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Prediction of Power Production for Wind Energy Using Machine Learning

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ABSTRACT:

Increasing the utilization of wind energy is having the great significance for the improvement in energy structure, which is cannot be done without the support of Wind Power Forecasting (WPF) technology. The historical database is portioned into different types based on characteristics and prediction models are recognized for each category respectively. Long Short Term Memory (LSTM) and Convolution Neural Networks (CNN), which are some well-known types of neural network models in machine learning that are renowned for their effectiveness in time series forecasting, making them suitable for wind power prediction. Both LSTM and CNN are designed for taking temporal dependencies in sequential data, making them well suited for time-varying behavior of wind speed and other factors for wind power prediction.

INTRODUCTION

Wind is known for its clean energy that exists on the planet. This energy type is unlimited, less expensive, inexhaustible, feasible and harmless to the ecosystem. Constructing wind energy structures can reduce the pollution by improving the power generation in future. These non-conventional energy resources are receiving more consideration because of their natural, eco-friendly and free of cost environmentally in clean nature. The variable and unpredictable behavior of wind poses a challenge for improving the performance of wind energy for good power supply [1]. The accurate forecasting of the wind power can reduce the adverse effect of wind power plants on power networks [8]. Accurate wind power estimating is one of the crucial technologies to deal with this problem. At present, there are physical technique, statistical technique and learning techniques. Different mechanisms are utilized for various time scales and various data sources. Statistical techniques and learning are used based on historical data for predicting wind power output over a six-hour period in the near future. Any of these three strategies can be utilized in view of numerical weather prediction for the forecast within 48 hours [6]. Statistical methods aim at describing the connection between predicted wind power throughputs directly by statistical analysis.

The method of machine learning employs AI algorithms capable of identifying intricate and nonlinear connections between input and output data. This approach aids in creating algorithms that learn from the data and make predictions based on it. Machine learning algorithms are effective in characterizing the dataset, relating input model features to the anticipated output, and predicting output features based on historical data [6]. Examples of machine learning models include Long Short-Term Memory (LSTM), Random Forest (RF), and Support Vector Machine (SVM) [4],Logistic chaos search optimization (LCASO) [2], Recurrent neural network, CNN [2], Back-propagation Neural Network (BPNN) [2], multi-layer feed forward neural network (MLFFNN) [4] etc. Selection of the appropriate ML model is very important thing. By taking into account of benefits and advantages, LSTM and CNN models are chosen for the prediction of wind power.

SYSTEM DESIGN

LSTM: The LSTM network is a specialized form of Recurrent Neural Network (RNN) designed to manage long-term dependencies in sequential data. It employs memory cells and gating mechanisms to regulate data flow, enabling selective retention or discarding of information. This architecture effectively mitigates the vanishing gradient issue. LSTMs are adept at handling and analyzing sequential data, including time series, text, and speech.

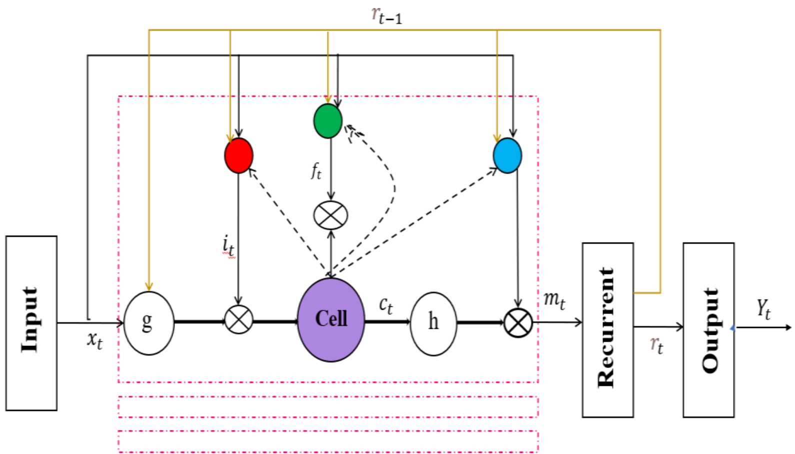

Fig 3.1 LSTM architecture in a single memory block is show for clarity.

