Energy Reports 8 (2022) 334–361

Contents lists available at ScienceDirect

Energy Reports

journal homepage: www.elsevier.com/locate/egyr

Review article

Energetics Systems and artificial intelligence: Applications of industry 4.0

Tanveer Ahmad [b], Hongyu Zhu [a], Dongdong Zhang [a,*], Rasikh Tariq [c], A. Bassam [c], Fasee Ullah [d], Ahmed S AlGhamdi [e], Sultan S. Alshamrani [f]

[a] *School of Electrical Engineering, Guangxi University, Nanning, 530004, China*
[b] *Energy and Electricity Research Center, International Energy College, Jinan University, Zhuhai, Guangdong Province, 519070, China*
[c] *Facultad de Ingeniería, Universidad Autónoma de Yucatán, Av. Industrias No Contaminantes por Anillo Periférico Norte, Apdo. Postal 150, Cordemex, Mérida 97203, Yucatán, Mexico*
[d] *Department of Computer Science and IT, Sarhad University of Science and Information Technology, Pakistan*
[e] *Department of computer engineering, collage of computers and information technology, Taif University, P.O. Box 11099, Taif 21944, Saudi Arabia*
[f] *Department of Information Technology, College of Computer and Information Technology, Taif University, P.O. Box 11099, Taif 21944, Saudi Arabia*

ARTICLE INFO

Article history:
Received 3 June 2021
Received in revised form 11 November 2021
Accepted 22 November 2021
Available online 16 December 2021

Keywords:
Applications of industry 4.0
Power sector
Artificial intelligence
Energetics systems
Energy storage
Sustainability

ABSTRACT

Industrial development with the growth, strengthening, stability, technical advancement, reliability, selection, and dynamic response of the power system is essential. Governments and companies invest billions of dollars in technologies to convert, harvest, rising demand, changing demand and supply patterns, efficiency, lack of analytics required for optimal energy planning, and store energy. In this scenario, artificial intelligence (AI) is starting to play a major role in the energy market. Recognizing the importance of AI, this study was conducted on seven different energetics systems and their variety of applications, including: i) electricity production; ii) power delivery; iii) electric distribution networks; iv) energy storage; v) energy saving, new energy materials, and devices; vi) energy efficiency and nanotechnology; and vii) energy policy, and economics. The main drivers are the four key techniques used in current AI technologies, including: i) fuzzy logic systems; ii) artificial neural networks; iii) genetic algorithms; and iv) expert systems. In developed countries, the power industry has started using AI to connect with smart meters, smart grids, and the Internet of Things devices. These AI technologies will lead to the improvement of efficiency, energy management, transparency, and the usage of renewable energies. In recent decades/years, new AI technology has brought significant improvements to how power system devices monitor data, communicate with the system, analyze input–output, and display data in unprecedented ways. New applications in the energy system become feasible when these new AI developments are incorporated into the energy industry. But on the contrary, much more investment is needed in global research into AI and data-driven models. In terms of power supply, AI can help utilities provide customers with renewable and affordable electricity from complex sources in a secure manner, while at the same time providing these customers with the opportunity to use their own energy more efficiently. Moreover, policy recommendations, research opportunities, and how industry 4.0 will improve sustainability have been briefly described.

Contents

1. Introduction 335
2. Artificial intelligence in different energetic systems 338
   2.1. The use of artificial intelligence in energy generation 338
      2.1.1. The use of artificial intelligence in power generation 339
      2.1.2. The use of artificial intelligence in renewable energy 340
   2.2. The use of artificial intelligence power delivery 341
      2.2.1. Artificial intelligence in power transmission and delivery 341
      2.2.2. Artificial intelligence in power system automation and control 342

* Corresponding author.
E-mail addresses: tanveer.ahmad.pk11@gmail.com (T. Ahmad), dongdongzhang@gxu.edu.cn, dongdongzhang@yeah.net (D. Zhang).

https://doi.org/10.1016/j.egyr.2021.11.256

2.3. The use of artificial intelligence in electrical distribution networks 343
2.3.1. The use of artificial intelligence in energy conversion and distribution 343
2.3.2. The use of artificial intelligence in integrated energy systems 344
2.4. The use of artificial intelligence in energy storage 345
2.4.1. The use of artificial intelligence in battery energy storage 345
2.4.2. The use of artificial intelligence in energy storage technologies and devices 347
2.5. The use of artificial intelligence in energy applications 349
2.5.1. Artificial intelligence in new energy applications and energy-saving technologies 349
2.5.2. The use of artificial intelligence in new energy materials and devices 351
2.6. The use of artificial intelligence for energy efficiency and nanotechnologies 351
2.7. The use of artificial intelligence for energy and economic policy 352
3. Challenges of energetics systems and artificial intelligence in different energy applications 352
4. Future policy recommendations and research opportunities 353
5. How will artificial intelligence and industry 4.0 improve the sustainability? 354
6. Conclusion 355
Declaration of competing interest 355
Acknowledgments 355
References 355

Nomenclature

AI	Artificial intelligence
ANNs	Artificial neural networks
ABB	ASEA Brown Boveri
GARCH	Autoregressive conditional heteroskedasticity
ARIMA	Autoregressive integrated moving average
BNEF	Bloomberg New Energy Finance
BP	British Petroleum
BIS	Business intelligence and strategy
CO2	Carbon dioxide
CAGR	Compound annual growth rate
DERs	Distributed energy resources
EM	Expectation–maximization
FACTs	Flexible alternating current transmission system
FL	Fuzzy logic
GA	Genetic algorithm
GW	Gigawatt
GDP	Gross domestic product
ISO	Independent system operators
ICT	Information communication technology
IMB	International Business Machines
IoT	Internet of Things
KNPC	Kuwait National Petroleum Company
ML	Machine learning
PV	Photovoltaic
PWC	PricewaterhouseCoopers
PLCs	Programmable logic controller
RTO	Regional transmission organizations
SDGs	Sustainable Development Goals
USA	The United States of America
TR	Trillion
UPFC	Unified power flow controller

1. Introduction

As the smart grid advances, the current energy system moves toward a future in which people can purchase whatever they need, sell it when excessive and trade the buying rights for other proactive customers (prosumers) (Tushar et al., 2020). The worldwide power grids have to face a continually rising energy demand, and at the same time, provide a reliable electricity supply (Strasser et al., 2015). Fossil fuels are currently dominating global electricity production, resulting in growing CO2 emissions and climate change. Around two-thirds of global emissions of greenhouse gases are from the energy sector (Egli et al., 2018). Reducing greenhouse gas emissions arising from electricity production cannot be accomplished until a wide scale is used for renewable energy like wind generators, photovoltaic (PV), biomass, and integrated heat and power systems (Cecati et al., 2011).

The Covid-19 crisis contributed to an unexpected fall in energy use (Chang et al., 2020). The trends of energy usage have also shifted dramatically, with strong declines in industries and businesses, while domestic use has risen as more people start work from home. Before COVID-19, industry 4.0 – which includes advanced analytics, connectivity, and automation – was thriving, allowing businesses to turn everything from manufacturing productivity to product customization, with increased market efficiency in operation, speed, and new business models. Industry 4.0 is predicted to be the driving force of economic growth. As per Capgemini's study, it is projected to boost the world economy by \$500 billion to \$1.5 trillion between 2018 and 2022 (Columbus, 2017). According to Microsoft, International Business Machines (IMB), and PricewaterhouseCoopers (PWC), 71% of executives believe that AI will have a significant impact on their business (Ernst & Young LPP Microsoft, 2019). 50% of companies that rely on AI over the next 5 to 7 years may double their cash flow (Columbus, 2020). 64% of industrial companies have already begun to invest in AI solutions. AI will contribute \$3.7 TR to the manufacturing sector by 2035 (European Commission, 2020). Fig. 1 visualized the AI actor's overview around the globe. More than half (61%) of all organizations identified are start-ups or small to medium-sized businesses led by research organizations at 23%. The remaining 16% are major organizations (Vogel et al., 2019). The regional focus is on Europe (49%) and the United States (33%), but there are some thrilling energy industries AI developments can also be found in countries such as India and Israel.

Opportunities for investment in AI: As it is estimated that global use of AI will hit \$7.78 billion by 2024 in the energy industry, with the industry projected to see a compound annual growth rate (CAGR) of 22.49% between 2019 and 2024 (AI Investment Opportunities, 2020). There is no question that it is a hot trend for many leading energy companies and investors to look to harvest AI's potential benefits to the energy industry. Business Intelligence and Strategy (BIS) analysis predicts that Northern America will

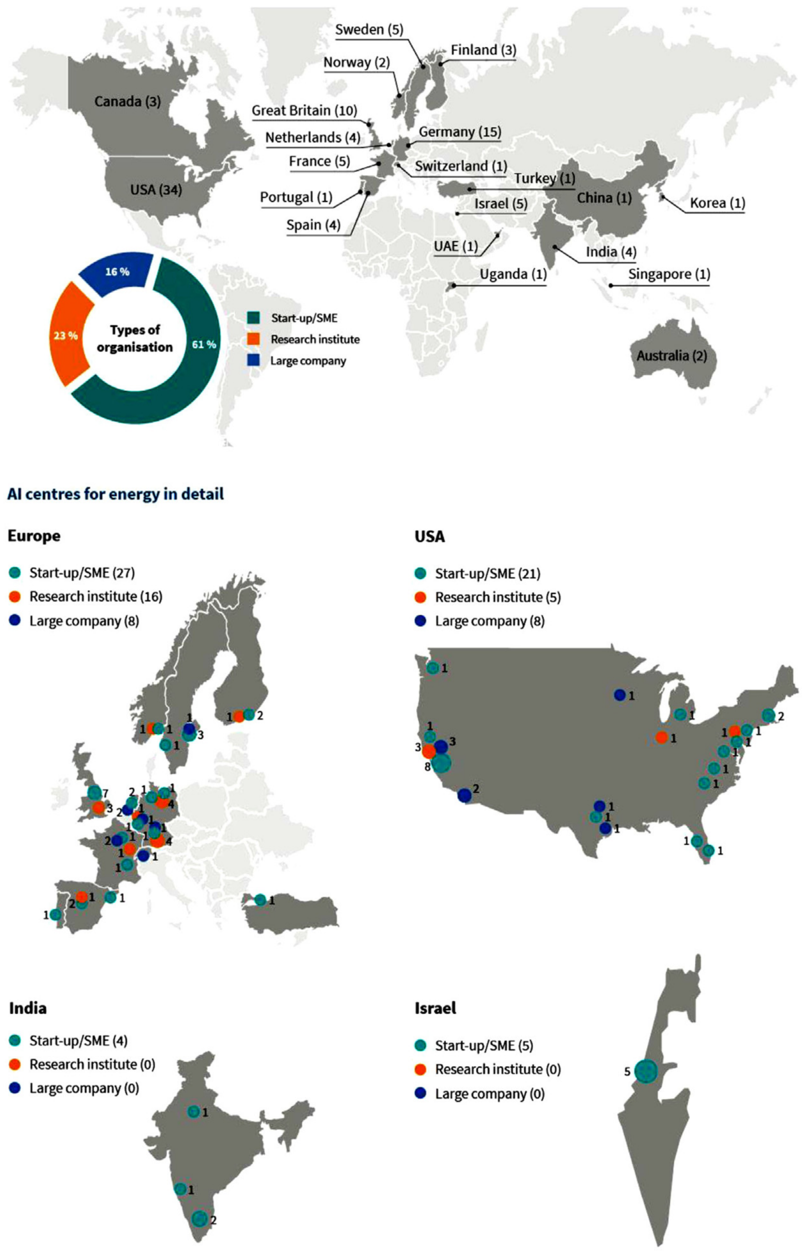

Fig. 1. AI actors around the world (Vogel et al., 2019).

be the leading energy supply market for AI by 2024 (Banga, 2020), while the increasing need for more decentralized power generation in Asia-Pacific is projected to see significant growth over the same time. Some of the main companies in this field that exploit AI's energy-related opportunities include: (1) Google DeepMind ; (2) Enel Xc; (3) Microsoft; (4) Equinor; (5) C3.ai; (6) Schlumberger; (7) General Electric; (8) Shell; (9) Siemens; 10) Rockwell Automation; 11) Schneider Electric; 12) Honeywell; 13) ASEA Brown Boveri (ABB); 14) Exxon Mobil; 15) British Petroleum (BP); 16) Royal Dutch Shell; 17) Baidu; 18) Tencent; etc.

In many power systems engineering fields, it was tough and tedious to overcome complicated issues at the start of the 1980s. Today, AI makes it possible to work with many constraints, such as cost-effective load delivery (Shi et al., 2020), load scheduling (Tushar et al., 2020; Zhang et al., 2020; Sung and Ko, 2015), optimization of scheduling and generation (Höllerer et al., 2020; Zhou et al., 2020; Basu, 2020; Jiekang et al., 2008; Ahmad, 2021; Liang and Liao, 2007), transmission capability (Nguyen et al., 2020; Vyas et al., 2016; Ahmad et al., 2021; Sidhu and Ao, 1995; Wang and Keerthipala, 1998), programmed power flows (Suman, 2021; Yun et al., 2020; King et al., 2015), actual and reactive power limit of generators (Ahmad et al., 2019; Cirrincione et al., 2009), bus voltages and transformer taps (Xu et al., 2020a; Shi et al., 2020). IoT and analytics would be critical for Industry 4.0 to recognize models (Ben et al., 2020; Yassine et al., 2019), patterns and to provide manufacturers with real-time intelligence on the fingerprints (Anon., 1992). Google reported three years earlier that its worldwide operations, such as its data centers and facilities, accounted for 100% of renewable energy (Hölzle, 2016). Google also is the biggest clean energy customer with 2.6 GW of solar and wind energy investments (Hölzle, 2016).

Types of problems solved using AI Algorithms includes three main types including: (i) classification algorithms (Lin et al., 2012; Iqbal et al., 2014; Zhang and Ahmad, 2021); (ii) clustering algorithms (Yuan et al., 2020; Schütz et al., 2018); and (iii) regression algorithms (Ali et al., 2020; Mohamed et al., 2012; Hong and Chao,

Table 1
Classification of ML and AI techniques.

Technique name	Learning approach	Tasks	Model sub-category	Purposes
Reinforcement learning	Q-learning	Decision-making sequential	Strategic planning and management	Decision making, real-time decisions in the energy industry
Supervised learning	Logistic regression	Classification	Dividing line approaches	Forecasting of an outage
	Support vector machine		Hyperplane parameters	Constructing different kinds of data groups
	Iterative Dichotomiser		Different decision tree models	Categorization of climate and weather data
	Bayesian inference		Bayesian regularization models	Used for grouping of the data
Unsupervised learning	k-means	Clustering	Cluster midpoints data mining	Identification of energy consumption data groups
Miscellaneous	Backpropagation	Miscellaneous	Different kinds/groups of artificial neural networks	Forecasting tasks, real-time energy applications
Unsupervised learning	Principal component analysis	Reduction in dimensionality	Combined network features	Used for complex decisions, used for simplification of complex decisions
Supervised learning	Linear regression	Regression	Regression line	Electricity and gas prices forecasting
	Regression tree methods and classification		Random forest approaches and decision tree models	Forecasting different kinds of data

2008). Classification algorithms are divided into five different subclasses includes (a) naive Bayes (Niazi et al., 2019; Ng et al., 2014), (b) random forest (Ma et al., 2018; Reddy and Sodhi, 2018), (c) k-nearest neighbors (Pinto et al., 2019; Khalilifar et al., 2019), (d) decision tree (Moutis et al., 2016; Mikučioniene et al., 2014), and (e) support vector machines (Jang et al., 2016; Yang et al., 2015). Clustering algorithms are divided into four different subclasses includes: (a) K-means clustering (Liu et al., 2018; Zatti et al., 2019), (b) expectation–maximization (EM) algorithm (Bracale et al., 2017), (c) Fuzzy C-means algorithm (Di Maio et al., 2011; de B. Franco and Steiner, 2018), and (d) hierarchical clustering algorithm (Tso et al., 2020; Wang et al., 2020a). Regression algorithms are divided into five different subclasses includes: (a) logistic regression (Kim et al., 2019; Yu and Ho, 2019), (b) linear regression (Ciulla and D'Amico, 2019; Yip et al., 2017), (c) lasso regression (He et al., 2019; Al-Obeidat et al., 2020), (d) multiple regression algorithm (Amiri et al., 2015; Lam et al., 2010; Gil Posada et al., 2016) and (e) multivariate regression (Ardakani and Seyedaliakbar, 2019; Qiu et al., 2019; Cheng and Cao, 2014; Bracale et al., 2020).

The following techniques of machine learning can be used in real-time applications: (1) supervised learning (Chen et al., 2018a; Buzau et al., 2019; Kim, 2020; Mohammadi et al., 2018; Henri and Lu, 2019); (2) unsupervised learning (Liu et al., 2019; Park et al., 2019; Bodnar et al., 2017); (3) reinforcement learning (Yan and Xu, 2020; Xu et al., 2020b; Wei et al., 2020; Munir et al., 2019; Cao et al., 2020; Yu et al., 2020); and (4) ensemble learning (Su et al., 2020; Du, 2019; Li et al., 2020; Zhnag, 2020; Meng et al., 2020; Xu et al., 2019).

Supervised learning: The method is used to learn the data when supplying the right responses or data labels.

Unsupervised Learning: The next classification is unsupervised learning, where the algorithm has no valid answers or responses, unlike supervised approaches, but the algorithm needs to combine and interpret related data.

Reinforcement learning: Rewards/feedback is given to the algorithm in reinforcement learning, with any proper forecast contributing to greater accuracy.

Ensemble learning: Although the three classes listed above cover most areas, the model's efficiency also tends to improve. In such instances, it may be useful to use ensemble approaches to improve the accuracy. Classifications, learning approach, specific tasks, and efficient use of ML and AI are given in Table 1.

New digital models will have a significant impact on energy generation, trade, and consumption. The following techniques are used in current AI technologies; (i) fuzzy logic systems (FL) (Khan et al., 2017; Jafari et al., 2019; Lagorse et al., 2009), (ii) artificial neural networks (ANNs) (Li et al., 2014; Liu and Zhang, 2016; Megahed et al., 2019; Venayagamoorthy et al., 2016; Chettibi et al., 2018), (iii) genetic algorithm (GA) (Ilbeigi et al., 2020; Xu et al., 2020c; Askarzadeh, 2018; Yildirim and Mouzon, 2012; Ospina et al., 2019; Lin et al., 2018), and (iv) expert system techniques (XPS) (Azmy, 2007; Leon et al., 1999; Ernesto Vázquez et al., 1997; Hsu and Su, 1991). These are the leading families of AI technology in the world of advanced power systems. Every other kind of neural network is able to perform such special tasks after training and infer a function through real-life observations like an approximation of functions, classification, data management, etc. Its key benefit is that it is able to learn algorithms, adapt complex structures online, compute fast parallel, and interpolate data intelligently. ANNs can be especially useful for issues, for example, in real-time operation (Xu et al., 2018), which require fast results. Power system protection can be implemented through ANN techniques (Ledesma et al., 2020). Fuzzy techniques were designed in 1965 and became popular in problem solving technologies (Kayapinar Kaya and Erginel, 2020). Fuzzification offers over-simplification, higher expressive power and better simulation of a dynamic problem at low cost (de Campos Souza, 2020). Because much of the study of the power system is carried out either with an estimate or with assumption-based data, fuzzy logic can be useful for generating an accurate and reliable output without uncertainty. It can be used for improving performance and modeling physical elements of power systems from small to large circuits.

During the 1960s and 1970s, the expert programs were developed and applied in the 1980s. It is also called rule-based or knowledge-based energy systems (GhaffarianHoseini et al., 2017). The information is generally stored in one of several ways, such as rules, decision-making processes, frames, and models. Expert systems are incredibly helpful because a large volume of data information and data which needs to be handled in a limited period. Methodologies for expert systems can be categorized as knowledge-based systems, rule-based systems, object-oriented methods, artificial neural networks, system architecture, case-based reasoning systems, database methodology, intelligent-based agent systems, ontology, and modeling.

While several approaches are being developed for improving the performance and study of the energy system, genetic algorithms are sensitive to solve all the constraints chosen. Genetic

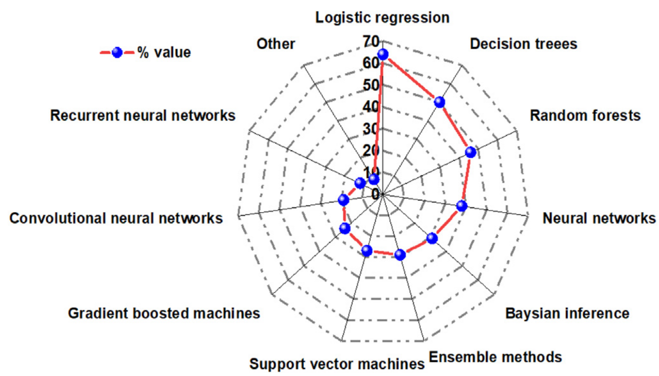

Fig. 2. The most widely used approaches for ML and data scientists (%).

algorithms are the best way to solve nonlinear and complex problems (Mayer et al., 2020). It is used to schedule power production (Tapia et al., 2020), transmission (Teegala and Singal, 2016; Lin and Yeh, 2011), and distribution (Pesaran et al., 2020; Torres et al., 2013). Further, it changes the output parameters to rectify and solve the voltage regulation issues and compensates for the use of reactive power.

Advantages of AI: The AI has several advantages, including better demand forecasting (Bedi and Toshniwal, 2019), direct automation (Lingmin et al., 2020), a safer workplace, refined root cause analysis, smooth 24/7 production, smarter workforce, yield enhancement, increased workplace safety, lower operational costs, improved identification of production defects, automated quality control, higher supply chain efficiency, better power product or equipment design, quick decision making, predictive maintenance (Garcia et al., 2006), testing and quality optimization (del Valle et al., 2008), etc.

Setbacks of AI: (1) Technology has changed the nature of work since the first industrial revolution, and the influence of AI on this area is possibly significant. It is predicted that AI developments would jeopardize 47% of jobs in the United States of America (USA) and a higher percentage in developed/developing countries (Frey et al., 2016). This issue has been increasingly addressed by discussions at the World Economic Forum in 2016 (Loebbecke and Picot, 2015). (2) 36% of industrial companies are concerned about integration and compatibility issues with AI solutions. (3)

Fig. 2 illustrates the most widely used approaches by ML and data scientist experts (Vogel et al., 2019). It is important to note that statistical techniques, for example, in supervised and reinforcement learning, can also be applied in various areas. One of the most widely used approaches is decision trees, logistic regression, ANNs, and random forests. The difference between statistical learning, statistics, AI, and ML is often difficult to distinguish among. It also depends on the questions and application (Vogel et al., 2019). Fig. 3 visualizes the different applications of AI in various energy systems (A.G., 2020). Automation of machinery and equipment, asset maintenance forecasts, machines, software and optimization and safety monitoring/incident prevention is the top-of-the-line AI applications with 30%, 25%, 28%, and 26%, respectively.

