electronics

MDPI

Review

Deep Learning for Forecasting-Based Applications in Cyber–Physical Microgrids: Recent Advances and Future Directions

Mohammad Reza Habibi *, Saeed Golestan, Josep M. Guerrero and Juan C. Vasquez

The Faculty of Engineering and Science, Aalborg University, 9220 Aalborg, Denmark
* Correspondence: mre@energy.aau.dk

Abstract: Renewable energy resources can be deployed locally and efficiently using the concept of microgrids. Due to the natural uncertainty of the output power of renewable energy resources, the planning for a proper operation of microgrids can be a challenging task. In addition, the information about the loads and the power consumption of them can create benefits to increase the efficiency of the microgrids. However, electrical loads can have uncertainty due to reasons such as unpredictable behavior of the consumers. To exploit a microgrid, energy management is required at the upper level of operation and control in order to reduce the costs. One of the most important tasks of the energy management system is to satisfy the loads and, in other words, develop a plan to maintain equilibrium between the power generation and power consumption. To obtain information about the output power of renewable energy resources and power consumption, deep learning can be implemented as a powerful tool, which is able to predict the desired values. In addition, weather conditions can affect the output power of renewable energy-based resources and the behavior of the consumers and, as a result, the power consumption. So, deep learning can be deployed for the anticipation of the weather conditions. This paper will study the recent works related to deep learning, which has been implemented for the prediction of the output power of renewable energy resources (i.e., PVs and wind turbines), electrical loads, and weather conditions (i.e., solar irradiance and wind speed). In addition, for possible future directions some strategies are suggested, the most important of which is the implementation of quantum computing in cyber–physical microgrids.

Keywords: artificial intelligence; deep learning; artificial neural networks; cyber–physical microgrids; load forecasting; renewable energy resources; weather condition; photovoltaic system; wind turbine; power consumption; quantum computing

check for updates

Citation: Habibi, M.R.; Golestan, S.; Guerrero, J.M.; Vasquez, J.C. Deep Learning for Forecasting-Based Applications in Cyber–Physical Microgrids: Recent Advances and Future Directions. *Electronics* **2023**, *12*, 1685. https://doi.org/10.3390/electronics12071685

Academic Editor: Carlos Andrés García-Vázquez

Received: 7 January 2023
Revised: 24 March 2023
Accepted: 27 March 2023
Published: 3 April 2023

1. Introduction

Renewable energy resources can be implemented into a small-scale power system by microgrids, which can have benefits (increasing the efficiency) and they can categorized into three different types, as follows [1]:

- AC microgrids,
- DC microgrids,
- Hybrid AC/DC microgrids.

Still, traditional power systems are working in the mode of AC, which can force the operators to use AC microgrids. However, DC systems have priorities when compared to AC systems with the term of different aspects and some of them are as follows [2,3]:

- Integration of renewable energy resources,
- Efficiency,
- Control.

Therefore, due to the advantage of the DC systems, the implementation of DC microgrids and also hybrid AC/DC microgrids can have its superiority. A microgrid can be exploited in two different fashions, i.e., [4],

- Grid-connected mode,
- Isolated or islanded mode.

In Figure 1, a cyber–physical microgrid in two different modes (i.e., grid-connected mode and islanded mode) is shown. As illustrated in Figure 1, a microgrid can be connected to an upper power system (where the upper power system can be different types of power systems, e.g., a traditional or a bulk power system, and distribution system) or a cluster of microgrids. In Figure 2, a graph of a cluster of microgrids is depicted. Additionally, in Figure 2, the challenges related to a cyber–physical cluster of microgrids is shown. Furthermore, to have a more practical view about the microgrids, some examples of power application, which can be considered a microgrid, are as follows:

- Small and local power systems, including renewable energy resources (e.g., wind turbine), batteries, and local loads, which have been studied previously in different papers, e.g., [5–10].
- Residential buildings where renewable-based power resources, energy storage systems, and loads can be connected to them, which have been discussed before and, for example, by [11–14].
- Shipboard power systems or marine power systems, which can include power resources to support the power system for satisfying the loads and energy storage systems to store and release the energy at the planed or proper times, where this type of microgrids has been studied in previous works, e.g., [15–18].
- Satellites, which can be considered as a space-based cyber–physical power systems, where have been discussed in previous works, such as [19–21].
- Lunar habitat microgrids, which can be considered as a new concept and the type of microgrids and has been studied previously by [22].
- Aircraft, which has been studied by works such as [23–26].
- Commercial buildings, which have been discussed before in papers such as [27–30].
- Data centers, which have been discussed in previous works, e.g., [31,32].
- Etc.

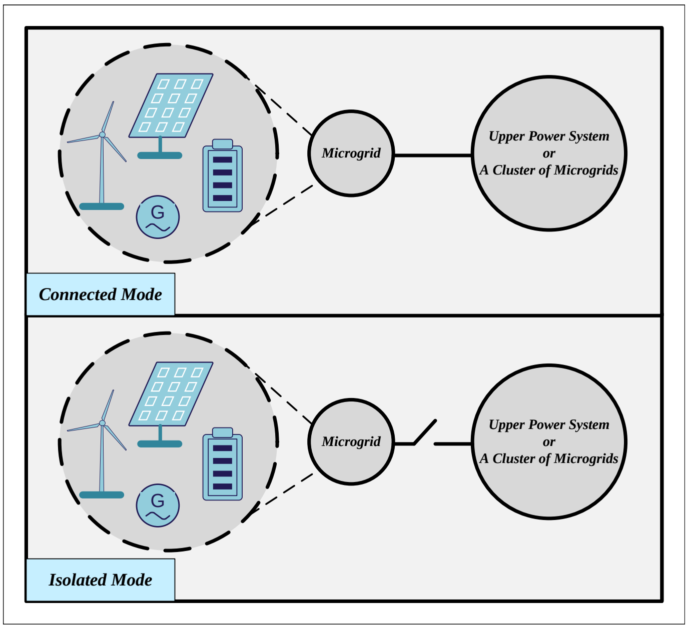

Figure 1. Two different modes of operation for a cyber–physical microgrid, i.e., connected to an upper grid that can be a cluster of microgrids or an upper power system, and isolated mode that works independently.

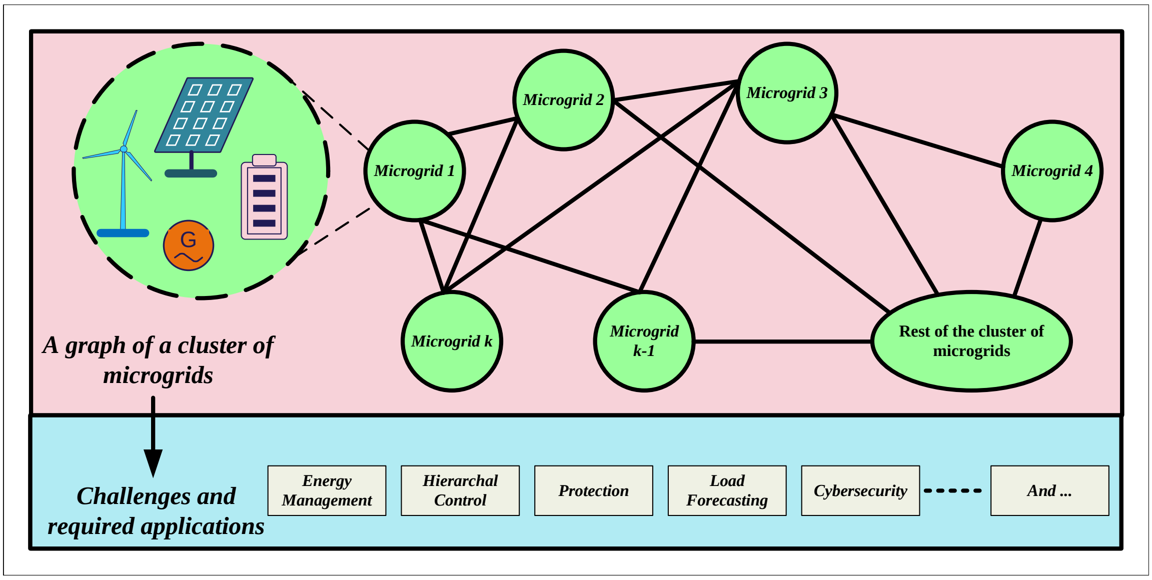

Figure 2. A graph of a cluster of microgrids, which shows the connection between the microgrids in the cluster with *k* microgrids. Each node is a microgrid and the edges represent the physical connections between microgrids. In addition, Figure 2 illustrates the issues, which should be considered in a cluster of microgrids to have a well-planned and proper operation.

For more clarification, Figure 3 depicts the mentioned practical applications of cyber–physical microgrids. It is important to note that, two of the mentioned applications (satellite and lunar habitat) can be considered as space-based microgrids. In addition, ships and aircraft can be considered a class of transportation-based microgrids. Additionally, residential buildings, commercial buildings, and data centers can be considered building-based microgrids, due to their structure. Finally, the local small-scale power systems, including renewable energy resources and local loads, can be considered traditional microgrids. The mentioned examples are categorized in Table 1. It is important to note that each of the mentioned examples can have special challenges which should be considered and solved to have a well-designed microgrid that operates properly. In Table 2, some of the challenges for the mentioned applications and their solutions are shown.

Table 1. The categorisation of different cyber–physical microgrids.

	Traditional Microgrid	Transportation-Based Microgrid	Space Microgrid	Building Microgrid
Small-Scale Power System	X			
Shipboard Power system		X		
Satellite			X	
Aircraft		X		
Data Center				X
Lunar Habitat			X	
Residential Building				X
Commercial Building				X

Table 2. The challenges and the main solutions of them in a practical cyber–physical microgrid.

	Protection Strategy	Secure Control	Communication-Based Strategies	Well-Designed Controllers	Optimization-Based Methods	Forecasting-Based Approaches
Physical Fault	X					
Cyber Issue		X	X			
Stability				X		
Economical Aspect					X	
Size of the Area					X	
Uncertainty						X
Environmental Issue					X	

