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Forecasting of Energy Power with Hybrid Multi-Variant Deep Belief Network

Krishanmoorthy Narasu Raghavan[1], Marshiana D. *[2], Jaiganesh J.[3], Thaj Mary Delsy T.[4], Godwin Immanuel G.[5]

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Abstract: Prediction of renewable energy power plays a vital role in the development of national economics. Because of the non-linear behavior of the climatic and environmental factors, predicting the energy power becomes quite challenging for the researchers. In recent years, the evolution of Deep Belief Networks has become popular in various domains since it handles the non-linear features for time series data and yields a promising result. In this article, three different models namely DBN, multi-variant CNN, and hybrid multi-variant CNN-DBN model were proposed and their performance metrics such as MSE, RMSE, MAP, and MAPE were evaluated and discussed in detail. It is evident from the value of the metric that the hybrid multi-variant CNN-DBN outperforms the other two models DBN and Multi-variant CNN.

Keywords: *Deep Belief Network, Convolutional Neural Network, Mean Absolute Error, ReLu Activation Function, Mean Square Error.*

1. Introduction

One of the leading industries in the national economy's foundational industry is the electric power sector which focuses on the implementation of strategy for the development of national economics. It is mandatory in the present situation due to the rising of people's standards of living, and social progress. Because of this, electricity has become a demanding part of our daily existence. The primary method of producing electricity in the past was power generation through thermal using fossil fuels, such as natural gas, coal, and other combustibles. However, the widespread use of thermal power will harm the environment by releasing numerous harmful gases during the combustion process and increasing the amount of non-renewable energy consumed [1]. With the application of the renewable energy development approach and the steady progress in constructing large clean energy bases worldwide, some new clean energy power generation has improved rapidly to address the issues of energy demand and environmental protection. Because they are widely available and safe to use, wind power generation and photovoltaic power generation as the most common representatives have been functional as generating systems by using wind energy and solar energy in these bases. Although solar energy has many benefits, including being clean, safe, and noiseless, it is also unpredictable, volatile, and intermittent [2], which can seriously jeopardize the security and stability of the power grid system. In contrast, wind energy is intermittent and unpredictable [3], which makes scheduling and planning for the grid more challenging. It also has a large storage capacity and low pollution. Overall, the influence of natural factors makes solar and wind power output unstable. This presents numerous challenges for scheduling of energy management systems and power grid planning, including new energy sources [4] and dependable power grid operation. Consequently, research into wind and photovoltaic power forecasting is crucial, and precise forecast outcomes are crucial for energy management, the stability and security of the power system, and power grid dispatching.

Several growing forecasting techniques have been developed in recent years for wind and PV power. These techniques can be categorized into two categories: data-driven and physical-model-based, depending on how the algorithm is viewed mathematically. The physical approach is centered on the principles of wind turbine power generation and solar panels. The power is computed by combining system parameters and energy conversion efficiency with weather forecast data, such as direction at different heights and wind speeds, horizontal direct radiation data, normal direct radiation data, barometric pressure data, total radiation data, temperature data, and so on [5,6]. The model is established to predict the weather conditions based on the independence assumption of the local law and the parameters of the designed model are comparatively hard to obtain, the estimating results show large abnormalities in long-term and medium-term prediction, even though the physical-model-based forecasting methods can reflect the internal law. While this is going on, data-driven techniques with robust nonlinear fitting capabilities can compensate for the limitations of the

[1,4,5] Sathyabama Institute of Science and Technology, Chennai, India
[2] Symbiosis Institute of Technology, (Pune campus), Lavale, Pune, 412115, Maharashtra, India.
ORCID ID: 0000-0002-5605-3537
[3] Chennai Institute of Technology, Chennai, India
** Corresponding Author Email: d.marshiana@gmail.com*

physical model approach. Artificial neural network techniques and Statistical learning, in particular, have been widely used in the fields of wind and PV power forecasting. Input–output mapping models are created by statistical learning techniques using past data from solar, wind, temperature meters, and humidity in addition to curve fitting parameter estimation techniques [7, 8]. High-speed computational time series forecasting techniques [9], large-sample-free grey theory techniques [11], robust fuzzy theory techniques [12], spatiotemporal correlation techniques that extract deep spatiotemporal attributes [13], support vector machines (SVM) [14], and further related techniques are examples of common statistical techniques.

