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Wind Power Generation Forecast using Artificial Intelligence Techniques

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Abstract— **It is crucial to be able to forecast wind power generation with the greatest degree of precision because wind has a significant degree of instability and the energy generated cannot be conserved on a big scale due to expensive costs. This research compares the efficiency of wind energy predictions one hour in advance employing artificial intelligence based techniques. RNN and LSTM are the two DL approaches while Decision Tree Regression, Support Vector Regression, and Random Forest Tree are three ML algorithms which have been developed then compared among themselves based on MSE scores to determine the best performing model. Additionally, Time Series Analysis on MATLAB is also performed to get more detailed understanding of the data in sequence on regular intervals of time.**

Keywords—wind energy, forecasting, machine learning.

I. Introduction

Wind Energy is a form of renewable energy that is getting huge attention worldwide. With increasing demand for electrical energy around the world due to rapid industrial and economic growth, conventional fossil fuel-based energy poses greater threats to the environment and raises global warming [1,2]. Hence, wind energy provides clean renewable energy that is environmentally friendly and has lower cost as well [3].

The installed capacity of wind power continues to rise as the sector expands quickly [2]. The existing wind power capacity worldwide in 2020 was 93 GW, a considerable increase of 52.96% from the installed capacity in 2019. Onshore and offshore wind power together have the potential to generate 86.9 GW and 6.1 GW of power, respectively, of recently commissioned capacity [4,5]. External weather factors like wind speed, wind direction, temperature, pressure etc. have huge impacts on the output power generated by the wind turbine. As the wind velocity fluctuates by just 1 m/s for a turbine on a wind farm with a big current capacity, the resultant power produced varies wildly. The nonlinear correlation between wind speed and wind power generation is the cause for this variation. To ensure sustainable energy development and to maximize the choice of wind farm sites, timely and accurate wind energy forecasting is essential [2, 3, 4].

To ensure accurate forecasting, a robust solution is proposed by deploying the concepts and algorithms of Machine learning (ML) as well as Deep learning (DL). ML and DL algorithms are trained and compared with each other in order to select/choose the best performing algorithm for our application. Furthermore, time series analysis is performed to analyze the behavior of the changing parameters on the output power in real time axis. For achieving the aim of accurate and efficient forecasting, best performing ML algorithm is further optimized by applying Genetics Algorithm.

The wind power forecasting system offers critical information for ensuring the correct incorporation of renewable electricity into the power grid and satisfies objectives regarding the efficient maintenance of trustworthy operational grids and trading in energy [4]. In order to ensure uninterrupted and continuous power supply, precise wind power predictions are needed at regular time intervals ranging from hours to many days in advance by electricity companies and operators. [6]

Recent research on wind power forecasting using deep learning algorithms demonstrated notable improvements. Indeed, the use of AI technologies is seen as the revolution in wind energy forecasting field. A multistep model based on Convolutional Neural Network (CNN) method with singular spectrum analysis, gated recurrent unit network, and support vector regression was developed by Liu et al. in their paper published in 2010 [7]. The results of the simulations demonstrated the success and effectiveness of their approach. Another illustration is given by Hong and Rioflorido11, who cascaded a CNN model with a neural network based on the radial basis function which employed double Gaussian function as the activation function [8]. The authors assert that their approach is extremely accurate at forecasting wind energy 24 hours in advance.

Currently, there is not a single weather prediction technology that can also estimate the output power generated by wind turbines without performing any further analysis on predicted weather data. Hence to address the problem, Numerical Weather Predictions Data (NWPD) is combined and processed through ML and DL algorithms to offer precise forecasts at time intervals from few hours to several days ahead. While statistical methods like autoregressive–moving-average (ARMA) and autoregressive integrated moving average (ARIMA) are also used for power forecasting which use historical data of generated output wind power [1].