Energy digitization is how modern technologies, including communication and information, are integrated into the energy sector and the latest data-driven models and interaction possibilities. This briefing study will focus on the use of AI in different energy systems. We will focus on three key areas of the energy industry, including power generation, power transmission and distribution, and energy storage. This study is also different from the current reviews in that we have covered all the main areas of the energy system and the energy industry. In the current reviews, only one part of the power system (e.g., production, transmission, distribution, storage of energy) was published as part of the review. Only specific AI models have been reviewed in existing studies. In this study, we discussed the new state-of-the-art developments and applications of Industry 4.0 and the use of AI. More specific and important information on this review has been obtained through high-quality references. The study's objective is to provide policy recommendations, research opportunities, and how industry 4.0 will improve sustainability in the energy sector. Main AI technologies, including: (i) fuzzy logic systems; (ii) artificial neural networks; (iii) genetic algorithms; and (iv) expert systems and their real-time use in energy applications are discussed. This review is a concise overview of the research as a whole, which seeks to provide important insights into the guidelines for those involved in data policy and regulation, energy sustainability in the use of AI in the energy sector, industry 4.0 applications in an easily digestible format. Table 2 represents the history and Industry: 4.0 revolution.

The rest of the study is organized into the following sections. Section 2 represents a brief review of AI in energy systems, including power and energy generation, the use of AI in renewable energy, power transmission, power system automation and control, energy conversion and distribution, integrated energy systems, battery energy storage, energy storage technologies and devices, new energy applications and energy-saving technologies, new energy materials and devices, energy efficiency and nanotechnology, energy policy and energy economics. Section 3 provides a detailed analysis of the upcoming challenges of AI in different energy systems. Future policy recommendations and research opportunities are presented in Section 4. Section 5 shows how industry 4.0 will improve sustainability, and Section 6 concludes this study.

2. Artificial intelligence in different energetic systems

In all fields of engineering, and in particular, in sustainable energy systems, the impacts of AI are increasingly growing. The AI has been applied in a large number of applications, for example, occupants satisfaction and smart buildings (Ouahiba et al., 2018), IoT security and safety system in smart cities (Zahmatkesh and Al-Turjman, 2020), energy-saving with the use of smart home concept (Pan et al., 2015), smart energy management (Zhou et al., 2016), improving wind turbine and unified power flow controller (UPFC) electrical stability (Dawn et al., 2019), new solar technologies (Badiei et al., 2020), wind (Aly, 2020), solar, load (Wang et al., 2020b), gas (Wei et al., 2019), and electricity price forecasting (Jasiński, 2020; Bedi and Toshniwal, 2019), Photovoltaic generation maximal power point monitoring on a fuzzy logic basis (Erixno and Rahim, 2020; Kermadi and Berkouk, 2017), grid stability and reliability (Shi et al., 2020), demand forecast and demand-side management (Antonopoulos et al., 2020), predictive maintenance (Foresti et al., 2020), renewable energy generation forecast (Ruhnau et al., 2020; Zhang and Yan, 2020; Wang et al., 2019), etc. Table 3 visualizes the AI in the energy industry and different states of development. This section discusses the use of AI in seven different ways, including: (i) electricity generation; (ii) power delivery; (iii) electrical distribution networks; (iv) energy storage; (v) energy applications; (vi) energy efficiency and nanotechnology in energy systems; and (vii) energy policy, and economics. A detailed overview of each part is provided below.

2.1. The use of artificial intelligence in energy generation

Worldwide, the energy market faces rising growth, productivity, changing demand and supply trends, and the lack of technology needed to handle it effectively. In emerging market countries,

Table 2
History and Industry: 4.0 revolution.

Industry 1.0 (1784) 1st revolution	Industry 2.0 (1870) 2nd revolution	Industry 3.0 (1969) 3rd revolution	Industry 4.0 (Present) 4th revolution
Steam power, mechanical manufacturing, weaving loom, waterpower,	Electrical energy, mass labor production, assembly line manufacturing, mass production,	Electronics, industrial automation, computers, communications, first programmable logic controller, robotics,	Cloud manufacturing, information exchange, digitization, cyber–physical systems, computing, IoT, cloud computing

Table 3
AI in the energy industry and different states of development.

Sr. #	Security and maintenance	Decision-making	Consumer services and distribution
1	Rapining, dismantling, maintenance	Operating optimization	Bills distribution and process automation
2	Predictive maintenance	Forecasting	Consumer participation and making the system easier for them
3	Security measures	Strategic business decisions and inventory optimization	Marketing measures and customization of different kinds of products

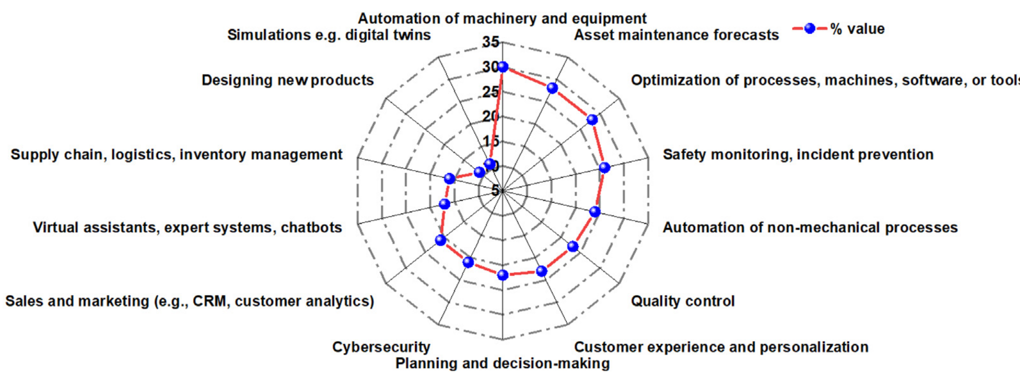

Fig. 3. The use of AI (%) in different energy sectors.

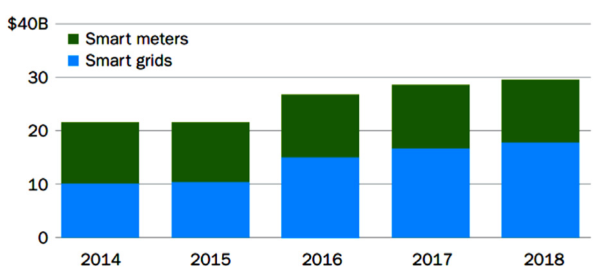

Fig. 4. 2014-2019 smart grid expenditure (billions of dollars) (Makala and Bakovic, 2020).

these challenges are more acute. Efficiency problems are especially problematic, since the prevalence of informal power grid connections means that a large amount of power is neither measured nor counted, resulting in losses and greater CO2 emissions, since consumers are not encouraged to use their energy efficiently (Makala and Bakovic, 2020). AI and related technologies have already become used by the power sector in advanced nations to enable communication between smart meters (Luan et al., 2015), smart grids (Yang et al., 2018), and the industrial internet of things (Tran-Dang et al., 2020). These systems can increase the management of power, efficiency, and transparency and keep increasing renewable energy sources (Makala and Bakovic, 2020). Fig. 4 demonstrates that smart meters have been given importance (Makala and Bakovic, 2020). Smart meters are a consumer preference decision-making choice. Customers can choose whether, at peak hours, for example, to turn "OFF" or "ON" their electricity, or to adjust their consumption patterns.

One of the Sustainable Development Goals (SDGs) is equitable access to affordable, secure, and sustainable clean electricity (Zhang, 2020). But it will remain just a goal, if the multiple energy hurdles plaguing the markets resulting from lack of adequate power generation, inadequate infrastructure for transmission and distribution, sustainability and environmental problems can be overcome by creative technologies and innovation (Ramirez et al., 2020). In addition, it poses diverse problems in power production, storage, delivery, and usage across countries, coupled with emerging and evolving technological advances and demand trends. AI can reduce energy consumption, reduce energy costs (Antonopoulos et al., 2020), and make the use of safe, green energy sources faster and more productive for grids worldwide. Emerging economies drive the AI implementation in the power sector. For instance, DeepMind, a branch of Google, uses ML models to forecast power production 36 h in advance using a neural network based on weather availability, and historical wind turbine data, to 700 megawatts of wind power in the Central United States (Elkin and Witherspoon, 2019). A more reliable smart grid would entail the growing growth of intermittent solar and wind generation along with volatile electricity loads, such as energy storage (batteries), electric vehicles, buses, and distributed renewable power (Jha et al., 2017), such as solar photovoltaics (Wang et al., 2020b). With AI, a smart grid can learn and adjust to the load and amount of varying renewable resources streaming through the modern infrastructure. AI will make decision making simpler for distributed generation.

2.1.1. The use of artificial intelligence in power generation

The use of AI in power and energy generation is well recognized. It includes optimization of operational performance through analytics, optimization of wind farms by forecasting wind speed, flexible distributed generation, integration of micro-generation, drone inspections of equipment, network-connected generation output, active demand management, autonomous optimization of generation, optimization of renewable generation, (Entchev and Yang, 2007; Antonopoulos et al., 2020), etc. Moreover, the AI is a very effective tool in power and energy generation for illustrating:

- Detect human errors: until it becomes a big issue;
- Optimize the schedule of power plants: increase profitability (Mbuwir et al., 2020);
- Predicting the merit order: optimizing the scheduling of the various power sources; and
- Predict malfunctions: forecast the system failures sooner and more precisely.

The AI models are used for operational and generation planning based on load forecasting, economic dispatch, hydrothermal generation, and optimization scheduling (Toopshekan et al., 2020). The active and reactive power limits of different power generations and generation units are controlled by AI. ML, AI, and their other collaborator's reinforcement learning, deep learning, etc., already have broad scope across a number of branches. Mostly in the energy sector, deep learning is very useful when algorithms for large databases are adapted. In historical cases of energy usage and generation, data sets are usually large and involve the right techniques for efficient visualization and interpretation. A more efficient grid or smart grid is required combined with the growing growth of solar and wind intermittent generation with intermittent electricity loads, like electric vehicles or buses, batteries, energy storage, and decentralized renewable electricity, such as roof solar PV systems. With the use of AI, the smart grid will be able to adapt and learn about the number of different renewable energy flows to the grid and the nature of intermittent loads.

How can the sector of energy production use AI? AI provides greater scope for controlling energy production and for fulfilling supplies of demand from diverse sectors. Given the paradigm shift in this global energy sector toward effective energy generation and storage methods for satisfying market demand for energy, the industry is working more toward decarbonization and decentralization (Di Silvestre et al., 2018). Furthermore, it is now the key responsibility of every organization to handle demand and supply instabilities while maintaining them. The production of renewable energy is the main source of electricity today's sense in which fossil-based energy is expected to come to an end soon. Therefore, companies want to use the AI potential to boost renewable energy access in various sectors and improve their performance. Big data and IoT sync with AI systems will greatly boost renewables' grid control when managing supply and demand (Singh et al., 2020a). AI also helps to control electricity in various utilities such as malls, restaurants, retail stores, and many more, as well as improve solar electricity generation as well as its supply. Integrating AI into 5G networks and sensor networks will lay the foundation for smart city services for the future (Serban and Lytras, 2020).

In terms of power production, AI technology has played an extremely important role. In the context of changes in the energy structure, electricity production has gradually shifted from traditional coal energy to low-carbon energy generation. Therefore, in the case of traditional coal energy and low-carbon energy mixed power generation, AI technology has brought more advantages to the development of the power production sector. On the one hand, during the operation of power generation equipment, AI technology can be used to monitor the operating status of various generators online in real time. First of all, real-time acquisition of generator performance data and various operating parameter data, including power generation, heat dissipation temperature during generator operation, etc., is collected through sophisticated sensor equipment. Then, the data is transmitted to the data processing center for real-time online analysis and processing, and a visual interface that is convenient for manual observation is realized through digital twin technology. Finally, through real-time online processed data, the implementation and operation status of various generators are reflected on the visual interface. What is important is that this kind of intelligent control system can automatically deal with some small problems encountered during the operation of the generator and reflect the processing process on the visual interface. On the other hand, the use of AI technology to achieve automatic prioritization of power generation resources, that is, without affecting the comfort of user-side energy consumption, priority is given to the application of low-carbon renewable resource power generation, then natural gas power generation, and finally coal-fired power generation. First, deep reinforcement learning is used to make short-term or ultra-short-term predictions for renewable energy power generation, and at the same time, mining and analyzing the energy consumption characteristics of the user side. Then, under the condition of satisfying the balance of supply and demand, the automatic prioritization of power generation from multiple resources is realized. Finally, in the process of sorting, coal-fired power generation gradually withdrew from the stage of history. Therefore, in the follow-up research, we will also focus on the above two aspects to explore the research of AI technology on the side of energy generation.

2.1.2. The use of artificial intelligence in renewable energy

While all countries aim to use AI to incorporate renewable energy and improve its efficiency, the implementation process will be a challenge. Due to the inherent volatility of wind and solar, current grids face numerous challenges in resolving renewable energy diversity (Figueiredo and da Silva, 2019). The technology aims to increase the efficiency of electricity generation, transmission, and distribution, reduce energy costs, and maximize the use of renewable energy (Shi et al., 2020). The electricity market has to make sure a balance occurs at all levels between supply and demand in order to be more competitive, greener, and more sustainable. The AI looks eager to help in this scenario. There is an opportunity to develop robots, and decision-making software at any stage of the value chain, from energy production to end customers, to help forecast supply and demand, manage the grid in real time, minimize downtime, optimize returns and enhance customer service as well as end user's experience (Antonopoulos et al., 2020).

AI allows power producers to optimize their efficiency by adjusting their generation in real time (Yousri et al., 2020). For example, ML techniques help improve/increase the production of wind turbines based on historical results, real-time contact with other wind farms and grid networks, and wind direction and direction transitions.

Big data and AI generate accurate forecasts that allow even more solar energy to be incorporated into the power grid. For example, the wind speed and wind power data are collected for forecasting analysis. AI-based software is then used to optimize this data. The result is that wind turbines of unprecedented precision allow more renewable energy to be deployed at lower prices than utilities would ever have believed possible. While solar energy is lagging behind wind power production, scientists worldwide are working to leverage the surplus of solar power further. Researchers investigate how to balance fluctuating wind energy with demand through AI, and effectively monitor the timing and cost of charge (Zhao et al., 2019).

AI can observe patterns and benefit from huge amounts of data. As a consequence, it may make improvements to optimize energy production, storage, and even delivery. Furthermore, this advancement is not strictly restricted to massive utility projects that are maintained by teams of technicians and engineers. This has an imminent ability to be scalable. In intelligent homes, workplaces and companies. In the next decade, the performance of renewable systems will be improved considerably by AI automation. In the wind and solar industries, this will become particularly prevalent. Operating and maintaining processes is another big advantage. This helps the possible component downtimes to be correctly measured. Not only does this help improve an installation's total productivity, but it also reduces the cost of replacement by raising the average life expectancy. Prediction systems for developing renewable energy based on AI are continually being developed, thereby promoting integration into the worldwide power grids. AI technology will also help renewable energy suppliers introduce new models of services and broaden their market position for increased participation. AI may also help build plans, policies and planning, for current and future use (Sharma et al., 2020).

How will AI Technology boost the sector of renewable energy?
(a) Centralized and smart control centers: for the processing of a lot of data, the electric grid is linked to devices and sensors. This data will provide the grid operators with new ideas for improved control operations when combined with AI. It provides the energy producer's ability to change supply cleverly to demand. In addition, advanced sensors and smart machines can allow forecasts of weather and load, which can increase renewable energy integration and efficiency.
(b) Improved microgrid integration: AI will assist in smart grid integration and centralized energy management. Once renewable energy generation units at the community level are connected to the primary grid, the grid's energy flow cannot be balanced or too hard to balance. In solving these congestion and quality problems, the IA driven control system may play a vital role.
(c) Improved reliability and safety: While the use of AI is the main target in the field of renewable energy, it can also boost stability, performance, and reliability. It will lead to understanding the pattern of energy use, the energy leakage, and the equipment's performance.
(d) Expand the market: AI integration can lead to the expansion of new service modeling techniques and promote greater participation of renewable energy suppliers in the industry. The AI-powered systems can analyze energy collection data and provide insights into energy usage. This data will help companies refine existing services and implement new models of operation. It could also help distributors reach market opportunities for the customer.
(e) The role of a smart grid with AI-enabled storage: AI integration with intelligent storage can provide the renewable energy sector with a secure and sustainable solution. This will also support microgrids to effectively handle local energy requirements while ensuring power-sharing with the national grid (Antonopoulos et al., 2020).

In the future, big data and AI will further improve decision-making and planning, inspections, quality tracking, certifications and optimization of the supply chain, which will generally maximize the performance of energy systems (Anon., 2019). But this brief aims to encourage further incorporation of variable renewable energy into power systems, where six main AI application categories can be established, as illustrated in Fig. 5. (1) Improved weather prediction is one of the prominent and key AI technologies for increasing renewable energy integration in the electricity network. (2) AI will further improve the power networks' operation by providing reliable supply and demand forecasts. (3) Precise demand forecasts and the projection of renewables can be used to increase cost-effectiveness as well as to maximize demand-side control and efficiency. (4) A large number of AI and Big Data are undergoing demand-side monitoring, developments in demand response (Huang et al., 2021), energy storage technologies and overall energy performance. (5) AI Integrated energy storage more efficiently, maximized the incorporation of renewable power, decreased local power demand price and maximized storage device owners' returns. (6) In order to maximize close to real-time business operations, advanced models based on AI are now being used. Such optimization is focused on a review of vast streams of different data in order to react rapidly to shifts in the market. Thus, three distinct classes of emerging technologies are further studied: (1) IoT and data generation; (2) decision-making and AI; and (3) blockchain and transactions, as visualized in Fig. 5.

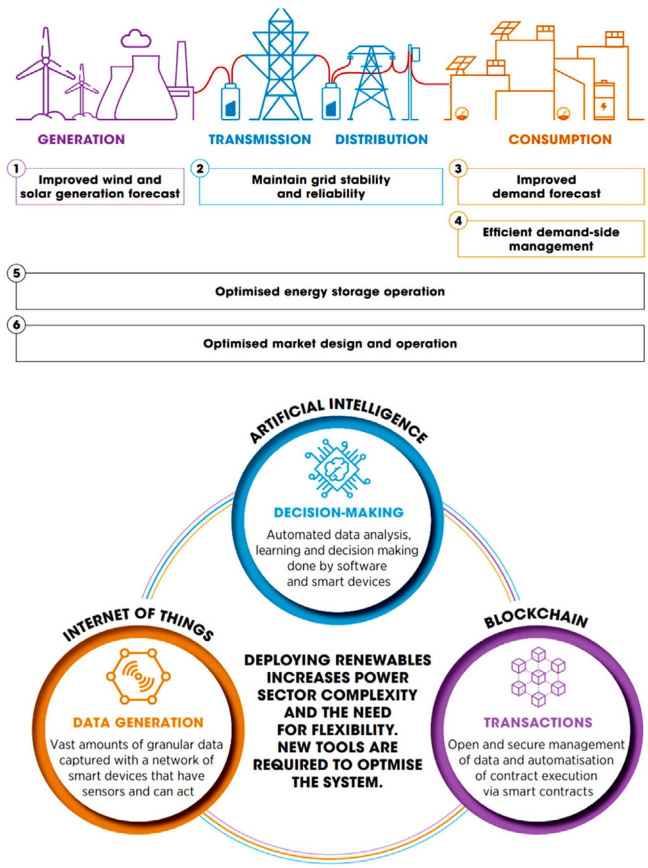

Fig. 5. Emerging AI technologies for integration into variable renewable energy and digital innovations (Anon., 2019).

Overall, the transforming energy scenario requires total investment in the energy industry to reach $110 trillion by 2050, or about 2% of the annual average gross domestic product (GDP) over the period (see Fig. 6). About 80% of this amount needs to be spent on renewables, energy conservation, power grid and end-use electrification. When looking at yearly, the global energy market needs an investment of USD 3.2 trillion annually to 2050. That compares with existing historical energy system investments (2014–2018) of about USD 1.8 trillion annually and in the expected energy scenario of USD 2.9 trillion per annum (IRENA, 2020; IEA, 2019).

2.2. The use of artificial intelligence power delivery

2.2.1. Artificial intelligence in power transmission and delivery

The AI models are used for optimal power flow and power transmission network capacity measuring, and system reliability (Sidhu and Ao, 1995). The use of AI technologies is popular in

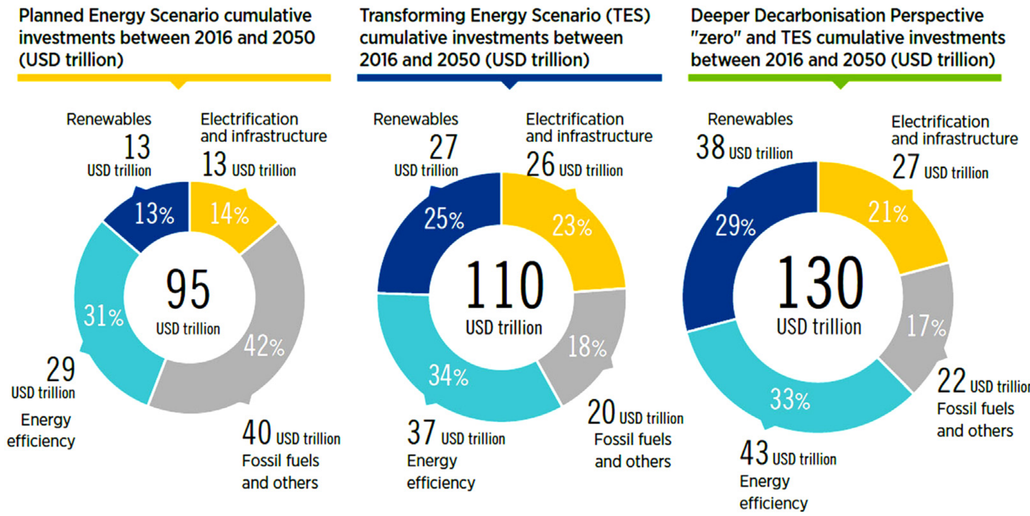

Fig. 6. New investment priorities: renewables, electrification of transport, and heat (IRENA, 2020; IEA, 2019).

frequency and voltage control for power system stability, control, and sizing of flexible alternating current transmission system (FACTs) devices. The following functions are applied to different AI techniques to increase the efficiency of a transmission line:

Environmental sensors: sensing the climate and weather dynamics and supplying expert systems with feedback.

ANNs: Trained to change the values of line parameters based on environmental conditions.

Fuzzy systems: Fault detection and diagnosis

Expert systems: To use the output as a line parameter value.

Fuzzy systems detect the pre-fault current and angular phasor differences between transmission faults. As inputs to expert systems, the environmental sensors detect environmental and air temperatures. The expert systems provide the value to be used for the output of the line parameters. ANNs enhance and test the reliability of the environmental sensor variables to adjust the line parameters within the particular limit if necessary to achieve the required transmission line performance. The AI prediction software, which makes forecasts using past network data and comprehensive weather data, helps the user to optimize flexibility and efficiency across the power distribution network.

