A review on Day-Ahead Solar Energy Prediction

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Abstract: ***Accurate day-ahead prediction of solar energy plays a vital role in the planning of supply and demand in a power grid system. The previous study shows predictions based on weather forecasts composed of numerical text data. They can reflect temporal factors therefore the data versus the result might not always give the most accurate and precise results. That is why incorporating different methods and techniques which enhance accuracy is an important topic. An in-depth review of current deep learning-based forecasting models for renewable energy is provided in this paper.***

Keywords: Day ahead prediction; solar energy; temporal factors.

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1. Introduction

At the moment, fossil fuels remain the world's most important source of energy. Hydrocarbons or its derivatives, such as coal, oil, and natural gas, are examples of fossil fuels. Fossil fuels develop over millions of years, and existing viable reserves are depleting more quicker than new fossil fuels are being created. Simultaneously, fossil fuels generate greenhouse gases, which exacerbate climate change such as global warming, endangering the environment on which humans rely. As a result, renewable energy has gained widespread attention in recent years. Renewable energy is energy that can be recycled in nature, such as solar, wind, tidal, and geothermal energy. Renewable energy sources outperform fossil fuels. Renewable energy provides at least two benefits over fossil fuels. First, renewable energy resources are numerous and renewable around the planet, and they are limitless. Second, renewable energy is clean, green, and low in carbon, making it advantageous to environmental protection. In particular, renewable energy may efficiently reduce sulphide (SO_2), carbide (CO), and dust emissions, lowering the danger of atmospheric pollution and the warming impact. Furthermore, the usage of renewable energy can help to limit the exploitation of natural fossil resources.

Renewable energy can also help to cut CO_2 emissions. Renewable energy can help minimise waste gas and waste liquid emissions during usage, so saving water resources. As a result, renewable energy has grown at a remarkable pace in recent years. Renewable energy accounted for 19.3% of worldwide energy consumption and 24.5% of power output in 2016, according to REN21's 2017 study [1]. Many nations, like the United States and China, have adopted a variety of regulatory regulations, incentives, and subsidies to stimulate the use of renewable energy.

Although renewable energy is regarded as the most promising alternative to fossil fuels because it is clean, green, and naturally replenished in a wide geographical area, it also introduces unscheduled uncertainty, endangering the reliability and stability of energy systems, particularly with large-scale renewable energy integration. On the one hand, renewable energy demonstrates high volatility, intermittentness, and unpredictability, which will surely raise the capacity of electric energy systems, raising the cost of power generation.

Physical techniques rely on numerical weather prediction (NWP) models, which simulate atmospheric dynamics based on physical principles and boundary conditions [2]. Limited area models, such as the fifth-generation mesoscale model and high-resolution fast refresh, are included in NWP models, as are global models, such as the global forecast system and integrated forecast model [3]. Many meteorological and geographical data, such as temperature, pressure, jaggedness, and orography, are considered input to NWP. Although physical approaches are effective for forecasting atmospheric dynamics, they necessitate a substantial amount of computer resources due to the vast amount of data required for calibration [8]. This is exacerbated when physical approaches make surprising predictions. As a result, physical approaches are unsuitable for short-term forecasting.

Aiming to reveal the mathematical connections between online time series data of renewable energy, statistical models are used by J.Hu *et al*. describing a research and application of a hybrid model based in “Meta learning strategy for wind power deterministic and probabilistic forecasting” [5]. The literature widely embraced the auto regressive moving average proposed by Aasim *et al*. [6], Bayesian method proposed by Y. Wang *et al*. [7], Kalman filter proposed by D. Yang [8], Markov Chain model proposed by W. Yun *et al*. in “A hybrid wind speed forecasting model based on phase space reconstruction theory and Markov model: a case study of wind farms in northwest China” [9], and grey theory proposed by L.Wu *et al*. in “Using a novel multi-variable grey model to forecast the electricity consumption of Shandong Province in China” [10]. O. Ait Maatallah *et al*. describes the development of a novel forecasting algorithm based on the Hammerstein model that can handle various asymmetric distributions, non-stationary profiles, and chaotic dynamics of wind energy [11]. A Bayesian-based adaptive resilient multi-kernel regression model for deterministic and probabilistic wind power forecasting was suggested by Y.Wang *et al*. in “Deterministic and probabilistic wind power forecasting using a variational Bayesian-based adaptive robust multi-kernel regression model” [12]. To achieve the time-series prediction of wave energy, a Kalman filter and time-varying regression technique were proposed by G. Reikard in “forcasting ocean wave energy: tests of time-series models” [13]. The case study demonstrates that the suggested strategy yields the most accurate predictions.