In this study/experiment, it has been proposed and developed a hybrid solution by combining the numerical weather predictions data and respective output power generated at the same instance of time by the wind turbines. Decision Tree Regression, Random Forest Regression and Support Vector Regression (SVR) are the ML algorithms, while Recurrent Neural Network (RNN) and Long-Short-Term Memory (LSTM) are the DL algorithms that are trained

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and analyzed based on their Mean Squared Error (MSE) scores to identify and choose the best performing algorithm for our application. Additionally, the Time Series Analysis is also performed on MATLAB to validate and co-relate the results obtained from the ML and DL algorithms.

II. Methodology

In this study four ML and two DL algorithms are trained and compared based on their MSE score as the common performance matrix along with implementing the two DL algorithms on MATLAB as well. In MALAB, Time Series Analysis is also performed to visualize and analyze the data points at specific and successive time instances.

The dataset is obtained from the Kaggle [9] that comprises hourly weather and output power generated for one whole year collected from the wind turbine farm in Texas. The weather data contains four parameters as Wind speed (m/s), Wind direction (deg), Pressure (ATM) and Air temperature ('C), while output power generated is measured in kW. Since this dataset has both numerical weather prediction values as well as output power generated. Hence, we may call it a hybrid of weather data and output power generated data.

Once the suitable dataset is selected, the next step is to perform Exploratory Data Analysis (EDA) to analyze and understand the dataset in detail. The large absolute values in the data result in instability. To prevent that instability, normalization technique is used in neural network models. In addition, normalization results in efficient generalization of data. As the dataset is cleansed and understood completely, now it is ready to feed to the ML and DL models for training and testing purposes.[10]

Finally, the results and performance of each ML and DL model/algorithm is compared based on a common performance matrix that is MSE score in this case. Lowering the MSE score higher is the performance of the model and vice versa.

III. Machine Learning Algorithms

Machine algorithms take a known set of data as input and known/labelled corresponding outputs to train and learn the patterns and generate reliable predictions for the similar newer data input. Supervised ML generally performs two tasks, classification and regression. As our application requires continuous real values on output as prediction, regression algorithms have been used in this study/experiment.

A. Machine Learning

Decision trees use a tree-like structure to generate regression models. It incrementally develops a corresponding decision tree while segmenting a dataset into ever-smaller sections. The outcome is a tree containing leaf nodes and decision nodes. Each of the two or more branches on a decision node represents a value for the characteristic being considered [11]. A decision regarding the numerical target is represented by a leaf node. The root node is the uppermost decision node in the hierarchy and therefore represents the most accurate forecast.

The basic decision-making power of this kind of model is based on the concept of standard deviation reduction to determine a numerical sample's homogeneity. The standard deviation reduction depends on the standard deviation's drop following the splitting of a dataset by a feature. Finding the feature that results in the biggest standard deviation reduction i.e., the branches with the highest degree of homogeneity is the key to building a decision tree. Mathematically.

$$SD = \sqrt{\frac{\sum(x_i - \bar{x})^2}{n}} \qquad (2.1)$$

where SD is standard deviation, x_i is each element in dataset, mean of x_i and n is total number of elements in dataset

$$SDR = SD_{before\ split} - SD_{after\ split} \qquad (2.2)$$

The MSE score of this model for our dataset is 0.1678. The hourly actual and predicted output power generated trend graph generated by decision tree regression can be visualized and observed in Figure 1.

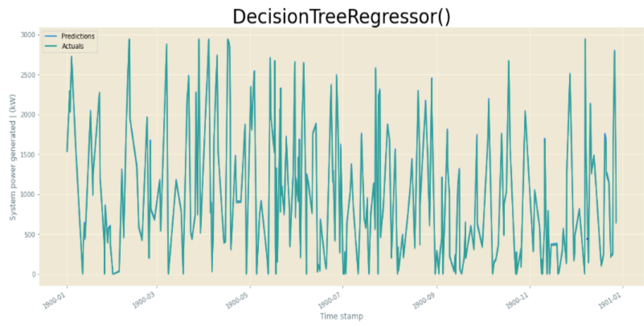

Fig 1 Decision Tree Regression.