Since the early 2000s, there has been a strong international and national interest in the popular concept of digitalization, the 'smart grid', which focuses on increasing information communication technology (ICT) components for electricity generation and distribution systems (Massoud Amin and Wollenberg, 2005). The implementation of digital technologies, from improved prediction to wind generation (Forbes, 2019; Chen, 2020) by changes in operational process and life management (Rhodes, 2020), could make energy distribution more efficient. Power networks could accomplish increased tracking and management of the power network components and the effective use of energy consumption data to drive greater optimization process, reliability, and customer preference. Using data-driven operational flexibility and intelligent occupancy-sensitive heating & lighting will also improve energy usage efficiency in buildings and transport. AI has become an extremely powerful method for reducing the risk of transmission of energy. For example, it can help balance the grid, detect energy theft, forecast and prevent grid failure, deter brownouts with real-time monitoring and AI forecasting, and differentiate the disturbances of the power system from cyber-attacks.

AI applications in power transmission and distribution networks include predicting future energy demand and pricing, direct energy trading, asset management, network monitoring, smart grid sensing, and autonomous agents for energy trading. Drone technology, like the inspection process on hard-to-reach transmission cables and networks, is currently in use in upstream power applications — it is expected to increase with the potential for drones to perform basic maintenance tasks. The potential advantages include improved control of mixed supply and demand and the potential to improve renewable energy portfolios of transmission and distribution networks. AI is able to boost electricity affordability. The stability can be improved by the detection of high risks and malfunctions. It will also increase protection by supplying utilities with the appropriate details to upgrade or fix these devices before they malfunction. Increased AI dependency entails risks. With more value for the provision, operating system and planning assets of data, communication, and AI, security becomes necessary. Considerable research to resolve possible vulnerabilities arising from the accelerated use of AI is necessary.

In addition, through the existing research and analysis, in the future research of the transmission network, AI technology is used to realize real-time online control and adjustment of the size and direction of the energy flow. Firstly, the power transmission process is monitored in real time through AI technology, and the energy flow flowing through the line is collected in real time, so as to grasp the size and direction of the energy flow of each branch and node in the system in real time. Then, the data processing center realizes the mining and analysis of the energy consumption behavior data of the demand-side users. Finally, through the interaction and coordination analysis of the energy supply end and the user side, real-time online control of the size and direction of the energy flow in the transmission network is realized. Therefore, in the subsequent transmission network, the automatic control strategy of the energy flow of the transmission network based on AI is of great significance to the development of the transmission network.

2.2.2. Artificial intelligence in power system automation and control

In several countries, grid automation and smart meters are now being introduced to create a dynamic balance between supply and demand so that the use of AI can be properly predicted and load dispatching optimized (Biagini et al., 2020). These smart grid projects allow the re-selling of surplus power to the grid by small private energy suppliers and homeowners (Liu et al., 2020).

Fuzzy logic (FL) has ideal power system applications such as voltage and reactive control, control and stability analysis, fault diagnosis, safety evaluation, load predicting, power security, etc.

Further, these models are useful for automation for power management and restoration, security margins, and fault diagnosis. For example, for the uncertainty of load changes and power production, a fuzzy value is used to represent the membership function of a certain uncertain load in the actual set, and the optimal power flow model of the power system is established, that is, the fuzzy optimal power flow. In addition, for some specific power systems applications, variable camshaft timing and computed tomography transient correction, the ANN models have been primarily applied. The AI models are used in multi-criteria decision making, fuzzy criteria signals, digital relays, and fuzzy settings. For the differential safety of power transformers, the applications of ANN and FL are largely applied.

The grid changes significantly with less load disturbance by providing utilities or loading suppliers. To keep these complex networks stable, high-resolution sensor technology is required. AI is capable of making precise predictions and detecting any disruptions or irregularities in real time (Ahmad et al., 2019; Chen, 2019). The interconnected grid and its integration of concentrated power with distributed energy supplies, like battery storage, solar, electric vehicles, and wind power, are about to become crucial for operation and development. Can AI help ensure a multi-directional, flexible power grid that is being delivered more seamlessly in a wider context? Effective integration of all the different power systems technology depends on data and connectivity. AI tools are important because they can process information and respond fast. The old models of physics on which we have depended for the past century cannot do so.

AI technologies are now beginning to improve industrial processes, aiming to develop modern protocols for industrial automation designed around expert systems, as a result of fast advances in ML techniques (Lee et al., 2018). AI process automation technologies, which ease frontline employee workflow, give organizations a great chance, but many challenges still exist. Companies are now unable to establish AI networks with large stores of current data. There are also many challenges to versatility in the development of AI applications and improving data quality training for ML algorithms. The challenges include: (i) increased risks to data protection; (ii) required trained employees; (iii) integrating issues for legacy systems; (iv) reskilling employees and training problems; (vi) resistance from human workers, etc.

In addition to just accuracy, it is important to concentrate on robustness. Systems must be designed to warn people when an algorithm has problems making a definite conclusion or suggestion, particularly when AI decisions affect industrial devices. The benefits of automation include: (i) addressing the skills gap; (ii) decreasing the labor cost; (iii) more cost-efficient operations; (iv) cost-efficient operations; (v) facilitate learners; (vi) achieving speed and precision beyond the capacities of human workers, etc.

2.3. The use of artificial intelligence in electrical distribution networks

The use of AI in energy conversion and distribution and energy integration systems is briefly discussed in this section.

2.3.1. The use of artificial intelligence in energy conversion and distribution

The increasingly decentralized energy supply leads to the decentralization of intelligence monitoring and control. The key emphasis is to upgrade individual agents who can learn individually about operational and trading techniques and add versatility to the entire structure of the elements they serve. In this context, the problems of network reliability and regional operating systems are also essential. AI training Agents transform decentralized energy networks for distribution network services into useful, pro-active assets (Adjerid and Maouche, 2020). This is designed to strengthen energy savings and help to overcome the rising complexity of the system as a whole.

Renewable energy firms (solar, wind, nuclear and hydro) have already significantly benefited in recent years from AI control, automated ML models and data science (Jha et al., 2017). These firms also reduced their costs, strengthened forecasts, and raised the return rate of their portfolios. Network management is one of the most important applications of AI in the energy sector (Singh et al., 2020b). There are several challenges in grid operation and management with the high penetration of a renewable energy source into the grid station (Shi et al., 2020). Problems such as voltage changes, frequency shift and high-frequency harmonic disturbances are more possible and might lead to failure to follow international standards. Therefore, new AI techniques to integrate these and other energy distributed resources into the grid are needed to resolve these problems.

The AI technologies can help to solve these issues, including large and small scale integration of photovoltaic (PV) systems in the power grid, monitoring of power quality in distributed energy resources (DERs) and PVs systems, issues of power quality and mitigating solutions, energy storage facility integration with PV plants, and distribution networks, control and modeling strategies for grid-connected PV systems, reliability and efficiency of PV inverters, wind/solar farms or on-board grid simulation, research and monitoring, advanced management strategies for robust and intelligent networks, dynamic performance and stability issues of seasonless control, resilience driven system design, predictive resilience analysis, advances in traditional methods of frequency counting, sync in communication networks of frequency and time, control and measurement of frequency stability, power reliability issues, power losses minimization and loss analysis methods, etc.

Local markets and microgrids are potential applications of AI in the distribution sector, as are network optimization against physical faults, microgeneration and energy optimization analytics in communities, and enabling embedded control to local microgrids. Big data analytic technologies in the energy system are mainly used in energy networks, especially power distribution networks, to ensure the efficiency and use of assets and customer use for demand and market services optimization (Rhodes, 2020). For example, based on blockchain technology to achieve dynamic interactions between various entities, such as achieving an orderly and coordinated interaction process among different entities such as users, suppliers, operators, and retail markets, thus realizing a highly intelligent transaction process within the distribution network. On the other hand, AI technology assists network operators in formulating a personalized energy service strategy. For example, during the operation of the distribution network, AI technology is used to collect and process various energy status data in the distribution network system in real time, and realize the intelligent energy resource optimization configuration of the distribution network according to the energy consumption characteristics of users. Although relevant research has given a certain description of this intelligent configuration, the intelligent configuration we proposed is very distinctive. That is, the distribution network system can provide different energy distribution schemes to the energy consumption side according to the economic efficiency of operation, so as to make certain suggestions for optimizing the energy consumption of the user side. A recent study estimated that the costs associated with a large cyber-attack in the London area could hit up to £111 million a day with water, rail, and telecommunications network failures (Oughton et al., 2019). In recent years, there have been many cyber-attacks on the energy system, including a successful attempt on the power grid in Ukraine in 2016 that resulted in

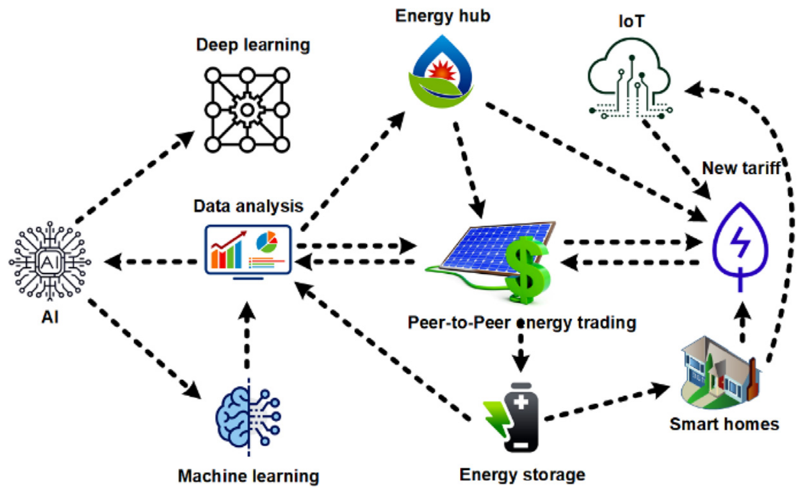

Fig. 7. Flexible energy market structure.

a blackout for a substantial part of Ukraine. The attack was theorized that overloading transformers would cause physical damage to the power grid infrastructure (Rhodes, 2020; Greenberg, 2019).

The 2016 study estimated that 75% of energy firms had been exposed to at least one intruder attempt in the previous year, and the US department of defense estimated that over 400 intruder attempts have occurred on U.S. energy infrastructure since 2011. Since 2011 they have been attacked systematically by hackers (Sachs, 2017). With automation and digitization continuing to progress in the energy industry, such measures are likely to be more widespread and potentially harmful. AI will help to overcome these problems. Fatima Zohra et al. (2018) and Poitiers et al. (2001) applied the AI control design for wind energy conversion operations. AI can be a very helpful and even strong tool to fulfill these criteria.

2.3.2. The use of artificial intelligence in integrated energy systems

AI provides the rare opportunity to learn the dynamics of a decentralized, interconnected energy transfer with state-of-the-art technologies. The new flexible energy industry environment is summarized in Fig. 7. In all energy industry value creation levels, AI technologies can be found:

(1) Maintenance and security security measures, predictive maintenance, dismantling, and repair and maintenance.

(2) General decision-making framework *operation and opinion, forecasting, strategic business decisions, and inventory optimization.*

(3) Customer services and distribution: general and bill distribution, automation process for measurements, facilitating engagement by active consumers.

In all three implementation areas, the contributions to the integrated energy transformation and its growth status to paving the way for the future is vital to identify and evaluate. The technological growth of AI is obviously not limited to the energy industry. The various technological facilities, infrastructure, and energy, industrial, building, and transportation industries must be organized and incorporated into an optimized and smart energy system concerning the incorporated energy transition 17. In the future, AI's interconnected technology transfer – i.e., technology fusion, power, transport, and heat – and the cross-sector optimization of energy systems, 82% of respondents agree AI would play a significant role (Vogel et al., 2019).

But how is AI used directly in the energy industry? What is the contribution of application domains to an effective integrated energy transition? How far have the applications progressed? These questions must be addressed. These problems are discussed in three stages systematically (Vogel et al., 2019):

(1) Study of AI technology areas in the energy sector: Present research-related AI technologies and those expected to appear in the near future will be screened thoroughly. At present, AI technology is mainly used in prediction and diagnosis in the energy field. In terms of forecasting, it mainly includes new energy generation forecasts and user-side energy consumption behavior forecasts. Simultaneously efficient and accurate forecasting on both sides of supply and demand is of great significance to the optimal operation of the integrated energy system. According to the forecast, the characteristics of the supply and demand balance are analyzed, so as to provide certain data support for the economy and energy saving of the entire system operation. In addition, in terms of fault diagnosis, AI technology can monitor the operating status of various energy equipment in the integrated energy system in real time, and perform alarm processing on equipment that has failed. Moreover, it can handle some minor faults online, thereby restoring the operating state of the equipment. These scenarios will be applied to different digital energy segments based on renowned companies' strategic tool map of technology dynamics.

(2) Evaluation of AI technology areas' contribution to the integrated energy transition: The implementation areas of AI are analyzed in terms of their relation to integrated energy transition. This appraisal will be made on the basis of five criteria: (1) to sustainable energy integration (Di Vaio et al., 2020; Bienvenido-Huertas et al., 2020), (2) to energy efficiency improvement (Mehmood et al., 2019), (3) power supply stability (Marx et al., 2012), (4) increased device efficiency (Mohanta et al., 2020), and (5) increased acceptance and engagement in the integrated energy transition. This evaluation will be carried out accordingly.

(3) Classification of growth status of AI fields: The present state of advancement of the AI technology areas will be analyzed and categorized in the energy sector. In certain fields, AI has already been introduced. At the same time, various methods are being developed and investigated. AI technology has been effectively applied and developed in various fields of energy system source, network, load, and storage. On the energy supply side, realize the intelligent energy supply and detection of multiple energy systems to ensure the optimal operation of the energy supply side while promoting the consumption of low-carbon clean energy. On the distribution network side, the coordinated management and control of multiple energy flows are realized, the optimal operation of multiple energy flows is realized, and the real-time online operation and maintenance management of various energy coupling components is carried out. On the load side, accurate analysis of the random behavior of users' energy consumption is implemented to realize the flexible management of user-side resources. On the energy storage side, artificial intelligence technology is used to explore more efficient energy storage technology, and the appropriate energy storage system can be automatically selected according to the geographical environment.

In this way, AI allows green energies to be incorporated into power stations to develop low-carbon hybrid electricity systems (Vinuesa et al., 2020). This will result in a much faster transition to the clean energy market by using AI. India currently has 75 GW deployed from diverse renewables (solar, wind, etc.), and has a renewable source of 175 GW target by 2022 (Thakker, 2019). Facing legislative efforts to promote clean energy investment, green energy deployment and extension remains a challenge. AI is seen as a potential way to maximize the use of green/renewable energy (NITI Aayog, 2018).

The world's energy market faces increasing integration challenges combined with rising production, efficiency, emerging demand and supply trends, and a lack of research required to maximize energy management operations. In developing market countries, these problems are more serious. AI and associated technology have started to be used for communications between smart meters, smart grids, and the Internet of Things (IoT) devices by the energy industry in developed countries. These technologies will lead to better electricity management, performance, transparency, and the usage of renewable energies.

2.4. The use of artificial intelligence in energy storage

AI could also help utilities determine the safety of small new supply consumers, like homes, by forecasting their storage unit lifetime and their deployment into a power storage device. In the REmap comparison scenario, the overall power storage capacity in terms of electricity will rise from a projected 4.67 TWh in 2017 up to between 6.62 and 7.82 TWh in 2030, up 42%–68% from 2017 (Fig. 8(A)). In the case of REmap doubling, where the renewable energy share of the global energy system doubled as of 2014, the storage capacity could grow to 11.89 TWh in 2030 and 15.27 TWh in 2030 or 155%–227% higher than in 2030 (U.S. DOE, 2017; Research, 2017; IRENA, 2017).

Historically, pumped hydro storage was used to convert energy sources from low demand to high demand periods in order to lower production costs (Fig. 8(B)). The cost-effectiveness of grid infrastructure for batteries and other thermal and mechanical energy storage devices is still more difficult. Relatively high costs and sometimes low-cost versatility substitutes mean that present economies are very market-specific. Nevertheless, battery–electric storage systems provide a variety of services today, which will only expand in the future as costs decline and efficiency increases. Competitive initiatives are more and more common on a utility-scale. The potential applications of electricity storage are visualized in Fig. 8(C). Different storage points explicate the emerging demand for new battery technologies for power generation, power transmission, thermal storage, distribution, residential and commercial levels. Electricity waste can be stored in batteries at different power system levels if proper storage systems are installed.

2.4.1. The use of artificial intelligence in battery energy storage

However, the energy industry is still very much behind in advancing energy storage systems (Barrett and Haruna, 2020). The existing energy storage technologies lack the infrastructure for high-efficiency energy comprehension and usage. The industry needs development and capacity planning breakthroughs, long-life (high battery operation), better profitability, etc.

The energy storage industry will make major strides by using AI and ML algorithms. AI-enabled energy storage allows us to capture and interpret the data and can help to increase the power used and mitigate future implications by using simulations.

(1) How to make standalone systems smart: AI can make things smarter and more usable for standalone systems. AI will improve the efficiency of electricity distribution, which is based on an end-user production–consumption cycle, to allow the processing of renewable sources. First, use AI technology to predict the data required by the system in advance, and evaluate the system's effective use of resources. Then, the remaining energy resources are sent to the energy storage system through the signal transmission equipment to signal the need for energy storage. Finally, through the intelligent response of the energy storage terminal, energy resources are allocated and stored to achieve optimal allocation and utilization of resources.

(2) Battery-intelligent storage: Intelligent-battery storage systems for renewable energy projects will always help to enhance economic value. AI opens several ways to optimize the infrastructure appropriately and boost consumer returns from a renewable energy storage facility. It can help to forecast, big data, deep learning, and grid-level computing to obtain these returns. In addition, battery intelligent storage can also protect the storage life of the battery to a certain extent. Smart storage takes into account the impact of the number of charging and discharging of energy storage equipment on the lifespan, and realizes flexible battery energy storage and discharge characteristics without affecting the user's energy use and system operation stability.

(3) Storage data: Smart storage collects information that can be continually logged and evaluated for loads, power production, weather, grid congestion nearby, etc. Achieve larger scale and more comprehensive data storage through cloud technology, and digitally drive the intelligent operation of energy storage equipment terminals. AI-enabled storage can drive adaptive storage supplies in real time that generate greater consumer and grid value.

(4) Intermittent nature of load: With more smart energy storage devices, it gets easier to harness renewable energy. Because of the intermittent nature of the load, AI allows addressing the problem of the intermittent variation of renewable energy at production stages. The paradigm shift toward a highly sustainable future could entail pairing green energy with AI-powered storage.

(5) Remotely monitoring: Battery intelligence applications enable diagnosing the issue with real-time data every single minute. Each battery can be tested remotely for battery health and causes of downtime, with the assistance of data visualization and real-time geotagging software.

(6) Predictive Maintenance: Having sufficient data gathered from the batteries, these systems can help to prevent possible faults or the need to replace batteries (weeks in advance). Based on the variable constraints of the energy storage operator, alerts for each battery may be set. This helps the operator see only batteries under a particular tag — geography, operating temperatures, types of batteries, etc.

Enabled electricity storage, including batteries, is being used to mitigate power generation uncertainty and lead to an increase in load demand from renewable energy sources. However, this strategy can have durability problems and limits, such as battery loss and accidental faults, which require ongoing monitoring and repair. ML tools could lead to a more stable and effective system by using AI-based ML algorithms to track and detect possible failures in energy storage systems. Energy demand and per kWh recovery will be more efficient, and energy storage more accurate and effective. ML will also allow asset suppliers – battery developers – to consider the expected battery life they manufacture.

In 2017, the Toyota research organization spent $35 million on artificial battery intelligence development, concentrating initially

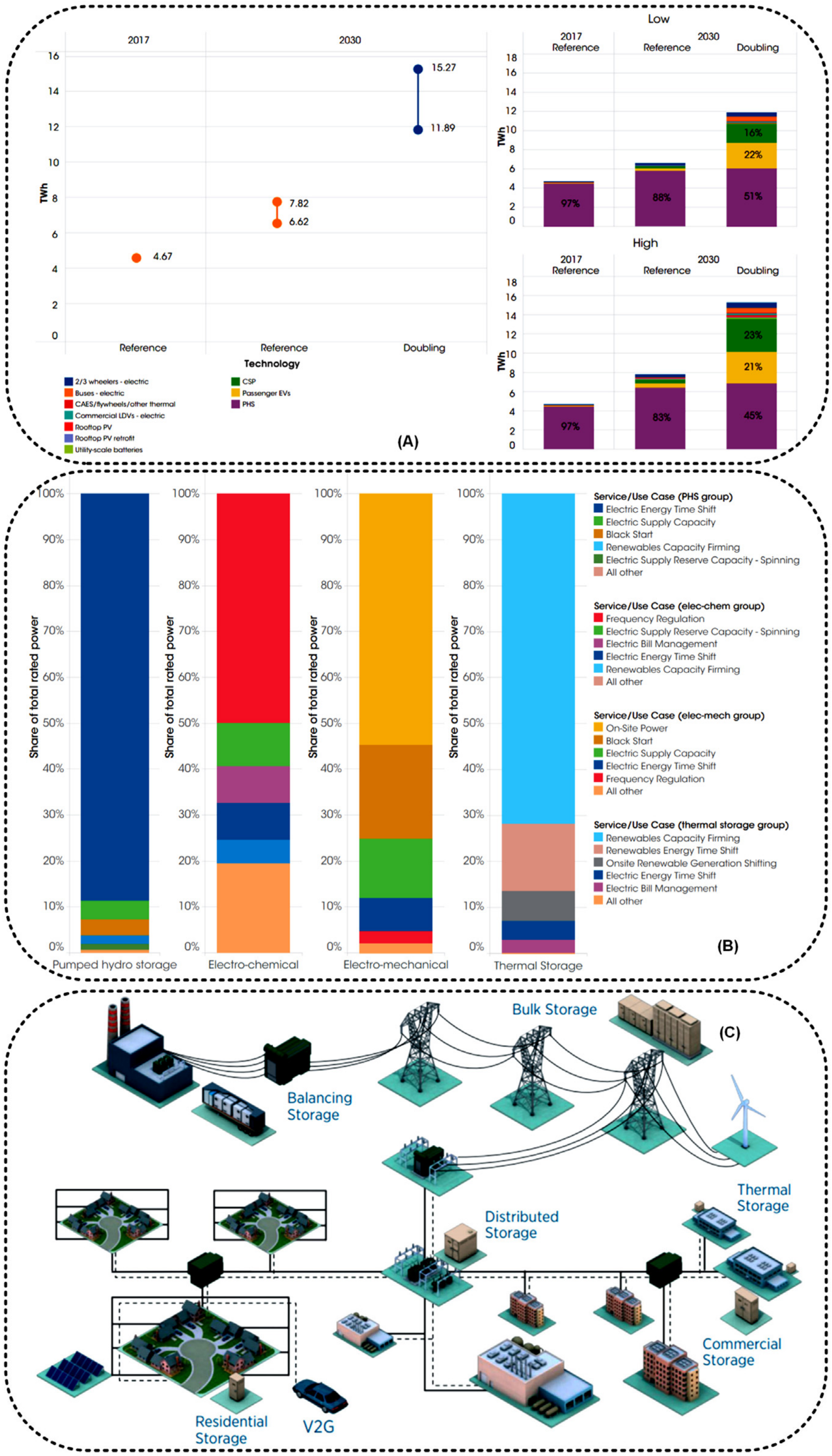

Fig. 8. (A) Source development of energy storage capacity, 2017–2030, (B) mid-2017, primary use-case and technology group, global energy storage power shares, (C) potential power system power storage locations, and applications (IRENA, 2017, 2015).

on novel technologies (Alto, 2017). It is reported that AI could effectively identify lithium-ion battery life span to 9% of the product's actual life cycle period. The experimental setup or process can take months or even years because batteries have a long lifetime. It is an expensive bottleneck in battery research. With incredibly fast charging, the only problem is that it heats up and the battery degrades. In an effort to decrease lithium-ion battery charging times down to five minutes, a Canadian organization uses AI. Once the battery reaches its maximum charging limit, the AI Charging algorithm pauses long enough for the battery to prevent damage. This dilemma will significantly be alleviated if AI is implemented to create new battery materials, battery life testing, and battery charge tracking. A team led by professors William Chueh and Stefano Ermon at Stanford University has

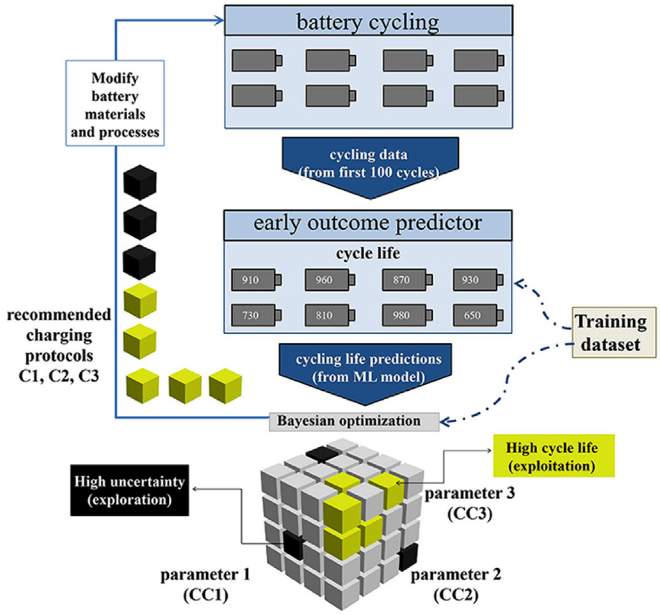

Fig. 9. Closed-loop optimization structure of AI for battery materials (Luo et al., 2020).

developed an ML approach that can decrease the test time by 98% (Attia et al., 2020; Luo et al., 2020). Fig. 9 demonstrates the structure with its closed-loop system (Attia et al., 2020). First, batteries are checked with the first 100 cycling data, particularly electrochemical (voltage and capacity, etc.) steps. Through using this data as feedback, research teams forecast cycling life early in the process. A Bayesian optimization method is sent to evaluate the next protocol for the cycling life predicted by the ML algorithm. This approach can predict early on the cycling number of each battery test and decrease the number of tests needed by improving the experimental design.