Due to their potential for data-mining and feature extraction, artificial intelligence-based forecasting models consistently outperform physical methods and statistical approaches with the advent of soft computing techniques. The nonlinear connection between input and output was commonly handled by support vector machines, artificial neural networks, extreme learning machine, and adaptive fuzzy neuron networks through error reduction. To perform real-time forecasting of carbon pricing in Shenzhen, a hybrid of mixed data sampling regression and back propagation neural network was built, which led to superior performance proposed by M. Han *et al*. in “Forecasting carbon prices in the Shenzhen market, China: The role of mixed-frequency factors” [18].

Based on generative adversarial networks and convolutional neural networks, W. Fei *et al*. [19] proposed a weather classification model for day-ahead photovoltaic power forecasting. It was discovered that weather classification is crucial in determining the most effective photovoltaic power forecasting model. A novel wave energy forecasting framework built on ANN was put out by J. Oh *et al*. in “Real-time forecasting of wave heights using EOF-wavelet-neural network hybrid model” [20]. Historical wave height and local meteorological information are included in this framework's inputs. The wave energy's current peak height is the output. On the basis of measurement data from China's east coast, the forecasting framework's validity was confirmed. A. Tascikaraogly *et al*. [21] provided a thorough analysis of the forecasting models currently in use for renewable energy, demonstrating the benefits of each model. To balance forecasting accuracy and parameter stability, for instance, a hybrid forecasting system made up of a denoising approach, multi-objective differential evolution algorithm, and fuzzy time series method was devised. To examine the large multi-step wind speed forecasting performance, the hybrid technique proposed by Y. Li *et al*. in “Smart wind speed forecasting approach using various boosting algorithms, big multi-step forecasting strategy” [23] based on wavelet packet decomposition, Elman neural networks, and boosting algorithm was developed. Furthermore, wavelet decomposition and least square support vector machines were employed to significantly reduce the stochasticity and unpredictability in wind energy. M. Ali *et al*. in their research titled “Significant wave height forecasting via an extreme learning machine model integrated with improved complete ensemble empirical mode decomposition” [16] suggested a new machine learning framework for forecasting significant wave heights in Australia's eastern coastline region based on extreme learning machines and empirical model deconstruction. This framework is essential for creating dependable ocean energy converters and may be thought of as a pertinent decision support framework. The approaches for forecasting renewable energy listed above, however, typically use shallow models as their central tenet of learning principles. Neural networks with no hidden layers or only one hidden layer are referred to as shallow models. In order to learn statistical principles from a large number of training samples and forecast unknown occurrences, shallow models were suggested in the 1980s. Back propagation algorithms, support vector machines, Boosting, and maximum entropy techniques are the primary types of shallow models. However, shallow model training requires a lot of expertise and experience. Additionally, superficial model theoretical analysis is challenging. As a result, shallow models have several limitations when used in real-world scenarios. In other terms, there are at least three major issues with shallow models:

(i) Feature selection via hand engineering: To manually choose characteristics from data on green energy, shallow learning algorithms need significant domain expertise proposed by M. Khodayar *et al.* in "Internal deep generative neural network for wind speed forecasting" [24]. Shallow models are ineffective for identifying the underlying nonlinear characteristics and high-level invariant patterns in renewable data because the time-consuming feature selection procedure heavily depends on subjective experience and is therefore inherently inaccurate.

