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A Review on Application of Artificial Intelligence Techniques in Microgrids

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***Abstract*— A microgrid can be formed by the integration of different components such as loads, renewable/conventional units, and energy storage systems in a local area. Microgrids with the advantages of being flexible, environmentally friendly, and self-sufficient can improve the power system performance metrics such as resiliency and reliability. However, design and implementation of microgrids are always faced with different challenges considering the uncertainties associated with loads and renewable energy resources (RERs), sudden load variations, energy management of several energy resources, etc. Therefore, it is required to employ such rapid and accurate methods, as artificial intelligence (AI) techniques, to address these challenges and improve the MG's efficiency, stability, security, and reliability. Utilization of AI helps to develop systems as intelligent as humans to learn, decide, and solve problems. This paper presents a review on different applications of AI-based techniques in microgrids such as energy management, load and generation forecasting, protection, power electronics control, and cyber security. Different AI tasks such as regression and classification in microgrids are discussed using methods including machine learning, artificial neural networks, fuzzy logic, support vector machines, etc. The advantages, limitation, and future trends of AI applications in microgrids are discussed.**

***Index Terms*—Microgrid, artificial intelligence, energy management, load forecasting, cyber security, protection, control, machine learning.**

I. INTRODUCTION

CONVENTIONAL power system is faced with problems such as depletion of fossil fuels, environmental pollution, and low efficiency. These issues have led to the new form of electricity generation locally at the distribution level using renewable/non-conventional distributed energy resources (DERs), known as microgrids (MGs). MGs, as low- or medium- voltage active distribution networks, can be advantageous in different ways, such as improving the energy efficiency and reliability of the system, reducing transmission losses and network congestion, and integration of clean energies. Despite the advantages of MGs, there are challenges in implementing MGs with DER units. These challenges include power quality and stability issues, MG's voltage and fault level changes, energy management, low inertia, more complicated protection schemes, load and generation forecasting, cyber-attacks, and cyber security.

Since MGs should operate in grid-connected and isolated modes, energy management and protection schemes in MGs are more complex than those in the usual distributed networks. Moreover, due to the rapid load variation in MGs and the variable RER generation, load/generation forecasting is needed in applications such as energy management.

Since microgrids rely on information and communication technologies, their security is critical. Therefore, they are vulnerable to different types of cyber-attacks so that cybersecurity techniques can provide safe operation of MGs.

To address with these challenges, advanced, accurate, and fast methods such as artificial intelligence (AI)-based techniques are required to guarantee efficient, optimal, safe, and reliable operation of MGs. AI refers to the computer-based systems' ability to perform tasks as intelligent as humans. AI-based systems can learn from the past experiences and solve problems. AI has been used in different applications, including MGs, to improve the system performance.

In MGs, different AI-based algorithms have been used in the literature for various applications such as energy management, load forecasting, renewable energy forecasting, fault detection and classification, cyber-attack detection[1]. Literature review demonstrates that AI-based techniques offer fast, accurate, and efficient solutions for MG applications.

There are several papers in the literature that review some applications of AI techniques in smart grids and power systems such as energy demand-side management[2], security and stability assessment[3], and power system resilience[4]. Some papers resented a review considering different power system or smart grid parameters such as energy management, load forecasting, demand response, and fault detection[5]–[7]. These studies have at least of the following drawbacks/differences:

(1) The study was carried out for power system and smart grids not for microgrids[2]–[7]. MGs have some specific characteristics and modes of operations and using the methods developed for conventional power system and smart grids may not be appropriate/accurate.
(2) Only one application in the system was reviewed[2]–[4].
(3) A few AI-based techniques and their applications have been considered[2], [4], [5].

The present paper tries to fill the shortcomings of the previous papers by presenting a comprehensive review on the application of AI techniques in MGs. To the best knowledge of the authors this is the first review paper on the application of the AI techniques in MGs with the following main contributions:

(1) A comprehensive review for the application of AI techniques in microgrid is presented for the first.

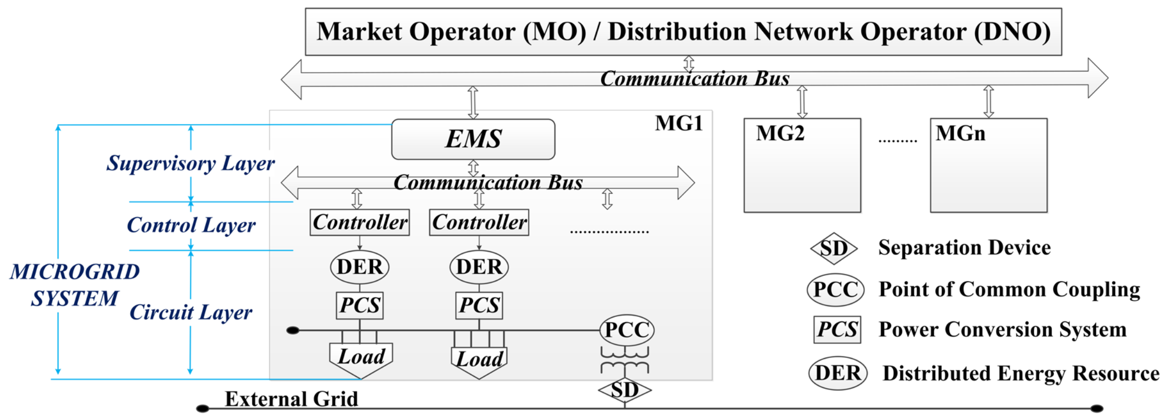

Fig. 1. Microgrid system and Control structure

(2) Different AI techniques such as regression-based, classification-based, and clustering-based methods are reviewed considering their applications in microgrids.
(3) Different applications in MGs such as energy management, load/generation forecasting, fault detection, power electronic, and cyber-attack detection are considered.

The rest of the paper is organized as follows:

In Section II, microgrids and developments are discussed. Section III presents a summary of AI techniques with an emphasis on power system applications. The application of AI techniques in microgrids is discussed in Section IV. Some discussions and future trends of AI utilization in MGs are given in Section V. Finally, the paper is concluded in Section VI.

II. Current Developments and Challenges of Microgrids

Increasing energy demand has arisen the idea of energy generation near the loads, which play an essential role in maintaining the security and economy of bulk power system. Integration of RERs, energy storage systems (ESSs), conventional generators, and loads in a local area form a microgrid, which is a self-sufficient and flexible small-scale grid, yet more environmentally friendly than individual unit.

The idea behind MGs is the ability to work even if the main grid cannot supply power and balance consumption and generation with a high level of reliability. To this end, DERs will produce power, while the surplus power production will be stored in the ESS. Subsequently, from control and production perspective, the grid will be decentralized. Furthermore, MGs can help to supply reliable electricity, higher penetration of RERs, and provide ancillary services to the utility[8]. Based on the type of sources, MGs can be categorized as AC, DC, or hybrid. In addition, they can be operated in either grid-connected or islanded mode when grid faults or islanding are occurred[9].