2.4.2. The use of artificial intelligence in energy storage technologies and devices

Prices of batteries reaching $1100 per kilowatt-hour in 2010 have subsequently declined to $156/ kWh in 2019 at 87% (Pack et al., 2019). According to Bloomberg New Energy Finance (BNEF)'s latest prediction, the average prices are expected to be nearly $100/kWh by 2023 (Pack et al., 2019). According to the predictions, the demand for batteries will be estimated at $116 billion annually by 2030, and this does not include supply chain investment. Electric vehicle demand is increasing in Europe, and supply chains are evolving. Battery manufacturers are significantly contributing to the region's development. This results in a reduction of some of the costs associated with importing cells from other countries, most notably transportation and import duties. While the path to $100/kWh by 2024 is extremely promising, hiccups are unavoidable. The possibility that the market will further reduce costs from $100/kWh to $61/kWh by 2030 is even less certain Pack et al. (2019). This is not because it is difficult, but because with AI, it is possible to take various options and routes.

A standout field of current battery development has been exploring solid electrolytes, with success. Previous studies demonstrate that many physical factors will influence Li-ion diffusion in solid materials because of complex interactions (like magnetic domain and orbit coupling effects). Total conductivity using current computer capability cannot yet be completely determined (Chen et al., 2019; De Klerk et al., 2016). Hatakeyama-Sato et al. (2020) at Waseda University have developed the largest ML database for Li-ion-conductive polymers to overcome the difficulties of estimating the properties of complicated chemical structures. This ML archive includes detailed knowledge about how the chemical composition is related to its conductivity. Fig. 10(A) shows their testing protocol for AI to forecast conductivity. The conductivity values for around 150 representative conductors were then expected, which were not trained for AI recorded at the beginning of 2019. The connection between observed and projected conductivity values is seen in Fig. 10(B). It turns out that certain drivers can be accurately forecasted. Typical electrolytes plasticized in ionic liquids, experimental and forecast values nearly correlated (Fig. 10(C)) with typical polyether and aliphatic polymers. This study indicates that experimental ML can be used to identify effective composites composed of typical chemicals, that can minimize experimental time considerably.

The challenges in energy storage technologies and devices include:

(1) Lack of standardization: One of the biggest shortcomings of current energy storage technology is the lack of standardization, even for battery manufacturers. The lack of standardization of energy storage equipment makes the production of various batteries uneven, and this is also a major obstacle to the further development and implementation of intelligent energy storage systems. Battery manufacturers are no exception, as a roadblock to further implementation is the failure of standardization.

(2) High prices: Costs have dropped so fast that policymakers may have incorrect notions of device costs, assuming batteries still cost the same thing as a few or even one year earlier. In addition, the current battery products are relatively low cost-effective, high prices and low life issues make it more difficult to further apply AI technology in energy storage systems.

(3) Inaccurate energy storage concept: Energy storage has an identification challenge, with policymakers and stakeholders from all over the world collaborating on how fast battery storage is to be defined. At present, a common understanding of energy storage systems is that energy storage systems can store energy when there is a surplus of electric energy, and release energy when there is a lack of energy, that is, to realize flexible regulation of the power grid. However, with the development of flexibility of multi-energy systems, people's perception of energy storage systems has gradually changed. The energy storage system has new definitions in terms of model, installation location and functional characteristics. For example, a variety of distributed energy storage systems on the user side have been established, effectively realizing a complementary flexibility on both sides of supply and demand.

(4) Market design and outdated regulatory policy: Regulatory action is lagging behind modern energy storage devices as would be predicted from new innovations. In addition to retail market rules, they would also have to be modified, especially with increasing growth in commercial, residential, and industrial sectors. A flexible, advanced, and open market mechanism is crucial to the advancement of the construction of intelligent energy storage systems. In addition, with the continuous development of electric vehicles, the flow characteristics of intelligent energy storage technology in the market will also become higher and higher.

The key market drivers of energy storage are **financial incentives** (e.g., this represents a growing recognition of the advantages that battery storage in the power supply chain will bring to policymakers.), **grid modernization** (e.g., the rise in battery capacity corresponds with attempts to modernize the infrastructure, and to transition to smart grids.), **material performance and cost improvements** (e.g., costs decrease as efficiency increase, particularly in relation to lithium-ion batteries that lead to development of electric vehicles and existing manufacturing economies of scale), **world movement toward renewables**

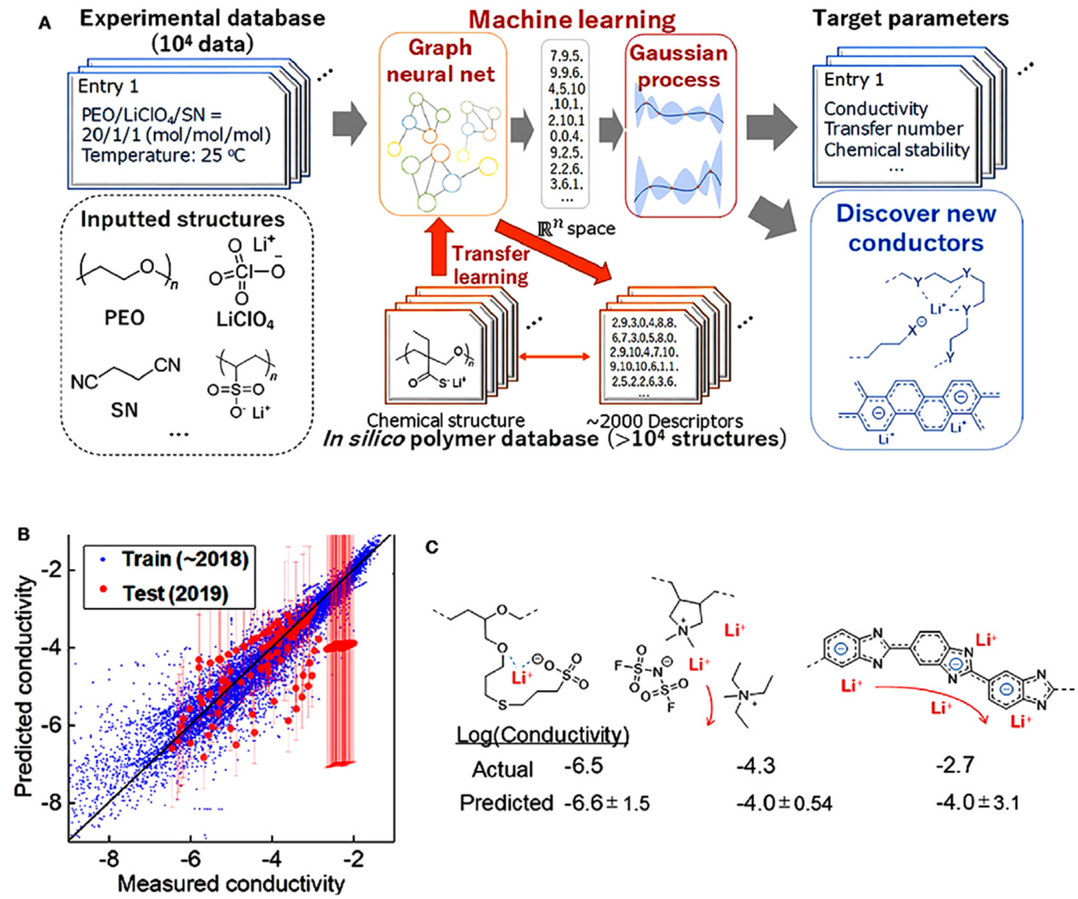

Fig. 10. (A) AI scheme to forecast solid polymer electrolyte conductivity, (B) relation between forecasted and measured conductivity. In both test and training datasets, the R2 values were 0.16 and 0.90, (C) Polymer-based conductors recently recorded for structures and conductivity of room temperatures (Luo et al., 2020; Hatakeyama-Sato et al., 2020; Notten et al., 2005; Hatakeyama-Sato et al., 2019).

sources (e.g., broad renewable energy funding and reduction in emissions have contribute to the development of battery storage technologies), **wholesale sector involvement in energy sector** (e.g., almost every country have evaluated redevelops the wholesale market system so as to provide power and auxiliary facilities for batteries.), **desire for self-sufficiency** (e.g., resiliency, ecological motives, independence from utilities and technical curiosity), and **national policy** (e.g., many countries use renewable energy storage as a way of reducing energy import dependency, enhancing their systems' stability and resiliency and pushing toward de-carbonization and environmental goals).

When installed at a customer's premises (behind the meter), energy storage can supply thirteen fundamental electricity resources to three large player groups. In Fig. 11, thirteen different services are provided to the three main stakeholders by batteries, including: (i) regional transmission organizations (RTO) services; (ii) utility serves; and (iii) customer services. Energy storage systems will offer a range of supporting services that benefit primarily independent system operators (ISOs/RTOs) and vertically integrated utilities in countries where power markets have not been transformed. These services includes; (i) energy arbitrage, (ii) frequency regulation, (ii) black start, and (iv) voltage support and spin/non-spin reserves. Utility services are normally divided into two categories. The key emphasis is to use energy-efficient infrastructure and renewable power capacity to delay substantial improvements in transmission and logistics facilities. The other operation plan includes the adequacy of capital and congestion relief in transmission. These utility services include; (i) resource adequacy, (ii) transmission deferral, (iii) distribution deferral, and (iv) transmission congestion relief. Customer programs such as bill processing give end-users clear advantages. The benefit of these facilities can also only be recorded when the storage is installed behind the meter. These services are as follows: (1) backup power, (2) time of use bill management, (3) demand charge reduction, and (4) self-increased PV consumption. A detailed analysis of the above-said services is given in Fitzgerald et al. (2015).

Furthermore, the lower half of Fig. 11 shows that energy storage values have changed dramatically across studies (Fitzgerald et al., 2015). Batteries installed only for a single primary utility are usually of limited financial advantage under the current cost structures, except in some industrial applications. However, since the production of main services only requires 1%–50% of a battery's lifespan, the remaining capacities to provision a stack of services to consumers change the market in favor of storage. Table 4 visualized the variety of facilities that electricity storage can provide for AI use (IRENA, 2017). Light green boxes show the energy storage devices supporting the direct integration of renewable energy.

In order to provide consistency of service (e.g., regulation of constant frequency and voltage) the demand and supply must be balanced in real time, reduce damage to electric equipment and ensure supply to all consumers. Both power grids need a certain degree of resilience, enabling grid operators to adapt to unanticipated demand shifts or the failure of significant supply chunks (e.g., interconnection or large offline stations). Flexibility provides operators with the tools to recover device balance easily.

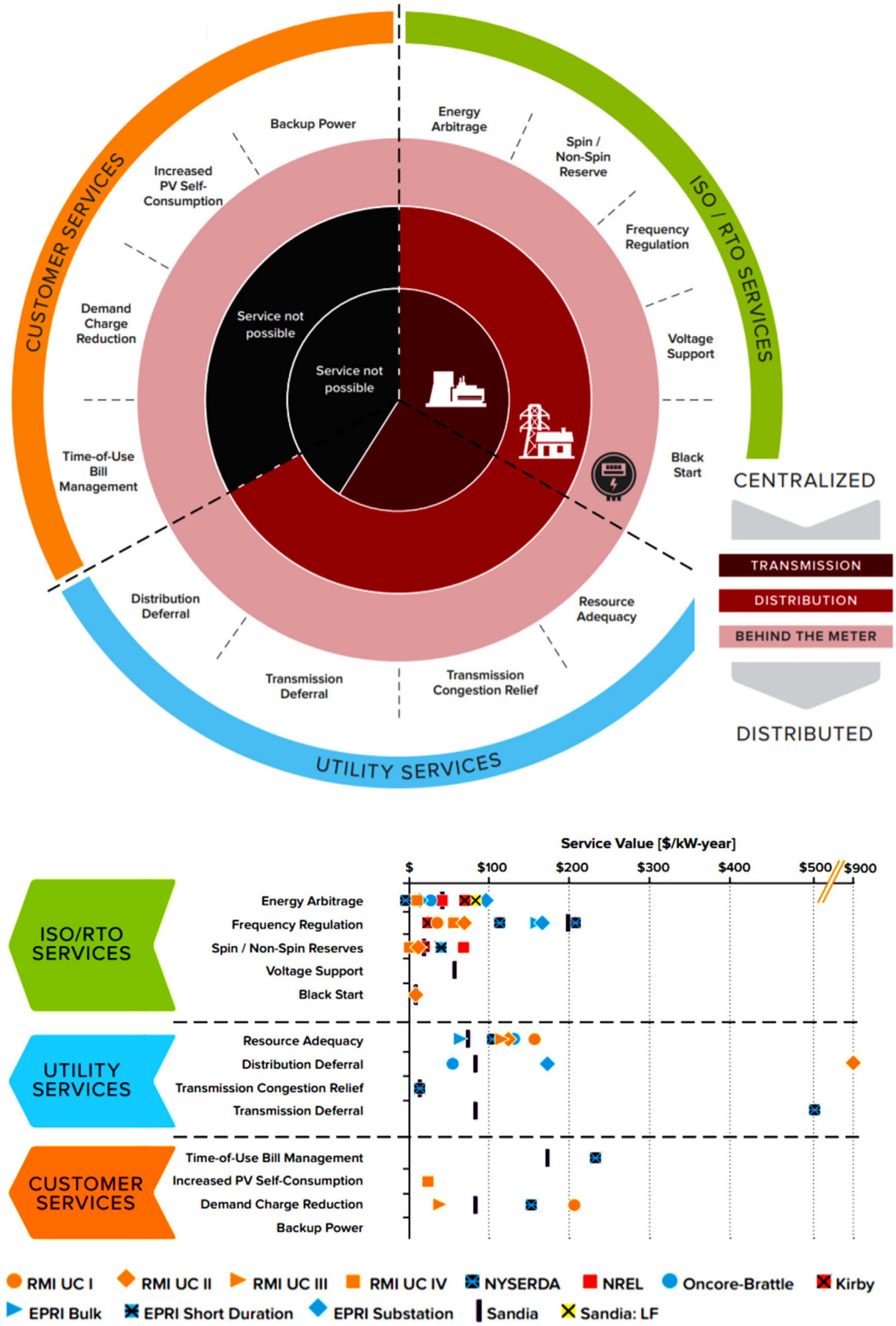

Fig. 11. Batteries can be allowed to accommodate up to 13 distinct classes to three major stakeholder groups (Fitzgerald et al., 2015).. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

2.5. The use of artificial intelligence in energy applications

2.5.1. Artificial intelligence in new energy applications and energy-saving technologies

Power businesses are at the early stage of adoption of AI (A.G., 2020). Digital applications and technologies have witnessed a boom in recent decades. Digital technologies are becoming smaller, more efficient, and interconnected with ever deeper impacts on industry, lifestyle, and well-being. The use of AI in energy applications includes: (i) energy forecasting and demand management, (ii) intelligent energy storage, (iii) increasing business profits and reducing losses of the power system. (iv) improve energy storage management, (v) cost-cutting, (vi) energy-saving technologies. (vii) optimal utilization, (viii) automation of demand response,

Table 4
The variety of facilities that electricity storage can provide for the use of AI.

Sr. #	Ancillary services	Transport Sector	Bulk energy services	Distribution infrastructure services	Off-grid	Customer energy management services	Transmission infrastructure services
1	Voltage support	Buses	Electric supply capacity	Voltage Support	Solar home systems	Power reliability	Transmission congestion relief
2	Regulation	Wheelers	Electric energy time-shift	Distribution upgrade deferral	Mini grids	Power quality	Transmission upgrade deferral
3	Black start	Commercial vehicles	–	–	System stability services	Demand charge management	–
4	Supplemental reserves Spinning, and nonspinning	Cars	–	–	Facilitating high share of variable renewable energy	Retail electric energy time-shift	–
5	–	–	–	–		Increased self-consumption of Solar Photovoltaics	–

(ix) electric vehicles in-home building sensors, (x) metering and billing demand response, (xi) local and microgrid market, (xii) enables local microgrids through built-in control, (xiii) optimization and analysis of network's physical faults, (xiv) microgrid optimization and data analytics, (xv) solar, wind, geothermal, gas and price forecasting, (xvi) different autonomous agents for energy trading, (xvii) smart grid monitoring and sensing and asset management, (xviii) power line inspection through drone technology, (xix) customer services and decision support, (xx) asset control management and local energy consumption data management, (xxi) energy theft detection (Ahmad, 2017; Chen et al., 2018b), (xxii) cybersecurity, (xxiii) (Zahraee et al., 2016; Ciulla et al., 2019; Mehmood et al., 2019; Suman, 2021), etc.

Global investment in electricity in 2018 was over USD 1.8 trillion, but the use of energy efficiency is still the main development field (World Energy Investment 2019, 2019). Investment in clean energies and energy conservation has not held pace over recent years, indicating a further lack of scope for environmental sustainability targets like the Paris Agreement methods (Matemilola et al., 2020). Fortunately, a mix of technologies and green energies will produce considerable efficiencies.

How will technologies continue to reduce energy use? The transformation of old and inefficient power systems will, of course, increase efficiency and quality of processes. However, the science of AI has grown so much further. AI will track and capture energy usage data by numbers, messages, pictures, and videos in factories and buildings. AI will control the use of electricity to measure what is found, for instance, during peak hours. Problems like bottlenecks and system faults can be identified — even before they occur. AI can compact and interpret data on a broader scale, predict potential challenges, and eventually maximize long-term energy usage. Although this goes beyond what humans were able to do individually before, it also needs personal experience. In order to solve particular problems in their own operation, technicians need to be skilled at adapting each AI solution.

Usage of IA in the industry: as most plants and manufacturing facilities are energy-intensive, data mining and AI can be beneficial to reduce consumption. A significant volume of energy – worth billions of dollars – globally is not being used. In specific, the following will be made possible to gain efficiencies in the industry:

(1) ***Predict energy demand and thus control production:*** Accurate prediction of energy demand is made by considering multiple uncertainties and random behaviors on the user side, so that energy production can be flexibly controlled with precise energy demand. This will help minimize fuel dependency or control fuel consumption and thus reduce carbon emissions (Chen et al., 2018b; Chen, 2018b).
(2) ***Reducing breakdowns:*** AI uses operational details and modeling to predict potential vulnerabilities of critical energy systems. By analyzing this potential vulnerability, emergency and maintenance measures can be taken in advance to reduce the frequency of system failure events.
(3) ***Managing power grids:*** Many AI applications work with various electricity sources, including wind, solar, and fossil fuels. Through real-time online analysis and processing of multiple energy data, coordinated management between different energy sources is realized, which is of great significance to the optimized operation and intelligent management of the power grid.
(4) ***Yield optimization:*** Maximize plant yields by process optimization. AI energy technology improves certain energy supply and energy use software. For example, smart homes can automatically adjust energy use time according to energy peak periods and energy prices, so as to optimize energy use.
(5) ***Cooling and heating:*** Heating and cooling waste reduction. For example, the application of AI technology to a commercial building can intelligently adjust the heat dissipation characteristics inside the building to achieve energy conservation in smart buildings.
(6) ***Utility costs:*** Reducing resource costs (like nitrogen, air, and water compressed) by efficiency enhancement and faster recognition of maintenance problems.

In addition to the obvious advantages of saving costs, lowering electricity usage would have positive environmental and global impacts. Many power systems challenges are based on a range of unfeasible requirements. AI methods are the only way to overcome hurdles. In power system applications, AI's existing solutions are:

(1) Power system reliability, energy planning for generation expansion, reactive power and transmission expansion.
(2) Power flow, stability and frequency, voltage control.
(3) Control of thermal power plants, control of fuel cells.
(4) Network security, fault analysis, automation for restoration management.
(5) Demand response, demand management, smart grids control and operations, network reconfiguration, operation, and distribution system planning.
(6) Wind and solar power operations, wind, weather, solar, load and electricity price forecasting.

