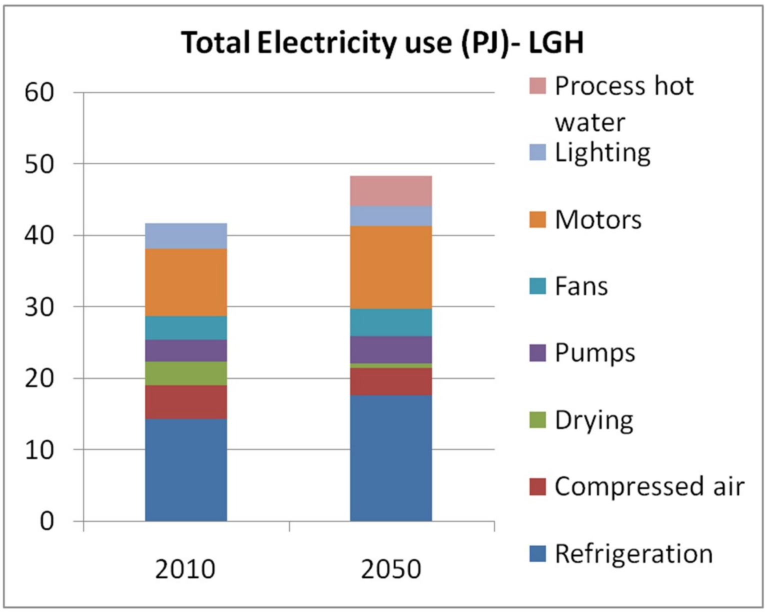


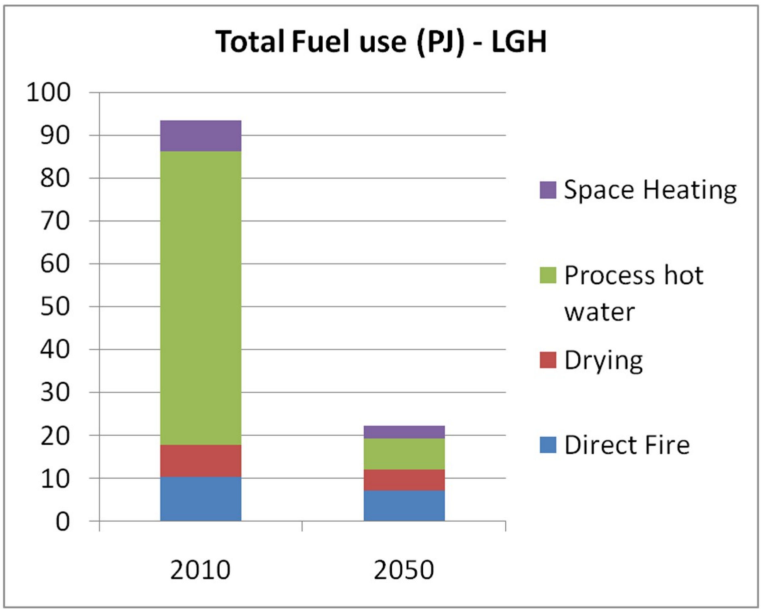

**Figure 9.** End-Use of biogas generated from anaerobic digesters in the LGH case. (Note that legends and colours in Figure 9 are aligned in sequential order for ease of interpretation).

### 3.4. Electricity and Heat use in the LGH Case

Figure 10 show the progression of the end-uses of electricity and fuel by the food manufacturing industry. Note that heat refers to the use of fuel to generate heat directly (such as gas boilers), or through the use of auxiliary heat (such as in CHPs), as opposed to heating applications performed through the use of electricity (such as electric ovens or electric boilers).




(**a**)




(**b**)

**Figure 10.** (**a**) Electricity end-uses in the LGH case; (**b**) fuel end-uses in the LGH case. (Note that legends and colours in Figure 10 are aligned in sequential order for ease of interpretation).

We observe from Figure 10 that the use of electricity increases, whilst heat reduces over the simulation horizon for the LGH case, even though food demand is increasing. This is mainly due to the industry adopting more efficient technologies such as CHPs and air-source heat pumps, which have considerably shifted the use of traditional heat (i.e. primary burning of fuel to produce heat), to secondary sources of heat through the use of electricity to produce heat. This has resulted in an apparent shift of energy end-use from heat to electricity as shown in Figure 10. These observations are in accordance with conclusions drawn by the Climate Change Committee and BEIS [40], which suggests that 2050 heat will be largely by air-source heat pumps for the majority of the building stock, and this study further shows that on the industrial level, CHPs will also be prominent.

Figure 11 shows the total energy generated from the use of CHP (particularly gas turbine CHPs which produce high temperature waste heat, as opposed to internal combustion engine, for instance) which consumes biogas to produce heat and electricity.

