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AN ANALYSIS OF DEEP LEARNING FOR RENEWABLE ENERGY FORECASTING

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ABSTRACT

Order to increase the accuracy of sustainable energy forecasting is important to power system planning, management, and operations as renewable energy becomes more prevalent in the worldwide electric energy grid. According of the sporadic and unpredictable nature of renewable energy data, this is a difficult job. To date, a variety of approaches have been developed to enhance the forecasting accuracy of renewable energy, including physical models, statistical methods, artificial intelligence techniques, and their hybrids. Deep learning has been widely described in the literature as a potential form of machine learning capable of finding intrinsic nonlinear characteristics and high-level invariant structures in data. This article offers a thorough and in-depth examination of deep learning-based renewable energy forecasting techniques in order to assess their efficacy, efficiency, and application potential. Deep belief network, stack auto-encoder, deep recurrent neural network, and others are the four categories of extant deterministic and probabilistic forecasting techniques based on deep learning. To enhance forecasting accuracy, we also analyze viable data preparation approaches and error post-correction procedures. Various deep learning-based forecasting techniques are thoroughly examined and discussed. Furthermore, we look at the present research efforts, difficulties, and study and future research orientations in this field.

KEYWORDS: *Artificial intelligence, Deep learning, Network, Renewable, Technique.*

INTRODUCTION

Fossil fuels have always been the world's most significant source of energy today. Hydrocarbons or its derivatives, such as coal, oil, and fossil fuels, are examples of fossil fuels. Fossil fuels take many generations to produce, and existing stocks are destroyed far quicker than new fossil fuels are created. Simultaneously, fossil fuels produce greenhouse gases, which exacerbate climate change also including global warming, putting people's livelihoods in jeopardy[1].

To begin with, renewable energy resources are plentiful and renewable across the globe, and they are unrenewable. Furthermore, renewable energy is clean, green, and low-carbon, making it good for environmental protection. In particular, renewable energy may efficiently decrease sulfide, carbide, and dust emissions, lowering the danger of air pollution and the greenhouse impact. Furthermore, the usage of renewable energy may help to decrease the use of natural fossil fuels while also achieving the goal of environmental protection. As a result, renewable energy has exploded in popularity in recent years. But even though renewable energy is seen as the another very promising alternative to fossil fuels because it is clean, green, and naturally replenished over a large geographic area, it also introduces schedulable uncertainty, which jeopardizes energy system reliability and stability, particularly with massive renewable energy integration. On the one hand, renewable energy is characterized by high volatility, intermittent nature, and unpredictability, all of which will certainly raise the reserve capacity of electric energy systems, raising the cost of power production. The utilization of renewable energy, on the other hand, necessitates a high number of power electronics, which lowers the power system's rotational inertia and therefore diminishes the system's stability margin. As a result, renewable energy forecasting is critical for reducing associated uncertainties, which is beneficial to electrical power and energy system planning, management, and operation. Due to the intermittent, chaotic, and unpredictable character of renewable energy data, reliable renewable energy forecasting remains a difficult job. Various methods for providing accurate renewable energy forecasts for the next several minutes in these next few days have been described in the literature. Physical approaches, statistical models, artificial intelligence techniques, and their hybrid methods are generally classified into four groups[2].

Physical technologies are based upon numerical weather prediction algorithms that simulate atmospheric dynamics using physical principles and boundary conditions to simulate atmospheric dynamics. Limited area models, such as in the fifth-generation mesoscale model and high resolution fast refresh, are included in NWP models, as are global models, including the global forecast system and integrated forecast model. Temperature, pressure, jaggedness, and orography are only a few of the climatic and geographical variables that go into NWP. Physical techniques are effective in predicting atmospheric dynamics, but they need a lot of computing resources since they require a variety of material to calibrate. This becomes much more problematic when physical techniques make unanticipated mistakes during prediction[3].

1.1.Basic structures of deep learning

This section will explain the fundamentals of deep learning, which in itself is important for improving forecasting accuracy for renewable energy sources. In general, three major kinds of deep learning were presented in this report: stacking auto-encoder, deep belief network, while deep recurrent neural network. Furthermore addition, forecasting models are developed based on stacked extreme learning machines, deep reinforcement learning, and convolutionary neural networks have been described. We'll now go over their fundamental architecture and the training processes that go with them[4].