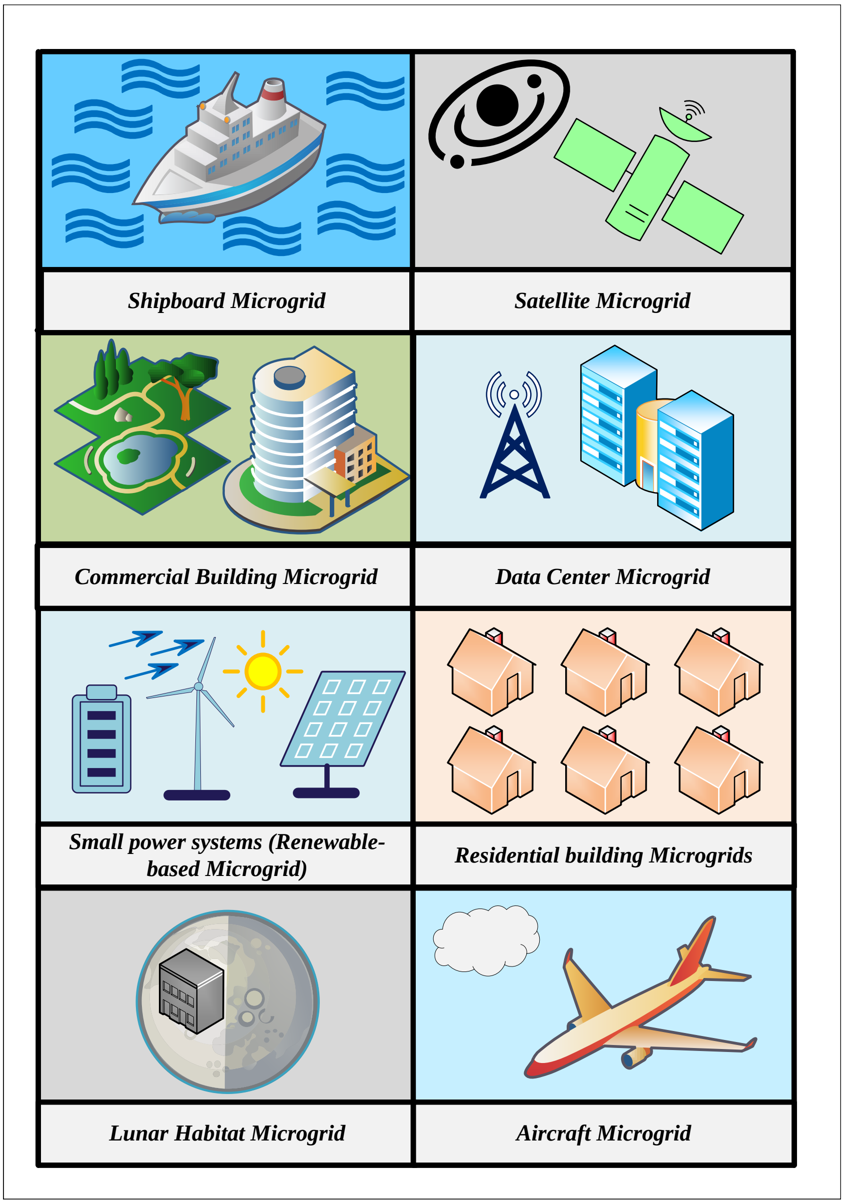

Figure 3. Some examples for different practical applications of a cyber–physical microgrid.

This paper will discuss the prediction of loads, power of renewable-based power resources (e.g., photovoltaic (PV) systems and wind turbines), and the forecasting of the weather conditions (e.g., solar irradiance and wind speed). This forecasting-based approach in a cyber–physical microgrid can support the system to solve the uncertainty problem, to have a more efficient energy management strategy, and to increase the reliability of the cyber–physical microgrid. This work focuses on prediction-based approaches, which are based on deep learning from artificial neural networks (ANNs) and recurrent neural networks (RNNs). It is important to note that forecasting-based strategies for some applications (e.g., power consumption, weather conditions, and output power of PVs and wind turbines) can be independent of the type of power application. In other words, a strategy for the prediction of wind speed in a large-scale power system can implemented to forecast the wind speed in a cyber–physical microgrid. As another example, the prediction strategy for the power of PVs can be used in many power-based systems, e.g., large-scale power systems, distribution systems, or cyber–physical microgrids. Therefore, the forecasting-based strategy can be deployed in many types of power-based systems directly or by some modifications. Therefore, this study tries to cover the works, which have been implemented or can be implemented in cyber–physical microgrids.

Therefore, based on the above explanations and discussions, some of the features and advantages of this paper can be listed as follows:

- This paper addresses and focuses on forecasting-based strategies in cyber–physical microgrids.
- Electrical loads and renewable energy resources can have direct and significant effects on a cyber–physical microgrid. In addition, the weather condition can affect the output power of renewable energy resources and the patterns of the load consumption. Therefore, in this paper, recent advances related to prediction of electrical loads, forecasting the output power of renewable energy resources, and anticipation of weather conditions are considered.
- In this paper, PVs and wind turbines are discussed as the popular renewable energy resources.
- In the case of the prediction of the meteorological data, this paper discusses wind speed and solar irradiance.
- Additionally, this paper discusses the advantages of deep learning for the implementation in cyber–physical microgrids.
- In addition, in this paper, the challenges, which can be faced by the deployment of deep learning in cyber–physical microgrids are discussed.
- In addition, this paper discusses future directions and works for this research line to address the current challenges.

For the rest of this paper, Section 2 will discuss about deep learning. In addition, in Section 3, deep learning-based strategies for load forecasting will be discussed. Furthermore, Section 4 is about the prediction methods to anticipate the power of PVs and wind turbines. Additionally, Section 5 is related to the deep learning-based forecasting approaches to predict the weather conditions, i.e., the wind speed and the solar irradiance. In Section 6, the advantages and the challenges of the deep learning in a cyber–physical microgrid will be evaluated. In addition, Section 6 will include future perspectives about this field of study. Further, a discussion to discuss this paper is prepared in Section 7. Finally, this paper will be concluded by Section 8.

2. Introduction to Deep Learning

Deep learning-based strategies, such as RNNs and ANNs, have been implemented to solve different problems in power applications, e.g., microgrids. For example, in [33], ANNs have been implemented in a hybrid AC/DC microgrid for the control application. As another example, deep learning has been deployed for a dynamic energy management application in a microgrid by [34]. Additionally, ref. [35] has used deep learning to have a sensorless control strategy for DC nanogrids. Furthermore, ref. [36] has implemented deep learning for the optimal power allocation in microgrids. In addition, neural networks have been used to enhance the power quality in a hybrid microgrid by [37]. In addition, ref. [38] has deployed RNNs for a protection application in AC microgrids. Further, in [39–43], ANNs have been implemented to increase the cybersecurity of DC microgrids by providing secure control layers. Additionally, for a more example, ANNs have been deployed in order to have a sensorless voltage estimation to calculate the total harmonic distortion in microgrids by [44]. In addition, an ANN-based method to have a sensorless control of DC microgrids has been introduced by [45]. For more instance, in [46], an RNN-based method has been proposed to identify the cyber-attacks in DC microgrids.

As mentioned above, deep learning can be implemented in many types of power systems and power electronics-based applications (such as cyber–physical microgrids) for different goals, e.g., protection, control, energy management, cybersecurity, estimation, sensorless strategies, etc. Therefore, deep learning can be considered as a proper data-based tool to improve the efficiency, reliability, flexibility, and security of power-based applications.

There are different types of ANNs and RNNs, which can make a deep learning-based applications. For example, some important architecture of ANNs and RNNs are as follows:

- Feed-forward neural network,
- Radial basis function neural network,
- Cascaded neural network,
- Non-linear autoregressive exogenous (NARX) neural network,
- Long short-term memory (LSTM) neural network,
- Convolutional neural network (CNN),
- Etc.

The existed parameters in a network and the structure of connections between different layers are the difference between different architecture of neural networks. Generally, in an ANNs, there can be different layers, which can be structured by neurons. Each neuron can have parameters such as weighting factors and bias factors. The deep learning-based applications receive the inputs. Then, each layer makes modification on data and transmit the new data to another layer, which can be the next layer. Finally, the last layer calculates the output of the ANN. In addition, before the implementation of a neural network, the proper values of the parameters of the neural network should be calculated. To calculate those parameters, a training part can be completed.

It is important to note that, in this paper, the forecasting-based strategies will be discussed. Typically, in this case, the deep learning-based application should calculate the future values of the desired output. Therefore, generally, a dataset should be created to use for the training part to train the neural networks and calculate the optimal values of the neural networks. The training of a neural network can be an optimization problem to find the optimal values of the parameters of the network. For this optimization, different traditional methods (e.g., gradient descent) can be implemented. However, other types of optimization-based strategies, such as metaheuristic optimization approaches, can be deployed to train a neural network. Some of the well-known metaheuristic optimization algorithms are as follows:

- Particle swarm optimization,
- Firefly algorithm,
- Teaching learning-based optimization,
- Genetic algorithm,
- Etc.

To conclude this section, a deep learning-based application can be designed with different layers. Additionally, before the implementation of the neural network, a training phase is required to find the values of the parameters and tune the network. Additionally, for the training, different approaches such as traditional mathematical-based methods, and metaheuristic optimization strategies can be used.

3. Deep Learning-Based Load Forecasting

In a cyber–physical microgrid, in addition to technical aspects (e.g., control and cybersecurity), economical aspects should be considered to have a more economic system. Therefore, optimizations-based concepts should be designed considering the costs (i.e., installation costs and operation costs). One of the most important constraint in a power-based application (i.e., DC microgrid) is load balancing. The goal of this constraint is to make the system responsible for satisfying the load and in other words, to be sure that the generated power from the power sources (e.g., PV and wind turbine) is equal to the power consumption in the system. Therefore, it is necessary to estimate the amount of the power consumption to have a well-designed and more accurate load balancing constraint and as a result, more accurate results, which can make the system more economic. For the estimation of the power consumption or load forecasting, ANNs and RNNs can be used as a powerful solution. Previously, some works have been performed for load forecasting, which can be used or modified for use in many types of power-based applications, e.g., cyber–physical microgrids. For example, in [47], application of a wavelet neural network has been used for the short-term load forecasting. In [47], an improved particle swarm optimization and chaos optimization algorithm have been implemented and the problem of the poor convergence and risk of the falling into the optimal local solution in wavelet neural network has been solved. As another example, a hybrid neural network has been used in [48] for short-term load forecasting. In [48], the ANN is based on a CNN (for the feature extraction, e.g., load, and weather features) and an LSTM (for time patterns). Furthermore, in [49], short-term load forecasting has been performed based on deep neural networks. It is important to note that, in [49], electricity price as an important factor has been considered. In [49], two primary layers have been included (the first layer was for the feature extraction and the purpose of the second layer was forecasting. In [49], for the first layer, CNN and LSTM have been used and for the second layer a fully connected ANN has been used.

In addition, in [50], the problem of the load forecasting has been solved based on a deep neuroevolution algorithm. In [50], the structure of the CNN has been used and an enhanced grey wolf optimizer is deployed to tune the hyperparameters of that. Additionally, another short-term residential load forecasting method has been introduced by [51]. In [51], the CNN and Gated Recurrent Units (GRU) have been implemented for the prediction of the load. Additionally, the proposed method of [51] consists of two main parts, i.e., data refinement, and training, respectively. Furthermore, another ANN-based load forecasting method has been introduced by [52]. In [52], the online training-based approach is deployed for hour-ahead load forecasting and the architecture of the ANN is based on the appropriate time-delay neural network. As mentioned above, there are some examples to use different types of the ANNs in different ways for the prediction of the electrical loads. This prediction can be used in different applications, e.g., energy management, electricity market, and even the hierarchical controller to have a more flexible, reliable, and efficient DC microgrids.

To conclude this section, deep learning-based strategies can be implemented to predict the loads and power consumption in a power application, e.g., a cyber–physical microgrid. To implement the deep learning-based strategy, it should be trained. Then, the trained deep learning-based strategy (e.g., an ANN) can be deployed to anticipate the values of loads. For more clarification, Figure 4 illustrates that how a cyber–physical microgrid can use an ANN to forecast the power consumption. Finally, for more works related to the load forecasting, refs. [53–70] can be considered.