Fig 3.1 shows the architectural flow of the LSTM-RNN model in a single memory block [1]. LSTM machine learning model, renowned for forecasting time series data which is used to learn patterns in wind and make a prediction about wind power. The input for the LSTM model at a specific time step is "$\boldsymbol{x_t}$". It can be a vector of real numbers representing the data at that time step, "$\boldsymbol{f_t}$" is the forget gate and it is a sigmoid function which determines the information from the "$\boldsymbol{C_{(t-1)}}$" (previous cell state) to forget. Values close to 0 means forget the information, while values close to 1 means keep the information, "$\boldsymbol{i_t}$" is the input gate and it is another sigmoid function which calculates what amount of the current input "$\boldsymbol{x_t}$" to store in the cell state. If it is close to 0 means ignore the input and if it is close to 1 means keep all the input, "g" is the candidate cell state and it is a "tanh" function that creates a new vector of values which can be stored to the cell state, "$\boldsymbol{C_t}$" is the cell state and it is a vector of values which represents LSTM's models memory. It is updated at each time step on the basis of forget gate, the input gate, and the candidate cell state, "*h*" represents the hidden state,"$\boldsymbol{r_{(t-1)}}$"represents the previous output gate value, which plays a vital role for calculating how much information from the"$\boldsymbol{C_{(t-1)}}$" i.e., previous cell state needs to incorporate into the current cell state $\boldsymbol{C_t}$. It acts as a memory of the previous output.

$C_t = f_t * C_{(t-1)} + i_t * g + r_{(t-1)} * (O_{(t-1)} * C_{(t-1)})$

In the above equation, $f_t * C_{(t-1)}$ represents the previous cells forgotten data weighted by the forget gate, i_t * g represents the new information appended for cell state from the current input and candidate cell state which is weighted by the input gate,$r_{(t-1)} * (O_{(t-1)} * C_{(t-1)})$ is the essential part that pointed out which represents the previous cell state's information that is modulated by the previous output gate and then scaled by the current output gate [1]. This permits the model for selecting the incorporate past results based on the current output gate.

A typical LSTM unit is made out of a output gate, forget gate, input gate and a cell. Input gate update the memory gate by arranging values of the input. Forget gate chooses what data to discard from the block. Output gate chooses what to output based on the input of the memory of the block. The cell is in control for remembering values for a time spans and this model can be utilized for ideal assessment of power generated by the system. LSTM can be used as a complex nonlinear unit to construct a larger deep neural network, that can mirror the impact of LSTM has the capability to facilitate deep learning.

CNN (Convolution Neural Network): In the realm of power system management, accurate classification of power generation is necessary for optimizing energy production and ensuring grid stability. For this task CNN is a effective algorithm, which is capable of exceptional capabilities in extracting patterns and making intelligent classifications from power system data. Architecture of CNN is shown in the figure 3.2. CNN acts as a classification model for the LSTM's prediction. Its architecture typically consists of several layers i.e., convolution layers, pooling layers and fully connected layers.

Convolutional layer: It removes the neighborhood designs from the arrangement of predicted power values.

Pooling layer: It samples the result from the convolutional layers, diminishing the dimensionality of the information and computational expense. The final layers in the CNN architecture are typically fully connected layers. These layers combine the features extracted by the convolutional and pooling layers and learn to map those features into discrete categories (low, mid, high) for wind power generation.

Fully Connected Layer: It fully integrates the layers as a classifier, utilizing the features obtained from the predicted power sequence. These layers use actuation capabilities like softmax to produce circulations for every class (low, mid and high).

PROPOSED METHODOLOGY

In the proposed framework, the principal philosophy of the model is displayed in Fig 3.3 which address the proposed methodology of proposed procedure which includes collection of data, pre-processing of the data, classification of data, selecting suitable model, model training and testing. Data collection is a process of gathering historical wind speed and additional information gathered from multiple sources as weather stations, sensors or historical records [1]. Data Pre-Processing is a process of cleaning the required data, because it may includes missing values, outliers and data normalization [1].Model selection is the method for choosing a Machine Learning (ML) algorithm suitable for time-series data, such as LSTM and CNN [1]. Train the chosen ML model with the training data. When the model performs well, integrate it into the wind power production system to provide real time wind energy predictions. Comparing the predicted values with actual generated values for computing metrics like RMSE (Root Mean Square Error), MAE (Mean Absolute error) and MAPE (Mean Absolute Percentage Error).