Figure 1 shows a multi-layer block diagram of a microgrid. All the physical components are connected through the circuit layer. The components consist of 1. DERs, which can be RERs, ESSs, or conventional generators; 2. power conversion systems (PCS), which integrate DER into the grid; 3. grid components, such as transmission lines, transformers, etc., and 4. loads. Moreover, functions to regulate local generation or consumption and ESS management are related to the control layer, and these functions usually follow the commands of upper-level controllers or supervisory layer[8].

The top-level control layer includes supervisory control and data acquisition (SCADA) functions and performs supervisory roles. This layer is the energy management system (EMS), whose goal is to provide functions like participation in the energy market, power quality control, and ancillary services, and optimize the system's operation[8].

The inherent uncertainties in MGs, which arise from both supply and demand sides, make EMS's functions a challenging task. The sources of these uncertainties are that the output of RERs naturally behaves intermittently, and the small size of MGs leads to higher volatility in load profile due to the weaker smoothing effect of load aggregation[10]. Because of this, old energy scheduling schemes cannot guarantee a reliable supply-demand balance in a MG. Thus, the EMS of a MG should be able to predict the possible uncertainties on the generation and demand sides and make the best decision as fast as possible before losing the system's stability. Meanwhile, the EMS must be run repeatedly to maintain the MG's energy production and consumption balance since the renewable generation varies continuously[10]. In addition, EMS should detect islanding and handle the smooth transition between grid-connected and islanded modes. Hence, an efficient scheme that considers the uncertainties of both supply and demand sides is an urgent requirement.

Communication network is used in MGs to transfer data including control and feedback signals between different components such as loads, utility, and sources to efficiently manage the system. However, gathering data from different sources may arise privacy concerns. On the other hand, heavy dependence upon communications technologies, makes power systems vulnerable to cyberattacks. Thus, cybersecurity is an issue that should be considered in microgrids studies.

Due to the integration of DERs in MGs, extra current and power can flow in a reverse direction toward the fault side and, as a result, the fault level is increased. Therefore, fault detection, classification, and protection of MGs are more complicated than radial networks. Furthermore, DER units in a MG should be protected in both grid-connected and islanded modes, where a fault current changes significantly for altering the modes. Therefore, islanding detection and adaptive protection are significant issues in MGs safe operation that must be taken into consideration for design and implementation.

The rapid development of AI with the aim of facilitating systems with intelligence brings significant advantages and has been successfully applied in numerous areas[11]. By applying AI methods, microgrids will be capable of human-like learning and reasoning so that the system autonomy can be improved. Considering the flexibility and advantages of AI methods, they can be employed to cope with major challenges of microgrids.

III. Artificial Intelligence Techniques and Their Applications in Power System

Most of the methods used in power system studies are based on physical modeling and analysis, which has become challenging to handle the increased system uncertainty and complexity. Therefore, AI techniques with self-learning capability and low dependence on mathematical models of physical systems can provide effective solutions[4].

A. Overview of Artificial Intelligence Techniques

AI mainly refers to developing systems like a computer, a computer-controlled robot, or a software with characteristics to act intelligently similar to humans and have the abilities to think, reason, and learn from past experience and solve problems.

Power systems mainly deal with big data generated due to the evolution of the system and the integration of different components such as DERs, electric vehicles, smart meters, ESSs, communication structures, etc. Since the conventional computational methods are not sufficient to handle and process the big data efficiently, AI methods are used in power systems to address the problem. The AI methods in power systems can be mainly categorized into the following classes[20]:

1) **Machine learning algorithms including:**
   - Supervised learning: a class of machine learning (ML) which learns a function to map inputs to outputs according to labeled datasets/example input-output pairs.
   - Unsupervised learning: a class of ML that learns patterns from unlabeled datasets.
   - Reinforcement learning (RL): a class of ML associated with the action of intelligent agents to maximize the notion of cumulative reward.
2) **Ensemble methods:** methods which combine the results of different AI algorithms to cope with the limitations of one algorithm with improved results.
3) **Expert Systems (ES):** a computer-based system emulating the decision-making ability of a human expert to resolve problems.

The schematic diagrams of some of the typical AI methods is shown in Fig. 2. These techniques can be used for different applications in power system to improve its performance, efficiency, and the other parameters/features.

B. Using AI for Power System Problems

Energy conversion systems have two possible classes that help define the requirement of advanced control systems: (i) unconstrained energy systems and (ii) constrained energy systems i.e. when there is finite energy and, most often, a finite maximum power, approaching . Fossil fuel (gas, coal, oil, hydrogen and thermodynamic cycles systems based on renewable energy (wind, solar, tidal, geothermal). The sustainability of renewables would be only if the amount of energy conversion is less than the recovery of such energy by the environment; but they are still constrained because the derivative of energy should be optimized, and typically a convex function would define such a real-time based optimization.

Several issues will have to be taken into consideration, and efficient energy conversion for electrical power systems will be advanced by AI on these premises:

- (1) Parameter variation that can be compensated with designer judgment, (2) Processes that can be modeled linguistically but not mathematically, (3) Setting with the aim to improve efficiency as a matter of operator judgment,

