Deep Learning based Techniques to Enhance the Performance of Microgrids: A Review

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***Abstract*—In the last few years, carbon emissions and energy demand have increased dramatically around the globe due to a surge in population and energy-consuming devices. The integration of renewable energy resources (RERs) in a power supply system provides an efficient solution in terms of low energy cost with lower carbon emissions. However, renewable sources like solar panels have irregular nature of power generation because of their dependence on weather conditions, such as solar radiation, humidity, and temperature. Therefore, to tackle this intermittent nature of solar energy, power prediction is necessary for efficient energy management. Deep learning and machine learning-based methods have frequently been implemented for energy forecasting in the literature. The current work summarizes the state-of-the-art deep learning-based methods that are proposed to forecast the solar power for proper energy management. We also explain the methodologies of solar energy forecasting along with their outcomes. At the end, future challenges and opportunities are uncovered in the application of deep and machine learning in this area.**

***Index Terms*—Deep learning based techniques; Forecasting; Artificial neural network; Machine learning; Weather forecasting; Energy forecasting; Renewable energy resources**

I. Introduction

The world is moving towards renewable energy resources (RERs) due to their low cost and huge contributions in alleviation of carbon emissions. RERs consist of various sources, including wind energy, bioenergy, hydropower, solar energy, etc., and usually, these sources operate in islanded or grid-connected modes. Fossil fuels-based energy sources are used in many countries to meet the power demand of the consumers; however, these resources are inefficient and inadequate [1]. Solar energy is generated through installing solar panels and it is available in most locations of the world. Moreover, solar energy plays a significant role in green energy among all RERs [2], [3]. Figure 1 shows yearly percentage of renewable energy contribution in total energy generation of some leading countries around the globe. This figure shows that Brazil is generating the highest renewable energy around the globe for meeting the power demand of the consumers.

Solar panel converts direct sunlight to electrical energy. One of its key characteristics is its intermittent and unpredictable nature as the energy generated from solar panels totally depends on environmental conditions, like temperature, solar radiation, etc. For instance, solar panels generate maximum electricity when the sun has high radiations (clear sky); in contrary, it generates minimum power (maybe zero) in night time or durng cloudy weather. However, a huge amount of fluctuation in energy generation from solar panels may create problems in power systems, including voltage irregulations, power distribution, and reserve power flow problems. Undesired voltage fluctuation is considered the main problem in power distribution due to solar panels and it may lead to instability of a microgrid [4].

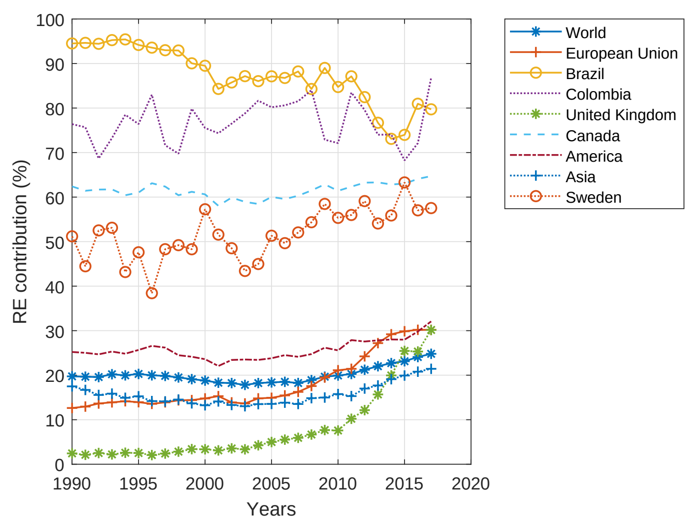

Fig. 1: Renewable energy contribution in total energy production around the globe [5]

To ensure the safe operation of the power system and the balance between energy demand and supply, accurate forecasting of power generation from solar panels is an exigent need. Such accurate forecasting enables the power utility operator to efficiently manage supply with demand and generate excess electricity from brown energy sources in case of less energy generation from renewable sources. The forecasting of solar energy generation is a complex task because it completely depends on weather conditions (e.g., temperature, humidity, solar irradiance, and cloud) [6], [7], [8]. Various forecasting models are used to predict solar energy in the literature and

