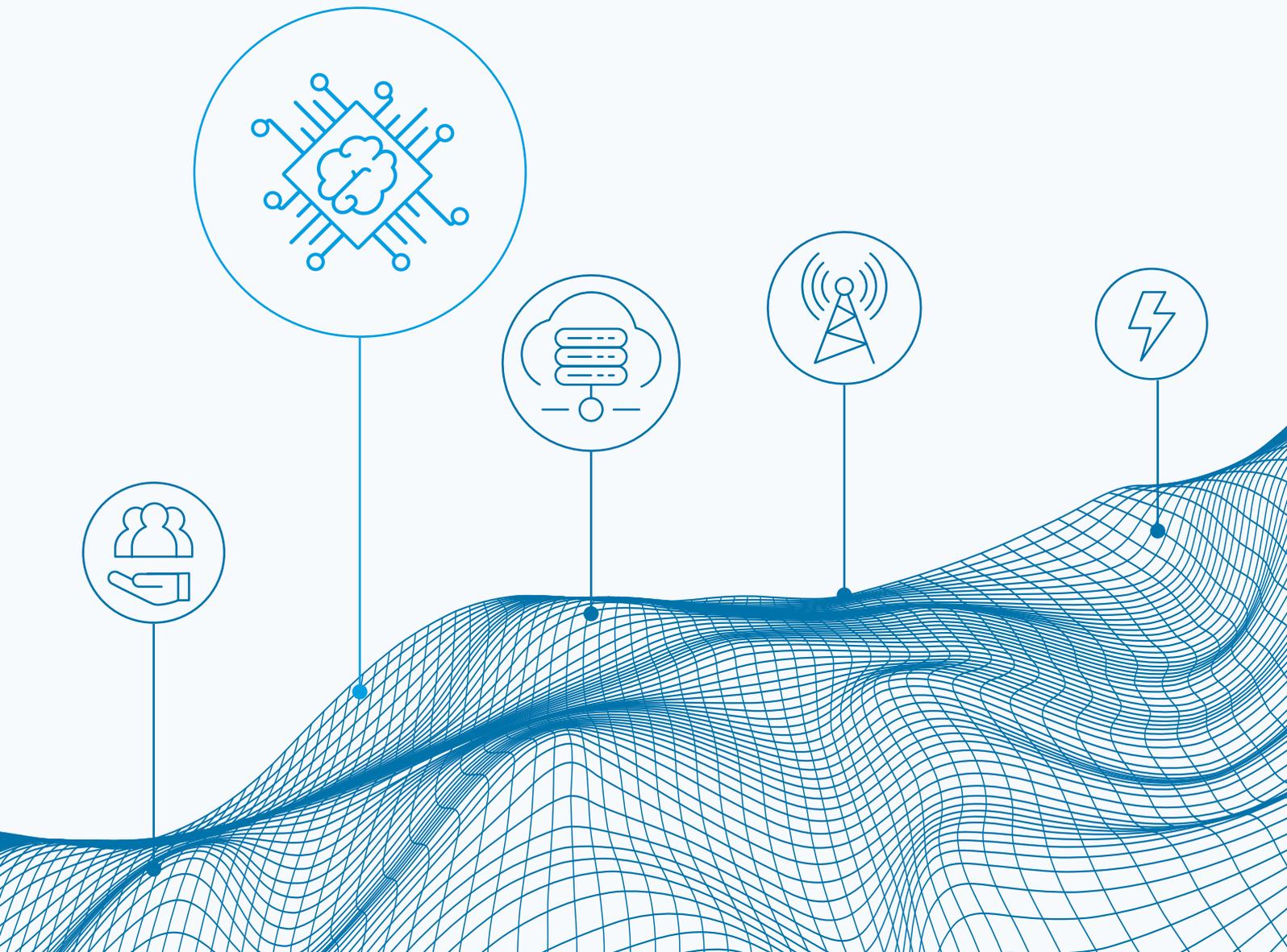


ARTIFICIAL INTELLIGENCE AND BIG DATA

INNOVATION LANDSCAPE BRIEF



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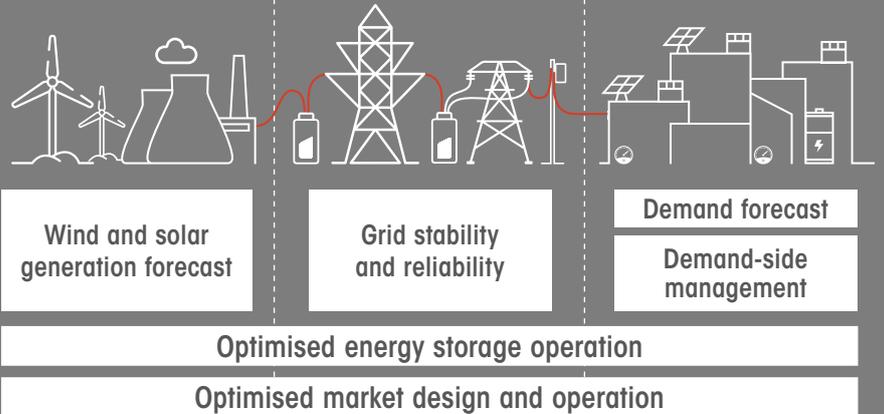
This document does not represent the official position of IRENA on any particular topic. Rather, it is intended as a contribution to technical discussions on the promotion of renewable energy.

1 BENEFITS

AI potential is being unlocked by the generation of big data and increased processing power.

In the energy sector, AI can enable fast and intelligent decision making, leading to increased grid flexibility and integration of VRE.

AI applications for wind and solar integration



2 KEY ENABLING FACTORS

-  Technological maturity
-  Availability and quality of data
-  Growing importance of cybersecurity
-  Training and re-skilling of energy sector professionals

3 SNAPSHOT

- EWeLiNE and Gridcast in Germany use AI to better forecast solar and wind generation, minimising curtailments.
- DeepMind AI has reduced cooling consumption at a Google data centre by 40%. It applies machine learning to increase the centre's energy efficiency.
- EUPHEMIA, an AI-based coupling algorithm, integrates 25 European day-ahead energy markets to determine spot prices and volumes.

WHAT IS ARTIFICIAL INTELLIGENCE?

Intelligent machines work and react more like humans. Artificial intelligence (AI) systems can change their own behaviour without explicit re-programming. They do so by collecting and analysing large datasets, or “big data”.

ARTIFICIAL INTELLIGENCE AND BIG DATA

Intelligent tools help manage complex power systems and extract value from new data. AI supports the decision-making process. Big data provides a clear overview, input for AI.

