State-of-the-Art Artificial Intelligence Techniques for Distributed Smart Grids: A Review

Syed Saqib Ali and Bong Jun Choi *

School of Computer Science and Engineering, Soongsil University, Seoul 06978, Korea; kazmi@soongsil.ac.kr
* Correspondence: davidchoi@soongsil.ac.kr; Tel.: +82-2-820-0923

Received: 12 May 2020; Accepted: 10 June 2020; Published: 22 June 2020

Abstract: The power system worldwide is going through a revolutionary transformation due to the integration with various distributed components, including advanced metering infrastructure, communication infrastructure, distributed energy resources, and electric vehicles, to improve the reliability, energy efficiency, management, and security of the future power system. These components are becoming more tightly integrated with IoT. They are expected to generate a vast amount of data to support various applications in the smart grid, such as distributed energy management, generation forecasting, grid health monitoring, fault detection, home energy management, etc. With these new components and information, artificial intelligence techniques can be applied to automate and further improve the performance of the smart grid. In this paper, we provide a comprehensive review of the state-of-the-art artificial intelligence techniques to support various applications in a distributed smart grid. In particular, we discuss how artificial techniques are applied to support the integration of renewable energy resources, the integration of energy storage systems, demand response, management of the grid and home energy, and security. As the smart grid involves various actors, such as energy producers, markets, and consumers, we also discuss how artificial intelligence and market liberalization can potentially help to increase the overall social welfare of the grid. Finally, we provide further research challenges for large-scale integration and orchestration of automated distributed devices to realize a truly smart grid.

Keywords: smart grid; artificial intelligence; distributed energy resources; distributed grid intelligence; demand response; home energy management; electricity market liberalization; energy storage system

1. Introduction

Increasing population worldwide demands more and more facilities, which in turn mandates the energy service providers to escalate their generation. Unfortunately, power generation globally is dominated by fossil fuels, which are the main contributor to CO$_2$ in the atmosphere. Increasing CO$_2$ emission threatens the world by global warming, as pointed out in the “World Energy Outlook 2019” by the International Energy Agency [1]. To cope with global warming due to increasing CO$_2$ emission from the traditional power system, governments around the world are encouraging renewable electric energy sources. For example, contributing the green energy, motivated by declining capital costs and the government tax benefits, the United States added 72 gigawatts (GW) of new wind and solar (photovoltaic) capacity between 2018 and 2021 [2]. Similar renewable sources addition is carrying out across the globe today.

Many types of research are being conducted in this domain, and recommendations are fluxing in the market. In accordance with the international target for the environment, the application of renewable energy sources (RES) can provide the alternative source to the dependence on fossil fuels by generating green energy options for the hazardous gas emission reduction and controlling the
peak load graph. The smart grid (SG) technology can support RES integration in future power systems. With advances in information communication technology (ICT) connected with consumer data, it can transform the electric power grid with high penetration of distributed generations in power systems [3]. Smart energy markets fascinated with artificial intelligence (AI) techniques can make it easier to design good policy incentives and allow consumers/utility to make decisions about their consumption/generation in an efficient way that contributes to the reduction of CO₂ emissions. The challenges for AI in the electrical power system are designing automation technologies for heterogeneous devices that learn to adapt their consumption against pricing signals with user constraints, developing means of communication between humans and controllers, and designing simulation and prediction tools for consumers and suppliers.

As the energy sector is increasingly becoming complex, intelligent tools/mechanisms are needed to manage the system effectively and make timely decisions. In general, the artificial neural network (ANN), reinforcement learning (RL), genetic algorithm (GA), and multi-agent systems are well-known AI techniques to solve the problems of classification, forecasting, networking, optimization, and control strategies [4]. Due to the lack of advanced automatic controllable resources, many system operations are still performed manually or at a basic level of automation. However, the inclusion of AI in the grid system would introduce innovations and give new directions to the electrical grid. The overall distributed SG concept with AI techniques is presented in Figure 1. Optimization of controllable loads using intelligent techniques results in cost reduction. For example, Neves et al. [5] propose a genetic algorithm for the management of standalone microgrids (MGs) to optimize the controllable loads. With increases in computing power and accessible data storage, AI techniques are offering much more efficient and powerful ways to handle the limitation of the traditional grid system. Besides, the application of distributed computing algorithms in SG has triggered many security issues. Physical and cyber attacks are the threats which can lead the infrastructure failure, privacy breach, disturbance, and denial of service (DoS) [6]. This paper reviews the current advances and challenges in the smart grid, distributed intelligence for future energy generation, and the role of distributed energy resources (DERs) in the future power system.

The remainder of the paper is organized as follows. Section 2 discusses the requirements for the future energy system. Sections 3–7, respectively, present AI techniques to support applications in distributed grid intelligence, renewable energy source integration, energy storage system integration, demand response management, and home energy management. Section 8 discusses economic aspects and market liberalization in the smart grid. Section 9 presents AI for security applications. Finally, Section 10 concludes the paper with a future outlook aimed to provide some insights into future research directions.
### 2. Future Energy System

Today’s provision of non-stop high-quality electricity safely and efficiently cannot be supported by the aged and crowded conventional distribution networks. Independent system operator (ISO) or regional transmission organization (RTO) heavily relies on a distributed management system to revamp the reliability and efficiency of the grid [7]. With the increase in consumption and generation, the electrical grid is going through a significant shift in the presence of intelligent techniques. Secure, ascendable, and always available bidirectional flow of power and real-time information are the souls of the future SG. The large-scale integration of DERs in the mainstream grid during the last two decades has changed the implementation and operational structure of the power system across the globe. The utility service providers ought to manage the fluctuating generations for DERs, which do not have advance inter-communicational resources. SG is a promising solution to enhance the existing electrical

---

**Figure 1. Overview of AI techniques in distributed smart grids.**
grid infrastructure by embedding with ICT more systematically, thus allowing greater integration of distributed components [8–15].

According to the definition of EU commission Task Force for Smart Grid, “Smart Grid is an electricity network that can cost-efficiently integrate the behavior and actions of all users connected to it—generators, consumers and those that do both—to ensure a low-loss, economically viable, sustainable power system with high quality and security of supply.” [16]. From NIST, the eight priority areas for standardization of the smart grid are [17]:

1. Demand response and consumer energy efficiency: Targets numerous customer segments to involve them in making efficient energy consumption by controlling and scheduling their consumption pattern.
2. Wide-area situational awareness (WASA): Provides the network operators accurate information at the right time to make appropriate decisions.
3. Energy storage: Stores energy for later use to facilitate consumers with cheaper electricity. It provides more flexibility and helps to balance the grid by providing back-up to the intermittent renewable energy sources.
4. Electric transportation: Provides economical energy, saves the environment, enhances living standards, and drives economic growth via various electric vehicles, e.g., plug-in electric vehicles (PEVs), battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs).
5. Network communications: Integrates smart energy components via bidirectional communication channels.
6. Advanced metering infrastructure (AMI): Gathers and analyzes information from smart meters and provides efficient/intelligent management opportunities to the consumers.
7. Distribution grid management: Improves the stability of the grid and reduces the losses.
8. Cybersecurity: Protects data collected from the smart grid via ICT from various cyber-attacks.

More recently, utilities are applying various distributed computing algorithms to coordinate distributed components of their power systems. Distributed Internet of Things (IoT) devices communicate, analyze, and control their operations individually or in collaboration with other devices through high-speed and bi-directional communication protocols in a distributed and independent manner [18]. Smart meters (SMs) and IoT connected via the Internet can improve the overall efficiency of the system, from simple load management of a household to complex power quality management of the grid system. These smart devices can interact with other devices and self-learn to make autonomous decisions. The growing digitization in the power system due to the advancement of distributed intelligent techniques has improved the overall system operation and reliability, including motoring, fault detection, maintenance, and RES integration. However, an increasing number of distributed devices with enabling technologies like AMI, to make multi-directional communication among devices and systems, has made the SG more complex and vulnerable to cyber terrorists [19]. Therefore, in this paper, we provide a comprehensive review of the AI techniques in various applications in the SG, namely distributed grid intelligence, renewable energy source integration, energy storage system integration, demand response management, and home energy management. In addition, we discuss the role of the distributed smart grid in market liberalization and present security issues in the SG.

3. Distributed Grid Intelligence

Distributed grid intelligence leverages energy management based on advanced communication means. An intelligent, cooperative architecture can optimize the energy resources/services to gain the maximum benefits. Intelligent algorithms can help to handle energy management, the configuration of new resources added to the system, and detect and recover from anomalies. The introduction of distributed generations adds new dimensions to the smart grid architecture as traditionally, the grid in most of the world act as a sink for the generations and have limited capacity to accept new penetration of resources. Intelligent distribution network comprises of three layers ranging from residential
consumer to system level. In the first layer, the smart devices manage the energy at a smart home, which includes smart meter (SM), home energy management system, inverters, and EV chargers. The second layer accomplishes the objectives such as group load management, information sharing, and grid reliability improvement at the community level with the help of smart devices like relays and smart switches. The system-level grid intelligence includes advanced monitoring and control devices throughout the distribution system, which respond to the information and responses from the first two layers [20].

3.1. Distributed Intelligence: Prosumer Side

The advancement in the power system allows a bidirectional flow of energy in SG. Domestic energy users can produce and consume (prosumers) electricity and also share with other energy users in the grid [21]. Millions of people share their energy resources from renewable sources on their residential, commercial, and industrial premises. The concept of centralized and fossil-fueled generation is to be replaced with an intelligent cooperative DER powers system where the prosumers share the electricity to harness maximum economic benefits. A smart residential community model is suggested in [22] that consists of domestic users and a local energy pool, where consumers are free to trade with the local energy pool and enjoy economic energy without investing in multiple RES units.

The use of AI techniques has rushed into the energy market with a potentially practical solution to make efficient use of distributed energy resources, support real-time and quick demand response since the last decade. The grid operators are striving for “all the decisions to be made in the power grid” from the switching of relays to large generators controls so that unwanted harmonics in the system could be mitigated through a mesh of sensors embedded across all the systems to deliver full efficiency of the power system. For this reason, intelligent algorithms are formulating and implementing with foresight, self-learning, and resilience to cope with random and systematic disturbances. AI is still striving for developing computationally efficient algorithms that can predict the generation and consumption data of smart prosumer with real-time electricity prices accurately so that profitable electricity trading decisions could be made [23]. For the last few years due to the rapid advancement of AI technology, expert system, ANN and fuzzy logic, have been utilized in the energy sector, to overcome technical issues [24], price prediction [25], energy forecasting [26,27], and fault detection [28]. These techniques are also useful in energy management in residential areas [29], inside a smart home leveraging DR program [30], and overall demand-side management (DSM) [31]. Qiao et al. [32] proposed an optimization for electric energy meter based on independent and identical distributed area load conditions. The error diagnosis analysis model and fault library model based on a deep learning approach are proposed in their work that can deeply predict the cause of error measured by the meter and can ensure to train the smart meter.