(ii) Limited capacity for generalization: Shallow models have shown to be excellent in approximating smooth target functions. The chaotic nature of the earth's weather system and the noisy environment, however, make renewable energy data intermittent, stochastic, and extremely variable, which introduces non-smooth properties to the forecasting target function. Therefore, limited generating capabilities and shallow models may not be appropriate to understand the intricate patterns in data on renewable energy.

(iii) Sample complexity: When the training dataset is tiny, shallow models perform well. But when environmental metres, remote sensors, and other pertinent technologies become more widely used, we enter the big data age, with the training data's exponential growth pattern clearly visible.

As a result of the abundance of renewable energy data, shallow models may experience network instability and parameter non-convergence. Because of the hand-engineered feature selection, poor generalisation capacity, and sample complexity, we are motivated to reconsider the deep learning-based renewable energy forecasting issue. Due to three key differences between deep learning and shallow models- strong generalisation capability, big-data training, and unsupervised feature learning - deep learning has gained a lot of attention in recent years. It has been widely used in pattern recognition, image processing, defect detection, classification, and forecasting applications and is naturally a type of shallow model substitute. A deep stochastic architecture based on the Boltzmann machine was recommended by the authors C. Zhang *et al.* in "Predictive deep Boltzmann machine for multiperiod wind speed forecasting" [26] for autonomous feature extraction. The acquired properties are quite useful and appropriate for wind energy forecasting. For day-ahead PV power production, Chang suggested a new integrating technique based on grey theory and deep belief networks, showing that the prediction accuracy and computing efficiency are better than the benchmarks. A fresh deep machine learning technique was created by L. Li *et al.* in "Maximization of energy absorption for a wave energy converter using the deep machine learning" [27] to forecast short-term wave energy. The outcomes of the forecasting are beneficial for the effective and efficient management of wave energy in the present. Deep recurrent neural network, deep convolutional neural network, and stacked extreme learning machine have also been regularly reported for forecasting renewable energy. It is well acknowledged that forecasting models based on deep learning demonstrate appealing performance in terms of accuracy, stability, and efficacy, which is advantageous for energy system planning, scheduling, and management. Statistics to date reveal that more than 100 papers have focused on predicting models based on deep learning. To the best of our knowledge, no one publication has yet been published which reviews them all collectively. Therefore, a thorough review article focusing on deep learning-based renewable energy forecasting is urgently needed to offer an overview of the state of the art in research as well as a systematic evaluation of the relevance and validity of individual studies. Renewable energy forecasting has recently attracted a lot of attention in the literature, and multiple review articles have been released. S. Sobri *et al.* in "Solar photovoltaic generation forecasting methods" [28] addressed time-series statistical, physical, and ensemble methodologies for PV power generation forecasting. F. Barbieri *et al.* in "Very short-term photovoltaic power forecasting with cloud modelling" [29] gave readers a thorough overview of numerous methods for estimating solar output over a relatively short time frame. In order to accomplish the massive integration of wind energy, C. Gallego-Castillo *et al.* in a review on the recent history of wind power ramp forecasting [30] published a survey on wind energy ramp forecasting. Additionally, the current state of cooperative and competitive ensemble approaches for forecasting wind and solar energy has been thoroughly examined. Solar and wind energy forecast's effects on electrical power and energy systems' consequences, operating costs, and benefits have been compiled by the author G. Notton *et al.* in "Intermittent and stochastic character of renewable energy sources: Consequences, cost of intermittence and benefit of forecasting" [31]. P.A.E.M. Janssen *et al.* in "Progress in Operational Wave Forecasting" [32] explored the development of sea wave energy operation prediction subject to energy balancing and statistically assess the interdependence of wave energy and thermal energy by carefully examining the input function of wind energy. Even though relevant studies have been thriving recently, the evaluation of renewable energy forecasting from the standpoint of deep learning has not yet been explored. This paper's major contribution is to examine the literature on renewable energy forecasting from the perspective of deep historical analysis, which contrasts with the previous works on related themes. So, the purpose of this study is to close this gap. The primary contribution of this work, as compared to other research on related subjects, is to examine the literature on predicting renewable energy from the perspective of deep learning-based techniques. Concisely, we group the essential building blocks of deep learning into four categories, including deep belief networks, stacking auto-encoders, deep recurrent neural networks, and others. We also group the associated training procedures. We investigate how deep learning-based forecasting models enhance forecasting precision. We review and analyse existing approaches, such as data preparation and mistake post-correction procedures. We also talk about the obstacles and potential future research directions in addition to the ongoing research activity. A broad introduction and categorization of forecasting for renewable energy based on deep learning are provided in Section 2 of this paper. Section 3 provides an overview of the often-applied deep architecture for deterministic and probabilistic forecasting of renewable energy. Section 4 discusses a number of methods for increasing accuracy. In Section 5, we also discuss the statistically promising performance, potential difficulties, and potential future paths of deep learning-based approaches. Finally, Section 5 draws conclusions.