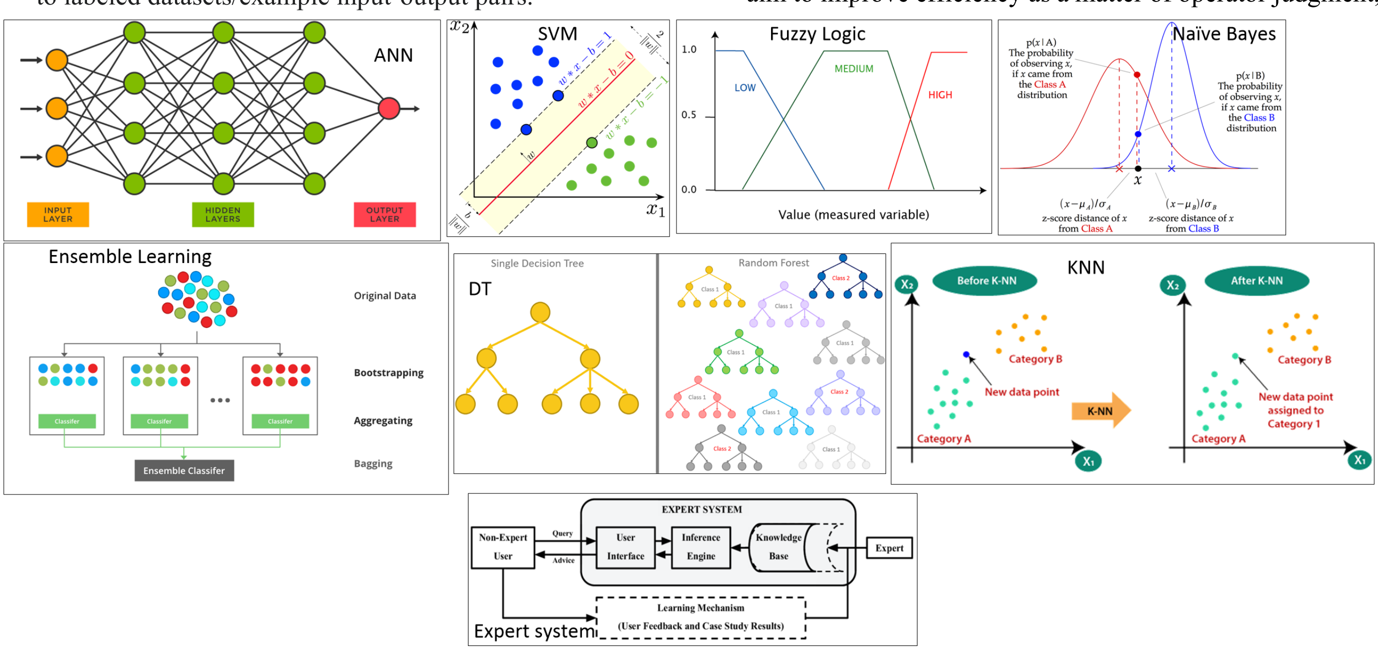

Fig. 2. Schematic diagram of some typical AI methods.

(4) When the system depends on operator skills and attention, (5) Whenever one process parameter affects another parameter, (6) Effects that cannot be attained by separate PID control, (7) Data intensive modeling (use of parametric rules) Parameter variation: temperature, density, impedance, (8) Non-linearities, dead-band, time delay, (9) Cross-dependence of input and output variables.

There are typically three paradigms, that can be used for energy conversion systems, with AI/ML: (i) a function approximation or input/output mapping, (ii) a negative feedback control, and (iii) a system optimization. The first one is the construction of a model, the second one is the comparison of a set-point with an output that can drive the system, the third one is a search for parameters and system conditions, that will maximize or minimize a given function. AI techniques such as fuzzy logic and neural network techniques make the implementation in a robust and reliable approach. Integration of modern power electronics, power systems, communications, information, and cyber technologies with high penetration of RERs has been at the edge and at the frontier for the design and implementation of microgrid and smart grid technology

Due to the importance and wide applications of ML techniques, these techniques and their applications in power systems are briefly reviewed in the next section.

B. Machine Learning

Three main ML types are: (1) supervised learning, (2) unsupervised learning, and (3) reinforcement learning. These techniques are used for different tasks such as regression, classification, clustering, and dimensionality reduction. Fig. 3 shows machine learning algorithms types[7]. Regression-based algorithms in which the output variable is a real or a continuous value were used in power system for network admittance, parameter and topology estimation, load forecasting, fault diagnosis, renewable power forecasting, load modeling, energy price forecasting, power flow modeling, power system online sensitivity identification [7]. Classification algorithms where the output variable is a discrete value were used for fault detection and classification, power quality disturbance classification, power system security assessment and classification, power system stability classification, and islanding classification. Among these algorithms, artificial neural networks (ANNs) and support vector machines (SVM), and decision tree have demonstrated robust and appropriate performance in classification problems.

Deep learning is based on ANNs representation learning which uses various layers for extracting different features from the raw input. Deep learning algorithms have been used for problems such as power system transient stability prediction, voltage instability prediction, load forecasting, and renewable power forecasting[12]. Generative adversarial network (GAN) that was introduced in 2014 is a deep leaning model and one of most promising methods for unsupervised learning in complex distributions. The GAN consists of two modules: the generative model (G) and the discriminative model (D). GAN techniques are used for power system dynamic security assessment with missing data [13], short-term scheduling of power systems[14], risk assessment [15], dynamic state estimation in power system[16], and phasor measurement unit data creation for improved event classification.

Traditional deep learning techniques are appropriate to extract the features of Euclidean data, whereas in different practical applications data are generated from non-Euclidean domains. To cope with this issue, researchers developed graph neural networks (GNNs). Graph is a kind of data structure, and the common graph structure consists of node and edge. The node contains entity information, while the edge contains relation information between entities. GNNs can be divided into five categories that are shown in Fig. 4.

Graph neural networks are deep learning algorithms that can use the attributes of nodes and edges to improve the abilities of extracting features. GNNs were used in power system studies for different applications. Some applications of GAN and GNNs as advanced AI techniques in power system studies are shown in Fig. 5.

Reinforcement learning as a machine learning methodology was used for energy management, attack detection, load frequency control, power system resilience, power flow studies, and power system stability control[17].

Clustering and dimensionality reduction techniques as unsupervised algorithms have been used for different problems such as predictive control of power plants, electricity customer classification, pattern recognition of load curves, reliability modeling of power plants, power quality assessment, power system capacity expansion modeling, electricity price forecasting, and load profiling [18].

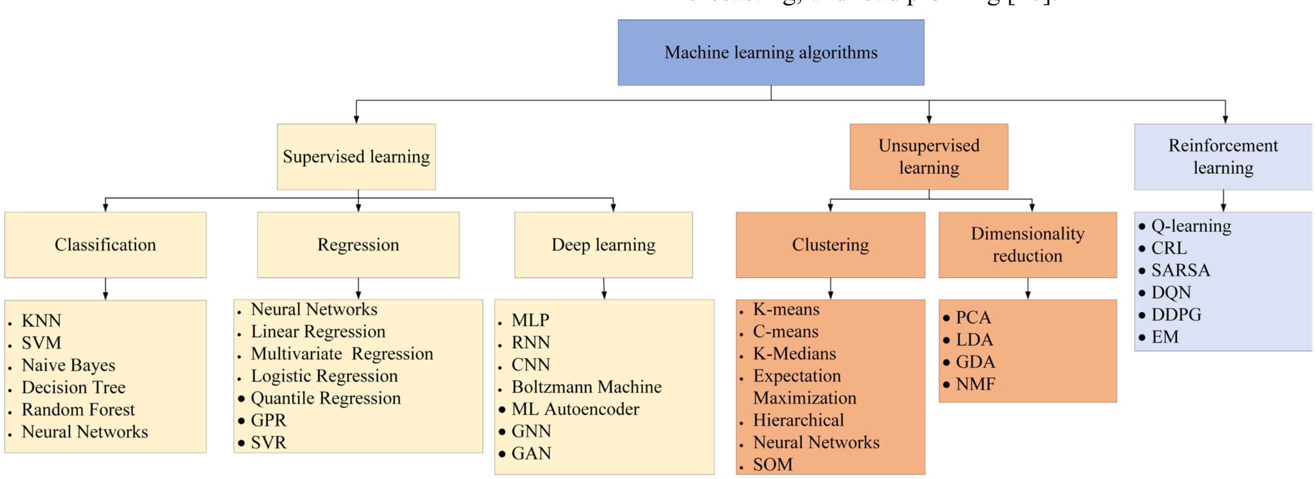

Fig. 3. Different types of machine learning algorithms.