3.2. Distributed Intelligence: Generation Side

The challenges for today’s power distribution systems are coordinating distributed energy resources, increasing acceptability for RES penetration, establishing proper plans, and defining operational strategies that can increase demand while reducing global greenhouse gas emissions. This may be achieved by optimizing resource adequacy, considering socio-economic impacts, and enhancing grid reliability [33,34]. These complex issues can be well addressed in SG technology since it aims to make the power system more resilient, self-organizing, and troubleshooting [10,35,36]. Installation of intelligent decentralized energy units, the smart grid has a lot to do in: distributed generation and storage capacity, distributed system automatic regulation and optimization, bidirectional flow of information and electricity, plug-in hybrid electric vehicles (PHEVs) [37]. This means there is a need for more and more intelligent and smart controllers beyond DERs to monitor and manage the distribution grid too. Much research and studies have been carried out regarding the operation and control of distributed generation [38–40]. If a certain benchmark is crossed, the system becomes unstable due to livability constraints. Distributed grid management can
provide energy management, monitoring, and fault detection [41]. Another issue concerning these
days regarding online voltage control is well addresses in [42]. The work presents a distributed grid
synchronization concept, where fluctuation of voltage profile due to mass integration of distributed
and renewable resources escalates the complexity of power controllers, which were typically designed
by the passivity hypothesis. This problem has been traditionally handled using complex non-linear
programming approaches, which depend upon the centralized computing schemes [43].

Several advanced, decentralized, intelligent, and highly pervasive computing frameworks
addressing such issues have been introduced in [44,45]. The promotion of cooperative controllers in
the SG for online voltage control distributes the operations among distributed units, which increases
processing speed and improve the reliability and efficacy of controllers. The centralized controllers
had been used to manage the information gathering and compute control solutions in DER [46,47],
which increased the burden (communication and computation) on the central controller thus making
the system more vulnerable. To tackle this issue, researchers have proposed various decentralized
control techniques that deal directly with the dispersed individual controller of the distributed
units, and control actions are taken in response to the local information [48,49]. In real-time
large-scale optimization problems, centralized algorithms may face challenges in managing rapidly
changing system conditions, such as high variability of renewable based distributed generators
(DGs) and controllable loads (CLs). Further, centralized algorithms may encounter computation
and communication bottlenecks while handling a large number of variables. A consensus based
dimension-distributed computational intelligent technique is proposed for real-time optimal control in
smart distribution grids in which a large number of DGs and CLs are presented in [50].

Distributed operation of power system architectures consists of energy management, power
management, converters management, and fault detection and restoration. Conventionally,
the supervisory control and data acquisition (SCADA) system is used to handle energy resources,
but this centralized architecture proved to be practically infeasible because of security and retard
operations [51]. These systems have become less effective because they typically involve human
interference for routine operations, as today, the grid and its inter-connectivity have become more
complex and require high speed and processing of data. Distributed load balancing algorithms are
designed to optimize loads of different peers in a distributed system. The nodes participating in the
load balancing algorithm communicate with each other and DERs for load shifting from a zone with
high consumption to a zone with low load. This migration normalizes their loads, thereby making the
system stable and resilient [52]. Monti et al. [53] focus on the control of electricity networks based on
distributed state estimation (LQR controller) and distributed intelligent systems. AI and blockchain
technology are helpful in distributed data storage in SG security [54]. Eck et al. [55] demonstrate the
progress of AI techniques deployment, to support distribution grid operators in handling mass RES
penetration based on the market for local energy trading. Table 1 summarizes the AI techniques used
for distributed grid management.

Table 1. AI techniques for distributed grid management.

| Ref.            | Year | Objective                                                                 | Used Techniques                           | Limitation                                                                                    |
|-----------------|------|---------------------------------------------------------------------------|-------------------------------------------|-----------------------------------------------------------------------------------------------|
| Johannesen et al. [27] | 2019 | Load forecasting by correlating lower distinctive categorical levels (season and day of the week) and weather parameters | Random forest regression, k-nearest neighbor regression, linear regression | Growth factors of population and income which also drive the load demand is not considered |
| Neves et al. [5] | 2018 | DR optimization goals on an isolated microgrid                             | GA, linear programming optimization       | A small number of appliances considered and integration of PV is not considered                |
Table 1. Cont.

| Ref.          | Year | Objective                                      | Used Techniques                                                                 | Limitation                                                                 |
|---------------|------|------------------------------------------------|--------------------------------------------------------------------------------|----------------------------------------------------------------------------|
| Ahmad et al.  | 2018 | Energy demand forecast                         | Compact decision tree (CTD), fit k-nearest classifier (FitcKnn), linear regression model (LRM), stepwise linear regression model | Applicable in small systems like buildings and small utility companies, but not efficient in a complex system and long-term forecasting |
| Mocanu et al. | 2016 | Energy prediction at the customer level        | Conditional restricted Boltzmann machine (CRBM) and factored conditional restricted Boltzmann machine (FCRBM) | The reduced number of steps from the original CRBM (i.e., three) can reduce the performance when there are increased number of variables |
| Utkarsh et al. | 2016 | Minimize active power losses in the power system | Consensus based distributed computational intelligent algorithm                  | Decision variables assigned to different agents is not part of the designer degrees of freedom, security issues may arise due to inadequate communication channel |
| Macedo et al. | 2015 | DSM to classify the load curve patterns of each consumer to give financial benefits | ANN                                                                          | User comfort reduced for incentives                                          |
| Ford et al.   | 2014 | Energy fraud detection                         | ANN                                                                          | Non-technical losses on the consumer premises are ignored while designing the model |
| Vaccaro et al.| 2013 | Voltage regulation in active networks          | Distributed consensus algorithm, Simulated annealing                          | Load mobility, fast-switching devices and loose connection problems are not considered |
| Asare et al.  | 2013 | Day-ahead load prediction                      | ANN                                                                          | Integration of HEM system, demand side management, and demand response applications are not considered |
| Ma et al.     | 2013 | Maintaining the voltage profile and economic operation of the power systems | GA                                                                           | Slow convergence speed, within limited searching time may not provide high-qualified solutions |
| Samadi et al. | 2012 | Smart pricing based on DSM and power companies data sharing | Vickrey–Clarke–Groves                                                        | Appliance scheduling may reduce the comfort level of consumers               |
| Colson et al. | 2011 | Microgrid energy management                    | Multi-agent system (MAS)                                                     | Observer agent algorithm is not shown                                         |

4. Integration of Renewable Energy Source

A mass movement from rural to urban areas across the globe in search of better opportunities resulted in an exponential increment in demand and supply. Currently, 55% of the world’s population residing in cities which will project to 68% by 2050, according to the United Nations [57]. Increasing demand for clean, sustainable, secure, and efficient sources of electricity requires integrating RES into existing power system infrastructure. There global RES share in electricity can attain a remarkable ratio in the coming years. As shown in Figure 2, there has been continuous growth in the generation of energy by RESs across the globe. The hydropower contributes the most at 1190 GW, followed by wind energy generation at 623 GW, and solar energy at 586 GW. There are some small contributions from biomass energy and geothermal energy at 14 GW and 500 MW, respectively, as shown in Figure 2.
4.1. RES Integration: Prosumer Side

The integration of renewable and storage energy resources at consumer premises is one of the key features of SG. Another key attribute is sharing the responsibility of managing the flow and consumption of energy by leveraging the enabling bidirectional communication technologies [21]. The RES, especially solar, produce on-site energy, which reduces large-scale, long-distance transmission line losses and large investment operating costs (for transformation and transmission of power).

Macedo et al. [31] integrate PV and energy storage system (ESS) with the local grid in a smart home to optimize energy consumption. For high energy consumption buildings, like hospitals, hotels, educational institutions, and commercial buildings, smart grid systems, together with RES and ESS, manage total energy consumption efficiently [59]. Elkazaz et al. [60] design an intelligent optimization algorithm for the optimal online operation of DERs (hybrid FC and PV) for residential applications. The reliability of the power system increased by reducing peaks and cost-saving for smart homes using RES is achieved in [61] when GA, binary particle swarm optimization (PSO), and Cuckoo search algorithms are embedded in the HEM system. Melhem et al. [62] propose mixed integer linear programming (MILP) to integrate PV system, micro-wind turbine system, battery storage, and gridable vehicles for residential energy management. Distributed energy appreciates maximizing the use of renewable energy sources and power generation technology to improve application efficiency and to reduce environmental hazards.

4.2. RES Integration: Generation Side

Due to the rising global temperature, we need non-fossil fuel based alternative energy solutions. Renewable generations are closer to where it is utilized and currently gaining popularity in the power systems arena. Due to the increasing deployment of renewable energy technologies, the power system dynamics are shifting to a new level that requires variable energy supply, bidirectional electricity flow, storage facilities, and processing of a huge amount of data. Navigant Research forecasts global microgrid (MG) generation capacity to grow from 1.4 GW in 2015 to 7.6 GW by 2024 [63]. Their intermittent behavior and limited storage capabilities present a new challenge to power system operators to maintain power quality and reliability.
Due to the lack of AI techniques, many system operations are still performed manually or done with a basic level of automation. However, numerous hindrances and challenges, such as complex end-to-end control techniques and customer participation, still need a lot of considerations [64]. Fault detection and safety analysis of DERs and MGs are discussed in [65] and encouraged the deployment of ESS and inverter controller during operation. Two MG operational approaches during an emergency, i.e., regarding inverter control mode and auxiliary energy source (STATCOM) mode, are also briefed in the paper. Kim et al. [66] analyzed the advantages of an advanced power distribution system loop structure from the perspective of loss reduction and voltage regulation. Furthermore, they presented a loop path selection algorithm for loss minimization. In the conventional system, one of the techniques for isolating a failure unit of generations from the grid was the islanding method. Darab et al. [67] deploy an AI technique to detect the fault and exact point of occurrence of a fault in DERs for rapid islanding of the affected unit.