The fundamental challenge of time series forecasting is to extract this arrangement from the data and apply it to project forthcoming data. Time series data can effectively represent the trend of a specific or unique random variable changing continuously over time [15]. Because of the clear trend in wind and PV power over time, time series forecasting, like the Autoregressive Integrated Moving Average model, is widely used in forecasting wind and PV power. Power forecasting is extremely difficult due to the nonlinear, stochastic nature of wind and photovoltaic data [18, 19]. It is challenging to artificially recreate their historical power and the nonlinear representation between the influencing factors of power and the time series power data [20]. Artificial neural network models, such as those with back propagation (BP) [21], radial basis function (RBF) [22], and so forth, are other significant data-driven techniques that can be used to forecast wind power and PV. The BP neural network can fit complex nonlinear functions and is highly capable of self-learning; however, because its network initialization is random, it has limited generalization capacity in prediction cases and an ease for dropping into local optimum.

Deep neural network (DNN) models can estimate any nonlinear function with deep structure and can capture the implied features of nonlinear data more effectively than the previously mentioned shallow neural network models. Different DNN models have been developed and are currently being used extensively in the fields of clean energy power prediction and image and audio recognition [32, 35]. One of the most effective RNNs for predicting wind and PV power is the LSTM and NARX. Recurrent neural networks (RNNs), as DNNs, have demonstrated notable performance in prediction and time-series forecasting and applications [25, 26]. Consequently, the GRU network has been used to forecast wind power and PV. Typically, Seq2Seq is implemented using the Encoder-Decoder framework. The model can be any of the following: CNN, RNN, LSTM, BLSTM, etc. The encoder and decoder portions can handle any text, speech, image, or video data. Additionally, Seq2Seq excels at utilizing data from distant global sequences. As a result, wind power prediction has also used Seq2Seq [36].

In section II, the introduction to the deep belief network its basic architecture, and the working flow process was illustrated clearly. Following this, the implementation of the DBN model CNN model and hybrid CNN DBN model was tested on a real filed dataset in section 3. The description of the dataset and the result obtained by these here models are well discussed in detail in the subsequent section. In section 4, the conclusion of the best model in the prediction of energy power was discussed in detail. A comparison of the performance metrics of these three models is also discussed in detail.

2. Deep Belief Network

The evolution of neural networks plays a vital role in various fields such as image processing, agriculture, and also in the power prediction sector. In the First Generation of Neural Networks, perceptron layers are used to identify an object or anything else by weighing it. It was primarily used for simpler technology—not for more complex technology. The Succeeding Generation of Neural Networks presented the concept of Backpropagation to address these issues. By reducing the error value significantly by comparing the predicted output to the desired output. Then directed acyclic graphs also referred as belief network was developed which help in solving inference and learning problems. Subsequently, Deep Belief Networks aided in the creation of objective values that leaf nodes could store and predict the future value more preciously.

Deep Belief Networks address problems with traditional neural networks. For instance, slow learning algorithms will easily get trapped in local minima due to improper parameter selection and it needs a lot of data for training purpose. It is composed of multiple layers of latent variables and these variables are referred to as feature detectors in binary classification problems. It is a kind of hybrid propagative graphical model which has no direction in the top two layers. Links to lower layers are directed by the layers above and it is also best example of an unsupervised deep learning algorithm.

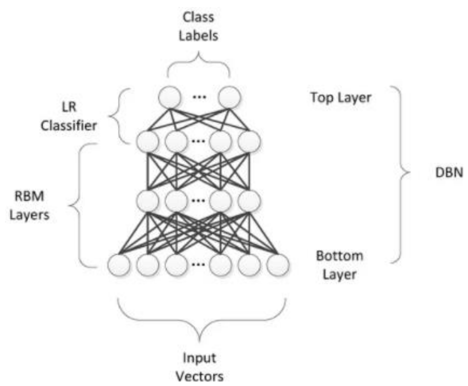

Fig. 1. Basic architecture of Deep Belief Network

One of the traditional algorithms in deep learning is DBN, which consists of several Restricted Boltzmann Machines (RBM). When compared to conventional machine learning algorithms, the DBN's superior feature extraction ability allows it to quickly analyze vast amounts of data and, by combining feature and deep learning, provide strong data-fitting capabilities. Unsupervised pre-training through layer-by-layer is used to obtain the network's initial parameters. This effectively resolves several issues brought about by the traditional neural network's random initialization of parameters; in addition to providing the network with good initial points, pre-training also effectively addresses the under-fitting and over-fitting issues that frequently arise in NN models.