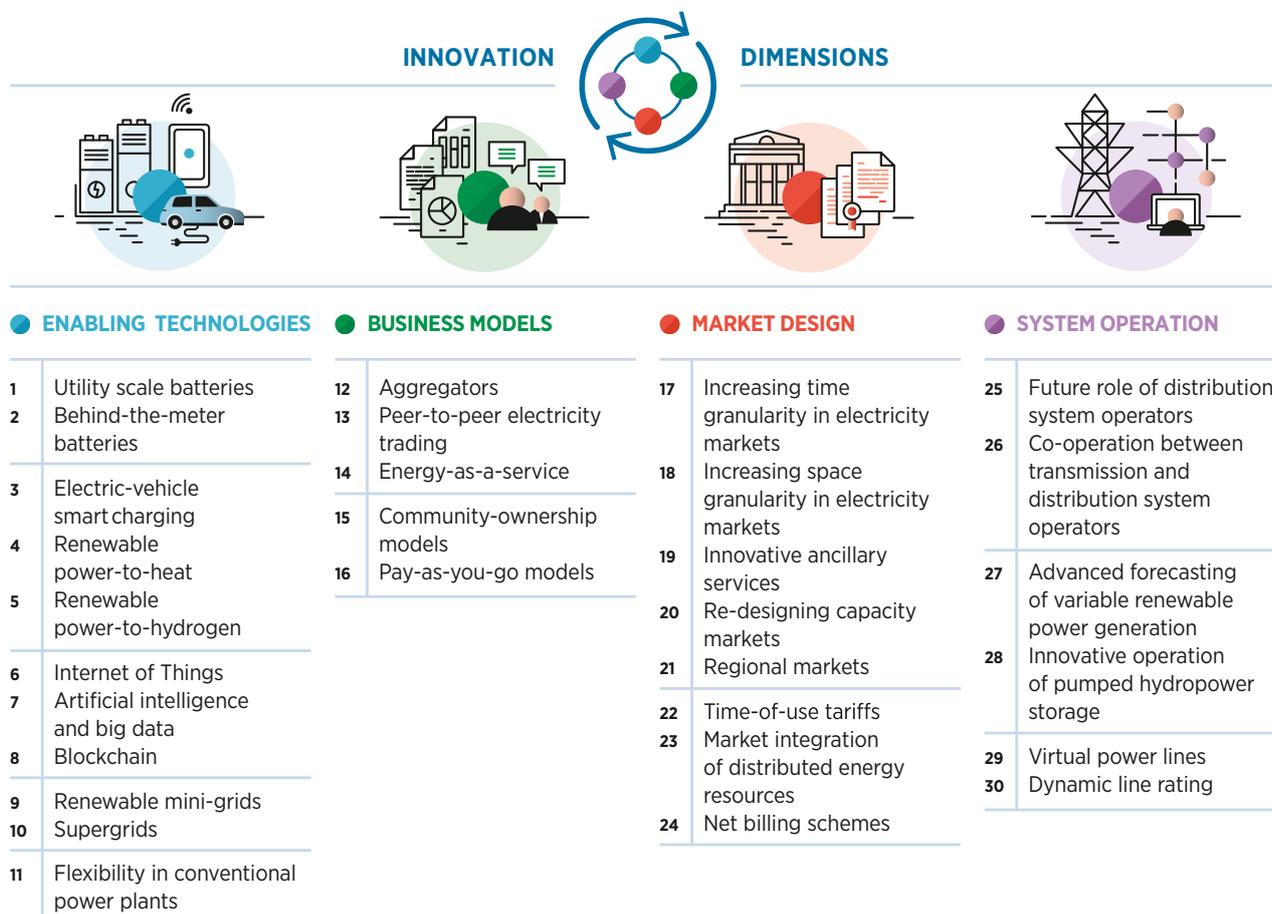
ABOUT THIS BRIEF

This brief is part of the IRENA project “Innovation landscape for a renewable-powered future”, which maps the relevant innovations, identifies the synergies and formulates solutions for integrating high shares of variable renewable energy (VRE) into power systems.

The synthesis report, *Innovation landscape for a renewable-powered future: Solutions to integrate variable renewables* (IRENA, 2019a), illustrates the need for synergies among different innovations

to create actual solutions. Solutions to drive the uptake of solar and wind power span four broad dimensions of innovation: enabling technologies, business models, market design and system operation.

Along with the synthesis report, the project includes a series of briefs, each covering one of 30 key innovations identified across those four dimensions. The 30 innovations are listed in the figure below.

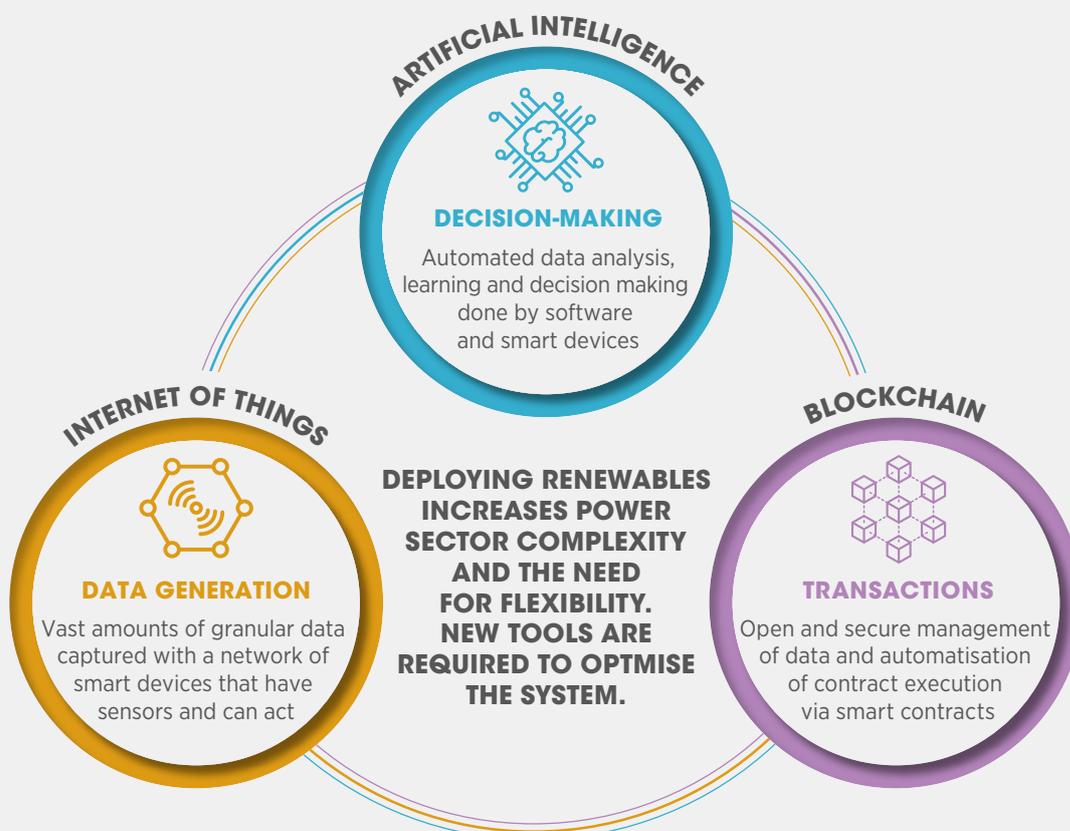


Digitalisation to support VRE integration

Digitalisation is a key amplifier of the power sector transformation, enabling the management of large amounts of data and optimising increasingly complex systems. For the power sector, digitalisation is essentially converting data into value (IRENA, 2019a). The growing importance of digitalisation in the power sector is also a consequence of advances in two other innovation trends: decentralisation and electrification. Decentralisation is led by the increased deployment of small power generators, mainly rooftop solar photovoltaic (PV), connected to the distribution grid. Electrification of transport and buildings (heating and cooling) involves large quantities of new loads, such as electric vehicles, heat pumps and electric boilers. All these new assets on the supply and demand sides are adding complexity to the power sector, making monitoring, management and control crucial for the success of the energy transformation.

Digital technologies¹ can support the renewable energy sector in several ways, including better monitoring, operation and maintenance of renewable energy assets; more refined system operations and control closer to real time; implementation of new market designs; and the emergence of new business models. Within the context of the *Innovation landscape for a renewable-powered future* report, IRENA's analysis focuses on one concrete application for digital technologies: the integration of VRE technologies into power systems. Accordingly, three specific digital technology groups are studied further: 1) the internet of things (IoT); 2) artificial intelligence (AI) and big data; and 3) blockchain. The analysis indicates that none of these are silver bullets, but rather reinforce each other as part of a toolbox of digital solutions needed to optimise the operations of an increasingly complex power system based on renewable energy.

Figure 1: Increased power sector complexity requires a combination of digital innovations



¹ These commonly include: digital twins; chatbots; the IoT; artificial intelligence and big data; distributed ledger technologies (DLT) such as blockchain; and augmented and virtual reality, among others.

This brief provides an overview of artificial intelligence (AI) and big data, along with their applicability in the energy sector. The focus is on how these technologies could contribute to increasing shares of VRE in the power system.