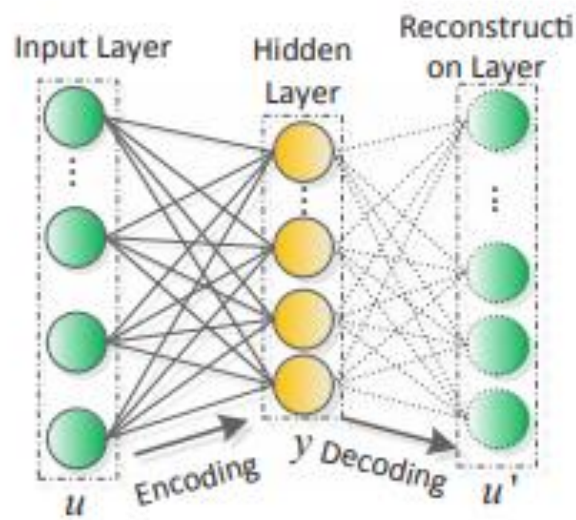

Figure 1: Illustrate the basic unit of an auto-encoder is made up of an encoder and a decoder

1.1.1. Stacked auto-encoder

A stacked auto-encoder is a fully convolutional network made up of several layers of auto-encoders, with each layer's outputs linked to the parameters of the next. As portrayed in Figure. 1, each auto-encoder (AE) is made up of an encoder and a decoder, with the goal of reconstructing its own inputs unsupervised. The AE is trained to minimize the reconstruction error across the input space using predefined distributional assumptions. The conventional squared error and cross-entropy objective functions may be utilized as the minimization objective function in general. Only its latent information in the hidden layer is used in the decoding process to recreate the inputs, suggesting that the latent variables already retain a lot of information from the input. As a result, the encoder and decoder's nonlinear transformation may be regarded as a sophisticated feature extractor capable of maintaining latent abstractions and invariant structures in input. After then, an SAE is created by discarding the decoder and stacking the encoders hierarchically. The first layer of an SAE is trained as an independent AE, with the input serving as the training dataset. Even before the first auto-training encoder's process is over, the first AE's hidden layer and the second hidden layer are regarded as a new AE. The training procedure is same to that of the first AE[5]. Multiple auto-encoders may be layered hierarchically in this manner by executing the encoding rule of each layer in a bottom-up order, and an SAE is formed as a result. Previous research has shown that SAE has a promising and stable performance for high-level feature abstractions and representations.

1.1.2. Deep belief network

Hinton was the first to create the deep belief network, which has since been used in a number of fields. It's a generative graphical model made up of unsupervised, basic networks (limited

Boltzmann machines) with bidirectional and symmetrical connections across layers. As presented in Fig. 2, a limited Boltzmann machine works as a stochastic neural network and comprised of one layer of Boolean visible neurons and one layer of binary-valued hidden units, with the first and b indicating their respective biases. A RBM's main goal is to learn a probability distribution across its input data space in order for its configuration to have desired characteristics[6]. The allocation is discovered by minimizing an energy model that is built as a function of network characteristics using thermodynamics.

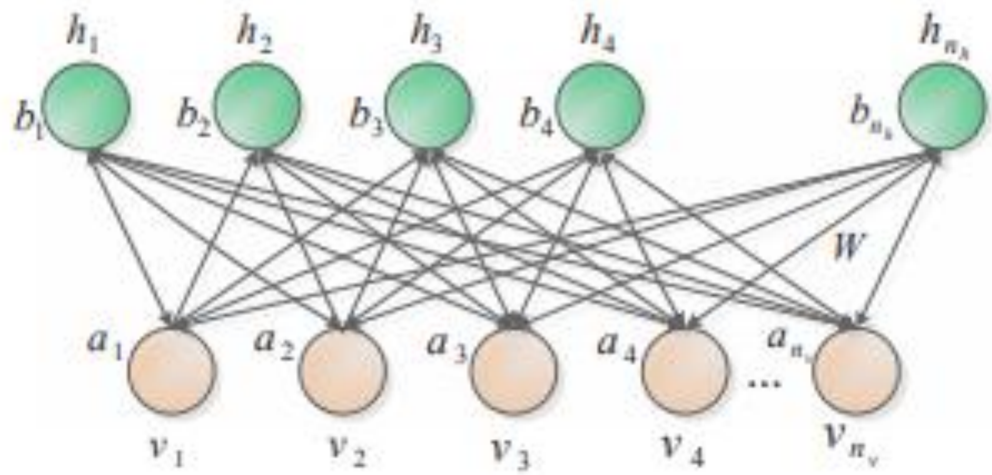

Figure 2: Illustrate the basic unit of Boltzmann machine works as a stochastic neural network

The clustering algorithms may then be determined by repeatedly estimating the engagement probability of the hidden layer supplied the visible layer and indeed the probability of the visible layer given the hidden layer. The estimate procedure, on the other hand, necessitates the calculation of reconstructed-data-driving probabilities across visible and concealed layers, which is very difficult in practice. Applying alternating Gibbs samplingto any stochastic state of the neurons until a particular convergence criteria, such as k-steps, is met is one viable approach.