2. Basic structures of Deep learning

The fundamental building blocks of deep learning, which is essential to improving forecasting accuracy for renewable energy sources, are presented in this section. In the literature, the three primary forms of deep learning-stacked auto-encoder, deep belief network, and deep recurrent neural network-were commonly used. Additionally, forecasting models based on stacked extreme learning machines, deep reinforcement learning, and deep convolutional neural networks have been published. We now go into further detail on their fundamental architecture and related training processes.

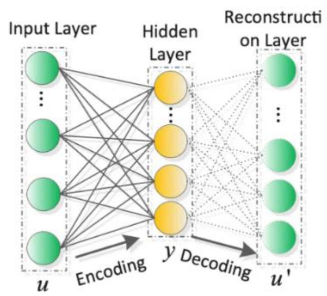

Figure 1: The basic unit of an auto-encoder

2.1 Stack auto-encoder (SAE)

The outputs of each layer of an auto-encoder in a stacked auto-encoder (SAE), which is a feedforward neural network, are coupled to the inputs of the layer above them. As seen in fig. 1, each auto-encoder (AE) consists of an encoder and a decoder and aims to rebuild its own inputs unsupervisedly. More specifically, the encoder uses the input u Rd to create a latent map y Rd in the hidden layer. The latent variables are then mapped into a reconstruction output vector u' that is the same size as u by the decoder. According to the predetermined distributional assumptions across the input space, the AE is trained to minimise the reconstruction error. As a general rule, the minimization objective function may be defined using the conventional squared error and cross-entropy. The fact that the decoding process only uses the latent information in the hidden layer to recreate the inputs shows that the latent variables have already stored a lot of the input's information. Because of this, the nonlinear transformation created by the encoder and decoder may be thought of as a sophisticated feature extractor that can preserve input's latent abstractions and invariant structures. A SAE is then produced by eliminating the decoder and stacking the encoders hierarchically. In more detail, the input is used as the training dataset for the first layer of an SAE, which is trained as an independent AE. The first auto-hidden encoder's layer and the second hidden layer are considered as a new auto-encoder when the training process is finished. The training procedure is the same as the initial AE procedure. By applying each layer's encoding rule in bottom-up order, numerous auto-encoders may be built hierarchically, and, at the end, an SAE is created as per S. Li *et al.* [33].

2.2 Deep Belief Network (DBN)

Hinton is credited with creating the deep belief network (DBN), which has been used in many fields. It is basically a generative graphical model made up of bidirectional and symmetrical connections between the various layers of restricted Boltzmann machines (RBM), which are simple, unsupervised networks as proposed by K. Wang *et al.* [34]. As depicted in Fig. 2, a limited Boltzmann machine functions as a stochastic neural network and consists of a layer of Boolean visible neurons and a layer of binary-valued hidden units, with a and b standing for the layers' respective biases. A RBM's main goal is to learn a probability distribution across the space of its input data in order to configure it with desirable attributes. An energy model that is optimised as a function of network characteristics using thermodynamics is used to learn the distribution.

