

Digitalisation of Energy



An Energy Futures Lab Briefing Paper

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Energy Futures Lab

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List of Acronyms

AI	Artificial Intelligence
ANN	Artificial Neural Network
BEIS	Department for Business, Energy and Industrial Strategy
CAD	Consumer Access Devices
CHP	Combined Heat and Power
DCC	Data Communications Company
DLT	Distributed Ledger Technology
DNO	Distribution Network Operator
DSO	Distribution Service Operator
EPSRC	Engineering and Physical Sciences Research Council
ESO	Energy Service Operator
EV	Electric Vehicle
GB	Giga-byte
GDPR	General Data Protection Regulation
GW	Giga-watt
HAN	Home Area Network
ICT	Information and Communications Technology
IoT	Internet of Things
IT	Information Technology
JiT	Just-in-Time
LAN	Local Area Network
LTE	Long-term Evolution
MW	Mega-watt
NCSC	National Cyber-Security Centre
O&M	Operations and Maintenance
PB	Peta-byte
R&D	Research and Development
SMETS2	Smart Metering Equipment Technical Specifications Version 2
TB	Tera-byte
TNO	Transmission Network Operator

Executive Summary

Digital technology has the potential to radically reshape the way we generate, trade and consume energy. Over the past decade, the incorporation of information and communications technology into the energy system has emerged as a significant driver of change in the sector but the pace and scale of that change is likely to increase dramatically over the decades to come.

This Briefing Paper investigates the key technologies that underpin the digitisation of energy and examines their potential impacts. The overarching objective of the paper is to *understand the effects new technologies will have on the current energy system, the new challenges they will pose, and the policies and regulatory measures which will assist in making them a success.*

Specifically, this paper considers four technological areas of digitalisation: big data; machine learning and AI; the Internet of things; and distributed ledger technology, often referred to as blockchain.

Almost all digital technologies and services rely on access to large, representative and good quality datasets. Data analytics require high-quality datasets for accuracy, while machine learning and artificial intelligence (AI) are dependent on datasets for learning. Data in the energy sector can be broadly divided into two groups: energy system data, consisting of network, balancing and capacity datasets; and customer and supplier data, consisting of billing, metering and usage datasets as well as personal data.

The availability and use of energy system data in the UK has historically been poor, owing to fragmented and siloed datasets and a lack of sectoral experience in managing large and diverse datasets. Efforts by BEIS, Ofgem and the Energy Systems Catapult to address this and provide baseline standards for data formatting and access are very welcome, though the fast-evolving nature of data usage and the debate around data privacy will require these organisations to ensure they have the appropriate skillsets embedded long-term to ensure effective oversight. Due to the potential of customer and supplier data to identify customer energy usage patterns, these datasets need to be handled with care for privacy and security reasons.

Big data, machine learning and artificial intelligence technologies are undoubtedly going to play a large part in the energy sector in the future. These technologies will require new ways of analysing, compiling and viewing datasets, and new skillsets capable of leveraging energy system data for national and commercial advantage. The leveraging of big data and machine learning technologies will help enable other potential economic models of energy system integration, models that are more decentralised and flexible, with a more direct link between generators, suppliers and consumers. However, these technologies should be applied with care; current machine learning techniques are only very good at solving certain subsets of problems, centred on classification of data and pattern identification, and are susceptible to poor-quality training data and human bias. The ‘black-box’ nature of these systems also makes it difficult, if not impossible, to explain why they make the decisions they do, presenting a possible barrier to implementation in critical parts of the energy sector. Understanding both the strengths and limitations of these technologies, and ensuring that organisations have the skills and knowledge required to implement them effectively, is essential to ensure their effective use.

Executive Summary

Distributed ledger technology, which allows the processing of encrypted transactions without the need for centralised control, has the potential to be utilised in several areas across the energy system, including metering and billing, carbon trading, grid management and decentralised peer-to-peer energy trading. While DLT could potentially provide low-cost, transparent, verifiable and cryptographically secure transactions without the need for a central authority, there are significant technical, regulatory, security and consumer trust challenges to overcome. DLT could prove transformative, or it could be that adapting DLT to the energy system on a large scale proves more expensive, disruptive and time-consuming than refining and evolving existing systems. Its potential, therefore, should not be underestimated, or importantly, overestimated.

Policymaking and regulation for a digitalised energy system will need to take account of many new factors. New entrants, new business models and more direct consumer engagement, with the attendant challenges of consumer protection, privacy and cyber-security, will require knowledgeable and flexible regulatory engagement. Due to the speed of advancement in digital technology and data science, regulatory approval for new products and services should be processed as quickly and cheaply as reasonably possible. Likewise, system data should be open and available where possible.

Overall, in order to ensure that they can take the greatest advantage of the new opportunities afforded by digitalisation, organisations should aim to build institutional knowledge and skillsets in understanding not just the technologies themselves, but also consumer reactions and behaviour; data collection, analysis and privacy; the effects and consequences of automation; and the risks of cyberattack. Digitalisation will almost certainly change how we supply, purchase and interact with energy, as well as the pathways we can take towards decarbonising the system. Digitalisation in the energy system should, therefore, be considered an integral part of decarbonisation, rather than a separate concern.

Introduction

Digitalisation of energy is the act of incorporating digital systems and information and communications technology (ICT), along with the new business models and interaction opportunities these support, into the energy system. Digital technology has advanced at an unprecedented rate over the last couple of decades, and even over the last few years, enabling massive changes in the way devices can communicate, monitor, analyse and display data. When these advances are applied to the energy sector, new applications across the energy system become possible.

The concept of digitalising energy systems has been around for some time, but development progress has ramped up dramatically over the last decade. The most well-known digitalisation concept, that of a ‘smart grid’ focusing on increasing ICT components in the transmission and distribution electricity grids, has been the focus of significant national and international interest since the early 2000s (Massoud Amin and Wollenberg, 2005). The rapid rate of advances in data science and communications technology, however, has enabled digitalisation applications across the entire energy supply and usage spectrum. Energy supply could become more efficient with the application of digital technologies, from better advance prediction of wind farm output (Forbes, 2019a) to improvements in O&M, operational life and process efficiency (IEA, 2017). The electricity networks could see greater monitoring and control of electricity network components and the smarter utilisation of energy demand data to drive greater optimisation, efficiency and consumer choice. Energy utilisation in buildings and transport could also become more efficient with the utilisation of data-driven demand response and smart occupancy-sensitive heating and lighting.

This Briefing Paper will focus on digitalisation efforts in networks, electricity supply, buildings and consumer engagement – digitalisation technologies to assist industrial decarbonisation will be covered in a separate paper. This Briefing Paper will investigate major trends in digital technologies for the energy sector. Section 1 will outline underlying digitalisation trends, while Section 2 will look at data in the energy sector. Section 3 will investigate big data, machine learning and AI technology, and Section 4 will explore Internet of Things devices. Section 5 will investigate distributed ledger technology and its applications. Section 6 will provide discussion, policy recommendations and conclusions.

Introduction

1. Underlying Digitalisation Trends

1.1. Overview

The last few decades have seen a revolution in digital technologies and applications. Digital devices have become smaller, more powerful and more interconnected, with increasingly profound implications for business, lifestyles and wellbeing. These trends are likely to accelerate in the coming decades, with the World Economic Forum describing the world as being at the brink of a 'Fourth Industrial Revolution', building on the digital revolution and *'characterized by a fusion of technologies that is blurring the lines between the physical, digital, and biological spheres'* (IEA, 2017).

The energy sector is not immune from the digital revolution. In recent years, the digitalisation of energy has become a major priority in the evolution of the energy sector. Digitalisation has been referred to as one of the three main drivers for change in the energy sector – the 'three D's' – along with decarbonisation and decentralisation (Di Silvestre *et al.*, 2018).

In order to appreciate the scope of the energy digitalisation revolution, it is important to understand the principles of the technologies and concepts which are underpinning the current wave of digital innovation.

1.1.1. Processing capabilities

The speed and processing capacity of microprocessors has long been thought to be guided by Moore's Law, a 1965 observation which states that the number of transistors in a dense integrated circuit, and thus the speed of processors, will double every two years. This has led to an exponential increase in processing power, with transistor counts rising from a few thousand in the early 1970s to near 10 billion

on consumer-level processors today. In terms of total capacity, it has been estimated that global general-purpose computing capacity grew at an annual rate of 58% to 2011 (Pool and López, 2011).

Moore's Law is expected to reach its limit in the near future (with some observers hypothesising that it has already ended) due to physical limits on transistor size (Pool and López, 2011). The most modern commercial processors have feature sizes of 7nm and transistors only a few hundred atoms across. Below this point, fabrication becomes increasingly difficult and quantum electron tunnelling effects make transistors less reliable. Processing improvements in the next decade will likely centre around more specialised chips designed to quickly process specific problem sets, rather than the more generalised processors mostly used today.

1.1.2. Data storage

The quantity of data which organisations and individuals can feasibly store has risen exponentially over the last couple of decades, with the cost of storage likewise massively decreasing. The quantity of data stored worldwide has doubled every year since 2005 to 33 zettabytes in 2018, and is expected to grow to 175 zettabytes by 2025 (Datanami, 2018). The cost of hard disk-based storage has dropped from \$4,400/GB in 1990 to £0.02 in 2017, with solid-state memory storage dropping from \$1,255/GB in 2000 to \$0.32/GB in 2017 (Computerworld, 2017). The cost of data storage is expected to continue to fall, with new advances in solid-state memory forecast to increase capacities and reduce costs (Greengard, 2019).

1.1.3. Wireless Communications and Distributed Computing

One of the major drivers of digitalisation has been communication, specifically wireless communication. This connectivity has dramatically improved the efficiency of digitalisation technologies by centralising data storage and processing – reducing energy use, redundancy and complexity. There are several standards for wireless communication, differing range, speed and energy usage, from Bluetooth, used for short-range low-bandwidth communication between small devices, to high-speed 4G and 5G mobile data standards for longer-range, higher-bandwidth applications. These are covered in Box 3.

This access to communications bandwidth has enabled a lot of computing functions to be undertaken away from the device, storing data and offloading processing to data centres across the world. This is known as distributed computing, of which the most well-known form is cloud computing. This shifts processing of data from personal devices to large data centres. This centralisation enables advanced methods of data processing through access to greater processing capabilities and far larger quantities of data. More advanced data analytics and training of machine learning models can be accomplished in the cloud than on separate individual devices, allowing greater understanding of trends, usages and preferences.

The upcoming rollout of 5G technologies will allow many more devices to be simultaneously connected in an area than 4G, along with very low latencies (the speed of interaction between devices). This is predicted to allow a substantial increase in connected devices (the ‘Internet of Things’), from self-driving vehicles to smart city sensors and logistic processors (KPMG, 2019).

1.2. Applications of digitalisation

1.2.1. Drivers of digitalisation in the energy sector

Digital technologies have seen inconsistent application in the energy sector, with oil and gas producers generally utilising advanced technologies in extraction and processing, but electricity utilities and suppliers tending towards conservatism in adoption (IEA, 2017).

- » **Prediction and optimisation throughout the energy system:** AI and machine learning can be trained to predict weather patterns, demand curves and network energy flows at a granular level. Other applications, such as optimisation of maintenance schedules, investment opportunities and community-level microgrids can also be addressed.
- » **Demand response and integration of renewables:** Smarter grid, metering and home technologies, along with smart charging for electric vehicles, can provide smart demand response facilities to aid the integration of variable renewables at multiple levels, from communities to nationwide.
- » **Smarter consumer tariffs, billing and services:** Digital technologies, through sensing and artificial intelligence can enable a greater range of consumer energy services, from personalised tariffs and time-of-use tariffs to bundling of energy supplies with services such as heating, transport or retail offerings.
- » **Increasing automation:** From the transport sector, where automated electric vehicles could dramatically change how we move around, to buildings, where smart thermostats, sensors and adaptive lighting can be used to optimise energy consumption, the increasing automation offered by digital technologies will change where and how we consume energy.

Table 1 shows some potential applications of digitalisation technologies in the electricity system, grouped by technology cluster and by their position in the value chain. This is not intended to be a comprehensive list, but an example of the diversity of applications in which digitalisation can play a part.

	Generation	Transmission	Distribution	Consumer
Big Data	Optimisation of operational efficiency through analytics	Forecasting of future load and pricing	Analytics for optimising microgeneration and storage in communities	Advice on usage and saving energy
AI/Machine Learning	Optimisation of wind farms through wind speed forecasting	Autonomous agents trading energy	Optimisation of networks against physical faults	Automation of demand response
Internet of Things	Drone inspection of equipment	Smart grid sensing, monitoring and asset management	Enabling local microgrids through embedded control	EVs, in-home/building sensors
Blockchain	Emissions certificates and certificates of origin	Direct energy trading	Microgrids and local markets	Billing, metering, demand response

Table 1 Some example applications of digitalisation in the electricity value chain

The expansion of the energy system into the digital space has attracted significant interest from new-entrant companies looking to provide digitalisation services and expertise across the energy sector. The Energy Systems Catapult has compiled a landscape of 184 UK digital energy businesses, divided into six sectors (Energy Systems Catapult, 2019c). These are arranged as seen in Table 2:

Residential and Public	Commercial and Industrial	DNOs/DSOs, TNOs, ESOs
Consumer Services		
Decision Support		
Transaction		
Asset Control Management		
Local Energy System Data		
Asset Operations and Data		
Domestic Batteries, EVs, Smart Appliances, Solar PVs	On-site Generation (CHPs, back-up generators), Chillers, Heat Pumps, Energy Storage Assets	Centralised Generation (coal, hydro), Distributed Generation (wind, solar), Large Scale Generation

Table 2 Categories of the Digital Landscape. Adapted from (Energy Systems Catapult, 2019c)

1. Underlying Digitalisation Trends

2. Data: the Foundation of Digitalisation

2.1. Overview

Data, simply packaged information accessible on an IT system, is central to the rapid advances seen in recent times in the digital space. The collection, processing, analysing and storing of data form the foundation of almost every other technology described in this paper, from providing the training sets to enable AI and machine learning to collecting and analysing the data collected by the components of the Internet of Things. New mathematical techniques, the rapidly reducing costs of data storage and processing and advances in distributed and cloud computing have allowed the quality and quantity of data processing, analysis and visualisation to improve drastically in the last fifteen years (Perrons and Jensen, 2015). Data has become a significant asset for many companies, with large technology companies such as Facebook and Google generating revenue almost exclusively from data-based products. These products leverage large datasets of users' actions, personal attributes and personally generated information to provide either customer-facing products, such as the storage and automatic classification of users' images, or company-facing products such as directed advertising and aggregated data on the preferences of population segments.