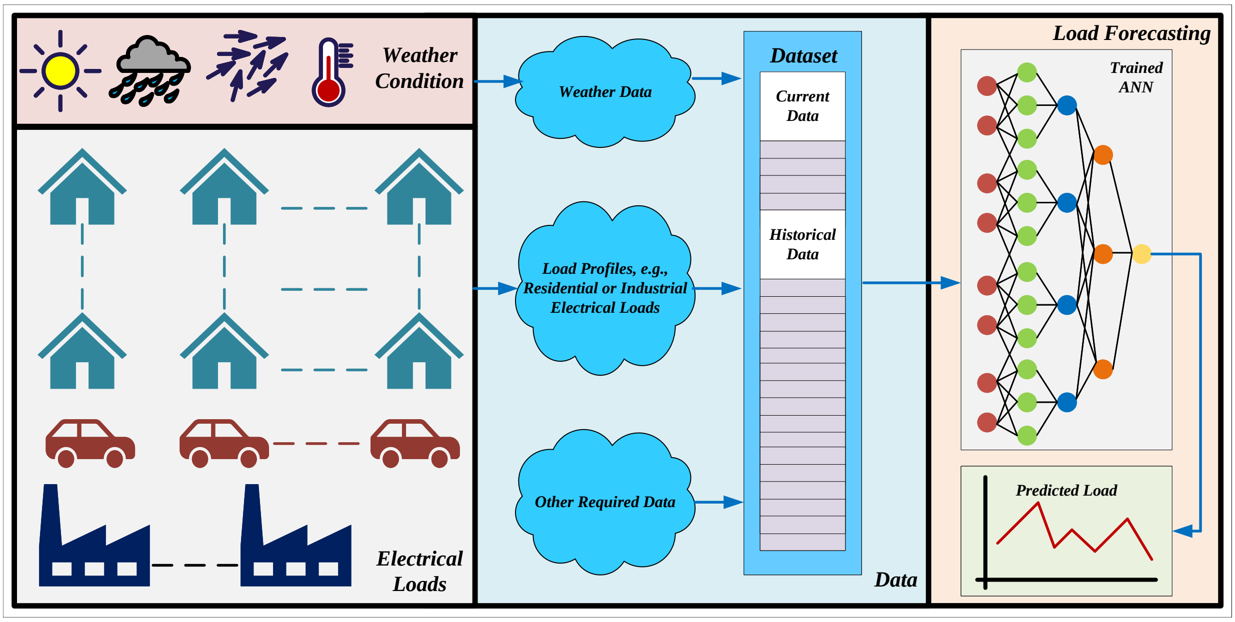

Figure 4. The implementation of deep learning for load forecasting in a cyber–physical microgrid. A dataset can be created to train the deep learning-based application (e.g., the ANN) to forecast the values of the loads. Then, based on Figure 4, the current values and the historical values of the desired inputs can be used to predict the future values of power consumption in a cyber–physical microgrid using the trained ANN.

4. Forecasting the Renewable Energy Resource Production

The deployment of renewable energy resources in microgrids can have advantages, e.g., reduction in greenhouse gas emission [71]. The prediction of the output power of renewable energy resources can have advantages for the system, e.g., allowing the system to have a more precise energy management and planning strategies. In this section, different methods to predict the power of PVs and wind turbines will be talked. Firstly, the forecasting strategies for the output power of PVs will be considered. Then, the prediction approaches for the power of wind turbines will be discussed.

4.1. PV Output Prediction

Previously, different works have been performed to predict the power of PVs. For example, in [72], ANNs have been implemented to predict the output power of PVs. Additionally, in [72], ANNs have been deployed in a deep manner and the type of the implemented deep learning-based strategy was CNNs. In addition, ref. [72] has implemented the proposed strategy for short-term forecasting. Furthermore, ref. [72] has used historical data from the system, temperature, and solar radiation as the input of the deep neural network to forecast the output power of the next 24 hours. As another example, ref. [73] introduced an ANN-based strategy to predict the output power of PVs using multi-layer feed-forward. The proposed method of [73] is a two-level strategy and it considers the shading condition. Furthermore, in [74], a gray-box neural network-based strategy has been proposed, which could be used to forecast the output power of PVs. In [74], a threshold has been specified to use for the online training of the neural network, when the error of the prediction is more than the threshold. In addition, in [75], deep belief network and gray theory-based data preprocessor have been deployed to predict day-ahead output power of PVs.

Furthermore, in [76], deep learning has been used for short-term prediction in PVs using LSTM and attention mechanism. Additionally, the results have been compared with other methods (i.e., persistent model, the auto-regressive integrated moving average model with exogenous variable, MLP, and the LSTM) by [76] using three indices. In addition, another ANN-based method has been introduced by [77] to forecast output power of PVs. In [77], the introduced approach is based on neural network ensemble [77]. In addition, the introduced neural network ensemble-based strategy in [77] was based on feedforward NNs (which have been trained deploying particle swarm optimization approach). Further, the wavelet transformation has been implemented for historical data related to PVs by [77]. Additionally, in addition to the wavelet transformation-based data of PV, meteorological parameters (i.e., wind speed, temperature, solar irradiance, and humidity) have been deployed as the inputs of the introduced ANN-based method by [77]. Additionally, for more study about the prediction for PVs, refs. [78–87] can be studied.

4.2. Wind Power Prediction

To forecast the power of wind power, various works have been performed before. As an example, in [88], a short-term prediction has been performed for the wind power. The proposed strategy of [88] has been deployed using the variational mode decomposition, convolutional long short memory neural network, and error series modelling. Furthermore, another study related to the short-term anticipation of the electrical wind power has been presented by [89]. In [89], an ANN/support vector machine has been implemented to determine how the wind patterns of the numerical weather prediction data and reference wind mast measurements are related to each other. In addition, an RNN-based approach for the prediction of the uncertain wind power has been introduced by [90]. In addition, in [90], the dragonfly algorithm has been deployed to optimize and tune the parameters of the implemented RNN. As another example, ref. [91] introduced a RNN-based strategy to forecast the wind power. A spatial-temporal strategy has been used to have a short-term anticipation by [91]. In addition, the introduced strategy of [91] involved an image learning approach and augmented convolutional network. Furthermore, in [92], sample similarity analysis has been used for the prediction of wind power. The proposed strategy of [92] contains two main steps, i.e., related to classification, and prediction. In addition, in [92], the CNN and LSTM have been deployed. Additionally, two small-world neural network-based approaches for the anticipation of the wind power have been deployed by [93]. The implemented strategies of [93] involved the Watts–Strogatz and a Newman–Watts small-world networks based on a BP neural network. For further studies related to the prediction of the wind power, refs. [94–102] can be reviewed.

To wrap up this section, Figure 5 can show a general structure to use a deep learning-based strategy (e.g., ANNs) in a cyber–physical microgrid to predict the output power of PVs and wind turbines. Based on Figure 5, a dataset can be existed and the desired inputs can be selected from the dataset to be implemented in the deep learning-based approaches to predict the output power of PVs or wind turbines.

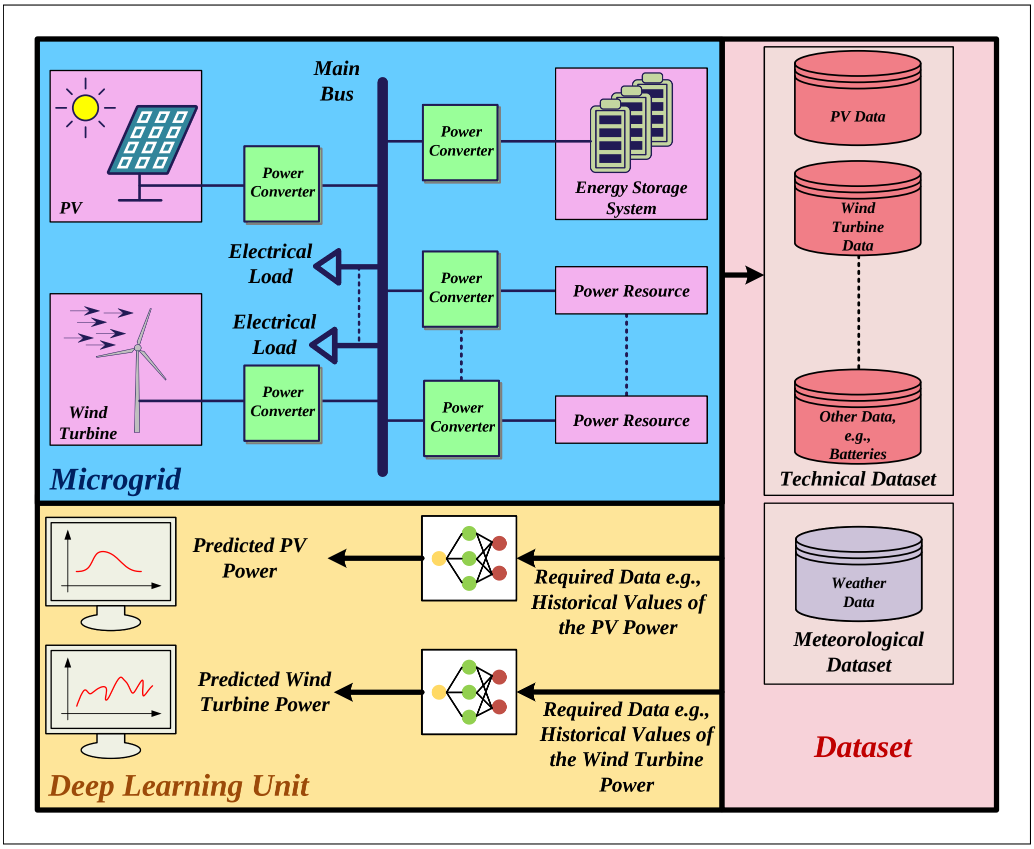

Figure 5. Deep learning-based tool (e.g., ANNs) to anticipate the future values of the power of PVs and wind turbines in a cyber–physical microgrid. Based on Figure 5, different inputs (historical values of the power of PVs and wind turbines, or meteorological data) can be used to be implemented in the deep learning-based strategy to predict the output power of PVs and wind turbines.

5. Deep Learning-Based Weather Prediction

As mentioned before, some parameters in cyber–physical microgrids (i.e., loads, and output power of renewable energy resources) can be planned to be predicted by deep learning. The deep learning-based solutions for the mentioned forecasting were discussed before in more details. However, other predictions (e.g., weather forecasting, such as wind speed) can be found in cyber–physical microgrids, which could be addressed and solved by deep learning-based approaches. It is important to note that, as mentioned before, typically, cyber–physical microgrids can include renewable energy resources (wind turbines and PVs), while the output power of them depends on the weather conditions (e.g., wind speed). Therefore, the methods, which focus on the weather condition prediction can be useful to support the system to have a more reliable cyber–physical microgrid and a well-planned operation of that. In the rest of this section, firstly, some previous works related to the prediction of wind speed will be discussed. Then, some works related to forecasting the solar irradiance will be talked.

5.1. Wind Speed Prediction

Previously, some works have been performed to predict the wind speed. For an example, in [103], the prediction capability of the ANNs has been deployed to have the day-ahead prediction of the wind speed. It is important to note that, the proposed approach of [103] contains two parts, i.e., a method for the input selection, and the ANN. Additionally, a two-stage information-theoretic-based input selection has been implemented to support the system to have the proper set of inputs for the training. In addition, another a day-ahead wind speed forecasting strategy has been introduced using ANNs by [104]. Additionally, five hybrid neural network-based strategies (i.e., two wavelet neural networks, extreme learning machine-based neural network, radial basis function neural network, and multi-layer perceptron neural network) have been considered in [104]. In [104], one of the wavelet neural networks has been trained using improved clonal selection algorithm and another one has been trained based on particle swarm optimization strategy. In addition, another strategy for the short-term prediction of wind speed has introduced by [105]. Additionally, a convolutional network, a LSTM, and channel attention with spatial attention have been implemented in [105]. In addition, for feature extraction of spatial information and time-series information have been deployed by the convolutional network and the LSTM, respectively, in [105]. Furthermore, a deep learning-based approach to anticipate the wind speed has been proposed by [106]. In [106], the introduced method is based on clustering and deep learning. Additionally, in [107], wind speed and power have been anticipated using ANNs. It is important to note that, in [107], feed-forward neural networks and cascaded feed-forward neural networks have been deployed. Additionally, in [107], the ANNs have been trained based on metaheuristic optimization-based strategies, e.g., particle swarm optimization.