Widespread AI techniques have been contributing to almost all the types of RES for the policy-making, design, estimation, optimization, management, and distribution [68]. Application of AI techniques in the wind, solar, geothermal, hydro, bio-energy, and hybrid RES are briefly discussed in [69–74]. Economic energy trading has been focused on by all the power system operators since its inception. Depending on the power forecasted by ANN, the MG energy trading model determines the optimal schedule for all the units by utilizing a genetic algorithm [75]. Development in the power system has shifted from a micro-energy network with a centralized supply to distributed and decentralized energy generations to achieve a ubiquitous state. Alsafasfeh et al. [76] propose distributed saddle point dynamics to optimize the power flow in a PV system. The industrial MG model with DERs in manufacturing industrial area in Ireland provided cheaper energy and steady grid operation than only grid operation [77]. Table 2 summarizes the AI techniques used for the integration of RES.

| Ref.          | Year | Objective Function                          | Used Techniques                                                                 | Limitation                                                                 |
|---------------|------|---------------------------------------------|-------------------------------------------------------------------------------|----------------------------------------------------------------------------|
| Darab et al.  | 2019 | Lighting strike detection, fault location   | Traveling wave method, impedance based method, ANN, support vector machine, fuzzy logic, genetic algorithm | Extra load due to islanding DG unit may reduce reliability on other DERs    |
|               |      | detection, and islanding                   |                                                                                |                                                                            |
| Blake et al.  | 2018 | Optimization of DERs, load forecasting      | ANN, Levenberg–Marquardt training algorithm                                  | Optimal sizing of ESS, operation of a CHP unit in a site with varying load, and control of charging/discharging of ESS need further elaboration |
|               |      |                                            |                                                                                |                                                                            |
| Javaid et al. | 2017 | Economical energy management with RES       | Binary PSO, GA, cuckoo search algorithm                                       | Consumers trade their consumption priorities for cheaper electricity price |
|               |      | integration                               |                                                                                |                                                                            |
| Elkazaz et al.| 2016 | Online optimal operation of DG for          | GA                                                                            | Considers only a small number of houses (i.e., 4) and residential sector consumers have varying consumption behavior |
|               |      | residential applications                   |                                                                                |                                                                            |
| Jaramillo et  | 2016 | Optimal scheduling of DERs                 | MILP                                                                          | Peak power cost is not considered in the objective function               |
|               |      |                                            |                                                                                |                                                                            |
| Melham et al. | 2016 | Integration of RESs in SG for residential   | MILP                                                                          | Residential consumer with DR program not considered                       |
|               |      | energy management                          |                                                                                |                                                                            |
| Changsong et  | 2009 | Energy trading and coordination of DERs     | ANN, GA                                                                       | Operation and degradation issues are not considered                        |
|               |      |                                            |                                                                                |                                                                            |
| Al-Alawi et al.| 2007| Minimizing fuel dependency, engine wear and | ANN                                                                           | Integration of DERs is not considered                                      |
|               |      | tear, and greenhouse gas emission          |                                                                                |                                                                            |
5. Integration of Energy Storage System

5.1. ESS Integration: Prosumer Side

Energy storage systems (ESS) are expected to play a major role in the future smart grid. They provide a back-up to the intermittent renewable sources and ensure continuous electricity supply to the consumers. Locally, they help in the management of the distribution grid by improving its efficiency and reducing costs. ESS helps in mitigating the peak residential energy demand on the local grid. Numerous incentive based demand response programs have been proposed in [78] to encourage the usage of such alternatives. Home ESS stores energy during the off-peak hours and deliver energy to the users in on-peak hours, which decreases the stress on the main power system and increases financial benefits. According to a report by Statistica, nearly 75.4 billion interconnected devices will be operating through the Internet globally by 2025 [79]. Batteries form the vital core of electric cars and mobile phones, helping us curb carbon emissions and stay connected. The large-scale deployment of ESS in the power system will give 600 million people access to electricity till 2030, which will help to reduce carbon emission in the power sector and transportation by 30% [80].

Using ESS with RES is the best way of reducing current fossil fuel consumption and utilizing green energy. It is an alternative solution for the intermittent power output of RESs, where storing excess generation to provide it in peak time, to fulfill the demand [81]. The three areas in which the batteries are increasingly playing important roles are: reducing CO₂ emission in generation and transportation, getting rid of fossil-fueled power system by making renewable power generation as a dispatchable energy source and off-grid access to electricity. ESS provides a value-added economic dispatch solution as market price and other economic system variants have a great impact on SG operation [82]. ESS is contributing its role in the smart city vision as the Park et al. [83] propose a micro-distribution ESS based smart LED streetlight system that utilizes dispersed/distributed storage devices and Intelligent LED system to energize the streetlights of the city. Storage sharing can reduce both space and investment costs for the user. Rahbar et al. [84] propose an algorithm that optimizes the energy-charged/discharged using the shared ESS concept to profit the consumers.

5.2. ESS Integration: Generation Side

Conventional grid designs focus less on data and energy storage, but a SG truly values both. The ESS is an integral component that can transform the current grid structure and operation. Intelligent energy management strategies capable of managing the dynamics of the distributed grid are required to ensure effective implementation and efficient usage of ESS [82]. It can provide targeted energy to all the components of the grid at a different level making the grid reliable and smarter. The authors encourage the deployment of energy storage systems within the electric grid system, supported with effective regulatory and financial policies for development and deployment within a storage based SG system in which storage is placed in a central role [85]. Beside lower wholesale energy prices to consumers, it also supports to reduce the low voltage distribution network investment [86].

Forecasting of voltage and frequency helps a lot in the SG concept as it assures the reliability of the grid. The integrating issues (regarding voltage and frequency) of ESS and local low-voltage distribution grid at a point of common coupling is addressed in [87] using ANN technology to forecast both voltage and frequency matching. Real-time distributed algorithm is proposed in [88], for the operator with distributed ESS, to balance the energy demand through charging and discharging of ESS. The work in [89] presents a simultaneous optimization using non-sequential quadratic programming algorithm for DG and ESS in grid-connected and standalone medium voltage MG, to minimize the energy losses in the distributed system. Table 3 summarizes the AI techniques used for integration of ESS.
Table 3. AI techniques for the integration of ESS.

| Ref.          | Year | Objective Function                                                                 | Used Techniques                                                                 | Limitation                                                                 |
|--------------|------|-----------------------------------------------------------------------------------|--------------------------------------------------------------------------------|----------------------------------------------------------------------------|
| Massi et al. | 2018 | Forecasting voltage and frequency at point of common coupling (PCC) between ESS and local grid | ANN                                                                            | Stability issues during under/over voltage and frequency condition is not considered |
| Ahmad et al. | 2017 | Optimized HEM system with RES and ESS for residential sector                      | GA, binary PSO, wind-driven optimization (WDO), bacterial foraging optimization (BFO), hybrid GA-PSO (HGPO) algorithms | User satisfaction and peak to access ratio of the existing techniques is better than the proposed algorithm |
| Sfikas et al.| 2015 | Minimization of total annual energy loss and cost of energy                       | Sequential quadratic programming                                                 | Integration of RES and losses at PCC are not considered                     |
| Rahbar et al.| 2016 | Shared ESS management                                                             | Convex optimization technique, profit coefficient technique                    | Fixed load profile of each user is considered                                |
| Sun et al.   | 2014 | Using Distributed ESS to provide real-time power balancing service for an electric power grid | Lyapunov optimization, Lagrange dual decomposition, fast iterative shrinkage-thresholding algorithm (FISTA) | Mechanism for communication between demand and supply while power balancing not elaborated |

6. Demand Response and Energy Management System

The term demand response (DR) is used for the programs designed to encourage end-users to make short-term reductions in energy demand in response to a price signal from the hourly electricity market, or a trigger initiated by the electricity grid operator [90]. DR changes the power consumption pattern of energy customers to match the demand and supply better. It provides consumers an opportunity to take part in grid operations by reducing or shifting their electricity usage patterns during peak consumption periods and emergencies in response to an hourly pricing scheme [36,91]. The smart consumers are also offered financial incentives. In Incentive based programs, the consumers are offered fixed or time-varying financial benefits in response to the reduction in their electricity consumption during peak times and contingencies [92]. Several other approaches regarding DR implementation have been actively investigated in recent years [93,94]. Gong et al. [95] propose a privacy-preserving scheme for incentive based demand response programs in the smart grid, which enables the demand response provider to compute individual demand curtailments and demand response rewards while preserving customer privacy. The scheme preserved customer privacy by separating the real identity and the fine-grained metering data, i.e., the DR can only learn either the real identity or the fine-grained metering data at a time but cannot link them together.

Following the advancement in ICT, the DR has also entered the arena of digitization, where intelligent techniques are embedded in the pool. This makes communication between the energy management system (EMS) and utility smarter. Kim et al. [96] propose two cloud based DR for speedy communication between the slave (EMS and SM) and master (utility). The data-centric communication and topic based group communication use a publisher/subscriber architecture in a cloud based demand model rather than traditional IP-centric communication. Making a DR program for islanded DERs is a complex task due to the absence of grid connection and market price signals. Ali et al. [97] propose a distributed DR program for islanded multi-MG networks based on welfare maximization by optimal power-sharing among different units without using any central entity. Different methods of forecasting electricity pricing from a linear statistical approach to the computational intelligent prediction model are discussed in [98].

Due to the availability of enough customer data, computing resources, and potential training algorithms, AI has now matured enough to forecast the electricity price even in the complex environment to the customer. A comparative analysis of such intelligent schemes has been investigated in this research focusing on deep learning (DL) and support vector regression (SVR). DR is the change
in electricity consumption pattern by end-users from their usual pattern according to the price of electricity over the time proposed by the utility, or to get financial incentives to compromise the power system reliability due to peak demand [99]. In SG, the demand prediction helps to decide on how much-generating units to be utilized efficiently so that the burden could be shared optimally to improve the reliability of the generators. Recently, many researchers have focused on leveraging AI techniques for energy demand prediction [56,100]. Lu et al. [30] propose an hour-ahead DR algorithm using reinforcement learning and ANN to overcome the uncertainty in future electricity prices, considering the user comfort and consumption behavior. In the presence of consumers and utility data, AI techniques can be utilized to model the load and demand prediction [101], as demand and supply prediction helps make many other decisions in SG. The types of energy management system in the smart grid with enabling techniques reviewed in this paper is shown in Figure 3.

![Energy Management System Diagram](image)

**Figure 3.** Energy management system in the SG system.

7. **Home Energy Management System**

Energy management includes monitoring, controlling, and saving of energy [102]. A HEM system is a combination of hardware and software program that allows the end-users to monitor their energy usage and production (for prosumers) and to manage the energy inside a home. A HEM system is an integral part of SG that can potentially enable DR applications for end-users. In a smart home, it manages and controls the energy utilization by scheduling the home appliances according to the scheduler technique embedded in the HEM controller [103]. The HEM controller, on the bases of information sent by the power service provider and smart meter, decides the pattern of the appliances on the smart home considering the constraints. According to the most recent DR and Advanced Metering Assessment published by the Federal Energy Regulatory Commission, more than half of customers’ electricity meters across North America are now SM [104].