The brief is structured as follows:

- I [Description](#)
 - II [Contribution to power sector transformation](#)
 - III [Key factors to enable deployment](#)
 - IV [Current status and examples of ongoing initiatives](#)
 - V [Implementation requirements: Checklist](#)
-



I. DESCRIPTION

AI and other intelligent tools

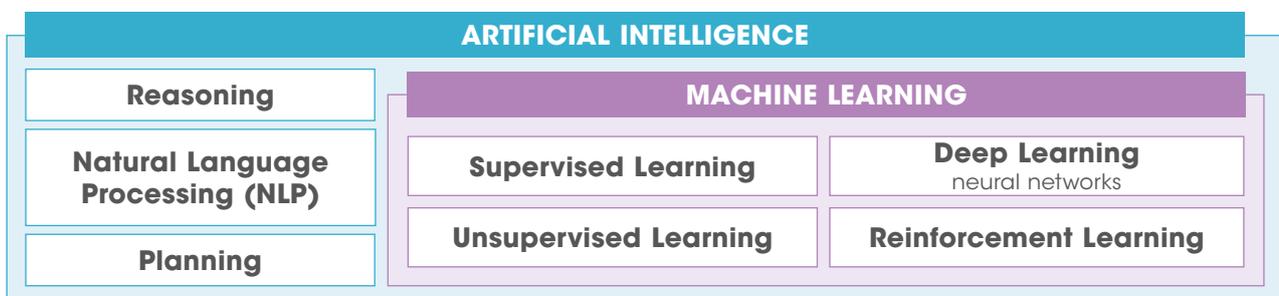
From mobile virtual assistants to image recognition and translation to a myriad of other uses, AI is playing an increasingly important role in our modern lives. While the term “AI” was coined in 1956, the past few years have seen rapid advances in AI use in many sectors. Over the coming decades, innovative uses of AI have the potential to increase the insight, efficiency, connectivity, reliability and sustainability of energy systems around the world.

But what is AI? While there is no standard definition, AI is referred to as an area of computer science that focuses on the creation of intelligent machines that work and react more like humans. **AI refers to systems that, in response to data observed, collected and analysed, change behaviour without being explicitly programmed** (WCO, 2019). At its core, AI is a series of systems that act intelligently, using complex algorithms²

to recognise patterns, draw inferences and support decision-making processes through their own cognitive judgement, the way people do. AI can be “weak”, in which case it is focused on narrow tasks (personal assistants like Apple’s Siri, chess-playing software, etc.) or it can be “strong”, also known as “general AI”, where machines are presented with unfamiliar tasks and are able to find a solution without any human intervention (SearchEnterpriseAI, 2019).

AI and machine learning³ are often used interchangeably but are not the same thing. Some authors describe machine learning as a subset of AI, where machines gather data and learn for themselves. Machine learning leverages algorithms and models to predict outcomes (IBM, 2019). Other “intelligent” tools, such as natural language processing, deep learning and neural networks, can also fall under the AI umbrella. In this brief, all such tools will be called “AI” or “machine learning”, as appropriate.

Figure 2: Collection of intelligent tools clustered as AI in the context of this brief



Adapted from IBM (2019).

² An algorithm is a process or a set of rules to be followed in calculations or other problem-solving operations, especially by a computer. Algorithms can perform calculation, data processing, automated reasoning and other tasks.

³ Machine learning is a form of AI that enables a system to learn from data rather than through explicit programming. However, machine learning is not a simple process. As the algorithms ingest training data, more precise models can be produced. A machine-learning model is the output generated when a machine-learning algorithm has been trained with data. After training, when a model is given an input, it will produce an output. For example, a predictive algorithm will create a predictive model. Then, when the predictive model is provided with data, it will produce a prediction based on the data that trained the model (IBM, 2019).

The use of AI continues at an impressive rate in e-commerce, politics, manufacturing, engineering, health care, transportation, finance, telecommunications, services and energy. And the impact is becoming ever more apparent (DNV GL, 2018). In addition, the

costs of applying AI are falling as the ease of use increases. Combined with the explosion of processing power and the generation and availability of large amounts of useful data, AI models are increasingly able to perform specific tasks without explicit instructions.

Here is a simple, practical example of machine learning:

A model is fed vast quantities of data, in this case a series of images (e.g. 100 000 pictures of dogs and 100 000 pictures of cats). All are labelled either “cat” or “dog” so that the computer can categorise their distinguishing features accordingly. The machine-learning model then applies what it has learned to new photos, without labels, and decides whether those are cats or dogs based on what it learned from the training dataset of 200 000 animal photos.

Big data

Extremely large datasets, both structured and unstructured, are referred to simply as “big data”.

The interlink between AI and big data is the need for intelligent tools to effectively analyse the large amounts of data being generated and convert it into value for the power sector (SAS, 2019).

The abundance of big data, along with the exponential growth in processing power witnessed over the past few decades, has created the ideal setting for AI. Globally in 2018, five exabytes⁴ of data were generated each and every day (Cisco, 2018). By 2025, it is estimated that 463 exabytes of data will be created each day (Desjardins, 2019). As the world steadily becomes more connected, with an ever-increasing number of electronic devices, data generation will continue to grow, requiring increasingly intelligent systems able to analyse this trove of data but also enabling the creation of ever more insightful AI, as the models can be better trained.

For the power sector, a major source of this new data will be the vast amount of internet-connected (IoT) devices, set to grow from 25 billion devices today to 75 billion by 2025 (Statista, 2018) (see the Innovation Landscape brief *Internet of things* [IRENA, 2019b]). IoT and new digital devices, such as smart appliances, intelligent inverters and home battery storage systems, are being powered by advances in data, analytics and connectivity. The use of AI is most useful for decision making in complex systems with massive amounts of data, where more traditional data analysis tools may be too time-consuming or may struggle to find optimal solutions (IBM, 2019).

As the power sector becomes increasingly complex, intelligent tools such as AI are needed to effectively manage systems and derive value from all the new data being generated. As AI algorithms ingest this data, it becomes possible to produce more precise models (IBM, 2019).

⁴ One exabyte is equal to one quintillion (1 000 000 000 000 000 000) bytes.