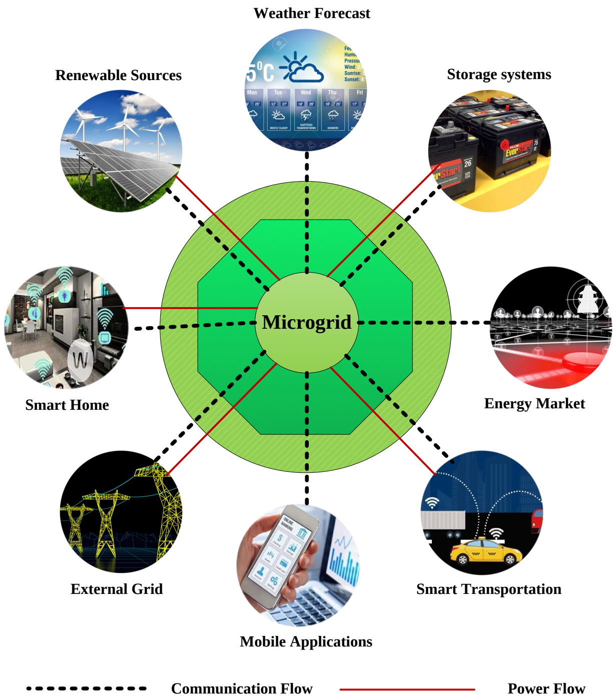

Fig. 2: A typical microgrid architecture [16]

these models are categorized into physical, statistical, and empirical models.

Accurate energy forecasting is essential for effective energy planning and management. A lot of forecasting methods are presented in the literature. For instance, [9] proposed a solar energy forecasting method using deep learning, [10] presentd a short-term solar energy forecasting method using statistical methods, while a recurrent neural network (RNN) model is used in [11]. Chen *et al.* developed a solar energy prediction model that is based on convolutional neural networks (CNN) [12] and the authors of [15] have developed a deep CNN based model that is used for solar energy forecasting. This paper presents a comprehensive review of the deep learning-based techniques that are used in the literature to predict solar energy. We have explained some key deep learning techniques in the Section II, while Section III presents deep learning in energy management systems (EMSs) and different solar energy forecasting models. Section IV uncovers the future challenges to current methods and opportunities. Finally, the last section concludes the study.

II. Deep Learning based Methods

This section presents the most commonly used deep learning based methods for energy management and power forecasting, namely, artificial neural networks (ANN), deep neural networks (DNN), convolutional neural networks (CNN), and recurrent neural networks (RNN).

A. Artificial Neural Networks

An artificial neural network (ANN) is designed on basis of working mechanism of the human nervous system [17]. Such a system learns to implement a task by only considering examples, without being programmed with any specific task rules. ANN is based on a collection of nodes or units called neurons. Neurons are the basic components of a neural network through which communication takes place. A simple architecture of ANN is depicted in Figure 3. A neuron receives input and produces output based on its internal activation function [18].

The output of some neurons is the input to other neurons forming a directed weighted graph. The functions as well as the weights that compute the activation are altered by a process known as learning. The parameters controlling the learning for ANNs are the number of hidden layers, the learning rate, and the maximum number of iterations. In hidden layers, the number of neurons varies. ANN training model uses the historical data to train itself and then make a prediction based on new input data. Various activation functions are used in ANN for computation, such as Softmax, Sigmoid, Rectified linear unit, etc.

B. Deep Neural Networks

Deep neural networks (DNN) belongs to the ANN family. They consist of multiple hidden layers between the input and output layers [19], [20]. A comparison of DNN with simple ANN is presented in Figure 3. The DNN processes the input with mathematical manipulation to produce the output, irrespective of whether the data relationship is linear or nonlinear. The neural network is trained using a training set, which results in the calculation of the probability of each output. A complex DNN contains more layers than other neural networks as shown in Figure 3.