Energy management is essential in the SG. HEM system, dynamic pricing, and load shifting are different applications that have been implemented by researchers in the past few years for efficient energy management at the demand side. It helps the end-user with cost-saving for society resources conservation and climate protection in the large sphere by integrating and optimally coordinating various energy resources without compromising work processes [105]. In the traditional grid,
the consumption readings were retrieved physically once in a month to calculate the electricity bill. The SG presents a network of SM that can collect, share, and provide updates (e.g., consumption pattern, pricing, priorities, network status, etc.) [106]. Several utility companies in the energy sector have deployed smart metering systems in residential and commercial sectors that provide consumer’s consumption behavior in real-time and allow utility companies to monitor the appliances remotely. Smart meters installed in the private home sphere are smart in the sense that the consumers can beneficially manage their electricity consumption based on consumers and utility parameters. The smart meter learns the consumer’s lifestyle, appliances the switching pattern, and communicates the information with the utility [107].

A HEM controller lacking a smart home becomes an organizational hassle because the user has to control every appliance in the home manually, which may result in excessive traffic on the distribution network and energy wastage. To address these problems, an integrated controller is needed to connect and manage smart devices. Jo et al. [108] proposed an integrated model that uses learning and training the intelligent efficient energy service (IE2S) model on the base of information generated by smart devices. Squartini et al. [109] propose an optimization algorithm for HEM scheduler to reduce electricity cost in a smart home with a renewable energy source and medium-size energy storage considering dynamic pricing. Kazmi et al. [110] evaluate the comparative performance of the HEM controller embedded with three different heuristic algorithms: harmony search algorithm, enhance differential evolution, and harmony search differential evolution.

AI is quickly becoming an essential part of our power sector and HEM system today, encouraging us to develop more efficient and safe energy production and management techniques. ICTs are an integral part of the HEM system for designing an optimal scheduler and making strategies for intelligent energy management. ANN and optimization algorithms are embedded in HEM controllers to integrate the battery storage and RES with the grid to reduce the energy cost for the smart consumers [111]. Different wireless sensor technologies have been used to communicate home appliances with the HEM controller. In the smart home, appliances are integrated through a wireless network like ZigBee, Bluetooth, and WiFi to collect data from them and communicate with the utility [112,113]. An intelligent HEM controller using ZigBee based on standard IEEE 802.15.4 has been designed to intelligently schedule an air-conditioner, heating system, and two-way communication flow for smart consumers in [114]. Recently, various AI techniques have been implemented in HEM controllers in smart homes to manage the load. The most commonly used AI techniques in HEM schedulers are ANN, fuzzy logic control (FLC), and adaptive neural fuzzy inference system (ANFIS). An ANN based residential thermal control strategy for a single-family home is developed in [115] to create a more comfortable thermal environment. A hybrid approach of GA and ANN algorithms is developed for weekly appliance scheduling to optimize electricity consumption in a residential sector with renewable sources (PV and wind generations) to maintain energy demand during peak hours [116]. A similar efficient hybrid algorithm of Lightning search algorithm (LSA) and ANN selects the optimum number of neurons of ANN hidden layers to make an efficient decision for scheduling air conditioner, water heater, washing machine, and refrigerator in a smart home [117]. It can reduce the peak load while guaranteeing user comfort. They have validated their better performance by comparing the results with a similar approach of hybrid PSO-ANN algorithm proposed in [118]. In another study, Sheikhi et al. [119] propose a model to utilize the cloud computing technology in DSM among a group of Smart Energy Hub. The purpose is to manage communications of data among various endpoints in scalable, online, and highly secure and propose efficient electricity management on the consumption side in the smart hub harnessing the benefits of cloud computing technology and game theory. Table 4 summarizes the AI techniques used for the demand response and HEM system.
Table 4. AI techniques for demand response and the HEM system.

| Ref.          | Year | Objective Function                                                                 | Used Techniques                                      | Limitation                                                                                     |
|---------------|------|-------------------------------------------------------------------------------------|------------------------------------------------------|-----------------------------------------------------------------------------------------------|
| Lu et al. [30] | 2019 | Hour-ahead DR algorithm for HEMs                                                    | RL, ANN                                              | RES integration and peak shaving is not considered                                            |
| Atef et al. [98] | 2019 | Electricity price forecasting                                                       | SVR, DL                                              | Separate price is needed for industrial and residential users                                  |
| Ali et al. [97] | 2019 | Distributed demand response program for islanded MG                                  | Diffusion strategy, consensus algorithm               | Residential user comfort is not considered                                                    |
| Ahmad et al. [100] | 2019 | Bulk energy consumption prediction, control, and management for utilities          | Polak–Ribiére gradient back propagation networks (PRGBNNs), gradient with descent adaptive learning rate momentum backpropagation (GDALBNNs) | End users are not considered                                                                   |
| Kazmi et al. [110] | 2017 | Demand side management for smart home                                               | Harmony search algorithm, enhance differential evolution and harmony search differential evolution | Integration of RES is not considered                                                          |
| Ahmed et al. [117] | 2016 | Home energy management scheduling                                                   | Lightning search algorithm (LSA), ANN                | Limited number of appliances are considered and efficiency decrease with an increased number of devices |
| Yuce et al. [116] | 2016 | Appliance scheduling in smart home                                                 | ANN, GA, ANN-GA                                      | User comfort and electricity price not considered                                             |
| Di Santo et al. [111] | 2018 | Active DSM of smart home with PV and ESS                                           | ANN                                                  | Number of appliances and their specifications in the smart home need to be considered         |
| Gong et al. [95] | 2015 | Privacy-preserving scheme for incentive based DR                                     | Zero-knowledge proof, Pedersen commitment             | Pricing scheme and RES integration are not highlighted                                        |
| Angelis et al. [93] | 2013 | Energy management system for smart home with RES, ESS, and domestic thermal system | MILP                                                 | Peak formation during high consumption period of the day on utility side is not considered     |
| Logenthiran et al. [103] | 2012 | Day-ahead DSM strategy based on load shifting technique                             | Evolutionary algorithm                                | User comfort, integration of RES, and economical benefits are not discussed                   |
| Kim et al. [96] | 2011 | Architectural and algorithmic aspects for large scale and fast demand response       | Cloud based demand response (CDR), bisection method, Illinois method | Consumers behave as price-taker and cannot exercise market power                             |
| Moon et al. [115] | 2010 | Thermal control of residential building (including air temperature and humidity)    | ANN                                                  | Economic benefits of consumers is not considered                                              |
| Parvania et al. [92] | 2010 | Scheduling reserves provided by DR resources in wholesale electricity market        | Stochastic mixed-integer programming (SMIP)          | Adding a large number of binary variables associated with DRP reserves does not add any significant computational efficacy |

8. Economic Aspect and Market Liberalization in Smart Grid

Transformation in power systems due to technological advancements budges institutional changes in it. Cooperative mechanisms of technical, institutional economics, and social aspects are required to put the smart grid in practice [120]. The RTO/ISOs are struggling for an efficient market based decision system since inception, keeping all stakeholders on the account. The key idea is to make
electricity market-liberal and truly open where new ISO/RTOs could access this industry, which will take electricity to medium and small-scale users’ accessibility. This will help to shift the centralized fossil fuel generation to green and clean energy too and provide new competition in the market, which may lead to innovations. There is a direct relationship between the consumer’s lifestyle and energy issues. The works in [121–124] discuss the pro-sustainability attitudes and values of electricity transition and consumption using various technological advancements, especially SM. Market liberalization has brought many changes in the energy sector with far-reaching technical and economic consequences. Due to increased digitization, the policymakers and market operators are striving to apply efficient techniques to catch up with the advancements. Xu et al. [125] propose energy market design architecture enabled with AI techniques and big data that can incorporate, coordinate, and manage complex systems of the power industry. A SG can decrease the amount of electricity consumed by houses and buildings and improve the reliability, security of the grid infrastructure by the integration of RES [110].

Advanced communication devices and huge data of consumers and utility service management collected by SM and ICT play an essential role in providing new services. It will also help to manage the electricity price in the market. The continuous liberalization of the electricity market, i.e., shifting from the monopoly system to competitive market structures, draws more and more attention from the investors in the power sector [126]. Through the virtual power plant (VPP) concept, DERs can get access and exposure across all energy markets. They can take benefit from VPP market intelligence to optimize their place to expand the potential of their revenue generation [127]. The essential feature of the modern smart grid is the electricity prices forecasting, as the market dynamics directly affect the behavior of grid operators such as GENCOs, traders, RTO/ISOs, and independent power producers (IPPs) in the diverging electrical market [128]. Increasing development in decentralized renewable generations will have a remarkable influence on deciding the future of the electricity market since they have been financed/purchased electricity from them without any compact agreements. Future electricity markets should be flexible enough to optimally handle the dynamics and uncertainties of RES generation along with dynamic and flexible benefits on the demand side. The small-scale smart prosumers should be encouraged to take part in policy-making to uplift the overall social welfare [129].

9. Smart Grid Security

The SG comprises various components located at many different locations, such as smart home appliances, distributed generating units, smart meters, and energy storage systems, providing numerous entry points to the grid. The physical security of the grid is equally vital to cybersecurity to withstand against moderate disasters. With the advanced control and communication system, SG is striving its best to ensure the security of distributed components using ICTs [130]. McLaughlin et al. [131] explain how malicious code can be embedded into smart appliances to get access to any part of the grid and how important data like user authentication keys can be hacked. In the real world, all the systems, including the SG, have vulnerabilities and complexities. Numerous issues arise in the grid system when cyber and physical systems are integrated with it, besides factors like human behavior, regulatory and political policies, and commercial interests. The integration and deployment of information communication technology in the SG network for collecting, storing, and analyzing using different sensors and smart measuring devices attract the intruders to access the grid and modify the operations.

Through AI techniques like ANN, the cyber-physical system (smart grid) can be made secure against cyber-attacks [132]. Critical issues related to the SG are individual privacy, security, and reliability in terms of communication and performance, and denial of service. Dogaru et al. [133] focus on a deep neural network to mitigate the impact of cyber-attack at a different level in the power grid and successfully identify through a case study the point of attack. Threats mean various possible actions (artificial or natural) that are capable of influencing the performance of the system [134]. These threats are hazardous if appropriate actions are not taken on time. The most prevalent threat is
breaching of consumer’s data privacy and malicious control of the devices and appliances in the smart home [135].

To enumerate all possible threats in the SG is not possible due to system complexities and the unidentifiable nature of sophisticated attacks. Lu et al. [136] categorize malicious threats in three different types based on their goals, i.e., network availability, data integrity, and information privacy. Besides technical challenges, the SG poses regulatory challenges too. Stakeholders and policymakers strive for their dominance due to which changes are expected randomly [6]. Smart devices designers need to ensure the standards of the SG.