Big Data, a term for the field of processing of massive datasets too large to analyse with conventional techniques, is providing analytics and insight that was impossible to gain before. Big data is closely related to machine learning and AI, and is therefore covered in Section 3.

2.2. Data in Energy

Data underpins almost all energy digitalisation efforts – without information, it is impossible to take informed decisions or predictions. The energy system historically has been centrally controlled and 'analogue', with little granular data available. This has begun to change since 2000, with data flow and collection in the energy sector, particularly in the electricity system, increasing sharply. Digital sensors across the networks and the advent of smart metering and more granular consumer data have led to an increase both in the quality and quantity of data collected. The energy sector now produces a vast quantity of data, from consumer usage and billing to sensing and monitoring devices throughout the network. However, due to a number of factors, including privacy and customer sensitivities, fragmentation of data ownership and network regulation, data usage is not as advanced in energy as in some other economic sectors.

In 2018, the Energy Systems Catapult published an Energy Data Review, which outlined a series of emerging models which would benefit from increased data collection and usage (Energy Systems Catapult, 2018). These are:

- » **Time-of-use optimisation:** Utilising storage, demand response and flexible distributed generation to respond to system constraints and changing prices.
- » **Marketplace optimisations:** New marketplaces directly connecting consumers and generators, potentially using distributed ledger technology.

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- » **Efficient consumption:** Utilising consumer data to increase the efficiency of consumption – potentially through intelligent heating and cooling systems.
- » **Lifestyle products:** Enabling consumers to tailor their environments to their preferences.
- » **Energy as a service:** Providing heating, transportation and other services instead of simply energy.
- » **Bundling:** Packaging services together into single propositions – for example, providing heating or transportation assets, energy and maintenance as a single service.

For the purposes of classification for privacy, data gathered directly from the energy sector can be split into two rough groups: consumer and supplier data, and system data (Energy Systems Catapult, 2018). System data includes the balance of supply and demand across the network, asset locations and capabilities, financial flows for settlements of EMR policies and network and generation capacity figures. Customer and supplier data include meter readings, including data from smart meters, customer personal data and billing and tariff data. Due to the fact this data will contain identifying markers on consumers’ usage patterns and personal information, data protection restrictions will be tighter than that for system data. Examples of data in both categories are shown below in Table 3 for the electricity sector.

System Data	Customer and Supplier Data
Location of system assets	Total energy usage and billing
Network-connected generation output	Energy usage by time
Energy flows through the network	Behind-the-meter generation output
Weather forecasting and monitoring	Personal customer data
Market reconciliation and settlement	Smart appliance demand response usage

Table 3 Examples of system and user data in the electricity sector.

2.2.1. System Data

The availability and use of energy system data in the UK has been historically poor, which stems from a few major drivers (Sandys *et al.*, 2018). Datasets tend to be fragmented, with data held in separate silos and accessed by separate system stakeholders. The sector is historically conservative, with a risk adverse culture due to the critical nature of the system, which leads to a reluctance to adopt new methods of data sharing and use. Leading from this, the sector has trouble attracting people with the skillsets to understand and manage large and diverse datasets. In addition, the regulated monopoly nature of many of the system players makes it more difficult for new entrants to challenge established business practices.

In October 2018, in response to concerns regarding the transparency, visibility and flexibility of energy system data, the Government established the Energy Data Taskforce to investigate how data could be better accessed and used across the system (BEIS, 2018a). The Taskforce released its first report in June 2019 (Sandys *et al.*, 2019). This report stated that there was an urgent need to redefine the visibility and use of system data, and that continuing on the present path would lead to reduced innovation, more expensive transformation of the system and the potential for increased risks to system stability.

The report makes several key recommendations:

- » **Digitalisation of the Energy System:** The Government and Ofgem should adopt overall principles to push digitalisation, including coherent digitalisation and data strategies backed up by the principle of continuous improvement. These should be part of licence and regulation measures such as Ofgem's RIIO price control method.
- » **Maximising Data Value:** Energy system data should be 'Presumed Open', meaning that it should be open to usage by anyone unless there are good reasons for it not to be, such as privacy or security issues.

- » **Visibility of Data:** A data catalogue should be established which would hold metadata containing the location, type and ownership of energy system datasets. Data should be easy to find, understand and search, and should be standardised where possible.
- » **Asset Registration:** Currently the registration of assets, especially smaller distributed generation and storage, is inconsistent and incomplete. This would provide a standardised portal for assets to be registered in a central database.
- » **A Digital System Map:** This proposal is to create an open, interoperable digital map of the energy system. This would be a single unified map of the energy system and the location of assets upon it, allowing better visibility of the system and faster identification and planning of future projects, additions and optimisations. This would be held as a public good by a non-commercial organisation.

In response, BEIS, InnovateUK and Ofgem have commissioned a set of principles on Energy Data Best Practice (Energy Systems Catapult, 2019b). These principles are currently under consultation and will be released in 2020. Consultation workshops have been held on the principles of discoverable data and metadata, privacy and security, and user needs and interoperability.

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2.2.2. Customer and Supplier Data

This category of data holds datasets which, unlike system data, either belongs to customers or could be used to identify them of their energy usage patterns. Data of this type includes customer energy usage figures at high spatial and temporal levels, billing and personal customer details, data from smart appliances and data from behind-the-meter distributed generation and storage installations. Linked data such as building type, construction materials and weather patterns are also important in this category, as they provide important context to interpreting the energy datasets (Webborn and Oreszczyn, 2019).

Due to the potential of this category of data to identify customer energy usage patterns, often on a very granular level, and the privacy and security issues that result from that. There has been concern and some controversy over the collection and usage of data from smart meters, often reported in the national press (The Guardian, 2017). Access to this data would also need to be compliant with the recently-introduced General Data Protection Regulation (GDPR) (Information Commissioner's Office, 2018). On the other hand, the collection and analysis of this data, particularly half-hour energy consumption data from smart meters, opens up substantial new public-interest opportunities both in energy usage research and in the development and operation of new policies, market structures and business models focusing on the demand side (Webborn and Oreszczyn, 2019).

Smart metering data is currently centrally collected and managed by the Data Communications Company (DCC), which is regulated by Ofgem (Smart DCC, 2016). Currently, access to data from smart meters is governed by a Data Access and Privacy Framework (BEIS, 2018b). This framework has as its core principle that consumers should have control over access to their energy consumption data,

except when this is needed for regulated purposes. In practice, this gives suppliers access to monthly consumption data, but they must obtain permission for half-hourly data. Network operators can access half-hourly data subject to agreement with Ofgem of a privacy plan showing how they will aggregate and anonymise the data. Currently, Western PowerGrid is the only company to have agreed a plan, with other DNOs (Distribution Network Operators) in the process of submission. Third parties can collect data as long as they obtain customer consent, sign up to become users of the DCC and meet requirements around security and privacy, a process which has been criticised as difficult to navigate (Frerk and Ward, 2019). Academics are designing methods of collecting and analysing anonymised data from smart meters – one prominent example is the Smart Energy Research Lab, funded by the EPSRC, which collects smart meter data from around 10,000 randomly selected households across the UK via the DCC, subject to customer approval (SERL, 2019). This is linked with local weather and home efficiency rating data, anonymised as far as practicable, and made accessible to UK researchers that have received strict ethics clearance and have had their research project approved by the lab's governance board.

Data from smart meters can also be accessed in detailed 10-second increments by in-home Consumer Access Devices (CADs), which have to be registered and paired to the smart meter's local in-home network by an energy supplier or another registered DCC user. These devices can then log, store and transmit this smart meter data to third-parties, bypassing the data access controls through the DCC. While this approach has advantages in both providing customer services and collecting research data, there are concerns that this in effect creates two levels of access to data, a carefully regulated 'walled garden' of access through the DCC and a less-regulated path through the CADs with more limited consumer protection (Frerk and Ward, 2019).

2.2.3. Discussion and Conclusions

Data collection, analysis and use has become a major part of almost every sector of the modern economy, with energy being no exception. As the energy system becomes more digitalised and ‘smart’, the amount of data which can be gathered has exponentially increased, allowing new avenues of research and more informed policymaking. Greater access to data can provide more accurate models of where, when and how energy is used, leading to a more efficient, optimised system and the potential for new tariffs and energy service propositions for consumers (Energy Systems Catapult, 2018).

Data access and use in the energy sector currently suffers from three major issues, however: 1) many datasets are fragmented and siloed, stemming from commercial interests, limited incentives to maintain datasets and confusion over rights and ownership; 2) there is little standardisation or interoperability throughout the system, with no central body providing and enforcing data standards in many cases; 3) researchers and suppliers face high barriers to access and analyse consumer data due to strong privacy regulations and some customer concerns over the use of their data.

As such, the recommendations produced by the Energy Data Taskforce to catalogue, map, standardise and open system data should be implemented where possible. Experiences in other sectors in opening datasets to third parties have proven broadly successful, and it is likely that access to system datasets will enable third parties to produce valuable applications, models and insights. This is likely to prove more valuable in more localised situations where existing stakeholders do not currently operate – such as applications to optimise energy flows between generation, storage and demand at community, street or even building level. This data is also extremely valuable in constructing models of the existing system for optimisation, system planning and forecasting purposes.

Data belonging to or emanating from customers is necessarily more complex with regard to privacy and security rules. In an effort to stimulate smart meter installation, governments have moved cautiously in privacy regulations – customers in the UK have to specifically opt-in to both smart meter installation and for their data to be used, for example (Webbourn *et al.*, 2019). More stringent recent data privacy regulations such as the GDPR have also made customer data more difficult to access by third parties. A more detailed discussion on customer data and usage can be found in our Briefing Paper ‘Unlocking the potential of residential electricity consumer engagement with Demand Response’ (Carmichael, Gross and Rhodes, 2018).

Overall, access and usage of data across the UK electricity sector is hampered by siloing, access issues, a lack of standardisation and interoperability concerns. Efforts by BEIS, Ofgem and the Energy Systems Catapult to address this and provide baseline standards for data formatting and access are very welcome, though the fast-evolving nature of data usage and the debate around the balance of data privacy will require these organisations to ensure they have the appropriate skillsets embedded long-term to ensure effective oversight.

2. Data: the Foundation of Digitalisation

3. Big Data, Machine Learning and AI

3.1. Big data

Analytics, the term for discovering and interpreting meaningful patterns in data, are essential for the utilisation of data in making decisions. As volumes of data have gotten larger, new techniques have been designed to manipulate and produce usable analytics for datasets too large for traditional data processing tools to process. 'Big Data' is the colloquial term for this new field. The most widely-used definition of Big Data is *'high-volume, high-velocity and/or high-variety information assets that demand cost-effective, innovative forms of information processing that enable enhanced insight, decision making, and process automation'* (Gartner, 2012). Big data does not necessarily refer simply to the size of the dataset, but the advanced information and analytics that can be interpreted from the raw data. As can be seen in the definition above, big data has been described as consisting of the 'three Vs':

- » **Volume:** The quantity of data generated and present in the dataset;
- » **Velocity:** The speed at which data is generated and added to the dataset;
- » **Variety:** The differing formats in which data is collected – images, text and audio, for instance. Some datasets may have a significant variety of data.

Two other 'Vs' have been added to some definitions. Though not universal, these can have some import to the energy sector:

- » **Veracity:** The 'trustworthiness' of the data – how much the data can be relied on as an accurate representation of the underlying sector or trend;

- » **Value:** The value the dataset holds in interpretation – whether financial or in providing research results.

Big data has seen many applications across healthcare, financial services, manufacturing and industry, and retailing. For many companies, the data they hold and the analytics they can derive from it provide their revenue sources and business model – Google and Facebook are two examples of large companies deriving revenue almost exclusively from products and targeted advertising derived from their datasets.

The openness of datasets varies between sectors and organisations, but several public-sector initiatives in providing open data have been very successful in stimulating innovation and providing better services for users. Transport for London publishes real-time mass transit data in an open format, which has led to the development of many route-planning and scheduling applications (Transport for London, 2019). Health Data Research UK provides data to researchers and consultants from the NHS to identify patterns in public health, effectiveness of drugs through the population and the degree of success of public health programmes such as smoking reduction efforts (Health Data Research UK, 2019).

3.1.1. Big Data in Energy

The major applications for big data analytics in the energy system are in energy networks, particularly the electricity transmission and distribution networks, to improve reliability and asset utilisation, and in consumer usage data for demand-response purposes and for optimising consumer services. Smart grids are projected to become major target application areas for big data services to integrate and assess incoming data from the multitude of sensors across the network (Jaradat *et al.*, 2015).

Sources of big data in the energy sector come from many different domains. Weather data, generation conditions and quantities, network data including line capacities, thermal monitoring and network conditions, consumption data including smart metering and demand response, pricing including dynamic tariffs, carbon intensity statistics and future data from electric vehicle fleets are all potential sources (Zhou, Fu and Yang, 2016).

