

Review

Distributed Energy Resources and the Application of AI, IoT, and Blockchain in Smart Grids

Nallapaneni Manoj Kumar ^{1,*}, Aneesh A. Chand ², Maria Malvoni ³, Kushal A. Prasad ², Kabir A. Mamun ², F.R. Islam ⁴ and Shauhrat S. Chopra ^{1,*}

¹ School of Energy and Environment, City University of Hong Kong, Kowloon, Hong Kong

² School of Engineering and Physics, The University of the South Pacific, Suva, Fiji; aneeshamitesh@gmail.com (A.A.C.); kushalaniketp@gmail.com (K.A.P.); kabir.mamun@usp.ac.fj (K.A.M.)

³ School of Electrical and Computer Engineering, National Technical University of Athens, 15780 Zografou, Greece; maria.malvoni@gmail.com

⁴ School of Science and Engineering, University of Sunshine Coast, Sippy Downs, QLD 4556, Australia; fislam@usc.edu.au

* Correspondence: mnallapan2-c@my.cityu.edu.hk (N.M.K.); sschopra@cityu.edu.hk (S.S.C.)

Received: 1 August 2020; Accepted: 27 October 2020; Published: 2 November 2020



Abstract: Smart grid (SG), an evolving concept in the modern power infrastructure, enables the two-way flow of electricity and data between the peers within the electricity system networks (ESN) and its clusters. The self-healing capabilities of SG allow the peers to become active partakers in ESN. In general, the SG is intended to replace the fossil fuel-rich conventional grid with the distributed energy resources (DER) and pools numerous existing and emerging know-hows like information and digital communications technologies together to manage countless operations. With this, the SG will be able to “detect, react, and pro-act” to changes in usage and address multiple issues, thereby ensuring timely grid operations. However, the “detect, react, and pro-act” features in DER-based SG can only be accomplished at the fullest level with the use of technologies like Artificial Intelligence (AI), the Internet of Things (IoT), and the Blockchain (BC). The techniques associated with AI include fuzzy logic, knowledge-based systems, and neural networks. They have brought advances in controlling DER-based SG. The IoT and BC have also enabled various services like data sensing, data storage, secured, transparent, and traceable digital transactions among ESN peers and its clusters. These promising technologies have gone through fast technological evolution in the past decade, and their applications have increased rapidly in ESN. Hence, this study discusses the SG and applications of AI, IoT, and BC. First, a comprehensive survey of the DER, power electronics components and their control, electric vehicles (EVs) as load components, and communication and cybersecurity issues are carried out. Second, the role played by AI-based analytics, IoT components along with energy internet architecture, and the BC assistance in improving SG services are thoroughly discussed. This study revealed that AI, IoT, and BC provide automated services to peers by monitoring real-time information about the ESN, thereby enhancing reliability, availability, resilience, stability, security, and sustainability.

Keywords: smart microgrids; modern power system; power infrastructure; distributed energy resources; machine learning; deep learning; Internet of Things; blockchain; electricity system networks; peer to peer network; renewable energy resources; electric vehicle as DER; cybersecurity; smart grid services; resilience; automated services in microgrids; energy Internet

1. Background

As economies develop, energy consumption trends start growing more or less analogously to economic growth [1]. The main reason for this is the sturdy and constructive link between energy

consumption and economic development [2]. Similarly, energy is an indispensable input for social development [3]. Apart from energy, socio-economic growth is also influenced by global geopolitical scenarios, new technological developments, and available natural resources [2,4,5]. Since all these factors influence the socio-economic growth, it becomes quite challenging to predict the associated uncertainties, which again have an influence on the energy supply and demand patterns [4]. Any adverse shocks to the energy sector will negatively impact socio-economic development [2]. Thus, a quest for adequate, reliable, resilient, equitable, secure, and affordable energy supplies is given a primary priority [2]. On the other side, the Internet's role and other smart systems in social progress are highly noticeable and are expected to increase in the near future [6]. Besides, there have been raised concerns about environmental safety, and it is argued that future energy supplies should meet the low carbon and other clean energy standards [7]. Thus, smart and sustainable energy supplies are commanded to ensure socio-economic development. Therefore, the impacts on socio-economic developments from providing energy through renewable energy resources (RER) as a substitute for fossil fuel generation technologies are more significant [4]. The trend for using distributed energy resources (DER), particularly renewable energy (RE) and energy storage systems (ESS), in the conventional electric grid (CEG) and also in the present power system infrastructure, has been given high priority in most nations. However, DER and ESS have increased progressively in the modern power system [8]. The main reason for the increased use of DER is due to the need for developing a decarbonized energy sector for the future. Additionally, RER's energy security, consistent improvements in power conversion efficiencies, and RE technologies falling cost favor the DER growth [9].

The CEG is a centralized system that generally connects the many small and large power generation plants under one roof and steadily transfers the power from the remote-generation station to the demand centers through extended transmission lines. The power flow would be high to a low voltage level in such systems, creating the one-directional flow from the electricity systems networks (ESN) to consumers [10]. Whereas the RE-based DER, in most cases, is localized and small in terms of megawatt production, generated voltages are relative to conventional power plants. When RE is integrated into CEG, severe frequency fluctuation can be seen, and this is due to regular loss of energy mostly elicited by RE's intermittent nature. Therefore, its integration to CEG poses a constraint [11]. However, with technological evolution seen in the electrical infrastructure in recent years, the use of RE-based DER in the electric grid has become possible [11]. The CEG has transitioned to the next level and is aided by technological changes and innovative energy generation, transmission, and distribution approaches. For having a detailed considerate of the electric grid evolution, the significant events that took part in its journey are considered, and these are depicted in Figure 1. In addition, these significant events were briefly described, which are as follows.

- The electric battery's invention that produces a continuous supply of electric current by Alessandro Volta is the first most significant event in 1800.
- The discovery of electromagnetic induction by Michael Faraday is the second most significant event in 1831.
- The incandescent bulb development by Thomas Edison and Joseph Swan is the third most significant event that happened between the years 1878–1879. This event has spread its roots in developing new kinds of bulbs.
- The development of direct current (DC) streetlamps in New York, the United States of America (USA) in 1882, is the fourth most significant event.
- The widespread use of alternating current (AC) systems since 1886 is the fifth most significant and the fate changing event in electric grid evolution.
- The invention of the first working models of induction motor by two eminent scientists Nikola Tesla and Galileo Ferraris had revolutionized the alternating current power system. It is the most significant event in the evolution of the electric grid.

- The power plant infrastructure development for supplying energy to the small communities began to start in 1896. Different types of AC power generating units have evolved in other parts of the world, which is considered the seventh most significant event in the electric grid evolution.
- The commercialization of power metal-oxide-semiconductor field-effect transistor (MOSFET) is the eighth most significant event. It is regarded as another big game-changer in the electric grid's evolution, which allowed integrating RE technologies into the grid.
- The ninth most significant event in the electric grid evolution is the deregulation of wholesale power from renewables and other power plants.
- The interconnection of photovoltaics (PV) and other power plants into the electric grid infrastructure is the tenth most significant event.
- DER integration with the electric grid had become popular between 2003 and 2004, and it is the eleventh most significant event in the electric grid evolution.
- Between 2008 to 2010, the guidelines for implementing microgrids (MGs), nanogrids (NGs) have evolved. Later, the methodology for implementing pilot-scale smart grids (SGs) also became a discussion topic among researchers and industrialists.
- In 2011, the smart power infrastructure demonstration took place, which emphasized ensuring reliability and security with ESN's intelligent elements, which is the thirteenth most significant event.
- High penetration of renewables-based MGs with higher peak capacities has become quite popular since 2013, which is the most significant achievement in electric grid evolution.
- From 2014 onwards, grid modernization has taken place, and the SG's have become economically viable for power generation. Their integration with the electric grid has also become possible due to the availability of technology.

With the above highlighted 15 most significant events, the CEG has taken a massive transition and is backed up by many new technologies playing their roles in achieving the SG motive.

The rise of RE use for electrification and offered support by the electronic power industry has given the scope for the development of DER-based MG [12]. MG consists of RER, most commonly small in size, and mainly used for generating power locally and sometimes distributed. However, when it comes to functionality, MG suffers from ensuring flexibility in managing the energy between loads. Besides, the lack of smart modulation of peers in the ESN makes the MG operations difficult [13]. Also, the intermittent nature of RER and uncertainties associated with EES and the loads are quite unpredictable, and the existing MG control cannot tackle them at the fullest. Thus, the deployment of RER-based MG and other DER components in the ESN experiences' reliability and resilience issues opens up the scope for the smart modulation of peers (e.g., consumer, producer, prosumer, regulatory authority, etc.) [13]. Therefore, ESN needs active network management techniques. For this, the existing MG should undergo a digital transition. To maximize RER's use, spur the need to develop alternatives to MG, a next-generation digital electric grid system called the SG is needed [10,14].

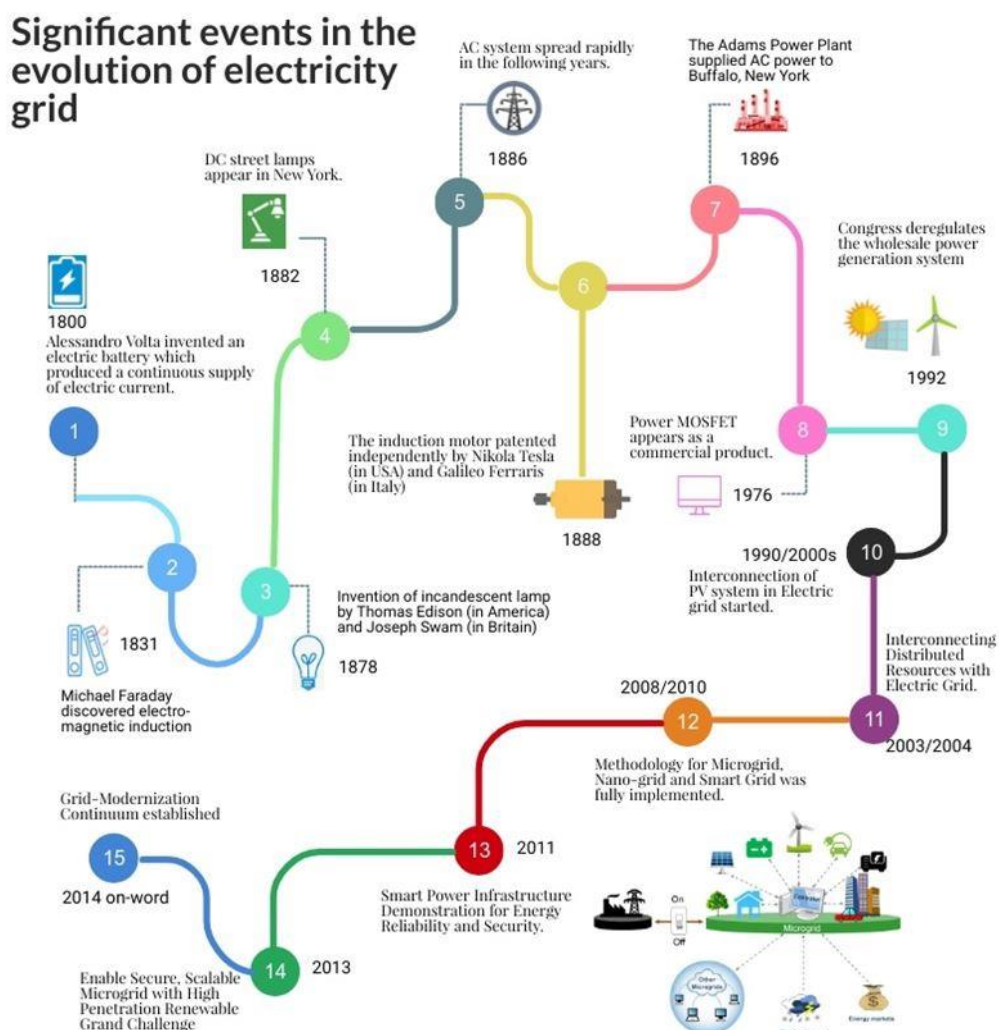


Figure 1. Fifteen most significant events in the evolution of the electricity grid (Note: DC—direct current, AC—alternating current, USA—United States of America, MOSFET—metal-oxide-semiconductor field-effect transistor).

1.1. Overview of a Smart Grid

Today, there is no generally acceptable SG definition. Its description and definition are not unique. It is still evolving, developing, and the concept is becoming more and more mature with time. The SG combines DER-based micro, mini, and nano-grids and supply systems control with a fine branch [15]. SG incorporates technology, structures, and protocols to make the ESN more intelligent and efficient. It is merely a radical modification of the existing ESN. In general, the SG is intended to substitute the fossil fuel-rich CEG with the DER and pools numerous existing and emerging know-hows like information and digital communications technologies together to manage countless operations [16]. The SG features such as computational ability, controllability, self-diagnosis, and healing pave the way for broader incorporation of RER, more active consumer and prosumer participation, the implementation of energy efficiency initiatives, and the consequent possible reduction of greenhouse gas (GHG) emissions. The SG enables the two-way flow of electricity and data between the ESN peers and its clusters. SG's self-healing capabilities allow the peers to become active partakers in ESN [17]. With this, the SG will be able to “detect, react, and pro-act” to disparities in usage and manifold issues and enhances the reliability, availability, resilience, stability, security, and, at the same time, ensures grid operations sustainably and affordably [13,18].

1.2. Role of Smart Grid in the Existing Power System and Its Implementation Barriers

As mentioned earlier in Section 1.1, SG is an intelligent digital electric grid with a pool of technologies and services. Depending upon the load type served and ESN type (e.g., residential, commercial, and industrial), the technologies and services used in SG vary, and they are clearly shown in Figure 2.

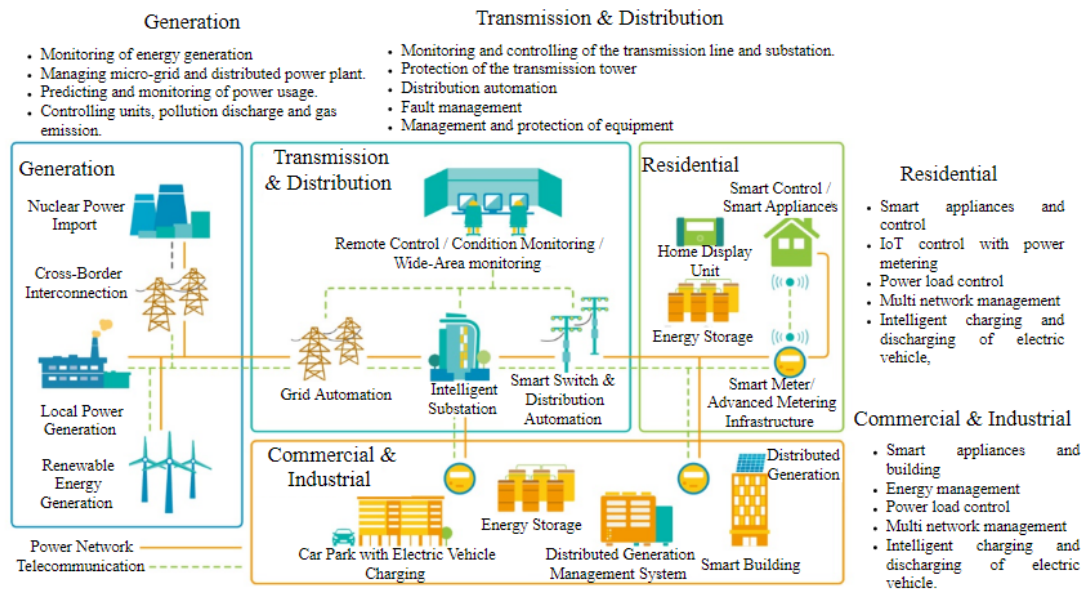


Figure 2. Smart grid services conceptual representation highlights renewable energy resources, energy storage systems, power electronics, information and communication technologies, energy management platforms, and cyber technologies.

From Figure 2, it can be understood that SG facilitates the consumers and prosumers to have increased choices in terms of controlling their electricity use and production. The SG also helps prosumers respond to electricity prices based on the changes in consumption and generation patterns. Not only the residential, commercial, and industrial loads, SG also facilitates connection and integrated operation with electric vehicle (EV) charging systems. In brief, “SG brings all elements of the electricity system production, delivery, and consumption closer together to improve overall system operation for the benefit of consumers and the environment.” Overall, the SG enhances ESN operation and control in the three significant domains (generation, transmission, and distributions) [19].

The existing SG framework is combined with multiple design scenarios and varies based on the operational area or the deployed application. Few of those operations and applications include energy-dependent operations in smart cities, energy-related home operations computerization, and energy conservation schemes by considering metering and tracking processes [20]. SG technologies and concepts will significantly reduce RER barriers and allow power grids to support a more significant percentage of variable and intermittent supplies from RER [21]. SG is crucial for the efficient use of DER and provides management of demand and supply of electricity from RE technologies and ESS by both users and suppliers of electricity.

One of SG’s crucial aims is to encourage peer’s active participation with automated transactions [20,22]. For building an automated distributed energy distribution network, data and data-driven decisions are needed. SG provides such data-driven decisions as they provide a two-way flow of electricity and the associated data. The SG’s smartness will allow for the time-shifting of electricity demand as influenced by RE’s intermittent nature and incorporation of ESS [23,24].

Overall, using SG, the CEG services will be replaced with high-level automation services, control techniques, sensors, computer servers for energy transaction record-keeping, power asset management platform, and many other new and emerging technologies, and all these are expected to operate

collectively, thereby enhancing the power grid operations [22]. SG's components will respond intelligently and digitally on time to the grid conditions based on energy demand, supply, and fault occurrences on the system working hand-in-hand to produce, deliver, and utilize energy most efficiently and reliably. With this, SG can automatically locate the fault, isolate it, and even restore services once the fault is cleared and record its activities on the grid performance data. This helps the grid reduce the number, impact, and duration of outages and interruptions [25].

Overall, the SG offers many benefits to the CEG. Here, the benefits associated with the renewable-based SG are summarized as follows.

- It enables a broader range of RER, DER, and ESS technologies that allow higher RE deployment with cost-effectiveness while increasing reliability and quality of power.
- Rapid response to ESS, such as flywheels, can address intermittency problems, enhancing the grid's overall reliability and power.
- Exchanges of real-time information make for a more flexible grid, achieving almost complete forecasting.
- Greater visibility enhances strategies for the price of forecasting.
- Assimilating clients into the power network as active players; energy savings made by reducing the peak demands and increasing energy quality and lowered GHG emissions.
- Regulation of voltage and subsequent load allows operating costs to be minimized based on the marginal output cost.

Even though SG offers many benefits, its implementation is also a challenging one. The challenges mainly lie with technology use. In addition to the technology, for the successful implementation of SG, each country needs to develop and articulate its SG vision, strategies, and means of achieving it. This helps to motivate fervor and resources (both technical and capital) toward modernizing the existing electric grid infrastructure.

Digital energy vision and its full understanding are fundamental for a smooth transition from conventional to SG systems and deploying existing and emerging technologies. Change to SG can be gradual and piecemeal until its full implementation is realized. It can start from the existing grid by introducing each of the SG technologies one at a time. It can also begin with a small pilot project as a nano grid, mini-grid, or microgrid in a remote geographical location and gradually be improved and extended. There are already numbers of such SG pilot projects worldwide in the USA, South Korea, Austria, and Canada. Furthermore, most countries in the advanced world are already gradually upgrading their existing grid to SG.

The obstacle to implementing SG reflects the preposition of interest by the provider and the consumer, accompanied by regulatory restrictions and technical norms obstructing SG solutions [26]. On the other side, issues associated with information flow, communication between the peers, and ESN resources management must be addressed. The question is, who will be managing these, the human workforce, or the digitalization? What would be an efficient way?

Furthermore, the questions related to ensuring reliability, resilience, and security should be considered while designing SG. Additionally, ensuring the computational and energy efficiency of the SG operations as it undergoes digitalization becomes critical. For handling such digital operations, computational tools are suggested. Possibly, fast computing methodologies have become one of the most vital tools in determining an SG service's success in the market. There exist numerous computational and digital tools, which include artificial intelligence (AI) [27,28], Internet-of-Things (IoT) [29–31], Big Data analytics [32–34], machine learning [35,36], deep learning [37–39], cloud computing [40–42], and Blockchain (BC) [43–45]. These technologies have been intelligently applied with various applications in networking, manufacturing, building management, transportation, and shipping to construct energy-efficient and sustainable systems. We believe such technologies can be leveraged in the energy sector, especially in the SG operations.