The AI models are used to bidding strategies and analyze electricity markets (Kong et al., 2019; P. and Vijaya Chandrakala, 2020). Operation and planning of power networks, demand-side responses, network configuration, control, and operation of the smart grid are the key features of AI technologies. The ANN networks have different numbers of hidden layers and different neurons in each layer. Processing speed can be changed by changing the number of neurons in order to improve the performance and reliability required.

2.5.2. The use of artificial intelligence in new energy materials and devices

In recent years, AI has progressed gradually in forecasting energy storage materials like solar energy conversion. A significant issue that has to be addressed immediately is how the most efficient optoelectronic material can be found. Considering a large number of materials available, both candidate materials and maximum processing are incredibly difficult to analyze thoroughly. Using AI technologies, modeling and optimization will improve the efficiency of material production. These technologies include molecular modeling, quantum mechanics, molecular dynamics, density function theory, metadynamics, transition state algorithms, and biased dynamics energy barriers (Yang et al., 2020). AI models for specifically predicting material properties can not only boost the screening process, but they can also explicitly construct the material's corresponding components. Further, AI is used in hydrogen peroxidation catalysts production.

Heating systems are central to the development of the manufacturing sector and convert raw materials into goods. The most efficient way to achieve productivity here is through renewable resources. Power is taken directly from wind turbines for the manufacturing process rather than the power grid as a result of a 45% reduction in energy bills. Energy savings could lead to a few years' payback time.

The industry has a large amount of contamination/pollution, one of the big challenges facing us in an environment where buildings need to be powered, heated, lit, and cooled. However, using safer, more effective, and green resources for materials would mean less waste and reduce the effect on climate and human health. Increasing awareness of the negative long-term impact of emissions has increased the need for clean, sustainable, and efficient energy and contributed to constructive energy conservation and compensation strategies. Investing in energy materials and conservation could also bring additional advantages for organizations, including reducing the carbon footprint and taking them closer to carbon targets.

AI will boost batteries, photovoltaics, and new energy materials for carbon capture (Wei et al., 2017a). Governments and corporations spend billions on systems for storing, transforming, and retaining energy (Bernstein et al., 2016). As silicon solar cells reach their efficiency limits, researchers are investigating alternatives based on quantum and perovskite points (Chu et al., 2016). Energy-saving batteries must become cheaper, more powerful, and reliable (Huskinson et al., 2014). Energy devices and technologies need to be assembled from abundant and safer material properties, such as nickel, carbon and copper, rather than gold or platinum (Wei et al., 2017a).

Huge amounts of experimental data on the characteristics of these materials are generated. There are, for instance, 65 databases at the US National Institute of Standards and Technology, each with 67,500 measurements. More than 1.7 million research papers on solar cells and batteries alone have already been published since 2010 (Wei et al., 2017a). AI computing methods are being developed, which automatically create structural elements and analyze their digital/electronic and other properties (Curtarolo et al., 2013). For example, the materials project uses supercomputers to determine the behavior of all known materials (Jain et al., 2013). At present, it lists forecast properties for over 700,000 materials (Wei et al., 2017a). Yet, there is still a great deal to go from the vast opportunity of converting this data into commercial and industrial applications.

AI-enabled ML – algorithms that have been learned to identify trends in data sets – may vastly improve energy materials/discovery. The results of quantum simulations were used to evaluate possible flow battery molecules and components, organic light-emitting diodes (Gómez-Bombarelli et al., 2016), carbon dioxide oxidation catalyst, and organic photovoltaic cells (Liu et al., 2016). Compared to the hundreds of hours it needs to change simulations, the techniques can forecast the required results in a few minutes. However, there are always challenges. For encryption materials, there is no uniform representation. Various applications demand various characteristics, such as elementary crystal structures, composition, and material conductivity. Well-cured substance experimental data readings are uncommon, and computer tests of different hypotheses rely on modeling and assumptions, which, under experimental conditions, may be far from realistic.

2.6. The use of artificial intelligence for energy efficiency and nanotechnologies

Energy efficiency: how to improve energy efficiency through AI; Many energy sources are now accessible with recent advancements in manufacturing techniques, encouraging more efficient use. It has become more difficult to run and maintain large power grid networks. By processing massive datasets in a short time frame, AI boosts those sources' performance and stability. This has led to the development of intelligent grids that are designed concurrently for effective control of multiple energy sources. Smart grids can effectively improve the comprehensive utilization efficiency of energy by adaptively controlling the coordinated operation of multiple energy sources. Active Network Management (ANM) from Siemens, for example, is a software package based on AI that runs grids automatically. It measures a grid's activity with numerous energy loads and then adjusts the grid to improve performance. In addition, DeepMind has intended to use AI in the energy sector in the world as well as the UK National Grid subsidiary. This collaborative operation will process large amounts of weather prediction and online search information, including forecasting models for spikes in demand for electricity.
Nano-computing: AI also offers a huge advantage over nanoscale protocols for the potential of nanocomputing. There are currently several ways that nano-computers can perform a function and can include everything from physical operations to programming methods. Since a number of these devices could be used to create new information representations for different applications in a large variety of industries, based on compact physical systems that allow large computing algorithms. According to the study of the Global Nanotechnology Market, the global nanotech industry is expected to rise by 17% per year until 2024. Brazil, the United States, and Germany will be the world's leading countries in this technology. And at the same time, the market valuation reaches 125 million dollars (Padma K., 2020).
Energy: nanotechnologies can produce more light and durable wind turbines, reduce costs, augment fuel efficiency, render thermal insulation of nano components using nanotech. This will conserve electricity and retain fossil fuels and therefore reduce emissions.

(1) Nanomaterials increase fuel efficiency by improving catalysis from raw petroleum materials. It reduces fuel generated by higher efficiency combustion and reduces friction in power plants and vehicles.
(2) Pipelines are also discovered using nanotechnology-functioning gas elevator valves in offshore activities, fractures in downwell crude.

(3) The production of faster, more powerful, lighter weight batteries with a higher density of power and a longer charging power.
(4) A Kyoto University semiconductor enables solar panels' production, doubling the amount of sunlight converted into electricity (Padma K., 2020).
(5) Cellulose can also be converted into ethanol for fuel through nano-biological engineering.
(6) It is also used for heat generation from many other methods. There are thin-film solar power panels that can be installed in computer cases for on-the-go power generation, as well as flexible piezoelectric nanowires that can be woven into clothing to generate useful energy from the sun.

More than 2000 peer-reviewed articles on perovskite material were analyzed in a study, and over 300 data points were then incorporated into the AI system they built (Li et al., 2019). The AI-enabled system was able to evaluate and forecast which perovskites are best used. AI can accelerate spray-on solar cell manufacturing, which can revolutionize the use of energy for users. The nanotechnology list can be classified into three types: (i) nanomaterials in the energy sector; (ii) nanostructure in the energy sector; (iii) and applications of nanotechnology. The nanomaterials in the energy sector include silicon-based nano semiconductors, nanocellulose-based materials (Wang et al., 2018), and graphene-based materials (Pumera, 2011). The nanostructure in the energy sector includes one (Wei et al., 2017b; Chen, 2018a) and two-dimensional nanomaterials (Zhu et al., 2018). The applications of nanotechnology include nanoparticle fuel additives (Ghamari and Ratner, 2017), lithium–sulfur based high-performance batteries (Goodenough and Kim, 2010; Bruce et al., 2011; Barghamadi et al., 2013; Jin et al., 2015), and nanomaterials in solar cells (Mann et al., 2016; Joo et al., 2009; Zhang et al., 2012; Li et al., 2018; Johlin et al., 2016; Sheehan et al., 2013; Branham et al., 2015).

2.7. The use of artificial intelligence for energy and economic policy

Many new elements would need to be taken into consideration in policy and legislation for a digitalized energy grid (Rhodes, 2020). New entrants, new market models, and stronger direct customer commitment will need an educated and versatile regulatory effort to meet the issues of privacy, consumer protection, and cybersecurity. As emerging innovations and data technology progress, regulatory approvals can be processed at the earliest and most competitive cost for new goods and services.

In almost every field of the global economy, data collection, analysis, and utilization have become a major factor in system operations. As technology is digitized and 'intelligent', the volume of information that can be accessed has grown exponentially, creating more study opportunities and informed policymaking. Greater data accessibility will provide more detailed models of where, when and how energy is being used, going to lead to more efficient, streamlined schemes and potential for new customer tariffs and energy market proposals (Consumers Vehicles Energy Integration, 2020). Given the heightened risk of disruption in a peer-to-peer environment, policy and regulations should be anticipated to be conservative and likely limited initially. Major players in the energy sector should ensure the institutional awareness of the latest emerging technologies, particularly in data analysis, ML, and automated, autonomous processes from regulated network monopolies, policymakers, regulators, and major suppliers. Understanding the applications and, most significantly, these innovations' constraints is more and more vital, and proper planning would continue to ensure that this information is integrated into operational practices (Rhodes, 2020).

In addition to AI innovations and data analytics, manufacturers turn to renewable energy throughout the clean energy sector to become even more competitive. A sustainable future looks more feasible, given all the innovative technologies needed to reduce energy consumption and deal with climate change.

Energy economics: ML provides new opportunities for creative finance and energy science (Ghoddusi et al., 2019). In applications relating to the financial and economic analysis of energy industries, like the estimation of prices and risk control, ML was also commonly used. A contrast between ML and standard models (i.e., GARCH and ARIMA) shows some of the reasons why ML is increasingly common in energy sciences. ML approaches benefit from the fact that the ML algorithm handles a vast range of unstructured and structured statistics and can take swift choices or forecasting over the methods suggested by traditional statistics. This is the case as ML models do not allow any predetermined assumption of the equation's functional structure, the relationship of parameters with the statistical parameter distribution. ML approaches have superior forecasting efficiency because their control of complex internal dynamics is more efficient (Cheng et al., 2019). A realistic base of AI and business applications will allow grow the company into an advanced, effective, profitable, and future-oriented organization with the confidence and knowledge required. The opportunity to conduct knowledge, strategy development, and improve business performance by incorporating essential AI leadership and control knowledge into the organization's functioning. Technology's accelerated growth will pose difficulties for designing sound policies in favor of competitiveness, identifying the business landscape and determining the degree of objectivity or disruption probabilities.

3. Challenges of energetics systems and artificial intelligence in different energy applications

Adoption of digital technologies faces a number of major challenges, some of which are technological in the energy sector, some of which are industry and regulatory in nature, and some of which are related to customer awareness, protection, and confidence (Andoni et al., 2019). Many bottleneck challenges still need to be addressed in the energy industry through the use of AI. The details of these are given below.

(1) Smart manufacturing security issues: The intelligent manufacturing process implies the use of an interconnected network system for the exchange of knowledge between production units and machining units between end-users within the industrial framework. To this end, network communication is needed and is arranged, particularly through the Internet. Internet exchange requires data authentication and information across the whole infrastructure at multiple points of special global identity and end-to-end encryption keys (Thoben et al., 2017). It is most essential to ensure the system's integrity and the process involved when developing networked structures, such as a smart process for the production (Phuyal et al., 2020).

(2) Smart integration: The synchronization of current equipment with new equipment produces some smart production technology deployment challenges. At this time, the old protocol is difficult to support the communication of the new device, it needs a new protocol to replace old protocols to support new machines in the energy sector. In addition, exploring a new protocol enables coordinated operation between current equipment and new equipment, thereby buffering the replacement of equipment and conducive to the economic operation of the system.

(3) Different kinds of data flow: It is not easy to ensure the fast, effective incorporation of the incoming data from multiple sources into a single coherent package. Data protection has become one of the century's major challenges, and AI simply continues to thrive on data, making data protection a natural challenge to AI in the energy industry. Power suppliers and the whole infrastructure are vulnerable to cyberattacks and data stealing. Cyber protection must be ensured before we truly approach the infrastructure's data as an important part of a national economy.

(4) Lack of financial experience: Infiltrate AI technology more comprehensively and deeply into the energy system, we need a significant number of AI workforce who have ample technological skills to drive this transformation, but this is not there to turn to the AI-enabled energy market. In addition, this technical deployment in the energy sector involves the production, improvement, and management of software involving a lot of capital and finance. Therefore, the lack of mature financial experience is also one of the key challenges for the development of highly intelligent energy systems.

(5) Adaptation: As for all new technologies, the biggest challenge is slowly embracing energy firms and spending time and money on AI. Although the current AI technology is developing rapidly, and it may have surpassed some of the current cognition in the computer field. Although AI technology itself has been well developed, these technologies are not very adaptable in other fields, such as electrical energy. This is mostly because of a lack of awareness and training in AI's entire potential. Therefore, strengthening the adaptability of AI technology in the electrical energy industry is also one of the key challenges for the highly intelligent development of the electrical energy industry.

(6) Computing power: The key elements of this AI are ML and deep learning (Guo et al., 2018, 2019), which require an always increasing amount of core and GPUs to function efficiently. It takes computing power from a supercomputer; indeed, supercomputers are not inexpensive. Not everybody can manage it by increasing the inflow of unprecedented data and increasing complex algorithms exponentially.

(7) Trust deficit: The uncertain nature of how deep learning methods forecast performance is one of the most significant factors which causes AI concern. This is mainly due to the large number of multiple uncertainties in the electrical energy system. There are random factors in the source–grid–load–storage of the energy system, and the generation–transmission–distribution–transmission of the power system. This is also one of the key challenges facing the development of AI prediction technology. In addition, emergencies such as extreme disasters, major epidemics, and disasters have also brought greater challenges to AI prediction technology.

(8) The challenges include the integration of renewable energy:

- Renewable energy variability is a widespread issue in all regions, increasing the share of energy sources in the grid and lowering levelized energy costs.
- The availability demands for renewable energy and supply depend primarily on the weather. The growing uncertainty is induced by the diverse customers and renewable grids deployment and the rise in self-generation and adoption of electric cars, which impact energy networks and producers more and more.

4. Future policy recommendations and research opportunities

AI would influence the future of nearly all industries and every individual. AI has played a leadership role in new technology like robotics, big data, and IoT and will continue to operate in the near future as a technological innovator. Future AI research is the hot topic of the day. Future policy recommendations and research opportunities are listed below:

(1) AI technology can perform four different tasks in industrial workplaces:

Maintenance and repair: The operation of industry is mainly driven by equipment. Therefore, real-time monitoring of the operating status of various equipment in the industrial system is essential. The development of AI technology has brought great opportunities for the intelligent operation, maintenance and overhaul of various equipment. How to make better use of AI technology is to achieve intelligent operation, maintenance and detection of system equipment, and to be able to intelligently handle minor problems and emergencies.

Scheduling and operations forecasting: The application of AI technology in the power enterprise sector can bring more optimized dispatching strategies and more efficient and intelligent operating mechanisms. How to make better use of AI technology to realize the coordinated and optimized operation of multiple subjects in the system, and realize the point-to-point interaction between different stakeholders based on blockchain technology.

Workforce training: In terms of employee training, AI technology has brought better opportunities for industrial operations. Multi-dimensional and multi-faceted training of employees is realized through virtual human–computer interaction and digital twin technology.

Process engineering and design: In the engineering design process, AI technology has brought new exploration content. In particular, the recently developed digital twin technology has brought many benefits to the engineering design process. First, use digital twin technology to conduct a virtual simulation of the engineering design, so as to verify the feasibility of the engineering through a clear visual interface.

(2) The energy industry can lead to the use of AI-based technologies to mitigate operational and business risks, improve the workforce's efficiency and safety, and build a more sustainable and reliable enterprise.

Predictive: By utilizing AI-based solutions, the energy industry can help reduce operational and business risk, increase performance, improve worker safety, and create a more secure and efficient sector.

Performance: To optimize procedures for increased performance and operating efficiency, it needs to incorporate different studies on AI. In combination with automated simulation tools, industry and asset-specific algorithms are used to delete method and object anomalies and pace resolution times. In combination with advanced AI simulation tools, industry and asset-specific algorithms are used to eradicate process and object anomalies and increase resolution times.

Prognostic: Future activities, strategies, and industry conditions are expected to reduce risk, improve performance, and increase sustainability as a result of the use of AI. Through reinforcement learning, neural networks, and deep learning, AI technology provides valuable insight into maintenance and operations strategies and identifies specific improvement areas.

Prescriptive: The most effective strategic judgment can be driven by root cause analysis, optimized strategies, and risk-based decision support. Discover the right way to accomplish the targets of increased productivity/efficiency and energy profitability/sustainability with the highest probability of achievement.

(3) Recurrent neural networks that were using ML algorithms and AI incorporate autoregressive and moving average terms in neuron transfer function in both seasonal and regular terms. They incorporate non-linearity into the transfer functions to accommodate non-linear variable dependences.

Table 5
AI is faster, cheaper, safer, more comfortable, and has higher return on assets.

Faster, cheaper, and safer power system networks.		
Efficiency	Comfort	Reliability
Cybersecurity response and threat detection, self-heating of grids, outage duration forecasting, and response management, shared and clever governance, fault detection, detection of grid anomalies, grid control and planning, Energy analytics, and efficiency, smart metering, etc.	Service and product matching, enhanced consumer experience, auto-adjustment, and personalization, streamline data from millions of sensors, support data experimentation, enhance customer experiences, grid simulation, and digital twin, grid diagnostics, etc.	Portfolio management and workflow, maintenance and optimization, efficient allocation of resources and assets, efficient use of storage, generators, and distribution, optimize millions of dispatch resources and decision parameters, scalability of experimentations and industrialization, etc.

Table 6
Potential AI Applications of distributed ledger technology in the energy industry (Rhodes, 2020).

Description	% Use
Carbon trading and green certificates	7%
Grid management	8%
Security, billing, and metering	9%
General-purpose initiatives	6%
Decentralized energy trading	33%
Electric e-mobility	7%
Tokens & investment, cryptocurrencies	19%

(4) There are four key elements of industrial AI. It includes (1) big data technology, (2) domain knowhows, (3) evidence, (4) cyber technology or cloud, and (5) analytics technology (Lee et al., 2018). We can increase the AI model to be reliable, integrated, and stable within the era by collecting the evidence and data patterns related to these elements.
(5) AI-based decisions should be transparent in order to build trust.

(1) Optimize processes: Thousands of production processes exist, but AI does not automate all of them. It must define and continue the opportunities of utmost importance appropriately.
(2) Long-term strategies are critical: Automation will take at least 5–10 years to complete. The method entails redesigning products to make them more automated and data-capable. As time goes on, more sophisticated data feeds will be required to allow for coordinated supply and demand chain preparation.
(3) Securing the AI future: If the energy industry takes the time and resources to investigate the opportunities of an AI-enhanced future for the energy market, it needs a strong role to develop a consistent plan and direction. It should also cultivate an economically prudent solution to the potential prospects presented by AI. Indeed, the pace of successful AI adoption would be placed at risk without such expertise and strategic leadership to facilitate the necessary improvements and investments.
(4) Commemorating its infrastructure improvements: It is also important that the IT infrastructure be modified to enable the use of AI and, in particular, the cutting-edge devices that enable data collection, analysis, and consumption in real time. AI gives users faster, cheaper, more comfort, and a higher return on assets. This can be seen in Table 5. Further, the potential of AI applications of distributed ledger technology in the energy industry is shown in Table 6.
(5) Address the lack of expertise: It should be a high priority to reskill workers to be successful in changing the development environment. Further, it is also essential to recruit young talent with the expertise required to support the IA initiatives. 33% of the use of AI is reported in decentralized energy trading systems.

5. How will artificial intelligence and industry 4.0 improve the sustainability?

As climate risks continue to threaten the world, industrial companies are trying to ensure that they are as competitive as possible, and that sustainability/profitability is maintained. Many companies strive to remain competitive while retaining profitability, through the incorporation and implementation of AI and ML into real-time industrial operations.

- ***What are the first steps in sustainable development?*** Companies are becoming more vigilant about sustainability, as customers and global leaders are pressing them to pursue "greener" solutions. The approaches of businesses to sustainability differ tremendously. In order to see real progress, it is necessary to grasp the program objectives and align the 'Three Ps.' Profitability, People, and Planet. Industry 4.0 is the most efficient way to solve the key pain points – production and waste energy – and to bring new infrastructure into service.
- ***Digital technologies:*** High energy input is needed for industrial processes. The bulk chemical industry uses the largest portion of US industrial energy, 28%, led by the 18% refining process. Use digital technology to mine a large amount of data in the industrial process, analyze the sensitivity of various data, and use optimization strategies to improve the efficiency of energy input in the industrial process. Efficiency is also subject to unexpected factors, such as fluctuating temperatures, shifts in the feedstock, problems with machinery, and equipment issues. The implementation of AI will refine processes around those possible factors and discover new efficiencies that inevitably influence the energy consumption and the bottom line of the industry.
- ***Efficiency:*** Advanced, predictive planning technologies for electric distribution networks will identify the issues in systems that could lead to unexpected downtimes. The ability to forecast means that activities go smoothly, reducing energy production and emissions without waste in inefficient operations. Kuwait National Petroleum Company (KNPC) is an example that reveals substantial changes in energy use by leveraging AI. To boost efficiencies in electricity use, both of these substantially decreased CO2 emissions and minimize the carbon footprint of KNPC, the organization used AI-based simulation software to minimize energy usage by $15 million annually and maximize the energy efficiency among available utilities.
- ***Which technologies, AI, ML, automation, robotics, or a combination of tech advancements have the biggest effect on sustainability?*** Industry 4.0, from predictive maintenance to augmented reality, would put greater insight into the operation and contribute to enhanced efficacy from planning and operations through to monitoring. AI-enabled technologies give technicians the knowledge they need to take smart, on-the-spot decisions, which lead to smoother operations and lower downtimes by leveraging the information of previous processes through ML. In addition, the use of AI-enabled condition monitoring will accelerate as organizations realize the importance of forecasting to make decisions that promote profitability and have a beneficial effect.

- ***How do we see reporting on sustainability in the next decade?*** The new AI-enabled technologies can improve resource consumption, visibility into process emissions, the product through a better economy, and better track raw materials. Visualization tools and performance changes make it possible for businesses to focus on pollution and waste prevention while maximizing energy use.

6. Conclusion

This study examined the expanding field of energy industry digitization and provided a review of key aspects of technologies, their implementations in the energy system, potential flaws, and implementation challenges. Reliable and efficient energy sources have been a major global requirement for reducing environmental effects. This is achieved by continuously monitoring consumption and power system equipment. It requires artificial intelligence-based modern technologies that are highly effective, precise, and automated, such as an energy management system, a smart sub-station, and monitoring/tracking/communication systems. Energy savings can be realized through the application of these technologies in the areas of generation, maintenance, operation, and monitoring of power equipment. A substantial amount of research has been conducted, and additional research is required to realize the full advantages of AI technology in terms of reducing costs through improved power system efficiency, distributed monitoring and control, electricity and investment markets, and the system of renewable energy resources, among other things. The AI helps reduce machine failure, improve quality control, lower costs, increase productivity, etc.