Deepening the hidden-to-output function in the second formulation of deep RNN makes it possible for the hidden states to be smaller. The main advantage of this formulation is that it is very effective in summarising the history of prior inputs, which makes it simpler to anticipate the output in real time. The third kind of deep RNN is deep hidden-to-hidden transition. It augments the total of the prior inputs, which are represented by the fixed-length hidden states, with a fresh data source. The hidden-to-hidden transition enables the hidden layers to quickly adapt to the varied patterns of the input while preserving an important summary of the prior knowledge. The universal approximation property of the deep hidden-to-hidden transition is its major benefit. The last form of deep RNN is created by piling several recurrent hidden layers on top of one another. Each stacked layer is encouraged to function at a distinct timeframe by this arrangement. To put it another way, stacked RNN may take into account various temporal scales in the input sequence. For projecting renewable energy, several deep RNN models have been put out by the authors Y. Qin *et al.* in “Hybrid forecasting model based on long short term memory network and deep learning neural network for wind signa” [35]. Deep RNNs, however, may make computations more complicated, particularly when time series data has lengthy tails proposed by C. Fan *et al.* in “Assessment of deep recurrent neural network-based strategies for short-term building energy predictions” [36]. Adopting recurrent and convolutional operators for model creation is one workable method. Bidirectional computations, which may account for the effects of both past and future conditions, are another potential remedy. Additional stored state that is directly controlled by the neural network may exist in a deep RNN. Additionally, a different neural network with time delays or feedback loops can replace the recorded states. These regulated storages serve as the foundation for gated recurrent units and extended short-term memory networks.

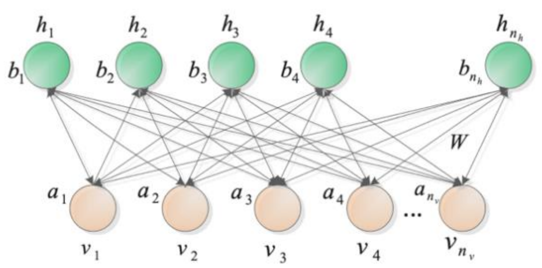

Figure 2: The basic unit of an Boltzman machine

2.3 Other Deep Learning Structures

Deep convolutional neural network (DCNN), stacked extreme learning machine, and generative adversarial networks are just a few of the additional deep learning architectures that have been suggested for feature extraction. Based on translation invariance features and shared-weights architecture, DCNN functions as a version of multilayer perceptions with little preprocessing put by the author H. Liu *et al.* in “Smart deep learning based wind speed prediction model using wavelet packet decomposition, convolutional neural network and convolutional long short term memory network” [37]. It was motivated by biological information processing, where the connection pattern between neurons mimics the structure of the visual system in animals. Basically, DCNN is made up of several pooling and convolution layers. When mapping low-level maps with local features into multiple high-level maps with global characteristics, the convolution layer uses a convolution operator. At order to decrease the memory footprints and number of network parameters and to make the feed forward and back propagation process simpler, weight sharing technique is typically used in the convolution layer. With this method, inputs from neurons in various locations are all given the same weight and bias across all neurons in the same output map. The input maps are really represented more succinctly by the pooling layer. By combining the input layer neuron clusters into a single neuron in the output layer, it minimises the size of the data dimensions. In this layer, average pooling and maximum pooling techniques are widely employed. A DCNN structure is created by alternately stacking the pooling layer and the convolution layer. A feedforward neural network with many layers is called a "Stacked Extreme Learning Machine" (SELM). A huge extreme learning machine (ELM) neuron network is split up into several stacked mini ELMs by SELM. The first two layers are essentially an original ELM in which the weights and biases of hidden neurons are generated at random. Expect the output weight vector that will be propagated after being reduced down to a proper dimension, even though the parameters of the subsequent ELM can either be produced at random or inherited from their ancestors. As long as the preceding ELM was properly trained, the input information is transferred to the following ELM. Another common unsupervised learning technique is the generative adversarial network (GAN). It is made up of a discriminative network and a generative network. In the context of a zero-sum game, these two networks compete with one another proposed by Z. Chen *et al.* in “Building occupancy modelling using generative adversarial network” [38]. The discriminative model in this paper seeks to learn a mapping function that translates the input to some desired output class label, whereas the generative network attempts to learn the joint probability distribution of the input data through the Bayes rule. In general, the discriminative network assesses candidates whereas the generative network produces them. GAN's ability to comprehend and explain the underlying structure of the input information, even in the absence of labels, is its greatest advantage. This advantage holds great promise for forecasting renewable energy since the unsupervised characteristics in the input data may be automatically learnt.