Challenges for big data applications in the energy sector include (Tu *et al.*, 2017):

- » **Speed of processing:** Data will need to be processed and analysed on a real-time basis, on the order of a few tens of milliseconds, in order to respond to faults and power variations. There is often a significant latency in sending data to a centralised cloud server, which may not therefore be able to provide a response in the time required. Edge computing, described in Section 4, could provide a solution to this issue.
- » **Data integration from multiple sources:** Data from sensors across an energy network will need to be integrated and fused into small numbers of datasets for visualisation and taking actions. There are challenges with ensuring that incoming data from multiple sources with multiple dimensions are integrated quickly and successfully into a single cohesive set.

- » **Visualisation:** As the velocity and variety of incoming data from across the network grows as digitalisation increases, network operators will need ways of visualising this data that enables them to spot correlations and trends.

Big data is useful not only to provide analytics and inform decision-making, but also to provide a training base for machine learning and artificial intelligence applications. These are covered in the next section.

3.2. Artificial Intelligence and Machine Learning

3.2.1. Overview

Artificial intelligence and machine learning technologies have become major drivers of the current digitalisation paradigm. The two technology areas are often confused – machine learning, technically a subset of artificial intelligence, refers to computer systems automatically improving at performing tasks with experience, whereas artificial intelligence is much broader, referring to computers being able to behave in ways which are commonly thought to require human intelligence (Iriondo, 2018). The definition of AI is vaguer and is seen as an aspirational and moving target as computers become more able to perform complex tasks. Many of the advances seen in recent years in this field can be characterised as machine learning (Lipton, 2018).

3. Big Data, Machine Learning and AI

3.2.1.1. Machine learning: the basics

Many recent machine learning advances have benefitted from big data collection and analytics, with advances in image recognition and natural language speech recognition, for example, having come from training sets made up of the vast image and audio datasets on the Internet. In effect, access to big datasets has enabled current machine learning technologies. As data collection and processing methods increase in scale and complexity, the capabilities of machine learning and AI technology will likewise increase.

Machine learning approaches are designed to create models to perform a specific task on a set of data inputs. The models are created utilising a set of sample data in order to 'train' the model to produce the desired results via a series of evolutionary iterations. Learning algorithms can be grouped into several categories:

- » **Supervised:** where the data set contains both sample inputs and required outputs (known as labelled data). The model learns how to translate the sample data into the desired outputs through a series of iterations, comparing its output against the intended output and altering its process accordingly.
- » **Unsupervised:** The model is provided unlabelled sample data with no specified outputs, and trains itself to recognise clusters of structures and information in the data set such as grouped data points or common features. *Semi-supervised* learning utilises a sample data set containing a small quantity of labelled data and a larger quantity of unlabelled data.
- » **Reinforcement:** Reinforcement learning is centred on training a model to react to a specific environment with a series of rewards and penalties. Unlike supervised learning, in reinforcement learning the model does not have access to the correct outcomes, instead learning from performing actions and being rewarded.

Machine learning can be carried out using a variety of methods, built around clustering and classifying a set of data. Linear and logistic regression, decision tree and random forest methods are commonly used to train machine learning methods (Vogel *et al.*, 2019). In recent years, significant progress has been made in a method known as an *artificial neural network* (ANN) – a model conceptually similar to biological systems of neurons. ANNs were inspired by the structure of the human brain, but have deviated significantly from this during their development. The main use of these networks is to cluster and classify large amounts of data in a reliable and efficient manner (Skymind, 2019). The networks act as interconnected layers of nodes, each node acting as an artificial neuron. The network is made up of input nodes, layers of 'hidden' neurons which process the inputs, and an output layer. For complex applications, there may be many hidden levels – this is known as '*deep learning*'. Neurons receive input and combine it with their internal algorithms – if the output is higher than a set threshold, the output is transferred to the next layer in the network (figure 1). The network is trained by adjusting threshold values so that input data produces an expected output.

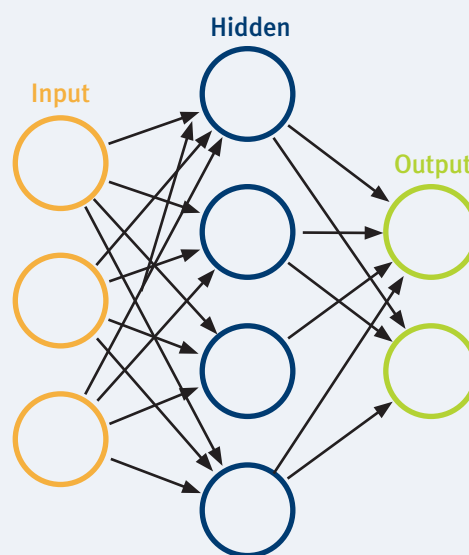


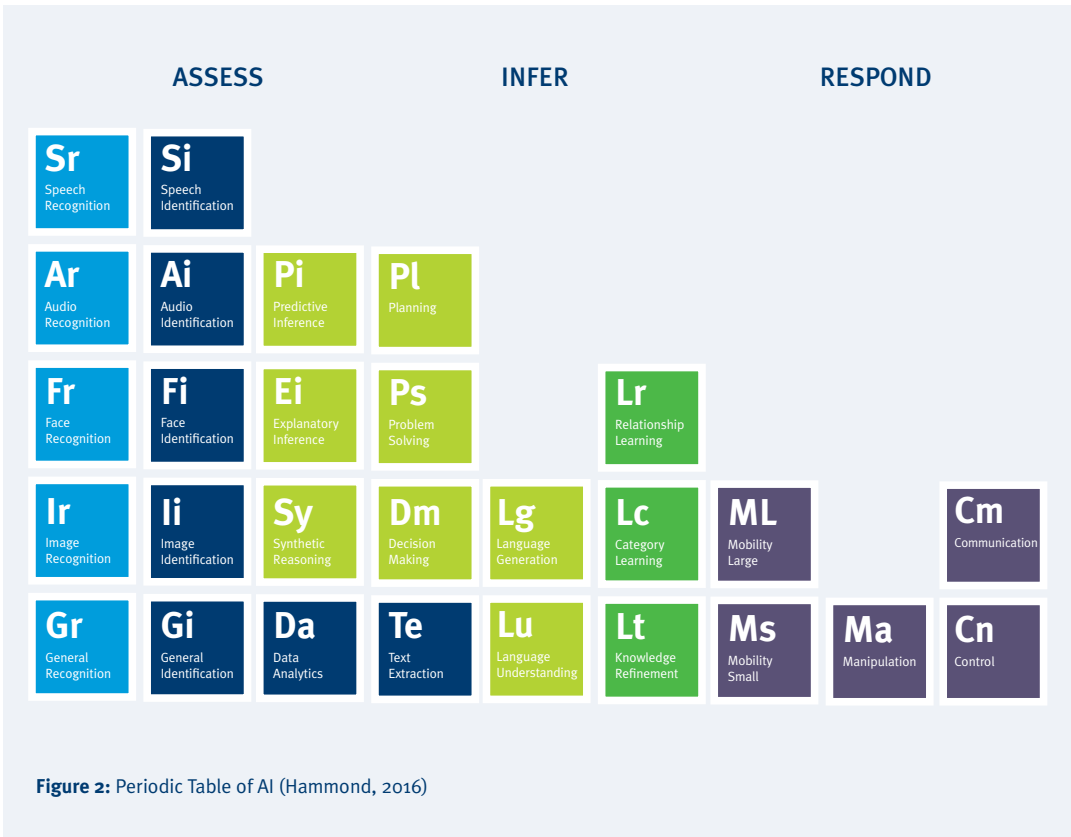
Figure 1: Conceptual model of artificial neural network

Complex deep learning models are often referred to as non-explainable – that is, they act as a ‘black box’, where inputs are transformed to the desired outputs through a number of hidden layers. Interpreting these hidden layers and explaining their function can be a significant challenge (Montavon, Samek and Müller, 2017).

3.2.2. Artificial Intelligence

Artificial intelligence refers in the broadest sense to the ability of machines to make decisions based on information. Unlike humans, modern AI programs can only currently solve very specific problems in clearly-defined areas and are developed to solve specific tasks. Modern AI research is multidisciplinary between computing and statistics – many AI implementations are based on statistical and algorithmic techniques that have existed for decades, but which have increased exponentially in effectiveness with the availability of cheap processing capabilities and big data techniques.

AI capabilities are widespread, but can be roughly grouped into three disciplines; *Assessing* (receiving and recognising information); *Inferring* (processing and learning from that information); and *Responding* (acting and taking appropriate decisions) (Hammond, 2016). Figure 2 shows the Periodic Table of AI, which groups various AI capabilities into these disciplines.



3. Big Data, Machine Learning and AI

AI and machine learning have contributed to many significant breakthroughs over the past decade. Image and voice recognition have improved immeasurably from previous deterministic methods. Machine translation between languages has also significantly improved – while still falling short of a competent human translator, many machine translations are readable and usable. Machine learning has led to greater personalisation of products based on customer preferences, from personalised music playlists and TV programme recommendations to suggestions on products to buy and services to use. AI has also shown proficiency in areas once thought dominated by human intelligence. AI chess players now can routinely beat the best human players, while in 2016, the best human Go player was beaten by an AI program. This is a significant achievement, as it was thought that computer dominance at Go was many years away.

Machine learning and AI research is currently extremely valuable, with many major corporations and national research funders sponsoring R&D, leading to a very quickly developing field. In the near future, AI applications could include fully autonomous vehicles, automation of ‘white-collar’ jobs such as accountancy and actuary and automation of complex assembly and construction processes. AI models of consumer demand are expected to become ever more sophisticated, with quickly-improving voice and image recognition and decision-making processes which could lead to automated customer service and fully checkout-free retail stores (The Guardian, 2018a).

3.2.3. Artificial Intelligence and Machine Learning in Energy

The increasing complexity of the energy system as it decarbonises provides significant opportunities for artificial intelligence operations. The system is moving from a centralised model to a more distributed one, with the number of assets in the energy system increasing rapidly. In addition to this, the

variability and inflexibility of many low-carbon sources provide an opportunity for autonomous optimisation of generation, storage and consumer use.

In the near future artificial intelligence is likely to become embedded across the energy system, with AI applications in energy predicted to extend across the entire energy value chain (Vogel *et al.*, 2019). There are four main areas in which AI is likely to play a key role:

- » Modelling and Optimisation;
- » Markets and Investment;
- » Maintenance and Security;
- » Customer-facing Services.

3.2.3.1. Modelling and Optimisation

This field incorporates energy system modelling, forecasting and prediction, as well as areas such as weather and wind speed forecasting. AI and machine learning are well-suited to optimisation and prediction applications, with artificial neural networks showcasing significant capabilities in this area. The availability of large datasets with high-quality weather and generation output data combined with more advanced simulation methods have led to quick advances in this field. A leader in this field is Google’s Deepmind subsidiary, famous for its development of reinforcement-learning algorithms to produce AIs capable of beating the best human players at chess and Go. In 2016, it announced that it had developed algorithms capable of optimising usage to reduce Google’s datacentre energy consumption by 15% by predicting load on the datacentre’s cooling systems and optimising accordingly (Jucikas, 2017). Following this, Deepmind entered into a partnership with National Grid in order to investigate applying this technology to a national network (Financial Times, 2017). However, these talks ended in 2019 without further agreement (Forbes, 2019b).

Probabilistic methods to predict wind speed and solar irradiance in order to optimise renewable generation output have likewise benefitted greatly from AI and machine learning (Iyengar *et al.*, 2017). Deepmind have developed a machine-learning model to predict the likely output of Google's US wind farms up to 36 hours ahead with a reasonable degree of accuracy (Forbes, 2019a). IBM have developed a sophisticated weather and generation forecasting model capable of forecasting weather and generation output in the US from 15 minutes up to 30 days in advance (Fortune, 2016). According to IBM, this technology is currently used by over 200 organisations. Open-source applications such as SolarCalculator are available for homeowners to estimate the output of solar PV panels on their property (solarcalculator.xyz, 2018).

» BOX 1: Renewables.ninja

Renewables.ninja is an open Web platform developed by Stefan Pfenninger and Iain Staffell at Imperial College (Pfenninger and Staffell, 2016). The platform allows the simulation of hourly power output from wind and solar plants located anywhere in the world. The platform combines sources of wind speed and solar irradiance data from NASA and EU SARA with PV and wind output simulation algorithms written by the authors (Pfenninger and Staffell, 2016). Users can select a point on a global map and run a simulation of solar or wind output, choosing values for capacity, positioning, and, for wind turbines, the model of turbine (Figure 3). The daily mean output and monthly capacity factor are then simulated, allowing users to understand the optimal positioning and sizing of renewable technologies for a given area.



Figure 3: A sample output from renewables.ninja

3. Big Data, Machine Learning and AI

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3.2.3.2. Markets and Investment

This area includes both autonomous AI agents for market interactions and investment models for market actors.

As energy systems become more decentralised and generation sources smaller, the costs of intermediary functions increase (Küfeoğlu *et al.*, 2019). The concept of autonomous AI brokers with the ability to trade energy in near real-time, perhaps utilising a blockchain implementation for transactions, has attracted interest as a potential, if radical, method for trading electricity without intermediaries. Several AI brokers have been designed and demonstrated in virtual environments – The Power Trading Agent Competition, an open-source competitive simulation of a retail power market, is an example of a testing ground for these agents (Ketter, Collins and Reddy, 2013). Annual competitions are run between AI brokers to determine the most competitive methods and agents (Rodríguez González *et al.*, 2019) (Morshed and Chowdhury, 2016).

3.2.3.3. Maintenance and Security

This area uses technology to predict and optimise maintenance schedules and efforts, as well as providing both cyber- and physical-security measures to energy assets.