One kind of generative stochastic ANN model that can study a probability distribution from its inputs is the restricted Boltzmann machine (RBM). It can build the model by stacking the RBMs. With the help of gradient descent and back-propagation fine-tune the resulting deep network. Associative memory in DBN is made up of symmetric and it provides undirected connections between the two levels of DBN. The relationships between all lower layers are indicated by the arrows pointing toward the layer nearby to the data. The lower layers' focused acyclic connections convert associative memory to observable variables. The input data is acknowledged by the lowest layer of visible units. The features that capture the relationships in the data are characterized by the hidden units. Every unit in a layer will be associated to every other unit in the layer above it. Training a property layer that can receive input signals directly from pixels is the first step. The values of this retired sub-caste are treated as pixels in a substitute retired sub-caste to learn the features of the preliminary acquired features. Every new sub-caste of parcels or feature requires addition of the network improves the inferior bound on the log-liability of the training data set.

The pre-training of DBN is carried out with the help of Greedy learning algorithm, which uses a layer-by-layer methodology for top-down generative weights. The relationship between variables in one layer and layer above is determined by these generative weights. It is important to keep in mind that building a Deep Belief Network requires training every RBM layer. For this purpose, initially the units and parameters values are set. Positive and negative phases comprise the Contrastive Divergence algorithm. The probabilities of visible units and weights are computed in order to determine the hidden layer’s binary states in the positive phase. Since it increases the likelihood of the training data set, it is referred to as the positive phase. The probability that the model will produce samples is decreased during the negative phase.

Each class type in RBM contains the network's layers and a vector that represents the layer's size. In the classification type of DBN. RBMs represent the number of classes in the respective dataset. As a result, the top layer can be trained to produce input data vector class labels and to classify unidentified data vectors. In more complex configurations, we use deep belief networks instead of deep feed-forward networks or even convolutional neural networks. They have the advantage of requiring less computing power. Unlike feed-forward neural networks, where computational complexity increases exponentially with the number of layers, it grows linearly with the number of layers and is less vulnerable to the vanishing gradients issue. Some examples of DBN applications are Image recognition, Video segments, Mo-cap data, and Recognition of speech.