In the literature, few studies were carried out by the researchers, and they showed the roles of these technologies in ESN operations [27–45]. On the other side, these promising technologies have gone through fast technological evolution in the past decade, and their applications have increased rapidly in ESN. Furthermore, new technologies are emerging, which enable data-driven decisions. Hence, this study discusses the SG and applications of AI, the IoT, and BC.

1.3. Key Contributions

This study mainly considers the three technologies, such as AI, IoT, and BC. Based on the considered technologies, a critical review is carried out to understand the offered services to the field of SG. The key contributions of this study are as follows.

- A comprehensive study of the DER, power electronics components and their control, electric vehicles (EVs) as load components, and communication and cybersecurity issues in SG are carried out.
- The techniques associated with AI, e.g., fuzzy logic (FL), knowledge-based systems (KbS), and artificial neural networks (ANN), have been briefly summarized, and their roles in DER-based SG are also thoroughly discussed.
- The IoT components, along with energy Internet architecture for SG applications, is presented.
- The role played by AI-based analytics in improving SG services is thoroughly presented.
- A comprehensive study on the IoT and BC enabled services like data sensing, data storage, secured, transparent, and traceable digital transactions among the peers within ESN and its clusters is carried out.
- Discussion is made on the AI, IoT, and BC to provide automated services to peers by monitoring the ESN's real-time information, determining reliability, availability, resilience, stability, security, and sustainability.

The paper is structured into ten sections. The role of numerous distributed energy resources and the DC, AC, and hybrid microgrids SG is briefly presented in Sections 2 and 3, respectively. The role of power electronic components and their control are briefly discussed in Section 4. In Section 5, the issues related to communication and cybersecurity are briefly presented. The application of AI, IoT, and Blockchain in SG is briefly discussed in Sections 6–8, respectively. The discussions in the context of reliability, availability, resilience, stability, security, and sustainability are made in Section 9, and, lastly, in Section 10, the concluding remarks were drawn.

2. Distributed Energy Resources in Smart Grids

The DER-based power system is a small to medium-scale decentralized power generation system that uses RER, and mostly these DER are located close to the load centers. DER provides an alternative or enhancement to the conventional power grid and can feed entire distribution systems [46,47].

DER-based onsite power generation is a less expensive option and a quick process, especially with the PV, wind turbine (WT), fuel cells, etc. Whereas the central power generating systems are relatively more extensive in installed peak capacities, their erection time is also relatively high compared to onsite DER-based power plants. The high-voltage transmission lines erection also takes more time [48]. DER reduces the load on electrical transmission lines. Besides, the DER-based ESN would offer energy to consumers at a lesser price.

At the same time, the DER-based ESN provides higher service reliability, improved power quality, and ensures consumer's energy independence. When DER uses any renewable technology, it has an excellent contribution to the power generation mix and is a part of the green solution for a sustainable environment. Government, policymakers, and power engineers worldwide are encouraging the incorporation of DER, primarily RER-based MG and SG, into power distribution systems. In recent years, nano-grids and mini-grids have also become quite popular in the ESN.

As mentioned earlier in Sections 1.1 and 1.2, the integration of DER into the CEG at the distribution level poses several technical challenges: islanding, grid stability, power quality issues, frequency variation, and reverse power flow [49–51]. These challenges can be adequately taken care of in the SG system. DER can be categorized as controllable loads such as distributed generation (DG), EES, and Demand Side Management (DSM).

In the following subsections, various types of DER that are used in SG are discussed.

2.1. Distributed Generation Technologies

DG is the small-scale power plants that feed MG that are a part of an SG. As mentioned earlier, these are small distribution units and are usually located very close to the load it powers [52].

In general, diverse energy resources can be integrated to form electrical energy systems to provide the locality's power needs. It can either be renewable or non-renewable generation. Non-renewable DG includes fossil fuel generation (e.g., coal, diesel, and natural gas). Renewable DG can be dispatchable in which the output power generated can be controlled by the amount of fuel injected into the system [53,54].

The dispatchable renewable DG includes hydro and biomass. Few non-dispatchable ones include solar PV and WT, in which the generated output cannot be controlled but is dependent on weather conditions.

Overall, the most common technologies for DG include only a selected DG considered here [8,53,54]:

- Solar PV power plants (SPVPP)
- Wind power plants (WPP)
- Hydroelectric power generation (HPG)
- Thermal power plants (TPP)
- Nuclear power plant (NPP)
- Energy storage systems (ESS)

Apart from the ESS, the electric loads that are integrated with the SG would include as follows:

- Electric vehicle (EV)
- Smart houses (SHs)
- Cities
- Factories

A typical schematic view of DG-based SG, showing various technologies used for power generation, is shown in Figure 3.

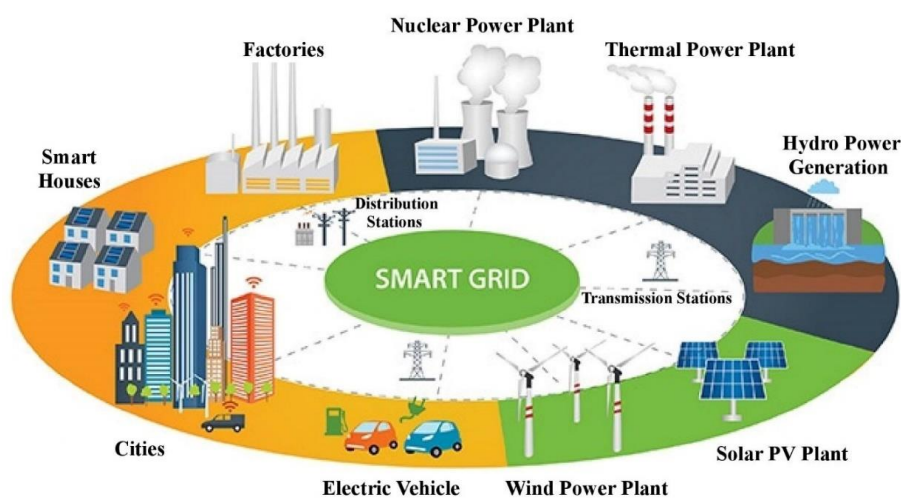


Figure 3. A schematic view of the smart grid showing a few of the dispatchable and non-dispatchable distributed generation technologies. Redrawn from Reference [53], 2018 eolas magazine.

A summary of the DG technologies highlighted in Figure 3 and a few others are explained briefly in the following subsections. The power modeling equations and related parameters that affect the power outputs are also briefly discussed in Table 1.

Table 1. Power modeling equations of different distributed energy resource technologies [13,55,56].

Distributed Energy Resources	Power Modeling Equation	Description of the Equation Parameters
Solar photovoltaics	$P_{PV} = \eta_{PV} \times \eta_{Inv} \times A_{PV} \times G_{PV} \times [1 + \gamma(T_{amb} + m_c \left(\frac{0.32}{8.91 + 2W_s} \right) G_{PV} - T_{ref})]$	<ul style="list-style-type: none"> The power output from the solar photovoltaic array is denoted by P_{PV} and is typically measured in kW. The efficiency parameters of the solar photovoltaic array and the inverter are denoted by η_{PV} and η_{Inv} and is typically given as a percentage. The area of the solar photovoltaic array is denoted by A_{PV} and is measured in m^2. The incident solar irradiance on the solar photovoltaic array is given by G_{PV} and typically measured in kW/m^2. The temperature coefficient of the solar photovoltaic module is given by γ and is measured in $\%/^{\circ}C$. The reference and ambient temperature at the installed location of the solar photovoltaic array is denoted by T_{ref} and T_{amb} and typically measured in $^{\circ}C$. Based on the installation type, the mounting co-efficient for the solar photovoltaic array can be decided and is denoted by m_c. The wind speeds experienced by the solar photovoltaic array at the installed site are denoted by W_s and typically measured in m/s.
Wind turbine	$P_m = \frac{1}{2} C_p \rho_a A v^3$	<ul style="list-style-type: none"> The power produced by the wind turbine is given by P_m and is typically measured in kW. The wind turbine's co-efficient of power is denoted by C_p. The density of the air is denoted by ρ_a. The wind turbine's swept area created by the wind blades is indicated by A and is typically measured in m^2. The incoming wind that hits the turbine blades with speed is indicated by v, measured in m/s.
Biomass energy	$P_{BG} = \frac{\eta_{BG} \times m_{BG} \times HV_{BG}}{3.6}$	<ul style="list-style-type: none"> Here, the BG represents the biogas generator. The output power from the BG is denoted by P_{BG} and typically measured in kW. The BG's power conversion efficiency is denoted by η_{BG} as a percentage. The biogas or other biomass-derived fuel's mass flow rate is indicated by m_{BG} and the units are kg/h. The biogas or biomass-derived fuel's heating value is given by HV_{BG} in MJ/kg.
Hydropower	$P_{HPG} = \eta \rho_w Q g h$	<ul style="list-style-type: none"> The power output from the hydro-power generation plant is denoted by P_{HPG} and the typical units are kW. The water density is denoted by ρ_w in kg/m^3. The dimensionless power conversion efficiency of the water turbine is denoted by η. The flow of water in the penstock is denoted by Q, and the units are m^3/s.
Battery energy storage	<p>State of the charge equation:</p> $E_{Bat}(t) = E_{Bat}(t-1)(1-\sigma) + [E_{Gen}(t) - \frac{E_{Required}(t)}{\eta_{Inv}}] \eta_B$ <p>Depth of the discharge equation:</p> $E_{Bat}(t) = E_{Bat}(t-1)(1-\sigma) - \left[\frac{E_{Required}(t)}{\eta_{Inv}} - E_{Gen}(t) \right]$	<ul style="list-style-type: none"> The energy stored in the battery is denoted by $E_{Bat}(t)$ and $E_{Bat}(t-1)$ for the time t and $t-1$. The units are Wh. The self-discharge rate on an hourly basis is given by σ. The hourly load demanded by the consumer power devices is represented in $E_{Required}(t)$. The efficiencies parameter of the inverter and battery energy storage system are η_{Inv} and η_B. The energy output generated for the time t by the distributed energy resources-based microgrid or smart grid is denoted by $E_{Gen}(t)$.

2.1.1. Solar Photovoltaic Power Plants

Solar PV power plants are the most commonly used renewables for power generation in the modern power system. At present, we see different types of SPVPP, e.g., rooftop, roof-integrated, building integrated, building attached, floating solar, etc. [57–60]. More or less, all these types of solar PV plants are capable of meeting the electricity loads with varying range and type from domestic to industrial. As of 2019, the global cumulative installed capacity is around 627 GW. In Figure 4, the cumulative installed PV capacities across the globe, measured in gigawatts (GW), are shown. Figure 3 shows that, among all other countries, China continues to lead in terms of its cumulative installations that accounted for approximately 204.7 GW. The European Union (EU), the USA, Japan, and India are also leading in global solar installations, and their cumulative installations are accounted

for 131.3 GW, 75.9 GW, 63.0 GW, and 42.8 GW, respectively [61]. Coming to the Asia-Pacific region alone, the cumulative PV installations in Australia and Korea were accounted for 14.6 GW and 11.2 GW, respectively, whereas, in the EU, Germany was leading in terms of its cumulative PV installations (approximately 49.2 GW) when compared with other EU countries. Next to Germany, with lesser than 50% installations, i.e., 20.8 GW, Italy stood in second place, and then the United Kingdom (U.K.) stood in third place with 13.3 GW of installations. The rest of the countries have their cumulative solar PV installations less than 10 GW.

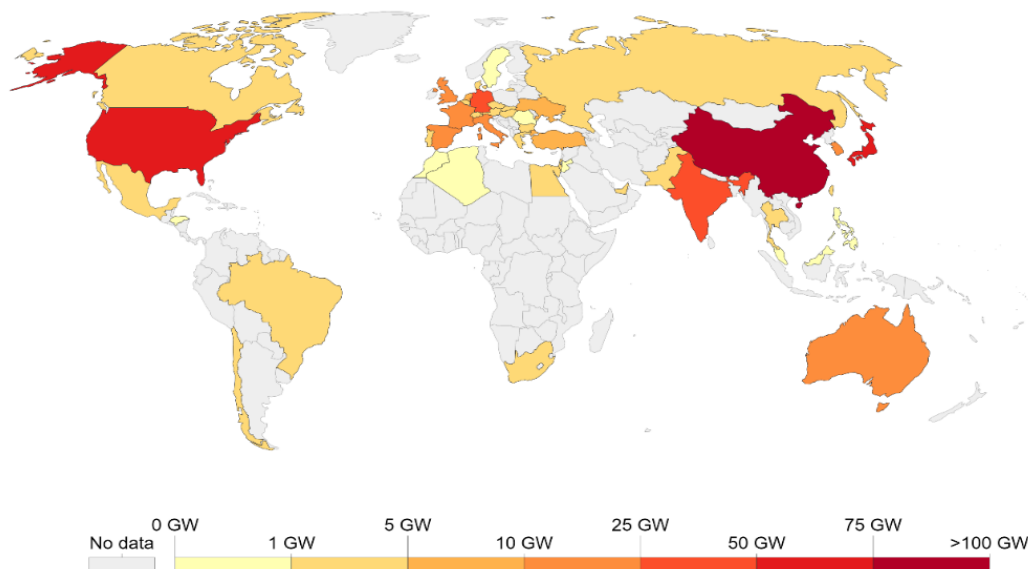


Figure 4. A global map highlights the cumulative installed solar photovoltaic capacity, measured in gigawatts (GW) [62]. (Data Source: British Petroleum (BP) Statistical Review of World Energy, 2020).

Overall, from Figure 4, it is understood that solar is widely accepted in many nations. PV is perhaps the most flexible of all the power generating technologies among the renewables. It is also easy to install with a minimal running cost, and, while its operation, the noise levels are almost negligible except for the buzzing sound of the electrical equipment [59]. On the other side, PV power plants are considered to be environmentally-friendly. PV technology is mature. It is still growing, and day by day, many advancements are seen in terms of power conversion efficiency and flexible design of the solar cells that are apt for installation onto any surface of new applications [57–60]. Most recently, the use of PV technology for distributed power generation is given high priority. In Figure 5, the distributed solar PV (DSPV) capacity growth by country/region is measured in gigawatts (GW) [63].

Even though PV has many benefits, it has a few significant disadvantages because its output is zero at night and can vary considerably during the day, depending on weather conditions [64]. Hence, in the PV plants, especially in DSPV, an ESS is highly recommended that enhances the operating reliability by providing the continuous power supply even in the night time [13].

SPVPP's also possesses a few main challenges: grid integration, performance-related issues, and power quality issues [64–66]. In addition to these, financing and social acceptance are also hindering solar PV growth. However, compared to other RER, the acceptance of PV as one of the DER is very high.

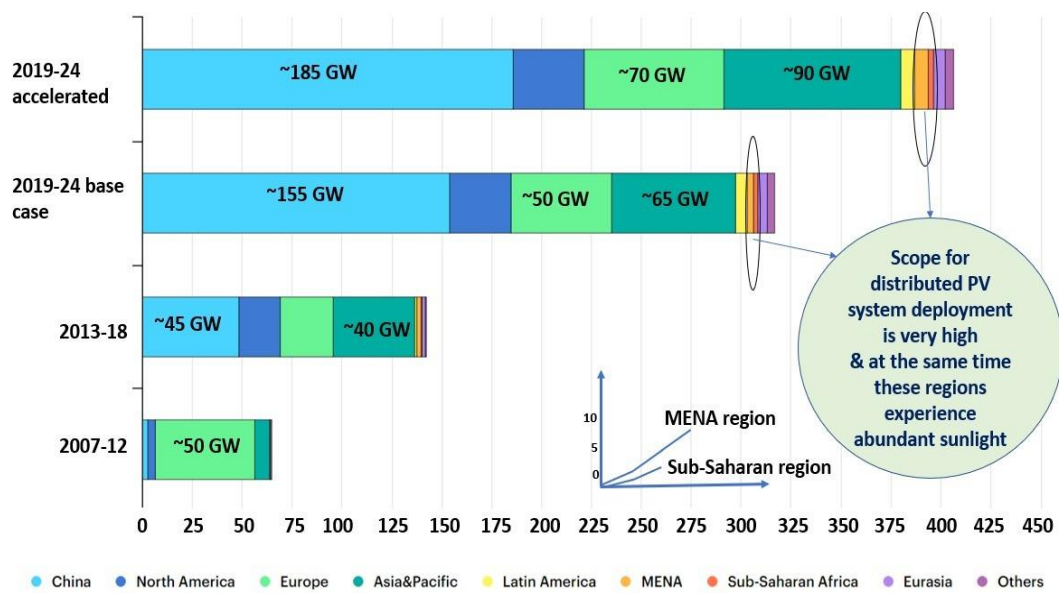


Figure 5. Distributed solar photovoltaic capacity growth by country/region showing the scope for future deployment in the Middle-East and North Africa region, measured in gigawatts (GW) (Data source: International Energy Agency (IEA), Renewables 2019).

2.1.2. Wind Power Plants

The wind energy resource is the second most crucial energy source among all the renewables widely accepted after solar PV. At present, there are two main types of WPP: onshore and offshore. These wind power plants operate by using kinetic energy (i.e., the airflow) to rotate the WT, spinning the generator rotor to produce electricity.

For harnessing the wind energy, WT’s are generally mounted at specific heights to capture most of the available energy and take advantage of high speed but less turbulent wind [67,68]. The most commonly seen WPPs are the horizontal axis and vertical axis WT (HAWT and VAWT).

In recent years, the novel type of WTs are evolved, which include curved WT, ducted WT, funnel based WT, ground-mounted wind turbo-generator [69,70]. A single WT can produce up to a few kW to 5 MW of electricity. Like photovoltaic, its power output is also intermittent, depending on wind availability. The role played by WT is very crucial in the modern power system across the globe. The cumulative wind power installation capacities are shown in Figure 6.

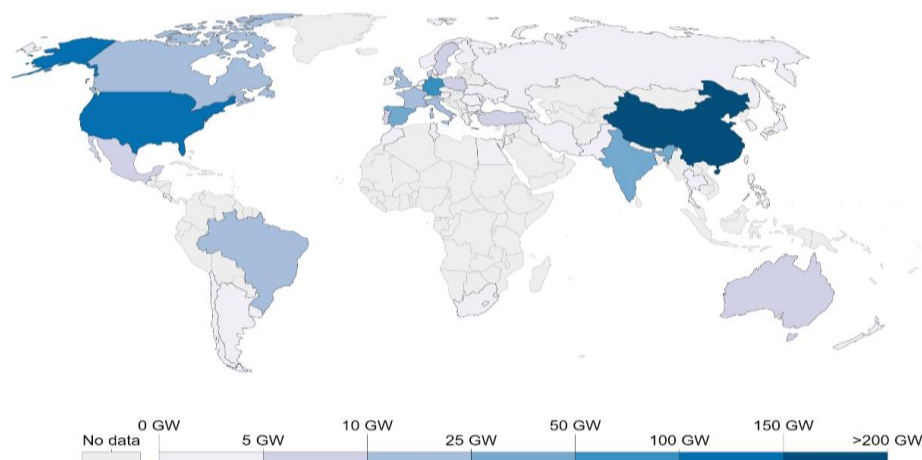


Figure 6. A global map highlights the cumulative installed wind power capacity, measured in gigawatts (GW) [71]. (Data source: British Petroleum (BP) Statistical Review of World Energy, 2020).

As of 2019, with a cumulative installation of WPP as 210.48 GW, China was in the first place, followed by the USA, Germany, India, Spain, Brazil, and Canada. The cumulative installed capacities of WPP in the USA, Germany, India, Spain, Brazil, and Canada are 103.58 GW, 60.82 GW, 37.51 GW, 25.55 GW, 15.36 GW, and 13.41 GW.