Additionally, for more studies, some methods have been proposed by [108–115] for the prediction of the wind speed.

5.2. Solar Irradiance Prediction

In addition to wind turbines, PVs are another popular renewable energy-based sources and they can play an important role to generate the power in DC microgrids as DC sources. Similarly to wind turbines, the output power of PVs relies on weather conditions. The estimation or prediction of the solar irradiance (as a weather condition) can support the system to have a precise estimation or forecasting of the output power of PVs, which can lead to a proper energy management system. Previously, some works have been performed to investigate and introduce the ANN-based approaches to predict the solar irradiance. For example, a method has been introduced to predict the solar irradiance using a deep learning-based structure (group solar irradiance neural network) by [116]. The proposed method of [116] includes a convolutional graph neural network and LSTM for detecting features and capture the temporal correlations, respectively. As another example, ref. [117] implemented the ANNs for the prediction of hourly solar irradiance. In [117], the Elman neural network and wavelet transform are employed. Furthermore, another deep neural network-based strategy for the prediction of the solar irradiance has been introduced by [118]. In [118], a deep CNN-LSTM structure is used to extract the appropriate features for forecasting the global horizontal irradiance. Additionally, in [119], a method for short-term prediction of solar irradiance has been introduced using LSTM. In [119], the clearness-index has been proposed, which can improve the accuracy of the forecasting on cloudy conditions. Additionally, more details and methods about the prediction of the solar irradiance can be found in [120–125].

It is important to note that, Figure 6 shows that how a deep learning-based strategy (an ANN) can be trained and used to predict the weather conditions (e.g., solar irradiance and wind speed).

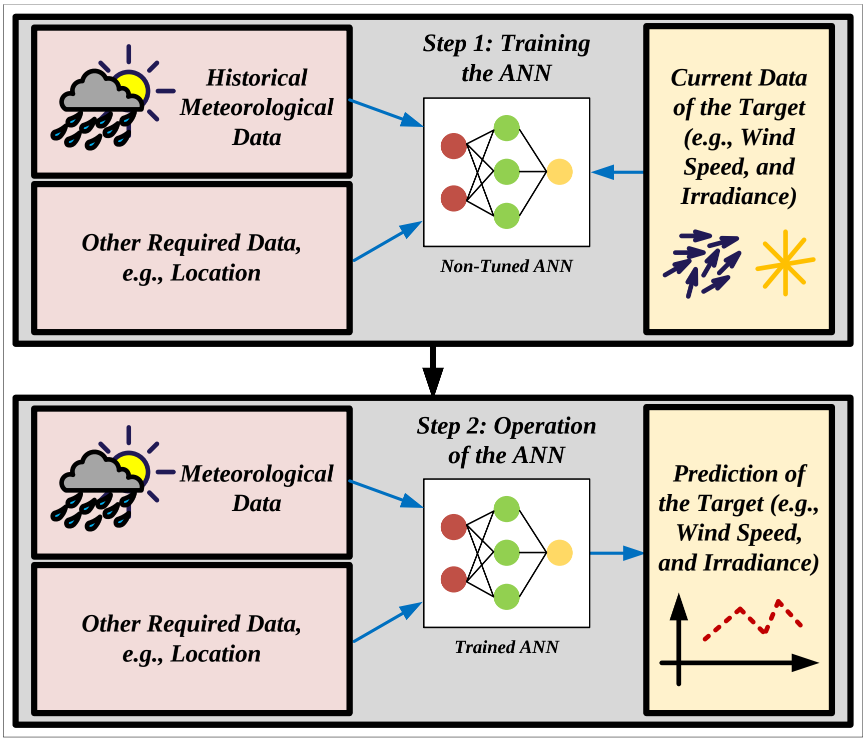

Figure 6. The implementation of a deep learning-based strategy (e.g., an ANN) for the forecasting the weather conditions (e.g., solar irradiance or wind speed). The prediction strategy contains two main steps. For the first step, a proper dataset should be gathered to create the input dataset, including desired data, e.g., meteorological data. Then, in the first step, the gathered data can be deployed to obtain the parameters of the ANN. Additionally, for the second step, the obtained parameters, which can be implemented to exploit the trained ANN to predict the desired parameters, e.g., wind speed and solar irradiance.

6. A Brief Overview and a Few Additional Considerations

In this paper, a comprehensive review of the implementation of deep learning-based approaches in cyber–physical microgrids has been prepared. There are different kinds of practical cyber–physical microgrids, e.g., shipboard microgrids, residential microgrids, commercial buildings, and aircraft microgrids. In addition, a cyber–physical microgrid can be made using local renewable energy resources, power converters, communication links, digital controllers, energy storage systems, electrical loads, and so on. Therefore, a cyber–physical microgrid can be a complicated system, which needs computation-based strategies to be planned and programmed for a proper operation. Typically, deep learning can be deployed as computation-based strategies in microgrids for handling and solving various types of application. For an example, deep learning can be used to develop a control method for a microgrid. In addition, deep learning can be used to propose a protection strategy for a microgrid. As another instance, a deep learning-based approach can be used in order to condition or health monitoring of the power components in a cyber–physical microgrid. In addition, deep learning can help a cyber–physical microgrid by prediction of the electrical loads, and output power of renewable energy resources. Therefore, deep learning can support wide varieties of applications in a cyber–physical microgrids, which can lead to a reliable, efficient, secure, resilient, or proper operation of a cyber–physical microgrid.

The main goal of this paper was to discuss about the implementation of deep learning for forecasting-based applications in cyber–physical microgrids, i.e., load forecasting, prediction of the output power of renewable energy resources, and weather prediction. Deep learning can be used to predict the future load profile in a power-based application such as a microgrid. In addition, due to the uncertainly in the output power production of renewable energy resources, deep learning can be implemented for the prediction of the output power of them. Furthermore, the weather conditions can affect the output power of renewable energy resources and also the electrical loads. Therefore, the prediction of weather conditions was also considered in this paper. It is important to note that, in the case of prediction of the output power of renewable energy resources, this paper focused on PVs and wind turbines. In addition, for the case of the prediction of the weather conditions, this paper considered the solar irradiance and the wind speed. It is clear that the knowledge (short-term, mid-term, and long-term information) about the future of the system can have its benefits. For more clarification, the knowledge about the future state of the system allows the operator to predict the required future actions and as a result, the implementation of deep learning for the prediction-based applications in a cyber–physical microgrid can support the system to have a more efficient, reliable, and precise operation and energy management.

As mentioned above, the implementation of deep learning can assist cyber–physical microgrids in several ways. To implement a deep learning-based application, some challenges can be faced, which should be considered. To have a more precise discussion about the benefits and issues related to the deployment of deep learning, the next part of this paper will discuss some advantages, challenges, and also future directions related to a deep learning-based approach.

7. Advantages, Current Challenges, and Future Perspectives

The implementation of deep learning in microgrids for forecasting-based applications can have its benefits and issues. In addition, to provide solutions for the challenges and solving them, some suggestions can be made, which may be under consideration or can be considered for future directions. In this section, the advantage and challenges regarding to deploy deep learning in the microgrids will be talked. Furthermore, solutions and future perspective of the implementation of deep learning in microgrids will be suggested.

7.1. Advantages

The implementation of deep learning in cyber–physical microgrid can have advantages such as:

- Clear implementation,
- Easy to understand,
- No need or a very slight need to have a knowledge about the entire studied application.

Generally, a two-step strategy can be used to implement deep learning in microgrids, i.e., step 1, which is related to the preparation a dataset and tuning parameters of the deep learning-based network using the prepared dataset, and step 2, which can be the deployment of the tuned deep learning-based network. Due to the general way of the deployment of a deep learning-based approach, the implementation of this and also the understanding of this can be easy and clear. However, details (e.g., number of inputs and outputs, architecture and the type of the deep learning-based network, and training approaches) regarding the mentioned steps can be varied considering the type of the problem in cyber–physical microgrids. In addition, deep learning works based on data and as a result, it does not require the detailed information of microgrids.

7.2. Challenges

As mentioned before, the implementation of deep learning has advantages. However, to deploy deep learning in cyber–physical microgrids, still some challenges can be faced:

- Requirement of a high volume of data,
- Difficult access to some data,
- Time consuming process for the training of the deep learning-based application,
- Data availability,
- Scalability of ANN-based strategies in cyber–physical microgrids,
- Unclean data.

For the training of a deep learning-based network, a proper dataset should be prepared. The dataset should have enough numbers of samples, which can be gathered under different scenarios. In addition, in some cases, it is hard to have an access to needed some data, e.g., in the industry. Additionally, even in the case of having access to data, during the operation of the systems, cyber or physical issues can make problems related to the availability of data, e.g., denial of service (DoS) cyber-attacks, and failure of the communication links. Furthermore, the gathered data from sensors are not reliable to be implemented directly in the processing in clouds, and their direct deployment can lead to non-precision outcomes [126]. It is important to note that the scalability of the ANN should be considered, and in the case of a large dataset in a cyber–physical microgrids, the ANN-based system can be faced challenges. In addition, after creating a proper dataset, the designed deep learning-based network should be trained to tune the parameters of the network. The training can be performed by an optimization strategy to find the optimal values of the parameters of the network. Typically, an optimization-based problem can require a time-consuming solution, which can be a challenge when the training phase is online.

7.3. Solutions and Future Perspectives

The implementation of deep learning can provide advantages and challenges. The exploration of solutions to overcome the issues can increase the efficiency and make the deployment of deep learning more easier and interesting rather than past. Typically, in a cyber–physical microgrid, the size of the dataset (e.g., in the case of a small dataset, the size of the dataset can be non-enough for complex systems), accessibility to data, the time of the training, and dirty data are important examples of issues related to an ANN-based system. To solve the challenges, some solutions can be suggested. For example, the following strategies can be deployed:

- Generating data in the case of small dataset,
- Considering the studied system as a gray-box,
- Quantum computing,
- Data cleaning.

Previously, some works have been completed to generate data. For example, ref. [127] has introduced a method based on the generative adversarial network (GAN). It is important to note that, the data generation in [127] was related to load forecasting. Additionally, the proposed approach has included two stages, i.e., stage 1 (which has deployed a conditional tabular GAN) and stage 2 (which was based on a deep learning-based architecture) in [127]. Then, in a case of a small dataset, the existing data can be used to produce more data and increase the size of the dataset. In addition, typically, deep learning can consider the studied system (e.g., cyber–physical microgrids) as a black-box without information about the entire of the system. Therefore, in this case, the operation of a deep learning-based network can be limited to data of the only available parameters of the system. Therefore, in the case of the need to the parameters, which are not available, the implementation of deep learning can be difficult or can be impossible to have a well-tuned network. In this case, the system can be considered as a gray-box. It can mean that there is not full access to information about the entire system and there is only the limited access to a part of the parameters of the entire system. Therefore, the accessible parameters can be implemented to calculate or estimate other non-accessible parameters of the entire system, for example using mathematical-based strategies. For more clarification, Figure 7 shows how a cyber–physical microgrid can be considered as a withe-box, gray-box, or black-box system. Additionally, quantum computing can be deployed in order to raise the speed of the computation. However, there are still very limited works, which have implemented quantum computing for power applications [128,129]. In addition, as mentioned before, the training phase of a deep learning-based network can require a significant amount of time. Therefore, quantum computing may reduce the required time to tune the parameters of the deep learning-based network. In addition, to have a reliable operation of neural networks, the implementation of dirty data should be avoided, and strategies should be deployed in order to clean data. Previously, some methods have been investigated to clean data. For example, a deep learning-based approach using stacked denoising autoencoders has been deployed to clean data related to a power device in [130]. Furthermore, ref. [131] has implemented local outlier factor and random forest to clean big data related to distribution networks. As another example, an abnormal data cleaning approach related to wind turbines has been introduced in [132]. Additionally, many other works have been performed for cleaning data, e.g., many works have been performed before to overcome the challenges related to data and neural networks. However, this direction (i.e., overcoming the issues related to data-driven-based strategies) is still an open direction and many other solutions can be proposed to address those challenges.