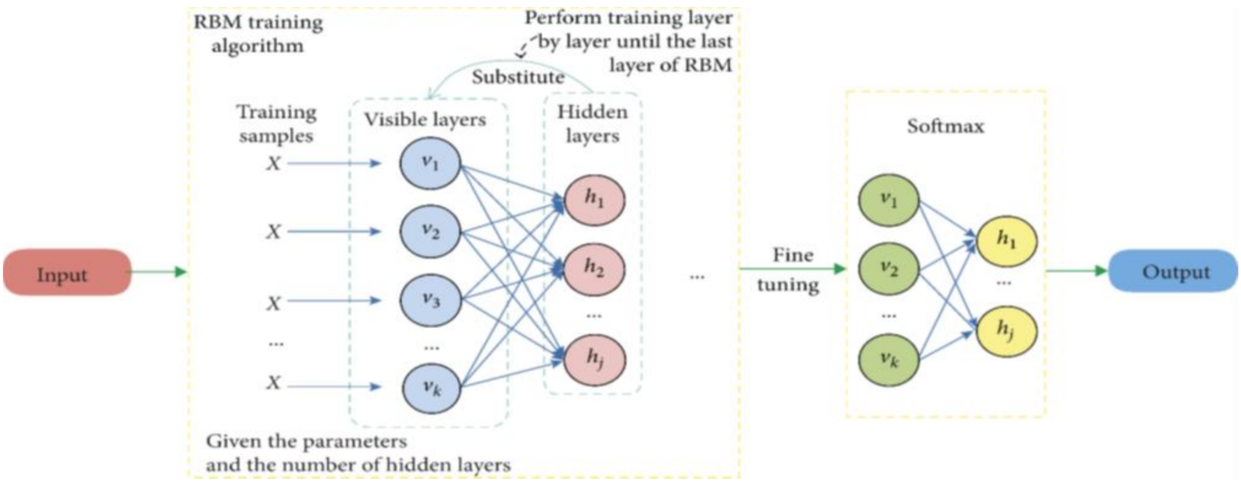

Fig 2. Workflow of Deep Belief Network

3. Proposed Hybrid CNN-DBN Model

The dataset used in this article consists of the amount of energy power generated based on various parameters such as humidity, pressure solar radiation, temperature, and wind speed. The energy value is based on the Global Horizontal Irradiance (GHI), which represents the amount of radiation from the sun by a horizontal surface. It also includes details like the length of daylight, presence, and absence of sunlight, and time duration of the sunlight availability. The last field is the weather type which gives information about the status of climate such as the sky is cloudy, clear, and rainy. All the above fields are collected and tabulated with a time interval period of 15 minutes. The dataset includes the data from the period January 1st, 2017 to August 31st, 2022 daily.

Figure 3 to 5 illustrates the analysis of the dataset used in this article. The average energy generated by the wind and sun in the mentioned period is taken and its average value is computed every month and its value is displayed in figure 3. It is observed that the average energy generation was high at around 900 Kilo watts in the period of June and it has the least power of 100 KW during the month of January and December of every year. Figure 4 illustrates the average solar radiance over a year every month is depicted. It also behaves same way as in the figure 3 giving high value of 60 in the month of June and least value of 5 during the month January and December of every year.

Another analysis of the dataset is the energy generated based on the Hours basis is displayed on the hour basis. During the noon period, the amount of energy generated was high and it has a low value when the sun is not present. Three different models namely DBN, Multi-variant CNN, and Multi-variant CNN-DBN model are tested on this dataset and performance metrics are evaluated for these models.

To train the dataset, initially, the dataset is stored in Excel format. The actual dataset has 17 columns including the amount of energy generated. For simulation purposes, out of 16 columns, only four important parameters namely pressure, humidity, wind speed, and sunlight radiance are considered and stored in a sheet along with the amount of energy power.