3. Deep Learning based forecasting models

Various deep learning models have been discussed in Section 2. These models, however, are actually utilised for feature extraction and cannot be used directly for projecting renewable energy. The overall organisation of predicting deterministic and probabilistic renewable energy based on deep learning is described in this section.

3.1 Deterministic forecasting models

In recent decades, researchers have explored both deterministic and probabilistic approaches to enhance the precision of wind power forecasting models. Figure 3 displays the various methodologies that have been devised and employed over time to improve the predictive outcomes of wind power forecasting [59]. Each technique offers distinct benefits, so it is essential to assess these benefits in relation to the specific area being studied.

The existing optimization approaches may be used to fine-tune the network architecture and model parameters. After then, all of the forecasted components are combined to recreate the forecasting findings. The rebuilt forecasting findings can then be corrected using a variety of error post-processing approaches.

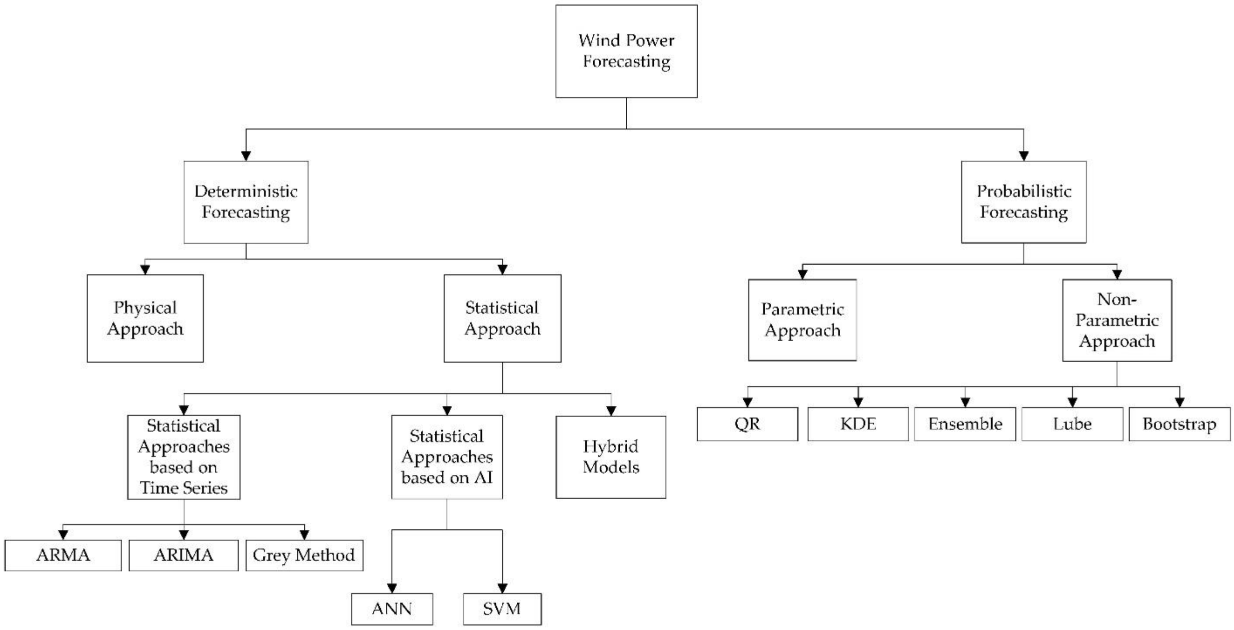

Figure 3: Cataloguing of different wind power forecasting methodologies [59]