Machine learning can be applied in a predictive maintenance condition monitoring role – utilising data on previous maintenance cycles, component lifetimes, failure modes and cost of outages to optimise maintenance and replacement timetables. Offshore wind turbines have a high cost of access to perform maintenance, and therefore optimisation of repair cycles has the potential to save significant costs. Machine learning models (utilising neural network and decision tree architectures) for wind turbine condition monitoring have shown early successes, though there is a need for larger public datasets to improve the models (Stetco *et al.*, 2019). Robotic technologies such as drones can also be used in conjunction with these models for visual inspection.

AI and machine learning can also be utilised to provide security services and early-warning systems for the energy networks against deliberate cyberattack or physical disruption of the energy system, either deliberate or unplanned. Deep learning neural networks can be used to scan usages across the networks, identifying patterns of consumption and energy flows and providing early warning of disruption (Merizalde *et al.*, 2019). Further discussion of cybersecurity can be found in Box 4.

3.2.3.4. Customer-facing Services

This area provides services to consumers to enable them to actively participate in the energy system more easily, including smart home energy management, integration of microgeneration and storage with virtual power plants, and bundling and billing of energy services. This area involves devices and services which interact directly with consumers and is therefore the most immediately visible area for advances to the average user. The use of machine learning to identify consumers' lifestyles, purchasing preferences and personal schedules is well-advanced in sectors such as e-commerce, fintech and social media, but have not as yet made significant inroads into the energy sector (Vogel *et al.*, 2019). This may change with the advent of smart meters and more personalised tariff options from energy suppliers – but as discussed in Section 2, customers would have to be happy to share their personal data.

As the number of prosumers (customers with on-site microgeneration, storage or demand response) increases, optimisation technologies become important for economic viability. Virtual power plants, where dozens to hundreds of microgeneration installations are connected and organised as a single unit, can be optimised using artificial neural networks to reduce supply prediction errors by up to a third compared to traditional methods (Macdougall *et al.*, 2016). In-home optimisation of consumption, storage and microgeneration can be likewise accomplished by AI and could be offered as part of a bundle of services by energy suppliers.

» BOX 2: Explainable AI

Explainable AI refers to AI in which the rationale for decisions can be understood by human experts. Current neural network deep learning methods produce a ‘black-box’, as explained in Section 3, for which even the designers of the network cannot explain why the model arrived at the decision it did. As the field of AI matures and AI applications begin to be used in critical applications, the pressure for ‘explainability’, the ability for the AI to justify its results and decisions, becomes greater. In fields such as criminal justice, healthcare, defence, autonomous transport and other areas in which human life may be greatly affected by a AI decision, it has been argued that there is an ethical right to explainability (Rudin, 2019). Above all, human operators need to trust AI decisions and results in order for AI to be effective.

In the energy sector, due to its criticality to welfare and economic importance, there is likely to be a demand for explainable AI. For industrial applications, plant and network managers will want to be able to justify the decisions an AI takes to ensure accountability, especially if there is economic fallout from a decision in terms of reduced output or plant closures. Likewise, regulators will want to see accountability for AI systems which have the potential to affect consumer welfare or system stability. The EU GDPR includes a ‘right to explanation’, though it is limited in scope.

However, some argue that there is a trade-off in capability, as well as security, in implementing explainable and transparent systems (Vogel *et al.*, 2019). There are substantial research efforts taking place to produce explainable AI. The US Defence Advanced Research Project Agency (DARPA) is currently funding a programme to research different methods of constructing explainable AI (DARPA, 2017). IBM launched an open-source toolkit to aid AI explainability in August 2019 (IBM, 2019).

3. Big Data, Machine Learning and AI

3.2.4. Limits of Machine Learning and AI

While machine learning, particularly the deep learning methods employed in artificial neural networks, has made very fast progress in the last few years, there are increasing concerns over whether this progress can be maintained. Neural networks are extremely specialised – a network adept at solving one problem will be completely useless at solving a different one – and are susceptible, through improperly categorised training datasets, to propagating human biases and misidentifying trends. Reproducing the results of machine learning algorithms is also difficult, if not impossible, without the exact training data, source code and initial conditions used to create the original algorithm, which are often unpublished. This makes it nearly impossible to benchmark new methods and algorithms, and is said by some researchers to be leading to an AI ‘reproducibility crisis’ (Hutson, 2018).

The scalability of deep learning neural network techniques to more complex problems also requires more computing power, often exponentially so. The non-profit research group OpenAI have released analysis showing that computing resource for the largest AI training runs doubles every 3-4 months on average (OpenAI, 2018). Facebook estimate the cost of state-of-the-art AI experiments are increasing ten-fold year-on-year (Wired, 2019a). While current AI techniques are well-suited to certain problems such as pattern recognition or game-playing, they seem more poorly-suited to fuzzier applications which require social and behavioural intelligence (Ars Technica, 2019b). There are efforts in the AI research community to develop more flexible and general techniques, but commercial fruition may be several years away.

3.3. Conclusions

Big data, machine learning and artificial intelligence technologies are undoubtedly going to play a large part in the energy sector going forward. These technologies will require new ways of analysing, compiling and viewing datasets, and new skillsets capable of leveraging energy system data for national and commercial advantage. The leveraging of big data and machine learning technologies will help enable other potential economic models of energy system integration – more decentralised and flexible, with a more direct link between generators, suppliers and consumers. However, these technologies should be applied with care – current machine learning techniques are only very good at solving certain subsets of problems, centred on classification of data and pattern identification, and are susceptible to poor-quality training data and human bias. The ‘black-box’ nature of these systems is also a barrier to explaining why they make the decisions they do, which is a possible barrier to implementation in critical parts of the energy sector. Understanding both the strengths and limitations of these technologies, and ensuring that organisations have the skills and knowledge required to implement them effectively, is essential to ensure their effective use.

4. The Internet of Things

4.1. Overview

The Internet of Things (IoT) is a term referring to the increase in appliances and objects with embedded sensors and internet connections. It was coined as a term by Kevin Ashton in 2009 (Ashton, 2009), initially referring to the incorporation of radio-frequency identification (RFID) tags into computer sensing and learning. In the last decade processors as well as sensing and communications technology have become considerably smaller, cheaper and energy efficient, allowing the incorporation of interconnected computational devices into a wide variety of appliances and objects.

This opens up a wide variety of applications in monitoring, analytics and machine learning, and automating real-world devices and systems. It has been described as the extension of the Internet into the real world, enabling seamless monitoring and control of real-world appliances from digital devices (Čolaković and Hadžialić, 2018). By 2025, it is predicted that over 75 billion IoT devices will be deployed globally (Figure 4).

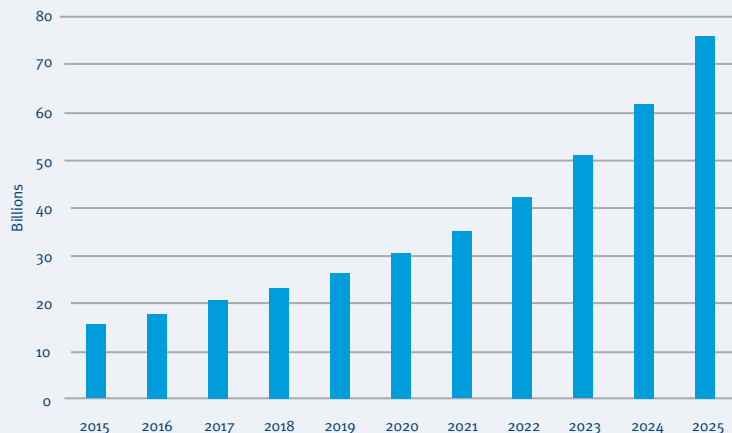


Figure 4: Projected number of IoT devices 2015-25. Data from (Statista, 2020)

4. The Internet of Things

Applications for IoT are varied and widespread. Consumers may be most aware of smart home technologies, in which home appliances, including lighting, heating, security services, cooking and refrigeration, and entertainment systems can be controlled remotely by mobile devices or by digital assistants such as Amazon's Alexa. The industrial sector utilises IoT technologies to manage production lines, process control and optimisation, while the commercial sector uses these technologies to optimise supply-chains, retailing and warehousing. Just-in-time (JiT) supply-chains, used heavily in manufacturing and retail, can be optimised using IoT technologies for monitoring and dispatch control (Čolaković and Hadžialić, 2018). Healthcare is another growth area for IoT with advances in remote monitoring of health conditions and environmental conditions (Dimitrov, 2016).

frequencies, offer extremely fast speeds but have very short ranges (approximately 300 metres maximum) due to atmospheric attenuation (Ars Technica, 2019a). Further development of the technology and build-out of antenna networks should help to alleviate these issues over the next few years.

4.2. Connectivity

Connecting a wide range of devices both to the wider Internet and to each other requires significant bandwidth. Currently, IoT devices utilise either local Wi-Fi or cable networks, which are fast and reliable but are localised in small areas, or cellular mobile 3G and 4G networks, which have a greater range but can suffer from latency, bandwidth and congestion issues.

5G cellular technology, currently in the early stages of commercial rollout, has several advantages for IoT devices. While the 4G standard supports approximately 60,000 connected devices per square kilometre, 5G is specified to support over a million in the same space (IHS Technology, 2019). Both latency – the delay between transmitting and receiving information – and bandwidth are significantly improved over the 4G standard, important for more complex and time-sensitive IoT devices such as autonomous vehicles. 5G technology however currently has issues with power consumption and the range of some of its supported frequencies – the frequencies above 24GHz, known as the millimetre-wave

» BOX 3: Wireless Communication Standards

Wi-Fi:

Wi-Fi wireless local networks began to achieve popularity in 1999 with the adoption of the IEEE 802.11b standard, which allowed LANs (Local Area Networks) to be created without requiring wires, although at lower bandwidths. Over the 2000s, Wi-Fi standards have evolved and the standard approved in January 2014, IEEE 802.11ac, can provide aggregate connections to handheld and tablet devices of 867Mbit/s.

Mobile networks:

3G mobile telephone networks were first offered in 2001, and were capable of providing connection speeds of over 2Mbit/s and often above 15Mbit/s. This speed is similar to many domestic Internet connections, and, along with smartphone technology, enabled a significant expansion in both mobile Internet usage and mobile applications. 4G Long Term Evolution (LTE) mobile standards, offering speeds usually between 50-100Mbit/s, are currently being rolled out in many countries after initial adoption in 2011. The 5G standard, which offers speeds up to several gigabits/second, is beginning to be rolled out in several countries, including the UK, though full nationwide coverage will not be achieved for several years.

Wireless Mesh Networking:

Wireless mesh networks are a form of ad-hoc wireless network in which devices self-organise into nodes with connections to all other devices within range, transferring data over the network in a peer-to-peer manner instead of all devices connecting directly to a single server. This style of networking has several advantages over the direct-connection method for large disparate collections of devices, as networks can be formed without additional infrastructure and are self-healing in case a component fails. There are bandwidth and data overhead issues which count against the technology for high-speed, low latency Internet access. However, for large numbers of devices transferring relatively small quantities of data, for example smart meters, it is a promising technology.

Zigbee:

Zigbee, a wireless data standard designed for machine-to-machine communication, is intended to provide low-power low-bandwidth self-organising networks. The standard is designed for domestic or small-commercial use, having a maximum range of between 10-100 metres between devices, with a data bandwidth of 250 Kbit/s. Zigbee is a mesh network, meaning that devices will automatically communicate with others within range and relay instructions from a central coordination device, extending the range of the network beyond the central coordination device. The Zigbee Alliance, an industry group, has developed the Zigbee Smart Energy Profile for smart metering and demand response functions. This standard has been incorporated into the UK Smart Meter Technical Specification to provide a Home Area Network (HAN) capable of supporting the In-Home Display, as well as providing connections to smart appliances, broadband links and other future devices.

Bluetooth:

Bluetooth, a short-range (up to 100m) wireless communication standard designed for mobile and audio devices, was first proposed in 1997, with implementations reaching many consumer devices by 2000. The standard has been developed continuously since then, and the latest specification, Bluetooth 5.0, was launched in late 2016 and includes several features designed to aid adoption of the Internet of Things.

4. The Internet of Things

4.2.1. Edge computing

The Internet of Things, with its multitude of sensing, measuring and monitoring devices, faces issues with bandwidth and latency. Traditional centralised cloud computing requires information to be uploaded whereupon it is processed and the results downloaded to the distributed devices. As the number of devices increases, more information needs to be uploaded at any one time, requiring increased bandwidth. Time-critical applications are also affected by latency – the time taken for signals to travel to the cloud, be processed and return. Edge computing refers to the capability for connected devices to do some or all of the required processing on-device or in nearby processing centres, reducing the information transfer and processing which needs to be completed on the centralised cloud (The Verge, 2019).

A good example of edge computing is the self-driving vehicle – these contain several high-bandwidth sensors such as video cameras and are required to make decisions based on the data received from these sensors very rapidly and reliably. For this reason, a lot of processing is done on-vehicle, avoiding issues around latency and connectivity. However, it is also desirable to have connections to the centralised cloud and surrounding vehicles for traffic-flow optimisation, incident reporting and security. As such, these tasks are offloaded to the cloud.

4.3. Robotics and Automation

Robotic technology is a vital part of automation and digitalisation efforts, allowing digital devices to reach into and control the physical world. The concept of robotics has been part of human discourse for hundreds of years, but robotics as an engineering/scientific discipline dates from post-WW2, with the first commercial and industrial robots being deployed in the early 1960s. In the subsequent decades, miniaturisation of electronics combined with smaller, higher-density batteries, has allowed

the development of smaller, more mobile and more capable forms of robot. The advent of the Internet and distributed computing has made robotics an increasingly important part of the emerging digitalisation paradigm, leveraging distributed computing and machine learning to allow greater automation of tasks than individual robots could before (Keisner, Raffo and Wunsch-Vincent, 2016).