As mentioned earlier, among the two main types of WPP, the onshore wind power installations are expected to grow faster than offshore. Figure 7 shows that the onshore and offshore WPP annual additions in the main and accelerated cases are shown. The growth of onshore and offshore installations by 2024 is forecasted, and they are expected to expand by 57% (850 GW) and three-fold (+43 GW) to 65 GW, respectively. However, in the coming years, the WPP installations in China and the USA are expected to slow down a little bit between 2021 and 2024. The global annual WPP installations are expected to be lower at ~50 GW. Coming to offshore WPP, the EU alone would account for half of the global installations between 2019–2024. This is due to the continuous support in new project development and the energy policy feed-in-tariff support. Upon precise observation of Figure 6, the WPP installations are less than 10 GW in most countries. The regions like Latin America, the Middle-East, and North Africa (MENA) region, Eurasia, and sub-Saharan Africa are also falling between 0 to 10 GW range. The WPP installation forecasts expected that these regions would have stable growth soon and eventually have grid integration [63].

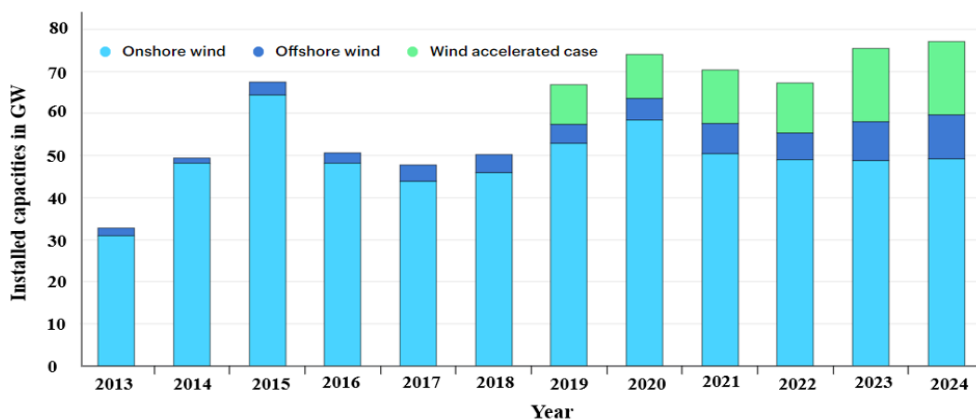


Figure 7. The annual additions of onshore and offshore wind power plant installations from the period 2013–2014 [63]. (Data source: International Energy Agency (IEA), Renewables 2019).

From Figures 6 and 7, it is clear that the deployment of WPP is immensely progressing. However, the WPP installations possess a few main challenges: grid integration, performance-related issues based on the eco-system, and power quality issues. In addition to these, financing and social acceptance are also hindering wind power growth.

2.1.3. Hydroelectric Power Generation Plants

The HPG plants work by using the power of falling water (usually in the dam) to turn a water turbine connected to a generator, which produces electricity. HPG is considered one of the RE technologies because the water cycle is endless and can be reused for power generation and serve other purposes. The hydro system is more or less clean, produces no waste, with very low emissions. The amount of electricity production can be easily increased or reduced quickly, which can meet high peak demand [72,73]. The HPG can be expressed as three types that convert moving water (mechanical energy) to electrical power, and these three types are given below.

Conventional Hydropower

Conventional HPG refers to the electricity generation from the water's energy. In conventional HPG, mostly the water is stored in dams or impoundments, through which a penstock like structure

is constructed, which allows water to free fall from the dam or reservoir height to the turbine generator [56].

Run-of-the-River Hydropower

The run-of-the-river HPG also harvests the energy from flowing water. Unlike the conventional HPG, the run-of-the-river HPG does not need a large dam or reservoir-like structures to store the water. Here, in most cases, water is freely falling from the river's upstream to rotate the turbine generator. In some situations, small dams may be used, and this is done only to allow the water flow to the penstock during specific uncertainties in terms of water flow [74].

Pumped Storage Hydropower

The pumped HPG also harvests the energy from water stored in overhead storage tanks. The principle behind power generation is the same as the conventional type. Here, in pumped storage hydropower, the excess energy is stored in water (e.g., motors were operated to pump the water to the overhead storage tank or the reservoir). During the peak hours, the stored water is allowed to free-fall onto the turbine, which spins the electric generator to produce electricity [75]. Mostly, in the hydropower sector, the above highlighted three types of HPG plants are used. In Figure 8, the annual energy generation from the hydropower plants across the globe is shown.

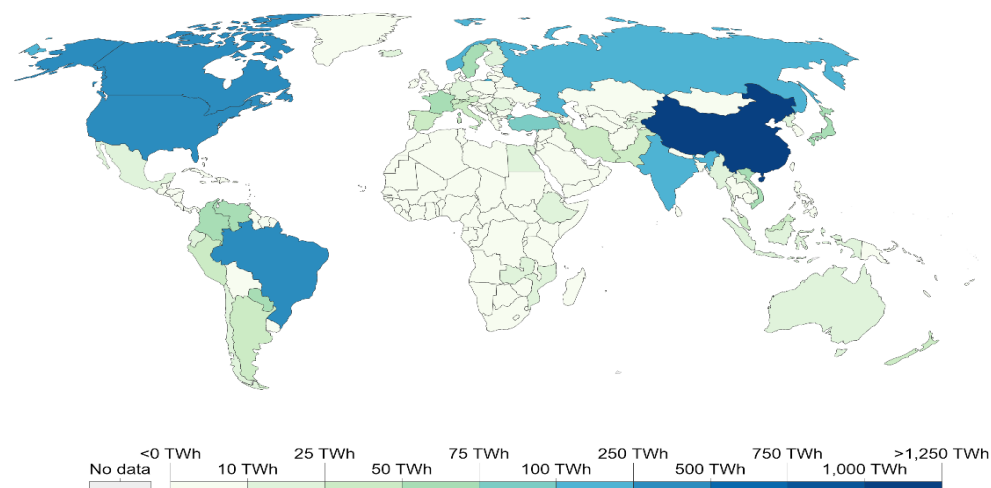


Figure 8. A global map highlights the annual hydropower generation in terawatt-hours (TWh) for the year 2019 [76] (Data source: British Petroleum (BP) Statistical Review of World Energy, 2020).

From Figure 8, it is understood that the role played hydropower in the modern power system is crucial. In countries like China, Canada, Brazil, and the USA, hydropower is considered one of the most preferred power generations based on potential availability [76]. In Figure 9, the hydropower generation statistics between the years 2000–2019 are shown for selected countries.

It is revealed that China is leading in hydropower production, followed by Brazil, Canada, and the USA [76]. The increase in energy generation trends presents hydropower's scope as one of the DER's for SG.

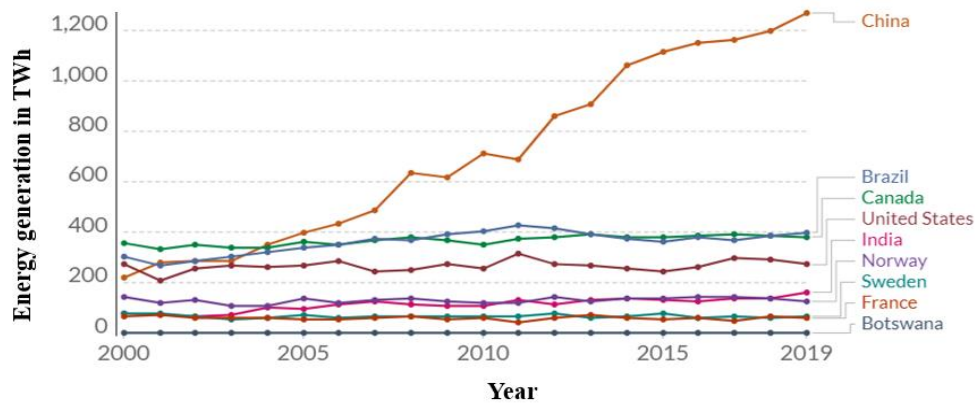


Figure 9. A chart showing annual hydropower generation in terawatt-hours (TWh) in selected countries [76] (Data source: British Petroleum (BP) Statistical Review of World Energy, 2020).

2.1.4. Thermal Power Plants

The power generation using TPP is the conventional approach where fossil fuel resources are burned, which is then used to generate steam. The produced steam activates a turbine, which, in turn, drives an electric generator. In TPP, the combustion approach is used, and the type of fuels used in the boiler are coal, natural gas, heating oil, and biomass [13].

Combined Cycle Gas Power Plants

Shortly abbreviated CCGPP, and these plants generally combine two different types of TPP. In CCGPP, in addition to the conventional TPP, gas turbines are used, which helps in using the residual gases to generate power by another cycle. By combining gas and thermal plants, the overall energy efficiency of the plant will be enhanced. Besides, the overall emissions from the residual gases are reduced [77].

Combined Recovery of Blast Furnace and Coke-Oven Gas

These plants come under the TPP category. They are most commonly used as a captive power plant in the blast furnace application industries, e.g., iron and steel. In most industries, conventional types of TPP are used. Still, few gases like blast furnace gas, coke-oven gas, etc. are released as by-products during industrial activity, especially in iron and steel [78–80]. For enhancing energy and environmental efficiency, these waste gases were recovered and used for power generation [78]. The most commonly used systems for this are the top-recovery turbines and gas expansion turbines. These types run on a combined mode with the captive power plant. On the other side, the residual heat is further recovered and used in the combined cycle for power generation [78–80].

Combined Heat and Power

Shortly, abbreviated CHP typically comes under the TPP category. In these power plants, simultaneous electricity generation and other usable thermal energy are possible. The usable thermal energy is captured within the system, which, otherwise, could be a waste. The CHP power plant is otherwise called a cogeneration system. The generated electricity can be used within a facility and exported to the electrical grid in the condition of surplus production [81,82]. The heat energy produced from the CHP plant can be used for industrial processes, and district heating, and other heat on-demand services [83]. The CHP-based power plants are fueled by various fuels, e.g., natural gas, fossil oil, and different fuel blends. With a CHP-based power plant, an approximate 30% GHG emission can be reduced compared to the conventional TPP [77].

Bioenergy

This is one of the RER that is mainly used for generating gas and other fuels. Different energy conversion approaches like combustion, gasification, and pyrolysis convert the biomass into useful electricity or other fuels [84].

In biomass power generation, China is leading, and it provides over 50% of new installations. The bioenergy market is relatively high in China, and the most concentrated bioenergy projects include co-generation and solid biomass to electricity. Brazil and India are the next-largest markets for bioenergy after China, whereas the EU record 3 GW new installations in 2018 [63].

Nuclear Power Plants

These power plants generally fall under the TPP. In NPP, the nuclear fission principle is used to generate electricity. In NPP, the nuclear reactors that act as a heat source are used in combination with the Rankine cycle for power generation. The heat liberated in the reactor is used for converting the water to steam, which, ultimately, spins the turbo-generator [85].

All the above-discussed TPPs are widely used in most countries for power generation. TPP drives most of the country's national energy mix and can be a vital DER in the electric grid. However, few of the above-discussed TPPs, e.g., combined heat and gas recovery systems, are restricted to localized energy grids (e.g., industrial MG, SG, etc.) within the industries. Overall, the role played by TPP as DER in SG is critical.

2.2. Electric Storage Systems

ESS can provide stability and enhance reliability for SG with massive penetration of RE [8,86]. In other words, it can compensate for RE intermittency. Energy storage facilities would allow the energy that would have been unused to be captured and retained in one form or the other and, later, converted to electrical use during peak periods or no renewable generation. ESSs are being developed in many ways and can be in the form of pumped hydro, compressed air, flywheel, batteries, and electromagnetic (supercapacitor), as shown in Figure 10 [86–90]. Storage plants can also assist in additional services like frequency stability and black start capability [8]. The ESS can also support the MG or SG by offering voltage support when there is low voltage in the ESN.

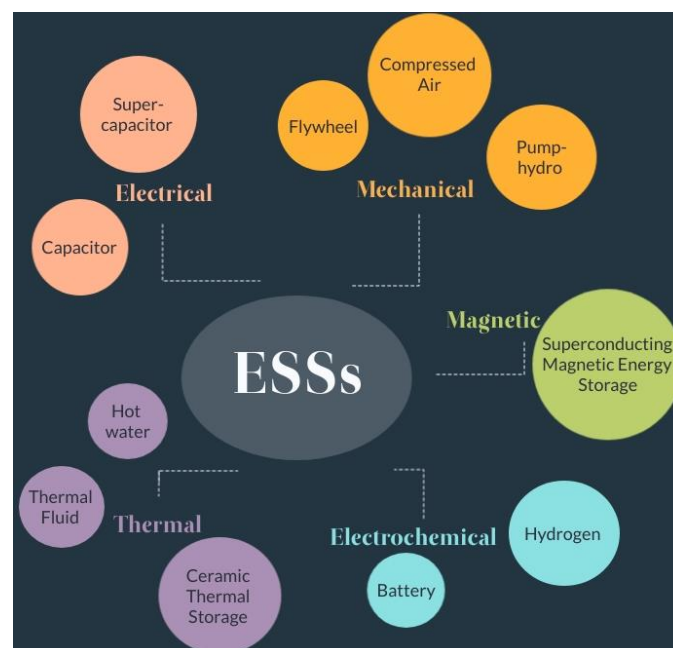


Figure 10. Different types of energy storage systems (Note: ESSs—energy storage systems).

2.3. Demand Side Management/Controllable Loads in a Smart Grid

Load management from the consumer's side would in balancing the supply and demand patterns in SG. For this, DSM techniques are used. These techniques are generally based on the consumer side's initiative to achieve the desired change in the demand profile [91]. The different DSM techniques used for the re-shaping load profile are presented in Figure 11.

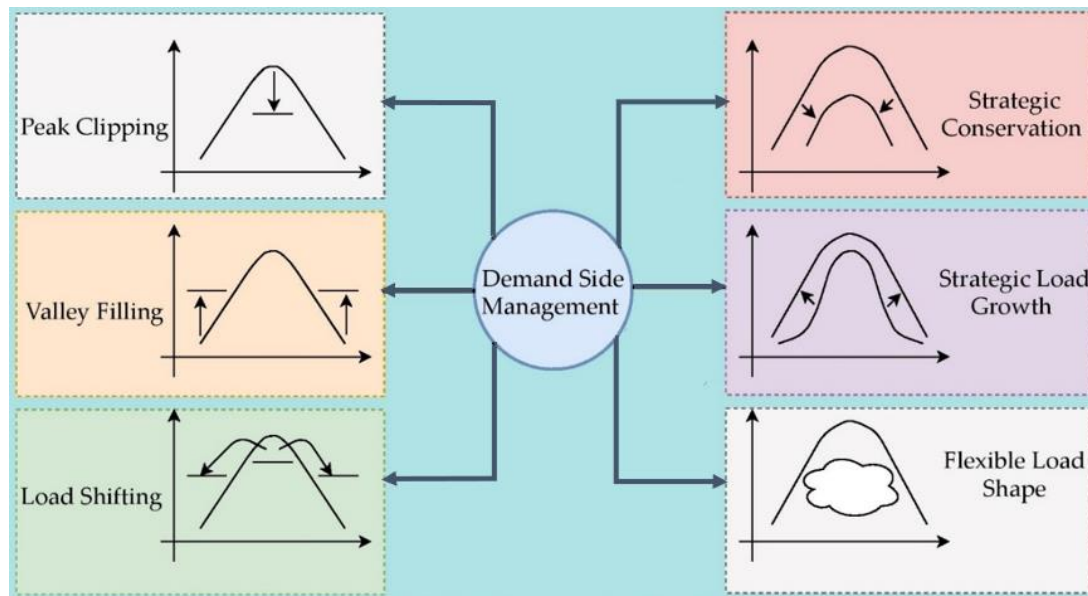


Figure 11. The six different demand-side management approaches are used in the smart grid (Redrawn with permission from [91], 2014, Elsevier).

DSM should result in the upkeep of electricity usage patterns efficiently. While having DSM-based decisions, the ESN peer can either reduce their energy consumption patterns or limit their electricity loads (i.e., the connected load) [92]. While managing the energy supply and demand patterns between ESN peers, DSM also manages real-time energy prices based on peer decisions.

The controllable loads (CL) are also favorable in managing the ESN's energy consumption patterns. The ESN peer would shut down their loads based on the informed decision and condition by the SG. In controllable loads, such decisions on loads shutting down happen without affecting the peer's comfort. Additionally, the peer's convenience is preferred in most cases, and, in some cases, the interruption would occur automatically, which is done only to ensure the critical operations [93]. The use of DSM and CL offers numerous advantages, including fast load balance, frequency control, peak shaving, and voltage stability.

2.4. Electric Vehicles as a Load Component in a Smart Grid

EV is an emerging technology that can be an essential SG component in the future [94–96]. As a result of the decarbonized transportation sector, EV's became the most crucial loads in SG [84]. The SG and EV will both have an impact on each other. Massive adoption of EV will substantially increase demand on the power grid, but this can be effectively managed through demand response (DR) and load scheduling. On the other hand, EV can provide support for the grid through its battery ESS. EV can capture excess non-dispatchable RE and use it to enable and support SG [97]. It is, thereby, balancing electric power demand with supply on the grid. The EV is part of green solutions for environmental and energy source sustainability [98,99].

If the EV technology is deployed widely, it will provide a large distributed energy storage capacity for the grid. The EV batteries are charged by SG at a time of excess generation, described as the

vehicle-to-grid (V2G), and may be used as an energy storage backup for the grid [100]. A typical control diagram of the EV charging station both in AC and DC configuration is shown in Figure 12.

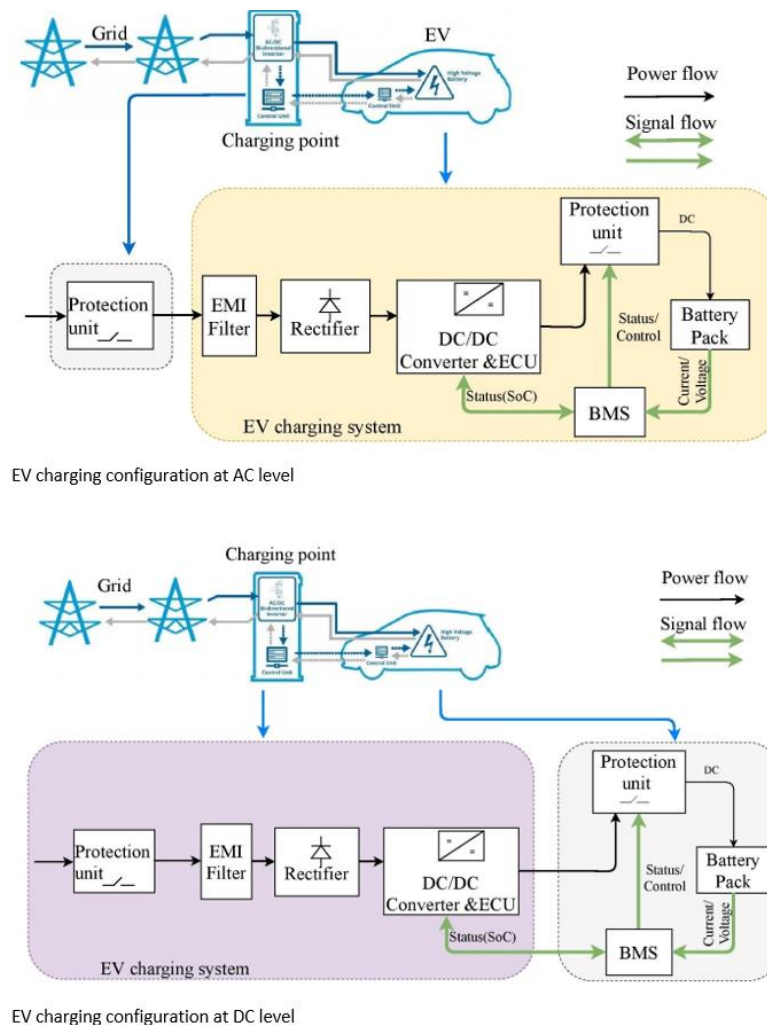


Figure 12. Control of electric vehicle charging system both in alternating current and direct current configurations (Note: EV—electric vehicle, EMI—electromagnetic interference filter, DC—direct current, ECU—electronic control unit, SoC—state of charge, BMS—battery management system, AC—alternating current).