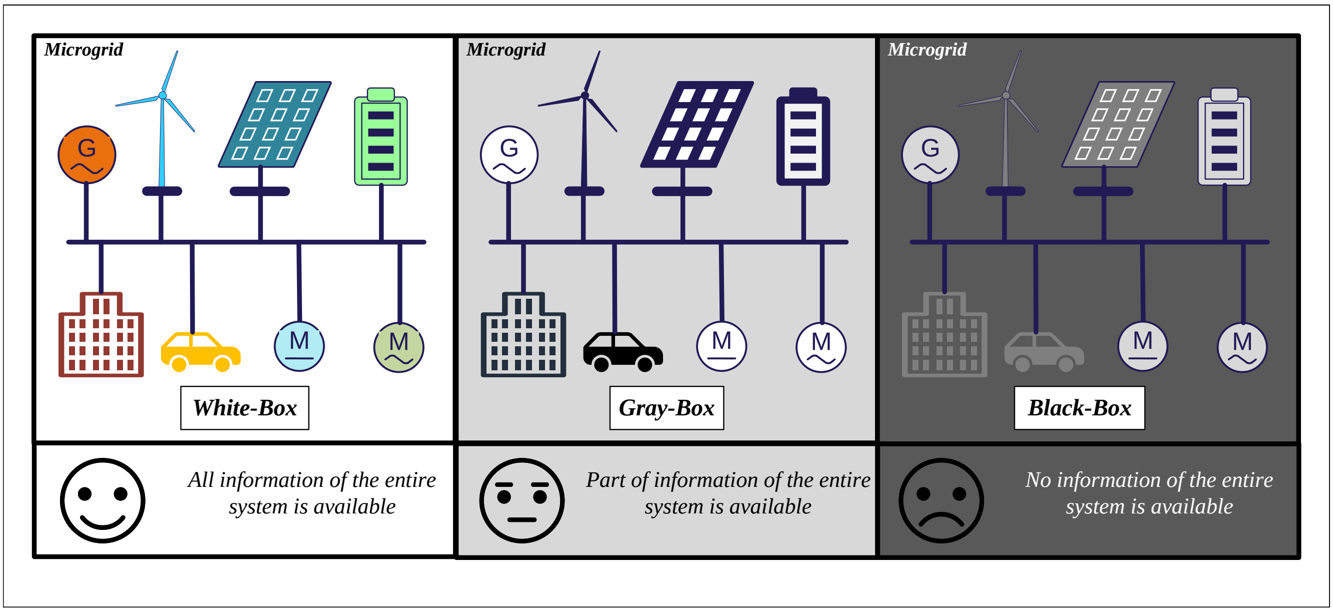

Figure 7. The white-box, gray-box, and black-box representation of a cyber–physical microgrid. In the case of a white-box consideration, there can be access to all possible information of the microgrid. Additionally, in the case of a gray-box application, there can be only access to some or few parameters. In addition, in the case of a black-box-based system, there is no access to the information about the entire of the studied microgrid.

It is important to note that, Table 3, summarizes and shows the advantages, challenges, and future solutions and directions related to deep learning in a cyber–physical microgrid.

Table 3. The summarizing of some advantages, issues, and also future directions related to the deployment of deep learning in a cyber–physical microgrid.

	Advantages	Issues	Future Directions and Solutions
1	Clear deployment	Data availability	Generation of Data
2	Easily understandable	Unavailability to some parameters or data	Considering the system as a gray-box.
3	The mathematical-based information of the entire system are not required.	Training to tune the parameters of the deep learning-based network can be a time consuming process.	Quantum computing
4	Typically just data are required	Unclean data	Data cleaning

8. Discussion

In this paper, the implementation of deep learning in cyber–physical microgrids has been discussed. A cyber–physical microgrid includes electrical loads as power consumers, which should be satisfied by power resources (e.g., renewable energy-based resources, e.g., PVs and wind turbines). Generally, in cyber–physical microgrids, an upper level of planning can be programmed to make an operation considering the energy management of them. Then, the hierarchical control strategy can be implemented to control the planned microgrids. For planning and energy management, power production and power consumption play key roles. To have an optimized operation of cyber–physical microgrids, the knowledge about the future of the system (e.g., the amount of the power production, and the power consumption) can be very useful. This information can support the system to make more precise decisions, and as a result it allows the operator to have a more efficient operation, and have a more reliable, secure, and flexible microgrid. Three important parameters for the prediction (short-term, mid-term, or long-term predictions) are the electrical loads, output power of the power resources, and the weather condition (which can affect the amount of the power production or the behaviour of the consumers and as a result the amount of the power consumption). Microgrids provide the opportunity to deploy renewable energy resources more easier. Therefore, the main power production in microgrids can be performed by renewable energy resources. Therefore, predicted information about the output power of renewable energy resources can be very important. One of the practical and efficient tools to predict the desired values in microgrids is deep learning and, as a result, this paper considered the methods which have used deep learning. So, briefly, in this paper, deep learning-based applications for forecasting the electrical loads, the power production of renewable energy resources, and weather conditions have been discussed. The studied types of the renewable energy resources were PVs and wind turbines, which can be considered as more interesting and accessible renewable energy resources. In addition, for the weather condition prediction, solar irradiance and wind speed have been talked, which can affect directly the output power of the PVs and wind turbines, respectively.

9. Conclusions

This paper discussed the recent advances for the prediction-based applications in power systems, which can be also used in cyber–physical microgrids. The studied applications include load forecasting, prediction of the power of renewable energy resources (i.e., PVs and wind turbines), and anticipation of the weather condition (i.e., solar irradiance and wind speed). The selected recent studies were based on deep learning and they proposed and developed forecasting-based strategies to address the mentioned prediction-based applications. Furthermore, significant benefits and advantages related to the deployment of deep learning in cyber–physical microgrids were discussed. Clear implementation of deep learning, easily understandability of deep learning, and independency to extra or more information (e.g., mathematical-based information about the cyber–physical microgrids) were mentioned as the advantages of using deep learning for cyber–physical microgrids. Additionally, for the implementation of deep learning in a cyber–physical microgrid, some challenges can be faced and this paper talked about the important possible issues, e.g., the requirement of a large-scale dataset, unavailability of some data, unclean dataset, and the processing time of the training phase. Furthermore, this paper talks about the strategies, which can be used (or are implemented) to solve the mentioned challenges or considered for the future directions. The mentioned solutions and future direction includes data generation, using more information of the system, and quantum computing. It is important to note that quantum computing can be considered an important strategy, which can have a great impact on this research topic (i.e., using deep learning for forecasting-based applications in cyber–physical microgrids). The implementation of quantum computing can allow to speed up some calculations, new protocols for data transmission, and new strategies or architectures to have quantum-based deep learning. Therefore, quantum computing-based deep learning can be considered as one of important research lines for future works of researchers. To conclude this paper, it is important to mention that the implementation of deep learning for forecasting in microgrids can support the system for a better planning strategy to have a more efficient and reliable operation of microgrids.

Author Contributions: Writing—original draft preparation, M.R.H.; Review or Editing or Supervision, M.R.H., S.G., J.M.G. and J.C.V. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by VILLUM FONDEN under the VILLUM Investigator Grant (no. 25920): Center for Research on Microgrids (CROM).

Data Availability Statement: Not applicable.

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

References

1. Ahmed, M.; Meegahapola, L.; Vahidnia, A.; Datta, M. Stability and Control Aspects of Microgrid Architectures–A Comprehensive Review. *IEEE Access* **2020**, *8*, 144730–144766. [CrossRef]
2. Dragičević, T.; Lu, X.; Vasquez, J.C.; Guerrero, J.M. DC Microgrids—Part II: A Review of Power Architectures, Applications, and Standardization Issues. *IEEE Trans. Power Electron.* **2016**, *31*, 3528–3549. [CrossRef]
3. Akpolat, A.N.; Habibi, M.R.; Baghaee, H.R.; Dursun, E.; Kuzucuoglu, A.E.E.; Yang, Y.; Dragicevic, T.; Blaabjerg, F. Dynamic Stabilization of DC Microgrids using ANN-Based Model Predictive Control. *IEEE Trans. Energy Convers.* **2021**, *37*, 999–1010. [CrossRef]
4. Saeed, M.H.; Fangzong, W.; Kalwar, B.A.; Iqbal, S. A Review on Microgrids' Challenges & Perspectives. *IEEE Access* **2021**, *9*, 166502–166517. [CrossRef]
5. Yang, Z.; Xia, L.; Guan, X. Fluctuation Reduction of Wind Power and Sizing of Battery Energy Storage Systems in Microgrids. *IEEE Trans. Autom. Sci. Eng.* **2020**, *17*, 1195–1207. [CrossRef]
6. Han, J.; Solanki, S.K.; Solanki, J. Coordinated Predictive Control of a Wind/Battery Microgrid System. *IEEE J. Emerg. Sel. Top. Power Electron.* **2013**, *1*, 296–305. [CrossRef]
7. Salman, U.T.; Al-Ismail, F.S.; Khalid, M. Optimal Sizing of Battery Energy Storage for Grid-Connected and Isolated Wind-Penetrated Microgrid. *IEEE Access* **2020**, *8*, 91129–91138. [CrossRef]
8. Chishti, F.; Murshid, S.; Singh, B. Natural Genetics Adapted Control for an Autonomous Wind-Battery Based Microgrid. *IEEE Trans. Ind. Appl.* **2020**, *56*, 7156–7165. [CrossRef]
9. Zou, H.; Tao, J.; Elsayed, S.K.; Elattar, E.E.; Almalaq, A.; Mohamed, M.A. Stochastic multi-carrier energy management in the smart islands using reinforcement learning and unscented transform. *Int. J. Electr. Power Energy Syst.* **2021**, *130*, 106988. [CrossRef]
10. Mohamed, M.A.; Abdullah, H.M.; El-Meligy, M.A.; Sharaf, M.; Soliman, A.T.; Hajjiah, A. A novel fuzzy cloud stochastic framework for energy management of renewable microgrids based on maximum deployment of electric vehicles. *Int. J. Electr. Power Energy Syst.* **2021**, *129*, 106845. [CrossRef]
11. Antoniadou-Plytaria, K.; Steen, D.; Tuan, L.A.; Carlson, O.; Fotouhi Ghazvini, M.A. Market-Based Energy Management Model of a Building Microgrid Considering Battery Degradation. *IEEE Trans. Smart Grid* **2021**, *12*, 1794–1804. [CrossRef]
12. Raza, S.A.; Jiang, J. A Benchmark Distribution System for Investigation of Residential Microgrids with Multiple Local Generation and Storage Devices. *IEEE Open Access J. Power Energy* **2020**, *7*, 41–50. [CrossRef]
13. Raza, S.A.; Jiang, J. Mathematical Foundations for Balancing Single-Phase Residential Microgrids Connected to a Three-Phase Distribution System. *IEEE Access* **2022**, *10*, 5292–5303. [CrossRef]
14. Alramlawi, M.; Li, P. Design Optimization of a Residential PV-Battery Microgrid with a Detailed Battery Lifetime Estimation Model. *IEEE Trans. Ind. Appl.* **2020**, *56*, 2020–2030. [CrossRef]
15. Xu, L.; Guerrero, J.M.; Lashab, A.; Wei, B.; Bazmohammadi, N.; Vasquez, J.C.; Abusorrah, A. A Review of DC Shipboard Microgrids—Part I: Power Architectures, Energy Storage, and Power Converters. *IEEE Trans. Power Electron.* **2022**, *37*, 5155–5172. [CrossRef]
16. Xu, L.; Guerrero, J.M.; Lashab, A.; Wei, B.; Bazmohammadi, N.; Vasquez, J.C.; Abusorrah, A. A Review of DC Shipboard Microgrids—Part II: Control Architectures, Stability Analysis, and Protection Schemes. *IEEE Trans. Power Electron.* **2022**, *37*, 4105–4120. [CrossRef]
17. Shariatzadeh, F.; Kumar, N.; Srivastava, A.K. Optimal Control Algorithms for Reconfiguration of Shipboard Microgrid Distribution System Using Intelligent Techniques. *IEEE Trans. Ind. Appl.* **2017**, *53*, 474–482. [CrossRef]
18. Hassan, M.A.; Su, C.L.; Pou, J.; Sulligoi, G.; Almakhles, D.; Bosich, D.; Guerrero, J.M. DC Shipboard Microgrids with Constant Power Loads: A Review of Advanced Nonlinear Control Strategies and Stabilization Techniques. *IEEE Trans. Smart Grid* **2022**, *13*, 3422–3438. [CrossRef]
19. Yaqoob, M.; Lashab, A.; Vasquez, J.C.; Guerrero, J.M.; Orchard, M.E.; Bintoudi, A.D. A Comprehensive Review on Small Satellite Microgrids. *IEEE Trans. Power Electron.* **2022**, *37*, 12741–12762. [CrossRef]
20. Lashab, A.; Yaqoob, M.; Terriche, Y.; Vasquez, J.C.; Guerrero, J.M. Space Microgrids: New Concepts on Electric Power Systems for Satellites. *IEEE Electrif. Mag.* **2020**, *8*, 8–19. [CrossRef]
21. Yaqoob, M.; Abubakr, H.; Alcala, J.M.; Lashab, A.; Guerrero, J.M.; Vasquez, J.C. A Comparative Study of MPPTs for Nano-Satellite Microgrid Applications under Spinning Flight Scenarios. In Proceedings of the IECON 2022—48th Annual Conference of the IEEE Industrial Electronics Society, Brussels, Belgium, 17–20 October 2022; pp. 1–6. [CrossRef]