4.4. Energy Sector Applications

Internet-connected devices are already being used in many parts of the energy sector. The most familiar to many energy consumers will be the smart meter, which provides a real-time readout of energy use and periodically uploads consumption data to suppliers. In the electricity networks, connected sensors are beginning to be widely deployed to monitor flow and conditions. The electricity sector is a prime candidate for edge computing technology, due to widely distributed resources and requirements for low latency in many applications (Cleantech Group, 2019). National Grid are exploring real-time optimisation of local assets using edge computing in conjunction with the software company Pixeom.

Robotics will affect the energy sector in several important ways. The most obvious is the development of self-driving vehicles, which have the potential to change transportation habits, modalities and therefore energy usage patterns and total usage. Drone technology is already used in upstream energy applications, including visual inspection of hard-to-reach areas of turbines, pipelines and transmission cables – this is expected to increase, with the possibility of drones being able to carry out simple maintenance operations. Robotics will more generally enable the automation of many tasks which are currently carried out by humans, displacing activity with the potential to affect employment patterns and societal structures. Analysis of these potential changes are outside the scope of this paper, but could have knock-on effect on energy usage patterns.

» BOX 4: Cybersecurity

Cybersecurity, the practice of ensuring electronic systems are secure against intentional disruption or data theft, is becoming increasingly essential to implement as systems become more complex, interconnected and essential for daily life. The energy system is a critical component of national infrastructure, and therefore is a tempting target for malicious attackers. The electricity networks have been relatively resilient to cyberattack in the past, as control systems were not easily remotely accessible and the systems were mostly ‘analog’, without a high degree of digitalisation. However, with the advent of smart grid technology and digital control systems, the risk of attack and the consequences become significantly greater. A recent study found the cost of a major cyberattack on the distribution network in the London region could be up to £111 million a day, with cascading failures on the water, rail and telecoms networks (Oughton *et al.*, 2019).

There have been several attempted cyberattacks on energy infrastructure over the last few years, with a successful attack on the Ukrainian electricity grid in 2016 leading to a blackout over a large portion of Kiev. This attack has been theorised to have attempted to cause physical damage to the grid infrastructure by overloading transformers (Wired, 2019b). Energy companies and electricity network operators are disproportionately targeted by hackers, with a 2016 survey reporting that 75% of energy companies had suffered at least one intrusion attempt in the past year, and the US Department of Homeland Security reporting in 2017 that over 400 intrusions had occurred at US energy facilities since 2011 (Ankura, 2019). As automation and digitalisation in the energy sector continues to advance, these attempts are expected to become more frequent and potentially more damaging.

The UK government operates the National Cyber-Security Centre (NCSC), which produces the Cyber Assessment Framework (CAF), a collection of principles and guidance for organisations which operate critical services, including energy (National Cyber Security Centre, 2019). These cover data and system security measures, understanding risks, monitoring network assets and supply chains, staff training and awareness and developing response and recovery plans in case of attack. There are, however, concerns over a shortage of cybersecurity skills in the UK along with vulnerable legacy infrastructure and concerns over the globalised nature of asset supply chains (The Parliamentary Office of Science and Technology, 2017).

5. Distributed Ledgers, Blockchain and Smart Contracts

5.1. Overview

Distributed ledger technology (DLT), of which blockchain technology is the most commonly known example, is a method of storing multiple synchronised and identical copies of a ledger across a network of devices (The Parliamentary Office of Science and Technology, 2018). This technology has been gaining considerable momentum in recent years due to its potential to enable peer-to-peer decentralised transactions. Applications in finance, logistics and supply, taxation and public registries and other sectors are currently being explored (PWC, 2016). The most popular and well-known applications of DLT have been the blockchain cryptocurrencies Bitcoin and Ethereum, which have demonstrated both the feasibility of large-scale distributed ledgers and the challenges of implementation, including wildly variable currency values, very high electricity usage and a slow rate of transactions (Bitcoin, for example, can only process 4-7 transactions per second on the blockchain, a rate an order of magnitude below centralised digital transaction services).

5.2. Key Concepts

DLT works using a network of computing devices, each containing a copy of the ledger. These devices communicate in a peer-to-peer fashion with no central coordinator. When a transaction between two parties is agreed, it is combined with all other transactions made through the same period to form a block. This block is encrypted and cryptographically verified via the efforts of the devices in the network, forming a tamper-proof record of the transactions, and is added to the end of the ledger. This sequence of transaction blocks is commonly referred to as a blockchain (German Energy Agency, 2016).

Ledgers can either be *permissioned*, in which users of the ledger must be part of a verified set of administrators to add data, or *permissionless*, in which any user can add data, provided it passes a ‘consensus mechanism’. The rationale for employing a permissionless distributed ledger is that there is no central authority controlling access. Instead, ledger updates are added by participants and are pushed out to every copy on the network. The integrity of the ledger is protected by a ‘consensus mechanism’, where a majority of the other participants on the network must verify and approve a transaction before the ledger can be updated. The distributed ledger is enabled via peer-to-peer technologies and cryptographic methods to ensure security and proof against tampering (Andoni *et al.*, 2019).

5.2.1. The Consensus Mechanism and Validation Methods

An important part of any DLT design is the method required to implement the consensus mechanism. Most current DLT utilise a *proof-of-work* algorithm, in which validators, known colloquially as miners, compete to solve a difficult cryptographic problem. The solution to this cryptographic problem forms the verification of the block, and the miner responsible for calculating it receives a financial reward – in the case of a cryptocurrency, paid in units of that currency. Criticisms of proof-of-work relate to transaction speed and energy use. As each block needs to be verified by miners through cryptographic solving, the time taken to verify transactions can vary from a few minutes in perfect circumstances through to hours or even days in congested networks, as seen recently on the Bitcoin blockchain (CoinCentral, 2017). In addition, as the mining activity required to maintain proof-of-work provides revenue from

the reward structures and the algorithms scale to the computational resource available, miners seeking profit can push the energy usage of the validation mechanism to extreme levels; in 2018, the Bitcoin network was estimated to use over 2.5GW – more than the energy consumption of Ireland (de Vries, 2018).

Proof-of-stake, an alternative means of verification, allocates blocks for verification to miners in rough accordance to how much of the underlying commodity tokens they own. This is designed to prevent the ballooning of energy required for verification and ensure that those who have a greater ‘stake’ in the blockchain bear more responsibility for verifying it, potentially avoiding risks from malicious actors. Proof-of-stake is currently untested in a large blockchain application, though the Ethereum cryptocurrency is currently in the process of moving to a proof-of-stake system.

Proof-of-authority verification, often stated as the most suitable for many energy sector applications, requires blocks to be validated by authorised nodes (Andoni *et al.*, 2019). This requires the network to be centralised under an authority or authorities and makes it more vulnerable to possible cyberattack on the authorised nodes, but has low verification energy use and, if properly implemented, should be fast and reliable. Proof-of-authority verification has not been implemented on a large scale, but is being investigated by several energy blockchain start-ups.

5.2.2. Smart Contracts

Smart contracts are a relatively new term referring to automated programmes which can be instructed to transfer currency or commodities. They are written as simple pieces of computer code which are encoded into the blockchain and are executed when certain conditions are met, changing the contents of the ledger to represent the outcome of the contract. Smart contracts, due to existing on the distributed ledger, are tamper-proof, publically available and should be self-enforceable, which means that they should

drastically reduce the costs of contracting, enforcement and compliance. This opens up the potential to form numerous smart contracts over low-value transactions. (Government Office for Science, 2016). Some cryptocurrencies have incorporated forms of smart contracts, with the Ethereum cryptocurrency being currently the most advanced implementation (Andoni *et al.*, 2019). Smart contracts have many potential uses owing to their ability to provide low-cost, automated services.

5.3. Distributed Ledger Applications in the Energy Sector

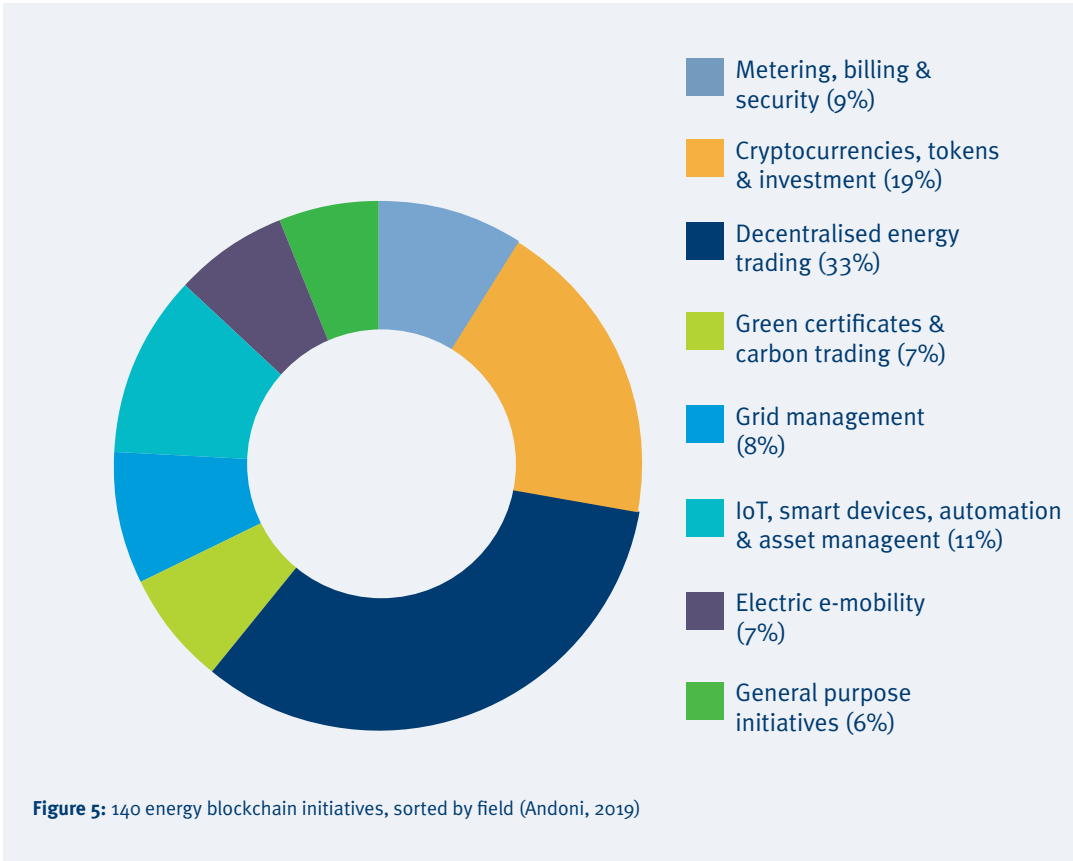
There has been interest in distributed ledger technology from stakeholders in the energy sector, owing to their potential in making peer-to-peer transactions more transparent, robust and not requiring central supervision. Distributed ledgers are relatively new, and not without significant challenges, as discussed below. However, as the energy industry explores more decentralised models, including peer-to-peer trading, microgrids and local demand response, DLT could provide an important factor for facilitating interactions without a central authority. While the DLT paradigm makes most sense in sectors such as finance, where there is no physical exchange of goods, electricity, due to its characteristics as an immediately-delivered commodity, is, in theory, well-suited for the technology (Eurelectric, 2019).

Utilities, technology providers and government bodies have identified several key areas in which distributed ledger technology could engage in the energy sector. A systematic review of blockchain technology in the energy sector (Andoni *et al.*, 2019) identified 140 separate blockchain initiatives currently taking place globally. These are divided into several areas, shown in Table 4 and Figure 5.

5. Distributed Ledgers, Blockchain and Smart Contracts

Metering, Billing and Security	Automated billing and advanced billing structures. Securing and verifying transactions and stakeholder identities
Decentralised Energy Trading	Wholesale market and commodity trading transactions
Green Certificates and Carbon Trading	DLT can allow verified origin certificates
IoT, Smart Devices, Automation and Asset Management	Automated decentralised P2P energy trading
Grid Management	Verified sensor information and data transfer between smart grid components
General Purpose Initiatives and Consortia	Development of base technology and platforms
Electric E-Mobility	EV chargers, EV shared fleets and other infrastructure could utilise DLT
Cryptocurrencies, Tokens and Investment	Transparent, verified records would improve auditing and regulation. Potential to allow small investors to directly invest in projects using tokens.