The unsupervised greedy method is used to pre-train the network parameters in the DBN training process. The 4 major stages are as follows:

a) Using an alternating Gibbs sampling and contrastive divergence method to adequately train the first RBM;

b) Configuring that the very first RBM's network parameters and thresholds, then utilizing the hidden neurons' results as the second RBM's input vector;

c) As much as the second RBM is completely trained, stacking it atop the first RBM;

d) Following the processes, stacking the remaining RBMs one by one. DBN's training process and binary construction make it highly successful for feature extractions, which makes it appealing in a variety of applications including time series forecasting.

1.1.3. Deep recurrent neural network

The term "deep recurrent neural network" comes from the term "recurrent neural network," which is a kind of artificial neural network in which nodes are connected to form a directed graph [64]. It uses feedback connections to remember the brain states at earlier time steps to simulate the temporal dynamic behaviors seen in time series data. Figure 3 depicts an RNN's usual structure. Unlike feedforward neural networks, RNNs can handle time series sequences of inputs using neural internal states, making them suitable for renewable energy forecasting[7].

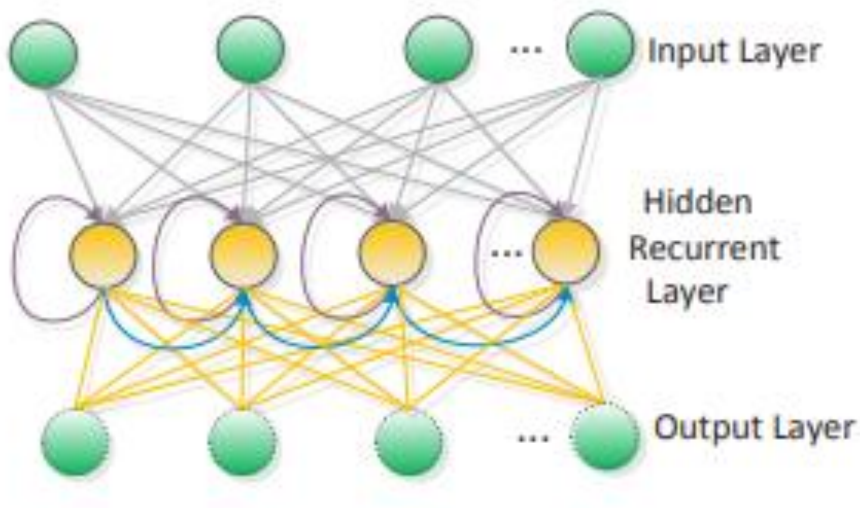

Figure 3: Schematic diagram shows the typical structure of a recurrent neural network

Deep RNN may be expressed in four distinct ways when compared to ordinary RNN. The first method is to deepen the input-to-hidden equation to learn additional non-temporal structure from either the inputs. This approach, rather than the affected by the following, tends to flatten the manifolds within which the data concentrations and untangle the underlying variation components. Because the connection between representation characteristics can be represented more simply, the deep information structure enables learning the temporal correlation between many times steps simpler. The second characteristic of deep RNN is to deepen the hidden-to-output function, which allows for more compact hidden states. One of most significant advantage of this formulation is its great efficiency in summarizing the history of prior inputs, making real-time output prediction simpler.

1.1.4. Additional deep learning structures

Many alternative deep learning structures, including deep convolutional neural networks, stacked extreme learning machines, and generative adversarial networks, have been suggested for feature extraction. Based on translation invariance features and shared-weights architecture, the deep convolutional neutral network serves as a variant of multilayer perceptions with minimum preparation. It must have been motivated by biological information processing, in which the connection arrangement between neurons mimics the visual structure of animals. DCNN is made up of a series of alternating convolution and pooling layers. The low-level maps with local characteristics are mapped into multiple high-level maps with global features via the convolution layer, which uses a convolution operator. Weight sharing is often used in the convolution layer to minimize memory footprints and the amount of network parameters, making the feed forward and back propagation process easier. With this method, all neurons in the same output map have the same weight and bias, even if their inputs come from different places. The pooling layer is a more condensed version of the input maps. It lowers data dimensionality by turning input layer neuron clusters into a single output layer neuron.