IV. Application of AI Techniques in Microgrids

Artificial intelligence can be applied in renewable energy systems and microgrid/smart grid. Some of these applications are as follows:
(1) Energy management systems, (2) Consumer load forecasting on the grid, (3) Forecasting of wind and PV generation curves, (4) Online fault diagnostics, protection schemes, and fault-tolerant control, (5) Cyber-attack detection (6) Sensorless robust estimation of feedback signals, (7) Noise and delayless filtering of signals, (8) Neural network modeling of static and dynamical system elements and real-time simulation by DSPs /FPGAs chips, (9) Intelligent scheduling of generation and storage, (10) High performance intelligent control of system elements, and (11) Real time pricing predictions of electricity with demand-side management

Some of the most important applications of AI in MGs are discussed in the following sections.

A. Microgrid Energy Management

Energy management in MGs is an important issue considering technical and economical operational aspects. EMSs can be divided into two categories such as model-based and model-free EMS. Model-based EMS relies on domain expertise for development of accurate models and parameters for a microgrid. Hence, this method is neither transferable nor scalable, which results in high development costs. On the other hand, the MG uncertainties may lead to redesign of parameters, which significantly increases the maintenance costs[19].

Model-free or data-driven methods include learning representations of close to optimal control schemes in the microgrid from its operational data. Using the learning-based methods can reduce the dependence on an explicit system model, improve the EMS scalability, and reduce the costs.

A data driven stochastic energy management for isolated microgrid based on GANs was proposed in[20] considering reactive power capability of DERs and reactive power cost. In this study, the GAN was used as a data driven scenario generation technique for modeling of the uncertainties in the output power of the RESs to be used in the stochastic programming formulation. Securing optimal energy management in microgrid using GANs was discussed in[21]. In this study, the effect of data integrity attacks on the central control of the MGs, which can result in severe blackouts and load shedding was investigated. In[22], a probabilistic power flow method based on GCN was proposed where the study has two main contributions; first, GCN framework utilizing no prior electrical knowledge but the topology of power grid. Second, it reduces computing time greatly with the high accuracy, compared classical Monte-Carlo methods.

Fuzzy logic controllers (FLCs) are independent of nonlinearities of the microgrid components; hence, they do not require complicated mathematical modeling, and this leads to a comprehensive EMS based on the simplified linguistic rules and reduces the control complexity specially for a microgrid with a large number of components and different operational modes. In[23], an energy management method based on FL supervisory for electric vehicles, including a fuel cell (FC) and two ESSs such as batteries and supercapacitors (SCs) was presented and implemented on an experimental microgrid. In[24], FL-based EMS method was proposed for optimal control of battery system in a residential microgrid. For FLC design in EMS studies, low complexity, including the input and rule numbers, must be taken into consideration [25].

Uncertainty handling is an issue for EMS of MGs where in[25] the battery was oversized to cope with this problem that is not an optimal solution. To handle uncertainties in EMS, load and renewable power such as wind and solar can be predicted using methods such as radial basis function NN, or combination of several ANNs or ANN with other techniques[26]. The objective of EMS-based studies employing different types of ANNs is mainly minimizing the production cost, better utilization of the RERs, and minimizing emission[26]. Considering the intermittency of RESs and the high stochasticity in market prices and loads, online EMS is more advantageous due to the capability to handle uncertainties by exploring real time data. The traditional online methods such as model predictive control utilize a separate forecaster, whereas reinforcement learning methods[27] can learn a function from historical data. However, RL techniques are usually faced with dimensionality problems generated by the continuous state and action space, complex constraints, and sluggish training.

A summary of AI-based techniques for EMS in MGs is given in TABLE I.

B. Load and Generation Forecasting in MGs

Considering the variable nature of load and increasing the penetration of RERs such as wind and solar energies in MGs, the uncertainty has been increased in MGs, and MGs are faced with challenges. Load and generation forecasting are considered as a solution to improve the MG stability and reliability for system operation and planning. However,

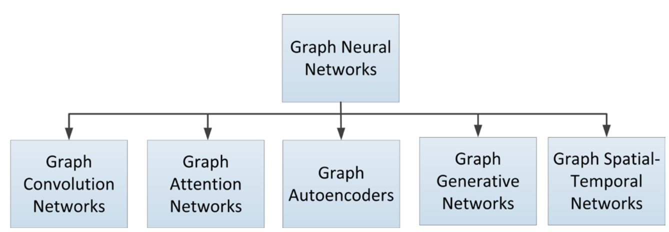

Fig. 4. Different categories of graph neural networks.

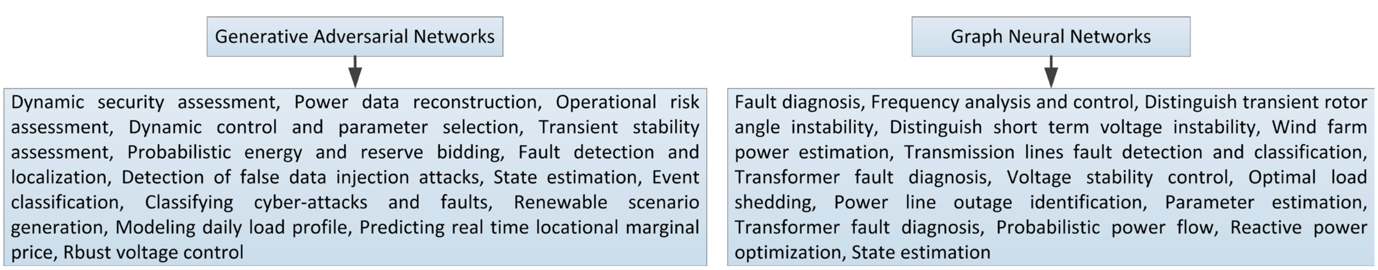

Fig. 5. Different applications of generative adversarial networks and graph neural networks in power system.

load/generation forecasting is challenging considering highly non-smooth and nonlinear behavior of the load/generation time series. Based on the time horizon of the studies, load forecasting (LF) can be categorized in short-term LF (STLF) (i.e., prediction of load from minutes to hours), mid-term LF (MTLF) (i.e., prediction of load from hours to weeks) and long-term LF (LTLF) (i.e., prediction of load for years). The electric load depends on some factors such as metrological data, time, season, event, type of customer[7].

Different tasks, including gathering data, data pre-processing, design and select models, implementation, and validation of models have been discussed in the literature for load and generation forecasting. Fig. 6 shows the diagram of designing a load forecasting model.

The first step in load and generation forecasting is preprocessing of the data to reduce noises and separate trend data to have more reliable data set. In this regard, different methods such as fuzzy information granulation function, wavelet decomposition method, principal component analysis method, empirical mode decomposition, and singular spectrum analysis have been used[28].

The next step after data preprocessing is using an algorithm for forecasting. In so doing, researchers have tried to develop new algorithms or improve the existing ones. AI-based methods are one of the most popular techniques for load and generation forecasting in MGs. These methods can be divided into single and hybrid models. In single models, techniques such as ANN, SVM, and FL, adaptive neuro-fuzzy inference system, self-organizing map, and extreme learning machines[29], [30] have been used, whereas in hybrid techniques a combination of algorithms were used such as ANN with wavelet, ANN with FL, ANN with SVM, ANN with metaheuristic algorithms, and SVM with other algorithms.