Table 4 Potential Applications of DLT in the Energy Sector (Andoni, 2019)

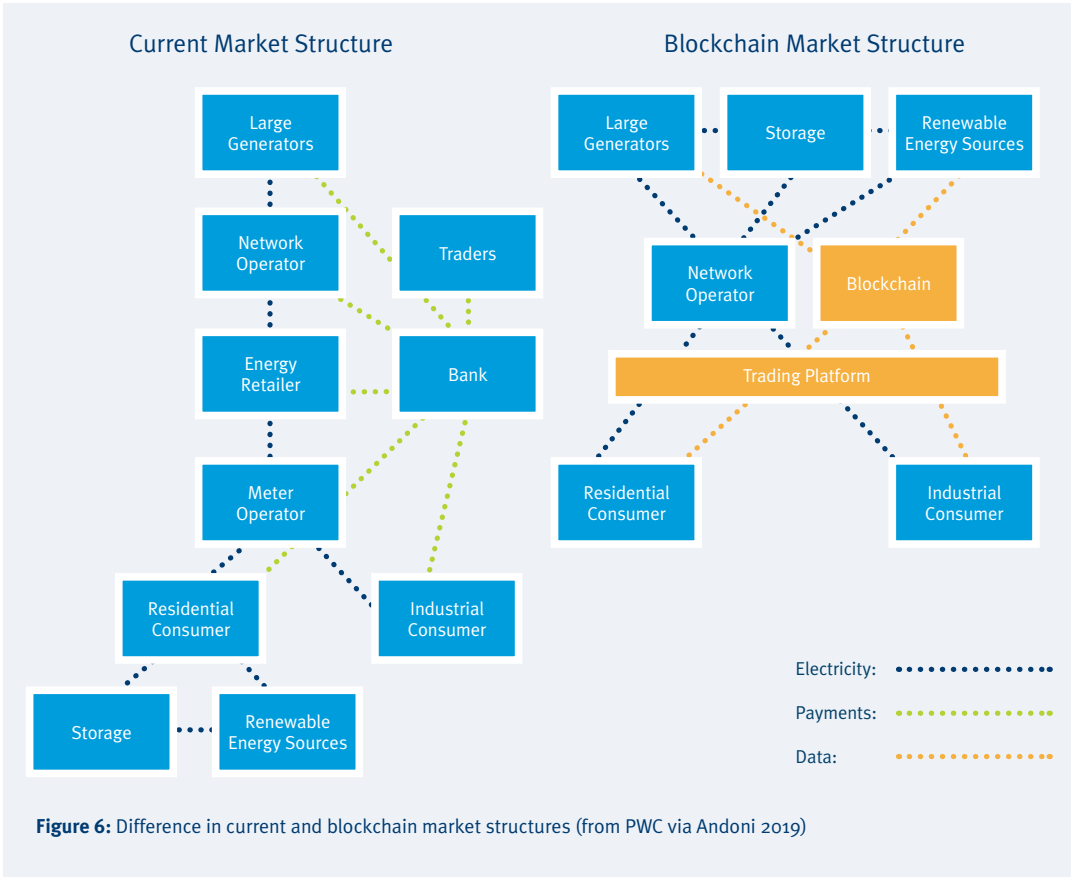


5.3.1. Energy markets and decentralised trading

Distributed ledger technology has the potential to significantly disrupt the current centralised wholesale market structure. DLT could allow generators to trade directly with consumers without intermediaries such as supply companies by operating through a trading platform (PWC, 2016). As can be seen in Figure 6, this structure would operate by consumers directly contracting energy through a trading platform. Energy delivery would be contracted between parties by recording in a central blockchain, and the transfer of both energy and payment would automatically occur at the time of delivery via an encoded smart contract. It would be easier to verify the exact source of supplied electricity through the DLT model, simplifying the process of issuing certificates of origin and calculating emissions on a per-user basis. Transactions recorded in the blockchain would be visible to all parties,

including the system operator for balancing purposes. This model could be combined with autonomous AI agents, who could scan the trading platform and book the lowest-priced energy for given time periods without direct human intervention (Ketter, Collins and Reddy, 2013).

This model would be extremely disruptive to the current market, requiring massive changes in structure (energy brokers and retail supply companies would largely disappear or change function dramatically), regulation and consumer engagement. In addition, a DLT-enabled wholesale market is an untested proposition and is unlikely to be adopted at scale on critical infrastructure without lengthy testing. As such, it is very unlikely that it would be adopted in the near future, notwithstanding the serious concerns around transaction times, energy use and privacy relating to DLT applications at present.



5. Distributed Ledgers, Blockchain and Smart Contracts

A more likely application for DLT in the near future would be community-level decentralised P2P energy trading, either across a self-contained microgrid or at distribution level. This would still entail considerable changes to centralised market, supply and balancing arrangements in most electricity markets – for such reasons, trials are currently taking place on a small scale on islanded or constrained parts of the networks. In the UK, Centrica are partnering with blockchain technology company LO3 to explore blockchain usage on a constrained part of the Cornwall network as part of their Local Energy Market trial (Centrica, 2018). Other trials are currently underway in New York, Japan and Australia, among others (PowerLedger, 2019).

5.3.2. Metering and demand-response applications

An obvious application for DLT is incorporation into smart meters and smart appliances for billing, usage and demand-response functionality. Smart meters would record usage information and directly to a blockchain, with appliances requesting and monitoring energy use in the same manner. Energy utilities could use this blockchain data to monitor usage at a more granular level than at present, as well as using the blockchain to send demand-response requests to appliances to consume less energy at times of high demand. This would allow a decentralised open platform for metering, billing and demand response, circumventing the need for a central data communications provider as seen at present (Mattila *et al.*, 2016). Virtual power plants, where dozens or hundreds of distributed generation or storage assets are combined to form a single larger plant for the market, could also be mediated via a blockchain to transparently track contributions and payment to the component assets.

Challenges for this model include privacy and security – which entities have access to read and change the blockchain – as well as technical issues with DLT implementation across meters and appliances. These are discussed in more detail below.

5.4. Challenges

Implementing DLT in the energy sector comes with a number of significant challenges - some technical, some market and regulatory and some to do with consumer acceptance, security and trust.

DLT is relatively new, with the conceptualisation of the modern Bitcoin blockchain dating from 2008 (Nakamoto, 2008) and almost all key developments taking place in the last eight years. As such, it is a relatively immature technology, with considerable development currently taking place, but with little consensus on final, mature forms of the technology for diverse applications. There is considerable debate over the future viability of DLT, with some experts seeing it as a transformative technology and others seeing DLT as innately slow, complex, expensive in energy use and computational time and vulnerable to manipulation and fraud. These experts see DLT in many applications as being inevitably outperformed by conventional competitors (The Guardian, 2018b).

5.4.1. Technical

Blockchain technology currently suffers from several key technical issues. Firstly, transaction speed is slow, with the speed of transactions reliant on the number of nodes available to process and verify blocks and the number of transactions currently being processed by the network. Bitcoin currently processes roughly 7 transactions per second on average, with Ethereum processing approximately 15. These times increase rapidly during periods of high activity (CoinCentral, 2017). By comparison, the Visa payment network processes around 24,000 transactions per second. Transaction costs also tend to be high, with the cost of transaction for Bitcoin about \$1 to be included in the next block. While faster DLT methods are being developed, such as ‘sharding’, a method for the parallel processing of transactions (Forbes, 2019c), the current slow speed of transactions limits its usage for high-throughput or time-critical energy sector functions.

Energy usage, particularly using the proof-of-work verification method, is also very high, with a great deal of electricity and processor power expended solving cryptographic problems. The Bitcoin network is currently estimated as using nearly 0.3% of the world's total electricity consumption (Cambridge Centre for Alternative Finance, 2019), by any metric inefficient for the utility provided. Once again, future developments in DLT could bring usage dramatically down, but it is questionable if a DLT implementation will ever be as efficient as a more centralised method.

As the blockchain needs to record every transaction made since its conception, the full chain will increase in size over time. As of June 2019, the Bitcoin blockchain is over 225GB, with a full copy required by every node on the network (Statista, 2019). Newer implementations including Ethereum require nodes to have only a partial copy of the blockchain, but even in this case the data storage requirements are still quite large. Data storage and processing requirements for blockchain nodes would be needed to be taken into account for internet-of-things connected devices – it is unlikely, for example, that the UK's current SMETS2 smart meter configuration provides enough capability to support blockchain applications.

5.4.2. Market and regulatory

Questions of ownership and control are central to DLT applications. Cryptocurrencies such as Bitcoin and Ethereum are designed, at least in theory, as permissionless – no organisation should have overall control over the system. While this has helped with rapid adoption, there is no oversight over transactions for consumer protection, leading to several high-profile cases of fraud and theft, or for the curtailing of transactions in illegal goods or money laundering. By contrast, the electricity system, as critical infrastructure, would need methods of controlling and managing the distributed ledger. This naturally points towards a more centrally-controlled, permissioned blockchain consisting of trusted nodes. This approach, while

providing the certainty of control required for the electricity system, at least partially removes one of the advantages of DLT – the lack of need for oversight in transactions between two actors – while retaining DLT's disadvantages of greater inefficiencies and longer transaction times compared to a centralised processing system.

Market arrangements would have the potential to change dramatically under a DLT-based system, as consumers and generators would be able to form direct contractual relationships without intermediaries such as energy suppliers. As such, consumers would be directly responsible for their own security and balancing, and would need to submit details of their projected usage and supply details to the System Operator for system-wide balancing and stability (PWC, 2016). This would require substantial changes in regulatory frameworks, with new regulations for direct trading of energy between consumers and more flexible tariff structures. In addition, the lack in a permissionless blockchain of a central authority monitoring and clearing transactions raises serious questions on responsibility and liability for transactions. The relative newness of DLT and the lack of experience with the technology in most sectors means that regulation may be initially more difficult and requiring of iteration and fine-tuning. Standardisation efforts throughout the sector are currently lacking, with several competing blockchain standards being pushed by various organisations. Given the increased potential for instability in a peer-to-peer system, it can be expected that policy and regulation will initially be conservative and possibly limiting.

5.4.3. Consumer acceptance, security and trust

Several proposed applications of DLT in the energy sector involve direct consumer engagement, from simple integration with energy billing through to complex applications involving peer-to-peer trading and smart home integration. At present, the most visible application of DLT is the Bitcoin cryptocurrency, which has seen considerable bad press coverage around

5. Distributed Ledgers, Blockchain and Smart Contracts

its facilitation of illegal trading, widespread fraud and theft, significant energy usage and rapidly fluctuating value (Ars Technica, 2019d; BBC News, 2019). It may well be the case that some consumers would feel uncomfortable entrusting their energy usage details to a blockchain system (PWC, 2016). Due to the way a blockchain operates, if a consumer loses their cryptographic key, they lose their access and data without recourse. There are also issues with visibility – a distributed blockchain is visible to its participants, and all transactions within the blockchain could therefore be publically viewed. In the case of DLT-based billing and metering, it could be, without a technological solution to this challenge, that all energy consumed by specific appliances in specific homes would be visible to any interested party, which would be an unacceptable loss of privacy to many consumers. While this may be a disadvantage for domestic consumers, industrial and commercial consumers may welcome the transparency and granularity of this data for tracking energy usage patterns.

In a decentralised permissionless DLT system, as seen in the major cryptocurrencies, there is no regulatory oversight entity able to reverse false or fraudulent transactions or mediate disputes. Transactions are irrevocable once completed, and fraud and theft from accounts is therefore attractive. An energy sector DLT would have to be designed from the ground up to be fully tamper-proof and secure, especially if it would be embedded into devices and used to regulate electricity flows across the network. Many start-ups and trials of energy DLTs are based on Ethereum technology, which has suffered serious hacks on both cryptocurrency stores and smart contracts (Ars Technica, 2019c; Nikolic *et al.*, 2019). While these security issues can be mitigated by designing the blockchain with a centralised oversight entity able to control and override transactions and moving to a fully permissioned model, this, as discussed above, loses some advantages in using the technology.

5.5. Conclusions

DLT technology is new and has had significant press coverage and venture capital investment. This inevitably leads to widely dissenting views about its uses and future viability. The IT consultancy Gartner, in the 2018 edition of its widely quoted Hype Cycle of emerging technologies, placed blockchain technology as high on the inflated expectations peak, indicating that while it is an interesting and viable technology, it is still overhyped as to its future uses and markets (Gartner, 2018). Any application of DLT will only be successful if it offers clear advantages over an equivalent conventional centralised solution.

As such, it is important to approach DLT with an understanding of its current advantages and limitations, as well as specific use cases in which the technology could prove beneficial. DLT can provide low-cost, transparent, verifiable and cryptographically secure transactions between peers without the need for centralised monitoring and control. In its current iterations, however, it is computationally- and energy- intensive, has potential privacy issues and is many times slower than more conventional methods. Research into designs to reduce these technological drawbacks are currently being worked on, but currently the technology is too immature to be utilised for radical, wide-ranging or system-critical uses in the short term. However, there are some use cases, such as certificates of origin, emissions tracking and identity management, which are low-throughput and non-critical to the second-to-second running of the system. DLT solutions to these applications could be explored in the near future without significant technical advances.

Moving from a centralised model with clear demarcations of legal responsibilities, liabilities and roles to a peer-to-peer decentralised system would be complex in any sector, let alone one as critical as energy. Cryptocurrencies have seen rapid adoption because they exist alongside the conventional banking system, not instead of it. It is difficult to envisage an analogous model for electricity supply, given the need to

maintain overall system balance and stability. Before embarking on large-scale applications, DLT should prove itself by providing low-cost and robust solutions to smaller, niche problems. As mentioned above, emissions certificates and carbon trading, especially across borders, could be one niche, as could billing for large industrial and commercial consumers. The anarchic natures of the large permission-less cryptocurrencies are also ill-suited for the energy system – it may well be that the ideal DLT implementation for energy is more centralised and controlled than technology advocates may claim.

DLT could prove transformative, or it could be that the scale of adapting DLT to the energy system on a large scale is more expensive, disruptive and time-consuming than refining and evolving current systems. Due to this, its potential should not be underestimated, or importantly, overestimated.

DLT has many significant hurdles to overcome before widespread adoption. Energy professionals should be aware of it and understand its characteristics, but should be wary of looking at it either as a ‘silver bullet’ which will solve issues with energy markets in a more distributed system, or viewing it too cynically through the lens of the major cryptocurrencies and their issues, without understanding the inherent flexibility of the technology.

5. Distributed Ledgers, Blockchain and Smart Contracts

6. Discussion and Recommendations

As can be seen by the evidence collected in this briefing paper, digitalisation is a broad, quickly-evolving collection of hardware technologies and software advances with the potential to change many, if not all, areas of the energy system and value chain. In general, there is a dichotomy in what is expected through digitalisation, between incremental improvement and transformative, disruptive change. This can be explained through the lens of a cultural difference between disciplines (Bichler, 2012). According to this view, actors in the conventional energy engineering disciplines take more of an incremental, component-oriented approach to digital technologies, viewing digitalisation to be a modernisation process involving the replacement of assets with improved versions while adding components such as smart metering in order to fulfil specific needs and requirements. This process of continuous improvement is considered a natural extension of the current paradigm, and indeed many in conventional engineering disciplines dislike terms such as ‘smart grid’ and ‘digitalisation’, viewing them as unhelpful buzzwords with vague definitions.