AI empowers energy industry/energy organizations to shift from reactive maintenance to predictive maintenance strategies. This enables front line workers to respond before costly failures occur and increases profitability over the assets' life cycle. The structure of industry 4.0 includes many phases to be designed to satisfy the needs of the supplier, including: (i) feature engineering; (ii) historical data collection; (iii) AI applications: ML and other approaches; (iv) integration with PLCs; (v) data aggregation; (vi) gateway and routing devices; (vii) connectivity by protocols for communication; (viii) the capture of live data via sensors; and (xi) dashboards for energy analysis and monitoring. Along with the proliferation of easy-to-use machine learning software and the continuous improvement of processing, data monitoring, and analytic tools, new operational efficiencies are expected. Data collection, data interpretation, and utilization are at the core theme of energy digitalization and thus need to get to the front line of stakeholders' vision. Robust cybersecurity initiatives must also be viewed as an integral part of the digitization initiative and should be implemented at the basic stage of design and execution.

Solar and wind stakeholder groups or stakeholders will undoubtedly benefit from AI in a variety of ways, including remote inspection, troubleshooting, and maintenance, ultrasonic receivers and transmitters, optimization of onshore solar and wind farms, efficient and effective solar panel inspection, autonomous drones equipped with real-time AI, and AI applications that expedite due diligence. Artificial intelligence is expected to play a significant role in reducing delivery failures in emerging markets and resolving maintenance and reliability issues. AI will also continue to incorporate renewable sources into the power grid and provide operational autonomy for distributed electricity systems/networks and microgrids. One critical field of focus in the coming years is how AI can enable/automate grids to integrate renewable energy sources.

What next: The Mission Innovation Global Partnership's renewable energy materials innovation challenge prioritizes the development of AI-enabled machine learning approaches. Volunteer government agreements fund cooperation, and countries must uphold their end of the bargain by making the necessary contributions.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was supported in part by the National Natural Science Foundation of China (5210071288); Key Laboratory of Special Machine and High Voltage Apparatus Shenyang University of Technology, Ministry of Education, China (NO. KFKT202006), Guangxi Young and Middle-aged Scientific Research Basic Ability Promotion Project, China (NO. 2020KY01009) and Taif University, Saudi Arabia Researchers supporting Project number (TURSP-2020/311).

References

Adjerid, H., Maouche, A.R., 2020. Multi-agent system-based decentralized state estimation method for active distribution networks. Comput. Electr. Eng. 86, 106652. http://dx.doi.org/10.1016/j.compeleceng.2020.106652.

A.G., S., 2020. Next-Gen AI in Energy: A Tool for Transition. Siemens AG Coop with Longit Res Ltd, Werner-von:1–6, https://assets.new.siemens.com/siemens/assets/api/uuid:fef90d09-6876-4510-b29b-bb6d60374793/siemens-next-gen-industrial-ai-energy-sector.pdf.

Ahmad, T., 2017. Non-technical loss analysis and prevention using smart meters. Renew. Sustain. Energy Rev. 72, 573–589. http://dx.doi.org/10.1016/j.rser.2017.01.100.

Ahmad, T., 2021. Methodological framework for short-and medium-term energy, solar and wind power forecasting with stochastic-based machine learning approach to monetary and energy policy applications. Energy 15, 120911. http://dx.doi.org/10.1109/MPE.2015.2461351.

Ahmad, Tanveer, Chen, Huanxin, Shah, Waha Ali, 2019. Effective bulk energy consumption control and management for power utilities using artificial intelligence techniques under conventional and renewable energy resources. Int. J. Electr. Power Energy Syst. 109, 242–258. http://dx.doi.org/10.1016/j.ijepes.2019.02.023.

Ahmad, T., Zhang, D., Huang, C., Zhang, H., Dai, N., Song, Y., et al., 2021. Artificial intelligence in sustainable energy industry: Status quo, challenges and opportunities. J. Clean. Prod. 289, 125834. http://dx.doi.org/10.1016/j.jclepro.2021.125834.

AI Investment Opportunities, 2020. Strateg intell 2020. https://www.pangea-si.com/ai-investment-opportunities/. (Accessed 10 May 2020).

Al-Obeidat, F., Spencer, B., Alfandi, O., 2020. Consistently accurate forecasts of temperature within buildings from sensor data using ridge and lasso regression. Future Gen. Comput. Syst. 110, 382–392. http://dx.doi.org/10.1016/j.future.2018.02.035.

Ali, M., Prasad, R., Xiang, Y., Deo, R.C., 2020. Near real-time significant wave height forecasting with hybridized multiple linear regression algorithms. Renew. Sustain. Energy Rev. 132, 110003. http://dx.doi.org/10.1016/j.rser.2020.110003.

Alto, P., 2017. Toyota Research Institute Brings Artificial Intelligence to the Hunt for New Materials. pp. 1–3, https://www.prnewswire.com/news-releases/toyota-research-institute-brings-artificial-intelligence-to-the-hunt-for-new-materials-300431635.html. (Accessed 10 July 2020).

Aly, H.H.H., 2020. A novel deep learning intelligent clustered hybrid models for wind speed and power forecasting. Energy 213, 118773. http://dx.doi.org/10.1016/j.energy.2020.118773.

Amiri, S.S., Mottahedi, M., Asadi, S., 2015. Using multiple regression analysis to develop energy consumption indicators for commercial buildings in the u.s. Energy Build. 109, 209–216. http://dx.doi.org/10.1016/j.enbuild.2015.09.073.

Andoni, M., Robu, V., Flynn, D., Abram, S., Geach, D., Jenkins, D., et al., 2019. Blockchain technology in the energy sector: A systematic review of challenges and opportunities. Renew. Sustain. Energy Rev. 100, 143–174. http://dx.doi.org/10.1016/j.rser.2018.10.014.

Anon., 1992. Effect of artificial-intelligence planning-procedures on system reliability. Microelectron. Reliab. 32, 592. http://dx.doi.org/10.1016/0026-2714(92)90563-z.

Anon., 2019. Artificial intelligence and big data innovation landscape brief. Irea 2019;IRENA 2019:1–24, https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2019/Sep/IRENA_AI_Big_Data_2019.pdf?.
Antonopoulos, I., Robu, V., Couraud, B., Kirli, D., Norbu, S., Kiprakis, A., et al., 2020. Artificial intelligence and machine learning approaches to energy demand-side response: A systematic review. Renew. Sustain. Energy Rev. 130, 109899. http://dx.doi.org/10.1016/j.rser.2020.109899.
Ardakani, M.K., Seyedaliakbar, S.M., 2019. Impact of energy consumption and economic growth on CO2 emission using multivariate regression. Energy Strategy Rev. 26, 100428. http://dx.doi.org/10.1016/j.esr.2019.100428.
Askarzadeh, A., 2018. A memory-based genetic algorithm for optimization of power generation in a microgrid. IEEE Trans. Sustain. Energy 9, 1081–1089. http://dx.doi.org/10.1109/TSTE.2017.2765483.
Attia, P.M., Grover, A., Jin, N., Severson, K.A., Markov, T.M., Liao, Y.H., et al., 2020. Closed-loop optimization of fast-charging protocols for batteries with machine learning. Nature 578, 397–402. http://dx.doi.org/10.1038/s41586-020-1994-5.
Azmy, A.M., 2007. Optimal power flow to manage voltage profiles in interconnected networks using expert systems. IEEE Trans. Power Syst. 22, 1622–1628. http://dx.doi.org/10.1109/TPWRS.2007.907961.
de B. Franco, D.G., Steiner, M.T.A., 2018. Clustering of solar energy facilities using a hybrid fuzzy c-means algorithm initialized by metaheuristics. J. Clean. Prod. 191, 445–457. http://dx.doi.org/10.1016/j.jclepro.2018.04.207.
Badiei, A., Golizadeh Akhlaghi, Y., Zhao, X., Shittu, S., Xiao, X., Li, J., et al., 2020. A chronological review of advances in solar assisted heat pump technology in 21st century. Renew. Sustain. Energy Rev. 132, 110132. http://dx.doi.org/10.1016/j.rser.2020.110132.
Banga, B., 2020. Banga B Global Artificial Intelligence (AI) in Energy Market – Analysis and Forecast, 2019-2024. BIS Res Inc, https://www.prnewswire.com/news-releases/global-ai-in-energy-market-to-reach-7-78-billion-by-2024--300984256.html. (Accessed 10 June 2020).
Barghamadi, M., Kapoor, A., Wen, C., 2013. A review on Li-S batteries as a high efficiency rechargeable lithium battery. J. Electrochem. Soc. 160, A1256–63. http://dx.doi.org/10.1149/2.096308jes.
Barrett, D.H., Haruna, A., 2020. Artificial intelligence and machine learning for targeted energy storage solutions. Curr. Opin. Electrochem. 21, 160–166. http://dx.doi.org/10.1016/j.coelec.2020.02.002.
Basu, M., 2020. Optimal generation scheduling of fixed head hydrothermal system with demand-side management considering uncertainty and outage of renewable energy sources. IET Gener. Transm. Distrib. 14, 4321–4330. http://dx.doi.org/10.1049/iet-gtd.2018.7103.
Bedi, J., Toshniwal, D., 2019. Deep learning framework to forecast electricity demand. Appl. Energy 238, 1312–1326. http://dx.doi.org/10.1016/j.apenergy.2019.01.113.
Ben, Atitallah S., Driss, M., Boulila, W., Ben, Ghézala H., 2020. Leveraging deep learning and IoT big data analytics to support the smart cities development: Review and future directions. Comput. Sci. Rev. 38, 100303. http://dx.doi.org/10.1016/j.cosrev.2020.100303.
Bernstein, A., Sargent, E.H., Aspuru-Guzik, A., Cogdell, R., Fleming, G.R., Van Grondelle, R., et al., 2016. Renewables need a grand-challenge strategy. Nature 538, 30. http://dx.doi.org/10.1038/538030a.
Biagini, V., Subasic, M., Oudalov, A., Kreusel, J., 2020. The autonomous grid: Automation, intelligence and the future of power systems. Energy Res. Soc. Sci. 65, 101460. http://dx.doi.org/10.1016/j.erss.2020.101460.
Bienvenido-Huertas, D., Farinha, F., Oliveira, M.J., Silva, E.M.J., Lança, R., 2020. Comparison of artificial intelligence algorithms to estimate sustainability indicators. Sustain. Cities Soc. 63, 102430. http://dx.doi.org/10.1016/j.scs.2020.102430.
Bodnar, T., Dering, M.L., Tucker, C., Edu, K.M., 2017. Using large-scale social media networks as a scalable sensing system for modeling real-time energy utilization patterns. IEEE Trans. Syst. Man Cybern. Syst. 47, 2627–2640. http://dx.doi.org/10.1109/TSMC.2016.2618860.
Bracale, A., Caramia, P., De Falco, P., Hong, T., 2020. A multivariate approach to probabilistic industrial load forecasting. Electr. Power Syst. Res. 187, 106430. http://dx.doi.org/10.1016/j.epsr.2020.106430.
Bracale, A., Carpinelli, G., De Falco, P., 2017. A new finite mixture distribution and its expectation-maximization procedure for extreme wind speed characterization. Renew. Energy 113, 1366–1377. http://dx.doi.org/10.1016/j.renene.2017.07.012.
Branham, M.S., Hsu, W.C., Yerci, S., Loomis, J., Boriskina, S.V., Hoard, B.R., et al., 2015. 15.7% Efficient 10-μm-thick crystalline silicon solar cells using periodic nanostructures. Adv. Mater. 27, 2182–2188. http://dx.doi.org/10.1002/adma.201405511.
Bruce, P.G., Freunberger, Stefan A., Hardwick, Laurence J., Tarascon, Jean-Marie, 2011. Li–O2 and Li–S batteries with high energy storage. Nature Mater. 11, 172. http://dx.doi.org/10.1038/nmat3237.
Buzau, M.M., Tejedor-Aguilera, J., Cruz-Romero, P., Gomez-Exposito, A., 2019. Detection of non-technical losses using smart meter data and supervised learning. IEEE Trans. Smart Grid 10, 2661–2670. http://dx.doi.org/10.1109/TSG.2018.2807925.
de Campos Souza, P.V., 2020. Fuzzy neural networks and neuro-fuzzy networks: A review the main techniques and applications used in the literature. Appl. Soft Comput. J. 92, 106275. http://dx.doi.org/10.1016/j.asoc.2020.106275.
Cao, J., Harrold, D., Fan, Z., Morstyn, T., Healey, D., Li, K., 2020. Deep reinforcement learning-based energy storage arbitrage with accurate lithium-ion battery degradation model. IEEE Trans. Smart Grid 11, 4513–4521. http://dx.doi.org/10.1109/TSG.2020.2986333.
Cecati, C., Citro, C., Piccolo, A., Siano, P., 2011. Smart operation of wind turbines and diesel generators according to economic criteria. IEEE Trans. Ind. Electron. 58, 4514–4525. http://dx.doi.org/10.1109/TIE.2011.2106100.
Chang, C.L., McAleer, M., Wang, Y.A., 2020. Herding behaviour in energy stock markets during the Global Financial Crisis, SARS, and ongoing COVID-19*. Renew. Sustain. Energy Rev. 134, 110349. http://dx.doi.org/10.1016/j.rser.2020.110349.
Chen, C., 2018a. One-dimensional nanomaterials for energy storage. J. Phys. D 51, 113002. http://dx.doi.org/10.1149/ma2016-03/2/626.
Chen, H., 2018b. Short and medium-term forecasting of cooling and heating load demand in building environment with data-mining based approaches. Energy Build. 166, 460–476. http://dx.doi.org/10.1016/j.enbuild.2018.01.066.
Chen, H., 2019. Deep learning for multi-scale smart energy forecasting. Energy 98–112. http://dx.doi.org/10.1016/j.energy.2019.03.080.
Chen, H., 2020. A review on machine learning forecasting growth trends and their real-time applications in different energy systems. Sustain. Cities Soc. 54, 102010. http://dx.doi.org/10.1016/j.scs.2019.102010.
Chen, H., Huang, R., Yabin, G., Wang, J., Shair, J., et al., 2018a. Supervised based machine learning models for short, medium and long-term energy prediction in distinct building environment. Energy 158, 17–32. http://dx.doi.org/10.1016/j.energy.2018.05.169.
Chen, D., Jie, J., Weng, M., Li, S., Chen, D., Pan, F., et al., 2019. High throughput identification of Li ion diffusion pathways in typical solid state electrolytes and electrode materials by BV-Ewald method. J. Mater. Chem. A 7, 1300–1306. http://dx.doi.org/10.1039/c8ta09345h.
Chen, H., Wang, J., Guo, Y., 2018b. Review of various modeling techniques for the detection of electricity theft in smart grid environment. Renew. Sustain. Energy Rev. 82. http://dx.doi.org/10.1016/j.rser.2017.10.040.
Cheng, M.Y., Cao, M.T., 2014. Accurately predicting building energy performance using evolutionary multivariate adaptive regression splines. Appl. Soft Comput. J. 22, 178–188. http://dx.doi.org/10.1016/j.asoc.2014.05.015.
Cheng, F., Li, T., ming, Wei.Y., Fan, T., 2019. The VEC-NAR model for short-term forecasting of oil prices. Energy Econ. 78, 656–667. http://dx.doi.org/10.1016/j.eneco.2017.12.035.
Chettibi, N., Mellit, A., Sulligoi, G., Massi Pavan, A., 2018. Adaptive neural network-based control of a hybrid AC/DC microgrid. IEEE Trans. Smart Grid 9, 1667–1679. http://dx.doi.org/10.1109/TSG.2016.2597006.
Chu, S., Cui, Y., Liu, N., 2016. The path towards sustainable energy. Nature Mater. 16, 16–22. http://dx.doi.org/10.1038/nmat4834.
Cirrincione, M., Pucci, M., Vitale, G., Miraoui, A., 2009. Current harmonic compensation by a single-phase shunt active power filter controlled by adaptive neural filtering. IEEE Trans. Ind. Electron. 56, 3128–3143. http://dx.doi.org/10.1109/TIE.2009.2022070.
Ciulla, G., D'Amico, A., 2019. Building energy performance forecasting: A multiple linear regression approach. Appl. Energy 253, 113500. http://dx.doi.org/10.1016/j.apenergy.2019.113500.
Ciulla, G., D'Amico, A., Lo Brano, V., Traverso, M., 2019. Application of optimized artificial intelligence algorithm to evaluate the heating energy demand of non-residential buildings at European level. Energy 176, 380–391. http://dx.doi.org/10.1016/j.energy.2019.03.168.
Columbus, L., 2017. Smart factories will deliver $500B in value by 2022, forbes 2017: 1–8. https://www.forbes.com/sites/louiscolumbus/2017/07/30/smart-factories-will-deliver-500b-in-value-by-2022/#41bfee0d2d22. (Accessed 10 June 2020).
Columbus, L., 2020. 10 Ways machine learning is revolutionizing manufacturing in 2019. forbes 2020. https://www.forbes.com/sites/louiscolumbus/2019/08/11/10-ways-machine-learning-is-revolutionizing-manufacturing-in-2019/#6ed531072b40. (Accessed 10 June 2020).
Consumers Vehicles Energy Integration, 2020. Energy Systems Catapult. Energy Data Rev Summ Rep 2019, https://es.catapult.org.uk/wp-content/uploads/2018/12/Energy_Data_Review_Summary_Final.pdf. (Accessed 05 September 2020).
Curtarolo, S., Hart, G.L.W., Nardelli, M.B., Mingo, N., Sanvito, S., Levy, O., 2013. The high-throughput highway to computational materials design. Nature Mater. 12, 191–201. http://dx.doi.org/10.1038/nmat3568.
Dawn, S., Tiwari, P.K., Goswami, A.K., 2019. An approach for long term economic operations of competitive power market by optimal combined scheduling of wind turbines and FACTS controllers. Energy 181, 709–723. http://dx.doi.org/10.1016/j.energy.2019.05.225.
De Klerk, N.J.J., Rosłoń, I., Wagemaker, M., 2016. Diffusion mechanism of Li argyrodite solid electrolytes for Li-ion batteries and prediction of optimized halogen doping: The effect of Li vacancies, halogens, and halogen disorder. Chem. Mater. 28, 7955–7963. http://dx.doi.org/10.1021/acs.chemmater.6b03630.

Di Maio, F., Secchi, P., Vantini, S., Zio, E., 2011. Fuzzy c-means clustering of signal functional principal components for post-processing dynamic scenarios of a nuclear power plant digital instrumentation and control system. IEEE Trans Reliab. 60, 415–425. http://dx.doi.org/10.1109/TR.2011.2134230.

Di Silvestre, M.L., Favuzza, S., Riva Sanseverino, E., Zizzo, G., 2018. How decarbonization, digitalization and decentralization are changing key power infrastructures. Renew. Sustain. Energy Rev. 93, 483–498. http://dx.doi.org/10.1016/j.rser.2018.05.068.

Di Vaio, A., Palladino, R., Hassan, R., Escobar, O., 2020. Artificial intelligence and business models in the sustainable development goals perspective: A systematic literature review. J. Bus. Res. 121, 283–314. http://dx.doi.org/10.1016/j.jbusres.2020.08.019.

Du, P., 2019. Ensemble machine learning-based wind forecasting to combine NWP output with data from weather station. IEEE Trans. Sustain. Energy 10, 2133–2141. http://dx.doi.org/10.1109/TSTE.2018.2880615.

Egli, F., Steffen, B., Schmidt, T.S., 2018. A dynamic analysis of financing conditions for renewable energy technologies. Nature Energy 3, 1084–1092. http://dx.doi.org/10.1038/s41560-018-0277-y.

Elkin, C., Witherspoon, S., 2019. Machine learning can boost the value of wind energy. Deep Blog. https://deepmind.com/blog/article/machine-learning-can-boost-value-wind-energy. (Accessed 1 August 2020).

Entchev, E., Yang, L., 2007. Application of adaptive neuro-fuzzy inference system techniques and artificial neural networks to predict solid oxide fuel cell performance in residential microgeneration installation. J. Power Sources 170, 122–129. http://dx.doi.org/10.1016/j.jpowsour.2007.04.015.

Erixno, O., Rahim, N.A., 2020. A techno-environmental assessment of hybrid photovoltaic-thermal based combined heat and power system on a residential home. Renew. Energy 156, 1186–1202. http://dx.doi.org/10.1016/j.renene.2020.04.101.

Ernesto Vázquez, M., Oscar, L., Héctor, J.C.M., Altuve, F., 1997. An on-line expert system for fault section diagnosis in power systems. IEEE Trans. Power Syst. 12, 357–362. http://dx.doi.org/10.1109/59.574959.

Ernst & Young LPP Microsoft, 2019. Artificial intelligence in Europe, outlook for 2019 and beyond. microsoft 2019: 41. https://pulse.microsoft.com/uploads/prod/2018/10/WE_AI_Report_2018.pdf.

European Commission, 2020. Shaping Europe's digital future. Invest AI manuf 2020. http://dx.doi.org/10.2759/48191, https://ec.europa.eu/digital-single-market/en/news/investing-ai-manufacturing.

Fatima Zohra, A., Ismail Khalil, B., Slimane, L., Youcef, S., Benyounes, M., 2018. Artificial intelligence control applied in wind energy conversion system. Int. J. Power Electron. Drive Syst. 9, 571. http://dx.doi.org/10.11591/ijpeds.v9.i2.pp571-578.

Figueiredo, N.C., da Silva, P.P., 2019. The merit-order effect of wind and solar power: Volatility and determinants. Renew. Sustain. Energy Rev. 102, 54–62. http://dx.doi.org/10.1016/j.rser.2018.11.042.

Fitzgerald, G., Mandel, J., Morris, J., Touati, H., 2015. The Economics of Battery Energy Storage. Rocky Mt Inst, pp. 1–41.

Forbes, 2019. DeepMind and google train AI to predict energy output of wind farms 2019. https://www.forbes.com/sites/samshead/2019/02/27/deepmind-and-google-train-ai-to-predict-energy-output-of-.

Foresti, R., Rossi, S., Magnani, M., Guarino Lo Bianco, C., Delmonte, N., 2020. Smart society and artificial intelligence: Big data scheduling and the global standard method applied to smart maintenance. Engineering 6, 835–846. http://dx.doi.org/10.1016/j.eng.2019.11.014.

Frey, C.B., Osborne, M.A., Holmes, C., 2016. Technology at work v2.0: The future is not what it used to be. http://dx.doi.org/10.1016/B978-0-323-04130-0.50004-2, Citi GPS 2016:156.

Garcia, M.C., Sanz-Bobi, M.A., del Pico, J., 2006. SIMAP: Intelligent system for predictive maintenance. application to the health condition monitoring of a windturbine gearbox. Comput. Ind. 57, 552–568. http://dx.doi.org/10.1016/j.compind.2006.02.011.

GhaffarianHoseini, A., Zhang, T., Nwadigo, O., GhaffarianHoseini, A., Naismith, N., Tookey, J., et al., 2017. Application of nD BIM integrated knowledge-based building management system (BIM-IKBMS) for inspecting post-construction energy efficiency. Renew. Sustain. Energy Rev. 72, 935–949. http://dx.doi.org/10.1016/j.rser.2016.12.061.

