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Healthcare with Wireless Communication and Smart Meters

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***Abstract*—** Smart health is an essential domain within smart cities. Internet-assisted communication with medical practitioners is now widely used. This is important for elderly or disabled patients, who may not be able to travel but have inexpensive and simple internet access they can take advantage of with video-call consultations. However, smart health based on the Internet of Things (IoT) and smart meters is not without its challenges. This paper reviews the benefits and challenges of innovations in healthcare, with emphasis on IoT and smart meters. A top-level smart health with smart meter system design flowchart is given, and the component and module diagram is proposed.

***Index Terms*—** Smart health, smart meter, data analytics, IoT

I. Introduction

MORE than 20 years ago, the World Health Organization (WHO) defined telemedicine as the delivery of healthcare services, by all healthcare professionals using information and communication technologies in the interest of advancing the health of individuals and their communities [1]. Smart healthcare can be defined as using mobile and electronic technology for better disease diagnosis, improved treatment, and enhanced quality of life for patients.

The COVID-19 pandemic has resulted in extensive concern and economic catastrophe for consumers and businesses across the globe. Indeed, several foundational shifts are arising from and being exacerbated by the spread of COVID-19. Examples include the push for interoperable data and data analytics use. In [2], issues driving change in the healthcare sector were examined, with questions and actions suggested to health leaders for consideration.

Smart healthcare, which measures users' living conditions and health status using small sensing devices and collecting their data over a network in daily life, is a new trend. The technologies of low power large-scale integrated circuits (LSI), wireless communications and small vital sensors have been rapidly advanced. It implies that the time-to-market of a wearable vital monitoring device has certainly been reduced. This device could be an effective tool for realising a smart healthcare world where people can enjoy a safe and healthy life with unconscious medical ICT support [3].

The key factor driving smart healthcare market growth is the growing demand for remote health monitoring. The smart healthcare market is expected to grow at a CAGR of 24.11% between 2019-2024. Internet of Things (IoT) in healthcare technologies, popularly known as IoMT (Internet of Medical Things), is one major technological innovation added to the healthcare industry [4].

In the UK, the number of people living with progressive neurodegenerative disorders, such as dementia, is increasing. Currently, there are no technological solutions capable of monitoring the progression of dementia 24 hours a day, seven days a week. Though telehealth solutions are available, they are often expensive, intrusive, and increase the cost of overall standard care plans. Consequently, large-scale usage within NHS trusts is not feasible.

However, with the introduction of the smart metering infrastructure, health and social care are possible. Smart meters can continually monitor household electricity consumption, capture the detailed habits of an individual's interactions with electrical devices, and identify anomalies or changes in a person's routine to correlate with disease progression.

II. Technology used in Healthcare

In combination with cloud computing, mobile edge computing, big data, artificial intelligence, and blockchain - 5G will drive upgrades and transformations in medical information systems and remote medical platforms. Cloud computing and edge computing encourage cost savings [5], scalability, and system flexibility; the demand for cloud computed healthcare solutions has grown exponentially.

Some technologies such as artificial intelligence (AI), Augmented Reality (AR), and the IoT have been around for years. AI can be used to collect data from searching histories. With the re-elaboration of big data, machine learning can save lives, and enable a diagnosis to be made even before human intervention. AI methods such as convolutional neural networks have been used to diagnose diseases [6]. Augmented reality is the use of displays, cameras, and sensors to overlay digital information in the real world. The global AR, virtual reality (VR), and mixed reality (MR) markets are forecasted to reach 30.7 billion US dollars total in 2021, rising to close to 300 billion US dollars by 2024 [7]. IoT applied to medicine requires the use of objects integrated by sensors that communicate with each other and exchange information. This exchange of information is necessary to predict disease diagnosis in advance and prevent illness.

A. Internet of Things

The consumer electronics industry is advancing at an astounding rate while smart health is one of the most important topics in consumer electronics and consumer technology [8]. There is a large increase in the share of electronic devices produced around the world that are manufactured with internet connectivity. IoT is an expansive network of "things" or devices that are connected to the internet, which facilitates their intercommunication. Fig. 1 shows the number of IoT connected devices worldwide from 2020 to 2030 [9].