B. Support Vector Regression

The objective of SVR is to minimize the error in predictions by identifying a function that approximately reflects the relation among the input variables and the continuous target variable. It looks for the hyperplane in a continuous space that best fits the data points. This is done by mapping the input parameters to a feature space with higher dimensions and then identifying a hyperplane which optimizes the gap (margin) between it and the nearest data points as well as reduces the prediction error. By utilizing a kernel function to translate the data to a higher-dimensional space, SVR may manage interactions between the input variables and the target variable that are not linear [12].

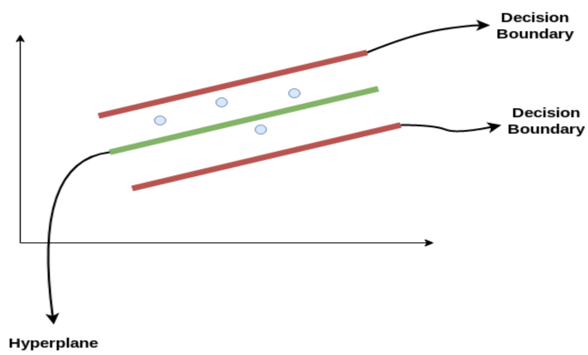

Fig 2 SVR Hyperplane.

In Figure 2, the green line is a hyperplane, and each of the red lines as the decision boundaries. The goal of using SVR is essentially to take consideration of the elements that fall

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inside the decision boundary lines. The hyperplane with the most points serves as our best fit line.

Assume that these lines are located at any distance from the hyperplane, let's say at distance 'a' and '-a', then equation of hyperplane is given as:

$$Y = wx + b \tag{3.1}$$

and the equations for the decision boundaries are given as:

$$wx + b = +a \tag{3.2}$$

$$wx + b = -a \tag{3.3}$$

Therefore, a hyperplane that fulfils our SVR must satisfy;

$$-a < Y - wx + b < +a \tag{3.4}$$

For our dataset, this model's MSE score is 12.4723. While the below graph shows the trend between actual and forecast values of the output power generated.

C. Random Forest Regression

Random Forest Regression is a supervised learning algorithm built on a large number of Decision Trees and the ensemble learning approach. As a bagging method, Random Forest runs all calculations concurrently without allowing for any interaction amongst the Decision Trees that are constructed.

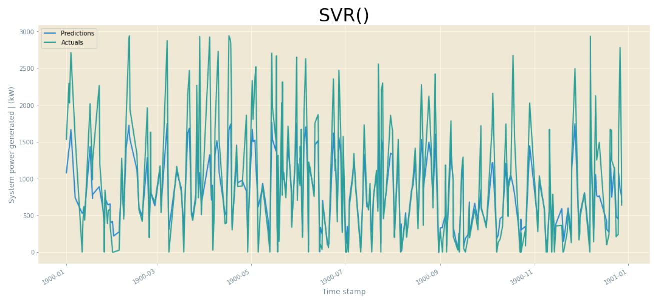

Fig 3. SVR results.

K subsets of the data are created by Random Forest from the initial data set D. The term "out-of-bag" samples refers to samples that don't fit into any subset. K trees are constructed using only a single subset. Additionally, every tree is constructed unless each node contains N samples or fewer. Furthermore, F attributes are chosen at random for each node. The final result for the Regression problem is created by averaging the predictions of the various trees [13]. One of them is utilized to partition the node *K* trained models into an ensemble. Below figure shows the working mechanism of the random forest tree.

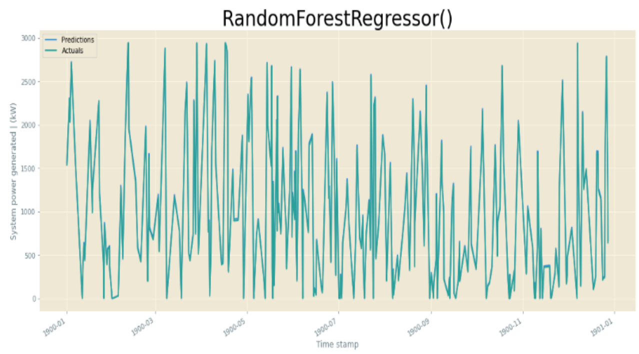

Fig 4. Working Mechanism of random forest tree.