9.1. Data Integrity and Information Privacy

User data stored and utilized in the smart grid has increased exponentially since the last decade. The ownership of data is also a big challenge in the smart grid from which almost every stakeholder takes benefit. Data integrity objective refers to preventing the data from modification of unauthorized person or a system like in smart grid the sensors data, SM data, and operator commands [137]. Privacy preservation techniques aim to prevent information disclosure to any unauthorized person or system without legal permission. Both the generation and consumer side data need to be secured from any intruder. The consumer’s behavior, appliances data, authentication keys, and utility plant’s data are always vulnerable due to a large number of interconnected devices. Shi et al. [138] propose a privacy-preserving aggregation of time-series data, in which a group of nodes uploads encrypted information of users to the data aggregator. The aggregator can only calculate the collective values of users periodically but cannot reveal any beneficial information. SMs are highly targeted by the hackers as it is the hub between utility and consumer and where all data about the consumer is stored and transferred [139]. The service provider facilitates the consumers on the base of information provided by the SM.

9.2. Denial of Service

Currently, with the exponential expansion of the Internet, a large portion of resources and communications in the smart grid are available online, which has provided the attackers with more scope for their malicious activities. A SG framework needs to guarantee its (resources and communications) inaccessibility to unauthorized persons or systems. An attack to make a SG network and resources unavailable to its destined users is called a puppet attack where the attacker target a particular node name as puppet node to enter the AMI network [140]. Large scale deployment of interconnected devices via the Internet in the smart grid exposes it to the IP based attackers. They can make the power system partially or totally unavailable for the consumers [141]. The adversaries can jam the communication channel by flooding the network traffic to launch a DoS attack, which makes the power system unstable. Lui et al. [142] investigate the effect of such an attack on load frequency control in the power grid by applying switch system theory. Boumikheld et al. [143] develop and intrusion detection system using data mining techniques to detect the DoS attack, which they termed as black hole attack in the smart grid. Different threats and issues related to grid security, along with potential solutions, are summarized in Table 5.
Table 5. AI techniques for various security challenges.

| Domain                        | Challenges                                                                 | Potential Solution                                                                 |
|-------------------------------|-----------------------------------------------------------------------------|-------------------------------------------------------------------------------------|
| Architecture                  | Protection of smart grid, substations, and ICT gadgets from various cyber attacks | AI based load estimator using sensors [144]                                          |
|                               | Power theft                                                                 | ANN based fraud detection [28]                                                      |
| Operation                     | Fault detection and separation                                              | Coordination among DERs, smart sensors [145], smart device standards [6]            |
|                               | Reliability and resiliency                                                  | Pervasive computing architecture using ubiquitous devices based on a trust model [146] |
| Data management               | Data integrity and consumer privacy                                         | Data encryption                                                                     |
|                               | Data security against cyber-attacks (active and passive)                    | Distributed data randomization [138]                                               |
|                               | Secure generation, monitoring, storing, and analysis of data                | Online voltage control using SCADA [42]                                             |
|                               | Denial of Service (DoS)                                                     | Hybrid fuzzy set based feed forward neural network [147]                            |
| Environment                   | Consideration of environmental factors, responding to natural disasters     | Smart grid forensic science [130]                                                   |
|                               | (earthquakes, lightnings, tree falling, etc.)                               |                                                                                     |
| Market liberalization         | Consumers awareness about the benefits of smart grid, RND investment, planning and regulatory policies by stakeholders, government support and private sector coordination in implementation, market liberalization and IPPs attraction | Social marketing, social norms approach [123]                                       |

10. Conclusions and Future Outlook

In this paper, we presented a comprehensive review of the state-of-the-art artificial intelligence techniques designed to support various applications in the future distributed SG, including the integration of renewable energy sources, integration of energy storage systems, demand response management, home energy management, and security. These techniques are expected to improve the performance further and ease the management of the SG. We also identified some limitations of the AI techniques presented in the literature. Some general areas of limitations are scalability, consideration of user satisfaction/preference, algorithm efficiency, security and privacy, stability under failures, algorithms efficiency, understanding of the intelligent tools by users and network operators, etc.

There remain some important research challenges to overcome these limitations and fulfill the requirements of the future distributed SG. Some of these challenges are outlined below:

- **Self-learning system**: AI and cloud computing utilization for predicting electricity generation and consumption can minimize outages and enhance SG security. With the changing input variables of the distributed agents, the system learns and adopts the required operation. Every node in the grid will be responsive, eco-sensitive, flexible, adaptive, and price-smart. Self-learning algorithms can help to update the system configurations after every event/operation to enhance the grid intelligence. Huge data availability with machine learning algorithms will increase the self-learning ability of the power system.

- **Complete automation**: SG can further advance by fully automating the network from electricity generation to distribution and grid service management. Currently, most of the operations in the power system are done manually or with a basic level of automation. Using distributed automation techniques, the speed, cost, outage management, reactive power management, preventive equipment’s activation, and DERs’ integration can be improved. The following areas are still striving for high-level intelligence to make the SG system completely automatic: remote devices monitoring, fault detection and restoration, automated feeder switching, voltage regulation, Non-technical losses reduction, real-time load balancing, DER integration, etc.
• Self-healing grid: SG equipped with automated controllers, sensors, and enabling techniques can utilize the real-time data for detecting and isolating anomalies and for reducing the burden on utilities and customers. Human intervention for recovery solution takes time, which can be shortened (frequency and duration of outages) using self-healing technology. Some potential research challenges are online self-assessment of the grid’s operating status, prompt implementation of precautionary control, and detection and rapid diagnosis of concealed faults.

• Plug-and-play: SG plug-n-play technology can facilitate and encourage customers to share energy generated on their premises with other smart users. Efficient distributed algorithms may be embedded in distributed controllers to manage energy among the DG units economically using plug-n-play operation.

• Cybersecurity: Security protocols need to explore new machine learning, information theory, and knowledge detection based techniques. Some potential research challenges are the application of the existing security protocols according to the requirements of SG applications, self-healing/adaptive security techniques, and integrative security protocols for distributed components.

• Skilled workforce: With the evolving technologies and standards in the SG, the workforce for the future power system operators needs advanced skills in various areas, such as intelligent techniques for monitoring and control of smart devices, cybersecurity, distributed system communication protocols, DER integration, regulatory issues, IPPs goals, utility decision-making applications, etc.

In sum, the application of AI techniques can be leveraged to reduce the power losses in the distribution grid to enhance power quality. Moreover, AI techniques can provide improved and automated management of distributed resources, enhancing the scope of smart grid services to build an even smarter grid.

Author Contributions: Conceptualization, S.S.A. and B.J.C.; investigation, S.S.A.; resources, S.S.A. and B.J.C.; writing, original draft preparation, S.S.A.; writing, review and editing, B.J.C.; visualization, S.S.A.; supervision, B.J.C.; project administration, B.J.C.; funding acquisition, B.J.C. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Soongsil University Research Fund (New Professor Support Research) 201910001163.

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

Abbreviations
The following abbreviations are used in this manuscript:

| Abbreviation | Description |
|--------------|-------------|
| ANFIS        | Adaptive neural fuzzy inference system |
| AI           | Artificial intelligence |
| ANN          | Artificial neural network |
| BEV          | Battery electric vehicle |
| CL           | Controllable load |
| DER          | Distributed energy resource |
| DG           | Distributed generator |
| DoS          | Denial of service |
| DR           | Demand response |
| DSM          | Demand side management |
| EMS          | Energy management system |
| EV           | Electric vehicle |
| ESS          | Energy storage system |
| FLC          | Fuzzy logic control |
| GA           | Genetic algorithm |
| HEM          | Home energy management |
| ICT          | Information communication technology |
| IoT          | Internet of Things |
ISO  Independent system operator
IPP  Independent power producer
LSA  Lightning search algorithm
MG   Microgrid
MILP Mixed integer linear programming
PCC  Point of common coupling
PEV  Plug-in electric vehicle
PHEV Plug-in hybrid electric vehicle
PSO  Particle swarm optimization
PV   Photovoltaic
RES  Renewable energy source
RL   Reinforcement learning
RTO  Regional transmission organization
RND  Research and development
SM   Smart meter
SG   Smart grid
SVR  Support vector regression
VPP  Virtual power plant
WASA Wide-area situational awareness

References

1. International Energy Agency. CO2 Emissions from Fuel Consumption Report—2019 Edition. Available online: http://wds.iea.org/wds/pdf/WorldCo2_Documentation.pdf (accessed on 12 May 2020).
2. U.S. Energy Information Administration. Annual Energy Outlook. 24 January 2019. Available online: https://www.eia.gov/outlooks/aeo/pdf/aeo2019.pdf (accessed on 12 May 2020).
3. Javaid, N.; Hafeez, G.; Iqbal, S.; Alrajeh, N.; Alabed, M.; Guizani, M. Energy Efficient Integration of Renewable Energy Sources in the Smart Grid for Demand Side Management. *IEEE Access* 2018, 6, 77077–77096. [CrossRef]
4. Ramos, C.; Liu, C. AI in Power Systems and Energy Markets. *IEEE Intell. Syst.* 2011, 26, 5–8. [CrossRef]
5. Neves, D.; Pina, A.; Silva, C.A. Comparison of Different Demand Response Optimization Goals on an Isolated Microgrid. *Sustain. Energy Technol. Assess.* 2018, 30, 209–215. [CrossRef]
6. Pearson, I.L. Smart Grid Cyber Security for Europe. *Energy Policy* 2011, 39, 5211–5218. [CrossRef]
7. Pilo, F.; Pisano, G.; Soma, G. Advanced DMS to Manage Active Distribution Networks. In Proceedings of the IEEE Bucharest Powertech Conference, Bucharest, Romania, 28 June–2 July 2009.
8. Gungor, C.; Sachin, D.; Kocak, T.; Ergut, S.; Buccella, c.; Cecati, C.; Hancke, P. A Survey on Smart Grid Potential Applications and Communication Requirements. *IEEE Trans. Ind. Inform.* 2012, 9, 28–42. [CrossRef]
9. Sechilariu, M.; Wang, B.; Locment, F. Building Integrated Photovoltaic System with Energy Storage and Smart Grid Communication. *IEEE Trans. Ind. Electron.* 2012, 60, 1607–1618. [CrossRef]
10. Gungor, C.; Sachin, D.; Kocak, T.; Ergut, S.; Buccella, c.; Cecati, C.; Hancke, P. Smart Grid Technologies: Communication Technologies and Standards. *IEEE Trans. Ind. Inform.* 2011, 7, 529–539. [CrossRef]
11. Specht, M.; Rohjans, S.; Trefke, J.; Uslar, M.; Vázquez, J.M.G. International Smart Grid Roadmaps and Their Assessment. *EAI Endorsed Trans. Energy Web* 2013, 13. [CrossRef]
12. NIST Framework and Roadmap for Smart Grid Interoperability Standards Release 2.0. NIST Publication 1108R2. 2012. Available online: https://www.nist.gov/system/files/documents/smartgrid/NIST_Framework_Release_2-0_corr.pdf (accessed on 12 May 2020).
13. IEC Smart Grid Standardization Roadmap. SMB Smart Grid Strategic Group (SG3). June, 2010. Available online: https://www.iec.ch/smartgrid/downloads/sg3_roadmap.pdf (accessed on 12 May 2020).
14. Basso, T. DeBlasio, R. *IEEE Smart Grid Series of Standards IEEE 2030 (Interoperability) and IEEE 1547 (Interconnection) Status*; National Renewable Energy Lab (NREL): Golden, CO, USA, 2012.
15. The German Roadmap e-Energy/Smart Grids 2.0. Smart grid standardization status, trends, and prospects. Technical Report, VDE Association of Electrical Electronic & Information Technologies. March 2013. Available online: https://www.dke.de/resource/blob/778304/96de7a637009007d65182d18c4d1a9aa/the-german-roadmap-e-energy-smart-grids-version-2-0-data.pdf (accessed on 12 May 2020).
16. European Commission. Smart Specialisation Platform—Smart Grid. Available online: https://s3platform.jrc.ec.europa.eu/smart-grids (accessed on 18 January 2020).
17. Annabelle, L. NIST and the Smart Grid. January 2010. Available online: https://csrc.nist.gov/CSRC/media/Presentations/NIST-and-the-Smart-Grid-Presentation/images-media/nist-and-smart-grid_ALee.pdf (accessed on 12 May 2020).