22. Dow, A.R.R.; Darbali-Zamora, R.; Flicker, J.D.; Palacios, F.; Csank, J.T. Development of Hierarchical Control for a Lunar Habitat DC Microgrid Model Using Power Hardware-in-the-Loop. In Proceedings of the 2022 IEEE 49th Photovoltaics Specialists Conference (PVSC), Philadelphia, PA, USA, 5–10 June 2022; pp. 0754–0760. [CrossRef]
23. Magne, P.; Nahid-Mobarakeh, B.; Pierfederici, S. Active Stabilization of DC Microgrids without Remote Sensors for More Electric Aircraft. *IEEE Trans. Ind. Appl.* **2013**, *49*, 2352–2360. [CrossRef]
24. Xu, Y.; Zhang, Z. Capacitor Energy-Based Current Sharing Control for More-Electric-Aircraft Onboard Microgrids with Parallel Sources. *IEEE Trans. Transp. Electrif.* **2022**, *8*, 4408–4417. [CrossRef]
25. Zhu, R.; Huang, Z.; Dinavahi, V. A Universal Wideband Device-Level Parallel Simulation Method and Conducted EMI Analysis for More Electric Aircraft Microgrid. *IEEE J. Emerg. Sel. Top. Ind. Electron.* **2020**, *1*, 162–171. [CrossRef]
26. Huang, Z.; Dinavahi, V. An Efficient Hierarchical Zonal Method for Large-Scale Circuit Simulation and Its Real-Time Application on More Electric Aircraft Microgrid. *IEEE Trans. Ind. Electron.* **2019**, *66*, 5778–5786. [CrossRef]
27. Liu, N.; Chen, Q.; Liu, J.; Lu, X.; Li, P.; Lei, J.; Zhang, J. A Heuristic Operation Strategy for Commercial Building Microgrids Containing EVs and PV System. *IEEE Trans. Ind. Electron.* **2015**, *62*, 2560–2570. [CrossRef]
28. Thirugnanam, K.; El Moursi, M.S.; Khadkikar, V.; Zeineldin, H.H.; Hosani, M.A. Energy Management Strategy of a Reconfigurable Grid-Tied Hybrid AC/DC Microgrid for Commercial Building Applications. *IEEE Trans. Smart Grid* **2022**, *13*, 1720–1738. [CrossRef]
29. Hong, M.; Yu, X.; Yu, N.P.; Loparo, K.A. An Energy Scheduling Algorithm Supporting Power Quality Management in Commercial Building Microgrids. *IEEE Trans. Smart Grid* **2016**, *7*, 1044–1056. [CrossRef]
30. Beer, S.; Gomez, T.; Dallinger, D.; Momber, I.; Marnay, C.; Stadler, M.; Lai, J. An Economic Analysis of Used Electric Vehicle Batteries Integrated Into Commercial Building Microgrids. *IEEE Trans. Smart Grid* **2012**, *3*, 517–525. [CrossRef]
31. Ding, Z.; Cao, Y.; Xie, L.; Lu, Y.; Wang, P. Integrated Stochastic Energy Management for Data Center Microgrid Considering Waste Heat Recovery. *IEEE Trans. Ind. Appl.* **2019**, *55*, 2198–2207. [CrossRef]
32. Yu, L.; Jiang, T.; Zou, Y. Distributed Real-Time Energy Management in Data Center Microgrids. *IEEE Trans. Smart Grid* **2018**, *9*, 3748–3762. [CrossRef]
33. Chettibi, N.; Mellit, A.; Sulligoi, G.; Massi Pavan, A. Adaptive Neural Network-Based Control of a Hybrid AC/DC Microgrid. *IEEE Trans. Smart Grid* **2018**, *9*, 1667–1679. [CrossRef]
34. Zeng, P.; Li, H.; He, H.; Li, S. Dynamic Energy Management of a Microgrid Using Approximate Dynamic Programming and Deep Recurrent Neural Network Learning. *IEEE Trans. Smart Grid* **2019**, *10*, 4435–4445. [CrossRef]
35. Akpolat, A.N.; Dursun, E.; Kuzucuoğlu, A.E. Deep Learning-Aided Sensorless Control Approach for PV Converters in DC Nanogrids. *IEEE Access* **2021**, *9*, 106641–106654. [CrossRef]
36. Guo, F.; Xu, B.; Zhang, W.A.; Wen, C.; Zhang, D.; Yu, L. Training Deep Neural Network for Optimal Power Allocation in Islanded Microgrid Systems: A Distributed Learning-Based Approach. *IEEE Trans. Neural Netw. Learn. Syst.* **2022**, *33*, 2057–2069. [CrossRef] [PubMed]
37. Satapathy, A.; Nayak, N.; Parida, T. Real-Time Power Quality Enhancement in a Hybrid Micro-Grid Using Nonlinear Autoregressive Neural Network. *Energies* **2022**, *15*, 9081. [CrossRef]
38. Mumtaz, F.; Khan, H.H.; Zafar, A.; Ali, M.U.; Imran, K. A State-Observer-Based Protection Scheme for AC Microgrids with Recurrent Neural Network Assistance. *Energies* **2022**, *15*, 8512. [CrossRef]
39. Habibi, M.R.; Dragicevic, T.; Blaabjerg, F. Secure Control of DC Microgrids under Cyber-Attacks based on Recurrent Neural Networks. In Proceedings of the 2020 IEEE 11th International Symposium on Power Electronics for Distributed Generation Systems (PEDG), Dubrovnik, Croatia, 28 September–1 October2020; pp. 517–521. [CrossRef]
40. Habibi, M.R.; Baghaee, H.R.; Dragičević, T.; Blaabjerg, F. False Data Injection Cyber-Attacks Mitigation in Parallel DC/DC Converters Based on Artificial Neural Networks. *IEEE Trans. Circuits Syst. II Express Briefs* **2021**, *68*, 717–721. [CrossRef]
41. Habibi, M.R.; Baghaee, H.R.; Blaabjerg, F.; Dragičević, T. Secure MPC/ANN-Based False Data Injection Cyber-Attack Detection and Mitigation in DC Microgrids. *IEEE Syst. J.* **2022**, *16*, 1487–1498. [CrossRef]
42. Habibi, M.R.; Baghaee, H.R.; Blaabjerg, F.; Dragičević, T. Secure Control of DC Microgrids for Instant Detection and Mitigation of Cyber-Attacks Based on Artificial Intelligence. *IEEE Syst. J.* **2022**, *16*, 2580–2591. [CrossRef]
43. Habibi, M.R.; Sahoo, S.; Rivera, S.; Dragičević, T.; Blaabjerg, F. Decentralized Coordinated Cyberattack Detection and Mitigation Strategy in DC Microgrids Based on Artificial Neural Networks. *IEEE J. Emerg. Sel. Top. Power Electron.* **2021**, *9*, 4629–4638. [CrossRef]
44. Adineh, B.; Habibi, M.R.; Akpolat, A.N.; Blaabjerg, F. Sensorless Voltage Estimation for Total Harmonic Distortion Calculation Using Artificial Neural Networks in Microgrids. *IEEE Trans. Circuits Syst. II Express Briefs* **2021**, *68*, 2583–2587. [CrossRef]
45. Akpolat, A.N.; Habibi, M.R.; Dursun, E.; Kuzucuoğlu, A.E.; Yang, Y.; Dragičević, T.; Blaabjerg, F. Sensorless Control of DC Microgrid Based on Artificial Intelligence. *IEEE Trans. Energy Convers.* **2021**, *36*, 2319–2329. [CrossRef]
46. Habibi, M.R.; Baghaee, H.R.; Dragičević, T.; Blaabjerg, F. Detection of False Data Injection Cyber-Attacks in DC Microgrids Based on Recurrent Neural Networks. *IEEE J. Emerg. Sel. Top. Power Electron.* **2021**, *9*, 5294–5310. [CrossRef]
47. Ge, L.; Li, Y.; Yan, J.; Wang, Y.; Zhang, N. Short-Term Load Prediction of Integrated Energy System with Wavelet Neural Network Model Based on Improved Particle Swarm Optimization and Chaos Optimization Algorithm. *J. Mod. Power Syst. Clean Energy* **2021**, *9*, 1490–1499. [CrossRef]