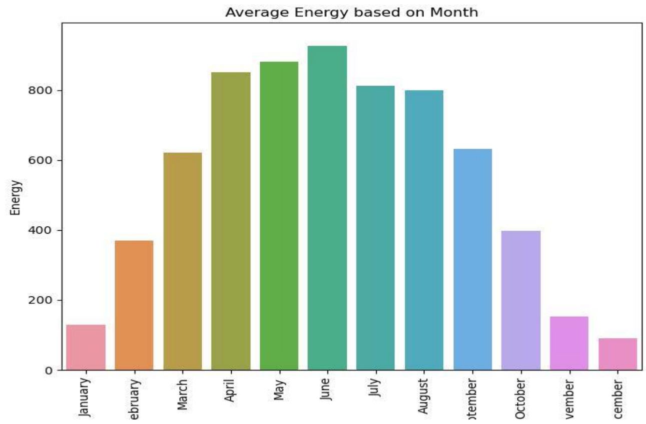

Fig 3. Illustration of Average Energy based on month**.**

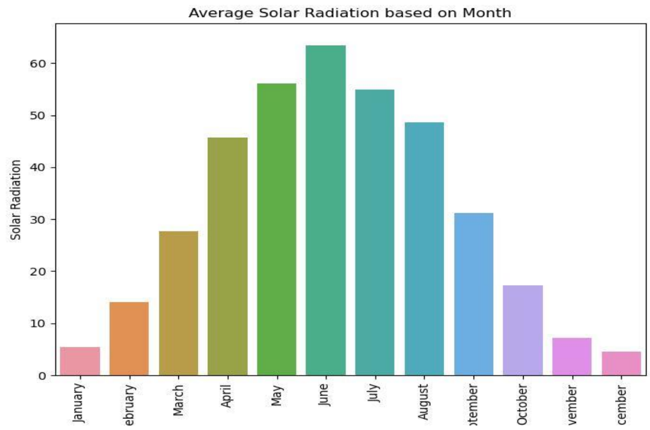

Fig 4. Illustration of Average Solar Radiation based on month

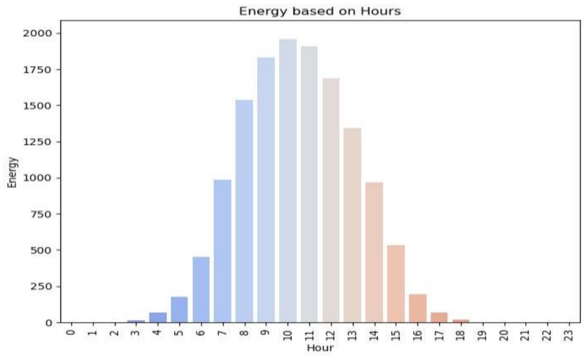

Fig 5. Illustration of Energy based on Hours

DBN model is designed with the input parameter of 4, one output layer with five hidden layers. Each hidden layers are designed with 10 neurons. Training of the dataset is carried out with the Re-Lu activation function in the input layer and the soft-max function in the output layer. The model is trained with the epoch value of 100. Simulation is carried out in four different cases by considering the above-mentioned parameters one after another (pressure, humidity, wind speed, and sunlight radiance). In the first case, only the pressure value is considered as an input variable. In the second case, pressure and humidity and so on.

The second model designed in the article is the multi-variant CNN model. In this model, the dataset is arranged properly before applying it to the CNN model. The dataset is bundled with 3 rows. The first bundle consists of the first three rows containing four parameter values and it is labeled with the energy generated by the four rows. The second bundle contains the second, third, and fourth input parameters are grouped with the output label of the fifth-row value of energy. It is the most important stage in the multi-variant CNN as it helps in CNN model to learn the features of the dataset properly and efficiently. These pre-processed datasets are given to the CNN model which consists of a CNN layer with 64 filters, kernel size of 2 with Re-Lu activation function. A max-pooling layer of 1, output dense neuron of 500 with an epoch value of 1000 was taken for simulation purposes.

The third and last model is the hybrid multi-variant CNN-DBN model. In this model, initially, datasets are pre-processed as mentioned in the multi-variant CNN model, and the DBN model is incorporated inside the CNN model, and then training and validation of the dataset are evaluated. In all three models, four different cases are considered depending on the number of input parameters considered for simulation. To analyze the performance of the three models, four different metrics were evaluated namely Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error MAPE.

The prediction of energy value for the dataset is evaluated using three different models and is illustrated in figures 6 to 8 with different perspectives. Prediction of energy value with only one parameter namely pressure using three models are estimated and displayed in Figure 6. It is evident from the figure that the prediction was not much good one. To enhance the performance of the model, input parameters are increased from one to four namely pressure, humidity, wind speed, and soar radiance and its prediction is depicted in figure 7. It is observed that by increasing the number of parameters, the prediction rate is almost closer to the actual one. To understand a better way for hybrid CNN-DBN models, the number of parameters is changing from one to four and its comparison of the predicted value with the actual value is determined and depicted in figure 8. As a number of the number of parameters are increased, the prediction is closer to the actual value.