For our dataset this algorithm has the lowest MSE of 0.1102 and has the best performance among all the ML and DL algorithms that are built and evaluated. The actual and predicted output power generated is shown in Figure 5.

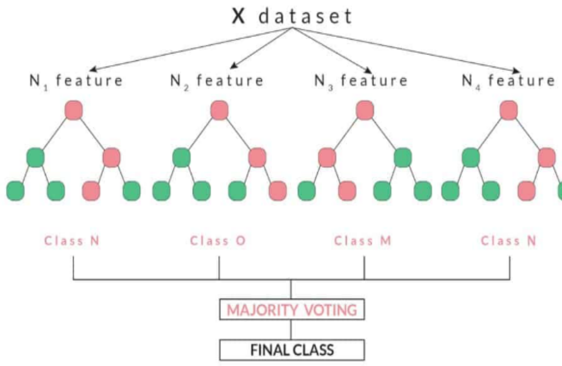

Fig 5. Random Forest Regressor.

D. Deep Learning

Deep learning neural networks, also known as artificial neural networks, aim to emulate the functioning of the human brain by utilizing biases, weights, and input data. These components work together to effectively analyze, categorize, and describe various aspects of the data. Deep neural networks consist of multiple interconnected layers of nodes, where each layer enhances the predictions or classifications made by the preceding layer. The process of propagating calculations through the network, from the input layer to the output layer, is referred to as forward propagation [14]. In a deep neural network, the input and output layers are visible and well-defined, while the intermediate layers are hidden and represent a black box with limited accessible information. The deep learning model takes input data at the input layer, processes it through the network, and produces the final prediction or categorization at the output layer [15]. Figure 6 provides a visual representation of the operational flow and interconnections between the layers in a deep learning model.

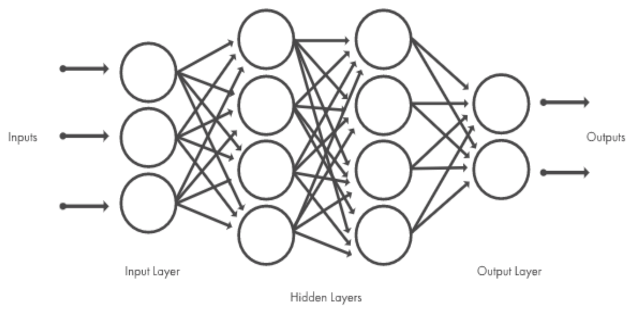

Fig 6. Layers of deep learning model.

E. Recurrent Neural Network

Recurrent neural network (RNN) is a kind of artificial neural network in which the outputs of the previous step are used as inputs for the next step. Each fixed activation function unit within the RNN represents a single time step. Every unit has an inner state that is referred to as its hidden state. The network's current knowledge of the past is represented by this concealed state at a particular time step. On each step, this invisible state is modified to reflect changes in the network's

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understanding of the past. The recurrence relation listed below is used to update the hidden state [14, 15].

$$h_t = f(h_{t-1}, x_t) \qquad (3.5)$$

where h_t is current state, h_{t-1} is next state and x_t is input state.

While the activation function is applied as:

$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t) \qquad (3.6)$$

where W_{hh} is recurrent neuron weight and W_{xh} is input neuron weight.

The MSE score for our application of this RNN model is 0.7670 and the actual vs predicted values trend can be observed in Figure 7.