II. CONTRIBUTION TO POWER SECTOR TRANSFORMATION

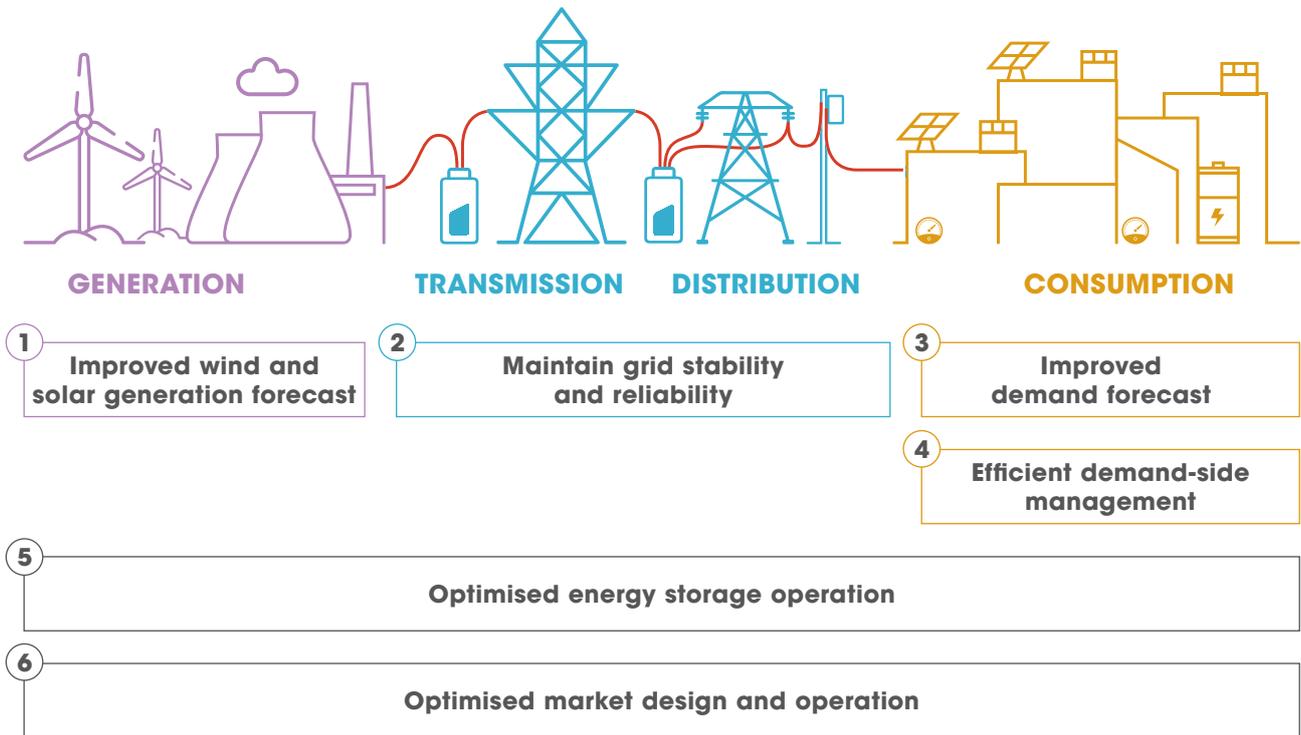
The power sector is undergoing a major transformation with the increased deployment of renewable energy technologies (solar PV and wind) that provide variable energy supply, distributed energy resources (DERs)⁵, bidirectional flow of electricity, large flows of data collected by IoT and other devices, increased use of energy storage, and the evolving role of utilities and consumers. Many system operation decisions are still taken and enacted manually, or with a basic level of automation, because of the small number of automatically controllable resources. However, the developments mentioned above would allow for a larger number of automatically controllable resources responding to needs from several stakeholders (e.g. consumers, generators, transmission and distribution operators, retailers). This advanced level of control enables optimisation of the system with more distributed resources while maximising system flexibility and reducing the

cost of operating a system with high shares of VRE. Thus, the role of AI and big data is evolving from a facilitating and optimising tool to a necessity for smart and fast decision making.

As previously discussed, AI and other digital technologies can support the renewable energy sector in a variety of ways. Most of the advances currently supported by AI have been in advanced weather and renewable power generation forecasting and in predictive maintenance. In the future, AI and big data will further enhance decision making and planning, condition monitoring, inspections, certifications and supply chain optimisation and will generally increase the efficiency of energy systems. However, this brief focuses on facilitating greater integration of VRE into power systems, where six main categories of application for AI can be identified, as shown in Figure 3.

⁵ DERs are small or medium-sized resources directly connected to the distribution network. DERs include distributed generation; energy storage (small-scale batteries); and controllable loads, such as electric vehicles, heat pumps or demand response (see the Innovation Landscape brief *Market integration of distributed energy resources* [IRENA, 2019c]).

Figure 3: Emerging applications of AI for VRE integration



Note: The categories listed are not exhaustive but identify concrete areas where AI is, at present, being used or tested for VRE integration.

1. Improved renewable energy generation forecast

Improved weather forecasting is one of the main AI applications that will improve the integration of renewables into the power system. Solar and wind generation provide an enormous amount of data, and renewable technologies have benefited from sensor technology being long established. Big data and AI can produce accurate power generation forecasts that will make it feasible to integrate much more renewable energy into the grid (MIT, 2014). For example, in 2015, IBM was able to show an improvement of 30% in solar forecasting while working with the US Department of Energy’s SunShot Initiative. The

self-learning weather model and renewable generation forecasting technology integrated large datasets of historical data and real-time measurement from local weather stations, sensor networks, satellites and sky image cameras (IBM, 2015).

Accurate VRE forecasting at shorter time scales can help generators and market players to better forecast their output and to bid in the wholesale and balancing markets, while avoiding penalties. For system operators, accurate short-term forecasting can improve unit commitment, increase dispatch efficiency and reduce reliability issues, and therefore reduce the operating reserves needed in the system.

A successful example is that of EWeLiNE, a research project using machine learning-based software in Germany, finished in 2017, and Gridcast, a follow-up project. Through AI, both projects forecasted power generation using data from solar sensors, wind turbine sensors and weather forecasts, which helped minimise curtailment of excess power generation.

2. Maintain grid stability and reliability

By providing accurate demand and supply forecasts, AI can further optimise the operation of the system, in particular in the context of decentralised systems with bidirectional electricity flow, which increases complexity in power systems.

Power distribution grid operators are confronted with great challenges because the number of decentralised energy generation systems, such as solar PV, has grown rapidly. The deployment of renewable energy technology leads to fluctuations and irregular peak loads in the power grid. AI can ensure that the power grid always operates at optimal load and can optimise the energy consumption of customers. Ideally, the electricity generated by the solar PV system in the home or within the neighbourhood grid would be consumed.

For example, in Riedholz, Switzerland, four companies (Adaptricity, AEK, Alpiq and Landis+Gyr), together with the Canton of Solothurn, are testing how AI solutions can ensure future grid stability and minimise investments in costly grid expansion in a pilot project called SoloGrid. The project investigates how GridSense, an algorithm that learns user behaviour through AI, can 1) control the primary electricity consumers, such as heat pumps, boilers, household batteries and charging stations for electric vehicles, and 2) integrate measurement data from solar PV systems for optimal grid operation. The algorithm continuously measures parameters such as grid load, consumption and generation, including weather forecasts and electricity prices, and optimises the generation and consumption of power. The technology reduces peak loads in the

power grid, balances the loads and stabilises the distribution grid (Warren, 2019).

Grid congestion at the transmission and distribution level is an important factor that slows the integration of wind and solar PV electricity into power systems. AI can increase the capacity of the power grids and reduce the need for new lines through better use of existing lines as a function of weather conditions. This is the case in, for example, the dynamic line rating projects implemented by the company Ampacimon or being investigated at the Karlsruhe Institute of Technology in the “PrognoNetz” project (KIT, 2019). AI-based systems, using large amounts of weather data, can ensure optimal use of existing power grids by adapting operation to the weather conditions at any time and therefore reducing congestion.

AI can also improve safety, reliability and efficiency in the power system by automatically detecting disturbances. The technology can enable automated data processing in real time and detect cases of emergency or appliance failure. As an example, researchers have provided AI models with examples of typical system outages to allow the algorithm to gradually learn to distinguish – and precisely categorise – normal operating data from defined system malfunctions. The algorithm was able to make split-second decisions on where there was an anomaly or fault, as well as the type and location of that disturbance. If one power plant should fail, an abrupt spike can be expected in the load placed on the other power plants. The increased load slows down the generators, and the frequency decreases. This calls for rapid (less than 500 millisecond [ms]) countermeasures, because if the frequency sinks below a threshold value, the operator may be forced to cut off sections of the grid for the sake of system stability. Since the algorithm can reach a decision within 20–50 ms, there would be sufficient time to implement the appropriate fully automated countermeasures. The algorithm is ready to be implemented, according to researchers, and work continues on the control and regulation of the relevant countermeasures (Fraunhofer, 2019).

3. Improved demand forecast

Accurate demand forecasting, together with renewable generation forecasting, can be used to optimise economic load dispatch as well as to improve demand-side management and efficiency.

Consumers produce an increasing stream of data that comes through the power grid itself. There has been a significant push to install smart meters that are able to send the information to utility providers as often as hourly. From this data, AI can predict not only network load but also consumption habits, and can accurately draw a consumption pattern for each consumer. This becomes even more relevant with the current deployment of DERs, such as electric vehicles, heat pumps and solar PV panels, which change the traditional load shape entirely.

BeeBryte, for example, is a French startup that uses AI to predict a building’s thermal energy demand in order to produce heating and cooling at the right times, maintaining comfort and temperature within an operating range set by the customer. This can result in savings of up to 40% on utility bills thanks to a combination of efficiency gains and load shifting to periods when electricity is cheapest, when renewable electricity is available in the system (BeeBryte, 2018).