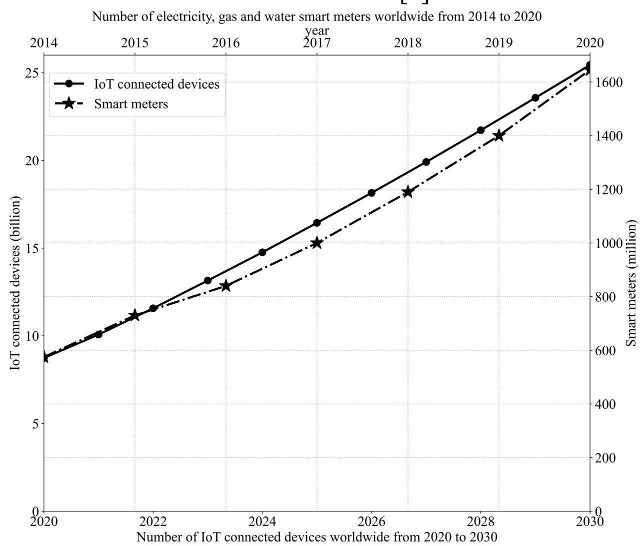


Fig. 1. Number of IoT connected devices worldwide from 2020 to 2030 and the number of electricity, gas, and water smart meters worldwide from 2014 to 2020.

The IoT has opened up a world of possibilities in the treatment and diagnosis of disease [10]. When connected to the internet, ordinary medical devices can collect invaluable data, give extra insight into disease progression and trends, enable remote care, and generally give patients more control over their lives and treatment.

IoT will significantly transition us into “smart cities.” With the help of sensors, IoT will make our cities more efficient, cost-effective, and safer places in which to live. Of course, much of this is a long way off. It would require some of our existing infrastructures to be replaced. With a projected global growth in IoT applications, it is expected that most industries will be impacted by IoT, most notably the healthcare sector.

Healthcare providers need to be able to upload and download high-definition images, like radiological scans, to traditional medical centres such as hospitals to better treat patients. With the emergence of new 5G technologies, healthcare-related IT services and applications are set to become better connected than ever, resulting in an enormous impact on both healthcare providers and patients alike. But right now, COVID-19, as a global emergency, is bringing the urgency of medical IoT deployments to the front line.

Recent modern IoT devices and network technology support this due to high-speed gigabit-class LTE connections, dual path wireless modems with link redundancy and traffic load management. Gigabit LTE links give remote doctors reliable and secure at-home and remote office connections that can provide the bandwidth required to enable real-time video and extremely large data files.

Any large scale IoT deployment will likely have a variety of new and legacy devices that use different technologies and serve multiple purposes. It is important to discuss the importance of connectivity and industry standards. The protocol stack chosen for device management can make or break a project. When it comes to protocols, regulated open standards are the safest option. There are many standards in place or under development to promote and give recommendations, and guidelines for IoT applications - some of these are related to smart healthcare.

TABLE I
PERCENTAGE OF THE WORLD POPULATION OVER 65 BETWEEN 2020 TO 2050
SOURCE: UN WORLD POPULATION PROSPECT 2008

Year	Of world population (%)
2000	6.8
2010	7.7
2020	9.2
2030	11.7
2040	14.1
2050	16.2

Data networks are used throughout the industry. It would make tremendous economic sense to enable any sensor to communicate using any data network. Smart sensors make this a reality. IEEE 1451 is a set of smart transducer interface standards describing a set of open, common, network-independent communication interfaces for connecting transducers to microprocessors, instrumentation systems, and control/field networks [11].

IEEE P2668 is a standard for the maturity index of the internet of things: Evaluation, grading and ranking. The scope of this standard is to measure the maturity of objects in an IoT environment, namely IoT objects which shall represent things or devices or the entire system, such as health infrastructure [12].