48. Goh, H.H.; He, B.; Liu, H.; Zhang, D.; Dai, W.; Kurniawan, T.A.; Goh, K.C. Multi-Convolution Feature Extraction and Recurrent Neural Network Dependent Model for Short-Term Load Forecasting. *IEEE Access* **2021**, *9*, 118528–118540. [CrossRef]
49. Kong, Z.; Zhang, C.; Lv, H.; Xiong, F.; Fu, Z. Multimodal Feature Extraction and Fusion Deep Neural Networks for Short-Term Load Forecasting. *IEEE Access* **2020**, *8*, 185373–185383. [CrossRef]
50. Jalali, S.M.J.; Ahmadian, S.; Khosravi, A.; Shafie-khah, M.; Nahavandi, S.; Catalão, J.P.S. A Novel Evolutionary-Based Deep Convolutional Neural Network Model for Intelligent Load Forecasting. *IEEE Trans. Ind. Inform.* **2021**, *17*, 8243–8253. [CrossRef]
51. Sajjad, M.; Khan, Z.A.; Ullah, A.; Hussain, T.; Ullah, W.; Lee, M.Y.; Baik, S.W. A Novel CNN-GRU-Based Hybrid Approach for Short-Term Residential Load Forecasting. *IEEE Access* **2020**, *8*, 143759–143768. [CrossRef]
52. Zamee, M.A.; Han, D.; Won, D. Online Hour-Ahead Load Forecasting Using Appropriate Time-Delay Neural Network Based on Multiple Correlation–Multicollinearity Analysis in IoT Energy Network. *IEEE Internet Things J.* **2022**, *9*, 12041–12055. [CrossRef]
53. Haque, A.; Rahman, S. Short-term electrical load forecasting through heuristic configuration of regularized deep neural network. *Appl. Soft Comput.* **2022**, *122*, 108877. [CrossRef]
54. Li, K.; Huang, W.; Hu, G.; Li, J. Ultra-short term power load forecasting based on CEEMDAN-SE and LSTM neural network. *Energy Build.* **2023**, *279*, 112666. [CrossRef]
55. Arastehfar, S.; Matinkia, M.; Jabbarpour, M.R. Short-term residential load forecasting using Graph Convolutional Recurrent Neural Networks. *Eng. Appl. Artif. Intell.* **2022**, *116*, 105358. [CrossRef]
56. Xu, L.; Hu, M.; Fan, C. Probabilistic electrical load forecasting for buildings using Bayesian deep neural networks. *J. Build. Eng.* **2022**, *46*, 103853. [CrossRef]
57. Feng, Q.; Qian, S. Research on power load forecasting model of economic development zone based on neural network. *Energy Rep.* **2021**, *7*, 1447–1452. [CrossRef]
58. Atef, S.; Nakata, K.; Eltawil, A.B. A deep bi-directional long-short term memory neural network-based methodology to enhance short-term electricity load forecasting for residential applications. *Comput. Ind. Eng.* **2022**, *170*, 108364. [CrossRef]
59. Chen, R.; Lai, C.S.; Zhong, C.; Pan, K.; Ng, W.W.; Li, Z.; Lai, L.L. MultiCycleNet: Multiple Cycles Self-Boosted Neural Network for Short-term Electric Household Load Forecasting. *Sustain. Cities Soc.* **2022**, *76*, 103484. [CrossRef]
60. Gao, R.; Du, L.; Suganthan, P.N.; Zhou, Q.; Yuen, K.F. Random vector functional link neural network based ensemble deep learning for short-term load forecasting. *Expert Syst. Appl.* **2022**, *206*, 117784. [CrossRef]
61. Velasco, L.C.P.; Arnejo, K.A.S.; Macarat, J.S.S. Performance analysis of artificial neural network models for hour-ahead electric load forecasting. *Procedia Comput. Sci.* **2022**, *197*, 16–24. [CrossRef]
62. Jha, N.; Prashar, D.; Rashid, M.; Gupta, S.K.; Saket, R. Electricity load forecasting and feature extraction in smart grid using neural networks. *Comput. Electr. Eng.* **2021**, *96*, 107479. [CrossRef]
63. Xiao, X.; Mo, H.; Zhang, Y.; Shan, G. Meta-ANN—A dynamic artificial neural network refined by meta-learning for Short-Term Load Forecasting. *Energy* **2022**, *246*, 123418. [CrossRef]
64. Jin, B.; Zeng, G.; Lu, Z.; Peng, H.; Luo, S.; Yang, X.; Zhu, H.; Liu, M. Hybrid LSTM–BPNN-to-BPNN Model Considering Multi-Source Information for Forecasting Medium- and Long-Term Electricity Peak Load. *Energies* **2022**, *15*, 7584. [CrossRef]
65. Chen, W.; Han, G.; Zhu, H.; Liao, L. Short-Term Load Forecasting with an Ensemble Model Based on 1D-UCNN and Bi-LSTM. *Electronics* **2022**, *11*, 3242. [CrossRef]
66. Liu, M.; Sun, X.; Wang, Q.; Deng, S. Short-Term Load Forecasting Using EMD with Feature Selection and TCN-Based Deep Learning Model. *Energies* **2022**, *15*, 7170. [CrossRef]
67. Zheng, C.; Eskandari, M.; Li, M.; Sun, Z. GA—Reinforced Deep Neural Network for Net Electric Load Forecasting in Microgrids with Renewable Energy Resources for Scheduling Battery Energy Storage Systems. *Algorithms* **2022**, *15*, 338. [CrossRef]
68. Alsharekh, M.F.; Habib, S.; Dewi, D.A.; Albattah, W.; Islam, M.; Albahli, S. Improving the Efficiency of Multistep Short-Term Electricity Load Forecasting via R-CNN with ML-LSTM. *Sensors* **2022**, *22*, 6913. [CrossRef] [PubMed]
69. Li, C.; Guo, Q.; Shao, L.; Li, J.; Wu, H. Research on Short-Term Load Forecasting Based on Optimized GRU Neural Network. *Electronics* **2022**, *11*, 3834. [CrossRef]
70. Sun, L.; Qin, H.; Przystupa, K.; Majka, M.; Kochan, O. Individualized Short-Term Electric Load Forecasting Using Data-Driven Meta-Heuristic Method Based on LSTM Network. *Sensors* **2022**, *22*, 7900. [CrossRef] [PubMed]
71. Lan, T.; Jermsittiparsert, K.; Alrashood, S.T.; Rezaei, M.; Al-Ghussain, L.; Mohamed, M.A. An Advanced Machine Learning Based Energy Management of Renewable Microgrids Considering Hybrid Electric Vehicles' Charging Demand. *Energies* **2021**, *14*, 569. [CrossRef]
72. Huang, C.J.; Kuo, P.H. Multiple-Input Deep Convolutional Neural Network Model for Short-Term Photovoltaic Power Forecasting. *IEEE Access* **2019**, *7*, 74822–74834. [CrossRef]
73. Meng, X.; Gao, F.; Xu, T.; Zhou, K.; Li, W.; Wu, Q. Inverter-Data-Driven Second-Level Power Forecasting for Photovoltaic Power Plant. *IEEE Trans. Ind. Electron.* **2021**, *68*, 7034–7044. [CrossRef]
74. Shah, A.A.; Ahmed, K.; Han, X.; Saleem, A. A Novel Prediction Error-Based Power Forecasting Scheme for Real PV System Using PVUSA Model: A Grey Box-Based Neural Network Approach. *IEEE Access* **2021**, *9*, 87196–87206. [CrossRef]
75. Chang, G.W.; Lu, H.J. Integrating Gray Data Preprocessor and Deep Belief Network for Day-Ahead PV Power Output Forecast. *IEEE Trans. Sustain. Energy* **2020**, *11*, 185–194. [CrossRef]
76. Zhou, H.; Zhang, Y.; Yang, L.; Liu, Q.; Yan, K.; Du, Y. Short-Term Photovoltaic Power Forecasting Based on Long Short Term Memory Neural Network and Attention Mechanism. *IEEE Access* **2019**, *7*, 78063–78074. [CrossRef]

77. Raza, M.Q.; Mithulananthan, N.; Li, J.; Lee, K.Y.; Gooi, H.B. An Ensemble Framework for Day-Ahead Forecast of PV Output Power in Smart Grids. *IEEE Trans. Ind. Inform.* **2019**, *15*, 4624–4634. [CrossRef]
78. Massaoudi, M.; Abu-Rub, H.; Refaat, S.S.; Trabelsi, M.; Chihi, I.; Oueslati, F.S. Enhanced Deep Belief Network Based on Ensemble Learning and Tree-Structured of Parzen Estimators: An Optimal Photovoltaic Power Forecasting Method. *IEEE Access* **2021**, *9*, 150330–150344. [CrossRef]
79. Du, L.; Zhang, L.; Tian, X. Deep Power Forecasting Model for Building Attached Photovoltaic System. *IEEE Access* **2018**, *6*, 52639–52651. [CrossRef]
80. Mei, F.; Gu, J.; Lu, J.; Lu, J.; Zhang, J.; Jiang, Y.; Shi, T.; Zheng, J. Day-Ahead Nonparametric Probabilistic Forecasting of Photovoltaic Power Generation Based on the LSTM-QRA Ensemble Model. *IEEE Access* **2020**, *8*, 166138–166149. [CrossRef]
81. Succetti, F.; Rosato, A.; Araneo, R.; Panella, M. Deep Neural Networks for Multivariate Prediction of Photovoltaic Power Time Series. *IEEE Access* **2020**, *8*, 211490–211505. [CrossRef]
82. Fan, T.; Sun, T.; Liu, H.; Xie, X.; Na, Z. Spatial-Temporal Genetic-Based Attention Networks for Short-Term Photovoltaic Power Forecasting. *IEEE Access* **2021**, *9*, 138762–138774. [CrossRef]
83. Wen, S.; Zhang, C.; Lan, H.; Xu, Y.; Tang, Y.; Huang, Y. A Hybrid Ensemble Model for Interval Prediction of Solar Power Output in Ship Onboard Power Systems. *IEEE Trans. Sustain. Energy* **2021**, *12*, 14–24. [CrossRef]
84. Wang, F.; Li, J.; Zhen, Z.; Wang, C.; Ren, H.; Ma, H.; Zhang, W.; Huang, L. Cloud Feature Extraction and Fluctuation Pattern Recognition Based Ultrashort-Term Regional PV Power Forecasting. *IEEE Trans. Ind. Appl.* **2022**, *58*, 6752–6767. [CrossRef]
85. Jinpeng, W.; Yang, Z.; Xin, G.; Jeremy-Gillbanks; Xin, Z. A Hybrid Predicting Model for the Daily Photovoltaic Output Based on Fuzzy Clustering of Meteorological Data and Joint Algorithm of GAPS and RBF Neural Network. *IEEE Access* **2022**, *10*, 30005–30017. [CrossRef]
86. Ge, L.; Xian, Y.; Yan, J.; Wang, B.; Wang, Z. A Hybrid Model for Short-term PV Output Forecasting Based on PCA-GWO-GRNN. *J. Mod. Power Syst. Clean Energy* **2020**, *8*, 1268–1275. [CrossRef]
87. Yang, T.; Li, B.; Xun, Q. LSTM-Attention-Embedding Model-Based Day-Ahead Prediction of Photovoltaic Power Output Using Bayesian Optimization. *IEEE Access* **2019**, *7*, 171471–171484. [CrossRef]
88. Sun, Z.; Zhao, M. Short-Term Wind Power Forecasting Based on VMD Decomposition, ConvLSTM Networks and Error Analysis. *IEEE Access* **2020**, *8*, 134422–134434. [CrossRef]
89. Buhan, S.; Özkazanç, Y.; Çadırcı, I. Wind Pattern Recognition and Reference Wind Mast Data Correlations With NWP for Improved Wind-Electric Power Forecasts. *IEEE Trans. Ind. Inform.* **2016**, *12*, 991–1004. [CrossRef]
90. Shi, Z.; Liang, H.; Dinavahi, V. Direct Interval Forecast of Uncertain Wind Power Based on Recurrent Neural Networks. *IEEE Trans. Sustain. Energy* **2018**, *9*, 1177–1187. [CrossRef]
91. Cheng, L.; Zang, H.; Xu, Y.; Wei, Z.; Sun, G. Augmented Convolutional Network for Wind Power Prediction: A New Recurrent Architecture Design With Spatial-Temporal Image Inputs. *IEEE Trans. Ind. Inform.* **2021**, *17*, 6981–6993. [CrossRef]
92. Miao, C.; Li, H.; Wang, X.; Li, H. Ultra-Short-Term Prediction of Wind Power Based on Sample Similarity Analysis. *IEEE Access* **2021**, *9*, 72730–72742. [CrossRef]
93. Wang, S.; Zhao, X.; Wang, H.; Li, M. Small-world neural network and its performance for wind power forecasting. *CSEE J. Power Energy Syst.* **2020**, *6*, 362–373. [CrossRef]
94. Wang, R.; Li, C.; Fu, W.; Tang, G. Deep Learning Method Based on Gated Recurrent Unit and Variational Mode Decomposition for Short-Term Wind Power Interval Prediction. *IEEE Trans. Neural Netw. Learn. Syst.* **2020**, *31*, 3814–3827. [CrossRef]
95. Hossain, M.A.; Chakrabortty, R.K.; Elsawah, S.; Gray, E.M.; Ryan, M.J. Predicting Wind Power Generation Using Hybrid Deep Learning With Optimization. *IEEE Trans. Appl. Supercond.* **2021**, *31*, 1–5. [CrossRef]
96. Ko, M.S.; Lee, K.; Kim, J.K.; Hong, C.W.; Dong, Z.Y.; Hur, K. Deep Concatenated Residual Network With Bidirectional LSTM for One-Hour-Ahead Wind Power Forecasting. *IEEE Trans. Sustain. Energy* **2021**, *12*, 1321–1335. [CrossRef]
97. Zhang, G.; Xu, B.; Liu, H.; Hou, J.; Zhang, J. Wind Power Prediction Based on Variational Mode Decomposition and Feature Selection. *J. Mod. Power Syst. Clean Energy* **2021**, *9*, 1520–1529. [CrossRef]
98. Peng, X.; Li, Y.; Dong, L.; Cheng, K.; Wang, H.; Xu, Q.; Wang, B.; Liu, C.; Che, J.; Yang, F.; et al. Short-Term Wind Power Prediction Based on Wavelet Feature Arrangement and Convolutional Neural Networks Deep Learning. *IEEE Trans. Ind. Appl.* **2021**, *57*, 6375–6384. [CrossRef]
99. Zhou, B.; Ma, X.; Luo, Y.; Yang, D. Wind Power Prediction Based on LSTM Networks and Nonparametric Kernel Density Estimation. *IEEE Access* **2019**, *7*, 165279–165292. [CrossRef]
100. Liu, X.; Yang, L.; Zhang, Z. Short-Term Multi-Step Ahead Wind Power Predictions Based On A Novel Deep Convolutional Recurrent Network Method. *IEEE Trans. Sustain. Energy* **2021**, *12*, 1820–1833. [CrossRef]
101. Abedinia, O.; Lotfi, M.; Bagheri, M.; Sobhani, B.; Shafie-khah, M.; Catalão, J.P.S. Improved EMD-Based Complex Prediction Model for Wind Power Forecasting. *IEEE Trans. Sustain. Energy* **2020**, *11*, 2790–2802. [CrossRef]
102. Lee, D.; Baldick, R. Short-Term Wind Power Ensemble Prediction Based on Gaussian Processes and Neural Networks. *IEEE Trans. Smart Grid* **2014**, *5*, 501–510. [CrossRef]
103. Daraeepour, A.; Echeverri, D.P. Day-ahead wind speed prediction by a Neural Network-based model. In Proceedings of the ISGT 2014, Washington, DC, USA, 19–22 February 2014; pp. 1–5. [CrossRef]
104. Abbasipour, M.; Igder, M.A.; Liang, X. A Novel Hybrid Neural Network-Based Day-Ahead Wind Speed Forecasting Technique. *IEEE Access* **2021**, *9*, 151142–151154. [CrossRef]