Understanding the consumer’s habits, values, motivations and even personality further bolsters the balancing and effectiveness of a smart grid. It also allows policies to be created more effectively and enables an understanding of the human motivations associated with renewable energy adoption and how to possibly change consumer behaviour to optimise the whole energy system (Jucikas, 2017).

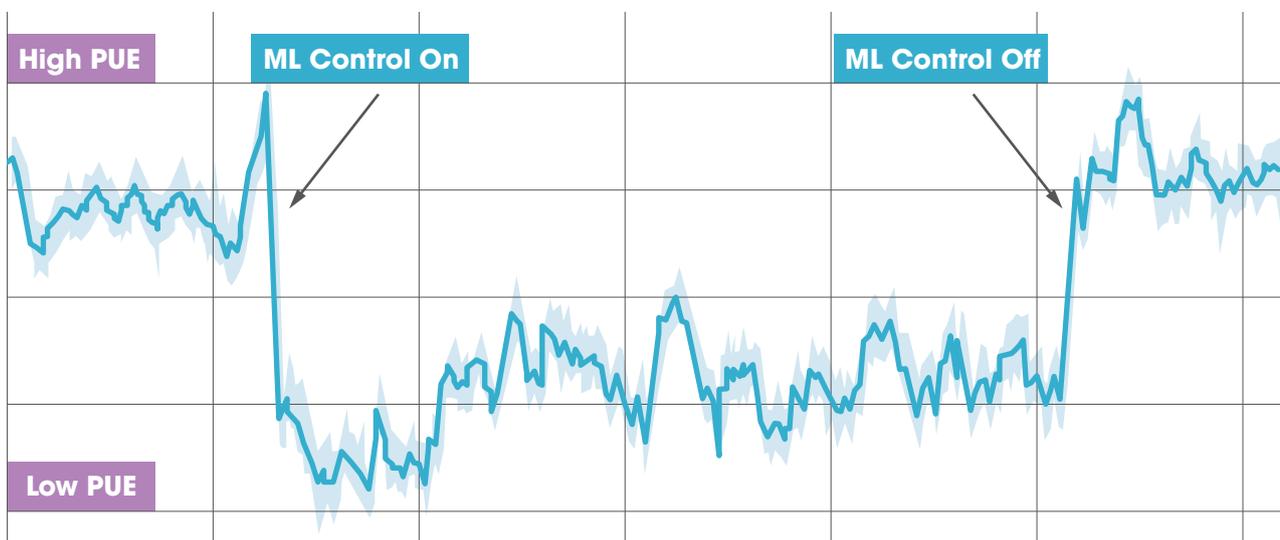


4. Efficient demand-side management

Demand-side management is witnessing a myriad of AI and big data activity, with advancements being made in demand response, energy management systems and overall energy efficiency. Using weather forecasts, occupancy, usage, energy prices and patterns identified in consumer behaviour, AI can optimise the energy management of a consumer's house, reducing their electricity bill.

Google's DeepMind AI, for example, reduced the energy used for cooling at one of Google's data centres by 40% in 2016 (a 15% overall reduction in power usage) using only historical data collected from sensors within the data centre (e.g. temperatures, power, pump speeds, setpoints) to improve data centre energy efficiency. The AI system predicts the future temperature and pressure of the data centre over the next hour and gives recommendations to turn the consumption on or off. The graph below shows a typical day of testing, including when Google turned the machine-learning recommendations on and off (Evans and Gao, 2016).

Figure 4: Machine-learning recommendations (on and off) on a typical day



Source: Evans and Gao (2016).

ML = machine learning; PUE = power usage effectiveness. The data centre industry uses the measurement PUE to measure efficiency. A PUE of 2.0 means that for every watt of computing power, an additional watt is consumed to cool and distribute power to the IT equipment. A PUE closer to 1.0 means nearly all the energy is used for computing.

In 2018, DeepMind took these innovations to the next level. Instead of its recommendations being implemented by people, DeepMind's AI system now directly controls data centre cooling, while remaining under the expert supervision of data centre operators. This cloud-based control system now delivers energy savings in multiple Google data centres (Gamble and Gao, 2018).

IBM has shown similar results using their machine-learning techniques (IBM, 2018a). Additionally, Grid Edge, an UK based company, reduced energy consumption in shopping centres and airports and provided energy managers the ability to better manage energy usage through the prediction of weather and of customer or new aircraft movements.

5. Optimised energy storage operation

Energy storage systems, in the form of large-scale batteries, aggregated small batteries (“behind the meter”) or plugged-in electric vehicles, are emerging as key enablers for renewable energy integration. AI can help operate these technologies in a more efficient way, maximising renewable electricity integration (including the reduction of generation forecast errors), minimising prices for electricity consumed locally and maximising returns for the owners of the storage system. For large-scale energy storage systems, this includes decisions on storing excess renewable electricity in a network of batteries and discharging the batteries to meet demand at a later point in time, while considering forecasted demand, renewable energy generation, prices and network congestion, among other variables.

As storage batteries can be activated quickly and can be used to manage excessive peaks and minimise the back-up energy needed from diesel generators, coal-fired power plants or other peaker plants, AI can be used to predict and make energy storage management decisions.

The speed and complexity of managing energy storage systems in a dynamic environment, encompassing many variables, requires advanced AI. AI research is studying decision making on a scale and with a complexity that surpasses that of a human operator, especially for networks of thousands of mixed energy storage units (electrical, thermal, etc.) installed at the end consumer side, at households or industrial installations.

In addition, AI can help estimate and extend the useful life of a storage unit by applying predictive logic algorithms to the charging and discharging data. Owners will deploy their storage pack according to the compensation for the services provided by the battery, as well as the impacts these services have on the state of health of the batteries. California-based company Stem has developed Athena, which uses AI to map out energy usage and allow customers to track fluctuations in energy rate to more efficiently use storage.

In Australia, for example, Tesla’s Hornsdale battery was a wake-up call, according to United States-based software-as-a-service platform provider AMS. By using AI, versatile battery storage systems can optimise opportunities to purchase electricity from the grid when prices are low and then to sell back to the market when prices are high. The Hornsdale battery has operated via an autobidder developed by Tesla, which has allowed the project to capture the best revenue streams to a degree that could not have been achieved by human bidders alone. “Relative to a human trader, algorithmic bidding software can increase the revenues of a battery by about five-times”, according to AMS. In its first year of operation, the Hornsdale battery generated an estimated \$24 million in revenue, while also providing between a \$40 and \$50 million reduction in frequency control ancillary service costs, savings that are ultimately to the benefit of consumers (Mazengarb, 2019). Cost savings such as these are likely to lead to an influx of algorithm development aimed at operating batteries in the most lucrative way.

6. Optimised market design and operation

Sophisticated models based on AI are also being deployed to optimise close to real-time market operations. Such optimisation relies on the analysis of large streams of diverse data to enable rapid response to market changes.

Intraday trading is particularly useful for adjusting to unforeseen changes in power production and consumption by putting market mechanisms to use before control reserves become necessary. This allows a power plant operator who suddenly loses production in a single block to buy additional power from other participants on the market and maintain the balancing group. Intraday trading is therefore a key component for direct marketing of power produced by renewable energy when quickly changing weather results in an unplanned shortfall or surplus of power from solar or wind power plants. The speed and complexity of operating intraday markets in a dynamic environment that encompasses many variables can be beyond a human operator; this would be an ideal application for advanced AI.

When coupling different markets to create regional markets, the complexity in market operations increases even more. An AI-based algorithm called EUPHEMIA was developed to calculate day-ahead electricity prices across Europe and allocate cross-border transmission capacity on a day-ahead basis. EUPHEMIA is used daily to compute in a coupled way day-ahead electricity prices for 25 European countries (Austria, Belgium, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, the Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden and the United Kingdom), with an average daily value of matched trades over EUR 200 million (NEMO Committee, 2019).