C. Convolutional Neural Networks

Convolutional neural networks (CNN) belong to the family of neural networks in deep learning. They are commonly used for visual image processing, energy management in smart grids, pattern recognition, etc. CNN is the updated version of a Multi-Layer Perceptron (MLP). MLP is also known as a fully connected layered network, which means every neuron in one layer is fully connected to all neurons of the next layer. This fully connected property often leads to an over-fitting problem with MLP. However, CNN uses different approaches for data regularization. Specifically, it exploits the hierarchical pattern of data and assembles it to multiple simpler patterns. On the basis of their translation invariance characteristics, CNN are also known as shift invariant or space invariant ANNs [21].

CNNs are inspired by the biological process [22], in which the neurons are fully attached to one another. It requires little pre-processing compared to other image processing algorithms. CNN works as a neural network, and it contains an input layer, output layer, and hidden layers. The difference between them is that CNN uses a series of different types of hidden layers, i.e., convolutional layer, flatten layer, dropout layer, pooling layer, fully connected layer, and normalization layers. The input and output of the hidden layers are hidden by an activation function. Rectifier linear unit (Relu) is mostly used as an activation function in CNN. The activation function sometimes involves the back-propagation method to produce

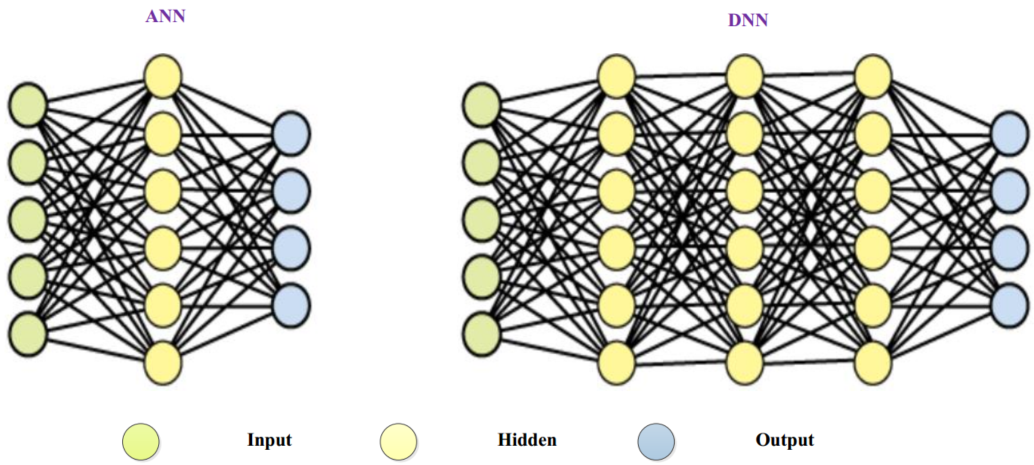

Fig. 3: Typical architectures of artificial neural networks (ANN) and deep neural networks (DNN)

a more accurate product or weight. The convolutional layer in CNN is used to downscale the input data in such a way that it becomes easy to process but the actual information remains the same.

D. Recurrent Neural Networks

Recurrent neural networks (RNNs) are a special kind of ANNs that are developed to process sequential data [23]. Usually, conventional networks provide training to each sample independently for each other; however, this type of independent training is not sufficient, especially for data exhibiting temporal relationships. RNN offers a solution to this problem by taking inputs sequentially. Unlike other feed-forward ANNs, they contain feedback connections in the units of the hidden layer. Therefore, the RNN can perform temporal processing and learn sequentially. Furthermore, unlike other ANNs, the RNN uses a hidden layer as a memory for storing sequential information. It is important to note that the RNN uses the same parameters (like U, V, W shown in Figure 4) for each layer instead of using different parameters for each layer like traditional DNNs.

Figure 4 presents the RNN being unfolded into a full network. For instance, if the RNN is used to make a prediction based on the sequence of the last 6 data inputs, then the network would be unfolded into a 6-layer neural network. In RNN calculations, x_t, o_t, and s_t show the input, output, and hidden state at time t, respectively.