18. Saleem, Y.C.N.; Rehmani, M.H.; Copeland, R. Internet of Things-Aided Smart Grid: Technologies, Architectures, Applications, Prototypes, and Future Research Directions. *IEEE Access* 2019, 7, 62962–63003. [CrossRef]

19. Khurana, H.; Hadley, M.; Lu, N.; Frincke, D. Smart Grid Security Issues. *IEEE Secur. Priv.* 2010, 8, 81–85. [CrossRef]

20. Jacobson, D.; Dickerman, L. Distributed Intelligence: A Critical Piece of the Microgrid Puzzle. *Electr. J.* 2019, 32, 10–13. [CrossRef]

21. Espe, E.; Potdar, V.; Chang, E. Prosumer Communities and Relationships in Smart grids: A Literature Review, Evolution and Future Directions. *Energies* 2018, 11, 2528. [CrossRef]

22. Zhou, S.; Hu, Z.; Gu, W.; Jiang, M.; Zhang, X.P. Artificial Intelligence based Smart Energy Community Management: A Reinforcement Learning Approach. *CSEE J. Power Energy Syst.* 2019, 5, 1–10. [CrossRef]

23. Ramchurn, S.; Vytenlingum, P.; Rogers, A.; Jennings, N. Putting the “Smarts” into the Smart Grid: A Grand Challenge for Artificial Intelligence. *Commun. ACM* 2012, 55, 86–97. [CrossRef]

24. Bose, B.K. Artificial Intelligence Techniques in Smart Grid and Renewable Energy Systems—Some Example Applications. *Proc. IEEE 2017*, 105, 2262–2273. [CrossRef]

25. Ghoddusi, H.; Creamer, G.G.; Rafizadeh, N. Machine Learning in Energy Economics and Finance: A Review. *Energy Econ.* 2019, 81, 709–727. [CrossRef]

26. Asare-Bediako, B.; Kling, W.L.; Ribeiro, P.F. Day-Ahead Residential Load Forecasting with Artificial Neural Networks using Smart Meter Data. In Proceedings of the IEEE Grenoble Conference, Grenoble, France, 16–20 June 2013.

27. Johannesen, N.J.; Kolhe, M.; Goodwin, M. Relative Evaluation of Regression Tools for Urban Area Electrical Energy Demand forecasting. *J. Clean. Prod.* 2019, 218, 555–564. [CrossRef]

28. Ford, V.; Siraj, A.; Eberle, W. Smart Grid Energy Fraud Detection using Artificial Neural Networks. In Proceedings of the IEEE Symposium on Computational Intelligence Applications in Smart Grid (CIASG), Orlando, FL, USA, 9–12 December 2014.

29. Mocanu, E.; Nguyen, P.H.; Gibescu, M.; Kling, W.L. Deep Learning for Estimating Building Energy Consumption. *Sustain. Energy Grids Netw.* 2016, 6, 91–99. [CrossRef]

30. Lu, R.; Hong, S.H.; Yu, M. Demand Response for Home Energy Management using Reinforcement Learning and Artificial Neural Network. *IEEE Trans. Smart Grid* 2019, 10, 6629–6639. [CrossRef]

31. Macedo, M.N.; Galo, J.J.; De Almeida, L.A.; Lima, A. Demand Side Management using Artificial Neural Networks in a Smart Grid Environment. *Renew. Sustain. Energy Rev.* 2015, 41, 128–133. [CrossRef]

32. Qiao, J.; Zhu, B.; Wang, X.; Luo, K. Application Research of Artificial Intelligence Technology in Error Diagnosis of Electric Energy Meter. In Proceedings of the IEEE International Conference on Cloud Computing and Big Data Analysis (ICCCBDA), Chengdu, China, 12–15 April 2019.

33. Vaccaro, A.; Popov, M.; Villacci, D.; Terzija, V. An Integrated Framework for Smart Microgrids Modeling, Monitoring, Control, Communication, and Verification. *Proc. IEEE 2010*, 99, 119–132. [CrossRef]

34. Li, F.; Qiao, W.; Sun, H.; Wan, H.; Wang, J. Smart Transmission Grid: Vision and Framework. *IEEE Trans. Smart Grid* 2010, 1, 168–177. [CrossRef]

35. Yang, Q.; Barria, J.A.; Green, T. Communication Infrastructures for Distributed Control of Power. *IEEE Trans. Ind. Inform.* 2011, 7, 316–327. [CrossRef]

36. Palensky, P.; Dietrich, D. Demand Side Management: Demand Response, Intelligent Energy Systems, and smart loads. *IEEE Trans. Ind. Inform.* 2011, 7, 381–388. [CrossRef]

37. Collier, S.E. Ten Steps to A Smarter Grid. *IEEE Ind. Appl. Mag.* 2010, 16, 62–68. [CrossRef]

38. Piagi, P.; Lasseter, R.H. Autonomous Control of Microgrids. In Proceedings of the IEEE Power Engineering Society General Meeting, Montreal, QC, Canada, 18–22 June 2006.

39. Lasseter, R.H. MicroGrids. In Proceedings of the IEEE Power Engineering Society Winter Meeting, Conference Proceedings (Cat. No. 02CH37309), New York, NY, USA, 27–31 January 2002.

40. Nichols, D.K.; Stevens, J.; Lasseter, R.; Eto, J.; Vollkommer, H. Validation of the CERTS Microgrid Concept—The CEC/CERTS Microgrid Testbed. In Proceedings of the IEEE Power Engineering Society General Meeting, Montreal, QC, Canada, 18–22 June 2006.
41. McMillin, B. Distributed Intelligence in the Electric Smart Grid. In Proceedings of the IEEE Annual Computer Software and Applications Conference, Taichung, Taiwan, 1–5 July 2015.
42. Etherden, N.; Vyatkin, V.; Bollen, M. Virtual Power Plant for Grid Services using IEC 61850. *IEEE Trans. Ind. Inform.* 2015, 12, 437–447. [CrossRef]
43. Vaccaro, A.; Zobaa, A. Voltage Regulation in Active Networks by Distributed and Cooperative Meta-Heuristic Optimizers. *Electr. Power Syst. Res.* 2013, 99, 9–17. [CrossRef]
44. Bidram, A.; Davoudi, A.; Lewis, L. A Multiobjective Distributed Control Framework for Islanded AC Microgrids. *IEEE Trans. Ind. Inform.* 2014, 10, 1785–1798. [CrossRef]
45. Ma, H.; Chan, K.W.; Liu, M. An Intelligent Control Scheme to Support Voltage of Smart Power Systems. *IEEE Trans. Ind. Inform.* 2013, 9, 1405–1414. [CrossRef]
46. Samadi, P.; Mohsenian, H.; Schober, R.; Wong, V. Advanced Demand Side Management for the Future Smart Grid using Mechanism Design. *IEEE Trans. Smart Grid* 2012, 3, 1170–1180. [CrossRef]
47. Duan, Q. A Price based Demand Response Scheduling Model in Day-ahead Electricity Market. In Proceedings of the IEEE Power and Energy Society General Meeting (PESGM), Boston, MA, USA, 17–21 July 2016.
48. Colson, C.; Nehrir, M.H. Algorithms for Distributed Decision-Making for Multi-agent Microgrid Power Management. In Proceedings of the IEEE Power and Energy Society General Meeting, Detroit, MI, USA, 24–28 July 2011.
49. Cha, H.; Won, D.; Kim, S.; Chung, Y.; Han, M. Multi-agent System based Microgrid Operation Strategy for Demand Response. *Energies* 2015, 8, 14272–14286. [CrossRef]
50. Utkarsh, K.; Trivedi, A.; Srinivasan, D.; Reindl, T. A Consensus based Distributed Computational Intelligence Technique for Real-Time Optimal Control in Smart Distribution Grids. *IEEE Trans. Emerg. Top. Comput. Intell.* 2016, 1, 51–60. [CrossRef]
51. Abou El-Ela, A.A.; El-Sehiemy, R.A.; El-Sebiny, A.M. Review of SCADA System for Distribution Power System Automation. *Eng. Res. J.* 2019, 42, 93–98.
52. Meng, F.; Akella, R.; Crow, M.L.; McMillin, B. Distributed Grid Intelligence for Future Microgrid with Renewable Sources and Storage. In Proceedings of the North American Power Symposium, Arlington, TX, USA, 26–28 September 2010.
53. Monti, A.; Ponci, F.; Benigni, A.; Liu, J. Distributed Intelligence for Smart Grid Control. In Proceedings of the IEEE International School on Nonsinusoidal Currents and Compensation, Lagow, Poland, 15–18 June 2010.
54. Salah, K.; Rehman, M.H.U.; Nizamuddin, N.; Al-Fuqaha, A. Blockchain for AI: Review and Open Research Challenges. *IEEE Access* 2019, 7, 10127–10149. [CrossRef]
55. Eck, B.; Fusco, F.; Gormally, R.; Purcell, M.; Tirupathi, S. AI Modelling and Time-series Forecasting Systems for Trading Energy Flexibility in Distribution Grids. In Proceedings of the ACM International Conference on Future Energy Systems, Phoenix, AZ, USA, 25–28 June 2019.
56. Ahmad, T.; Chen, H. Utility Companies Strategy for Short-Term Energy Demand Forecasting using Machine Learning Based Models. *Sustain. Cities Soc.* 2018, 39, 401–417. [CrossRef]
57. United Nations. World Urbanization Prospect: The 2018 Revision. Available online: https://population.un.org/wup/Publications/Files/WUP2018-Report.pdf (accessed on 12 May 2020).
58. IRENA. Renewable Capacity Highlights. 31 March 2020. Available online: https://www.irena.org/Statistics/View-Data-by-Topic/Capacity-and-Generation/Statistics-Time-Series (accessed on 12 May 2020).
59. Jaramillo, L.; Weidlich, A. Optimal Microgrid Scheduling with Peak Load Reduction Involving an Electrolyzer and Flexible Loads. *Appl. Energy* 2016, 169, 857–865. [CrossRef]
60. Elkazzaz, M.H.; Hoballah, A.A.; Azmy, A.M. Operation Optimization of Distributed Generation using Artificial Intelligence Techniques. *Ain Shams Eng. J.* 2016, 7, 855–866. [CrossRef]
61. Javaid, N.; Ullah, I.; Akbar, M.; Iqbal, Z.; Khan, F.A.; Alrajeh, N.; Alabed, M.S. An Intelligent Load Management System with Renewable Energy Integration for Smart Homes. *IEEE Access* 2017, 5, 13587–13600. [CrossRef]
62. Melhem, F.; Moubayed, N.; Gruender, O. Residential Energy Management in Smart Grid Considering Renewable Energy Sources and Vehicle-to-Grid Integration. In Proceedings of the IEEE Electrical Power and Energy Conference (EPEC), Ottawa, ON, Canada, 12–14 October 2016.
63. Navigant Research. Press Rel. March 2016. Available online: https://www.navigantresearch.com/news-and-views/global-microgrid-capacity-is-expected-to-grow-from-14-gw-in-2015-to-76-gw-in-2024 (accessed on 12 May 2020).