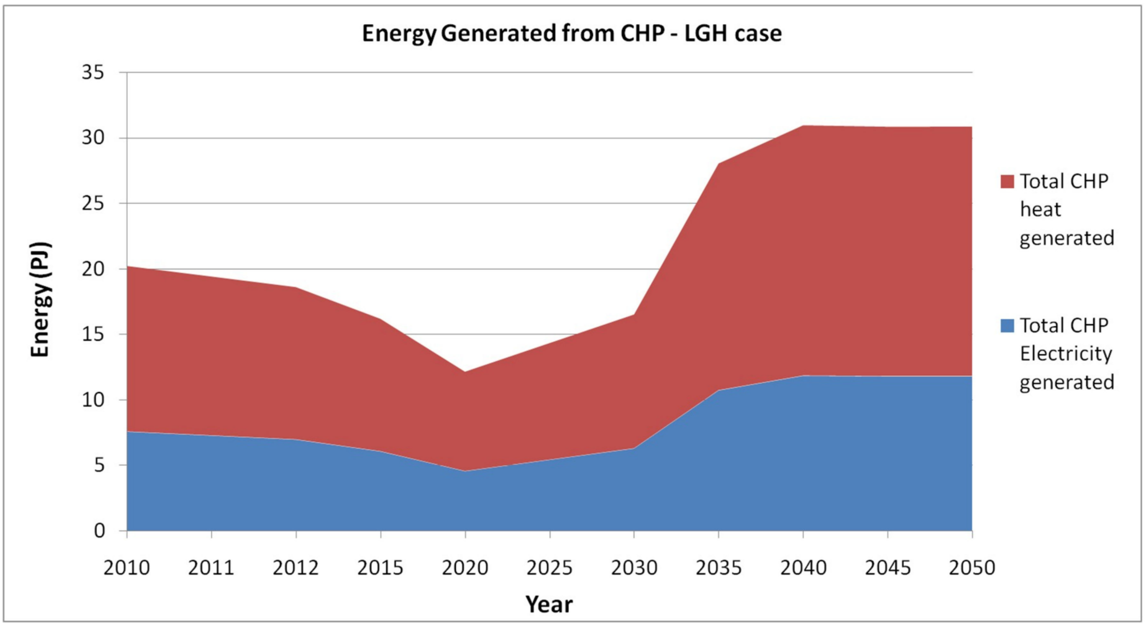



**Figure 11.** Energy generated from CHP through the use of natural gas and biogas.

Figure 11 shows a significant increase in the generation of heat and electricity from CHP technologies in the industry. The source of fuel is both natural gas and biogas until 2030, and thereafter, only biogas is used in CHPs as shown in Figure 4. The dip in energy produced between 2020 and 2030 is due to the base year capacity of CHP gradually reducing over its lifetime of 25 years from the base year, and the model gradually having to install new CHP capacity until 2035, where all the base CHPs have to be replaced. The simulation results have shown that in a UK economy constrained by the 80% reduction in GHG emissions, the food manufacturing sector will become heavily dependent on Gas Turbine CHPs, fuelled by biogas, and electricity from a decarbonised grid.

## 4. Conclusions

This study investigated the energy and technology mix of the food processing industry in the UK in order to provide a benchmark where policy makers, industry leaders and factory operators can base decisions to invest in order to enable the sector to comply with the 80% emissions reduction by 2050, relative to the 1990 levels. The results show that the industry will have to change drastically to using approximately 30% decarbonised grid electricity and 70% biogas, as opposed to the current ratio of 92% natural gas and 7% grid electricity. This is particularly due to the fact that the majority of UK emissions come from power generated from fossil fuels, and in that respect the power generation sector will have to be decarbonised. The model predicts a reduction in carbon factors of grid electricity, which will in turn translate to a lower embedded carbon emissions in the food processing industry using grid electricity.

The results also show that the use of fossil fuels and natural gas will be completely reduced towards 2050 for both the base and LGH cases, and partly replaced by grid electricity, and heat and electricity generated on-site from CHP using biogas from AD with organic waste as feedstock. Of all wastes produced, 92% of wastes will go to AD and be consumed through CHPs, whilst the remaining 8% is dried and processed to be burned in biomass boilers. All biogas generated from AD will tend to go to CHPs towards 2050 to generate both heat and electricity. This model has shown that in a low greenhouse gas UK economy, the food processing sector will become heavily dependent on Gas Turbine CHPs, fuelled by biogas, and electricity from a decarbonised grid. This will involve particular investments into anaerobic digesters, CHPs, heat pumps and general electrification of the industry. The model has calculated a total discounted investment cost of £4.1tn for the BAU case and £4.6tn for the LGH case over the entire simulation horizon. The results from this paper are in line with the observations made from focus group and modelling works carried out by BEIS (then DECC) [11]) which showed that grid decarbonisation, electrification of heat and biomass/biogas used in CHPs should become the prominent technologies to enable the UK food Manufacturing industry to meet its emission targets.

It should be noted, however, that the UK is currently in a turbulent economic situation with Brexit, and this adds another degree of complexity in modelling the economy. However, the purpose of this research is to develop a model allowing parametric simulations and analyses to develop trends under different economic, trade and dietary situations, and hence develop a basis for relevant policy makers to make decisions.

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**Conflicts of Interest:** The authors declare no conflicts of interest.

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