In terms of market design, AI can increase time granularity in electricity markets and enable real-time markets. The use of AI is being explored to support trading and dispatch decisions for generation assets in the close to real-time trading markets, focusing on when the generators should commit to trade to maximise the option value of flexible capacity. An example is Origami Energy, a startup company based in Cambridge, United Kingdom, using AI to predict asset availability and balancing mechanism market prices in near real time to successfully bid in the frequency response markets.

With the use of advanced analytics and machine learning, various operational optimisation problems can be solved and new insights for medium- and long-term strategy can be derived – such as to forecast when an asset will be available, the value of flexibility and how an asset should best be used to derive most value (Pöyry, 2018).

Other AI applications in the power sector

In addition to directly supporting the integration of VRE, AI can be used in other applications for power systems. These include increased visibility into energy leakage, consumption patterns and equipment functioning status. For instance, predictive analytics can take sensor data from a wind turbine to monitor wear and tear and predict with a high degree of accuracy when the turbine would need maintenance. Strategy in targeting where to deploy the real-time sensing is also necessary. For example, some assets last a very long time and outlast the sensors several times over.

With the help of AI, GE in Japan succeeded in enhancing wind turbine efficiency, reducing maintenance costs by 20% and increasing power output by 5% (Nikkei, 2017). McKinsey's Utilityx achieved maintenance and replacement cost savings of 10–25% through predictive maintenance (McKinsey & Company, 2019). Uruguay's National Agency for Research and Innovation and the Uruguay Ministry of Industry, Energy and Mining are also exploring AI for the predictive maintenance of wind power plants in a project conducted jointly with the utility UTE and the School of Engineering of the University of the Republic⁶.

Where such markets are in place, AI could also enhance the integrity of the electricity market as well as transparency in the regulator's tasks of monitoring and investigating the trading activity. For example, the European Agency for the Cooperation of Energy Regulators (ACER) uses a market surveillance system called ARIS, which automatically screens and analyses the data collected to identify anomalies that might constitute cases of market abuse according to European legislation (ACER, 2015).

6 Based on discussions during the IRENA Innovation Day in Uruguay, July 2019.

III. KEY FACTORS TO ENABLE DEPLOYMENT

Technological maturity

AI is not a new technology. However, the recent advances in processing power, data collection and communications are opening the door to AI applications in the power sector. Nevertheless, more investment and research are required to maximise its potential. This investment includes funding for research and development.

For example, through algorithm tuning (*i.e.* optimisation of the choice of parameters whose value is set before the machine-learning process starts), predictive models can become more precise.

Availability and quality of data

One of the key challenges with AI is the quality of the large datasets (big data) with which to develop the models. The data available today is not always sufficient or of good enough quality to develop systems that can handle complex scenarios. However, digital technologies are evolving to address these issues, (*e.g.* cloud servers and better management of data), which leads to less data being needed and better structuring of data, which in turn has an impact on the need to perform more calculations.

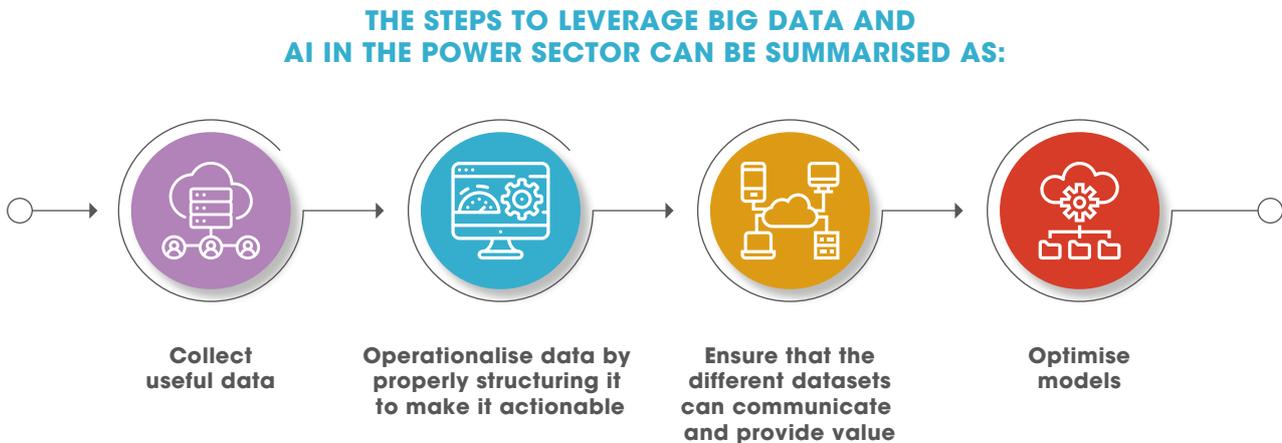
Fortunately, the expansion of computing power seen in recent years is now being complemented by exponential growth in the availability of data, due largely to IoT devices coming online (see the Innovation Landscape brief *Internet of things* [IRENA, 2019b]).

Another concern regarding data is the problem of bias. If the source of the data being fed into the AI systems is biased in nature, then the decision-making processes will also be biased, leading to erroneous or undesired results. Thus, bias in AI systems must be reduced as far as possible. Also, since the machines are developed with their own sense of discretion, at times it may be difficult or impossible to predict the decision made by the machines or explain the logic used.

Opening up public sector data can spur private sector innovation. Setting common data standards can also help (Chui et al., 2018). For example, in the European Union, “Regulation (EU) No. 543/2013 of 14 June 2013 on submission and publication of data in electricity markets” established the rules for the Transparency Platform, which is an online data platform for European electricity system data (European Union, 2013). The Transparency Platform is operated by the European Network of Transmission System Operators for Electricity and contains, among other information, data items on load, generation, transmission, balancing and outages, which could be used by private sector companies to develop new business models and offer new services to consumers.

The availability of end consumer data, like data on loads from household consumers and their electric vehicle charging patterns, could be a concern from a privacy point of view. For example, in the European Union, “Regulation (EU) 2016/679 of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data” sets strict rules (European Union, 2016).

Figure 5: The steps to leverage big data and AI in the power sector



Growing importance of cybersecurity

Like any information and communications technology (ICT) advancement, an important factor for consideration is cybersecurity. Cybersecurity will be a growing issue as both ICT and electricity networks become increasingly interconnected and new digital technologies and means of communication become widespread. Attacks on grids have increased in recent years, and some have proven successful. These attacks pose a threat to the critical infrastructure that keeps the energy system going – not just the electricity grid, but the highly interconnected and interdependent natural gas, water, communications and fuel distribution systems (AEE Institute, 2018).

The introduction of advanced and intelligent technologies into the power sector presents both opportunities and challenges. The increasing number of connected devices has provided a vast surface area for attacks that exploit IoT devices with weak security, as shown recently with the Mirai IoT botnet and others (Cloudflare, 2019). Modern power grids will open new modes of communication and interaction between increasingly diverse and numerous market participants (e.g. consumers via aggregators) and connected devices. For this reason, as well as having opportunities to reap new benefits, modern power grids are exposed to security vulnerabilities in new ways (Walton, 2018).

But AI may help address the issue of cybersecurity. IBM, for example, is working to reduce this risk, training AI to improve its knowledge so as to “understand” threats and cyber risk; identify relationships between threats, such as malicious files, suspicious IP addresses or insiders; and reduce the amount of time security analysts need to make critical decisions and launch an orchestrated response to remediate the threat (IBM, 2018b). Protections under development aim to make an increasingly complex, interactive and distributed electricity system more resilient against cyberattacks (AEE Institute, 2018).

Microsoft has also introduced the Azure Sphere, a secured microcontroller unit running its own operating system and supported by Microsoft cloud services for periodic updates, in an effort to deliver end-to-end IoT security that responds to emerging threats (Microsoft, 2019). For more information on how these devices can be used to automate and secure demand-side management, see the Innovation Landscape brief *Internet of things* (IRENA, 2019b).