Ghamari, M., Ratner, A., 2017. Combustion characteristics of colloidal droplets of jet fuel and carbon based nanoparticles. Fuel 188, 182–189. http://dx.doi.org/10.1016/j.fuel.2016.10.040.

Ghoddusi, H., Creamer, G.G., Rafizadeh, N., 2019. Machine learning in energy economics and finance: A review. Energy Econ. 81, 709–727. http://dx.doi.org/10.1016/j.eneco.2019.05.006.

Gil Posada, J.O., Abdalla, A.H., Oseghale, C.I., Hall, P.J., 2016. Multiple regression analysis in the development of NiFe cells as energy storage solutions for intermittent power sources such as wind or solar. Int. J. Hydrog. Energy 41, 16330–16337. http://dx.doi.org/10.1016/j.ijhydene.2016.04.165.

Gómez-Bombarelli, R., Aguilera-Iparraguirre, J., Hirzel, T.D., Duvenaud, D., Maclaurin, D., Blood-Forsythe, M.A., et al., 2016. Design of efficient molecular organic light-emitting diodes by a high-throughput virtual screening and experimental approach. Nature Mater. 15, 1120–1127. http://dx.doi.org/10.1038/nmat4717.

Goodenough, J.B., Kim, Y., 2010. Challenges for rechargeable Li batteries. Chem. Mater. 22, 587–603. http://dx.doi.org/10.1021/cm901452z.

Greenberg, A., 2019. New clues show how Russia's grid hackers aimed for physical destruction. Wired 2019. https://www.wired.com/story/russia-ukraine-cyberattack-power-gridblackout-destruction/.

Guo, Y., Tan, Z., Chen, H., Li, G., Wang, J., Huang, R., et al., 2018. Deep learning-based fault diagnosis of variable refrigerant flow air-conditioning system for building energy saving. Appl. Energy 225, 732–745. http://dx.doi.org/10.1016/j.apenergy.2018.05.075.

Guo, Y., Wang, J., Chen, H., Li, G., Huang, R., Yuan, Y., et al., 2019. An expert rule-based fault diagnosis strategy for variable refrigerant flow air conditioning systems. Appl. Therm. Eng. 149, 1223–1235. http://dx.doi.org/10.1016/j.applthermaleng.2018.12.132.

Hatakeyama-Sato, K., Tezuka, T., Nishikitani, Y., Nishide, H., Oyaizu, K., 2019. Synthesis of lithium-ion conducting polymers designed by machine learning-based prediction and screening. Chem. Lett. 48, 130–132. http://dx.doi.org/10.1246/cl.180847.

Hatakeyama-Sato, K., Tezuka, T., Umeki, M., Oyaizu, K., 2020. Ai-assisted exploration of superionic glass-type Li+ conductors with aromatic structures. J. Am. Chem. Soc. 142, 3301–3305. http://dx.doi.org/10.1021/jacs.9b11442.

He, Y., Qin, Y., Wang, S., Wang, X., Wang, C., 2019. Electricity consumption probability density forecasting method based on LASSO-quantile regression neural network. Appl. Energy 233–234, 565–575. http://dx.doi.org/10.1016/j.apenergy.2018.10.061.

Henri, G., Lu, N., 2019. A supervised machine learning approach to control energy storage devices. IEEE Trans. Smart Grid 10, 5910–5919. http://dx.doi.org/10.1109/TSG.2019.2892586.

Höllerer, S., Papaxanthos, L., Gumpinger, A.C., Fischer, K., Beisel, C., Borgwardt, K., et al., 2020. Large-scale DNA-based phenotypic recording and deep learning enable highly accurate sequence-function mapping. Nature Commun. 11, 1–15. http://dx.doi.org/10.1101/2020.01.23.915405.

Hölzle, U., 2016. 100% Renewable is just the beginning. google 2016:1–4. https://www.google.com/intl/en/about/values-in-action/renewable/.

Hong, Y.Y., Chao, Z.T., 2008. Development of energy loss formula for distribution systems using FCN algorithm and cluster-wise fuzzy regression. IEEE Power Eng. Rev. 22, 80. http://dx.doi.org/10.1109/mper.2002.4312155.

Hsu, Y.Y., Su, C.C., 1991. A rule-based expert system for steady-state stability analysis. IEEE Trans. Power Syst. 6, 771–777. http://dx.doi.org/10.1109/59.76724.

Huang, C., Zhang, H., Song, Y., Wang, L., Ahmad, T., Luo, X., 2021. Demand response for industrial micro-grid considering photovoltaic power uncertainty and battery operational cost. IEEE Trans. Smart Grid http://dx.doi.org/10.1109/TSG.2021.3052515, In press.

Huskinson, B., Marshak, M.P., Suh, C., Er, S., Gerhardt, M.R., Galvin, C.J., et al., 2014. A metal-free organic-inorganic aqueous flow battery. Nature 505, 195–198. http://dx.doi.org/10.1038/nature12909.

IEA, 2019. World Energy Invest 2019. http://dx.doi.org/10.1787/4f4f25b4-en.

Ilbeigi, M., Ghomeishi, M., Dehghanbanadaki, A., 2020. Prediction and optimization of energy consumption in an office building using artificial neural network and a genetic algorithm. Sustain. Cities Soc. 61, 102325. http://dx.doi.org/10.1016/j.scs.2020.102325.

Iqbal, M., Azam, M., Naeem, M., Khwaja, A.S., Anpalagan, A., 2014. Optimization classification, algorithms and tools for renewable energy: A review. Renew. Sustain. Energy Rev. 39, 640–654. http://dx.doi.org/10.1016/j.rser.2014.07.120.

IRENA, 2015. IRENA battery storage for renewables: Market status and technology outlook. Irena 2015:60. http://www.irena.org/documentdownloads/publications/irena_battery_storage_report_2015.pdf.

IRENA, 2017. IRENA electricity storage and renewables: Costs and markets to 2030. Electricity-Storage-and-Renewables-Costs-and-Markets 2017:132, http://www.climateaction.org/images/uploads/documents/IRENA_Electricity_Storage_Costs_2017.pdf.

IRENA, 2020. Global Renewables Outlook. Int Renew. Energy Agency, Abu Dhabi, ISBN: 978-92-9260-238-3, pp. 1–54.

Jafari, M., Malekjamshidi, Z., Lu, D.D.C., Zhu, J., 2019. Development of a fuzzy-logic-based energy management system for a multiport multioperation mode residential smart microgrid. IEEE Trans. Power Electron. 34, 3283–3301. http://dx.doi.org/10.1109/TPEL.2018.2850852.

Jain, A., Ong, S.P., Hautier, G., Chen, W., Richards, W.D., Dacek, S., et al., 2013. Commentary: The materials project: A materials genome approach to accelerating materials innovation. APL Mater. 1, 1–12. http://dx.doi.org/10.1063/1.4812323.

Jang, H.S., Bae, K.Y., Park, H.S., Sung, D.K., 2016. Solar power prediction based on satellite images and support vector machine. IEEE Trans. Sustain. Energy 7, 1255–1263. http://dx.doi.org/10.1109/TSTE.2016.2535466.

Jasiński, T., 2020. Use of new variables based on air temperature for forecasting day-ahead spot electricity prices using deep neural networks: A new approach. Energy 213, 118784. http://dx.doi.org/10.1016/j.energy.2020.118784.

Jha, S.K., Bilalovic, J., Jha, A., Patel, N., Zhang, H., 2017. Renewable energy: Present research and future scope of artificial intelligence. Renew. Sustain. Energy Rev. 77, 297–317. http://dx.doi.org/10.1016/j.rser.2017.04.018.

Jiekang, W., Jianquan, Z., Guotong, C., Hongliang, Z., 2008. A hybrid method for optimal scheduling of short-term electric power generation of cascaded hydroelectric plants based on particle swarm optimization and chance-constrained programming. IEEE Trans. Power Syst. 23, 1570–1579. http://dx.doi.org/10.1109/TPWRS.2008.2004822.

Jin, K., Zhou, X., Liu, Z., 2015. Graphene/sulfur/carbon nanocomposite for high performance lithium-sulfur batteries. Nanomaterials 5, 1481–1492. http://dx.doi.org/10.3390/nano5031481.

Johlin, E., Al-Obeidi, A., Nogay, G., Stuckelberger, M., Buonassisi, T., Grossman, J.C., 2016. Nanohole structuring for improved performance of hydrogenated amorphous silicon photovoltaics. ACS Appl. Mater. Interfaces 8, 15169–15176. http://dx.doi.org/10.1021/acsami.6b00033.

Joo, S.H., Park, J.Y., Tsung, C.K., Yamada, Y., Yang, P., Somorjai, G.A., 2009. Thermally stable Pt/mesoporous silica core-shell nanocatalysts for high-temperature reactions. Nature Mater. 8, 126–131. http://dx.doi.org/10.1038/nmat2329.

Kayapinar Kaya, S., Erginel, N., 2020. Futuristic airport: A sustainable airport design by integrating hesitant fuzzy SWARA and hesitant fuzzy sustainable quality function deployment. J. Clean. Prod. 275, 123880. http://dx.doi.org/10.1016/j.jclepro.2020.123880.

Kermadi, M., Berkouk, E.M., 2017. Artificial intelligence-based maximum power point tracking controllers for photovoltaic systems: Comparative study. Renew. Sustain. Energy Rev. 69, 369–386. http://dx.doi.org/10.1016/j.rser.2016.11.125.

Khalilifar, M., Joorabian, M., Seifosadat, G., Shahrtash, S.M., 2019. Estimation of voltage instability inception time by employing k-nearest neighbour learning algorithm. IET Gener. Transm. Distrib. 13, 2907–2918. http://dx.doi.org/10.1049/iet-gtd.2018.6284.

Khan, M.M.S., Faruque, M.O., Newaz, A., 2017. Fuzzy logic based energy storage management system for mvdc power system of all electric ship. IEEE Trans. Energy Convers. 32, 798–809. http://dx.doi.org/10.1109/TEC.2017.2657327.

Kim, Y.J., 2020. A supervised-learning-based strategy for optimal demand response of an HVAC system in a multi-zone office building. IEEE Trans. Smart Grid 11, 4212–4226. http://dx.doi.org/10.1109/TSG.2020.2986539.

Kim, H., Hong, T., Kim, J., 2019. Automatic ventilation control algorithm considering the indoor environmental quality factors and occupant ventilation behavior using a logistic regression model. Build. Environ. 153, 46–59. http://dx.doi.org/10.1016/j.buildenv.2019.02.032.

King, J.E., Jupe, S.C.E., Taylor, P.C., 2015. Network state-based algorithm selection for power flow management using machine learning. IEEE Trans. Power Syst. 30, 2657–2664. http://dx.doi.org/10.1109/TPWRS.2014.2361792.

Kong, X., Liu, D., Xiao, J., Wang, C., 2019. A multi-agent optimal bidding strategy in microgrids based on artificial immune system. Energy 189, 116154. http://dx.doi.org/10.1016/j.energy.2019.116154.

Lagorse, J., Simoes, M.G., Miraoui, A., 2009. A multiagent fuzzy-logic-based energy management of hybrid systems. IEEE Trans. Ind. Appl. 45, 2123–2129. http://dx.doi.org/10.1109/TIA.2009.2031786.

Lam, J.C., Wan, K.K.W., Liu, D., Tsang, C.L., 2010. Multiple regression models for energy use in air-conditioned office buildings in different climates. Energy Convers. Manage. 51, 2692–2697. http://dx.doi.org/10.1016/j.enconman.2010.06.004.

Ledesma, J.J.G., do Nascimento, K.B., de Araujo, L.R., Penido, D.R.R., 2020. A two-level ANN-based method using synchronized measurements to locate high-impedance fault in distribution systems. Electr. Power Syst. Res. 188, 106576. http://dx.doi.org/10.1016/j.epsr.2020.106576.

Lee, J., Davari, H., Singh, J., Pandhare, V., 2018. Industrial artificial intelligence for industry 4.0-based manufacturing systems. Manuf. Lett. 18, 20–23. http://dx.doi.org/10.1016/j.mfglet.2018.09.002.

Leon, C., Meijias, M., Luque, J., Gonzalo, F., 1999. Expert system for the integrated management of a power utility's communication system. IEEE Power Eng. Rev. 19, 47.

Li, W., Elzatahry, A., Aldhayan, D., Zhao, D., 2018. Core-shell structured titanium dioxide nanomaterials for solar energy utilization. Chem. Soc. Rev. 47, 8203–8237. http://dx.doi.org/10.1039/c8cs00443a.

Li, S., Fairbank, M., Johnson, C., Wunsch, D.C., Alonso, E., Proao, J.L., 2014. Artificial neural networks for control of a grid-connected rectifier/inverter under disturbance, dynamic and power converter switching conditions. IEEE Trans. Neural Netw. Learn. Syst. 25, 738–750. http://dx.doi.org/10.1109/TNNLS.2013.2280906.

Li, T., Fong, S., Li, X., Lu, Z., Gandomi, A.H., 2020. Swarm decision table and ensemble search methods in fog computing environment: Case of day-ahead prediction of building energy demands using IoT sensors. IEEE Internet of Things J. 7, 2321–2342. http://dx.doi.org/10.1109/JIOT.2019.2958523.

Li, J., Pradhan, B., Gaur, S., Thomas, J., 2019. Predictions and strategies learned from machine learning to develop high-performing perovskite solar cells. Adv. Energy Mater. 9, 1–10. http://dx.doi.org/10.1002/aenm.201901891.

Liang, R.H., Liao, J.H., 2007. A fuzzy-optimization approach for generation scheduling with wind and solar energy systems. IEEE Trans. Power Syst. 22, 1665–1674. http://dx.doi.org/10.1109/TPWRS.2007.907527.

Lin, C.C., Deng, D.J., Kuo, C.C., Liang, Y.L., 2018. Optimal charging control of energy storage and electric vehicle of an individual in the internet of energy with energy trading. IEEE Trans. Ind. Inf. 14, 2570–2578. http://dx.doi.org/10.1109/TII.2017.2782845.

Lin, C.W., Yang, Y.T.C., Wang, J.S., Yang, Y.C., 2012. A wearable sensor module with a neural-network-based activity classification algorithm for daily energy expenditure estimation. IEEE Trans. Inf. Technol. Biomed. 16, 991–998. http://dx.doi.org/10.1109/TITB.2012.2206602.

Lin, Y.K., Yeh, C.T., 2011. Maximal network reliability with optimal transmission line assignment for stochastic electric power networks via genetic algorithms. Appl. Soft Comput. J. 11, 2714–2724. http://dx.doi.org/10.1016/j.asoc.2010.11.002.

Lingmin, C., Jiekang, W., Fan, W., Huiling, T., Changjie, L., Yan, X., 2020. Energy flow optimization method for multi-energy system oriented to combined cooling, heating and power. Energy 211, 118536. http://dx.doi.org/10.1016/j.energy.2020.118536.

Liu, P., Jiang, W., Wang, X., Li, H., Sun, H., 2020. Research and application of artificial intelligence service platform for the power field. Glob. Energy Interconnect. 3, 175–185. http://dx.doi.org/10.1016/j.gloei.2020.05.009.

Liu, Q., Kamoto, K.M., Liu, X., Sun, M., Linge, N., 2019. Low-complexity non-intrusive load monitoring using unsupervised learning and generalized appliance models. IEEE Trans. Consum. Electron. 65, 28–37. http://dx.doi.org/10.1109/TCE.2019.2891160.

Liu, M., Pang, Y., Zhang, B., De Luna, P., Voznyy, O., Xu, J., et al., 2016. Enhanced electrocatalytic CO2 reduction via field-induced reagent concentration. Nature 537, 382–386. http://dx.doi.org/10.1038/nature19060.

Liu, G., Yang, J., Hao, Y., Zhang, Y., 2018. Big data-informed energy efficiency assessment of China industry sectors based on K-means clustering. J. Clean. Prod. 183, 304–314. http://dx.doi.org/10.1016/j.jclepro.2018.02.129.

Liu, Q., Zhang, Q.J., 2016. Accuracy improvement of energy prediction for solar-energy-powered embedded systems. IEEE Trans. Very Large Scale Integr. (VLSI) Syst. 24, 2062–2074. http://dx.doi.org/10.1109/TVLSI.2015.2497147.

Loebbecke, C., Picot, A., 2015. Reflections on societal and business model transformation arising from digitization and big data analytics: A research agenda. J. Strateg. Inf. Syst. 24, 149–157. http://dx.doi.org/10.1016/j.jsis.2015.08.002.

Luan, W., Peng, J., Maras, M., Lo, J., Harapnuk, B., 2015. Smart meter data analytics for distribution network connectivity verification. IEEE Trans. Smart Grid 6, 1964–1971. http://dx.doi.org/10.1109/TSG.2015.2421304.

Luo, Z., Yang, X., Wang, Y., Liu, W., Liu, S., Zhu, Y., et al., 2020. A survey of artificial intelligence techniques applied in energy storage materials r & d. Front. Energy Res. 8. http://dx.doi.org/10.3389/fenrg.2020.00116.

Ma, S., Chen, M., Wu, J., Wang, Y., Jia, B., Jiang, Y., 2018. High-voltage circuit breaker fault diagnosis using a hybrid feature transformation approach based on random forest and stacked auto-encoder. IEEE Trans. Ind. Electron. 66, 9777–9788. http://dx.doi.org/10.1109/TIE.2018.2879308.

Makala, B., Bakovic, T., 2020. Artificial Intelligence in the Power Sector. Int Financ Corp, https://www.ifc.org/wps/wcm/connect/bd3a196d-a88f-45af-bbc6-e0b00790fba8/EMCompass_Note_81-05-web.pdf?MOD=AJPERES&CVID=n72pj5g.

Mann, S.A., Grote, R.R., Osgood, R.M., Alù, A., Garnett, E.C., 2016. Opportunities and limitations for nanophotonic structures to exceed the Shockley-Queisser limit. ACS Nano 10, 8620–8631. http://dx.doi.org/10.1021/acsnano.6b03950.

Marx, D., Magne, P., Nahid-Mobarakeh, B., Pierfederici, S., Davat, B., 2012. Large signal stability analysis tools in DC power systems with constant power loads and variable power loads-A review. IEEE Trans. Power Electron. 27, 1773–1787. http://dx.doi.org/10.1109/TPEL.2011.2170202.

Massoud Amin, S., Wollenberg, B.F., 2005. Toward a smart grid: Power delivery for the 21st century. IEEE Power Energy Mag. 3, 34–41. http://dx.doi.org/10.1109/mpae.2005.1507024.

Matemilola, S., Fadeyi, O., Sijuade T. Paris Agreement, 2020. Encycl. Sustain. Manag. 1–5. http://dx.doi.org/10.1007/978-3-030-02006-4_516-1.

Mayer, M.J., Szilágyi, A., Gróf, G., 2020. Environmental and economic multi-objective optimization of a household level hybrid renewable energy system by genetic algorithm. Appl. Energy 269, 115058. http://dx.doi.org/10.1016/j.apenergy.2020.115058.

Mbuwir, B.V., Spiessens, F., Deconinck, G., 2020. Distributed optimization for scheduling energy flows in community microgrids. Electr. Power Syst. Res. 187, 106479. http://dx.doi.org/10.1016/j.epsr.2020.106479.

Megahed, T.F., Abdelkader, S.M., Zakaria, A., 2019. Energy management in zero-energy building using neural network predictive control. IEEE Internet of Things J. 6, 5336–5344. http://dx.doi.org/10.1109/JIOT.2019.2900558.

Mehmood, M.U., Chun, D., Zeeshan, Han, H., Jeon, G., Chen, K., 2019. A review of the applications of artificial intelligence and big data to buildings for energy-efficiency and a comfortable indoor living environment. Energy Build. 202, 109383. http://dx.doi.org/10.1016/j.enbuild.2019.109383.

Meng, J., Cai, L., Stroe, D.I., Ma, J., Luo, G., Teodorescu, R., 2020. An optimized ensemble learning framework for lithium-ion battery state of health estimation in energy storage system. Energy 206, 118140. http://dx.doi.org/10.1016/j.energy.2020.118140.

Mikučioniene, R., Martinaitis, V., Keras, E., 2014. Evaluation of energy efficiency measures sustainability by decision tree method. Energy Build. 76, 64–71. http://dx.doi.org/10.1016/j.enbuild.2014.02.048.

Mohamed, A., Salehi, V., Mohammed, O., 2012. Real-time energy management algorithm for mitigation of pulse loads in hybrid microgrids. IEEE Trans. Smart Grid 3, 1911–1922. http://dx.doi.org/10.1109/TSG.2012.2200702.

Mohammadi, M., Al-Fuqaha, A., Guizani, M., Oh, J.S., 2018. Semisupervised deep reinforcement learning in support of IoT and smart city services. IEEE Internet of Things J. 5, 624–635. http://dx.doi.org/10.1109/JIOT.2017.2712560.

Mohanta, B.K., Jena, D., Satapathy, U., Patnaik, S., 2020. Survey on IoT security: Challenges and solution using machine learning, artificial intelligence and blockchain technology. Internet of Things 11, 100227. http://dx.doi.org/10.1016/j.iot.2020.100227.

Moutis, P., Skarvelis-Kazakos, S., Brucoli, M., 2016. Decision tree aided planning and energy balancing of planned community microgrids. Appl. Energy 161, 197–205. http://dx.doi.org/10.1016/j.apenergy.2015.10.002.

Munir, M.S., Abedin, S.F., Tran, N.H., Hong, C.S., 2019. When edge computing meets microgrid: A deep reinforcement learning approach. IEEE Internet of Things J. 6, 7360–7374. http://dx.doi.org/10.1109/JIOT.2019.2899673.

Ng, S.S.Y., Xing, Y., Tsui, K.L., 2014. A Naive Bayes model for robust remaining useful life prediction of lithium-ion battery. Appl. Energy 118, 114–123. http://dx.doi.org/10.1016/j.apenergy.2013.12.020.

Nguyen, M.T., Truong, L.H., Tran, T.T., Chien, C.F., 2020. Artificial intelligence based data processing algorithm for video surveillance to empower industry 3.5. Comput. Ind. Eng. 148, 106671. http://dx.doi.org/10.1016/j.cie.2020.106671.

Niazi, K.A.K., Akhtar, W., Khan, H.A., Yang, Y., Athar, S., 2019. Hotspot diagnosis for solar photovoltaic modules using a Naive Bayes classifier. Sol. Energy 190, 34–43. http://dx.doi.org/10.1016/j.solener.2019.07.063.

NITI Aayog, 2018. National Strategy for Artificial Intelligence Acknowledgments. p. 115, https://niti.gov.in/writereaddata/files/document_publication/NationalStrategy-for-{AI}-Discussion-Paper.pdf.

Notten, P.H.L., Veld, J.H.G.O.H., Van Beek, J.R.G., 2005. Boostcharging Li-ion batteries: A challenging new charging concept. J. Power Sources 145, 89–94. http://dx.doi.org/10.1016/j.jpowsour.2004.12.038.

Ospina, J., Gupta, N., Newaz, A., Harper, M., Faruque, M.O., Collins, E.G., et al., 2019. Sampling-based model predictive control of PV-integrated energy storage system considering power generation forecast and real-time price. IEEE Power Energy Technol. Syst. J. 6, 195–207. http://dx.doi.org/10.1109/jpets.2019.2935703.