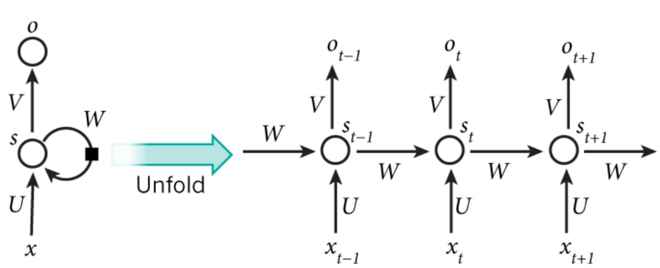

Fig. 4: An example of RNN architecture [24]

III. Deep Learning in Energy Management Systems

Smart microgrids nowadays integrates RERs, such as solar panels and wind turbines, along with energy storage systems. A typical architecture of a microgrid is depicted in Figure 2. Due to the intermittent power generation from renewable resources, precise power forecasting has become crucial to achieve efficient energy management. In this section, we will uncover the deep learning based techniques used to predict solar energy generation, summarized in Table I of this study.

A. Solar Energy Forecasting

Energy management in the residential or commercial sector plays a vital role in enhancing grid stability and reliability. When smart homes are integrated with RERs (e.g., wind turbines, solar panels, etc.) for power generation, it is necessary to predict the energy generation from these sources for efficient energy management. Energy generation from these sources may be predicted on the basis of 1 hour, 2 hours, 10 hours, 1 day etc. A lot of solar prediction studies are presented in the literature and in this section, we have critically analyzed them.

In [9], the authors have developed a solar forecasting method using deep learning. In this work, 21 solar panels are considered for electricity generation and one-day-ahead prediction is performed by deep learning. Multi-layer perceptron (MLP) [25] is used as a base architecture in their work, which consists of multiple layers as presented in Figure 5. In addition, they have explored the use of deep belief networks (a type of deep neural network) and two types of recurrent neural networks. Finally, the deep learning forecasting results are compared with each other as well as to physical models showing promising results for recurrent neural networks.

Xwegnon *et al.* have proposed a statistical method for short-term spatio-temporal prediction of solar energy generation [10]. This paper considers the prediction for a very short time horizon (1 to 6 hours). Distributed power plants are used in this work as sensors and their spatio-temporal dependencies are exploited to enhance the forecasting accuracy. Furthermore, the computational complexity of the proposed model is low,

TABLE I: Summary of solar energy forecasting methods

Ref.	Method(s)	Compared method(s)	Location	Horizon	Outcome/observation(s)
[9]	Auto-LSTM	MLP, ANN, DNN, DBN, LSTM	Germany	Hourly	The newly proposed hybrid algorithm shows efficacy in terms of accuracy; however, the DBN performence is close to the proposed auto-LSTM forecasting method. [RMSE of proposed method: 0.0713; compared method: 0.0714].
[10]	Spatio-temporal model	Auto-regressive, Random Forest	France	15-minutes	The proposed statistical model shows higher performance in terms of accuracy and execution time over counterparts. [nRMSE is improved up to 20% higher than the benchmark methods].
[11]	LSTM	GRU, RNN, Naive DL	France	Hourly	The LSTM forecasting model shows supremacy to compared algorithms. [RMSE of proposed method: 0.2115 and compared method: 0.2198]
[12]	Gaussian process regression-based CNN	Persistence, ridge regression, Fully-connected NN	Oklahoma, USA	Hourly	The newly developed gaussian process regression based CNN method shows efficacy in terms of minimum MAE. [MAE of proposed method: 212642; compared method: 439952]
[14]	DNN (‘SolarisNet’)	ANN, SVR, Gaussian Process Regression	India	Hourly	The proposed SolarisNet forecasting model presents higher accuracy and it is validated through RMSE. [RMSE of proposed method: 1.7661; compared method: 2.7930]
[15]	Deep RNN	FNN, SVR, LSTM	Canada	Hourly	Results validate the performance of their proposed deep RNN over counterparts in terms of RMSE. [Mean RMSE of proposed method: 0.068; compared method: 0.18]
[32]	ALHM model	ANN, SVM	-	Hourly and 5-minutes	Based on GA and time-varying multiple linear model, the proposed hybrid model is able to make precise prediction of energy generated from solar panels [MAPE of proposed method: 13.68; compared method: 20.39]
[33]	Hybrid LSTM-RNN	ANN, Bagged Regression Trees, Multiple Linear Regression	Aswan and Cairo, Egypt	Hourly	The newly developed hybrid algorithm provides a very small error rate compared to benchmarks. [RMSE of proposed method: 82.15; compared method: 384.89]
[34]	High-precision Deep CNN	SVM, Random Forest, Decision Tree, MLP, LSTM	Tainan, Taiwan	Hourly	The proposed high-precision deep CNN shows efficacy in terms of minimum error rate. [Average MAE of proposed method: 112.2640; compared method: 143.2721]
[35]	DNN Ensemble	SVR	Oklahoma, USA	Hourly	The developed DNN uses minibatch training, dropout regularization, and weight initialization to exploit and introduce independent randomness in natural way. Results validate that the DNN ensemble model is robust and has higher accuracy for a single network. [Average MAE of proposed method: 209.09; compared method: 222.52]
[36]	Hybrid Gradient Boosting Trees w/ feature engineering technique	Quantile Regression Forests	Porto, Portugal	Hourly	The presented work proposes a framework to extract features from NWP grid using domain knowledge. In addition, they proved that this information can enhance the forecast efficiency in existing algorithms. [The proposed method shows average point forecast improvement 16.09% over counterparts]
[37]	SVM-RBF	Linear Regression, Past-predicts Future Models	USA	Hourly	The SVM-RBF shows productiveness in terms of higher accuracy. [The proposed method improves accuracy by 27% over existing methods]