B. Smart Meters

Smart meters not only measure power and energy but also provide the communication gateway features to pass the information from the network gateway of utilities’ peak demand requests to the consumers’ appliances, such as heating and air-conditioning systems. Alternatively, it can be done with a data concentrator via the Automatic Metering Infrastructure (AMI) wireless network and back to the utilities through Wide Area Network (WAN) [13]. Fig. 1 shows the number of electricity, gas, and water smart meters worldwide from 2014 to 2020 [14].

A modern smart city is full of lives that normally demand communication using WiFi or Bluetooth for wireless delivery in the same frequency band. Thus, the application of ZigBee to AMI in high-traffic areas needs to be handled with special consideration to mitigate the potentially hostile interferences [15]. In the design, multiple parameters are indicative for consideration, for instance, high power and high throughput for fast data transmission and low latency. However, these factors may produce different effects, e.g., the high latency normally occurs in noisy communications. A practical solution is needed by optimizing these key parameters. Some of the difficulties in smart meter data are summarised below.

For data quality, real-world databases include inconsistent, incomplete and noisy data. Therefore, several data preprocessing techniques, including data cleaning, integration, transformation and reduction need to be applied to minimise noise, inconsistencies and incompleteness in data. In many cases, the current techniques will be too slow to achieve a workable solution for real-life problems.

Turning to data explosion - when smart metering is fully deployed and operated at a 30-minute sampling rate, energy suppliers will need to ingest, store and process at least around 4500 to 9000 times more of the current data size, reaching 50 terabytes. Managing data sets in such a large volume requires a scalable solution that can grow for practical use [16].

Another urgent problem is due to the lack of standards. To take advantage of these large new data sets, it is essential to gain access to data; develop the data management and programming capabilities to work with large-scale data sets. New approaches to describing and analysing the information contained in big data must be developed [17]. Standards for data description and communication are essential. These facilitate data reuse by making it easier to import, export, compare, combine and understand data. Standards also eliminate the need for each data originator to develop unique descriptive practices [18].

The big data in smart grids is generated from various sources, such as energy consumption data measured by the widespread smart meters [19]. With the huge increase in data size introduced by an increasing number of physical devices, the large-scale advent of incomplete and uncertain data cannot be avoided and may be attributed to inaccurate data readings and collections [20]. Current methods for non-intrusive load monitoring problems assume that the number of appliances in the target location is known, however, this may not be realistic. In real-world situations, the initial setup of the site can be known but new appliances may only be added by users after some time, especially in a household. In this sense, current methods without detecting new appliances may not accurately monitor loads of different appliances and scenarios. In this work, a novel new appliance detection method is proposed for non-intrusive load monitoring with imbalance classification for appliances switching on or off. The prediction of appliances being switched on or off is an important step in load monitoring and it is inherently heavily imbalance, e.g. air conditioning is rarely switched off while some appliances, e.g. coffee machines are rarely switched on that is, the switching on frequencies for coffee machines and air conditioning in a household are different, making the problem imbalanced [21].

Non-Intrusive Load Monitoring (NILM) only requires data from a smart meter to disaggregate appliance-level data. The NILM is cost-effective and friendly for the new installation and replacement of appliances. The disaggregation problem is usually solved by machine learning methods, e.g. sparse coding and Hidden Markov Model. The NILM problem can be transformed into a multi-label classification problem, such that the on/off state of each appliance is classified simultaneously at each time step. When the NILM problem is treated as a multi-label classification problem, it is inherently a class imbalance problem because some appliances are frequently used, e.g. refrigerators while others may only be occasionally in operation, e.g. coffee machines. Class imbalance is a common issue in many real-world applications, such as diagnosis of rare diseases, fault diagnosis, and anomaly detection. Class imbalance problems occur when one class severely out-represents another [22], i.e. a class consists of much more samples than other classes.