New entrants into the energy sector – ICT providers, technology start-ups, service providers and others – often see digitalisation through the lens of a systemic innovation, in which the increasing level and quality of communication and connectivity between installed digital technologies allows the energy system to be seen holistically, enabling radical new business models and technologies to be developed and utilised. In this model, the development of a smart grid is seen as more analogous to a 3G wireless mobile network, in that by providing wide-scale communication and information, it enables a wealth of devices and applications to provide new services to customers.

This tension between these competing paradigms, and therefore between more established actors in the energy sector and new entrants, is important to understand when discussing the impact of digitalisation in the energy sector. Due to several factors surrounding energy – its position as critical to human welfare and the economy and the natural conservatism this engenders; the existence of regulated monopolies over large parts of the system; large and expensive physical assets and infrastructure; and significant national localisation making global provision of some products more difficult – penetration of digital technologies and services have in several areas been lesser than in other major sectors. One exception is upstream fossil fuel extraction and refining, which has employed cutting-edge robotics, modelling and digital sensing technologies for some time.

There are substantial prizes to be won in digitalising the energy sector. As the sector transitions to a low-carbon structure based on variable and more distributed generation, active demand management, active consumer participation and greater electrification, the opportunities in system optimisation alone could lead to substantial operational savings and deferred investment in network physical reinforcement. Data analytics combined with machine learning techniques can provide evidence for investment decisions as well as informed predictions on generation output, demand and maintenance cycles. Energy markets have the potential to be more automated and localised to community levels with the use of AI agents, and distributed ledger and smart contract technology could provide decentralised authentication of energy and carbon trading.

However, there are considerable challenges in effectively deploying new digital technology and the aligned business models and patterns of engagement. As discussed above, there is a tension between more established actors and new entrants in the energy sector as to how to view digitalisation – either as a process to make current sector arrangements more efficient or as a paradigm shift towards a radically different energy system and market. These different outcomes require different policies, regulation, skillsets, action from incumbents and business development and are therefore to an extent mutually exclusive. The structure and capabilities of the energy system will also be affected – the degree of decentralisation, degree of active customer engagement and structure of energy markets will rely to a great extent on the digital technologies and strategies which are implemented and the policies and regulatory measures that govern them.

This means that any strategy for digitalising the energy system cannot be seen as a separate endeavour to the wider ambitions of decarbonisation – differing pathways to decarbonising the energy system will require different implementations of digital technology, and likewise the implementation of energy digitalisation will open decarbonisation pathways that may be more attractive in economic or wellbeing terms. The impact of digital technologies on the energy system needs to be considered by policymakers and regulators as a holistic part of decarbonisation, rather than a separate concern.

This will also require flexibility – both in regulation and in development and demonstration. Unlike many other sectors (retail, fintech, hotels, taxis, to give some examples), it is very difficult for new entrants to quickly disrupt the energy sector through digital services due to regulatory measures and established regulated monopolies. While some conservatism is necessary due to the importance of the energy sector to both the modern economy and human wellbeing, there needs to be effective paths to market for new and potentially disruptive

services and business models. Regulatory measures need to be as open and flexible as reasonably possible in order to trial new concepts, technologies and models on the energy system and to allow new entrants into the sector to effectively offer products to consumers and compete with established market actors. Due to the speed of advancement in digital technology and data science, regulatory approval for new products and services should be processed as quickly and cheaply as reasonably possible. Likewise, system data should be open and available where possible. As has been seen in other sectors, data availability has been an important factor in the growth of new digital services.

Demonstration projects, which interact with real consumers where possible, are essential. A great deal of digitalisation technologies and services rely on consumer consent, acceptance and active interaction. Testbeds that allow new entrants to demonstrate technology and to obtain consumer feedback are a way to achieve this – the Living Lab operated by the Energy Systems Catapult being a good example (Energy Systems Catapult, 2019a).

7. Conclusions

This Briefing Paper has reviewed the expanding area of digitalisation of energy and has provided an overview of key component technologies, their applications in the system, their potential limitations and obstacles to their implementation. In a rapidly digitalising world, it is useful for industry, policymakers, regulators and other energy stakeholders to understand these technologies and their implications in order to make informed decisions. Five areas, which are detailed below, emerge as the most important:

- » **Technology** – Major actors throughout the energy sector, from policymakers and regulators to the regulated network monopolies and large suppliers, should ensure they have institutional knowledge of new digital technologies, particularly in the fields of data analysis, machine learning and digital automation. Understanding the applications and, importantly, limitations of these technologies is increasingly essential, and appropriate upskilling will help to ensure that this information is embedded in organisational decisions.
- » **The Consumer** – Many of the more potentially transformative applications of digitalisation rely on much greater consumer engagement than at present – including time-of-use tariffs, selling electricity on the market and automation of household consumption and demand response. This will require many stakeholders, principally supply companies but also potentially including network operators, regulators and generators, to take a far more active approach to customer engagement than at present, working with individual consumers and understanding localised needs.
- » **Data and Data Privacy** – Data collection, analysis and usage is at the heart of digitalisation and therefore needs to be at the forefront of stakeholders' thinking. Generated data from system functions should be standardised, centralised and open where possible. Common data standards should be implemented sector-wide. Generated data from consumers is a more sensitive area given widespread concerns around privacy and security coupled with more stringent regulation such as the GDPR. Stakeholders should establish best practice guidelines in order to balance privacy, security and consumer trust with access and usage. This is not an easy balance to strike, but it is essential for the adoption of many digital technologies and practices.
- » **Automation** – One of the biggest 'prizes' of digitalisation is automation, either physically or in the digital realm. Machine learning and autonomous AI are very powerful tools, and their effective use has the potential to drastically change the energy sector. However, these tools' effectiveness is based on the quality of their data sources, both in training and in the field. Furthermore, the 'black-box' nature of many of these methods may be an issue in many applications, especially those which are safety-critical in the energy sector. Where possible, these tools should be explainable and transparent as to the datasets they utilise and the methods used for their training.
- » **Cybersecurity** – With the increasing use of digital technologies comes the risk of cyberattack, where data is stolen or operations disrupted by malicious third-party actors. The energy system, as a piece of critical infrastructure, is a tempting target for disruption. Robust cybersecurity measures

should therefore be considered as an integral aspect of digitalisation efforts and need to be incorporated at a base level of design and implementation.

The energy sector is undergoing its most significant change in over half a century, driven by both the decarbonisation imperative and by the potential of new digital technologies to transform and decentralise the sector. These technologies are quickly-evolving and require new commitments, policies, regulation and expertise in order to implement in the most effective manner. However, the prize, in terms of greater efficiency, flexibility and the ability to pursue a greater range of pathways to decarbonisation, is substantial.

7. Conclusions

Bibliography

Andoni, M. et al. (2019) 'Blockchain technology in the energy sector: A systematic review of challenges and opportunities', *Renewable and Sustainable Energy Reviews*. Pergamon, pp. 143–174. doi: 10.1016/j.rser.2018.10.014.

Ankura (2019) *Cyber Attacks and the Energy Sector*. Available at: <https://ankura.com/insights/cyber-attacks-and-the-energy-sector/> (Accessed: 17 October 2019).

Ars Technica (2019a) *5G deployment stands ready to supercharge the Internet of Things*. Available at: <https://arstechnica.com/information-technology/2019/12/5g-deployment-stands-ready-to-supercharge-the-internet-of-things/> (Accessed: 6 January 2020).

Ars Technica (2019b) *A sobering message about the future at AI's biggest party*. Available at: <https://arstechnica.com/information-technology/2019/12/a-sobering-message-about-the-future-at-ais-biggest-party/> (Accessed: 14 January 2020).

Ars Technica (2019c) *Almost \$500,000 in Ethereum Classic coin stolen by forking its blockchain*. Available at: <https://arstechnica.com/information-technology/2019/01/almost-500000-in-ethereum-coin-stolen-by-forking-its-blockchain/> (Accessed: 15 August 2019).

Ars Technica (2019d) *Berkeley researcher on the only way to fix cryptocurrency*. Available at: <https://arstechnica.com/information-technology/2019/02/researcher-counts-the-reasons-he-wants-cryptocurrency-burned-with-fire/> (Accessed: 15 August 2019).

Ashton, K. (2009) *That 'Internet of Things' Thing*, *RFID Journal*. Available at: <http://www.rfidjournal.com/article/print/4986> (Accessed: 2 May 2019).

BBC News (2019) *Binance exchange hackers steal bitcoins worth \$41m*. Available at: <https://www.bbc.co.uk/news/technology-48199375> (Accessed: 15 August 2019).

BEIS (2018a) *Energy Data Taskforce – Terms of Reference*. Available at: <https://www.gov.uk/government/groups/energy-data-taskforce> (Accessed: 19 September 2019).

BEIS (2018b) *Review of the Data Access and Privacy Framework*. Available at: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/758281/Smart_Metering_Implementation_Programme_Review_of_the_Data_Access_and_Privacy_Framework.pdf (Accessed: 23 September 2019).

Bichler, M. (2012) *Smart Grids and the Energy Transformation: Mapping Smart Grid Activities in Germany*.

Cambridge Centre for Alternative Finance (2019) *Cambridge Bitcoin Electricity Consumption Index (CBECI)*. Available at: <https://www.cbeci.org/comparisons/> (Accessed: 9 August 2019).

Carmichael, R., Gross, R. and Rhodes, A. (2018) *Unlocking the potential of residential electricity consumer engagement with Demand Response*. Available at: <http://imperial.ac.uk/energy-futures-lab>.

Centrica (2018) *Cornwall Local Energy Market*. Available at: <https://www.centrica.com/innovation/cornwall-local-energy-market> (Accessed: 13 August 2019).

Cleantech Group (2019) *Energy & Power Shifts from IoT Cloud to Edge Computing*. Available at: <https://www.cleantech.com/energy-power-shifts-from-iot-cloud-to-edge-computing/> (Accessed: 22 November 2019).

CoinCentral (2017) *How Long do Bitcoin Transactions Take?* Available at: <https://coincentral.com/how-long-do-bitcoin-transfers-take/> (Accessed: 8 August 2019).

Čolaković, A. and Hadžialić, M. (2018) 'Internet of Things (IoT): A review of enabling technologies, challenges, and open research issues', *Computer Networks*. Elsevier, 144, pp. 17–39. doi: 10.1016/j.COMNET.2018.07.017.

Computerworld (2017) *Data storage goes from \$1M to 2 cents per gigabyte*. Available at: <https://www.computerworld.com/article/3182207/cw50-data-storage-goes-from-1m-to-2-cents-per-gigabyte.html> (Accessed: 10 May 2019).

DARPA (2017) *Explainable Artificial Intelligence*. Available at: <https://www.darpa.mil/program/explainable-artificial-intelligence> (Accessed: 21 October 2019).

Datanami (2018) *Global DataSphere to Hit 175 Zettabytes by 2025*, IDC Says, Datanami. Available at: <https://www.datanami.com/2018/11/27/global-datasphere-to-hit-175-zettabytes-by-2025-idc-says/> (Accessed: 3 June 2019).

Dimitrov, D. V. (2016) 'Medical Internet of Things and Big Data in Healthcare', *Healthcare Informatics Research*, 22(3), p. 156. doi: 10.4258/hir.2016.22.3.156.

Energy Systems Catapult (2018) *Energy Data Review Summary Report*. Available at: https://es.catapult.org.uk/wp-content/uploads/2018/12/Energy_Data_Review_Summary_Final.pdf (Accessed: 9 September 2019).

Energy Systems Catapult (2019a) *Energy Systems Catapult Living Lab*. Available at: <https://es.catapult.org.uk/capabilities/digital-and-data/living-lab/> (Accessed: 21 November 2019).

Energy Systems Catapult (2019b) *Have your say on Energy Data Best Practice*. Available at: <https://es.catapult.org.uk/news/have-your-say-on-energy-data-best-practice/> (Accessed: 16 December 2019).

Energy Systems Catapult (2019c) *UK Digital Energy Landscape*. Available at: https://es.catapult.org.uk/news/digital-energy-landscape/?dm_i=554B,3080,1S8D7M,CM9R,1 (Accessed: 28 October 2019).

Eurelectric (2019) *Blockchain in Electricity: a Critical Review of Progress to Date*. Available at: http://www.energie-nachrichten.info/file/01_Energie-Nachrichten_News/2018-05/80503_Eurelectric_1_blockchain_eurelectric-h-DE808259.pdf (Accessed: 12 August 2019).

Financial Times (2017) *DeepMind and National Grid in AI talks to balance energy supply*. Available at: <https://www.ft.com/content/27c8aeao-06a9-11e7-97d1-5e720a26771b> (Accessed: 24 October 2019).

Forbes (2019a) *DeepMind and Google Train AI To Predict Energy Output Of Wind Farms*. Available at: <https://www.forbes.com/sites/samshead/2019/02/27/deepmind-and-google-train-ai-to-predict-energy-output-of-wind-farms/>

Forbes (2019b) *Google DeepMind's Talks With National Grid Are Over*. Available at: <https://www.forbes.com/sites/samshead/2019/03/06/google-deepminds-talks-with-national-grid-are-over/#2c8bf9031914> (Accessed: 24 October 2019).

Forbes (2019c) *What Could Sharding Mean For Enterprise Blockchain Adoption?* Available at: <https://www.forbes.com/sites/yoavvilner/2019/06/11/what-could-sharding-mean-for-enterprise-blockchain-adoption/#1c4a852d2c75> (Accessed: 12 August 2019).

Fortune (2016) *How Data And Machine Learning Are Changing The Solar Industry*. Available at: <https://fortune.com/2016/09/14/data-machine-learning-solar/> (Accessed: 25 October 2019).