which makes it easy to use and appropriate for large scale applications. Simulation results validate their proposed model in terms of high accuracy as compared to other state-of-the-art models. The authors of [11] have designed a prediction model for solar irradiations, which is based on RNN. In particular, they use two variants of RNN, namely gated recurrent unit (GRU) and long short-term memory (LSTM) [26]. At the end, simulations are performed to verify the performance of RNN variants in terms of solar irradiation forecasting. Results show that GRU and LSTM are more suitable for time series prediction compared to simple RNN.

Another work proposes a solar forecasting model with numerical weather prediction (NWP) and CNNs [12]. Moreover, to train the CNN, a Gaussian process (sci-kit learn library v0.19.0 [13]) is used to transform the incoming solar energy values to the main grid. The proposed CNN is further able to map the 6×6 inputs to 31×31 output on the basis of the transposed convolution operation. At the end, the proposed CNN is validated through simulations and satisfactory accuracy is presented as compared to three benchmark models: persistent method, fully connected NN, and ridge regression methods. Subhadip *et al.* have developed a deep NN, namely SolarisNet, for global solar prediction [14]. They have used minimum meteorological parameters, i.e., minimum temperature, maximum temperature, and hourly data of sunshine. Experiments have been performed to check the adequacy of the proposed SolarisNet model while data is taken from the meteorological department of India. Experimental results validate that the proposed model is more efficient as compared to existing models, i.e., support vector regression (SVR) [27], Gaussian process regression [28] and ANN [29], [30].

In [15], another solar energy forecasting method is developed using deep RNN (DRNN). The developed network is trained, tested, and validated on real-time data obtained from the National Resources of Canada [31]. Experimental results are compared with other existing forecasting methods, which

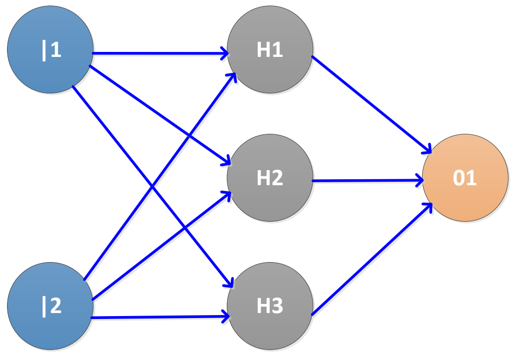

Fig. 5: An example of Multi-Layer Perceptron (MLP)

show the effectiveness of their proposed scheme. The paper [32] proposed a new adaptive learning hybrid model for short and long term solar intensity prediction. To tackle the dynamic and linear properties of the data, a time-varying multiple linear model is developed. After that, a genetic algorithm back-propagation neural network (GABPNN) is applied to learn non-linear relationships in the data. Their proposed novel adaptive learning hybrid model is able to capture the temporal, linear, and non-linear relationships present in the data. Simulation results validate that the proposed prediction model outperforms multiple benchmark models in both long-term and short-term forecasting of solar intensity.