Among the LF techniques, the application of ANN in MGs has received much attention. The performance of ANN-based forecasting algorithms depends on the appropriate parameter tuning like layers and nodes. In addition, many ANN learning algorithms such as gradient based methods may get trapped in the local extremum or suffer from the overfitting in extracting the mapping functions[31]. To address this issue, combining ANN algorithms or combining ANN with other techniques have been proposed[38],[39]. However, although hybrid methods can improve the performance, they have more parameters. Hence, methods such as metaheuristic or trial and error were used for fine-tuning of the parameters of the ANN.

RERs such as wind and solar with intermittent nature are an inseparable part of the microgrids; hence, increasing the forecast accuracy of these sources is a critical issue for different tasks such as management and control. Studies have used different AI-based techniques for wind speed/wind energy and irradiance/solar energy prediction such as ANN [34], SVM, and hybrid methods such as a combination of ANN and SVM. In[35], GANs and CNNs based weather classification model was proposed for day ahead short-term photovoltaic power forecasting. In[36], a data-driven method for scenario generation using GANs was presented, which is based on two interconnected deep neural networks. A distribution-free technique for wind power scenario generation, using sequence GANs was presented in[37].

Support vector machine helps load and generation forecasting that is defined by a convex optimization problem. SVM has the advantage over ANNs to not trap in local minima. Support vector regression (SVR) machines were proposed for generation forecasting and load forecasting in different studies[38] to tackle the two main problems of ANNs for load forecasting in real world i.e. overfitting and curse of dimensionality. Other metaheuristic algorithms have been used to optimize the performance of SVM, such as particle swarm optimization (PSO), and genetic algorithm (GA). Another important issue in load or generation forecasting using SVR is the selection of kernel functions that may affect the computational time and accuracy. In this regard, multiple kernel learning based was studied in[39] for load forecasting; another study investigates the performance of SVR for load forecasting with four kernel functions, including linear, radial basis function, polynomial, and sigmoid. In SVM-based models with a large number of dataset, a significant portion of the machine memory and computation time is devoted to the storage and calculation of the matrix. Therefore, SVM-based algorithms are

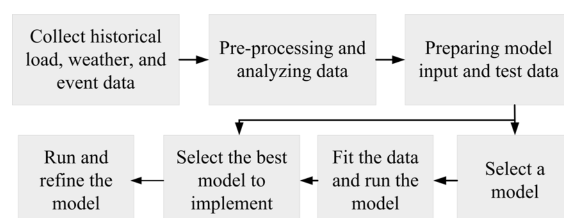

Fig. 6. Diagram of developing a load forecasting model[79].

difficult for the training of large-scale datasets. To address with this problem, recurrent neural network was employed[40]. A

TABLE I
SUMMARY OF AI-BASED TECHNIQUES FOR EMS IN MGS

Ref.	Proposed method	Contribution	Limitation	Demonstration
[23]	Fuzzy logic	A distributed EMS to control the energy flow in the hybrid energy systems using multi-agent FL, flexible to a chaining configuration	Battery degradation is not considered, system losses are not considered	Simulation models
[24]	Fuzzy logic	Low complexity FL controller of only 25-rules for EMS of microgrid, minimizing the grid power profile fluctuations	Battery degradation is not considered, battery is oversized to handle uncertainties	Simulation, experimental with real microgrid
[25]	Bee colony and ANN and Markov chain	Minimizing production cost, increasing convergence speed, improving efficiency and accuracy under uncertain conditions, demand response is considered	Voltage and frequency regulation, and battery degradation is not considered.	Experimental MG test bed
[26]	Reinforcement learning and dynamic programming	Maximizing reliability, self-sustainability, environmental friendliness, battery life, and customer satisfaction	Dynamic state prediction, real time implementation, and coordination of active and reactive power dispatches were not considered	Simulation models
[27]	Imitation learning	Resolve dimensionality issues arising from the continuous state and action space, complex constraints, and sluggish training in RL EMS, reduce training time	Battery degradation is not considered, complex formulation, system losses are not considered, only economic aspect of microgrids is considered.	Numerical studies, simulation models

summary of AI-based techniques for load and generation forecasting in MGs is given in TABLE II.

C. Fault Detection and Protection Schemes in Microgrids

Protection of MGs is different from the protection of distribution systems and traditional techniques due to their characteristics. The traditional protection schemes may not operate appropriately in MGs due to the following issues[41]: (1) Variation of fault currents in different operation modes; (2) Bidirectional power flow; (3) Dynamic characteristic of DGs operating in MGs; (4) Topological changes in the power grid due to the intermittent nature of DGs; (5) Type of DGs; (6) Location, number, size, and control type of DGs.

The main challenges with MG protection are higher level of fault current, variation of the short-circuit level, blinding protection, false tripping, automatic reclosing prohibition, unsynchronized reclosing, reduction in the reach of distance relays, and relay interoperability[41].

1) Fault and Islanding Detection and Classification in MGs Using AI Techniques

For MGs protection, fault detection is a key function. Traditional fault detection and classification used in distribution systems may not be straightly applied to MGs due to the existence of DERS and different topologies. Therefore, these methods should be changes/updated based on factors such as MGs' dynamic, topology, operation modes, and generating unit characteristics. Methods used in the literature for fault detection and classification in MGs that can be categorized in three main groups such as signal processing-based methods, AI-based methods, and model-based methods [42].

Different AI-based techniques were applied in the literature, such as type-2 FL [43], decision tree-induced fuzzy rule base intelligent protection scheme[44], FL for islanding detection [45], ANNs and SVMs for fault detection and classification. In[46], a real-time fault detection and localization method based on GANs was proposed for all electric ship MVDC power system. The results showed that the accuracy of the classification method is 99% with anti-noise capability. In [47], a domain adaptation combined with deep convolutional generative adversarial network (DA-DCGAN)-based methodology was proposed for DC series arc fault diagnosis in photovoltaic systems.

Graph convolutional networks have been widely used for fault diagnosis in microgrid and power system such as transmission line transient faults[48], transformer faults[49], and power line outage[50]. GCN was used in[51] for fault location in distribution network. The proposed method integrates multiple measurements at various buses while taking system topology into account.

In[52], the performance of several ML techniques such as decision tree, K-nearest neighbor (KNN), support vector machine, and Naïve Bayes were compared for fault classification in MGs considering optimal wavelet function where the KNN showed a better performance with the accuracy of 95.63% compared to the other methods.

2) AI-Based Protection Schemes

Conventional protection strategies such as differential and directional protection, distance protection, overcurrent relays, under/over voltage, and under/over frequency may require some modifications to be used for MG protection[42]. One of the methods used for MG protection is adaptive protection in which the settings are updated according to the variations and dynamics of MGs. In[41], a review of adaptive protection of MGs was presented where some AI techniques are used. In[53], an adaptive overcurrent protection strategy was discussed for distributed systems with distributed generators and fault current limiters. In[54], a rule-based adaptive protection strategy was presented for MGs employing ML techniques.