Frerk, M. and Ward, J. (2019) *Smart Meter Energy Data: Public Interest Advisory Group*. Available at: <https://docs.wixstatic.com/ugd/>

Gartner (2012) *What Is Big Data? – Gartner IT Glossary*. Available at: <https://www.gartner.com/it-glossary/big-data/> (Accessed: 15 April 2019).

Gartner (2018) *Gartner Hype Cycle for Emerging Technologies, 2018*. Available at: <https://www.gartner.com/smarterwithgartner/5-trends-emerge-in-gartner-hype-cycle-for-emerging-technologies-2018/> (Accessed: 16 August 2019).

German Energy Agency (2016) *Blockchain in the energy transition: A survey among decision-makers in the German energy industry*. Available at: www.esmt.org (Accessed: 2 August 2019).

Government Office for Science (2016) *Distributed Ledger Technology: beyond block chain*. Available at: <https://youtu.be/4sm5LNqL5jo> (Accessed: 18 July 2019).

Greengard, S. (2019) 'The future of data storage', *Communications of the ACM*, 62(4), pp. 12–12. doi: 10.1145/3311723.

Hammond, K. (2016) *The Periodic Table Of AI*. Available at: <https://www.datasciencecentral.com/profiles/blogs/the-periodic-table-of-ai> (Accessed: 21 October 2019).

Health Data Research UK (2019) *Health Data Research UK*. Available at: <https://www.hdruk.ac.uk/> (Accessed: 19 September 2019).

Hutson, M. (2018) 'Artificial intelligence faces reproducibility crisis', *Science*. American Association for the Advancement of Science, pp. 725–726. doi: 10.1126/science.359.6377.725.

IBM (2019) *Introducing AI Explainability 360*. Available at: <https://www.ibm.com/blogs/research/2019/08/ai-explainability-360/> (Accessed: 21 October 2019).

IEA (2017) *Digitalisation of Energy*. Available at: www.iea.org/t&c/ (Accessed: 11 January 2019).

IHS Technology (2019) *5G and Massive IoT*. Available at: <https://technology.ihs.com/611104/5g-and-massive-iot> (Accessed: 6 January 2020).

Information Commissioner's Office (2018) *Guide to the General Data Protection Regulation*. Available at: <https://www.gov.uk/government/publications/guide-to-the-general-data-protection-regulation> (Accessed: 26 September 2019).

Iriondo, R. (2018) *Differences Between AI and Machine Learning and Why it Matters*. Available at: <https://medium.com/datadriveninvestor/differences-between-ai-and-machine-learning-and-why-it-matters-1255b182fc6> (Accessed: 16 May 2019).

Iyengar, S. et al. (2017) 'A Cloud-based Black-Box Solar Predictor for Smart Homes', *ACM Transactions on Cyber-Physical Systems*, 1(4). doi: 10.1145/3004056.

Jaradat, M. et al. (2015) 'The internet of energy: Smart sensor networks and big data management for smart grid', in *Procedia Computer Science*. doi: 10.1016/j.procs.2015.07.250.

Jucikas, T. (2017) *Artificial Intelligence and the future of energy – WePower – Medium*. Available at: <https://medium.com/wepower/artificial-intelligence-and-the-future-of-energy-105ac6053de4> (Accessed: 24 October 2019).

Keisner, A., Raffo, J. and Wunsch-Vincent, S. (2016) 'Robotics: Breakthrough Technologies, Innovation, Intellectual Property', *Foresight and STI Governance*, 10(20), pp. 7–27. doi: 10.17323/1995-459X.2016.2.7.27.

Ketter, W., Collins, J. and Reddy, P. (2013) 'Power TAC: A competitive economic simulation of the smart grid', *Energy Economics*. North-Holland, 39, pp. 262–270. doi: 10.1016/J.ENERCO.2013.04.015.

KPMG (2019) *Converging 5G and IoT*. Available at: <https://home.kpmg/xx/en/home/campaigns/2019/06/converging-5g-and-iot.html> (Accessed: 28 October 2019).

Küfeoğlu, S. et al. (2019) *Digitalisation and New Business Models in Energy Sector*. Available at: www.eprg.group.cam.ac.uk (Accessed: 22 October 2019).

Lipton, Z. (2018) *From AI to ML to AI: On Swirling Nomenclature & Slurried Thought*. Available at: <http://approximatelycorrect.com/2018/06/05/ai-ml-ai-swirling-nomenclature-slurried-thought/> (Accessed: 21 May 2019).

Macdougall, P. et al. (2016) 'Applying machine learning techniques for forecasting flexibility of virtual power plants', in *2016 IEEE Electrical Power and Energy Conference, EPEC 2016*. Institute of Electrical and Electronics Engineers Inc. doi: 10.1109/EPEC.2016.7771738.

Massoud Amin, S. and Wollenberg, B. F. (2005) 'Toward a smart grid: power delivery for the 21st century', *IEEE Power and Energy Magazine*, 3(5), pp. 34–41. doi: 10.1109/MPAE.2005.1507024.

Mattila, J. et al. (2016) *Industrial Blockchain Platforms: An Exercise in Use Case Development in the Energy Industry*. Available at: <http://pub.etla.fi/ETLA-Working-Papers-43.pdf> (Accessed: 15 August 2019).

Merizalde, Y. et al. (2019) 'Maintenance models applied to wind turbines. A comprehensive overview', *Energies*, 12(2), pp. 1–41. doi: 10.3390/en12020225.

Montavon, G., Samek, W. and Müller, K.-R. (2017) 'Methods for Interpreting and Understanding Deep Neural Networks'. Available at: <https://arxiv.org/abs/1706.07979>

Morshed, M. and Chowdhury, P. (2016) *Predicting Prices in the Power TAC Wholesale Energy Market*. Available at: <http://www.cs.waikato.ac.nz/ml/weka/>. (Accessed: 22 October 2019).

Nakamoto, S. (2008) *Bitcoin: A Peer-to-Peer Electronic Cash System*. Available at: www.bitcoin.org (Accessed: 9 August 2019).

National Cyber Security Centre (2019) *CAF Guidance*. Available at: <https://www.ncsc.gov.uk/> (Accessed: 14 October 2019).

Nikolic, I. et al. (2019) *Finding The Greedy, Prodigal, and Suicidal Contracts at Scale*. Available at: <https://github.com/MAIAN-tool/> (Accessed: 15 August 2019).

OpenAI (2018) *AI and Compute*. Available at: <https://openai.com/blog/ai-and-compute/> (Accessed: 14 January 2020).

Oughton, E. J. et al. (2019) 'Stochastic Counterfactual Risk Analysis for the Vulnerability Assessment of Cyber-Physical Attacks on Electricity Distribution Infrastructure Networks', *Risk Analysis*. John Wiley & Sons, Ltd (10.1111), 39(9), pp. 2012–2031. doi: 10.1111/risa.13291.

Perrons, R. K. and Jensen, J. W. (2015) 'Data as an asset: What the oil and gas sector can learn from other industries about "Big Data"', *Energy Policy*. Elsevier, 81, pp. 117–121. doi: 10.1016/J.ENPOL.2015.02.020.

Pfenninger, S. and Staffell, I. (2016) 'Long-term patterns of European PV output using 30 years of validated hourly reanalysis and satellite data', *Energy*. Elsevier Ltd, 114, pp. 1251–1265. doi: 10.1016/j.energy.2016.08.060.

Pool, I. D. S. and López, P. (2011) 'The World's Technological Capacity to Store, Communicate, and Compute Information', *Science*. American Association for the Advancement of Science, 221(4611), pp. 609–613. doi: 10.1126/science.221.4611.609.

PowerLedger (2019) *Peer-to-Peer solar power trading (RENew Nexus)*. Available at: <https://www.powerledger.io/project/renew-nexus/> (Accessed: 13 August 2019).

PWC (2016) *Blockchain-an opportunity for energy producers and consumers?* Available at: www.pwc.com/utilities (Accessed: 15 July 2019).

Rodríguez González, A. Y. et al. (2019)

'A competitive and profitable multi-agent autonomous broker for energy markets', *Sustainable Cities and Society*. Elsevier, 49, p. 101590. doi: 10.1016/J.SCS.2019.101590.

Rudin, C. (2019) 'Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead', *Nature Machine Intelligence*. Springer Science and Business Media LLC, 1(5), pp. 206–215. doi: 10.1038/s42256-019-0048-x.

Sandys, L. et al. (2018) *ReDesigning Regulation: Powering From the Future*. Available at: <https://www.imperial.ac.uk/media/imperial-college/grantham-institute/public/publications/collaborative-publications/Redesigning-Regulation---Powering-from-the-future.pdf> (Accessed: 11 February 2019).

Sandys, L. et al. (2019) *A strategy for a Modern Digitalised Energy System*. Available at: <https://es.catapult.org.uk/wp-content/uploads/2019/06/EDTF-A-Strategy-for-a-Modern-Digitalised-Energy-System-FINAL-REPORT-1.pdf> (Accessed: 13 June 2019).

SERL (2019) *Smart Energy Research Lab*. Available at: <https://serl.ac.uk/> (Accessed: 10 October 2019).

Di Silvestre, M. L. et al. (2018) 'How Decarbonization, Digitalization and Decentralization are changing key power infrastructures', *Renewable and Sustainable Energy Reviews*. Pergamon, 93, pp. 483–498. doi: 10.1016/J.RSER.2018.05.068.

SkyMind (2019) *A Beginner's Guide to Neural Networks and Deep Learning*. Available at: <https://skymind.ai/wiki/neural-network> (Accessed: 21 October 2019).

Smart DCC (2016) *Smart DCC Licence*. Available at: <https://www.smartdcc.co.uk/about/smart-dcc-licence/> (Accessed: 26 September 2019).

solarcalculator.xyz (2018) *Solar Calculator*. Available at: <http://www.solarcalculator.xyz/> (Accessed: 25 October 2019).

Statista (2019) *Bitcoin blockchain size 2010-2019*. Available at: <https://www.statista.com/statistics/647523/worldwide-bitcoin-blockchain-size/> (Accessed: 9 August 2019).

Statista (2020) *IoT: number of connected devices worldwide 2012-2025* | Statista. Available at: <https://www.statista.com/statistics/471264/iot-number-of-connected-devices-worldwide/> (Accessed: 6 January 2020).

Stetco, A. et al. (2019) 'Machine learning methods for wind turbine condition monitoring: A review', *Renewable Energy*, 133, pp. 620–635. doi: 10.1016/j.renene.2018.10.047.

The Guardian (2017) *Is your smart meter spying on you?* Available at: <https://www.theguardian.com/money/2017/jun/24/smart-meters-spying-collecting-private-data-french-british> (Accessed: 23 September 2019).

The Guardian (2018a) *Amazon's first checkout-free grocery store opens on Monday*. Available at: <https://www.theguardian.com/business/2018/jan/21/amazons-first-automated-store-opens-to-public-on-monday> (Accessed: 21 October 2019).

The Guardian (2018b) *Bitcoin is based on the blockchain pipe dream*. Available at: <https://www.theguardian.com/business/2018/mar/05/bitcoin-is-based-on-the-blockchain-pipe-dream> (Accessed: 15 August 2019).

The Parliamentary Office of Science and Technology (2017) *Cyber Security of UK Infrastructure*, Postnote. doi: 10.3109/10428194.2015.1121263.

The Parliamentary Office of Science and Technology (2018) *Blockchain & Distributed Ledger Technology (DLT)*, World Bank. Available at: <https://www.worldbank.org/en/topic/financialsector/brief/blockchain-dlt>.

The Verge (2019) *What is edge computing?* Available at: <https://www.theverge.com/circuitbreaker/2018/5/7/17327584/edge-computing-cloud-google-microsoft-apple-amazon> (Accessed: 22 November 2019).

Transport for London (2019) *Open Data Users*. Available at: <https://tfl.gov.uk/info-for/open-data-users/> (Accessed: 19 September 2019).

Tu, C. et al. (2017) 'Big data issues in smart grid – A review', *Renewable and Sustainable Energy Reviews*. Pergamon, 79, pp. 1099–1107. doi: 10.1016/J.RSER.2017.05.134.

Vogel, L. et al. (2019) *Artificial Intelligence for the Integrated Energy Transition*. Available at: https://www.dena.de/fileadmin/dena/Publikationen/PDFs/2019/dena-REPORT_Artificial_Intelligence_for_the_Integrated_Energy_Transition.pdf

de Vries, A. (2018) 'Bitcoin's Growing Energy Problem', *Joule*. Elsevier, 2(5), pp. 801–805. doi: 10.1016/j.joule.2018.04.016.

Webborn, E. et al. (2019) 'Utilising smart meter data for research and innovation in the UK', *In: Proceedings of ECEEE 2019 Summer Study on energy efficiency*. (pp. pp. 1387-1396). ECEEE: Belambra Presqu'île de Giens, France. (2019) . ECEEE. Available at: <http://discovery.ucl.ac.uk/10075955/> (Accessed: 10 October 2019).

Webborn, E. and Oreszczyn, T. (2019) 'Champion the energy data revolution', *Nature Energy*. Springer US, 4(August), pp. 624–626. doi: 10.1038/s41560-019-0432-0.

Wired (2019a) *Facebook's Head of AI Says the Field Will Soon 'Hit the Wall'* . Available at: <https://www.wired.com/story/facebooks-ai-says-field-hit-wall/> (Accessed: 14 January 2020).

Wired (2019b) *New Clues Show How Russia's Grid Hackers Aimed for Physical Destruction* / *WIRED*. Available at: <https://www.wired.com/story/russia-ukraine-cyberattack-power-grid-blackout-destruction/> (Accessed: 17 October 2019).

Zhou, K., Fu, C. and Yang, S. (2016) 'Big data driven smart energy management: From big data to big insights', *Renewable and Sustainable Energy Reviews*. Pergamon, 56, pp. 215–225. doi: 10.1016/J.RSER.2015.11.050.



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