Policy makers will need to strike a balance between supporting the development of AI technologies and managing any risks from malicious actors, as well as the irresponsible use of AI techniques and the data they employ. Policy makers have an interest in supporting broad adoption of AI, since AI can lead to greater labour productivity, economic growth and societal prosperity. Tools to help policy makers include public investments in research and development as well as support for a variety of training programmes, which can help nurture AI talent.

Training and re-skilling of energy sector professionals

For actors in the energy sector to exploit the full potential of digital transformation, automating tasks to provide the time and resources for greater innovation is not enough. The radical shift that digitalisation may usher in also brings with it the need to change the way human capital is managed and developed. Energy sector actors, and enterprises in general, need to invest in re-

skilling and training their employees to manage and operate power assets and systems that are digitalised, otherwise the promise of a more effective and efficient energy sector will not be fully realised. Re-skilling is key to avoiding loss of jobs. Making the right decisions about what to automate, prioritisation for automation, extent of automation and where to apply AI, as well as decisions about people whose roles are impacted, still rest within the human domain. Learning can impact these decisions positively.



IV. CURRENT STATUS AND EXAMPLES OF ONGOING INITIATIVES

The following is a non-exhaustive sampling of companies, consortiums and foundations working at the intersection of AI and the power sector, particularly related to VRE integration.

Table 1 Companies, consortiums and foundations working on IoT in the power sector

Project (company)	Service provided	Description
BeeBryte (France, Singapore)	Demand forecast and demand-side management	BeeBryte aims to minimise utility bills with AI algorithms and automated control of heating-cooling equipment (e.g. HVAC), pumps, electric vehicle charging points or batteries. Using advanced weather forecasts, occupancy, consumption and electricity price signals, BeeBryte maintains processes and temperature within an operating range set by the customer, resulting in up to 40% savings.
DCbrain (France)	Grid stability and reliability	DCbrain enables the optimisation of flows and consumptions, the identification and prevention of network anomalies and the simulation of network evolution.
DeepMind, Google (United States)	Demand forecast and demand-side management	DeepMind develops programs that can learn to solve complex problems without needing to be taught how. DeepMind has tested its machine-learning algorithms at Google's data centres in an effort to reduce power consumption.
DeJoule, Smart Joules (India)	Demand forecast and demand-side management	DeJoule is an air conditioning optimisation platform with a built-in software that uses AI to facilitate demand-side management and enhance the efficiency and performance of air conditioning systems while decreasing costs for consumers.
EUPHEMIA, N-SIDE (Europe)	Optimised market operation	EUPHEMIA is a coupling algorithm that integrates European day-ahead energy markets to determine spot prices and volumes. It covers 25 European countries (Austria, Belgium, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, the Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden and the United Kingdom).
EWELiNE (Germany)	Renewable energy generation forecasting	EWELiNE uses AI to predict the supply of renewable energy days in advance. EWELiNE takes real-time data from solar power plants and wind turbines around Germany and feeds it into an algorithm that calculates the renewable energy output for the next 48 hours. This algorithm uses machine learning, and the researchers compare real data with EWELiNE predictions to refine the algorithm and improve its accuracy.
Fraunhofer (Germany)	Grid stability and reliability	Fraunhofer Institute has developed an AI algorithm that can log and compress up to 4.3 million datasets a day, process that data to develop accurate predictions for grid operators, detect any network anomalies and act on them within 20–50 milliseconds.

Project (company)	Service provided	Description
Grid Edge (United Kingdom)	Grid stability and reliability	Grid Edge provides cloud-based software services that allows consumers to predict, optimise and control their energy demand.
IBM Watson (United States)	Grid stability and reliability	IBM is using analytics to power decision making; sustainably balance supply and demand to deliver safe, secure and reliable electricity service from conventional and renewable energy sources; monitor and manage grids holistically; improve network reliability; resolve issues faster; and lower costs through smart metering.
Infosys (Global, India)	Demand forecast and demand-side management	Infosys supports energy sector participants by applying machine learning to the data generated by advanced sensors, smart meters and intelligent devices behind the meters. By applying AI to this data, the industry can gather granular consumption insights that it can use to propose new services to consumers, while creating an opportunity for retail suppliers.
MindSphere, Siemens (Germany)	Demand forecast and demand-side management	MindSphere is a cloud-based solution that collects and analyses IoT data to provide demand-side management and higher control of industrial-scale connected devices.
Nnergix (Spain, United States)	Renewable energy generation forecast	Nnergix provides solar and wind power forecasting for energy markets and system operators.
PSR and Kunumi (Brazil)	Advanced forecasting System and market operation	PSR and Kunumi are integrating AI and new analytical methods to provide forecasting and optimise energy systems under uncertainty, including operations, planning and trading.
SmartNet (European Union)	Grid stability and reliability	SmartNet provides instruments to improve co-ordination between transmission system operators and distribution system operators by exchanging monitoring information as well as information for the acquisition of ancillary services from actors in the distribution segment.
Tomorrow (Denmark)	Demand forecasting and demand-side management	Tomorrow created an AI algorithm that automatically extracts insights about CO ₂ emissions from various types of data. These insights are then used by different tools, such as the ElectricityMap, which displays in real time the CO ₂ emissions of electricity generation, imports and exports in different countries worldwide. The algorithm could facilitate demand-side management by using connected devices only when the CO ₂ content of electricity is low (e.g. charging electric vehicles with renewable electricity).
Utilityx, McKinsey (United States)	Predictive maintenance	Utilityx helps asset managers optimise productivity using predictive maintenance. Advanced analytics are used to transform network data into a condition-based strategy, driven by the health and criticality of an asset.
Verv (United Kingdom)	Demand forecast and demand-side management	Verv home energy assistant seeks to reduce consumer energy bills by using AI to learn about home appliances and their behaviour, giving customers real-time energy usage statistics.

Table data sourced from individual websites. TWh = terawatt-hours.

V. IMPLEMENTATION

REQUIREMENTS: CHECKLIST

<p>TECHNICAL REQUIREMENTS</p> 	<p>Hardware:</p> <ul style="list-style-type: none"> • Smart grids and smart meters to collect large amounts of high-quality, granular data <p>Software:</p> <ul style="list-style-type: none"> • Software specific to the AI technology used in a particular system • Cloud platform (if data is not stored locally) • Large amounts of granular data to train models <p>Human expertise:</p> <ul style="list-style-type: none"> • Data scientists able to develop machine-learning algorithms and continuously improve models that can be applied to the power sector, especially to VRE integration • Renewable power sector stakeholders able to understand digital technologies and work with data scientists to apply AI techniques to integrate VRE into power systems (e.g. system operators working with ICT experts or data scientists gaining expertise in the power sector)
<p>POLICIES NEEDED</p> 	<ul style="list-style-type: none"> • Assess the impact of AI on jobs, promote re-skilling to prevent job loss, and create new job opportunities • Allow public access to data so that anyone can use or develop digital technologies • Inform and empower consumers, including prosumers, to participate in demand-side management programmes • Enable funding of research and development of AI applications
<p>REGULATORY REQUIREMENTS</p> 	<ul style="list-style-type: none"> • Define data privacy regulation for consumers, and create incentives to participate in pilot projects as data providers • Define cybersecurity protocols • Define protocols for the interoperability of big data • Ensure algorithms comply with existing power sector regulation, or adapt, where necessary
<p>STAKEHOLDER ROLES AND RESPONSIBILITIES</p> 	<ul style="list-style-type: none"> • System operators: Adopt an innovative approach to system operation by enhancing co-operation among distribution and transmission system operators; account for evolving role of distribution system operators • DER owners/operators (e.g. aggregators): Participate in pilot projects as data providers • ICT companies: Work closely with power sector actors (e.g. system operators) to develop tailored AI solutions for the integration of VRE into the power system

ACRONYMS AND ABBREVIATIONS

AI	artificial intelligence	ms	millisecond
DER	distributed energy resource	PV	photovoltaic
ICT	information and communications technology	VRE	variable renewable energy
IoT	internet of things		

BIBLIOGRAPHY

ACER (2015), *ACER's annual report on its activities under REMIT in 2014*, Agency for the Cooperation of Energy Regulators, Ljubljana, www.acer.europa.eu/Official_documents/Acts_of_the_Agency/Publication/REMIT%20Annual%20Report%202015.pdf.