From data mining point of viewpoint, the analysis of uncertain elements in MG can be carried out by Pearson correlation coefficient; then, a hybrid ANN-SVM model is used for state recognition where adaptive reconfigurations can be implemented with improved decision-making to change the relay settings and the grid topology to achieve the intelligent reliable operation. In[55], a central protection system with overcurrent protection capability was implemented for reconfigurable MGs based on fuzzy logic and graph algorithms. In[56], a numerical relay was developed with a hybrid fuzzy-optimization approach for adaptive relay settings and optimal coordination. A summary of AI-based techniques for MG protection is given in TABLE III.

D. AI Methods for Power Electronic Control in MGs

Power electronic devices are an important part of a microgrid that connect RESs, ESSs, and some loads to the AC or DC buses. AI was used in the literature for applications in

TABLE II
SUMMARY OF AI-BASED TECHNIQUES FOR LOAD AND GENERATION FORECASTING IN MGS

Ref.	Proposed method	Contribution	Limitation	Demonstration
[31]	ANFIS model, MLP-ANN, and RBF-ANN	forecasting ambient temperature and wind speed, load, and solar irradiance with high accuracy, and reduce MG operation cost	Complicated structure of the model, high number of parameters and difficulty in tuning them	Simulation
[33]	ANN	Wind speed forecasting with the novelty of forecasting the general trend of the incoming year by designing a data fusion algorithm employing several ANNS	Low accuracy for situations with the lack of updated data, dependence on the periodic updates for developing the model	Simulation using real metrological data of regions in Malaysia
[34]	ANN	Forecasting global horizontal irradiance using four ANNs including non-linear autoregressive, feedforward, long short-term memory and echo state network, echo state network has the best accuracy	The method filters the data every time a new forecast is requested, which might limit the applicability of the method, the convergence speed of algorithms has not discussed	Simulation using real data
[36]	PSO and SVM	Using least square SVM and PSO algorithm for load forecasting with spikes, higher accuracy compared to SVR, SVM, and ANN, avoid problems of data insufficiency, bad data, or data volatility	Difficulty in training of large-scale dataset by SVM due to consumption of a significant amount of machine memory and computation time by storing and calculating the matrix	Simulation using Peng-Hu Island data
[38]	Recurrent Neural Network	Using LSTM recurrent neural network to predict the load of non-residential consumers employing multiple correlated sequence information, better performance compared to other methods	Ignoring some external factors in load forecasting, such as the current economic orientation and policy support in the region has not considered	Simulation using real data in China

power electronics such as design, control, and maintenance[11]. Application of AI for control of power electronic devices include tuning of PID controller parameters, MPPT in wind and PV systems, modulation, and energy management.

Conventional control has provided several methods for designing controllers for dynamic systems. All of them require a mathematical formulation for the system to be controlled, and a certain approach that will be used to design a closed-loop control. These control approaches will have a variety of ways to utilize information from mathematical models. Sometimes they do not consider certain heuristic information early in the design process but use heuristics when the controller is implemented to tune it (tuning is invariably needed since the model used for the controller development is not perfectly accurate).. Fuzzy logic and neural networks approach exactly these lack of real-life understanding by heavily math-oriented control designers, by allowing heuristics and learning from past case studies or numerical data, usually retrofitting an excellent performance controller which most of the time excel when compared to heavily mathematical control design approaches. To implement an ANN-based controller, at first in the system identification stage, a neural network model of the plant to be controlled is developed. In the control design stage, such a neural network plant model will be used to train a controller; three possible architectures can be used after the system identification, (i) model predictive control, (ii) the adaptive inverse model-based control, and (iii) model reference control. Heuristic algorithms can be used for fine-tuning of parameters.

FL controller was used in the literature to control the output voltage of a phase shifted PWM (PS-PWM) soft-switching DC-DC converter [57], and to control the duty ratio of DC/DC boost converters integrated with PV systems [58]. One of the drawbacks of fuzzy controllers can be computational demand that may affect the converter response in sudden variation of load. This issue can be solved using look-up tables considering appropriate interpolation methods.

Other methods such as a neuro-fuzzy controller [59], optimized back propagation ANN [60], and adaptive fuzzy-neural-network control [61] were used to control the output voltage of converter by controlling parameters such as the duty cycle of switches. Some studies employed optimization algorithms such as GA [62], whale optimization [63], to further improve the performance of converters controlled by AI techniques by optimizing and tuning the controller parameters.

One of the important issues in RESs is maximum power point tracking that is done by controlling the power electronic converters. Therefore, different AI-based maximum power point tracking techniques such as FLC and ANNs were proposed. FLC has an efficient performance compared to other MPPT techniques, and it provides a higher degree of freedom to tune parameters in MPPT of PV systems. Using FLCs the modifications in the control system will be easier, and as a result, the system will be more compatible considering the system uncertainties and nonlinearities[64].

ANNs have been used for MPPT control systems. Modules' inputs such as irradiation/temperature, short circuit current, or open circuit voltage can be considered as the inputs of the ANN to control the converter or an input to another controller[65]. Since ANNs can provide a sufficiently accurate MPPT without requiring extensive knowledge about the system model/parameters they have used in wind [66] and PV systems. A summary of AI-based techniques for MG power electronics control is given in TABLE IV.

E. Microgrid Cyber-Attack Detection Using AI Techniques

Due to the growing number of cyber-physical systems (CPSs), their importance has become more highlighted, and attention has been paid to study these systems. Microgrids, as an example of CPSs, are vulnerable to different cyber-attacks. Therefore, cyber-attacks detection in MGs has become a significant issue due to the increasing use of MGs in different applications from renewable power generation, to electric power distribution and electric transportation[67]. These cyber-attacks include false data injection (FDI), sensor attacks, communication latency, denial of service (DoS) attacks, control system attack, etc.[68]. Microgrid stability, reliability, and economy can be affected by these attacks, and they are threats to the safe and efficient operation of the system.

Methods for cyber-attack detection have been proposed in the literature among them the AI-based techniques have attracted more attention due to their efficiency and accuracy. These techniques include deep learning[69], recurrent neural network[70], Hilbert-Huang transform and deep learning[71], deep learning, wavelet transform, and singular values approach[67], ANN[72], SVM, AI-ES fuzzy system [73].