A new solar power forecasting model is developed by Abdel-Nasser *et al.* in [33], where the proposed model is based on deep long short-term memory RNN (LSTM-RNN) and considers the temporal changes during constructing prediction models. They have analyzed the effectiveness of five different LSTM models with different architectures. At the end, they performed a comparative study to confirm the productiveness of their proposed model. For comparison purposes, they considered some widely used forecasting models such as bagged regression trees, NNs, and multiple linear regression. The work [34] proposes a high precision deep CNN model, named SolarNet, for solar irradiation forecasting. Real-time experiments are performed to check the validity of the proposed model. It is assured from results that the proposed SolarNet shows high performance over counterparts in terms of higher accuracy.

Another work presented in [35] has developed two prediction models for daily solar radiation and wind energy predictions, which are based on DNNs. Input for these models is taken from numerical weather systems. Kaggle data set is used for model training and testing. This work also introduces DNN ensembles to improve single DNN predictions by lowering variance, while experiments validate that the randomness in DNN training elements result in effective and robust DNN ensembles. Another solar and wind energy forecasting framework is presented in [36], where the authors explore the information from a grid of numerical weather predictions (NWP). Proposed methodology has considered gradient boosting algorithm along with feature engineering techniques, which extract the information from the NWP grid. Furthermore, the authors have provided a comparison with the methodology having only one NWP point for a specific location. The results show that the forecasting accuracy is improved, using MAPE, by 12.85% and 16.09% for wind and solar energy, respectively. Another machine learning-based solar energy prediction model is developed in [37], where the authors have predicted weather information. They have also performed a comparison with multiple regression methods to show the effectiveness of their technique. Simulation results show that their proposed machine learning-based method achieves 27% higher accuracy than existing techniques.

IV. Current Challenges

Deep learning-based techniques have been considered a beneficial means to enhance the performance of smart microgrids. These are efficient methods that provide possible strategic solutions for accurate forecasting of power generation from solar panels. This section outlines some promising research opportunities / directions of deep learning-based methods implemented in solar energy prediction.

Big energy data analytics is an emerging, promising research area, which needs special attention from the research community. With the advent of sensor technology, wireless communication, cloud computing, and advanced metering infrastructure, an enormous amount of data will become available, including energy consumption data, energy generation data, temperature data, humidity data, etc. It is important to make this data accessible to researchers and industry in order to open new opportunities for improving the performance of smart microgrids. The work [38] presents a comprehensive vision for big data energy management, including energy generation, transmission, distribution and transformation, and demand-side management. They discuss in detail smart data sources along with their characteristics. Furthermore, this study has also proposed a process model for big data energy management.

Machine learning and deep learning-based techniques depend on historical data and perform future predictions on the basis of old data. However, a heavy reliance on big data requires a huge amount of storage devices. Furthermore, the need for large-scale processing is another big challenge when using deep learning-based methods. Unnecessary features and data redundancy are the main causes of data complexity and high computation. The computation time of redundant training data is often much higher than training of clean data. Machine learning techniques and other classifiers can be used to remove the redundancy from data and make the training data faster, while at the same time, help improve the accuracy of classification and regression. So, a forecasting system is needed that requires low processing along with low storage.

V. Conclusion

In this paper, we have presented a review on solar energy prediction and its impact on smart microgrids. Energy generation from solar panels is intermittent in nature because of its dependency on weather conditions, i.e., temperature, irradiation, humidity, etc. For the efficient utilization of the generated energy from solar panels, an accurate energy forecasting is required. Machine learning and deep learning-based tools are considered effective ways for energy forecasting on the basis of historical data. So, we have presented a detailed review on the current deep learning-based methods as well as reviewed the efforts of researchers in enhancing the performance of deep learning-based techniques in microgrids. Finally, we have also unfolded the current challenges and future trends in deep learning methods to enhance the forecast accuracy in microgrids.

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