64. Mohn, T. Campus microgrids: Opportunities and Challenges. In Proceedings of the IEEE Power and Energy Society General Meeting, San Diego, CA, USA, 22–26 July 2012.

65. Huang, J.; Jiang, C.; Xu, R. A Review on Distributed Energy Resources and Microgrid. Renew. Sustain. Energy Rev. 2008, 12, 2472–2483.

66. Kim, J.; Cho, S.; Shin, H. Advanced Power Distribution System Configuration for Smart Grid. IEEE Trans. Smart Grid 2013, 4, 353–358. [CrossRef]

67. Darab, C.; Tarnovan, R.; Turcu, A.; Martineac, C. Artificial Intelligence Techniques for Fault Location and Detection in Distributed Generation Power Systems. In Proceedings of the IEEE International Conference on Modern Power Systems (MPS), Cluj Napoca, Romania, 21–23 May 2019.

68. Jha, S.; Bilalovic, J.; Jha, A.; Patel, N.; Zhang, H. Renewable Energy: Present Research and Future Scope of Artificial Intelligence. Renew. Sustain. Energy Rev. 2017, 77, 297–317. [CrossRef]

69. Ma, L.; Luan S.; Jha, A.; Zhang, Y. A Review on the Forecasting of Wind Speed and Generated Power. Renew. Sustain. Energy Rev. 2009, 13, 915–920.

70. Kalogirou, S. Artificial Neural Networks in Renewable Energy Systems Applications: A Review. Renew. Sustain. Energy Rev. 2001, 5, 373–401. [CrossRef]

71. Satrape, J.V. Potential Impacts of Artificial Intelligence Expert Systems on Geothermal Well Drilling Costs; No. DOE/16299-T4, MCD-033-87-TA; Meridian Corp: Alexandria, VA, USA, 1987.

72. Kishor, N.; Saini, R.; Singh, S. A Review on Hydropower Plant Models and Control. Renew. Sustain. Energy Rev. 2007, 11, 776–796. [CrossRef]

73. Shabani, N.; Akhtari, S.; Sowlati, T. Value Chain Optimization of Forest Biomass for Bioenergy Production: A Review. Renew. Sustain. Energy Rev. 2013, 23, 299–311. [CrossRef]

74. Al-Alawi, A.; Al-Alawi, S.; Islam, S. Predictive Control of an Integrated PV-Diesel Water and Power Supply System using an Artificial Neural Network. Renew. Energy 2007, 32, 1426–1439. [CrossRef]

75. Chen, C.; Duan, S.; Cai, T.; Li, B.; Yin, J. Energy Trading Model for Optimal Microgrid Scheduling based on Genetic Algorithm. In Proceedings of the IEEE International Power Electronics and Motion Control Conference, Wuhan, China, 17–20 May 2009.

76. Alsafasfeh, Q.; Saraereh, O.A.; Khan, I.; Choi, B.J. Robust Decentralized Power Flow Optimization for Dynamic PV System. IEEE Access 2019, 7, 63789–63800. [CrossRef]

77. Blake, S.T.; Sullivan, T.J.D. Optimization of Distributed Energy Resources in an Industrial Microgrid. Procedia CIRP 2018, 67, 104–109. [CrossRef]

78. Deng, R.; Yang, Z.; Chow, M.Y.; Chen, J. A Survey on Demand Response in Smart Grids: Mathematical Models and Approaches. IEEE Trans. Ind. Inform. 2015, 11, 570–582. [CrossRef]

79. Statista Survey Rep. 2016. Available online: https://www.statista.com/statistics/471264/iot-number-of-connected-devices-worldwide (accessed on 12 May 2020).

80. World Economic Forum. Global Battery Alliance, Insight Rep. Available online: http://www3.weforum.org/docs/WEF_A_Vision_for_a_Sustainable_Battery_Value_Chain_in_2030_Report.pdf (accessed on 12 May 2020).

81. Oh, H. Optimal Planning to Include Storage Devices in Power Systems. IEEE Trans. Power Syst. 2010, 26, 1118–1128. [CrossRef]

82. Fathima, A.H.; Palanisamy, K. Energy Storage Systems for Energy Management of Renewables in Distributed Generation Systems. Energy Manag. Distrib. Gener. Syst. 2016, 157. [CrossRef]

83. Park, S.; Kang, B.; Choi, M.; Jeon, S.; Park, S. A Micro-Distributed ESS based Smart LED Streetlight System for Intelligent Demand Management of the Microgrid. Sustain. Cities Soc. 2018, 39, 801–813. [CrossRef]

84. Rahbar, K.; Moghadam, M.R.V.; Panda, S.K.; Reindl, T. Shared Energy Storage Management for Renewable Energy Integration in Smart Grid. In Proceedings of the IEEE Power & Energy Society Innovative Smart Grid, Minneapolis, MN, USA, 6–9 September 2016.

85. Zame, K.; Brehm, C.; Nitica, A.; Richard, C.L.; Schweitzer, G. Smart Grid and Energy Storage: Policy Recommendations. Renew. Sustain. Energy Rev. 2018, 82, 1646–1654. [CrossRef]

86. Wang, Z.; Gu, C.; Li, F.; Bale, P.; Sun, H. Active Demand Response using Shared Energy Storage for Household Energy Management. IEEE Trans. Smart Grid 2013, 4, 1888–1897. [CrossRef]
87. Massi, P. An ANN based Grid Voltage and Frequency Forecaster. In Proceedings of the IET International Conference on Power Electronics, Machines and Drives, Liverpool, UK, 17–19 April 2018.
88. Sun, S.; Dong, M.; Liang, B. Real-Time Power Balancing in Electric Grids with Distributed Storage. *IEEE J. Sel. Top. Signal Process.* 2014, 8, 1167–1181. [CrossRef]
89. Sfikas, E.E.; Katsigiannis, Y.A.; Georgilakis, S. Simultaneous Capacity Optimization of Distributed Generation and Storage in Medium Voltage Microgrids. *Int. J. Electr. Power Energy Syst.* 2015, 67, 101–113. [CrossRef]
90. Ahmad, A.; Khan, A.; Javaid, N.; Hussain, M.; Abdul, W.; Almogren, A.; Alami, A.; Azim, I. An Optimized Home Energy Management System with Integrated Renewable Energy and Storage Resources. *Energies* 2017, 10, 549. [CrossRef]
91. Park, S.; Hussain, A.; Kim, H. Impact Analysis of Survivability-Oriented Demand Response on Islanded Operation of Networked Microgrids with High Penetration of Renewables. *Energies* 2019, 12, 452. [CrossRef]
92. Parvania, M.; Fotuhi, M. Demand Response Scheduling by Stochastic SCUC. *IEEE Trans. Smart Grid* 2010, 1, 89–98. [CrossRef]
93. Angelis, F.; Boaro, M.; Fuselli, D.; Squartini, S.; Piazza, F.; Wei, Q. Optimal Home Energy Management Under Dynamic Electrical and Thermal Constraints. *IEEE Trans. Ind. Inform.* 2012, 9, 1518–1527. [CrossRef]
94. Gorges, D.; Liu, S. Energy Management in Smart Grids with Electric Vehicles based on Pricing. *IFAC Proc. Vol.* 2013, 46, 182–189. [CrossRef]
95. Gong, Y.; Cai, Y.; Guo, Y.; Fang, Y. A Privacy-Preserving Scheme for Incentive based Demand Response in the Smart Grid. *IEEE Trans. Smart Grid* 2015, 7, 1304–1313. [CrossRef]
96. Kim, H.; Kim, Y.; Yang, K.; Thotttan, M. Cloud based Demand Response for Smart Grid: Architecture and Distributed Algorithms. In Proceedings of the IEEE International Conference on Smart Grid Communications (SmartGridComm), Brussels, Belgium, 17–20 October 2011.
97. Ali, H.; Hussain, A.; Bui, V.; Jeon, J.; Kim, H. Welfare Maximization-Based Distributed Demand Response for Islanded Multi-Microgrid Networks using Diffusion Strategy. *Energies* 2019, 12, 3701. [CrossRef]
98. Atef, S.; Eltawil, A. A Comparative Study using Deep Learning and Support Vector Regression for Electricity Price Forecasting in Smart Grids. In Proceedings of the IEEE International Conference on Industrial Engineering and Applications (ICIEA), Tokyo, Japan, 12–15 April 2019.
99. Qdr, Q. Benefits of Demand Response in Electricity Markets and Recommendations for Achieving Them; Technology Report; US Department Energy: Washington, DC, USA, 2006.
100. Ahmad, T.; Chen, H.; Shah, W.A. Effective Bulk Energy Consumption Control and Management for Power Utilities using Artificial Intelligence Techniques Under Conventional and Renewable Energy Resources. *Int. J. Electr. Power Energy Syst.* 2019, 109, 242–258. [CrossRef]
101. Sangpetch, T.; Lo, K.L. Stochastic Modeling and AI Techniques for Power System Reinforcements in a Competitive Energy Market. In Proceedings of the IET International Conference on Power System Management and Control, London, UK, 17–19 April 2002.
102. Energy Lens. *Energy Management Software 9; BizEE Energy Lens*; Swansea, UK. Available online: https://www.energylens.com/ (accessed on 12 May 2020).
103. Logenthiran, T.; Srinivasan, D.; Shun, T. Demand Side Management in Smart Grid using Heuristic Optimization. *IEEE Trans. Smart Grid* 2012, 3, 1244–1252. [CrossRef]
104. FERC 2018 Demand Response and Advanced Metering Report. Available online: https://www.ferc.gov/legal/staff-reports/2018/DR-AM-Report2018.pdf (accessed on 12 May 2020).
105. Marmiroli, M. Developing and Testing a Next Generation Energy Management System. *IEEE Smart Grid Resour. Cent.* 2014. Available online: https://resourcecenter.smartgrid.ieee.org/publications/newsletters/SGNL0177.html (accessed on 12 May 2020).
106. Simmhan, Y.; Aman, S.; Cao, B.; Giakkoupis, M.; Kumbhare, A.; Zhou, Q.; Paul, D.; Fern, C.; Sharma, A.; Prasanna, V. An Informatics Approach to Demand Response Optimization in Smart Grids; Technology Report; DOE: Washington, DC, USA, 2011.
107. Lodder, A.; Wisman, T. Artificial Intelligence Techniques and the Smart Grid: Towards Smart Meter Convenience while Maintaining Privacy. *J. Internet Law* 2016, 19, 20–27.
108. Jo, H.; Yoon, Y.I. Intelligent Smart Home Energy Efficiency Model using Artificial TensorFlow engine. *Hum. Centric Comput. Inf. Sci.* 2018, 8, 9. [CrossRef]
Squartini, S.; Boaro, M.; Angelis, F.; Fuselli, D.; Piazza, F. Optimization Algorithms for Home Energy Resource Scheduling in Presence of Data Uncertainty. In Proceedings of the IEEE International Conference on Intelligent Control and Information Processing (ICICIP), Beijing, China, 9–11 June 2013.