EV charging can be through the AC or DC grid, and this will enable the vehicle to discharge its battery electrical energy into the grid (V2G) when demand is very high. This serves to mitigate the intermittent nature of RE and provide the needed stability for the SG. The fallen price of solar PV, battery for EV, and the developments seen in an electric grid can absorb many intermittent renewables, which is expected to enhance EV adoption [59,84]. The EV technology can even be extended to serve as an electrical source or sink with bi-directional charging ability in which it can be charged and discharged between vehicle and home (V2H), vehicle and building (V2B), providing electric power for the home, building, and to the grid and from home by building a charging point to EV [97–100]. The full benefit of EV being a part of the SG system will lead to a new energy business model and provide a unique value for energy customers. The EV batteries can be charged in off-peak times. The same charged EV batteries can be used as a source of energy supply when peak periods occur. EV controls in SG are not well defined yet and are still evolving. Besides, the development of standards for EVs is also in progress.

3. AC, DC, and Hybrid Microgrids-Based Distributed Generation

MG is a segment of the main electric power grid that can be disconnected or isolated from the central grid and operates independently. MG has its autonomous power generating sources (preferably more than one source of power generation), which may also include ESS and is situated close to the load center [101–104]. The MG can integrate multiple DER's (the DER's include the renewables like wind, solar, biomass, or non-renewable or energy storage like pump hydro, batteries, flywheel, etc.) that are briefly discussed in Section 2.1. Currently, with the available DERs, we can design the AC and DC MG. In addition to these, their combination, i.e., hybrid AC/DC MGs, can be designed. In Figure 13, the few common configurations of MGs are shown [103,104].

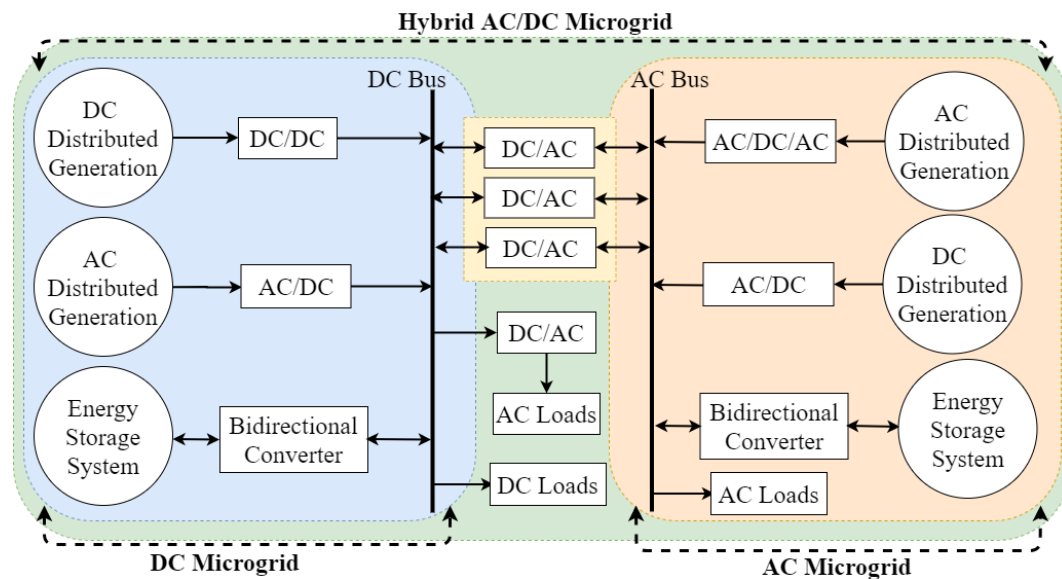


Figure 13. Typical microgrid design configuration showing the alternating current, direct current, and hybrid alternating current/direct current microgrid (Note: DC—direct current, AC—alternating current).

During the operation, the power system can choose any of the DER. Depending on each consumer or prosumer's load demand and power availability, this may be selected automatically to balance the load with supply. With this, the MG enables the reliability and resilience of the power system [13,55]. MG's can automatically isolate themselves from the main electric grid due to an islanding issue and continue to power its loads [18]. Power quality issues, outage occurrence, and electric grid supply change can be broadly considered as the islanding issues in the main electric grid [101]. The microgrid in an islanded mode enables it to maintain high reliability to the supplied territory. The switch that performs islanding and connecting operation usually has an intelligent controller that monitors the central grid's conditions and responds appropriately to disconnect from or reconnect to the main electric grid. The electric power can flow in either direction, from MG to grid, and vice versa, depending on which is most technically and economically favorable. In other words, MG can inject its excess generated power into the main electric grid and can also take supply from the conventional grid if its sources are not available or available. Still, the price of the central grid is lower [12]. Depending upon the MG configuration, the cost of the electricity would vary [55].

As mentioned earlier, MG offers energy trading opportunities to its peers, depending on the price, time of use, and supply and demand patterns [13]. In contrast, this feature is not applicable for CEG. The CEGs are not designed to accommodate DER at the distribution level [105]. Therefore, incorporating DERs to the grid directly at distribution poses many technical challenges. Hence, it is necessary to follow specific technical procedures and standards in integrating DERs into MG, considering SG's building block.

4. Power Electronic Components and Their Control in Smart Grids

Power electronics in the SG system performs the essential function of coupling the DERs to the electric power grid. It also boosts, regulates, and does the conversion of DC to DC or DC to AC electricity, particularly in grid integration of RE [106,107]. The unregulated voltage output of RE sources' distributed energy and intermittency requires power electronics to interface to the grid [108]. The DER's voltage output could be in DC or AC form with variable frequency. Power electronics like high voltage direct current (HVDC), voltage source inverter (inverter), and boost converter provide ancillary services for the grids in the form of power quality improvement, reactive power support, and electric grid stability and control. Of crucial importance among power electronics is the inverter. The inverter integrates most RE technologies and ESS to the electric grid. A smart inverter can serve several different operations to help an electric power system operate with better stability, reliability, and efficiency [12,13].

4.1. Volt-VAR Control

The injection of reactive power to control voltage is known as Volt-VAR control [109,110]. Smart inverters are capable of providing reactive power at the point of connections to the grid to regulate the grid voltage. Thus, preventing the severe stability challenges of grid voltage fluctuations occasioned by the variability of renewable solar photovoltaics even during sunny hours of the day. An inverter is designed and programmed in such a way that its reactive power output at any time is dependent on the grid voltage at that time [110]. Another way is to employ a communication link to enable the power converter to inject its reactive power by the command of the grid operator. In their control functions at the point of interfacing with the grid, the inverter can monitor current, voltage, frequency, and phase angles and communicate this data to the grid operator in real-time. This information can further process for appropriate actions or decision-making.

4.2. Ramp-Rate Control

Non-dispatchable RE production output like PV and wind goes up and down swiftly several times, even within a couple of minutes, which may create complications for the operators [111]. A smart inverter with a built-in small amount of a supercapacitor can limit or reduce the rate of up and down output power ramping.

4.3. Frequency and Voltage Event Ride-Through

As a requirement, the inverter cannot release their output into the grid when the output parameters like voltage and frequency from the renewable are not within the acceptable range for grid characteristics [112]. Nonetheless, there may be a very brief momentary period of low and high voltage or low and high frequency on the grid. In this period, further loss from renewable sources might aggravate these grid conditions. Frequency and voltage event ride through is technologies or techniques that permit the inverter to remain online and assist the grid during this short period of voltage and frequency deviation.

5. Communication and Cybersecurity in a Smart Grid

In SG, ensuring effective communication between the peer is essential, and, at the same time, the data related to SG operations should be protected. In this regard, the role of communication and ensuring cybersecurity is discussed in Sections 5.1 and 5.2.

5.1. Role of Communication in the Smart Grid

One of the SG system's critical features is the two-way flow of information and two-way flow of electricity and real-time communication among components in the system.

The communication system is crucial in grid integration of DER's and aid in restructuring the ESN topology based on the need for adjusting for the efficient flow of electric power [113]. Being a vast system, SG needs a range of networking and communication technologies that can enable timely and high-speed two-way interactions among components, users, and operators. The medium of these communications can be wired (power line communication, fiber optics, and copper cables) and wireless communication, including Wi-Fi, cellular, microwave, etc. [114,115].

In the traditional approach, technicians go physically to power equipment/systems to collect data and consumer's terminal to take readings on a periodical basis for system monitoring and billing purposes. In SG systems, smart meters and sensors will provide real-time information and remote monitoring and store all previous data. All this information is made available on a communication platform to the central location with all concerned points through communication technologies using wired or wireless communication for access [115,116]. This helps operators be fully aware of the power system's health and predict and ascertain the system's condition ahead of time and, thereby, give appropriate notification to consumers. Examples are notifications on possible outages with duration, energy price, and amount of energy available at a given time. Consumers also can adjust their power usage patterns based on available information on their consumption rate and energy cost, which they can easily access on a communication platform even through their mobile phone in the comfort of their location.

5.2. Role of Cybersecurity in a Smart Grid

Cybersecurity in SG is essential as there is a need to prevent abuse, malicious activities, and unauthorized access to a two-way flow of information on the grid system [115,116]. Consumers or the prosumer or any other peer within ESN have a lot of information about their consumption and trading patterns. Hence, the data needs to be protected from hacking, theft, and loss. Full implementation of the SG system without adequate cybersecurity measures can open the system to a sophisticated cyber-attack, which can compromise the system and cause stability problems for the grid. Cyber-attack can also cause fraud, like the destruction of information and manipulation of energy consumption data. Cybersecurity should be aimed at integrity, confidentiality, and timely availability of data [113,117]. The cybersecurity system should also detect cyber-attacks and information security violations and automatically send alerts to the peer. This will help the peer to respond to protect the integrity of the system.

6. Application of Artificial Intelligence, Machine Learning, and Deep Learning in Smart Grids

With the growth of computational methods, particularly in data management and analysis, several ML approaches have been implemented in various industries [118]. According to the current situation, most of the researchers have concentrated their studies on DL too. The DL has been treated as an emerging area for feature extraction and handling a considerable amount of data where ML methods fail. Altogether, AI encloses numerous subfields, counting as ML, DL, Big Data computer vision, neural network, natural language processing, etc. [118]. DL employs large neural networks with many layers of processing units, advancing computing power, and enhancing training techniques to learn versatile patterns from vast amounts of data. DL is typically a sub-branch of ML, and DL is another sub-branch of AI, as shown in Figure 14.

The appropriate proliferation of AI technologies is essential for suitable applications, especially in the SG applications [119]. SG is a collection of existing and emerging technologies working together to monitor and manage the ESN properly. Based on its nature, SG was able to generate huge data, given the scope for data analysis [120]. At present, in SG, standard data mining methods are applied. The traditional data mining analysis tool adopted by industries were ML, ANN, genetic algorithm (GA), FL, KbS, support vector machine (SVM), etc. [119–123]. These methods were mainly used to get better outcomes in terms of exact electricity demand estimation. These methods were also applied to forecast energy production and consumption patterns based on peer behaviour in the ESN. Among all

methods, DL plays a vital role in SG applications. Several AI techniques are summarized in Table 2. It can be examined that, with a certain success level, AI tools are applied for forecasting the electrical load. This also improves the neural network's training ability to achieve positive outcomes of the load forecast model instead of traditional techniques. A variety of hybrid forecasting approaches are used to increase predictive accuracy. DL is a subset of ML that has deeper inner hidden layers cascaded into the network, which initially occasioned from a multi-layer ANN [124–126].

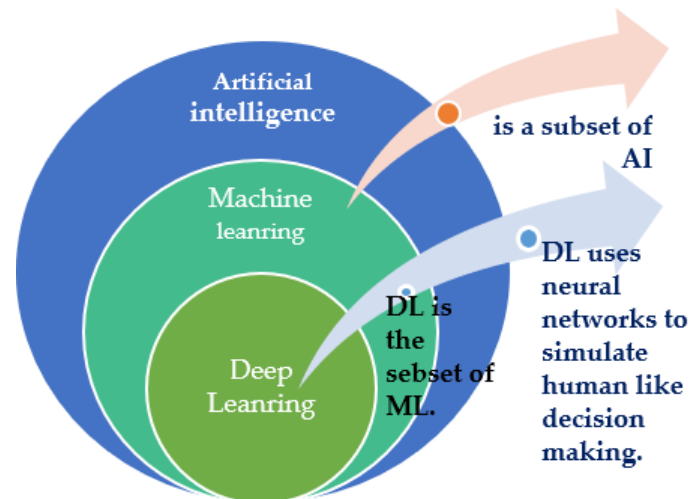


Figure 14. Representation of artificial intelligence, machine learning, and deep learning (Note: AI—artificial intelligence, DL—deep learning, ML—machine learning).

Having said that, DL has a broader application in all data mining, data performance, and prediction. There are different types of methods associated with DL shown in Figure 15.

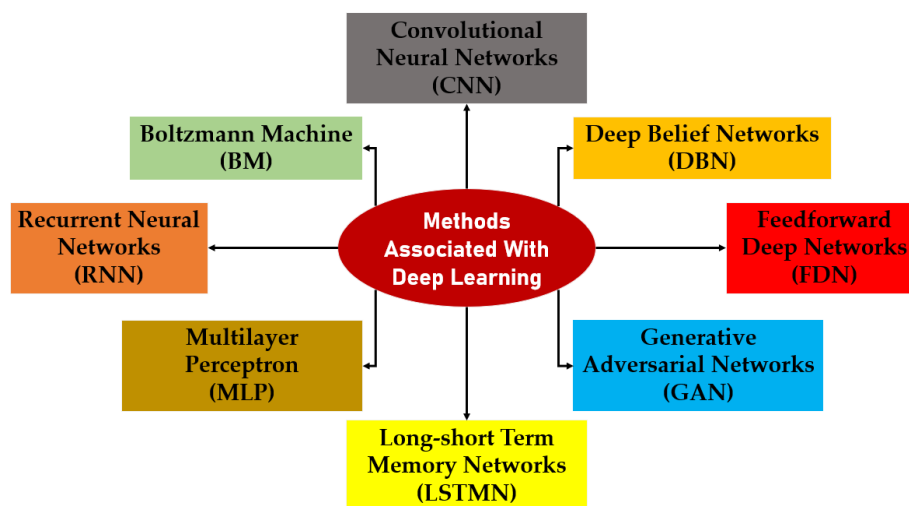


Figure 15. Methods associated with deep learning.

Among the above-listed methods in Figure 15, the two approaches, namely CNN and RNN, are commonly used in SG research. For analyzing and understanding the spatial distribution data, the CNN method can be used. The other method, RNN, can handle the time-series data effectively. SG is presented as massive data mining, load forecasting, and load balancing opportunities. DL is a handy tool that improves and builds an intelligent SG. Figure 16 shows a schematic of the DL in the application of SG. Despite growing technology for SG and EMS, there are still many barriers to accurate load forecasting in large-scale data.

Table 2. The summary of the studied artificial intelligence techniques and their applications in a smart grid.

Keyword from Title	Methods	Highlights	Discussion	Reference
ANN, load forecasting, SG	– Three-layer ANN and BP learning	<ul style="list-style-type: none"> – algorithm proposed and designed for SG – Short-term load forecast model based on ANN – ANN forecast model trained with a BP-based learning technique. 	<ul style="list-style-type: none"> – NN efficiency is harmed by intrinsic gradient-based defects that include slow convergence and increased computational complexity. – A low percentage of samples and insufficient network training impact predicted model efficiency. 	[119]
ANN, Short-term load forecasting	– GA with SVR	<ul style="list-style-type: none"> – A short-term load forecasting object was set for this research. – CGA with the SVR technique applied. 	<ul style="list-style-type: none"> – It strengthens forecast model efficiency by resolving sudden and unexpected convergence, gradually approaching the optimal comprehensive solution or trapping into a local optimal level. – Likewise, the SVRCGA driven forecast model portrays similar forecast models with improved performance. 	[120]
NN, self-model, seasonal impact of weather, exogenous variables	<ul style="list-style-type: none"> – ANN – Genetic – BP model 	<ul style="list-style-type: none"> – Utilizing improved GA along with BP training methodology and short-term load forecasting using ANN is proposed. 	<ul style="list-style-type: none"> – To every BP based NN's local minima issue resolved with enhanced GA's global search capabilities. – The suggested forecasting model suggests improved results than other forecasting systems. 	[121]
Load forecasting, ACO, GA, FL.	– NFN with an improved GA	<ul style="list-style-type: none"> – A GA approach is being used to achieve the optimum set of fuzzy rules, and the FL is applied in forecasting for managing qualitative parameter information. 	<ul style="list-style-type: none"> – The expected results suggest that the MAPE of the hybrid methodology introduced is 1.56%. 	[122]
ANN, statistical methods, short-term peak load forecasting	– CGASA with SVR	<ul style="list-style-type: none"> – Demonstrated a forecast model to improve the model's statistical accuracy with CGASA's short-term load forecast model based on SVR. 	<ul style="list-style-type: none"> – The conclusions from this analysis revealed an increased forecast outcome relative to the models ARIMA and TF-ϵ-SVR-SA. 	[123]

Table 2. Cont.

Keyword from Title	Methods	Highlights	Discussion	Reference
Toward self-healing energy infrastructure systems	– Context Agent-based intelligent model	– A context agent-based control technique is applied to large national infrastructures.	– This approach enables the self-healing of the SG for different responses. The common ones are threats, component failures, and other disruptive events.	[127]
Optimal operation of distribution feeders in SGs	– Intelligent Nonlinear Programming	– An intelligent nonlinear programming technique to minimize the amount of electricity drawn in a substation.	– The positive impact of such a method resulted in a reduction in energy losses. – The design limited the switching operation. – Good system performance.	[128]
Demand response forecasting in SGs: Use of anthropologic and structural data for short-term multiple loads forecasting	– ANN and SVM based StLF model for SG.	– The common approaches applied is ANN and SVM. – Short-term forecasting model for various loads.	– This study concludes that the demand response in SG was well developed. – The goals were achieved by designing the models that support the forecasting of short-term multi-loads.	[129]
Real-time operation, SG, FCN networks, optimal power flow	– NN trained with GA, FC, and N-NA.	– algorithm applied to a network is an NN-based model with adaptive training using GA, FC, and N-NA for integrating DSM and AMS.	– The presented model significantly enhanced RER's exploitation and ensured the other services like saving in energy and allowing the customers to participate actively in the energy market.	[130]
Real-time energy information infrastructure, STG, Router network management	– Intelligent EMS system	– power quality and power grid transmission network are critically reviewed, focusing on the STG infrastructural needs.	– The EMS concept and a framework for transfer from the currently configured power network to the SG network were achieved. – The power quality and information infrastructure were effectively handled in this approach. – A ubiquitous measurement of the phasor recognizing the volume and rate of data.	[131]

Table 2. Cont.

Keyword from Title	Methods	Highlights	Discussion	Reference
SGM, RE generation	– WNN	<ul style="list-style-type: none"> – a model of the WNN is designed using a multi-agent system knowledge base. – Helped with limiting features and predicting energy generation using NN. 	<ul style="list-style-type: none"> – A compelling work is presented whereby EMS with RE generation is modeled. – The WNN showed a better performance in EMS of an RER. 	[132]
SGM architecture, The multi-agent energy system, Energy demand forecasting, Virtual power plants	– MLPNN	<ul style="list-style-type: none"> – SGM virtual power plants with RERs using MLPNN. 	<ul style="list-style-type: none"> – MLP's NN embeds a collection of multi-agents for forecasting the collective energy demand across the ESN. 	[133]

Note: Artificial Neural Network (ANN), Smart Grid (SG), Backpropagation (BP), Neural Network (NN), Genetic Algorithm (GA), Support Vector Regression (SVR), Chaotic Genetic Algorithm (CGA), Chaotic Genetic Algorithm Simulated Annealing (CGASA), Ant Colony Optimization (ACO), Neural Fuzzy Network (NFN), Fuzzy Logic (FL), Mean Absolute Percentage Error (MAPE), Autoregressive Integrated Moving Average (ARIMA), Support Vector Machine (SVM), Short-Term Load Forecast (StLF), Fully Conventional Neural (FCN), Fuzzy Clustering (FC), Neuron-By-Neuron Algorithms (N-NA), Demand Side Management (DSM), Active Management Schemes (AMS), Renewable Energy Resources (RER), Smart Transmission Grid (STG), Energy Management System (EMS), Smart Grid Management (SGM), Renewable Energy (RE), Wavelet Neural Network (WNN), Multi-Layer Perceptron's Neural Network (MLPNN), Multi-Layer Perceptron's (MLP's), Electricity System Network (ESN).