TABLE III
SUMMARY OF AI-BASED TECHNIQUES FOR MICROGRID PROTECTION STUDIES

Ref.	Proposed method	Contribution	Limitation	Demonstration
[41]	Naive Bayes and decision trees	Suitable features extraction from local electrical measurements and using Naive Bayes and decision trees classifiers for better fault discrimination and localization, performance of j 48 decision tree is better than Naive Bayes	Grid-connected mode and transition from grid-connected to islanded modes are not considered, (HIF), fault direction, and topology change are not considered	Numerical simulation
[42]	FL	Using an interval type-2 fuzzy logic system for detection, classification, and localization of the faults in MGs, less computation burden than the training-based approaches	Only single-phase faults are considered, high impedance fault (HIF), fault direction, and topology change are not considered	Simulation
[44]	ANFIS	Using ANFIS-based islanding detection for microgrids, accurate and fast, decrease the NDZ due to combination of passive techniques, does not affect power quality	Dependency of the performance of the method on the quality of training samples, sampled time, and number of samples	Simulation end experimental
[46]	DT and ANN	Overcurrent adaptive protection for distributed systems with DGs and FCL, capability of OC relays for communication based on data generated by FFT to evaluate their own operating conditions	The transient response of FCL is not discussed	Simulation
[47]	ANN and SVM	Using a rule-based adaptive protection scheme employing ANN-SVM methodology, analysis of uncertain elements in an MG by Pearson correlation coefficients from data mining, topology change, and fault location are considered	Many data sets, complexity, high computational burden and training	Simulation on a microgrid model at Aalborg University and IEEE 9-bus system

GANs were used for cyber-attack detection in MGs and power systems. In[74], a data-driven learning-based algorithm was proposed for detecting unobservable FDIAs in distribution systems. In this study, the autoencoders were integrated into GAN framework, which successfully detects anomalies under FDIAs. A new generative adversarial framework was proposed in[75] for classifying cyber-attacks and faults, learning from skewed class distributions.

Other ML-based techniques such as KNN, K-means, Q-learning, extended nearest neighbor, dynamic Bayesian networks have been used in the literature to detect and mitigate cyber-attacks in smart grids that a summary of them could be found in[76]. The accuracy of these methods was reported to be more than 93.76% for Hilbert-Huang transform and deep learning technique, 95% for deep learning, wavelet transform, and singular values approach, and 96% for singular value decomposition and fast Fourier transform.

Cybersecurity measures of energy systems and microgrids is still considered as accessories, not as a build-in function[77], especially with the lack of updated standards and common market trends. Hence, multidisciplinary approaches are required to be taken to consider economic and social development that have been forgotten or neglected in the literature. A summary of AI-based techniques for MG power electronics control is given in TABLE V.

F. AI Techniques for Other Applications in Microgrids

Using AI for control Applications in MGs is not limited to power electronics. Induction motors/generators are widely used in MGs. An induction motor/generator has a very complicated instantaneous model based on decoupled d-q equations, trigonometrical Park and Clarke transformations, where an inverse model is resolved mathematically in order to control torque and flux with virtual d-q currents, then such controller response is reverse-calculated in real-time in order to generate the pulse-width modulation of transistors in a three-phase inverter that commands the induction machine. It seems that fuzzy logic and neural networks are natural solutions for induction motor speed control, optimization of flux, and signal processing of non-linear functions.

Another application of AI in MGs could be intelligent monitoring and protection. As an example, a small-scale wind farm integrated into a microgrid could be designed for intelligent monitoring and protection. In such an application, the signals to be acquired should be:

- Wind Signals: velocity, wind direction, turbulence of blade, yaw angle, shaft torque, mechanical brake signal, tip-speed-ratio
- Gear box: oil temperature, oil viscosity, noise intensity, vibration, nacelle temperature
- Turbine Signals: Blade speed, shaft speed, pitch angle, pitch angle control signal, bearing temperatures, vibration
- Generator: Bearing temperatures, shaft vibration, stator winding temperature distribution, rotor magnet temperatures, shaft torque, stator voltages, phase sequence, percentage of terminal voltages and currents imbalance, stator currents RMS, average, peak, stator frequency, active power, reactive power
- Converter: Converter temperatures, cooling fluid velocity, dc-link voltage, dc-link current, dc-link power, ac line voltages, output frequency, phase unbalance of voltages, ac line currents, phase unbalance of currents, active power, reactive power, motoring/regeneration mode
- Fourier and Wavelet expansion of selected signals

The signals can be monitored with the help of sensors, or adaptive sensorless estimation, to determine the general health condition of a wind farm, such as indicated in Fig 7. The health conditions could be “excellent” if the variation of the signals remains confined in a highly satisfactory range. If some signals go beyond this range but are yet very safe, the system can be defined as “very good”. Similarly, for other ranges, the health index can be classified as “good”, “fair”, “poor”, “unsafe”, etc. If some signals degrade, the diagnostic messages for the signals can be generated independently. If any signal goes beyond the safe range, for a fault condition, the system can be shut down for protection. Similar health monitoring principles can be extended to PV or other systems, eventually implemented in a real-time smart-grid platform (such as Opal-RT or other possible solutions). Real-world function approximation problems are basically system modeling solutions, which can be algebraic solutions, i.e., a mapping of input to output, or

TABLE IV
SUMMARY OF AI-BASED TECHNIQUES FOR POWER ELECTRONICS CONTROL IN MICROGRIDS

Ref.	Proposed method	Contribution	Limitation	Demonstration
[56]	FLC	Using FLC to control output voltage of a phase shifted PWM soft-switching DC-DC converter, using derived look up tables from original FLC to suppress high computational demand, reduce costs	High computational demand when using original FLC, unavailability of fuzzy information and the optimizing parameters of the when lookup table is used	Simulation and experimental laboratory setup
[57]	FLC	Duty ratio control of boost converter is investigated with MPPT techniques such as constant voltage controller and FLC, fuzzy logic-based controller is implemented to reconciled the duty ratio of DC-DC boost converter	Stability of the system is not investigated, dynamic performance of the system under varying conditions is not considered, convergence of controller is not discussed	Simulation
[59]	Back propagation ANN controller	Using back propagation ANN to control boost converters in PV systems, Optimization of ANN structure for simple hardware implementation and enhanced performance, sharp changes in temperature and irradiance are considered	Stability analysis is not given, systematic procedure for ANN design is not considered, optimal structure is based on trial and error of a few choices that may not be global solution	Simulation of commercial PV array models
[65]	ANN-based reinforcement learning for MPPT in wind turbines	Using ANN for MPPT in PMSG wind turbines, the MPPT algorithm has online learning capability through a combination of the ANNs and the Q-learning method, improve efficiency, adaptive to system aging	Wind speed range is limited and all scenarios are not considered, transition from MPPT to constant power region is not discussed	Simulation and experimental emulator
[66]	ANN for MPPT in PV systems	ANN-based Levenberg-Marquardt (LM), Bayesian Regularization, and Scaled Conjugate Gradient (SCG) algorithms are used for MPPT in PV systems, LM has better performance	Optimal design of networks has not discussed, more real data in clean and cloudy conditions is required to compare performance of algorithms in real conditions	Simulation, using real filed data for training