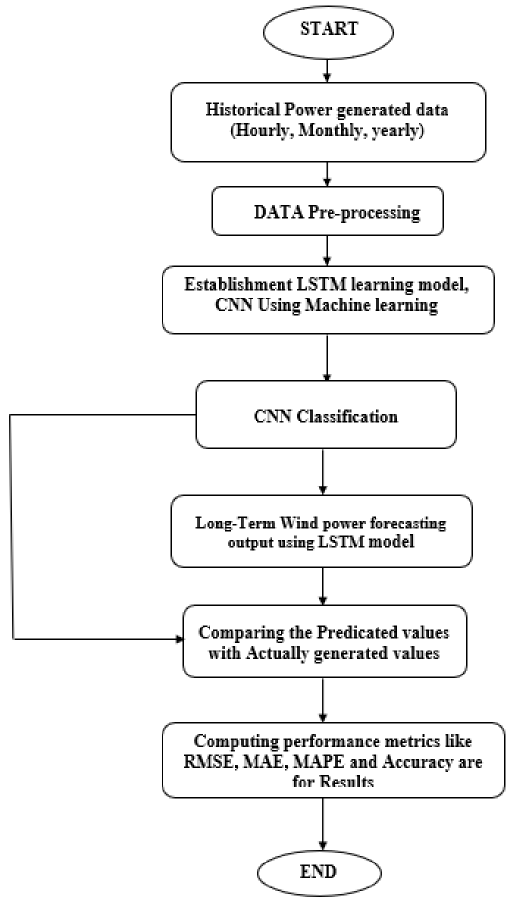

Fig 3.3 Data-flow diagram.

The above Fig 3.3 describes the architectural flow of wind power forecasting to achieve accurate predictions by using LSTM and CNN ML algorithms.

RESULTS AND DISCUSSIONS

After forming the LSTM model, we performed experiments to acquire the perfect look back and the neurons which are required by the LSTM. After getting the look back, neuron number and certain other parameters right for the model we performed a few experiments and predictions. The outcomes are as follows.

Prediction of 12 hours

Fig 4.1 represents the 12 hours data predicted with the below model configurations. Input Batch Size is 1, Epochs is 7, Number of Neurons is 10, Predicted_values_exp is12 and Look Backs is 24.

Prediction of next 24 hours (2Day)

Fig 4.2 represents the 24 hours data predicted with the below model configurations. All the configurations remain as same as the predication of 12 hours but Predicted_values_exp is changed to 24.

Prediction of next 24 hours (2days)

Fig 4.3 represents the 48 hours data predicted with the below model configurations. All the configurations remain as same as the predication of 12 hours but Predicted_values_exp is changed to 48.

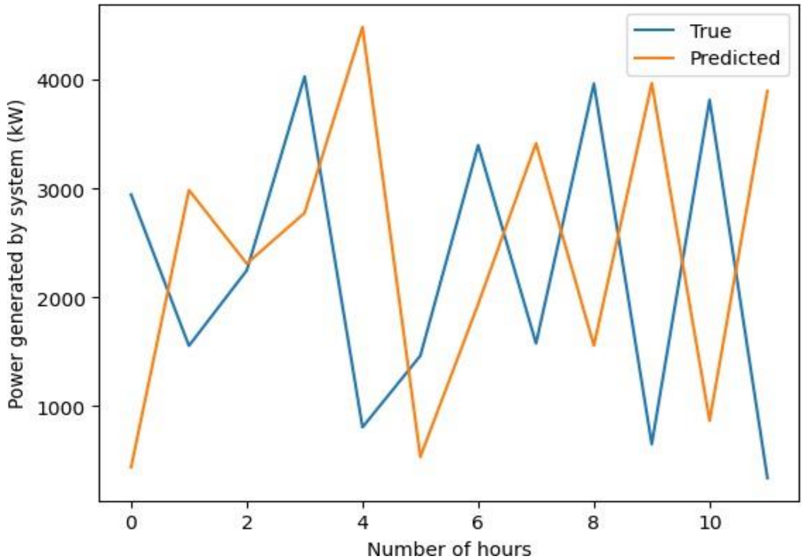

Fig 4.1 12 hours prediction.