Ouahiba, T., Fatima, B., Thafath, H., 2018. Smart buildings and occupants satisfaction: The case of cyber park of sidi abdallâh and some residential buildings in Algeria. Lect Notes Netw. Syst. 35, 3–14. http://dx.doi.org/10.1007/978-3-319-73192-6_1.

Oughton, E.J., Ralph, D., Pant, R., Leverett, E., Copic, J., Thacker, S., et al., 2019. Stochastic counterfactual risk analysis for the vulnerability assessment of cyber-physical attacks on electricity distribution infrastructure networks. Risk Anal. 39, 2012–2031. http://dx.doi.org/10.1111/risa.13291.

P., K., Vijaya Chandrakala, K.R.M., 2020. New interactive agent based reinforcement learning approach towards smart generator bidding in electricity market with micro grid integration. Appl. Soft Comput. 106762.

Pack, B., Fall, P., Market, A., Up, R., Market, W., 2019. Battery Pack Prices Fall as Market Ramps Up with Market Average At $156/KWh in 2019. BloombergNEF 2019:Veronika Henze, https://about.bnef.com/blog/battery-pack-prices-fall-as-market-ramps-up-with-market-average-at-156-kwh-in-2019/.

Padma K., Preeti, 2020. Nanotechnology and its applications in medicine, energy and transportation. Ind Wired 2020, https://industrywired.com/nanotechnology-and-its-applications-in-medicine-energy-and-transportation/. (Accessed 10 April 2020).

Pan, J., Jain, R., Paul, S., Vu, T., Saifullah, A., Sha, M., 2015. An Internet of Things framework for smart energy in buildings: Designs, prototype, and experiments. IEEE Internet of Things J. 2, 527–537. http://dx.doi.org/10.1109/JIOT.2015.2413397.

Park, L., Jeong, S., Kim, J., Cho, S., 2019. Joint geometric unsupervised learning and truthful auction for local energy market. IEEE Trans. Ind. Electron. 66, 1499–1508. http://dx.doi.org/10.1109/TIE.2018.2849979.

Pesaran, H.A.M., Nazari-Heris, M., Mohammadi-Ivatloo, B., Seyedi, H., 2020. A hybrid genetic particle swarm optimization for distributed generation allocation in power distribution networks. Energy 209, 118218. http://dx.doi.org/10.1016/j.energy.2020.118218.

Phuyal, S., Bista, D., Bista, R., 2020. Challenges, opportunities and future directions of smart manufacturing: A state of art review. Sustain. Futur. 2, 100023. http://dx.doi.org/10.1016/j.sftr.2020.100023.

Pinto, T., Faia, R., Navarro-Caceres, M., Santos, G., Corchado, J.M., Vale, Z., 2019. Multi-agent-based CBR recommender system for intelligent energy management in buildings. IEEE Syst. J. 13, 1084–1095. http://dx.doi.org/10.1109/JSYST.2018.2876933.

Poitiers, F., M. Machmoum, R.L., MEAD, 2001. Control of a doubly-fed induction generator for wind energy conversion systems. IEEE Trans. Renew. Energy 3, 373–378.

Pumera, M., 2011. Graphene-based nanomaterials for energy storage. Energy Environ. Sci. 4, 668–674. http://dx.doi.org/10.1039/c0ee00295j.

Qiu, S., Li, S., Wang, F., Wen, Y., Li, Z., Li, Z., et al., 2019. An energy exchange efficiency prediction approach based on multivariate polynomial regression for membrane-based air-to-air energy recovery ventilator core. Build. Environ. 149, 490–500. http://dx.doi.org/10.1016/j.buildenv.2018.12.052.

Ramirez, A.D., Boero, A., Rivela, B., Melendres, A.M., Espinoza, S., Salas, D.A., 2020. Life cycle methods to analyze the environmental sustainability of electricity generation in ecuador: Is decarbonization the right path? Renew. Sustain. Energy Rev. 134, 110373. http://dx.doi.org/10.1016/j.rser.2020.110373.

Reddy, M.V., Sodhi, R., 2018. A modified S-transform and random forests-based power quality assessment framework. IEEE Trans. Instrum. Meas. 67, 78–89. http://dx.doi.org/10.1109/TIM.2017.2761239.

Research, G., 2017. GTM: Us energy storage installations grew 100% in 2016. https://www.energy-storage.news/news/gtm-us-energy-storage-installations-grew-100-in-2016.

Rhodes, A., 2020. Digitalisation of Energy. Imp Collage London, pp. 1–48, https://file:///C:/Users/IOSTC/Downloads/Digitalisation%20of%20Energy-%20An%20Energy%20Futures%20Lab%20Briefling%20Paper%20(4).pdf.

Ruhnau, O., Hennig, P., Madlener, R., 2020. Economic implications of forecasting electricity generation from variable renewable energy sources. Renew. Energy 161, 1318–1327. http://dx.doi.org/10.1016/j.renene.2020.06.110.

Sachs, D.S., 2017. Cyber Attacks and the Energy Sector. pp. 1–8, https://ankura.com/insights/cyber-attacks-and-the-energy-sector/. (Accessed 17 October 2020).

Schütz, T., Schraven, M.H., Fuchs, M., Remmen, P., Müller, D., 2018. Comparison of clustering algorithms for the selection of typical demand days for energy system synthesis. Renew. Energy 129, 570–582. http://dx.doi.org/10.1016/j.renene.2018.06.028.

Serban, A.C., Lytras, M.D., 2020. Artificial intelligence for smart renewable energy sector in Europe - Smart energy infrastructures for next generation smart cities. IEEE Access 8, 77364–77377. http://dx.doi.org/10.1109/ACCESS.2020.2990123.

Sharma, G.D., Yadav, A., Chopra, R., 2020. Artificial intelligence and effective governance: A review, critique and research agenda. Sustain. Futur. 2, 100004. http://dx.doi.org/10.1016/j.sftr.2019.100004.

Sheehan, S.W., Noh, H., Brudvig, G.W., Cao, H., Schmuttenmaer, C.A., 2013. Plasmonic enhancement of dye-sensitized solar cells using core-shell-shell nanostructures. J. Phys. Chem. C 117, 927–934. http://dx.doi.org/10.1021/jp311881k.

Shi, Z., Yao, W., Li, Z., Zeng, L., Zhao, Y., Zhang, R., et al., 2020. Artificial intelligence techniques for stability analysis and control in smart grids: Methodologies, applications, challenges and future directions. Appl. Energy 278, 115733. http://dx.doi.org/10.1016/j.apenergy.2020.115733.

Sidhu, T.S., Ao, Z., 1995. On-line evaluation of capacity and energy losses in power transmission systems by using artificial neural networks. IEEE Trans. Power Deliv. 10, 1913–1919. http://dx.doi.org/10.1109/61.473363.

Singh, S.K., Rathore, S., Park, J.H., 2020a. Blockiotintelligence: A blockchain-enabled intelligent IoT architecture with artificial intelligence. Future Gen. Comput. Syst. 110, 721–743. http://dx.doi.org/10.1016/j.future.2019.09.002.

Singh, S., Sharma, P.K., Yoon, B., Shojafar, M., Cho, G.H., Ra, I.H., 2020b. Convergence of blockchain and artificial intelligence in IoT network for the sustainable smart city. Sustain. Cities Soc. 63, 102364. http://dx.doi.org/10.1016/j.scs.2020.102364.

Strasser, T., Andrén, F., Kathan, J., Cecati, C., Buccella, C., Siano, P., et al., 2015. A review of architectures and concepts for intelligence in future electric energy systems. IEEE Trans. Ind. Electron. 62, 2424–2438. http://dx.doi.org/10.1109/TIE.2014.2361486.

Su, H.Y., Liu, T.Y., Hong, H.H., 2020. Adaptive residual compensation ensemble models for improving solar energy generation forecasting. IEEE Trans. Sustain. Energy 11, 1103–1105. http://dx.doi.org/10.1109/TSTE.2019.2931154.

Suman, S., 2021. Artificial intelligence in nuclear industry: Chimera or solution? J. Clean. Prod. 278, 124022. http://dx.doi.org/10.1016/j.jclepro.2020.124022.

Sung, M., Ko, Y., 2015. Machine-learning-integrated load scheduling for reduced peak power demand. IEEE Trans. Consum. Electron. 61, 167–174. http://dx.doi.org/10.1109/TCE.2015.7150570.

Tapia, A., Reina, D.G., Millán, P., 2020. Optimized micro-hydro power plants layout design using messy genetic algorithms. Expert Syst. Appl. 159, 113539. http://dx.doi.org/10.1016/j.eswa.2020.113539.

Teegala, S.K., Singal, S.K., 2016. Optimal costing of overhead power transmission lines using genetic algorithms. Int. J. Electr. Power Energy Syst. 83, 298–308. http://dx.doi.org/10.1016/j.ijepes.2016.04.031.

Thakker, A.Y., 2019. By the Numbers: India's Progress on Its Renewable Energy Target. CSIS CogitAsia n.d., https://www.cogitasia.com/by-the-numbers-indias-progress-on-its-renewable-energy-target/.

Thoben, K.D., Wiesner, S.A., T., Wuest, 2017. "Industrie 4.0" and smart manufacturing-a review of research issues and application examples. Int. J. Autom. Technol. 11, 4–16. http://dx.doi.org/10.20965/ijat.2017.p0004.

Toopshekan, A., Yousefi, H., Astaraei, F.R., 2020. Technical, economic, and performance analysis of a hybrid energy system using a novel dispatch strategy. Energy 213, 118850. http://dx.doi.org/10.1016/j.energy.2020.118850.

Torres, J., Guardado, J.L., Rivas-Dávalos, F., Maximov, S., Melgoza, E., 2013. A genetic algorithm based on the edge window decoder technique to optimize power distribution systems reconfiguration. Int. J. Electr. Power Energy Syst. 45, 28–34. http://dx.doi.org/10.1016/j.ijepes.2012.08.075.

Tran-Dang, H., Krommenacker, N., Charpentier, P., Kim, D.S., 2020. Toward the internet of things for physical internet: Perspectives and challenges. IEEE Internet of Things J. 7, 4711–4736. http://dx.doi.org/10.1109/JIOT.2020.2971736.

Tso, W.W., Demirhan, C.D., Heuberger, C.F., Powell, J.B., Pistikopoulos, E.N., 2020. A hierarchical clustering decomposition algorithm for optimizing renewable power systems with storage. Appl. Energy 270, 115190. http://dx.doi.org/10.1016/j.apenergy.2020.115190.

Tushar, W., Saha, T.K., Yuen, C., Smith, D., Ashworth, P., Poor, H.V., et al., 2020. Challenges and prospects for negawatt trading in light of recent technological developments. Nature Energy 1–8. http://dx.doi.org/10.1038/s41560-020-0671-0.

U.S. DOE, 2017. DOE Global Energy Storage Database. United States Department of Energy. Office of Electricity & Energy Reliability., Database 2017, http://www.energystorageexchange.org/projects. (Accessed 10 July 2020).

del Valle, Y., Venayagamoorthy, G.K., Mohagheghi, S., Hernandez, J.C., Harley, R.G., 2008. Particle swarm optimization: Basic concepts, variants and applications in power systems. IEEE Trans. Evol. Comput. 12, 171–195. http://dx.doi.org/10.1109/TEVC.2007.896686.

Venayagamoorthy, G.K., Sharma, R.K., Gautam, P.K., Ahmadi, A., 2016. Dynamic energy management system for a smart microgrid. IEEE Trans. Neural Netw. Learn. Syst. 27, 1643–1656. http://dx.doi.org/10.1109/TNNLS.2016.2514358.

Vinuesa, R., Azizpour, H., Leite, I., Balaam, M., Dignum, V., Domisch, S., et al., 2020. The role of artificial intelligence in achieving the sustainable development goals. Nature Commun. 11. http://dx.doi.org/10.1038/s41467-019-14108-y.

Vogel, L., Richard, P., Brey, M., Mamel, S., Schätz, K., 2019. Artificial Intelligence for the Integrated Energy Transition. Dtsch Energie-Agentur GmbH, pp. 1–55, https://www.dena.de/fileadmin/dena/Publikationen/PDFs/2019/dena-REPORT_Artificial_Intelligence_for_the_Integrated_Energy_Transition.pdf.

Vyas, B.Y., Das, B., Maheshwari, R.P., 2016. Improved fault classification in series compensated transmission line: Comparative evaluation of Chebyshev neural network training algorithms. IEEE Trans. Neural Netw. Learn. Syst. 27, 1631–1642. http://dx.doi.org/10.1109/TNNLS.2014.2360879.

Wang, H., Keerthipala, W.W.L., 1998. Fuzzy-neuro approach to fault classification for transmission line protection. IEEE Trans. Power Deliv. 13, 1093–1102. http://dx.doi.org/10.1109/61.714467.

Wang, H., Lei, Z., Zhang, X., Zhou, B., Peng, J., 2019. A review of deep learning for renewable energy forecasting. Energy Convers. Manage. 198, 111799. http://dx.doi.org/10.1016/j.enconman.2019.111799.

Wang, S., Liu, H., Pu, H., Yang, H., 2020a. Spatial disparity and hierarchical cluster analysis of final energy consumption in China. Energy 197, 117195. http://dx.doi.org/10.1016/j.energy.2020.117195.

Wang, H., Liu, Y., Zhou, B., Li, C., Cao, G., Voropai, N., et al., 2020b. Taxonomy research of artificial intelligence for deterministic solar power forecasting. Energy Convers. Manage. 214, 112909. http://dx.doi.org/10.1016/j.enconman.2020.112909.

Wang, X., Yao, C., Wang, F., Li, Z., 2018. Cellulose-based nanomaterials for energy applications. Small 14, 1704152. http://dx.doi.org/10.1002/smll.201704152.

Wei, J., De Luna, P., Bengio, Y., Aspuru-Guzik, A., Sargent, E., 2017a. Use machine learning to find energy materials. Nature 552, 23–25. http://dx.doi.org/10.1038/d41586-017-07820-6.

Wei, N., Li, C., Peng, X., Li, Y., Zeng, F., 2019. Daily natural gas consumption forecasting via the application of a novel hybrid model. Appl. Energy 250, 358–368. http://dx.doi.org/10.1016/j.apenergy.2019.05.023.

Wei, P., Xia, S., Chen, R., Qian, J., Li, C., Jiang, X., 2020. A deep-reinforcement-learning-based recommender system for occupant-driven energy optimization in commercial buildings. IEEE Internet of Things J. 7, 6402–6413. http://dx.doi.org/10.1109/JIOT.2020.2974848.

Wei, Q., Xiong, F., Tan, S., Huang, L., Lan, E.H., Dunn, B., et al., 2017b. Porous one-dimensional nanomaterials: Design, fabrication and applications in electrochemical energy storage. Adv. Mater. 29, 1602300. http://dx.doi.org/10.1002/adma.201602300.

World Energy Investment 2019, 2019. World energy invest 2019. http://dx.doi.org/10.1787/4f4f25b4-en.

Xu, C., Chen, H., Xun, W., Zhou, Z., Liu, T., Zeng, Y., et al., 2019. Modal decomposition based ensemble learning for ground source heat pump systems load forecasting. Energy Build. 194, 62–74. http://dx.doi.org/10.1016/j.enbuild.2019.04.018.

Xu, H., Dominguez-Garcia, A.D., Sauer, P.W., 2020a. Optimal tap setting of voltage regulation transformers using batch reinforcement learning. IEEE Trans. Power Syst. 35, 1990–2001. http://dx.doi.org/10.1109/TPWRS.2019.2948132.

Xu, X., Xu, X., Jia, Y., Xu, Y., Xu, Z., Xu, Z., et al., 2020b. A multi-agent reinforcement learning-based data-driven method for home energy management. IEEE Trans. Smart Grid 11, 3201–3211. http://dx.doi.org/10.1109/TSG.2020.2971427.

Xu, Y., Zhang, M., Ye, L., Zhu, Q., Geng, Z., He, Y.L., et al., 2018. A novel prediction intervals method integrating an error & self-feedback extreme learning machine with particle swarm optimization for energy consumption robust prediction. Energy 164, 137–146. http://dx.doi.org/10.1016/j.energy.2018.08.180.

Xu, Z., Zheng, Z., Gao, X., 2020c. Energy-efficient steelmaking-continuous casting scheduling problem with temperature constraints and its solution using a multi-objective hybrid genetic algorithm with local search. Appl. Soft Comput. J. 95, 106554. http://dx.doi.org/10.1016/j.asoc.2020.106554.

Yan, Z., Xu, Y., 2020. Real-time optimal power flow: A Lagrangian based deep reinforcement learning approach. IEEE Trans. Power Syst. 35, 3270–3273. http://dx.doi.org/10.1109/TPWRS.2020.2987292.

Yang, L., He, M., Zhang, J., Vittal, V., 2015. Support-vector-machine-enhanced Markov model for short-term wind power forecast. IEEE Trans. Sustain. Energy 6, 791–799. http://dx.doi.org/10.1109/TSTE.2015.2406814.

Yang, X., Luo, Z., Huang, Z., Zhao, Y., Xue, Z., Wang, Y., et al., 2020. Development status and prospects of artificial intelligence in the field of energy conversion materials. Front. Energy Res. 8. http://dx.doi.org/10.3389/fenrg.2020.00167.

Yang, H., Zhang, J., Qiu, J., Zhang, S., Lai, M., Dong, Z.Y., 2018. A practical pricing approach to smart grid demand response based on load classification. IEEE Trans. Smart Grid 9, 179–190. http://dx.doi.org/10.1109/TSG.2016.2547883.

Yassine, A., Singh, S., Hossain, M.S., Muhammad, G., 2019. IoT big data analytics for smart homes with fog and cloud computing. Future Gen. Comput. Syst. 91, 563–573. http://dx.doi.org/10.1016/j.future.2018.08.040.

Yildirim, M.B., Mouzon, G., 2012. Single-machine sustainable production planning to minimize total energy consumption and total completion time using a multiple objective genetic algorithm. IEEE Trans. Eng. Manage. 59, 585–597. http://dx.doi.org/10.1109/TEM.2011.2171055.

Yip, S.C., Wong, K.S., Hew, W.P., Gan, M.T., Phan, R.C.W., Tan, S.W., 2017. Detection of energy theft and defective smart meters in smart grids using linear regression. Int. J. Electr. Power Energy Syst. 91, 230–240. http://dx.doi.org/10.1016/j.ijepes.2017.04.005.

Yousri, D., Babu, T.S., Mirjalili, S., Rajasekar, N., Elaziz, M.A., 2020. A novel objective function with artificial ecosystem-based optimization for relieving the mismatching power loss of large-scale photovoltaic array. Energy Convers. Manage. 225, 113385. http://dx.doi.org/10.1016/j.enconman.2020.113385.

Yu, F.W., Ho, W.T., 2019. Load allocation improvement for chiller system in an institutional building using logistic regression. Energy Build. 201, 10–18. http://dx.doi.org/10.1016/j.enbuild.2019.07.044.

Yu, L., Xie, W., Xie, D., Zou, Y., Zhang, D., Sun, Z., et al., 2020. Deep reinforcement learning for smart home energy management. IEEE Internet of Things J. 7, 2751–2762. http://dx.doi.org/10.1109/JIOT.2019.2957289.

Yuan, Qian S., Hong, Jia Z., Li, K., 2020. A multi-objective evolutionary algorithm based on adaptive clustering for energy-aware batch scheduling problem. Future Gen. Comput. Syst. 113, 441–453. http://dx.doi.org/10.1016/j.future.2020.06.010.

Yun, J., Jayababu, N., Kim, D., 2020. Self-powered transparent and flexible touchpad based on triboelectricity towards artificial intelligence. Nano Energy 78, 105325. http://dx.doi.org/10.1016/j.nanoen.2020.105325.

Zahmatkesh, H., Al-Turjman, F., 2020. Fog computing for sustainable smart cities in the IoT era: Caching techniques and enabling technologies - an overview. Sustain. Cities Soc. 59, 102139. http://dx.doi.org/10.1016/j.scs.2020.102139.

Zahraee, S.M., Khalaji Assadi, M., Saidur, R., 2016. Application of artificial intelligence methods for hybrid energy system optimization. Renew. Sustain. Energy Rev. 66, 617–630. http://dx.doi.org/10.1016/j.rser.2016.08.028.

Zatti, M., Gabba, M., Freschini, M., Rossi, M., Gambarotta, A., Morini, M., et al., 2019. k-MILP: A novel clustering approach to select typical and extreme days for multi-energy systems design optimization. Energy 181, 1051–1063. http://dx.doi.org/10.1016/j.energy.2019.05.044.

Zhang, D., 2020. A critical review of comparative global historical energy consumption and future demand: The story told so far. Energy Rep. 6, 1973–1991. http://dx.doi.org/10.1016/j.egyr.2020.07.020.

Zhang, D., Ahmad, T., 2021. Using the internet of things in smart energy systems and networks. Sustain. Cities Soc. 68, 102783. http://dx.doi.org/10.1016/j.scs.2021.102783.

Zhang, F., Che, R., Li, X., Yao, C., Yang, J., Shen, D., et al., 2012. Direct imaging the upconversion nanocrystal core/shell structure at the subnanometer level: Shell thickness dependence in upconverting optical properties. Nano Lett. 12, 2852–2858. http://dx.doi.org/10.1021/nl300421n.

Zhang, W., Gao, B., Tang, J., Yao, P., Yu, S., Chang, M.F., et al., 2020. Neuro-inspired computing chips. Nature Electron. 3, 371–382. http://dx.doi.org/10.1038/s41928-020-0435-7.

Zhang, H., Yan, B., 2020. A review on renewable energy and electricity requirement forecasting models for smart grid and buildings. Sustain. Cities Soc. 55, 102052. http://dx.doi.org/10.1016/j.scs.2020.102052.

Zhao, X., Wang, C., Su, J., Wang, J., 2019. Research and application based on the swarm intelligence algorithm and artificial intelligence for wind farm decision system. Renew. Energy 134, 681–697. http://dx.doi.org/10.1016/j.renene.2018.11.061.

Zhnag, D., 2020. Novel deep regression and stump tree-based ensemble models for real-time load demand planning and management. IEEE Access 8, 48030–48048.

Zhou, K., Fu, C., Yang, S., 2016. Big data driven smart energy management: From big data to big insights. Renew. Sustain. Energy Rev. 56, 215–225. http://dx.doi.org/10.1016/j.rser.2015.11.050.

Zhou, Y., Zhai, Q., Zhou, M., Li, X., 2020. Generation scheduling of self-generation power plant in enterprise microgrid with wind power and gateway power bound limits. IEEE Trans. Sustain. Energy 11, 758–770. http://dx.doi.org/10.1109/TSTE.2019.2905280.

Zhu, Y., Peng, L., Fang, Z., Yan, C., Zhang, X., Yu, G., 2018. Structural engineering of 2D nanomaterials for energy storage and catalysis. Adv. Mater. 30, 1706347. http://dx.doi.org/10.1002/adma.201706347.