When NILM is considered a multi-label classification problem, the target is to classify if an appliance is switched on or off at a given time step. Proper techniques, such as resampling should be employed to improve the robustness and effectiveness of these systems [23]. With the consent of the householder, data from their smart meter could be used to help them. For example, if there were no signs of electrical usage or heating in the house of an elderly person, a text alert could be sent out to a carer or trusted relative to suggest that they check on them. As reported in [24], two billion people will be aged 60 and over by 2050, making up 22% of the world's population. Table I shows the percentage over 65 extrapolated between 2020 to 2050.

It also reported that over the next 20 years, the number of people in their 80s and 90s living alone will dramatically increase. Older, single people living alone are more likely to have a higher risk for adverse physical and mental health outcomes. As there are several million of smart meters available, it is possible to create a platform to support future services on a large scale and at a good value. It is foreseen that energy data can be analysed to recognise behavioural patterns and assist with monitoring particular health conditions. The potential is there to help shorten the length of stay of people in hospital and even prevent unnecessary hospital visits.

The installation of smart meters at home sets up a platform upon which innovative new products and services can be built. Reference [25] reported what this might look like in the rapidly advancing world of digital health and care, with potentially huge benefits for vulnerable groups. While many of the ideas in this report are at an early stage of development, it is clear from the pace and direction of innovation in the health sector that the use of energy data will have a significant role in the UK's future. An overview of the use of smart meter data in health and care applications has been given. A small number of research projects have presented evidence of the ability to use digital energy data to recognise activities or usage patterns that could be associated with a variety of health conditions. Several companies also integrate such data into their health monitoring service offerings alongside other technology. As yet, there is no clinical trial evidence of the effectiveness of using digital energy data to improve health outcomes. Potentially recognisable health-relevant features include detecting inactivity due to injuries such as falls, sleep disturbance, memory problems, changes in activity patterns, low activity levels, occupancy and unhealthy living conditions. Furthermore, the possibility of using digital energy data to inform diagnosis and public health, drawing parallels with initiatives in other areas was raised, but there is no evidence at the moment that this will be possible or practical. However, the potential could be huge.

III. Case Study

There are many applications in the use of new techniques in healthcare. A case study on smart meters for healthcare is illustrated here. Alerting relatives, carers or health practitioners to events that may require a response, such as when someone has been incapacitated by a fall. This functionality has already been the subject of research as described in [26].

A short overview of smart health with smart meters was reported in [27]. Before the availability of smart meter data, utilities relied on substation data or customer participation in-home audits. They might have also leveraged local government records to see what appliances might be installed in a home. But the data was limited, and it was not real-time or seasonally specific.

It is foreseen that by investigating advanced machine learning and load disaggregation techniques of this highly accurate sensing network, detailed habits of an individual's interactions with electrical devices can be assessed; smart meter electricity readings can be used to support social care that meets a person's individual needs, maximises independence and promotes a sense of security for those living alone [28, 29].

Reference [28] reported that the measured energy dataset is taken from 12 households and collected by the smart meter with an interval of an hour for one month. The dataset is grouped according to the feature pattern. It was shown how the clustering result of the Sum Square Error (SSE) has a connection trend to indicate normal or abnormal behaviour of electricity usage and leads to determining the assumption of the consumer's health status.

The UK EPSRC supported a study that involves testing a remote patient monitoring system for people with self-limiting conditions such as Dementia. The system requires no direct interaction from the patient. It aims to develop novel technology to assess an individual's personal physical and mental health by monitoring their electricity usage at home. This is achieved by processing data collected from smart meters, which capture detailed habits of an individual's interactions with electrical devices. The data can identify when an individual gets up, goes to bed, eats, their location within the home and a bad night's sleep.

Reference [29] explored this idea further and presented a new approach for unobtrusively monitoring people in their homes to support independent living. The UK NHS has conducted a trial to assess how data from smart meters could help monitor at-home patients. The work was to see how information on energy usage can be interpreted by artificial intelligence (AI) algorithms to check on patients [30]. The Department for Business, Energy and Industrial Strategy (BEIS) mentioned being able to monitor a patient at home shows how innovative technologies enabled by smart meters can improve many aspects of a patient's life, not just the energy use.