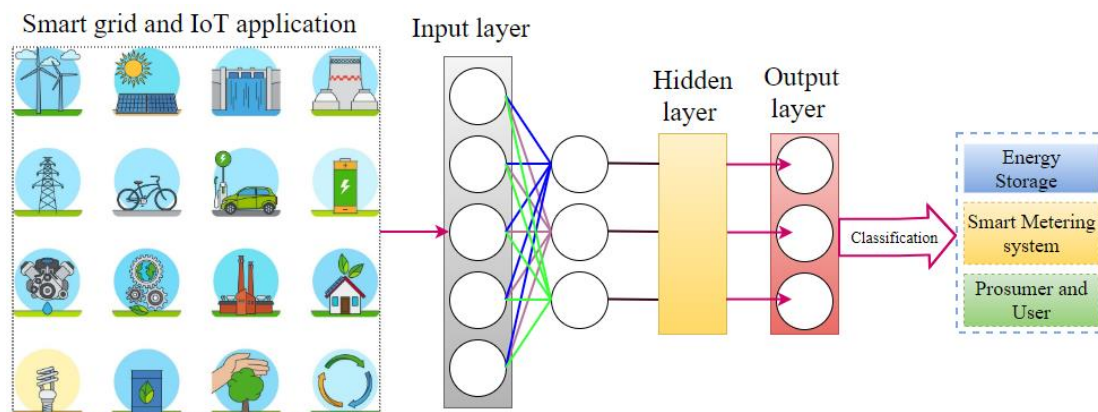


Figure 16. A schematic of applying deep learning for energy management applications in smart grids based on data from the internet of things (IoT) device (Adapted and returned to smart grid context based on the artwork with permission from [134], 2020, IEEE).

Table 3 shows some common advantages and disadvantages of DL [134]. Integrating such methods allow the system to extract the most relevant attributes for carrying out the analysis. Additionally, it helps in capturing the ESN’s distributions patterns where there is a scope for analyzing the complex data.

Table 3. The common advantages and disadvantages of deep learning (A portion of the Table is adapted with permission from [134], 2020, IEEE).

Methods	Advantages	Disadvantages
CNN	CNN’s are robust, extremely competitive performing, supervised DL approaches. With added features of CNNs, its scalability is improved, and the duration of their training combined with those of ANNs is enhanced. CNN’s provide possible IoT privacy uses because they can dynamically learn functionality from raw data on protection.	CNN’s include high computational costs. Therefore, it is challenging to implement them on commodity-constrained platforms to support onboard safety features.
RNN	RNNs also includes their equivalents better performance with serial data in many scenarios. In some cases, IoT security data consists of serial data. Thus, RNNs have a possible application in IoT protection.	The major downside of RNNs is the problem of gradients vanishing or exploding.
AE	AEs are theoretically significant for the extraction of functionality. For representation learning, AEs can be used effectively to learn features instead of the manually designed features used in conventional ML and minimize dimensionality without prior knowledge of the data.	AEs use a large number of computing resources. While AEs can easily train to capture training data characteristics, if the training dataset is not representative of a test data set, AEs can only confuse the learning process rather than reflect the characteristics.
RBM	Using a feedback system on RBMs allows multiple critical features to be extracted from an unsupervised approach.	RBMs include high computational costs. Hence, it is challenging to incorporate them on resource-constrained IoT devices to support onboard protection systems.
DBN	DBNs are non-supervised methods of learning, trained iteratively with unlabeled data to represent significant features.	DBNs have high computational costs due to the large number of parameters generated by the lengthy initialization process.
GAN	In GAN, the only way to produce a sample is by going through the model, as with DBNs and RBMs, in which the Markov network requires an unknown number of iterations.	GAN is unpredictable and demanding preparation. It is a difficult task to learn how to generate discrete data through GAN.
EDLN	Mixing DL optimization algorithms may lead to a diversity of models, enhancing model efficiency and generalization of models.	The system’s time complexity can be increased significantly.

Note: Artificial Neural Network (ANN), Deep Learning (DL), Internet of Things (IoT), Conventional Neural Network (CNN), Recurrent Neural Network (RNN), Autoencoder (AE), Machine Learning (ML), Restricted Boltzmann Machine (RBM), Deep Belief Network (DBN), Generative Adversarial Network (GAN), Ensemble of Deep Learning Network (EDLN).

7. Application of Internet-of-Things and Energy Internet in Smart Grids

IoT and the Energy Internet (EI) are two other areas in which their roles in SG is quite considerable [135]. These two concepts are emerging communication technologies. In Figure 17, a summary of different IoT components is shown. IoT implementations in related applications have many benefits, such as reducing human interference in the interconnecting devices process. The most significant impacts in the power market, home appliances, garbage management, and smart cities (SC) are seen in the literature [136–141]. The IoT gateways are joining the “data collection, transmission, and processing” networks of SG [139]. For instance, an IoT gateway device allows the data to be routed through the IoT network and bi-directional communication (i.e., device-to-gateway and gateway-to-cloud) [136,138,140].

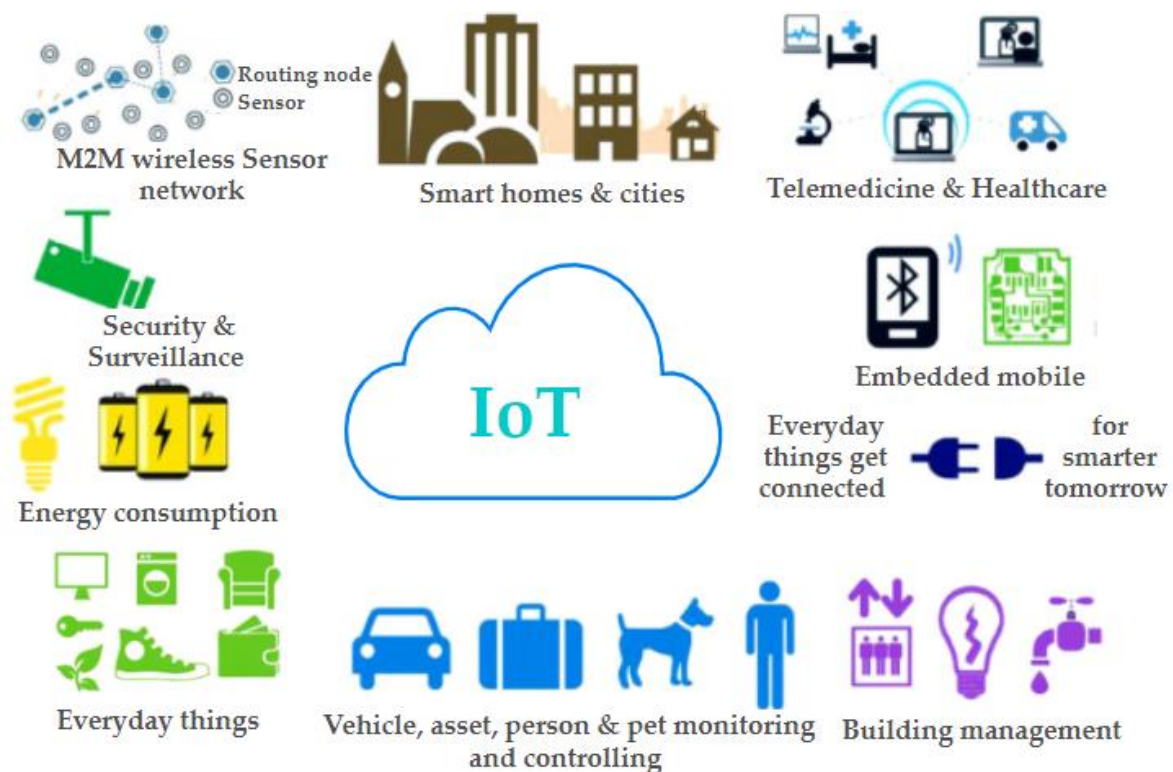


Figure 17. A summary of different components of the Internet of Things technologies platform (Note: M2M—machine 2 machine, IoT—internet of things).

SG, ESN, and IoT nodes may be the potential solution to tomorrow’s global energy crisis [142]. The existing SG framework, combined with IoT and EI, can be applied to numerous energy-related applications. These include SC, intelligent home monitoring systems, and energy-harvesting technologies like metering, monitoring, and EMS. One of SG’s critical components is continuous connectivity and communication, which provides equipped devices with these capabilities. In Reference [143], Kabalci et al. presented different decentralized networking such as Neighbour Area Network (NAN), Home Area Network (HAN), Wide Area Network (WAN), and Field Area Network (FAN), which are responsible for the roles-based data transfer between utility data centers, substations, and smart meters within and outside of the ESN, as shown in Figure 18.

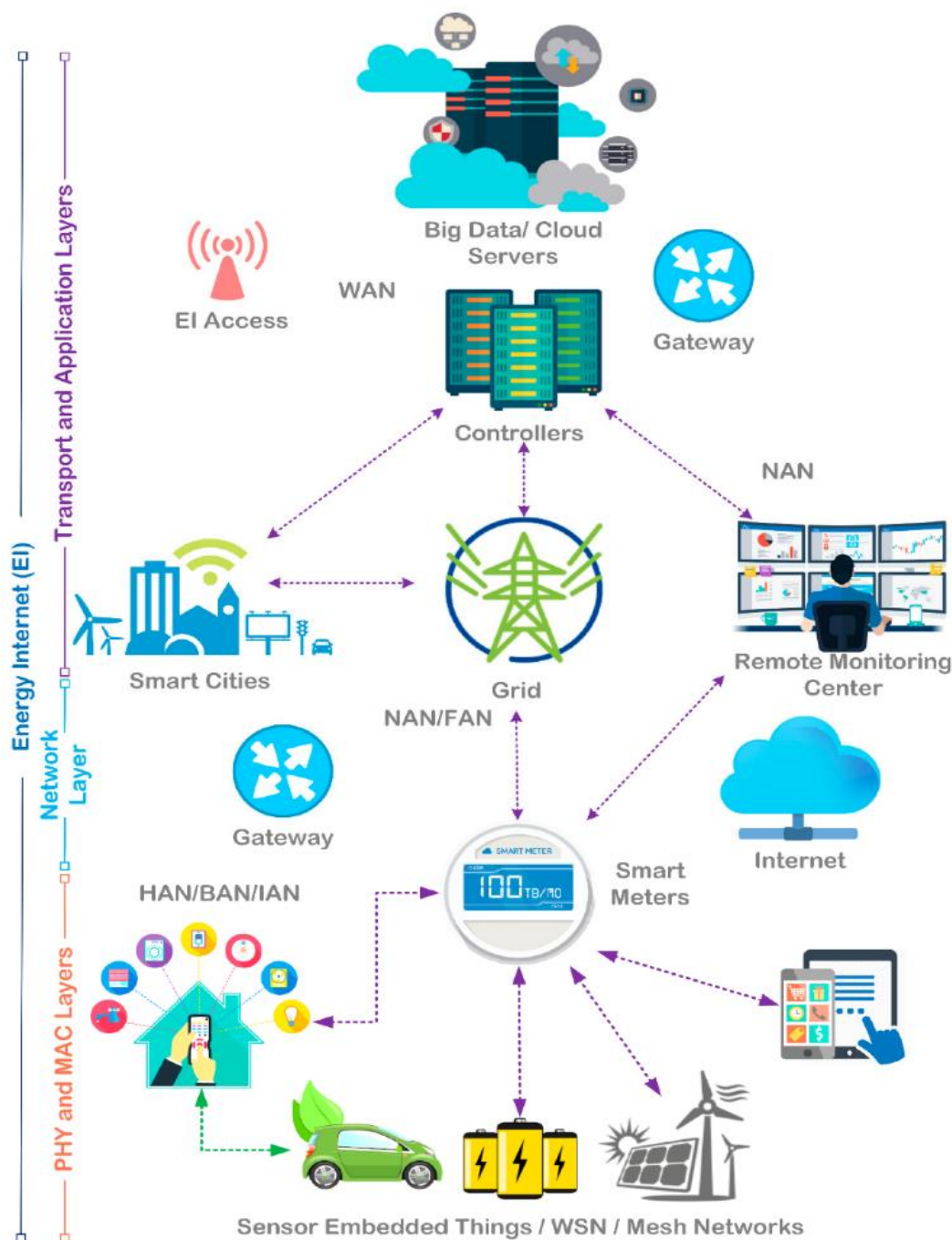


Figure 18. The Internet of Things and energy internet-based smart grid platform (Reprinted with permission from [143], 2019, MDPI). (Note: WAN—wide area network, NAN—near-me area network, FAN—flexible access network, HAN—home area network, BAN—body area network, IAN—Internet area network, WSN—wireless sensor network, PHY—physical, MAC—media access control).

7.1. IoT Components in the Context of Smart Grids

The communication and transmission of data from the SG are divided into information and operation data. The information comprises meter readings, utility bills, power rates, marking and patterns, and customers’ geographic position in SG. The operational data includes a network’s real-time current and voltage levels, condenser banks, fault positions, and energy storage values. The central and peripheral technologies make SGs consist of different intelligent devices specified below.

7.1.1. Advanced Sensing and Measurement

SG incorporates smart metering, which gathers data on electricity prices and usage for customers and utilities, including the time and amount of electricity consumed. This assesses system safety, grid integrity and supports advanced protective relays [144–146]. This allows customer choice and response to demand and helps to alleviate grid congestion. Advance monitoring and analysis improve grid stability through early identification of faults, allowing operating system isolation and power outage prevention.

7.1.2. Automatic Monitoring and Control

SG provides real-time tracking and display of energy system device conditions and efficiency through linkages and over large geographic areas, helping device operators and users recognize and optimize power system modules, actions, and output [145,147,148]. SG's monitoring and control technologies produce data and provide a visual representation of the system status to help inform the decision, mitigate wide-area disturbances, and improve distribution capacity and reliability.

7.1.3. Renewable Resources Forecasting

The challenges of the intermittent nature of renewable, particularly wind and solar, call for an accurate forecast. Advanced precise estimates of wind and solar energy availability can alleviate negative impacts on the grid's required spinning reserves [149]. Advanced forecasting will provide preliminary information on resources, load, and grid conditions. This would help in effective scheduling and dispatch, which assist in proper planning according to consumers' load requirements from analyzed data. The forecast would bring about a dynamic nature in all power system levels while balancing variable generation by keeping the grid stable [150].

7.1.4. Information and Communication Technology

The present power system infrastructure involves connections of all significant power system operational facilities (generating, transmission, and primary distribution substation) to the system control center, part of a conventional power system [151,152]. However, this communication is extended throughout distribution networks and offers high-speed two-ways communication flows that make the SG dynamic interactive for real-time information exchange [153–155]. SG employs ICT technology at each level of the power system right from generation down to consumer appliances to improve electric power services, grid reliability and efficiency, cost reduction, and enhanced environmental-friendliness.

7.1.5. Distribution Automation

Distribution automation (DA) is a technique for automated control that maximizes electricity distribution networks' performance to make the grid more reliable and efficient. DA is an essential component of SG. It helps to readjust the distribution topology to incorporate renewable variability, power ramping, and bi-directional power flows [156]. DA provides for sensing and monitoring of voltage and power factors at different points on the distribution circuit. If it senses deviation from the expected range, it triggers automatic control of voltage regulating devices [157]. This allows the injection of reactive power and voltage to be regulated to the pre-set value. When a fault or outage occurs, with DA, the fault's real-time occurrence can be identified and located faster and more accurately by operators, even at remote locations. Therefore, there will not be a need for time wastage on manual fault tracing, and consumers will not need to report to the distribution company.

8. Application of Blockchain in Smart Grids

Blockchain (BC) technology first came to the limelight with the bitcoin and has been widely accepted by researchers in various disciplines. Followed by the bitcoin blockchain, the different BC platforms were developed. Though there were other BC platforms, they have classified into three main

types: public blockchain, private blockchain, and federated blockchain. These three BC types have various technical features. Bitcoin and Ethereum are the two typical public blockchains. Any BC node is open to all participants in the public BC type, and each user can participate. Therefore, in public BC, all the participants will have access to public BC transaction information.

Private BC is the second type, where the participants will have restricted access to the transaction information. In Private BC, a participant can only participate in and view information regarding the transaction if the node is given access rights. The third BC type is the federated one, where it has combined features of public and private BC [158]. Its emergence in the energy sector offered numerous applications in SG [159–161]. BC-based on the smart contract allows a peer in the ESN or SG to perform an energy trading transaction (e.g., electricity sale) directly with another peer (peer-to-peer) and invoice it. This peer-to-peer concept needs transactions to be stored on a platform that is part of the ESN. The peers are the participants involved in the electricity trades (typically, the consumer, prosumer, regulatory authority, etc.) [162,163]. For several years, the centralized model has performed well, but with the rise in the volume of data shared during the trading process, there is a possibility that the servers encounter bottlenecks and a single point of failure, making them vulnerable to attack [10]. The BC servers' critical function that is part of the distributed energy network is to ensure trust and preserve a backup of all the transactions. The trust process is one of BC's main principles, preventing the spread of tainted information. In a permission-less or public BC (system without access limitation), the introduction of new information on to block must be allied with specific resources like fuel cost and computational tools. For example, the consensus proof-of-work (PoW) mechanism entails participating nodes to solve the hash code and to validate the node [10,162,163]. Hence, the PoW consensus creates computational expenses due to adding new information (the next block) [164]. A BC offers a centralized computing architecture that allows peers to communicate without a single governing body. However, in the absence of intermediaries, the BC-based systems still rely on the predefined laws' consistency while maintaining protection, efficiency, and accuracy. The BC platform is currently evolving and tackles many problems, but many issues remain open, posing a challenge to scholars.

More recently, there has been a fast growth of automated decision-making support systems [165,166]. A BC is a useful tool in this environment for recording the activities and decisions by practicing the proof-of-work needed to attach a verified block to the chain. The machines may also be used to build the proof-of-work for a mining method. ML methods may be used to detect any suspicious and illicit behaviour that may occur on the BC in real-time. ML and BC will also have plenty of synergies and immersive implementations. For data mining and security, the two systems can work together. When Big Data-based AI solutions are implemented through a BC deployment, the way the systems operate can be continuously tested by a comprehensive and accurate database of all the decisions. AI systems exploit data collected from sensors for analytics, and decision-making can be tracked at various points while the process is placed into a BC paradigm. One of the key benefits of implementing Big Data technology in BC is increasing accuracy and data security. Both are described as critical aspects of the BC paradigm. The data exchange should become easier and more common, as BC deployment guarantees protection and originality.

An "intelligent contract" is a virtual protocol that automatically performs the default transaction processes without needing a third-party intervention. An example of this in smart energy systems would include developing fully self-governing smart contracts between an energy supplier and a customer who controls both the sale and the payment separately and safely [167,168]. If the client does not make the price, the smart contract system would immediately terminate the supply until the transaction is completed, provided the partners have already agreed to use this provision in their contract. However, such growth presents a challenge to conventional business models related to energy finance, which may risk being removed from the consumer sector for payments.

The use of the BC in SG could provide our present and future energy grid with multiple advantages. The developed decentralized trading network gives much of its advantages to the electrical system, connected explicitly with the BC features and working concepts. BC's key benefits in ESN

features and operating principles are decentralizing confidence and increasing protection, durability, openness, and scalability and providing less bureaucracy and growing computing capability [4,169,170]. Several new BC frames in the intelligent grids could be taken from these benefits, as stated in Table 4.

Table 4. Role of blockchain in the microgrids and smart grids.