1.2.Forecasting models based on deep neural networks

Numerous deep learning models are examined. These systems, on the other hand, are employed for feature extraction and can also be directly accustomed renewable energy forecasts. This section explains the basic framework of deep learning-based deterministic and probabilistic renewable energy forecasting.

1.2.1. Models of deterministic forecasting

In summary, Figure 4 depicts a deep learning-based objective forecasting system for renewable energy. It includes data preparation approaches, a deep learning-based feature extractor, regression algorithms, and error post-processing tools, as demonstrated. The raw renewable energy time series analysis is first decomposed into various components with varying frequencies using data preparation methods. Outliers and behaviors are better in each component than in the original data. Then, for each component's forecasting, a feature extractor and a repressor are built separately. Using current optimization methods, the network topologies and model parameters may be fine-tuned. The forecasting findings are then rebuilt by adding all of the predicted components together. Finally, to rectify the rebuilt forecasting findings, different error post-processing methods may be used.

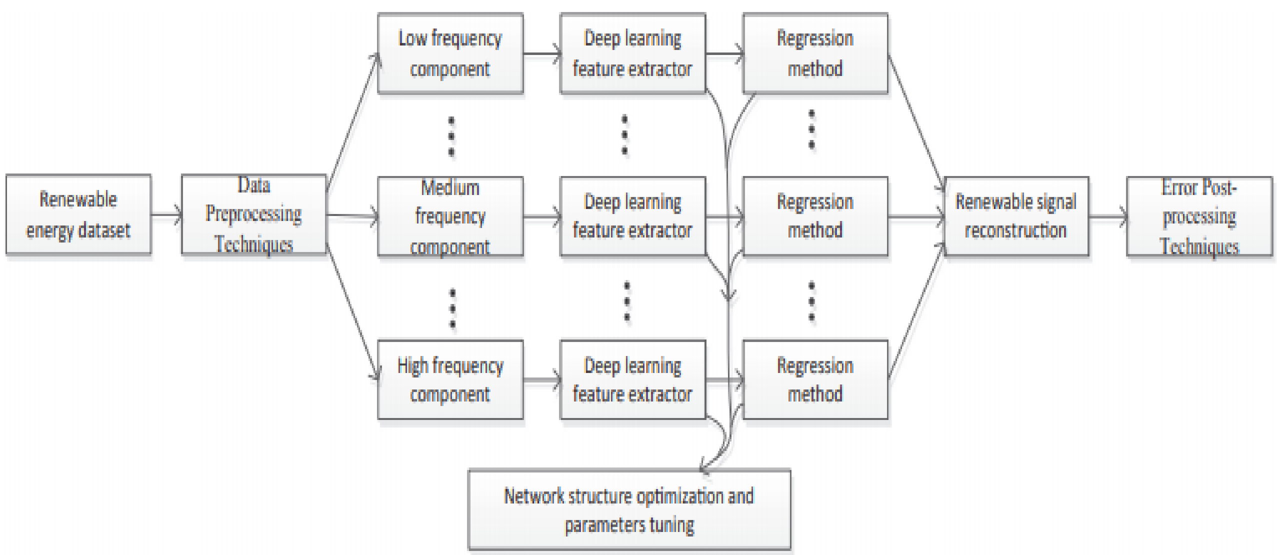

Figure 4: A general framework for renewable energy forecasting

1.2.2. Techniques for data preprocessing

Raw renewable energy information is prone to a wide range of irregularities, including fluctuation and spikes. The forecasting performance is harmed by these irregularities, which have nonlinearity and non-stationarity characteristics. As a result, a number of data preprocessing schemes have been developed to biodegrade the renewable energy signal up into multiple components with better information variance and isolated occurrence behavior. The adverse consequences of irregularities on forecasting accuracy can indeed be appropriately mitigated with the help of all these data preprocessors. Wavelet decomposition but instead empirical mode decomposition were indeed two of the most prominent used methods in the literature. Those certain decomposition methods have also been reported, including Fourier transform, seasonal adjustment method, and vibrational mode decomposition. Wavelet transform and wavelet packet decomposition make up WD. Two components are used to perform multi-resolution time series data analysis in the time and frequency domains. The approximate and detail subseries are obtained using a low-pass and high-pass filter, respectively. The variation between wavelet transform but instead wavelet packet decomposition is that even the former consists of dividing the original signal into several minimum and maximum frequency components, whereas the latter divides it into several high and low frequency components. WD techniques have been shown to be very useful in forecasting performance improvement because the decomposed thread always have fewer outliers and lower uncertainties[8].