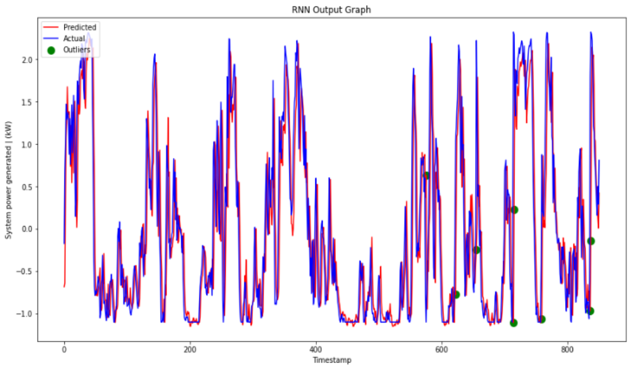

Fig. 7 RNN Output Graph

F. Long-Short-Term Memory

LSTM algorithms offer an advantage over simple RNN (Recurrent Neural Network) models as they can capture long-term dependencies within a dataset. The essential element of an LSTM model is the "cell state," which serves as a memory cell capable of retaining its state over time. In the accompanying diagram, the cell state is depicted by a horizontal line traversing the top portion. It can be visualized as a conveyor belt, allowing data to flow through without any alteration or distortion [16]

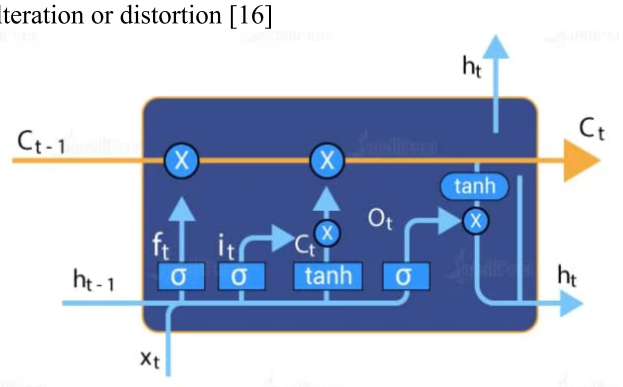

Fig 8. LSTM model. [17]

In LSTMs (Long Short-Term Memory), gates are responsible for regulating the flow of information into and out of the cell state. These gates determine whether information should be added or removed from the cell. The mechanism is aided by a sigmoid neural network layer and a pointwise multiplication operation. The sigmoid layer produces a number between zero and one, where zero signifies that "nothing should be allowed through" and one indicates that "everything should be allowed through. This mechanism effectively controls the flow of information within the LSTM architecture, ensuring relevant information is retained and irrelevant information is filtered out.

The MSE score of LSTM model for wind forecast data is 01779 while the output power generated actual and predicted by the model can be visualized in Figure 9.

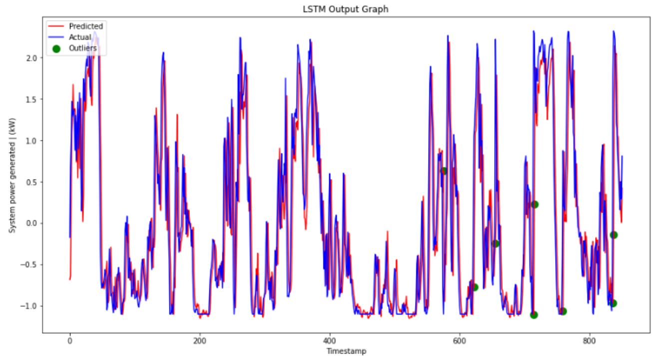

Figure 9 LSTM output graph.

G. Time Series Analysis

Time series analysis (TSA) is a method used to analyze a collection of data points that are gathered and recorded over a specific period of time. Unlike random or sporadic data collection, time series analysis involves capturing data points at regular intervals throughout a predefined timeframe [18].

The analysis of time series data allows us to examine how variables evolve and fluctuate over time, distinguishing it from other types of data analysis. Consequently, time becomes a crucial element as it not only unveils the changes in the data points over the duration of the analysis but also reveals the corresponding outcomes. Furthermore, time series analysis provides additional data sources and establishes a predefined order of data dependencies [19].

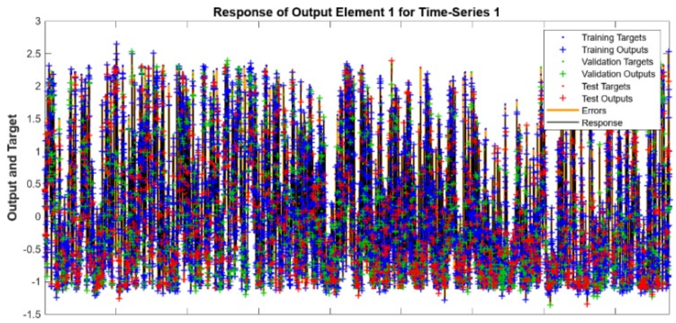

Fig 10. Response of output element 1.