3.2 Data processing techniques

Original raw data on renewable energy always shows a range of anomalies, including fluctuation and spike. The forecasting ability is harmed by these abnormalities' nonlinearity and nonstationary characteristics. In order to break down the renewable energy signal into many components with better behaviour in terms of data variance and outliers, numerous data pre-processing approaches have been proposed. These data pre-processors can effectively reduce the detrimental effect of anomalies on predicting accuracy. Two of the most popular techniques in literature are wavelet decomposition (WD) and empirical mode decomposition (EMD) proposed by J. Wang *et al.* in "Wind Speed Forecasting Based on Multi-Objective Optimization and Echo State Network" [40]. In addition, many decomposition techniques, including the Fourier transform, the seasonal adjustment method, and the variational mode decomposition, have been presented. Wavelet transform and wavelet packet decomposition are the two components of WD. Both of them are used to analyse time series data in the time and frequency domains at many resolutions. The approximation and detail subseries are obtained using a low-pass and a high-pass filter, respectively. Wavelet transform decomposes the original signal into one low frequency component and numerous high frequency components, whereas wavelet packet decomposition separates the same signal into several low and high frequency components. Because the de-composed sub-signals usually display better outliers and reduced uncertainty, it has been shown by F. Ziel *et al*. in their research titled "Probabilistic mid- and long-term electricity price forecasting" [42] that WD approaches are particularly beneficial in predicting performance enhancement. The Fourier transform is a crucial tool for digital electronics and signal processing. A signal's original form is broken down into several sine and cosine components using this method proposed by Z. C. Yang in "Modelling and forecasting monthly movement of annual average solar insolation based on the least-squares Fourier-model" [43]. Each component repeatedly displays a certain frequency in time. The Fourier transform's ability to eliminate random noise and highlight frequency change trends is its greatest advantage. However, it also has an obvious flaw: if there are too many frequency components, the computational load will definitely increase. A statistical technique called the seasonal adjustment method separates the input signal into trend and seasonal components.

To reach the final forecast result, the trend component's prediction is corrected using the seasonal prediction put by J. Wang *et al*. in "A novel hybrid approach for wind speed prediction" [44]. Similar to this, a time series signal is divided into a number of band-separated modes with distinct sparsity characteristics using a process called varying mode decomposition. Each mode, or subseries, has properties that are known in advance. The implementation of this decomposition approach for predicting renewable energy has been the subject of several researches proposed by J. Naik *et al*. in "A multi-objective wind speed and wind power prediction interval forecasting using variational modes decomposition based Multi-kernel robust ridge regression" [45]. Other decomposition techniques have also been used for signal decomposition in recent research, including atomic sparse decomposition, intrinsic time-scale decomposition, and bernaola galvan algorithm put by Z. Qian *et al*. in "A review and discussion of decomposition-based hybrid models for wind energy forecasting applications" [46].