Kazmi, S.; Javaid, N.; Mughal, M.J.; Akbar, M.; Ahmed, S.; Alrajeh, N. Towards Optimization of Metaheuristic Algorithms for IoT Enabled Smart Homes Targeting Balanced Demand and Supply of Energy. IEEE Access 2017, 7, 24267–24281. [CrossRef]

Di Santo, K.G.; Santo, S.G.; Monaro, R.M.; Saidel, M.A. Active Demand Side Management for Households in Smart Grids using Optimization and Artificial Intelligence. Measurement 2018, 115, 152–161. [CrossRef]

Nowak, S.; Schaefer, F.; Brzozowski, M.; Kraemer, R.; Kays, R. Towards a Convergent Digital Home Network Infrastructure. IEEE Trans. Consum. Electron. 2011, 57, 1695–1703. [CrossRef]

Khan, F.; Rehman, A.; Arif, M.; Aftab, M.; Jadoon, B. A Survey of Communication Technologies for Smart Grid Connectivity. In Proceedings of the International Conference on Computing, Electronic and Electrical Engineering (ICE Cube), Quetta, Pakistan, 11–12 April 2016.

Han, D.; Lim, J. Smart Home Energy Management System using IEEE 802.15.4 and ZigBee. IEEE Trans. Consum. Electron. 2010, 56, 1403–1410. [CrossRef]

Moon, J.W.; Kim, J. ANN based Thermal Control Models for Residential Buildings. Build. Environ. 2010, 45, 1612–1625. [CrossRef]

Yuce, B.; Rezgui, Y.; Mourshed, M. ANN-GA Smart Appliance Scheduling for Optimized Energy Management in the Domestic Sector. Energy Build. 2016, 111, 311–325. [CrossRef]

Ahmed, M.; Mohamed, A.; Homod, R.; Shareef, H. Hybrid LSA-ANN based Home Energy Management Scheduling Controller for Residential Demand Response Strategy. Energies 2016, 9, 716. [CrossRef]

Gharghan, S.K.; Nordin, R.; Ismail, M.; Ali, A. Accurate Wireless Sensor Localization Technique based on Hybrid PSO-ANN Algorithm for Indoor and Outdoor Track Cycling. IEEE Sens. J. 2015, 16, 529–541. [CrossRef]

Sheikhi, A.; Rayati, M.; Bahrami, S.; Ranjar, A.; Sattari, S. A Cloud Computing Framework on Demand Side Management Game in Smart Energy Hubs. Int. J. Electr. Power Energy Syst. 2015, 64, 1007–1016. [CrossRef]

Veldman, E.; Geldmeijer, D.; Knigge, J.D.; Han S.J. Smart Grids Put into Practice: Technological and Regulatory Aspects. Compet. Regul. Netw. Ind. 2010, 11, 287–306. [CrossRef]

D’Oca, S.; Corgnati, S.; Buso, T. Smart Meters and Energy Savings in Italy: Determining the Effectiveness of Persuasive Communication in Dwellings. Energy Res. Soc. Sci. 2014, 3, 131–142. [CrossRef]

Sagebiel, J.; Muller, J.; Rommel, J. Are Consumers Willing to Pay More for Electricity from Cooperatives? Results from an Online Choice Experiment in Germany. Energy Res. Soc. Sci. 2014, 2, 90–101. [CrossRef]

Harries, T.; Rettie, R.; Studley, M.; Burchell, K.; Chambers, S. Is social Norms Marketing Effective? A Case Study in Domestic Electricity Consumption. Eur. J. Mark. 2013, 47, 1458–1475. [CrossRef]

Hansla, A. Value Orientation and Framing as Determinants of Stated Willingness to Pay for Eco-labeled Electricity. Energy Effic. 2011, 4, 185–192. [CrossRef]

Xu, Y.; Ahokangas, P.; Louis, J.N.; Pongracz, E. Electricity Market Empowered by Artificial Intelligence: A Platform Approach. Energies 2019, 12, 4128. [CrossRef]

Ogasawara, J. Current Status and Evaluation of Electricity Market Liberalization in Japan, USA and Europe; IEEE: New York, NY, USA, 2005.

Saboori, H.; Mohammad, M.; Taghe, R. Virtual Power Plant (VPP), Definition, Concept, Components and Types. In Proceedings of the IEEE Asia-Pacific Power and Energy Engineering Conference, Wuhan, China, 25–28 March 2011.

Vaccaro, A.; ElFouly, T.; Canizares, C.; Bhattacharya, K. Local Learning-ARIMA Adaptive Hybrid Architecture for Hourly Electricity Price Forecasting. In Proceedings of the IEEE Eindhoven PowerTech, Eindhoven, The Netherlands, 29 June 2015.

Pinson, P. Future Electricity Markets; Projects Magazine: New York, NY, USA, 2015. Available online: https://orbit.dtu.dk/files/118779831/5s-broadaudience.pdf (accessed on 12 May 2020).

Erol-Kantarci, M.; Mouftah, H.T. Smart Grid Forensic Science: Applications, Challenges, and Open Issues. IEEE Commun. Mag. 2013, 51, 68–74. [CrossRef]

McLaughlin, S.; Podkuiiko, D.; McDaniel, P. Energy Theft in the Advanced Metering Infrastructure. In International Workshop on Critical Information Infrastructures Security; Springer: Berlin/Heidelberg, Germany, 2009; pp. 176–187.
132. Dogaru, D.; Dumitrache, I. Cyber Security of Smart Grids in the Context of Big Data and Machine Learning. In Proceedings of the International Conference on Control Systems and Computer Science (CSCS), Bucharest, Romania, 28–30 May 2019.

133. Dogaru, D.; Dumitrache, I. Cyber Attacks of a Power Grid Analysis using a Deep Neural Network Approach. *J. Contr. Eng. Appl. Inform.* **2019**, *21*, 42–50.

134. Mendel, J. Smart Grid Cyber Security Challenges: Overview and Classification. *e-Mentor* **2017**, *68*, 55–66. [CrossRef]

135. Goel, S.; Hong, Y. Security Challenges in Smart Grid Implementation. In *Smart Grid Security*; Springer: Berlin/Heidelberg, Germany, 2015; pp. 1–39.

136. Lu, Z.; Lu, X.; Wang, W.; Wang, C. Review and Evaluation of Security Threats on the Communication Networks in the Smart Grid. In Proceedings of the IEEE Military Communication Conference, San Jose, CA, USA, 31 October–3 November 2010.

137. Lu, R. *Privacy-Enhancing Aggregation Techniques for Smart Grid Communications*; Springer: Berlin/Heidelberg, Germany, 2016.

138. Shi, E.; Chan, H.; Rieffel, E.; Chow, R.; Song, D. Privacy-Preserving Aggregation of Time-Series Data. In Proceedings of the Annual Network & Distributed System Security Symposium (NDSS), San Diego, CA, USA, 7 February 2011.

139. Lai, C.; Loi, L. Application of Big Data in Smart Grid. In Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics, Kowloon, China, 9–12 October 2015.

140. Yi, P.; Zhu, T.; Zhang, Q.; Wu, Y.; Li, J. A Denial of Service Attack in Advanced Metering Infrastructure Network. In Proceedings of the IEEE International Conference on Communications (ICC), Sydney, NSW, Australia, 10–14 June 2014.

141. Wang, K.; Du, M.; Maharjan, S.; Sun, Y. Strategic Honeypot Game Model for Distributed Denial of Service Attacks in the Smart Grid. *IEEE Trans. Smart Grid* **2017**, *8*, 2474–2482. [CrossRef]

142. Liu, S.; Liu, X.; El Saddik, A. Denial-of-Service (DoS) Attacks on Load Frequency Control in Smart Grids. In Proceedings of the IEEE PES Innovative Smart Grid Technologies Conference (ISGT), Washington, DC, USA, 24–27 February 2013.

143. Boumkheld, N.; Ghogho, M.; Koutbi, M. Intrusion Detection System for the Detection of Blackhole Attacks in a Smart Grid. In Proceedings of the IEEE International Symposium on Computational and Business Intelligence (ISCBII), Olten, Switzerland, 5–7 September 2016.

144. Khanna, K. Panigrahi, B.K. Joshi, A. AI based Approach to Identify Compromised Meters in Data Integrity Attacks on Smart Grid. *IET Gener. Transm. Distrib.* **2017**, *12*, 1052–1066. [CrossRef]

145. Telang, A.S.; Bedekar, P.; Wakde, S.D. Towards Smart Energy Technology by Integrating Smart Communication Techniques. In *Techno-Societal*; Springer: Berlin/Heidelberg, Germany, 2020; pp. 673–681.

146. DAngelo, G.; Rampone, S.; Palmieri, F. Artificial Intelligence-Based Trust Model for Pervasive Computing. In Proceedings of the IEEE International Conference on P2P, Parallel, Grid, Cloud and Internet Computing, Krakow, Poland, 4–6 November 2015.

147. Wang, Y.; Gu, D.; Wen, M.; Xu, J.; Li, H. Denial of Service Detection with Hybrid Fuzzy Set based Feed Forward Neural Network. In *International Symposium on Neural Networks*; Springer: Berlin/Heidelberg, Germany, 2010; pp. 576–585.

© 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/).