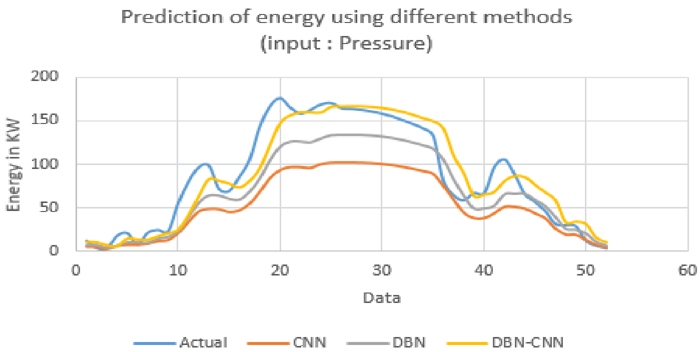

Fig 6. Prediction of Energy considering one parameter

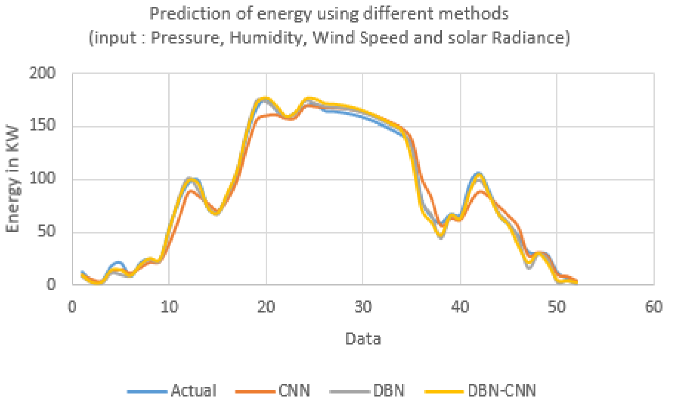

Fig 7. Prediction of Energy considering Four Parameters

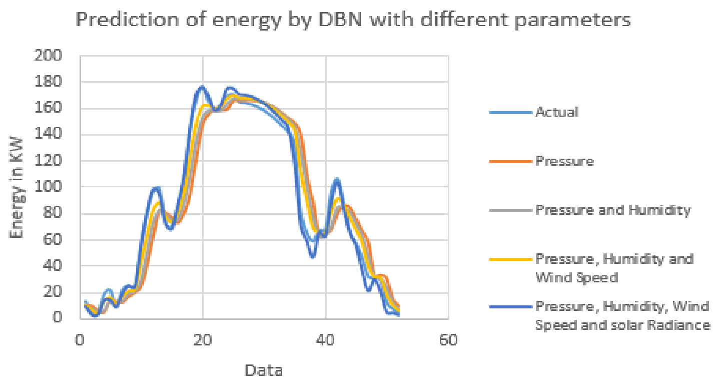

Fig 8. Prediction of Energy by DBN model considering different parameters

4. Conclusion

Table I: Estimation of Performance metrics for different test set data with three different methodologies

Test Signal	Method	Performance Metrics			
		MSE	RMSE	MAE	MAPE
1	CNN	45.15	6.72	5.78	10.15
	DBN	15.45	3.93	2.50	3.92
	DBN-CNN	13.69	3.7	2.04	3.21
2	CNN	93.89	9.69	7.62	12.10
	DBN	84.82	9.21	6.97	10.11
	DBN-CNN	76.21	8.73	6.27	9.37
3	CNN	16453.19	128.27	87.16	28.87
	DBN	12210.25	110.5	75.89	20.95
	DBN-CNN	10920.25	104.5	71.81	20.22
4	CNN	46341.17	215.27	139.03	32.81
	DBN	45710.44	213.8	141.01	33.60
	DBN-CNN	40493.51	201.23	131.87	35.78
5	CNN	174.24	13.2	10.69	38.70
	DBN	138.29	11.76	9.01	25.25

	DBN-CNN	129.96	11.4	8.61	26.00
6	CNN	54508.24	233.47	160.76	28.18
	DBN	32055.32	179.04	113.82	18.48
	DBN-CNN	28002.68	167.34	113.63	18.49
7	CNN	50927.52	236.49	147.94	160.56
	DBN	43756.27	209.18	124.25	122.47
	DBN-CNN	33606.22	183.32	120.56	129.47

The prediction of the energy value for one test set was estimated using three different models and discussed in detail in the previous section. To validate the performance of these models, a few performance metrics namely MSE, RMSE, MAE, and MAPE for these three models are estimated using different test sets. Seven different test sets are considered from the dataset and their predictions were evaluated using three models metrics values are depicted in Table 1. It is evident from the table that the hybrid CNN-DBN model outperforms the other model DBN and Multi-variant CNN model.

Author contributions

Krishnamoorthy Narasu Raghavan: Conceptualization, Field study **Marshian:** Software, Validation., Field study **Jaiganesh:** Visualization, Investigation, Writing-Reviewing **Thaj Mary Delsy:** Writing-Reviewing. **Godwin Immanuel:** Writing-Reviewing, Field study

Conflicts of interest

The authors declare no conflicts of interest.

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