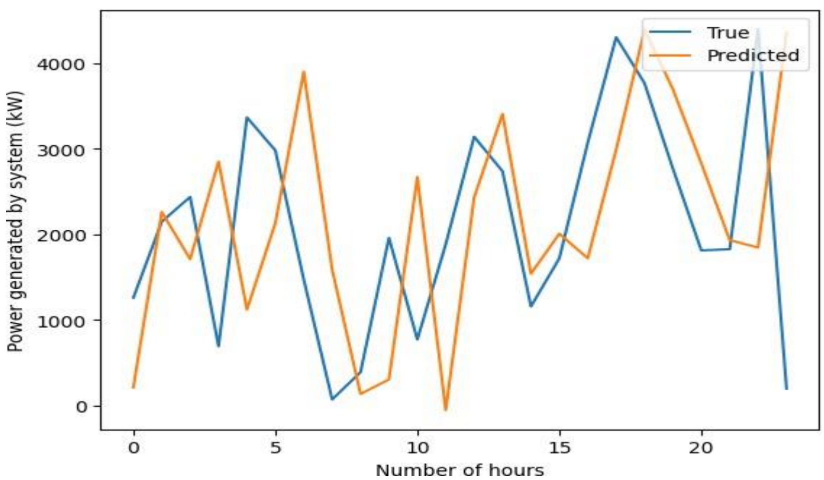

Fig 4.2 24 hours (1-day) prediction.

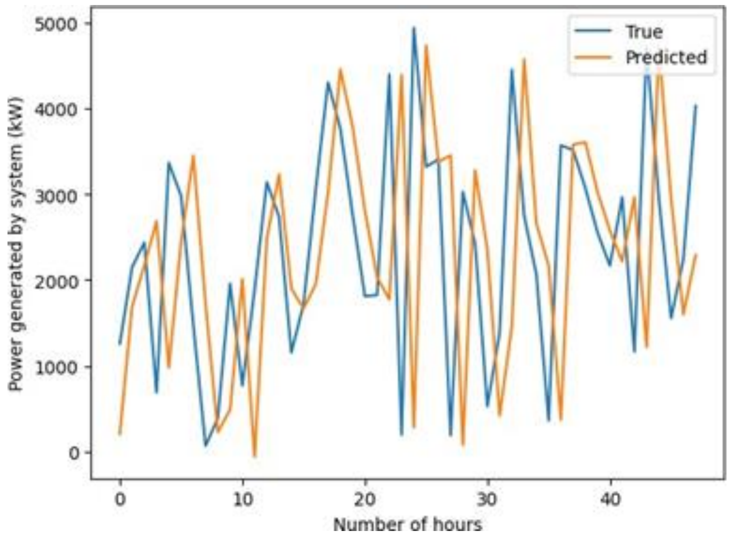

Fig 4.3 48 hours (2-days) prediction.

CONCLUSION

In this task, prediction of wind energy is attained by using both LSTM and CNN models. To classify the power levels into low, mid and high categories CNN model is utilized. By pre-processing the data and designing an appropriate CNN, we can create an accurate classification system. The LSTM model is employed for predicting future power generation in time series based on environmental factors such as wind speed, air temperature, air pressure, and wind direction. The LSTM's capacity to capture long-term conditions in sequential data made it well suited for this task. By pre-processing the data, designing LSTM model and training the model, we create a forecasting framework for power generation. Integration of LSTM and CNN models gave a comprehensive approach to deal with predicting wind power. The CNN model classifies based on current power, while the LSTM model predicts the future power based on environmental variables. This combined approach can be highly beneficial for improving power generation systems for providing valuable vision for resource management and decision making.

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