TABLE V
SUMMARY OF AI-BASED TECHNIQUES FOR CYBER-ATTACK DETECTION IN MICROGRIDS

Ref.	Proposed method	Contribution	Limitation	Demonstration
[1]	SVM	Using SVM to detect stealthy attacks in smart grid, utilizing supervised learning and trains a distributed SVM, proposing an ML-based method that requires no training data and detects the deviation in measurements, provide optimal results with lower computational complexities	Load changes and other fault and transient conditions are not considered	Simulation
[68]	Deep learning	Recognizing the behavior patterns of FDI attacks using the historical measurement data and employing the revealed features to detect the FDI attacks in real-time using deep learning, proposing electricity theft model, higher accuracy compared to SVM and ANN	The success of the proposed detection scheme is dependent on the sensitivity of the pattern recognition, modeling of practical behaviors of the FDI attacks is not considered, the number of the sensing units is not minimum	Simulation on IEEE 118-bus system and MGs
[69]	Recurrent NN	Using recurrent NN to detect FDIAs in DC MGs and identify the attacked DER units, the method works based on the time-series analysis and a nonlinear auto-regressive exogenous model NN to estimate dc voltages and currents	The performance of the system can be affected when large number of units available or multiple loads change simultaneously, well-tuned ANN required for appropriate performance	Simulation in Simulink and real-time simulation using OPAL-RT
[71]	ANN	A method based on an ANN-based reference tracking application to remove the FDIAs in parallel DC-DC converters in DC microgrids, considering load changes, varying FDIAs, and time delay of control signals	Mostly focused on FDIAs with a constant value of the false data, time-varying false data can affect the system	Simulation
[72]	Coupled ANN-fuzzy expert	Using a coupled AI-ES physical model-checking technique to detect tampered-with circuit breaker switching control commands due to cyber-attacks or human error	changes in the system topology, such as the addition of the new buses or power equipment and load changes are not considered	Simulation on IEEE 14-bus system and MGs

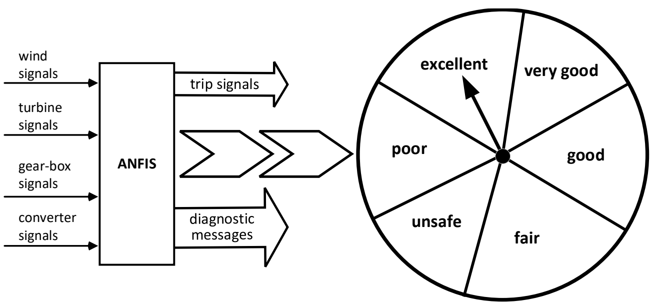

Fig. 7. AI Based wind-farm health monitoring system

state-space solutions, i.e., memory-based equations, where the output will depend on the internal states plus past inputs.

A neural network is a very simple way for learning functions that can be used to support energy forecasting, load-flow modeling of large power systems, learning of non-linear functions in power electronics and power systems, estimation of ill-modeled systems, for example, temperature variation effect of induction motor rotor resistance, non-linear response of capacitors, loss modeling of transformer core, lifetime expectation of protection circuits and so many other applications that are usually very difficult to find a function approximation using pure mathematical theory. Function approximation can be useful in several problems related to signal processing in power electronics, microgrid/power systems, and power quality. One example is the estimation of distorted waves.

V. DISCUSSIONS AND FUTURE RESEARCH TRENDS

Artificial intelligence techniques have been used in the literature for different applications in microgrids, such as energy management, load and generation forecasting, fault detection and protection, power electronics control, and cyber security. It has been a constant challenge for researchers to find optimal AI-based solutions to design, manufacture, develop, and operate new generations of industrial systems efficiently, reliably, and durably as possible. Getting enough information about the system that is to be modeled is the first step in the system identification and modeling process. Besides, a clear statement of the modeling objectives is necessary for making an efficient model. Industrial systems may be modeled for condition monitoring, fault detection and diagnosis, sensor validation, system identification or design, and optimization of control systems. AI techniques such as fuzzy logic and artificial neural networks have the computational power to solve many complex problems; it can be used for function fitting, approximation, pattern recognition, clustering, image matching, classification, feature extraction, noise reduction, extrapolation (based on historical data), and dynamic modeling and prediction. The performance and efficiency of MGs can be improved by using AI-based methods. However, there are several challenges to employ and implement AI-based techniques in MGs that should be addressed. The future trends of AI in MGs are shown in Fig. 8.

VI. CONCLUSION

This paper presents a review of the application of AI techniques in microgrids. Microgrid recent developments and their characteristics was discussed at first. Then, a brief overview of AI techniques was presented. Finally, the applications of AI techniques in microgrid were discussed. Literature review shows that using AI models for different applications of MG is increasing due to their advantages. These models can be developed based on the data gathered from the system without requiring the exact model and characteristics of the system. The accuracy of the results of different models depends on enough data availability, accurate feature extractions, parameter tuning, and other factors and conditions. Despite all advantages, there are still challenges to implement AI models in real-world MGs that should be addressed to achieve results with high-accuracy, better efficiency, and reliability.

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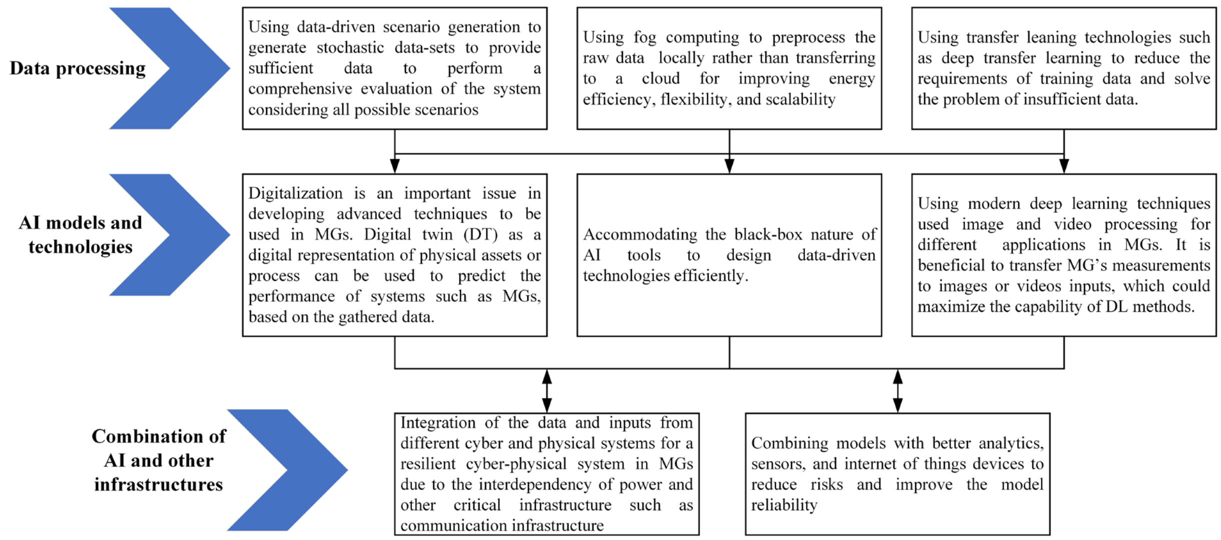

Fig. 8. Future trends of applications on AI in microgrids

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