LITERATURE REVIEW

Considering electric infrastructures are aging, traditional power grids are being updated into smart grids that allow two-way communications between consumers and utilities, making them more susceptible to cyber-attacks. However, owing to the assault cost, the attack method may change significantly from one operating situation to the next from the adversary's viewpoint, which has not been taken into account in prior research. As a result, two-stage sparse cyber-attack models for smart grid with full and partial network information are presented in this article. Then, in order to efficiently identify existing cyber-attacks, a defensive mechanism based on interval state estimation (ISE) is created in a novel way. The lower and upper limits of each state variable are represented as a dual optimization problem in this mechanism, with the goal of maximizing the system variable's variation intervals. Finally, a common deep learning algorithm, known as a stacked auto-encoder, is intended to extract nonlinear and non-stationary characteristics in electric load data. These characteristics are then used to enhance electric load forecasting accuracy, resulting in a narrower range of state variables. A parametric Gaussian distribution is used to represent the uncertainty in predicting mistakes. Comprehensive testing on different IEEE benchmarks have proven the validity of the suggested cyber-attack models and defensive mechanisms[9].

Laura Frías-Paredes et al. studied the wind and solar energy generation have grown in popularity in recent years, and it is anticipated that these energy sources will account for a significant portion of overall energy output in the future. They do, however, have intrinsic unpredictability, which means that energy production fluctuates in unpredictable ways. As a result, forecasting mistakes have a significant influence in the costs and effects of renewable energy integration, management, and commercialization. This research makes a significant contribution to the problem of evaluating prediction models, particularly in the time component of prediction error, which improves on earlier pioneering findings. In order to evaluate the accuracy of energy forecasting, a novel technique for matching time series is developed. This technique is based on a novel set of step patterns, which are an important part of the algorithm for calculating the temporal distortion index (TDI). This family reduces the transformation's mean absolute error (MAE) in comparison to the reference series (the actual energy series) and also provides for precise control of the prediction series' temporal distortion. The use of Pareto frontiers as characteristic error curves is enabled by the simultaneous consideration of temporal and absolute mistakes. To demonstrate the findings, real-world wind energy predictions are utilized[10].

DISCUSSION

Along with its capacity to deal with large amounts of data and high-performance computing power, deep learning management systems have grown rapidly. There's now a lot of research on using deep learning to predict renewable energy. Deep learning-based forecasting models, on the other hand, face two major issues. Conquering these obstacles will aid in improving the deep learning prediction model's accuracy. There seem to be a large couple of published on deterministic renewable energy prediction to date. However, deep learning-based probabilistic forecasting models have received insufficient attention. The probabilistic forecasting model can quantify the uncertainties in renewable energy time-series data numerically. As a direct consequence, probabilistic renewable energy forecasting is critical for the economic operation and day-to-day management of the electric power and energy system. This article's comparative analysis can assist renewable energy forecasting professionals in determining which deep learning algorithm can help them improve their forecasting tools. This publication fills in the gaps in order to explore the potential of deep learning in the context of renewable energy forecasting.

CONCLUSION

The above paper presents a comprehensive review of recent deep learning-based renewable energy forecasting models. A multi-layer perceptron with multiple hidden layers is what deep learning is. It mainly a consequence features to create more abstract high-level features or characterizes attribute categories to learn about the input data's inherent nature. Deep learning-based forecasting models are classified into the following categories in this paper: DCNN, DRNN, DBN, SAE, and other deep learning models. Either every type of forecasting model is explained in great detail. In furthermore, some data preprocessing and post processing techniques are presented in this report in order to improve prediction accuracy. The publication then goes on to show a large number of simulation results that demonstrate the feasibility and effectiveness of deep learning-based forecasting models. Ultimately, we go over some of the challenges that deep learning-based prediction models face, as well as some of the future research directions that could be pursued. This article's comparative analysis may aid renewable energy forecasting experts in determining which deep learning algorithm can help them improve their forecasting tools. This publication fills in the gaps in order to explore the potentials of deep learning in the context of renewable energy forecasting.

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