The MSE score for TSA performed in MATLAB is 0.1171. The changes in the actual and predicted data points can be visualized and analyzed in Figure 11.

IV. Results and Discussion

By comparing the MSE scores of all the applied algorithm, it is evident that there is notable difference in the performance of each model. This difference of performance between different algorithms is caused by the nature of the algorithm i.e. whether the algorithm is deterministic, stochastic or probabilistic.

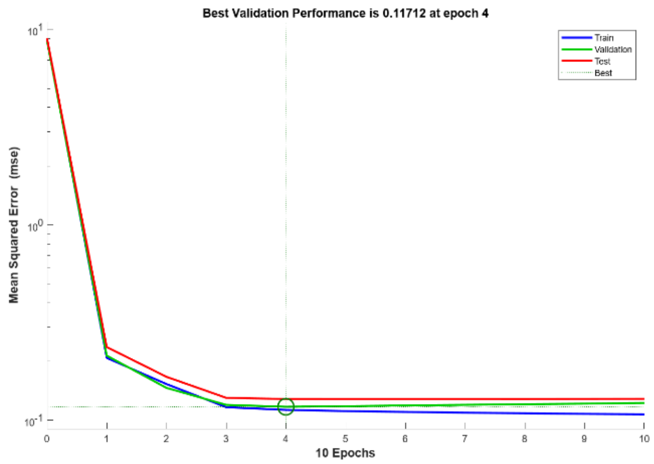

Fig 11. Best Validation Performance.

As shown in Table I, it can be easily observed and established that both the DL algorithms (i.e. RNN & LSTM) have MSE score higher than the two ML algorithms except SVR. In this case SVR has the highest MSE, hence it is the least effective model. While Random Forest has the best MSE score followed by the Time Series Analysis of LSTM performed on MATLAB. While SVR n Decision Tree also perform well. But the most effective and efficient algorithm for this Wind Energy Dataset model is Random Forest Regression.

TABLE I. RESULTS COMPARISON FOR DIFFERENT ALGORITHMS.

S. No.	Model Name	MSE Score
1	Decision Tree Regression	0.1678
2	Support Vector Regression (SVR)	12.4723
3	Random Forest Regression	**0.1102**
4	Recurrent Neural Network	0.7670
5	Long-Short Term Memory (LSTM)	0.1779
6	Time series Analysis (TSA) of LSTM	**0.1171**

V. CONCLUSION AND FUTURE WORK

Wind energy is renewable energy that is powered by wind, and its use can help to solve the ever-increasing energy demands. The consistent availability of wind energy faces major difficulties due to the randomness and complexity of the wind. Big data and AI advancements have made wind energy forecasting possible and more reliable.

A comparison study of various wind power forecasting algorithms was conducted in this work. Decision Tree Regression, SVR and Random Forest Tree are three the ML algorithms while RNN and LSTM are the two DL methods that were trained and compared with each other on the basis of their MSE score to choose the best performing model. Additionally, TSA is also performed on MATLAB to further validate and get a detailed insight of the results obtained from ML and DL algorithms. It is observed that Random Forest Tree has the lowest MSE score of 0.1102 among all the ML and DL algorithms and is the most suitable model for our application/dataset. All of the aforementioned techniques were used to anticipate wind energy one hour in advance.

In future endeavors, Genetic Algorithm (GA) based optimization of some of the AI Algorithms is recommended for implementation. GA is a generative algorithm that further optimizes and boosts the performance of an AI model. [20] GA is a heuristic optimization approach designed to address searching and optimizing issues. It is part of the computationally useful evolutionary algorithms. The idea of natural selection and genetics is applied by genetic algorithms to offer answers to issues.

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