The Role Played by Blockchain in Microgrids and Smart Grid	Reference
<ul style="list-style-type: none"> – A multi-agent coalition and blockchain were used for energy trading in an active distribution network. – A multi-agent coalition and blockchain supported the prosumer network and allowed negotiations related to electricity trading. – Energy trading transaction settlement was done using the blockchain protocol, and trust and security are ensured. 	[171]
<ul style="list-style-type: none"> – Blockchain is used in energy demand-side management within electricity systems networks. – Game-theoretic approach was modeled for demand-side management and an integrated energy storage system. – Enabled the reduction in peak-to-average ratio, which benefits the electrical grid. – Due to supply-side constraints, dips in the load patterns are observed, and smoothening has become a bit easier with blockchain-based energy trading. 	[172]
<ul style="list-style-type: none"> – Laboratory-scale model of the blockchain model was the implementation exchange of solar energy. 	[173]
<ul style="list-style-type: none"> – Internet of energy management with blockchain was discussed with various aspects: review, solutions, and challenges. 	
<ul style="list-style-type: none"> – Secure energy trading and payment transactions are enabled in V2G-based microgrids – Faster verification, reliability improvements, and immutability are significant benefits offered by the blockchain. 	[174]
<ul style="list-style-type: none"> – An incentive for maximized green energy exchanges has become more comfortable with the blockchain. 	[175]
<ul style="list-style-type: none"> – A clean energy was designed with BC application with the IoE to balance building production with energy trading, 	[176]
<ul style="list-style-type: none"> – An efficient and secure data management platform with lowered network delay. 	[177]

Note: Vehicle to Grid (V2G), Blockchain (BC), Internet of Energy (IoE).

The realization of the above-discussed benefits and the BC roles highlighted in Table 4 needs a suitable layer architecture for the typical SG shown in Figure 19a. A three-layer BC architecture that automates the SG services and enhances security and data protection in SG is shown in Figure 19b–d [167].

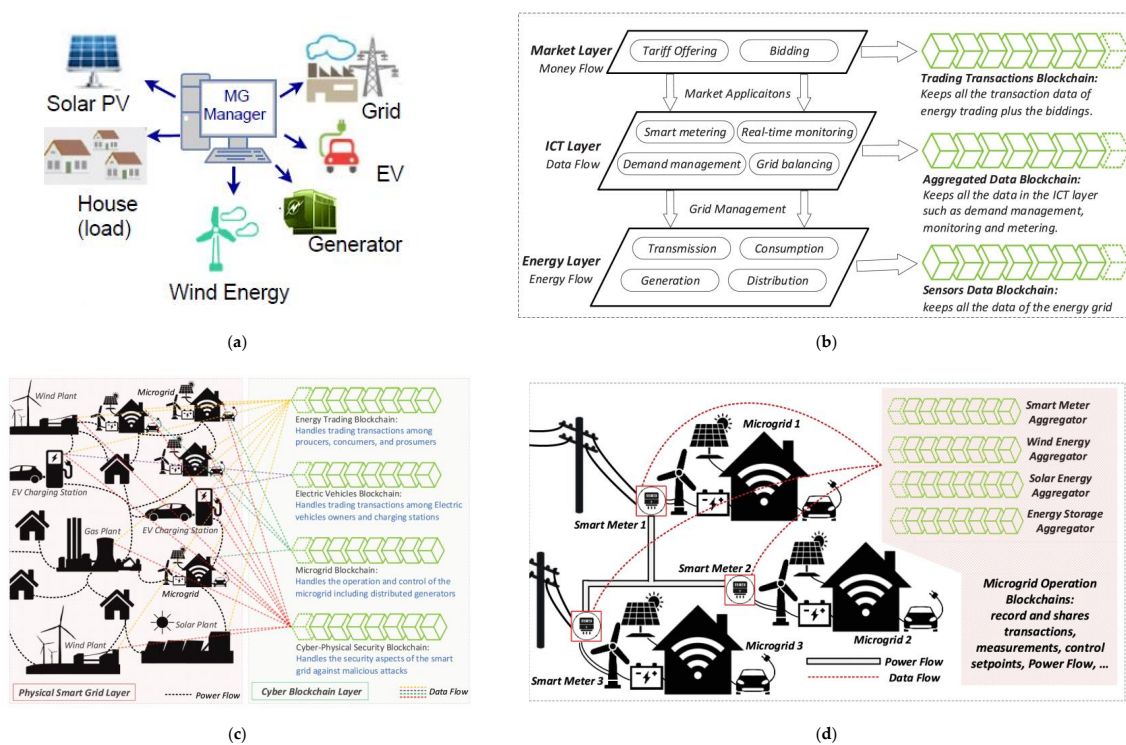


Figure 19. Blockchain for smart grid (a). hybrid renewable energy microgrid with microgrid manager (Note: PV—photovoltaics, MG—microgrid, PV—electric vehicle) (b). A three-layer blockchain architecture for enhancing security and data protection in a smart grid along with applications (Note: ICT—information and communication technologies) (Reprinted with permission [167], 2019, IEEE). (c). A new cyber layer for smart grids using blockchain (Reprinted with permission [167], 2019, IEEE), and (d). Using blockchain for microgrid services automation (Reprinted with permission [167], 2019, IEEE).

9. Discussion on the Benefits and Services Offered by the Smart Grid

A comprehensive discussion on DER and different digital technologies like AI, ML, DL, IoT, EI, and BC in the SG context is carried out in the previous sections. Based on the knowledge provided in Sections 2, 3, 4, 5, 6, 7, 8, it is understood that the RER's contribution to future SG development would be very high.

It is also clear that the EV penetration to SG would increase in the near future and be a vital component in the SG configuration. Based on its inherent nature, SG will be able to “detect, react, and pro-act” to changes in system functioning and energy usage, ensuring timely grid operations. These features in DER-based SG can be accomplished at the fullest level using AI, IoT, and BC. The investigation of these digital technologies had also informed the same. However, the cost involved in transitioning from the CEG to the SG is very high, but the benefits are numerous and will eventually reduce electricity costs. With the shift to SG, the current ESN could have the following services.

- Support a more significant proportion of RE as SGs are well-designed with technology support that effectively controls the ESN by taking the uncertainties associated with RE,
- Acts as a better response system that mitigates the sudden disturbance by offering the services related to repair and faster restoration,
- Live statistics on the energy consumptions patterns and suggestions on improving energy efficiency,
- Live information on electricity generation prices along with the forecasted price based on the time of use,
- Peak demand adjustment within the ESN, based on the flexible and convenient time of operation,
- Enhanced grid efficiency and improvements in energy trading, metering, and RE integration,

- Flexible and sustainable energy trading is ensured and a choice of low carbon electricity selection while trade is possible,
- Advanced support for EV penetration and home energy management,
- Extended support is offered for plug-in energy infrastructures (e.g., city surveillance systems, public lighting, energy on-demand services).

In addition to the above highlighted benefits, with digital advancement, the SG services were further enhanced. Especially with the use of AI, IoT, and BC, automated peer services have improved. This has become possible by monitoring real-time information about the ESN in the context of reliability, availability, resilience, stability, security, and sustainability. In the following paragraphs, the discussion on AI, IoT, and BC's contribution to reliability, availability, resilience, stability, security, and sustainability enhancement is made.

Reliability, availability, and stability are the SG's critical services to the peers in the ESN. Due to the increased complexity of the ESN in the modern power sector, meeting reliability, availability, and stability objectives are becoming more challenging. Effective monitoring of the SG using the digital tools could help address the issues related to aggravated grid congestion and massive transfers of energy over long distances. Furthermore, the challenges of increasing energy consumption and peak demand, and aging infrastructure are addressed by promoting maximizing asset utilization [160,178]. Digital tools like AI, IoT, and BC could provide the fullest control and allow effective monitoring of the above-highlighted issues, improving the overall ESN performance [13].

Resilience is another key criterion that needs to be ensured in the SG. An ESN can sustain, rapidly recover, and learn to adapt its structure to unexpected disruptive events. It is believed that SG is capable of being resilient to disruptions. The causes of disruption might be "extreme weather events, asset failure, natural disasters, power surges, acute accidents, and even operational errors by the workforce" [13,18]. Such uncertain situations should be predicted earlier to have informed decisions. Digital tools like AI, IoT, and BC help predict the disruption based on the systems' knowledge it has. For example, the IoT tools can detect any sought of faults that might cause a resilience issue and inform those to carry out the analytics for understanding the ESN robustness [160]. The AI-based analytics estimates the system robustness and allows the data-driven decisions to take appropriate actions to improve the robustness and ensure a quick recovery [178]. Here, the BC offers its service in providing the energy balances by facilitating the involved peers to be a part of the energy trading schemes. This allows the ESN to bounce back to its normal state [169].

Security issues that lie with peer communication in the ESN can be addressed using IoT and BC systems [158]. The BC's trust and transparent features ensure that information flow between the peers is always secure and happens through a specific channel based on the defined agreement on the smart contracts [162,163]. Additionally, the BC traceability feature allows us to quickly identify the destruction of information and manipulation of energy consumption data. Similarly, the IoT and BC systems provide data integrity, data confidentiality, and timely data [158].

Sustainability is another crucial criterion that a modern power system should have, and it is clearly defined under sustainable development goal 7 (SDG7) [55]. Ensuring ESN's sustainability might be a difficult task as it involves numerous components, and each contributes to a certain amount of GHG. Tracking each component and the type of resources based on the sustainability indicators may not be possible in CEG [179,180]. The amount of emissions released based on the type of DER used can also impact SG's sustainability. In SG's case, the concept of asset management or ESN infrastructure management could help us monitor these data [179]. However, the digital advancement of SG with IoT and BC could help us to monitor and estimate the number of resources consumed for a typical SG [179]. The BC enabled product traceability, and the life cycle assessment tool can easily allow sustainability scores for SG [180,181].

Overall, this critical investigation of the selected three digital technologies revealed a broader scope in SG. On the other side, the above discussion also in line with the existing literature.

10. Conclusions

This study has illustrated the concept of SG in detail and provided much information on its conceptual technologies, technicality, and the pooled technologies. The DER and pools of numerous existing and emerging know-hows like information and digital communication technologies are discussed. The full implementation of SG and its performance-related services are thoroughly discussed.

The promotion of locally available DER's, especially RER for stable, reliable, sustainable, and affordable electricity, is given importance and a brief discussion on all the possible DERs. Also, the DER's detailed progress concerning the SG on a global scale is discussed. A discussion is carried out on the SG that can support and be supported by emerging EV technology. Overall, it is meant to reduce the dependence of the transport sector on oil. SG offered fully automated services and intelligently monitored information right from generation and down to equipment it powers, and it incorporated peer behaviors.

The monitored information allows the operations like “detect, react, and pro-act” in DER-based SG, and they can be accomplished at the fullest level with the use of AI, IoT, and BC. The techniques associated with AI include fuzzy logic, expert systems, and artificial neural networks, and the advances they brought in controlling the DER-based SG are provided. The IoT and BC enabled services like data sensing, data storage, secured, transparent, and traceable digital transactions are briefly discussed. The role played by AI-based analytics, IoT components along with energy Internet architecture, and the BC assistance in improving SG services like reliability, availability, resilience, stability, security, and sustainability are presented.

Overall, this study provided an overview of DER and the applications of three leading digital technologies like AI, IoT, and BC in SG.

Author Contributions: Conceptualization, N.M.K. and S.S.C. Data curation, N.M.K. and A.A.C. Funding acquisition, N.M.K. and S.S.C. Resources, S.S.C. Supervision, S.S.C. Visualization, N.M.K. and A.A.C. Writing—original draft, N.M.K. and A.A.C. Writing—review and editing, N.M.K., M.M., K.A.P., K.A.M., F.R.I. and S.S.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

References

- Gilland, B. Population, Economic Growth, and Energy Demand, 1985–2020. *Popul. Dev. Rev.* **1988**, *14*, 233. [[CrossRef](#)]
- Chopra, S.S.; Khanna, V. Interconnectedness and interdependencies of critical infrastructures in the US economy: Implications for resilience. *Phys. A Stat. Mech. Appl.* **2015**, *436*, 865–877. [[CrossRef](#)]
- Burney, N.A. Socioeconomic development and electricity consumption A cross-country analysis using the random coefficient method. *Energy Econ.* **1995**, *17*, 185–195. [[CrossRef](#)]
- Vasylieva, T.; Lyulyov, O.; Bilan, Y.; Streimikiene, D. Sustainable Economic Development and Greenhouse Gas Emissions: The Dynamic Impact of Renewable Energy Consumption, GDP, and Corruption. *Energies* **2019**, *12*, 3289. [[CrossRef](#)]
- Frei, C.; Whitney, R.; Schiffer, H.W.; Rose, K.; Rieser, D.A.; Al-Qahtani, A.; Thomas, P.; Turton, H.; Densing, M.; Panos, E.; et al. *World Energy Scenarios: Composing Energy Futures to 2050* (No. INIS-FR-14-0059); Conseil Francais de l'Energie: Paris, France, 2013.
- Avgerou, C. Discourses on ICT and development. *Inf. Technol. Int. Dev.* **2010**, *6*, 1–18.
- Mangla, S.K.; Luthra, S.; Jakhar, S.; Gandhi, S.; Muduli, K.; Kumar, A. A step to clean energy—Sustainability in energy system management in an emerging economy context. *J. Clean. Prod.* **2020**, *242*, 118462. [[CrossRef](#)]
- Babu, T.S.; Vasudevan, K.R.; Ramchandaramurthy, V.K.; Sani, S.B.; CheMud, S.; Lajim, R.M. A comprehensive review of hybrid energy storage systems: Converter topologies, control strategies and future prospects. *IEEE Access* **2020**, *8*, 148702–148721. [[CrossRef](#)]

9. Elavarasan, R.M.; Shafiullah, G.; Padmanaban, S.; Kumar, N.M.; Annam, A.; Vetrichelvan, A.M.; Mihet-Popa, L.; Holm-Nielsen, J.B. A Comprehensive Review on Renewable Energy Development, Challenges, and Policies of Leading Indian States with an International Perspective. *IEEE Access* **2020**, *8*, 74432–74457. [CrossRef]
10. Kumar, N.M. Blockchain: Enabling wide range of services in distributed energy system. *Beni-Suef Univ. J. Basic Appl. Sci.* **2018**, *7*, 701–704. [CrossRef]
11. Bajaj, M.; Singh, A.K. Grid integrated renewable DG systems: A review of power quality challenges and state-of-the-art mitigation techniques. *Int. J. Energy Res.* **2019**, *44*, 26–69. [CrossRef]
12. Das, S.R.; Ray, P.K.; Sahoo, A.K.; Ramasubbareddy, S.; Babu, T.S.; Kumar, N.M.; Alhelou, H.H.; Siano, P. Performance of Hybrid Filter in a Microgrid Integrated Power System Network Using Wavelet Techniques. *Appl. Sci.* **2020**, *10*, 6792. [CrossRef]
13. Kumar, N.M.; Ghosh, A.; Chopra, S.S. Power Resilience Enhancement of a Residential Electricity User Using Photovoltaics and a Battery Energy Storage System Under Uncertainty Conditions. *Energies* **2020**, *13*, 4193. [CrossRef]
14. Lamb, M.; Agarwal, R. Deploying Digital Assets: Natural Gas Utilities Using Smart Grid Technologies to Modernize Infrastructure. *Nat. Gas Electr.* **2020**, *36*, 1–11. [CrossRef]
15. Dafalla, Y.; Liu, B.; Hahn, D.A.; Wu, H.; Ahmadi, R.; Bardas, A.G. Prosumer Nanogrids: A Cybersecurity Assessment. *IEEE Access* **2020**, *8*, 131150–131164. [CrossRef]
16. Atalay, M.; Angin, P. A Digital Twins Approach to Smart Grid Security Testing and Standardization. In Proceedings of the 2020 IEEE International Workshop on Metrology for Industry 4.0 & IoT (MetroInd4.0&IoT), Roma, Italy, 3–5 June 2020. [CrossRef]
17. Ferdous, S.M.; Shafiullah, G.M.; Shahnian, F.; Elavarasan, R.M.; Subramaniam, U. Dynamic Frequency and Overload Management in Autonomous Coupled Microgrids for Self-Healing and Resiliency Improvement. *IEEE Access* **2020**, *8*, 116796–116811. [CrossRef]
18. Kumar, S.A.; Subathra, M.S.P.; Kumar, N.M.; Malvoni, M.; Sairamya, N.J.; George, S.T.; Suviseshamuthu, E.S.; Chopra, S.S. A Novel Islanding Detection Technique for a Resilient Photovoltaic-Based Distributed Power Generation System Using a Tunable-Q Wavelet Transform and an Artificial Neural Network. *Energies* **2020**, *13*, 4238. [CrossRef]
19. Reddy, M.Y.; GM, S.R.; Madhusudhan, E.; Al Muhteb, S. Securing smart grid technology. In *2012 International Conference on Graphic and Image Processing*; International Society for Optics and Photonics: Bellingham, WA, USA, 2013; Volume 8768, p. 87684E.
20. Calvillo, C.F.; Sánchez-Miralles, A.; Villar, J. Energy management and planning in smart cities. *Renew. Sustain. Energy Rev.* **2016**, *55*, 273–287. [CrossRef]
21. Phuangpornpitak, N.; Tia, S. Opportunities and Challenges of Integrating Renewable Energy in Smart Grid System. *Energy Procedia* **2013**, *34*, 282–290. [CrossRef]
22. Clastres, C. Smart grids: Another step towards competition, energy security and climate change objectives. *Energy Policy* **2011**, *39*, 5399–5408. [CrossRef]
23. Ontario Smart Grid Progress Assessment: A Vignette, Ontario Smart Grid Forum. September 2013. Available online: http://www.ieso.ca/en/Learn/Ontario-Power-System/etno/-/media/files/ieso/document-library/smart_grid/Smart_Grid_Progress_Assessment_Vignette.pdf (accessed on 21 March 2020).
24. Zahedi, A. A review of drivers, benefits, and challenges in integrating renewable energy sources into electricity grid. *Renew. Sustain. Energy Rev.* **2011**, *15*, 4775–4779. [CrossRef]
25. Markovska, N.; Duic, N.; Mathiesen, B.V.; Guzović, Z.; Piacentino, A.; Schlör, H.; Lund, H. Addressing the main challenges of energy security in the twenty-first century—Contributions of the conferences on Sustainable Development of Energy, Water and Environment Systems. *Energy* **2016**, *115*, 1504–1512. [CrossRef]
26. Cuadra, L.; Del Pino, M.; Borge, J.C.N.; Salcedo-Sanz, S. Optimizing the Structure of Distribution Smart Grids with Renewable Generation against Abnormal Conditions: A Complex Networks Approach with Evolutionary Algorithms. *Energies* **2017**, *10*, 1097. [CrossRef]
27. Kaloudi, N.; Li, J. The AI-Based Cyber Threat Landscape. *ACM Comput. Surv.* **2020**, *53*, 1–34. [CrossRef]
28. Ahmad, I.; Kazmi, J.H.; Shahzad, M.; Palensky, P.; Gawlik, W. Co-simulation framework based on power system, AI and communication tools for evaluating smart grid applications. In Proceedings of the 2015 IEEE Innovative Smart Grid Technologies—Asia (ISGT ASIA), Bangkok, Thailand, 3–6 November 2015. [CrossRef]