The capacity to identify use patterns of individual appliances allows for a greater understanding to be developed of the behavioural patterns of occupants. For example, unusual energy use overnight may be evidence that an occupant is experiencing sleep disturbances. Furthermore, analysis of the combination of uses of appliances, and variations in these offers the potential to infer different forms of household practices, which can then be linked back to more understanding of the social purposes of that sequence of appliance use.

Presently, there is no established way to classify the behaviours and pathologies detected by smart meter health studies. It is suggested to take a pragmatic approach to track the diminishing range of daily tasks, such as cooking, that a patient can perform as self-limiting conditions worsen. In this way, occupant health conditions might be detected through changes in appliance use by observing smart meter data. Each of these changes may be related to memory problems, the decline of social relationships, the deterioration of personal hygiene and hyperactivity or inactivity.

Depression is mentioned in [31] as a condition that their outlined energy use monitoring architecture may be able to detect in its early stages. Wider infrastructural architectures required to integrate smart meters with home area networks, consumer access devices (CAD) and cloud computing facilities were reported in Reference [32]. Reference [33] reported that appliances that have been focused on include kettles. The alarm system monitors kettle activity and sends a notification when the kettle has not been used as expected. Reference [34] used an energy monitor at a 1-10 second measurement frequency to train a device identifier, extracting a unique energy use profile for each device. The data were categorised into abnormal and normal usage patterns. Such processes are common in NILM and as the sophistication of NILM increases, a wider range of devices will be detected with greater accuracy. In another use case, Reference [35] gave social workers the progression of health as night-time activity related to the progression of Alzheimer's disease. Remote activity monitoring of electricity use records provided an extra tool for the social worker to aid their understanding of the development of the condition.

A typical challenge for implementing smart meters is how to integrate them within the infrastructure and set up custom-tailored smart metering use cases. One way to achieve these goals is by using an IoT platform that offers out-of-the-box solutions and templates for smart metering.

Reference [30] reported an initial six-month clinical trial has been completed. Energy readings were monitored every 10 seconds and used to identify interactions with appliances in multiple homes. By detecting how often and when appliances are used, routine behaviour was established. This provided the possibility to identify any abnormal behaviour when the interaction pattern changed and can be used to raise alerts when required. The results demonstrate that the system can monitor and support patients in an unobtrusive and personalised manner.

There are conflicting views on the impact of smart meters on health. As radiofrequency (RF) radiation is a possible carcinogen, and smart meters give off RF radiation, it is possible that smart meters may increase cancer risk. However, Public Health England (PHE) has carried out an extensive program of research to assess exposures from smart meters as the technology is rolled out in the UK. The results confirm that exposure to radio waves from smart meters is well below the guidelines set by the International Commission on Non-Ionizing Radiation Protection (ICNIRP) [36]. The study also concluded that exposure to the radio waves produced by smart meters is likely to be much lower than that from other everyday devices such as mobile phones. For a quantitative comparison, the readers could refer to Reference [37].

Reference [38] identified several barriers to adopting smart meter data at a large-scale level. There is the unavailability of funding and a lack of collaboration between computer science, governments, engineering, energy and healthcare - therefore studies remain only theoretical, with little evidence of real-world validity and demonstration projects. The penetration of smart meters remains slow in most countries. For example, in the UK, despite rapid deployment, smart meters remain the lesser-used metering technology by households due to connectivity issues. In addition, there are other challenges identified for using smart meters. Firstly, the distributed nature of smart metering systems makes their implementation costly. Secondly, the installation of smart meters raises data privacy concerns. Thirdly, compliance with industry protocols and guidelines to ensure various standards is needed. Fourthly, smart meters communicate with mobile technology and a weak signal can disrupt communication. However, in balance, it is believed that opportunities are more than challenges, and the use of smart meters in telecare should be a reality. More financial support is needed to carry out wider clinical trials to formulate policies and business models.

As mentioned, based on non-intrusive load monitoring, it can identify the type of appliances using the aggregated load profile measured with a smart meter. The load disaggregation can be solved with machine learning. One possible implementation is to get all the aggregated load patterns from the smart meter transmitted with wireless communications technology to a data centre or cloud and then analyse them with an intelligent algorithm to obtain various individual loads of each appliance by a service provider. By comparing historical information with many well-developed techniques such as deep neural networks, it can make recommendations with a decision support system.