105. He, J.; Yang, H.; Zhou, S.; Chen, J.; Chen, M. A Dual-Attention-Mechanism Multi-Channel Convolutional LSTM for Short-Term Wind Speed Prediction. *Atmosphere* **2023**, *14*, 71. [CrossRef]
106. Kosanoglu, F. Wind Speed Forecasting with a Clustering-Based Deep Learning Model. *Appl. Sci.* **2022**, *12*, 3031. [CrossRef]
107. Ellahi, M.; Usman, M.R.; Arif, W.; Usman, H.F.; Khan, W.A.; Satrya, G.B.; Daniel, K.; Shabbir, N. Forecasting of Wind Speed and Power through FFNN and CFNN Using HPSOBA and MHPSO-BAACs Techniques. *Electronics* **2022**, *11*, 4193. [CrossRef]
108. Zhang, Y.; Zhao, Y.; Gao, S. A Novel Hybrid Model for Wind Speed Prediction Based on VMD and Neural Network Considering Atmospheric Uncertainties. *IEEE Access* **2019**, *7*, 60322–60332. [CrossRef]
109. Yang, L.; Zhang, Z. A Deep Attention Convolutional Recurrent Network Assisted by K-Shape Clustering and Enhanced Memory for Short Term Wind Speed Predictions. *IEEE Trans. Sustain. Energy* **2022**, *13*, 856–867. [CrossRef]
110. Chen, G.; Li, L.; Zhang, Z.; Li, S. Short-Term Wind Speed Forecasting With Principle-Subordinate Predictor Based on Conv-LSTM and Improved BPNN. *IEEE Access* **2020**, *8*, 67955–67973. [CrossRef]
111. Zhang, Y.; Chen, B.; Zhao, Y.; Pan, G. Wind Speed Prediction of IPSO-BP Neural Network Based on Lorenz Disturbance. *IEEE Access* **2018**, *6*, 53168–53179. [CrossRef]
112. Shi, Z.; Liang, H.; Dinavahi, V. Wavelet Neural Network Based Multiobjective Interval Prediction for Short-Term Wind Speed. *IEEE Access* **2018**, *6*, 63352–63365. [CrossRef]
113. Dolatabadi, A.; Abdeltawab, H.; Mohamed, Y.A.R.I. Hybrid Deep Learning-Based Model for Wind Speed Forecasting Based on DWPT and Bidirectional LSTM Network. *IEEE Access* **2020**, *8*, 229219–229232. [CrossRef]
114. Ma, Z.; Guo, S.; Xu, G.; Aziz, S. Meta Learning-Based Hybrid Ensemble Approach for Short-Term Wind Speed Forecasting. *IEEE Access* **2020**, *8*, 172859–172868. [CrossRef]
115. Li, Y.; Chen, X.; Li, C.; Tang, G.; Gan, Z.; An, X. A Hybrid Deep Interval Prediction Model for Wind Speed Forecasting. *IEEE Access* **2021**, *9*, 7323–7335. [CrossRef]
116. Jiao, X.; Li, X.; Lin, D.; Xiao, W. A Graph Neural Network Based Deep Learning Predictor for Spatio-Temporal Group Solar Irradiance Forecasting. *IEEE Trans. Ind. Inform.* **2022**, *18*, 6142–6149. [CrossRef]
117. Huang, X.; Shi, J.; Gao, B.; Tai, Y.; Chen, Z.; Zhang, J. Forecasting Hourly Solar Irradiance Using Hybrid Wavelet Transformation and Elman Model in Smart Grid. *IEEE Access* **2019**, *7*, 139909–139923. [CrossRef]
118. Jalali, S.M.J.; Ahmadian, S.; Kavousi-Fard, A.; Khosravi, A.; Nahavandi, S. Automated Deep CNN-LSTM Architecture Design for Solar Irradiance Forecasting. *IEEE Trans. Syst. Man Cybern. Syst.* **2022**, *52*, 54–65. [CrossRef]
119. Yu, Y.; Cao, J.; Zhu, J. An LSTM Short-Term Solar Irradiance Forecasting Under Complicated Weather Conditions. *IEEE Access* **2019**, *7*, 145651–145666. [CrossRef]
120. Prado-Rujas, I.I.; García-Dopico, A.; Serrano, E.; Pérez, M.S. A Flexible and Robust Deep Learning-Based System for Solar Irradiance Forecasting. *IEEE Access* **2021**, *9*, 12348–12361. [CrossRef]
121. Wu, Z.; Li, Q.; Xia, X. Multi-timescale Forecast of Solar Irradiance Based on Multi-task Learning and Echo State Network Approaches. *IEEE Trans. Ind. Inform.* **2021**, *17*, 300–310. [CrossRef]
122. Si, Z.; Yu, Y.; Yang, M.; Li, P. Hybrid Solar Forecasting Method Using Satellite Visible Images and Modified Convolutional Neural Networks. *IEEE Trans. Ind. Appl.* **2021**, *57*, 5–16. [CrossRef]
123. Moreno, G.; Martin, P.; Santos, C.; Rodríguez, F.J.; Santiso, E. A Day-Ahead Irradiance Forecasting Strategy for the Integration of Photovoltaic Systems in Virtual Power Plants. *IEEE Access* **2020**, *8*, 204226–204240. [CrossRef]
124. Golam, M.; Akter, R.; Lee, J.M.; Kim, D.S. A Long Short-Term Memory-Based Solar Irradiance Prediction Scheme Using Meteorological Data. *IEEE Geosci. Remote Sens. Lett.* **2022**, *19*, 1–5. [CrossRef]
125. Huang, C.; Wang, L.; Lai, L.L. Data-Driven Short-Term Solar Irradiance Forecasting Based on Information of Neighboring Sites. *IEEE Trans. Ind. Electron.* **2019**, *66*, 9918–9927. [CrossRef]
126. Wang, T.; Ke, H.; Zheng, X.; Wang, K.; Sangaiah, A.K.; Liu, A. Big Data Cleaning Based on Mobile Edge Computing in Industrial Sensor-Cloud. *IEEE Trans. Ind. Inform.* **2020**, *16*, 1321–1329. [CrossRef]
127. Moon, J.; Jung, S.; Park, S.; Hwang, E. Conditional Tabular GAN-Based Two-Stage Data Generation Scheme for Short-Term Load Forecasting. *IEEE Access* **2020**, *8*, 205327–205339. [CrossRef]
128. Habibi, M.R.; Golestan, S.; Soltanmanesh, A.; Guerrero, J.M.; Vasquez, J.C. Power and Energy Applications Based on Quantum Computing: The Possible Potentials of Grover's Algorithm. *Electronics* **2022**, *11*, 2919. [CrossRef]
129. Golestan, S.; Habibi, M.; Mousazadeh Mousavi, S.; Guerrero, J.; Vasquez, J. Quantum computation in power systems: An overview of recent advances. *Energy Rep.* **2023**, *9*, 584–596. [CrossRef]
130. Dai, J.; Song, H.; Sheng, G.; Jiang, X. Cleaning Method for Status Monitoring Data of Power Equipment Based on Stacked Denoising Autoencoders. *IEEE Access* **2017**, *5*, 22863–22870. [CrossRef]
131. Liu, J.; Cao, Y.; Li, Y.; Guo, Y.; Deng, W. A big data cleaning method based on improved CLOF and Random Forest for distribution network. *CSEE J. Power Energy Syst.* **2020**, 1–10. [CrossRef]
132. Wang, Z.; Wang, L.; Huang, C. A Fast Abnormal Data Cleaning Algorithm for Performance Evaluation of Wind Turbine. *IEEE Trans. Instrum. Meas.* **2021**, *70*, 1–12. [CrossRef]