29. Abdul-Qawy, A.S.; Pramod, P.J.; Magesh, E.; Srinivasulu, T. The Internet of Things (IoT): An Overview. *Int. J. Eng. Res. Appl.* **2015**, *1*, 71–82.
30. Chen, X.; Liu, J.; Li, X.; Sun, L.; Zhen, Y. Integration of IOT with smart grid. In Proceedings of the IET International Conference on Communication Technology and Application (ICCTA 2011), Beijing, China, 14–16 October 2011. [CrossRef]
31. Digiteum Team. The Role of IoT in Smart Grid Technology. In Digiteum. 10 September 2019. Available online: <https://www.digiteum.com/iot-smart-grid-technology> (accessed on 21 March 2020).
32. Shyam, R.; Ganesh, H.B.; Kumar, S.S.; Poornachandran, P.; Soman, K.P. Apache Spark a Big Data Analytics Platform for Smart Grid. *Procedia Technol.* **2015**, *21*, 171–178. [CrossRef]
33. Munshi, A.A.; Mohamed, Y.A.-R.I. Big data framework for analytics in smart grids. *Electr. Power Syst. Res.* **2017**, *151*, 369–380. [CrossRef]
34. Bhattarai, B.P.; Paudyal, S.; Luo, Y.; Mohanpurkar, M.; Cheung, K.W.; Tonkoski, R.; Hovsopian, R.; Myers, K.S.; Zhang, R.; Zhao, P.; et al. Big data analytics in smart grids: State-of-the-art, challenges, opportunities, and future directions. *IET Smart Grid* **2019**, *2*, 141–154. [CrossRef]
35. Pisica, I.; Eremia, M. Making smart grids smarter by using machine learning. In Proceedings of the 2011 46th International Universities Power Engineering Conference (UPEC), Soest, Germany, 5–8 September 2011.
36. Finn, D.P.; De Rosa, M.; Milano, F.; Finn, D.P. Demand response algorithms for smart-grid ready residential buildings using machine learning models. *Appl. Energy* **2019**, *239*, 1265–1282. [CrossRef]
37. Xia, Z. An Overview of Deep Learning. In *Deep Learning in Object Detection and Recognition*; Springer: Singapore, 2019; pp. 1–18. [CrossRef]
38. Anthony, L.F.W.; Kanding, B.; Selvan, R. Carbontracker: Tracking and predicting the carbon footprint of training deep learning models. *arXiv* **2020**, arXiv:2007.03051.
39. Sengupta, S.; Basak, S.; Saikia, P.; Paul, S.; Tsalavoutis, V.; Atiah, F.; Ravi, V.; Peters, A. A review of deep learning with special emphasis on architectures, applications and recent trends. *Knowl. Based Syst.* **2020**, *194*, 105596. [CrossRef]
40. Yigit, M.; Gungor, V.C.; Baktir, S. Cloud Computing for Smart Grid applications. *Comput. Netw.* **2014**, *70*, 312–329. [CrossRef]
41. Okay, F.Y.; Ozdemir, S. A fog computing based smart grid model. In Proceedings of the 2016 International Symposium on Networks, Computers and Communications (ISNCC), Yasmine Hammamet, Tunisia, 11–13 May 2016. Available online: <https://doi.org/10.1109/ISNCC.2016.7746062> (accessed on 30 September 2020).
42. Sami, I.; Ali, S.M.; Nazir, S.; Khan, I.; Asghar, R.; Abid, M.A.; Ullah, Z.; Khan, B.; Mehmood, C.A. Cloud Computing (CC) Centers-A Fast Processing Engine in Smart Grid. In Proceedings of the 2019 International Conference on Electrical, Communication, and Computer Engineering (ICECCE), Swat, Pakistan, 24–25 July 2019. [CrossRef]
43. Hassan, N.U.; Yuen, C.; Niyato, D. Blockchain Technologies for Smart Energy Systems: Fundamentals, Challenges, and Solutions. *IEEE Ind. Electron. Mag.* **2019**, *13*, 106–118. [CrossRef]
44. Kim, S.-K.; Huh, J.-H. A Study on the Improvement of Smart Grid Security Performance and Blockchain Smart Grid Perspective. *Energies* **2018**, *11*, 1973. [CrossRef]
45. Cherian, J.R. An Overview of Blockchain Technology and its Applications in the Society. *CYBERNOMICS* **2020**, *2*, 29–31.
46. Worighi, I.; Maach, A.; Hafid, A.; Hegazy, O.; Van Mierlo, J. Integrating renewable energy in smart grid system: Architecture, virtualization and analysis. *Sustain. Energy Grids Netw.* **2019**, *18*, 100226. [CrossRef]
47. Islam, F.R.; Mamun, K.A. Possibilities and Challenges of Implementing Renewable Energy in the Light of PESTLE & SWOT Analyses for Island Countries. In *Smart Energy Grid Design for Island Countries: Challenges and Opportunities*; Springer International Publishing: Cham, Switzerland, 2017; pp. 1–19. [CrossRef]
48. Notton, G.; Nivet, M.-L.; Voyant, C.; Paoli, C.; Darras, C.; Motte, F.; Fouilloy, A. Intermittent and stochastic character of renewable energy sources: Consequences, cost of intermittence and benefit of forecasting. *Renew. Sustain. Energy Rev.* **2018**, *87*, 96–105. [CrossRef]
49. Kumar, A.; Meena, N.K.; Singh, A.R.; Deng, Y.; He, X.; Bansal, R.; Kumar, P. Strategic integration of battery energy storage systems with the provision of distributed ancillary services in active distribution systems. *Appl. Energy* **2019**, *253*, 113503. [CrossRef]

50. Prakash, K.; Lallu, A.; Islam, F.; Mamun, K. Review of Power System Distribution Network Architecture. In Proceedings of the 3rd Asia-Pacific World Congress on Computer Science and Engineering (APWC on CSE), Nadi, Fiji, 5–6 December 2016; pp. 124–130. [CrossRef]
51. Karimi, M.A.; Mokhlis, H.; Naidu, K.V.S.; Uddin, S.N.; Bakar, A. Photovoltaic penetration issues and impacts in distribution network—A review. *Renew. Sustain. Energy Rev.* **2016**, *53*, 594–605. [CrossRef]
52. Islam, F.R.; Al Mamun, K.; Amanullah, M.T.O. *Smart Energy Grid Design for Island Countries*; Springer: Berlin/Heidelberg, Germany, 2017.
53. Eolas Magazine. Smart Grid Evolution. March 2018. Available online: <https://www.eolasmagazine.ie/smart-grid-evolution/> (accessed on 24 March 2020).
54. Elavarasan, R.M.; Shafiullah, G.M.; Kumar, N.M.; Padmanaban, S. A State-of-the-Art Review on the Drive of Renewables in Gujarat, State of India: Present Situation, Barriers and Future Initiatives. *Energies* **2019**, *13*, 40. [CrossRef]
55. Kumar, N.M.; Chopra, S.S.; Chand, A.A.; Elavarasan, R.M.; Shafiullah, G. Hybrid Renewable Energy Microgrid for a Residential Community: A Techno-Economic and Environmental Perspective in the Context of the SDG7. *Sustainability* **2020**, *12*, 3944. [CrossRef]
56. Vishnupriyan, J.; Manoharan, P. Demand side management approach to rural electrification of different climate zones in Indian state of Tamil Nadu. *Energy* **2017**, *138*, 799–815. [CrossRef]
57. Kumar, N.M. Performance of single-sloped pitched roof cadmium telluride (CdTe) building-integrated photovoltaic system in tropical weather conditions. *Beni Suef Univ. J. Basic Appl. Sci.* **2019**, *8*, 2. [CrossRef]
58. Kumar, N.M.; Subramaniam, U.; Mathew, M.; Ajitha, A.; Almakhlles, D.J. Exergy analysis of thin-film solar PV module in ground-mount, floating and submerged installation methods. *Case Stud. Therm. Eng.* **2020**, *21*, 100686. [CrossRef]
59. Kumar, N.M.; Yadav, S.K.; Chopra, S.S.; Bajpai, U.; Gupta, R.P.; Sanjeevikumar, P.; Blaabjerg, F. Operational performance of on-grid solar photovoltaic system integrated into pre-fabricated portable cabin buildings in warm and temperate climates. *Energy Sustain. Dev.* **2020**, *57*, 109–118. [CrossRef]
60. Kumar, N.M.; Kanchikere, J.; Mallikarjun, P. Floatovoltaics: Towards improved energy efficiency, land and water management. *Int. J. Civ. Eng. Technol.* **2018**, *9*, 1089–1096.
61. IEA. Task1: Strategic PV Analysis and Outreach. In *Snapshot of Global PV Markets 2020*; Masson, G., Ed.; IEA: Paris, France, 2020; pp. 10–15. ISBN 978-3-906042-94-7.
62. Installed Solar Energy Capacity, 2019. Cumulative Installed Solar Capacity, Measured in Gigawatts (GW). Available online: https://ourworldindata.org/grapher/installed-solar-pv-capacity?tab=map&time=earliest.latest&country=OWID_WRL~{}USA~{}CHN~{}JPN~{}Europe~{}IND (accessed on 29 September 2020).
63. IEA. Renewables 2019-Market Analysis and Forecast from 2019 to 2024. Available online: <https://www.iea.org/reports/renewables-2019> (accessed on 30 September 2020).
64. Rajput, P.; Malvoni, M.; Kumar, N.M.; Sastry, O.S.; Jayakumar, A. Operational Performance and Degradation Influenced Life Cycle Environmental–Economic Metrics of mc-Si, a-Si and HIT Photovoltaic Arrays in Hot Semi-arid Climates. *Sustainability* **2020**, *12*, 1075. [CrossRef]
65. Rajput, P.; Malvoni, M.; Kumar, N.M.; Sastry, O.; Tiwari, G. Risk priority number for understanding the severity of photovoltaic failure modes and their impacts on performance degradation. *Case Stud. Therm. Eng.* **2019**, *16*, 100563. [CrossRef]
66. Jerin, A.R.A.; Prabaharan, N.; Kumar, N.M.; Palanisamy, K.; Umashankar, S.; Siano, P. Smart grid and power quality issues. In *Hybrid-Renewable Energy Systems in Microgrids*; Elsevier BV: Amsterdam, The Netherlands, 2018; pp. 195–202.
67. Schubel, P.J.; Crossley, R.J. Wind Turbine Blade Design. *Energies* **2012**, *5*, 3425–3449. [CrossRef]
68. Islam, F.; Lallu, A.; Mamun, K.A.; Prakash, K.; Rattan, A.A. Impact of wind generators in power system stability. *WSEAS Trans. Power Syst.* **2018**, *13*, 235–248.
69. Sunny, K.A.; Kumar, P.; Kumar, N.M. Experimental study on novel curved blade vertical axis wind turbines. *Results Eng.* **2020**, *7*, 100149. [CrossRef]
70. Kumar, N.M.; Subathra, M.; Cota, O.D. Design and Wind Tunnel Testing of Funnel Based Wind Energy Harvesting System. *Procedia Technol.* **2015**, *21*, 33–40. [CrossRef]

71. Installed Wind Energy Capacity, 2019. Cumulative Installed wind Energy Capacity Including Both Onshore and Offshore Wind Sources, Measured in Gigawatts (GW). Available online: https://ourworldindata.org/grapher/cumulative-installed-wind-energy-capacity-gigawatts?tab=map&time=1997.latest&country=CHN~{}DNK~{}Asia%20Pacific~{}Europe~{}IND~{}Middle%20East~{}GBR~{}USA~{}South%20%26%20Central%20America~{}OWID_WRL~{}TWN~{}Africa (accessed on 30 September 2020).
72. Aggidis, G.; Luchinskaya, E.; Rothschild, R.; Howard, D. The costs of small-scale hydro power production: Impact on the development of existing potential. *Renew. Energy* **2010**, *35*, 2632–2638. [[CrossRef](#)]
73. Hammid, A.T.; Awad, O.I.; Sulaiman, M.H.; Gunasekaran, S.S.; Mostafa, S.A.; Kumar, N.M.; Khalaf, B.A.; Al-Jawhar, Y.A.; Abdulhasan, R.A. A Review of Optimization Algorithms in Solving Hydro Generation Scheduling Problems. *Energies* **2020**, *13*, 2787. [[CrossRef](#)]
74. Sharma, H.; Singh, J. Run off river plant: Status and prospects. *Int. J. Innov. Technol. Explor. Eng.* **2013**, *3*, 210–213.
75. Deane, J.; Gallachóir, B.Ó.; McKeogh, E. Techno-economic review of existing and new pumped hydro energy storage plant. *Renew. Sustain. Energy Rev.* **2010**, *14*, 1293–1302. [[CrossRef](#)]
76. Hydropower Generation, 2019. Hydropower Generation, 2019. Annual Hydropower Generation is Measured in Terawatt-Hours (TWh). Available online: <https://ourworldindata.org/grapher/hydropower-consumption?tab=chart&time=2000.latest&country=CHN~{}IND~{}BWA~{}USA~{}SWE~{}FRA~{}CAN~{}BRA~{}NOR> (accessed on 30 September 2020).
77. Özder, E.H.; Özcan, E.C.; Eren, T. Sustainable personnel scheduling supported by an artificial neural network model in a natural gas combined cycle power plant. *Int. J. Energy Res.* **2020**, *44*, 7525–7547. [[CrossRef](#)]
78. Kumar, N.M.; Subathra, M.S.P.; Cota, O.D. Waste energy recovery in iron and steel industries for CO₂ emission reduction: A case study. *J. Environ. Res. Dev.* **2015**, *10*, 149.
79. Kumar, N.M.; Kumar, G.H.K. Power generation using Green Technology in Iron and Steel industry. In Proceedings of the 2015 IEEE 9th International Conference on Intelligent Systems and Control (ISCO), Coimbatore, India, 9–10 January 2015. [[CrossRef](#)]
80. Nallapaneni, M.K. Impact of clean development mechanism on eco-friendly energy recovery technology. *Procedia Technol.* **2015**, *21*, 54–58. [[CrossRef](#)]
81. Palzer, A.; Henning, H.-M. A comprehensive model for the German electricity and heat sector in a future energy system with a dominant contribution from renewable energy technologies—Part II: Results. *Renew. Sustain. Energy Rev.* **2014**, *30*, 1019–1034. [[CrossRef](#)]
82. Ellamla, H.R.; Staffell, I.; Bujlo, P.; Pollet, B.G.; Pasupathi, S. Current status of fuel cell based combined heat and power systems for residential sector. *J. Power Sources* **2015**, *293*, 312–328. [[CrossRef](#)]
83. Lake, A.; Rezaie, B.; Beyerlein, S. Review of district heating and cooling systems for a sustainable future. *Renew. Sustain. Energy Rev.* **2017**, *67*, 417–425. [[CrossRef](#)]
84. Karmaker, A.K.; Hossain, A.; Kumar, N.M.; Jagadeesan, V.; Jayakumar, A.; Ray, B. Analysis of Using Biogas Resources for Electric Vehicle Charging in Bangladesh: A Techno-Economic-Environmental Perspective. *Sustainability* **2020**, *12*, 2579. [[CrossRef](#)]
85. Salehabadi, A.; Ahmad, M.I.; Ismail, N.; Morad, N.; Enhessari, M. Overview of Energy. In *Energy, Society and the Environment. SpringerBriefs in Applied Sciences and Technology*; Springer: Singapore, 2020; pp. 9–26. [[CrossRef](#)]
86. Suberu, M.Y.; Mustafa, M.W.; Bashir, N. Energy storage systems for renewable energy power sector integration and mitigation of intermittency. *Renew. Sustain. Energy Rev.* **2014**, *35*, 499–514. [[CrossRef](#)]
87. Chen, H.; Cong, T.N.; Yang, W.; Tan, C.; Li, Y.; Ding, Y. Progress in electrical energy storage system: A critical review. *Prog. Nat. Sci.* **2009**, *19*, 291–312. [[CrossRef](#)]
88. Chand, A.A.; Prasad, A.K.; Mamun, A.K.; Islam, F.; Manoj, N.K.; Rajput, P.; Sanjeevikumar, P. Microgrid Modeling and Simulations. In *Microgrids*; Informa UK Limited: London, UK, 2020; pp. 59–79.
89. Sharma, A.; Tyagi, V.; Chen, C.; Buddhi, D. Review on thermal energy storage with phase change materials and applications. *Renew. Sustain. Energy Rev.* **2009**, *13*, 318–345. [[CrossRef](#)]
90. Zhao, H.; Wu, Q.; Hu, S.; Xu, H.; Rasmussen, C.N. Review of energy storage system for wind power integration support. *Appl. Energy* **2015**, *137*, 545–553. [[CrossRef](#)]
91. Gelazanskas, L.; Gamage, K.A. Demand side management in smart grid: A review and proposals for future direction. *Sustain. Cities Soc.* **2014**, *11*, 22–30. [[CrossRef](#)]

92. Saffari, M.; De Gracia, A.; Fernández, C.; Belusko, M.; Boer, D.; Cabeza, L.F. Optimized demand side management (DSM) of peak electricity demand by coupling low temperature thermal energy storage (TES) and solar PV. *Appl. Energy* **2018**, *211*, 604–616. [[CrossRef](#)]
93. Palensky, P.; Dietrich, D. Demand Side Management: Demand Response, Intelligent Energy Systems, and Smart Loads. *IEEE Trans. Ind. Informatics* **2011**, *7*, 381–388. [[CrossRef](#)]
94. Mwasilu, F.; Justo, J.J.; Kim, E.-K.; Do, T.D.; Jung, J.-W. Electric vehicles and smart grid interaction: A review on vehicle to grid and renewable energy sources integration. *Renew. Sustain. Energy Rev.* **2014**, *34*, 501–516. [[CrossRef](#)]
95. Islam, F.R.; Pota, H. Design a PV-AF system using V2G technology to improve power quality. In Proceedings of the IECON 2011—37th Annual Conference of the IEEE Industrial Electronics Society, Melbourne, VIC, Australia, 7–10 November 2011. [[CrossRef](#)]
96. Moslehi, K.; Kumar, R. A Reliability Perspective of the Smart Grid. *IEEE Trans. Smart Grid* **2010**, *1*, 57–64. [[CrossRef](#)]
97. Islam, F.R.; Pota, H.R.; Ali, M.S. V2G technology for designing active filter system to improve wind power quality. In Proceedings of the AUPEC 2011, Brisbane, QLD, Australia, 25–28 September 2011.
98. Islam, F.R.; Pota, H.R. V2G technology to improve wind power quality and stability. In Proceedings of the 2011 Australian Control Conference, Melbourne, VIC, Australia, 10–11 November 2011.
99. Islam, F.R.; Pota, H.R.; Mahmud, M.A.; Hossain, M.J. Impact of PHEV loads on the dynamic performance of power system. In Proceedings of the 2010 20th Australasian Universities Power Engineering Conference, Christchurch, New Zealand, 5–8 December 2010.
100. Sami, I.; Ullah, Z.; Salman, K.; Hussain, I.; Ali, S.M.; Khan, B.; Mehmood, C.A.; Farid, U. A Bidirectional Interactive Electric Vehicles Operation Modes: Vehicle-to-Grid (V2G) and Grid-to-Vehicle (G2V) Variations Within Smart Grid. In Proceedings of the 2019 International Conference on Engineering and Emerging Technologies (ICEET), Lahore, Pakistan, 21–22 February 2019. [[CrossRef](#)]
101. Prakash, S.S.; Mamun, K.; Islam, F.R.; Cirrincione, M. Design of a Hybrid Microgrid for a Rural Community in Pacific Island Countries. In Proceedings of the 2017 4th Asia-Pacific World Congress on Computer Science and Engineering (APWC on CSE), Nadi, Fiji, 11–13 December 2017. [[CrossRef](#)]
102. Alsaidan, I.; Alanazi, A.; Gao, W.; Wu, H.; Khodaei, A. State-of-the-Art in Microgrid-Integrated Distributed Energy Storage Sizing. *Energies* **2017**, *10*, 1421. [[CrossRef](#)]
103. Planas, E.; Andreu, J.; Gárate, J.I.; De Alegría, I.M.; Ibarra, E. AC and DC technology in microgrids: A review. *Renew. Sustain. Energy Rev.* **2015**, *43*, 726–749. [[CrossRef](#)]
104. Chand, A.A.; Prasad, A.K.; Islam, F.; Mamun, A.K.; Kumar, N.M.; Rajput, P.; Sanjeevikumar, P.; Nithiyananthan, K. AC/DC Microgrids. In *Microgrids*; Informa UK Limited: London, UK, 2020; pp. 41–58.
105. Prado, J.C.D.; Qiao, W.; Qu, L.; Agüero, J.R. The Next-Generation Retail Electricity Market in the Context of Distributed Energy Resources: Vision and Integrating Framework. *Energies* **2019**, *12*, 491. [[CrossRef](#)]
106. Järventausta, P.; Repo, S.; Rautiainen, A.; Partanen, J. Smart grid power system control in distributed generation environment. *Annu. Rev. Control* **2010**, *34*, 277–286. [[CrossRef](#)]
107. Shen, J.; Jiang, C.; Li, B. Controllable Load Management Approaches in Smart Grids. *Energies* **2015**, *8*, 11187–11202. [[CrossRef](#)]
108. Colak, I.; Sagiroglu, S.; Fulli, G.; Yesilbudak, M.; Covrig, C.-F. A survey on the critical issues in smart grid technologies. *Renew. Sustain. Energy Rev.* **2016**, *54*, 396–405. [[CrossRef](#)]
109. Grainger, J.; Civanlar, S. Volt/Var Control on Distribution Systems with Lateral Branches Using Shunt Capacitors and Voltage Regulators Part I: The Overall Problem. *IEEE Trans. Power Appar. Syst.* **1985**, *11*, 3278–3283. [[CrossRef](#)]
110. Jahangiri, P.; Aliprantis, D.C. Distributed Volt/VAr Control by PV Inverters. *IEEE Trans. Power Syst.* **2013**, *28*, 3429–3439. [[CrossRef](#)]
111. Marcos, J.; Storkel, O.; Marroyo, L.; Garcia, M.; Lorenzo, E. Storage requirements for PV power ramp-rate control. *Sol. Energy* **2014**, *99*, 28–35. [[CrossRef](#)]
112. Flannery, P.S.; Venkataramanan, G. Unbalanced Voltage Sag Ride-Through of a Doubly Fed Induction Generator Wind Turbine With Series Grid-Side Converter. *IEEE Trans. Ind. Appl.* **2009**, *45*, 1879–1887. [[CrossRef](#)]
113. Zhu, Z.; Lambotharan, S.; Chin, W.H.; Fan, Z. Overview of demand management in smart grid and enabling wireless communication technologies. *IEEE Wirel. Commun.* **2012**, *19*, 48–56. [[CrossRef](#)]