AEE Institute (2018), *Cybersecurity in a Distributed Energy Future: Addressing the Challenges and Protecting the Grid from a Cyberattack*, Advanced Energy Economy Institute, Washington, DC, https://info.aee.net/hubfs/Cybersecurity_FINAL_WP_AEEInstitute_1.18.18.pdf.

BeeBryte (2018), "Unlocking the '5th fuel': Increased energy efficiency with machine learning + big data", BeeBryte, <https://innovationweek.irena.org/-/media/Files/IRENA/Innovation-Week/SessionalDocuments/IRENA-IW18-AI-02-Dirand-Unlocking-the-fifth-fuel-05-Sept-18.pdf>.

Cisco (2018), "Internet of things (IoT) data continues to explode exponentially. Who is using that data and how?", Cisco, <https://blogs.cisco.com/datacenter/internet-of-things-iot-data-continues-to-explode-exponentially-who-is-using-that-data-and-how>.

Chui, M. et al. (2018), *Notes from the AI Frontier: Applications and Value of Deep Learning*, McKinsey Global Institute, New York, www.mckinsey.com/-/media/mckinsey/featured%20insights/artificial%20intelligence/notes%20from%20the%20ai%20frontier%20applications%20and%20value%20of%20deep%20learning/notes-from-the-ai-frontier-insights-from-hundreds-of-use-cases-discussion-paper.ashx.

Cloudflare (2019), "What is the Mirai botnet?", Cloudflare, www.cloudflare.com/learning/ddos/glossary/mirai-botnet.

European Union (2013), "Regulation (EU) No. 543/2013 of 14 June 2013 on submission and publication of data in electricity markets and amending Annex I to Regulation (EC) No 714/2009 of the European Parliament and of the Council", *Official Journal of the European Union*, L 163/1, <https://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2013:163:0001:0012:EN:PDF>.

European Union (2016), "Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC (General Data Protection Regulation)", *Official Journal of the European Union*, L 119/1, <https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32016R0679>.

Desjardins, J. (2019), "How much data is generated in a day?", World Economic Forum, www.weforum.org/agenda/2019/04/how-much-data-is-generated-each-day-cf4bddf29f.

DNV GL (2018), "Making renewables smarter. The benefits, risks and future of artificial intelligence in solar and wind energy", DNV GL, www.dnvgl.com/publications/making-renewables-smarter-104362.

Evans, R., and J. Gao (2016), "DeepMind AI reduces Google data centre cooling bill by 40%", Google DeepMind, <https://deepmind.com/blog/deepmind-ai-reduces-google-data-centre-cooling-bill-40>.

Fraunhofer (2019), "Artificial intelligence automatically detects disturbances in power supply grids", Fraunhofer, www.fraunhofer.de/en/press/research-news/2019/research-news-april-2019/artificial-intelligence-automatically-detects-disturbances-in-power-supply-grids.html.

Gamble, C. and J. Gao (2018), "Safety-first AI for autonomous data centre cooling and industrial control", Google DeepMind, <https://deepmind.com/blog/safety-first-ai-autonomous-data-centre-cooling-and-industrial-control>.

GE Power (2018), “GE’s digital energy software solutions. End-to-end, integrated and interoperable”, GE Power, www.ge.com/power/software.

IBM (2015), “Machine learning helps IBM boost accuracy of U.S. Department of Energy solar forecasts by up to 30 percent”, IBM, www-03.ibm.com/press/us/en/pressrelease/47342.wss.

IBM (2018a), “IoT and machine learning to reduce energy use in cooling systems”, IBM, www.ibm.com/blogs/research/2018/07/reduce-energy-cooling.

IBM (2018b), “Artificial intelligence for a smarter kind of cybersecurity”, IBM, www.ibm.com/security/artificial-intelligence.

IBM (2019), “Data science and machine learning”, IBM, www.ibm.com/analytics/machine-learning.

IEA (2017), *Digitalization & Energy*, International Energy Agency, Paris, www.iea.org/publications/freepublications/publication/DigitalizationandEnergy3.pdf.

IRENA (2019a), *Innovation landscape for a renewable-powered future*, International Renewable Energy Agency, Abu Dhabi, www.irena.org/publications/2019/Feb/Innovation-landscape-for-a-renewable-powered-future.

IRENA (2019b), the Innovation Landscape brief *Internet of things*, International Renewable Energy Agency, Abu Dhabi.

IRENA (2019c), the Innovation Landscape brief *Market integration of distributed energy resources*, International Renewable Energy Agency, Abu Dhabi, https://cms.irena.org/-/media/Files/IRENA/Agency/Publication/2019/Feb/IRENA_Market_integration_2019.ashx?la=en&hash=0159D68FE18E008822F2E8880F8CD2340DE7E540.

Jucikas, T. (2017), “Artificial intelligence and the future of energy”, Medium, <https://medium.com/wepower/artificial-intelligence-and-the-future-of-energy-105ac6053de4>.

KIT (2019), “Artificial intelligence improves power transmission”, Karlsruhe Institute of Technology, www.kit.edu/kit/english/pi_2019_055_artificial-intelligence-improves-power-transmission.php.

Mazengarb, M. (2019), “Tesla big battery paves way for artificial intelligence to dominate energy trades”, Renew Economy, <https://reneweconomy.com.au/tesla-big-battery-paves-way-for-artificial-intelligence-to-dominate-energy-trades-31949>.

McKinsey & Company (2019), “Performance management and optimization for the electric-power industry”, McKinsey & Company, www.mckinsey.com/solutions/utilityx.

Microsoft (2019), “Azure Sphere”, Microsoft Azure, <https://azure.microsoft.com/en-us/services/azure-sphere>.

MIT (2014), “Smart wind and solar power”, MIT Technology Review, www.technologyreview.com/s/526541/smart-wind-and-solar-power.

NEMO Committee (2019), *EUPHEMIA Public Description: Single Price Coupling Algorithm*, NEMO Committee, www.nordpoolspot.com/globalassets/download-center/pcr/euphemia-public-description.pdf.

Nikkei (2017), “AI to propel wind farm efficiency in Japan”, Nikkei Asian Review, <https://asia.nikkei.com/Business/AI-to-propel-wind-farm-efficiency-in-Japan>.

Pöyry (2018), “Pöyry and Infosys jointly introduce an artificial intelligence framework for industry, utilities and infrastructure organisations”, Pöyry, www.poyry.com/news/poyry-and-infosys-jointly-introduce-an-artificial-intelligence-framework-for-industry-utilities-and-infrastructure-organisations.

SAS (2019), “Big data: What it is and why it matters”, SAS, www.sas.com/en_us/insights/big-data/what-is-big-data.html.

SearchEnterpriseAI (2019), “Predictive storage analytics, AI deliver smarter storage”, Tech Target, <https://searchstorage.techtarget.com/essentialguide/Predictive-storage-analytics-takes-management-to-the-next-level>.

Statista (2018), “Internet of things (IoT) connected devices installed base worldwide from 2015 to 2025 (in billions)”, Statista, www.statista.com/statistics/471264/iot-number-of-connected-devices-worldwide.

Walton, R. (2018), “Cybersecurity and the distributed grid: A double-edged sword”, Utility Dive, www.utilitydive.com/news/cybersecurity-and-the-distributed-grid-a-double-edged-sword/523285.

WCO (2019), *Study Report on Disruptive Technologies*, World Customs Organization, Brussels.

Warren, C. (2019), “Can artificial intelligence transform the power system?”, EPRI Journal, <http://eprijournal.com/can-artificial-intelligence-transform-the-power-system>.

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