In summary, a top-level logic flowchart of the smart health based on a smart meter system is summarised in Table II and Fig. 2 gives the component and module diagram for the system. This system could promote bioinformatics which is the integration of different subjects such as data science, biology, and statistics to capture and analyse biological information. Combined with the reducing cost of high-throughput DNA and RNA- sequencing, bioinformatics has made genomic and proteomic data analysis more efficient and effective but has also created new challenges concerning data storage and security.
Bioinformatics presents a powerful tool to model and monitor biomedical and healthcare data with massive potential to improve the understanding of how diseases develop and/or spread. For example, the probability of developing metabolic disorders increases with certain genetic mutations, and these can be identified by comparing individual- to population-level genetic data using bioinformatics tools. Combined with the use of electronic medical records i.e. patient history and physiological data, such as electroencephalogram and electrocardiogram obtained from various electronic components, a personalized treatment plan can be derived.

The present proposed system integrates the use of smart meter data and could be used to develop predictive models to give more accurate, relevant and timely health warnings to patients and their care providers. Integrating smart meter data with existing translational bioinformatics resources will accelerate the implementation of data-driven medicine in the clinical setting and will play an imperative role in a smart city environment to improve disease diagnosis, prevention and intervention.

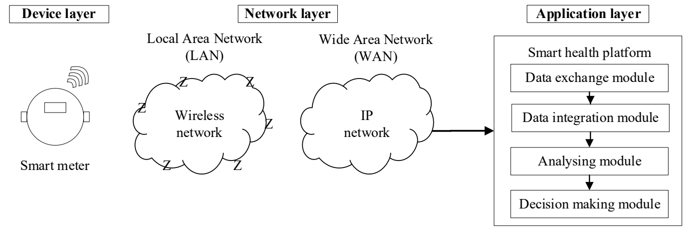
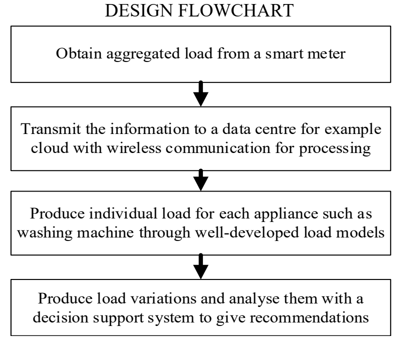


Fig. 2. A component and module diagram for smart health with a smart meter system. Wireless network - NB-IoT, Lora etc.; Internet Protocol (IP) Network - gateway, data concentrator etc. Data exchange module consists of historical information database, weather information, energy usage data. Data integration module is for data checking, data prepossessing. Analysing module produces energy usage patterns with AI methods such as deep learning. Decision making module produces a list of recommendations based on risk assessment techniques for healthcare workers and doctors for action.

TABLE II
A TOP-LEVEL SMART HEALTH WITH SMART METER SYSTEM DESIGN FLOWCHART



Ⅳ. Conclusion

An overview of smart health with wireless communication and smart meters is given. Advances in science and technology are changing medical practice. However, the benefits have also added complexity, making it increasingly difficult for healthcare professionals to be confident that they base their decisions on the latest information. Clinical decision support tools, particularly those based on AI, can help. The growing availability, standardization, and integration of data from disparate sources across systems and institutions raise new challenges. Successful digitalization goes beyond implementing new technologies and tools but has an impact on the broader healthcare infrastructure.

The scientific reason underlying smart meter data for health monitoring is that a change in health will lead to a change in behaviour, and so the use of appliances will change and result in a change in energy use patterns. Such ongoing monitoring is already an established part of telehealthcare, however, there is currently only indicative evidence of the potential use. This kind of resource should be fully looked at carefully. Developing software for medical devices or software as a medical device compliant with standards is not a trivial thing but an essential requirement for the certification of quality management systems and software development.

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