114. Baimel, D.; Tapuchi, S.; Baimel, N. Smart grid communication technologies-overview, research challenges and opportunities. In Proceedings of the 2016 International Symposium on Power Electronics, Electrical Drives, Automation and Motion (SPEEDAM), Anacapri, Italy, 22–24 June 2016. [\[CrossRef\]](#)
115. Gungor, V.C.; Sahin, D.; Kocak, T.; Ergut, S.; Buccella, C.; Cecati, C.; Hancke, G.P. A Survey on Smart Grid Potential Applications and Communication Requirements. *IEEE Trans. Ind. Informatics* **2012**, *9*, 28–42. [\[CrossRef\]](#)
116. Gungor, V.C.; Sahin, D.; Kocak, T.; Ergut, S.; Buccella, C.; Cecati, C.; Hancke, G.P. Smart Grid Technologies: Communication Technologies and Standards. *IEEE Trans. Ind. Informatics* **2011**, *7*, 529–539. [\[CrossRef\]](#)
117. Kappagantu, R.; Daniel, S.A. Challenges and issues of smart grid implementation: A case of Indian scenario. *J. Electr. Syst. Inf. Technol.* **2018**, *5*, 453–467. [\[CrossRef\]](#)
118. Hossain, E.; Khan, I.; Un-Noor, F.; Sikander, S.S.; Sunny, S.H. Application of Big Data and Machine Learning in Smart Grid, and Associated Security Concerns: A Review. *IEEE Access* **2019**, *7*, 13960–13988. [\[CrossRef\]](#)
119. Zhang, H.-T.; Xu, F.-Y.; Zhou, L. Artificial neural network for load forecasting in smart grid. In Proceedings of the 2010 International Conference on Machine Learning and Cybernetics, Qingdao, China, 11–14 July 2010. [\[CrossRef\]](#)
120. Lee, K.; Cha, Y.; Park, J. Short-term load forecasting using an artificial neural network. *IEEE Trans. Power Syst.* **1992**, *7*, 124–132. [\[CrossRef\]](#)
121. Raza, M.Q.; Baharudin, Z.; Badar-Ul-Islam, B.-U.-I.; Zakariya, M.A.; Khir, M.H.M. Neural Network Based STLF Model to Study the Seasonal Impact of Weather and Exogenous Variables. *Res. J. Appl. Sci. Eng. Technol.* **2013**, *6*, 3729–3735. [\[CrossRef\]](#)
122. Ghanbari, A.; Abbasian-Naghneh, S.; Hadavandi, E.; Ghanbari, A. An intelligent load forecasting expert system by integration of ant colony optimization, genetic algorithms and fuzzy logic. In Proceedings of the 2011 IEEE Symposium on Computational Intelligence and Data Mining (CIDM), Paris, France, 11–15 April 2011. [\[CrossRef\]](#)
123. Marín, F.J.; Sandoval, F. Short-term peak load forecasting: Statistical methods versus artificial neural networks. In Proceedings of the International Work-Conference on Artificial Neural Networks, Lanzarote, Spain, 4–6 June 1997. [\[CrossRef\]](#)
124. Hafeez, G.; Alimgeer, M.U.A.K.S.; Wadud, Z.; Shafiq, Z.; Khan, M.U.A.; Khan, I.; Khan, F.A.; Derhab, A. A Novel Accurate and Fast Converging Deep Learning-Based Model for Electrical Energy Consumption Forecasting in a Smart Grid. *Energies* **2020**, *13*, 2244. [\[CrossRef\]](#)
125. He, Y.; Mendis, G.J.; Wei, J. Real-Time Detection of False Data Injection Attacks in Smart Grid: A Deep Learning-Based Intelligent Mechanism. *IEEE Trans. Smart Grid* **2017**, *8*, 2505–2516. [\[CrossRef\]](#)
126. Zhang, D.; Han, X.; Deng, C. Review on the research and practice of deep learning and reinforcement learning in smart grids. *CSEE J. Power Energy Syst.* **2018**, *4*, 362–370. [\[CrossRef\]](#)
127. Amin, M. Toward self-healing energy infrastructure systems. *IEEE Comput. Appl. Power* **2001**, *14*, 20–28. [\[CrossRef\]](#)
128. Paudyal, S.; Canizares, C.A.; Bhattacharya, K. Optimal Operation of Distribution Feeders in Smart Grids. *IEEE Trans. Ind. Electron.* **2011**, *58*, 4495–4503. [\[CrossRef\]](#)
129. Javed, F.; Arshad, N.; Wallin, F.; Vassileva, I.; Dahlquist, E. Forecasting for demand response in smart grids: An analysis on use of anthropologic and structural data and short term multiple loads forecasting. *Appl. Energy* **2012**, *96*, 150–160. [\[CrossRef\]](#)
130. Siano, P.; Cecati, C.; Yu, H.; Kolbusz, J. Real Time Operation of Smart Grids via FCN Networks and Optimal Power Flow. *IEEE Trans. Ind. Inform.* **2012**, *8*, 944–952. [\[CrossRef\]](#)
131. Bose, A. Smart Transmission Grid Applications and Their Supporting Infrastructure. *IEEE Trans. Smart Grid* **2010**, *1*, 11–19. [\[CrossRef\]](#)
132. Ricalde, L.J.; Ordoñez, E.; Gamez, M.; Sanchez, E.N. Design of a smart grid management system with renewable energy generation. In Proceedings of the 2011 IEEE Symposium on Computational Intelligence Applications in Smart Grid (CIASG), Paris, France, 11–15 April 2011. [\[CrossRef\]](#)
133. Hernandez, L.; Baladron, C.; Aguiar, J.M.; Carro, B.; Sanchez-Esguevillas, A.; Lloret, J.; Chinarro, D.; Gomez-Sanz, J.J.; Cook, D. A multi-agent system architecture for smart grid management and forecasting of energy demand in virtual power plants. *IEEE Commun. Mag.* **2013**, *51*, 106–113. [\[CrossRef\]](#)
134. Al-Garadi, M.A.; Mohamed, A.; Al-Ali, A.K.; Du, X.; Ali, I.; Guizani, M. A Survey of Machine and Deep Learning Methods for Internet of Things (IoT) Security. *IEEE Commun. Surv. Tutor.* **2020**, *22*, 1646–1685. [\[CrossRef\]](#)

135. Chin, W.-L.; Li, W.; Chen, H.-H. Energy Big Data Security Threats in IoT-Based Smart Grid Communications. *IEEE Commun. Mag.* **2017**, *55*, 70–75. [[CrossRef](#)]
136. Kumar, N.M.; Mallick, P.K. The Internet of Things: Insights into the building blocks, component interactions, and architecture layers. *Procedia Comput. Sci.* **2018**, *132*, 109–117. [[CrossRef](#)]
137. Al-Turjman, F.; Abujubbeh, M. IoT-enabled smart grid via SM: An overview. *Futur. Gener. Comput. Syst.* **2019**, *96*, 579–590. [[CrossRef](#)]
138. Kumar, N.M.; Dash, A.; Singh, N.K. Internet of Things (IoT): An Opportunity for Energy-Food-Water Nexus. In Proceedings of the 2018 International Conference on Power Energy, Environment and Intelligent Control (PEEIC), Greater Noida, India, 13–14 April 2018. [[CrossRef](#)]
139. Kumar, N.M.; Atluri, K.; Palaparthi, S. Internet of Things (IoT) in Photovoltaic Systems. In Proceedings of the 2018 National Power Engineering Conference (NPEC), Madurai, India, 9–10 March 2018. [[CrossRef](#)]
140. Manoj Kumar, N.; Dash, A. Internet of Things: An Opportunity for Transportation and Logistics. In Proceedings of the International Conference on Inventive Computing and Informatics (ICICI), Coimbatore, Tamil Nadu, India, 23 November 2017.
141. Yerraboina, S.; Kumar, N.M.; Parimala, K.S.; Jyothi, N.A. Monitoring the smart garbage bin filling status: An IoT application towards waste management. *Int. J. Civil Eng. Technol.* **2018**, *9*, 373–381.
142. Motlagh, N.H.; Mohammadrezaei, M.; Hunt, J.; Zakeri, B. Internet of Things (IoT) and the Energy Sector. *Energies* **2020**, *13*, 494. [[CrossRef](#)]
143. Kabalci, Y.; Kabalci, E.; Padmanaban, S.; Hossain, E.; Blaabjerg, F. Internet of Things Applications as Energy Internet in Smart Grids and Smart Environments. *Electronics* **2019**, *8*, 972. [[CrossRef](#)]
144. Gungor, V.C.; Lu, B.; Hancke, G.P. Opportunities and Challenges of Wireless Sensor Networks in Smart Grid. *IEEE Trans. Ind. Electron.* **2010**, *57*, 3557–3564. [[CrossRef](#)]
145. Hancke, G.P.; Silva, B.D.C.E.; Hancke, J.G.P. The Role of Advanced Sensing in Smart Cities. *Sensors* **2012**, *13*, 393–425. [[CrossRef](#)]
146. Ouyang, Y.; He, J.; Hu, J.; Wang, S.X. A Current Sensor Based on the Giant Magnetoresistance Effect: Design and Potential Smart Grid Applications. *Sensors* **2012**, *12*, 15520–15541. [[CrossRef](#)]
147. Meral, M.E.; Çelik, D. A comprehensive survey on control strategies of distributed generation power systems under normal and abnormal conditions. *Annu. Rev. Control* **2019**, *47*, 112–132. [[CrossRef](#)]
148. Amin, S.M.; Wollenberg, B. Toward a smart grid: Power delivery for the 21st century. *IEEE Power Energy Mag.* **2005**, *3*, 34–41. [[CrossRef](#)]
149. Pirhooshyaran, M.; Scheinberg, K.; Snyder, L.V. Feature engineering and forecasting via derivative-free optimization and ensemble of sequence-to-sequence networks with applications in renewable energy. *Energy* **2020**, *196*, 117136. [[CrossRef](#)]
150. Chan, S.-C.; Tsui, K.M.; Wu, H.C.; Hou, Y.; Wu, Y.-C.; Wu, F.F. Load/Price Forecasting and Managing Demand Response for Smart Grids: Methodologies and Challenges. *IEEE Signal Process. Mag.* **2012**, *29*, 68–85. [[CrossRef](#)]
151. Lopes, J.P.; Hatziargyriou, N.; Mutale, J.; Djapic, P.; Jenkins, N. Integrating distributed generation into electric power systems: A review of drivers, challenges and opportunities. *Electr. Power Syst. Res.* **2007**, *77*, 1189–1203. [[CrossRef](#)]
152. Barker, P.P.; De Mello, R. Determining the impact of distributed generation on power systems. I. Radial distribution systems. In Proceedings of the 2000 Power Engineering Society Summer Meeting (Cat. No.00CH37134), Seattle, WA, USA, 16–20 July 2000. [[CrossRef](#)]
153. Kim, J.; Filali, F.; Ko, Y.-B. Trends and Potentials of the Smart Grid Infrastructure: From ICT Sub-System to SDN-Enabled Smart Grid Architecture. *Appl. Sci.* **2015**, *5*, 706–727. [[CrossRef](#)]
154. Dragičević, T.; Siano, P.; Prabakaran, S.R. Future Generation 5G Wireless Networks for Smart Grid: A Comprehensive Review. *Energies* **2019**, *12*, 2140. [[CrossRef](#)]
155. Rodríguez-Molina, J.; Martínez-Núñez, M.; Martínez, J.-F.; Pérez-Aguilar, W. Business Models in the Smart Grid: Challenges, Opportunities and Proposals for Prosumer Profitability. *Energies* **2014**, *7*, 6142–6171. [[CrossRef](#)]
156. ARC Advisory Group. Distribution Automation a Top Priority for Smart Grid Utilities. In Control Engineering. 25 July 2012. Available online: <https://www.controleng.com/articles/distribution-automation-a-top-priority-for-smart-grid-utilities/> (accessed on 30 September 2020).

157. Yildirim, O.; Eristi, B.; Eristi, H.; Unal, S.; Erol, Y.; Demir, Y. FPGA-based online power quality monitoring system for electrical distribution network. *Measurement* **2018**, *121*, 109–121. [[CrossRef](#)]
158. Kumar, N.M.; Mallick, P.K. Blockchain technology for security issues and challenges in IoT. *Procedia Comput. Sci.* **2018**, *132*, 1815–1823. [[CrossRef](#)]
159. Ajomand, N.; Ullah, H.S.; Aslam, S. A Review of Blockchain-based Smart Grid: Applications, Opportunities, and Future Directions. *arXiv* **2020**, arXiv:2002.05650.
160. Nallapaneni, M.K.; Chopra, S.S. Enhancing the Resilience of Urban Networked Community Microgrids: Blockchain-enabled Flexible Energy Trading Strategy. In *Actionable Science for Urban Sustainability, AScUS-2020*; AScUS Unconference: Segovia, Spain, 3–5 June 2020.
161. Lombardi, F.; Aniello, L.; De Angelis, S.; Margheri, A.; Sassone, V. A Blockchain-based Infrastructure for Reliable and Cost-effective IoT-aided Smart Grids. In *Proceedings of the Living in the Internet of Things: Cybersecurity of the IoT Conference*, London, UK, 28–29 March 2018. [[CrossRef](#)]
162. Ahl, A.; Yarime, M.; Goto, M.; Chopra, S.S.; Kumar, N.M.; Tanaka, K.; Sagawa, D. Exploring blockchain for the energy transition: Opportunities and challenges based on a case study in Japan. *Renew. Sustain. Energy Rev.* **2020**, *117*, 109488. [[CrossRef](#)]
163. Ahl, A.; Yarime, M.; Tanaka, K.; Sagawa, D. Review of blockchain-based distributed energy: Implications for institutional development. *Renew. Sustain. Energy Rev.* **2019**, *107*, 200–211. [[CrossRef](#)]
164. Shi, N. A new proof-of-work mechanism for bitcoin. *Financ. Innov.* **2016**, *2*, 31. [[CrossRef](#)]
165. Zhang, P.; White, J.; Schmidt, D.C.; Lenz, G.; Rosenbloom, S.T. FHIRChain: Applying Blockchain to Securely and Scalably Share Clinical Data. *Comput. Struct. Biotechnol. J.* **2018**, *16*, 267–278. [[CrossRef](#)]
166. Jin, F.; Pei, L.; Chen, H.; Langari, R.; Liu, J. A Novel Decision-Making Model with Pythagorean Fuzzy Linguistic Information Measures and Its Application to a Sustainable Blockchain Product Assessment Problem. *Sustainability* **2019**, *11*, 5630. [[CrossRef](#)]
167. Musleh, A.S.; Yao, G.; Muyeen, S.M. Blockchain Applications in Smart Grid—Review and Frameworks. *IEEE Access* **2019**, *7*, 86746–86757. [[CrossRef](#)]
168. Gai, K.; Wu, Y.; Zhu, L.; Qiu, M.; Shen, M. Privacy-Preserving Energy Trading Using Consortium Blockchain in Smart Grid. *IEEE Trans. Ind. Inform.* **2019**, *15*, 3548–3558. [[CrossRef](#)]
169. Mylrea, M.; Gourisetti, S.N.G. Blockchain for smart grid resilience: Exchanging distributed energy at speed, scale and security. In *Proceedings of the 2017 Resilience Week (RWS)*, Wilmington, DE, USA, 18–22 September 2017. [[CrossRef](#)]
170. Pop, C.; Cioara, T.; Antal, M.; Anghel, I.; Salomie, I.; Bertoncini, M. Blockchain Based Decentralized Management of Demand Response Programs in Smart Energy Grids. *Sensors* **2018**, *18*, 162. [[CrossRef](#)] [[PubMed](#)]
171. Luo, F.; Dong, Z.Y.; Liang, G.; Murata, J.; Xu, Z. A Distributed Electricity Trading System in Active Distribution Networks Based on Multi-Agent Coalition and Blockchain. *IEEE Trans. Power Syst.* **2019**, *34*, 4097–4108. [[CrossRef](#)]
172. Thomas, L.; Zhou, Y.; Long, C.; Wu, J.; Jenkins, N. A general form of smart contract for decentralized energy systems management. *Nat. Energy* **2019**, *4*, 140–149. [[CrossRef](#)]
173. Pipattanasomporn, M.; Kuzlu, M.; Rahman, S. A Blockchain-based Platform for Exchange of Solar Energy: Laboratory-scale Implementation. In *Proceedings of the 2018 International Conference and Utility Exhibition on Green Energy for Sustainable Development (ICUE)*, Phuket, Thailand, 24–26 October 2018. [[CrossRef](#)]
174. Li, Z.; Kang, J.; Yu, R.; Ye, D.; Deng, Q.; Zhang, Y. Consortium Blockchain for Secure Energy Trading in Industrial Internet of Things. *IEEE Trans. Ind. Inform.* **2017**, *14*, 3690–3700. [[CrossRef](#)]
175. Skowronski, R. On the applicability of the GRIDNET protocol to Smart Grid environments. In *Proceedings of the 2017 IEEE International Conference on Smart Grid Communications (SmartGridComm)*, Dresden, Germany, 23–27 October 2017. [[CrossRef](#)]
176. Imbault, F.; Swiatek, M.; Beaufort, R.; Plana, R. The green blockchain Managing decentralized energy production and consumption. In *Proceedings of the 2017 IEEE International Conference on Environment and Electrical Engineering and 2017 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe)*, Milan, Italy, 6–9 June 2017. [[CrossRef](#)]
177. Wu, L.J.; Meng, K.; Xu, S.; Li, S.Q.; Ding, M.; Suo, Y.F. Democratic Centralism A Hybrid Blockchain Architecture and Its Applications in Energy Internet. In *Proceedings of the 2017 IEEE International Conference on Energy Internet (ICEI)*, Beijing, China, 17–21 April 2017. [[CrossRef](#)]

178. Nallapaneni, M.K.; Chopra, S.S. Blockchain-based Online Information Sharing Platform for Improving the Resilience of Industrial Symbiosis-based Multi Energy Systems. In *Actionable Science for Urban Sustainability, AScUS-2020*; AScUS Unconference: Segovia, Spain, 3–5 June 2020.
179. Kumar, N.M.; Chopra, S.S. Blockchain based digital infrastructure for circular economy. In Proceedings of the 8th International World Conference on Applied Science, Engineering and Management (WCSEM 2019), Fukuoka, Japan, 5–9 December 2019.
180. Kumar, N.M.; Chopra, S.S. Blockchain technology for tracing circularity of material flows. In Proceedings of the 10th International Conference of the International Society for Industrial Ecology (ISIE 2019), Beijing, China, 7–11 July 2019.
181. Kumar, N.M.; Chopra, S.S.; Rajput, P. Life cycle assessment and environmental impacts of solar PV systems. In *Photovoltaic Solar Energy Conversion*; Elsevier BV: Amsterdam, The Netherlands, 2020; pp. 391–411.

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



© 2020 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<http://creativecommons.org/licenses/by/4.0/>).