3.3 Probabilistic forecasting models

Deterministic point predictions may not be enough in actual electric power and energy systems to capture the inherent uncertainty of data from renewable sources [47]. In order to help with the planning, management, and operation of the electric energy systems, probabilistic predictions that include quantitative uncertainty information about renewable energy are anticipated to be useful. The main goal of the probabilistic forecasting approach is to give each predicted outcome a probability. A probabilistic forecast is represented by a whole probability set. There are two types of approaches for probabilistic renewable energy prediction: parametric and nonparametric methods, with or without assumptions on distribution shape. The time series data for renewable energy is typically considered in parametric approaches to follow prior distributions like Gaussian proposed by H. Wang *et al*. in "Deep learning based ensemble approach for probabilistic wind power forecasting" [25], beta proposed by H. Bludszuweit *et al*. in "Statistical Analysis of Wind Power Forecast Error" [48], and gamma put by A. Bracale *et al*. in "A Bayesian Method for Short-Term Probabilistic Forecasting of Photovoltaic Generation in Smart Grid Operation and Control" [49]. Once the distribution is known, a variety of statistical techniques, including the auto-regression model, maximum likelihood, and quick Bayesian approach, may be used to determine its parameters. In order to statistically evaluate the distribution parameters of historical wind power, Pinson suggested a parametric auto-regression model [50]. On the basis of 10-mins-ahead probabilistic forecasting at the Horns Rev wind farm in Denmark, the suggested method's superiority is shown. A novel multivariate Kalman filter model for multi-step probabilistic wind power forecasting was proposed in by M. Poncela *et al*. in "Automatic tuning of Kalman filters by maximum likelihood methods for wind energy forecasting" [51]. An expectation maximisation algorithm-based quasi-maximum likelihood technique was used to update the model parameters in real-time. The probabilistic prediction intervals for horizons of 15 min and 24-48 h were constructed using a stochastic time series developed using a Bayesian technique put by A. Bracale *et al*. in "A Bayesian-based approach for the short-term forecasting of electrical loads in smart grids" [52]. The results show a 27-31% improvement over probabilistic persistence. However, parametric probabilistic forecasting techniques have a tendency to convert deterministic forecasts into probabilistic ones, necessitating the use of a deterministic forecaster beforehand. As a result, probabilistic forecasters tend to use nonparametric techniques.

Table 1: Probabilistic forecasting methods used in the literature

Category	Methods	Ref.
Parametric method	Auto-regression model	[50]
	Regression model	[56]
	Maximum likelihood	[51]
	Bayesian approach	[51]
Nonparametric method	Bootstrapping method	[42], [37]
	Quantile regression	[12], [32]
	Lower upper bound estimate	[26], [31]
	Gradient boosting	[33], [42]
	Kernel density estimation	[46], [47], [48]
	Analog ensemble	[49], [50], [51]

Table 2: Merits, demerits and Applications of various deep-learning algorithms

Algorithms	Merits	Demerits	Applications
DRNN	Able to process tome series data, High computation efficiency.	Incapable of accurately describing the characteristics of the incoming data.	There is time-series data in the data on renewable energy.
DCNN	Capable of processing image data, great for feature extraction.	Low computation efficiency.	Images are either included in the renewable energy data or can be created from it.
DBN	Unsupervised feature extraction.	Processing of multidimensional renewable energy data is not possible.	The characteristics of data on renewable energy cannot be identified.
GAN	Can generate new data from the same input data.	Incapable of accurately describing the characteristics of the incoming data.	Renewable energy data has lot of missing data.
DMP	Ease of implementing.	Incapable of accurately describing the characteristics of the incoming data.	There is less renewable energy data.
SELM	High computation efficiency.	Its power to extract features has not been thoroughly shown.	The computing power available is constrained.
SAE	Easy to be implemented.	Network optimization might be challenging.	Data on renewable energy is rather incomplete.

4. Conclusion

In-depth analysis of current deep learning-based forecasting models for renewable energy is provided in this paper. A multi-layer perceptron with several hidden layers is what deep learning is. It combines low-level characteristics to create higher-level, more abstract features or characterises attribute groups to determine the fundamental nature of incoming data. The five categories DCNN, DRNN, DBN, SAE, and additional deep learning models are used to categorise deep learning-based forecasting models in this research. We thoroughly describe each sort of forecasting model. The accuracy of the predictions can be increased by using various data preparation and postprocessing techniques, which are also covered in this work. The study then provides a substantial amount of simulation data that demonstrate the viability and efficiency of the deep learning-based forecasting models. Finally, we go through a number of issues and potential future research areas for prediction models based on deep learning. The accuracy of the predictions can be increased by using various data preparation and post processing techniques, which are also covered in this work. The study then provides a substantial amount of simulation data that demonstrate the viability and efficiency of the deep learning-based forecasting models. Finally, we go through a number of issues and potential future research areas for prediction models based on deep learning.

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