WIND FORECAST PREDICTION USING LSTM

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ABSTRACT

The integration of renewable energy sources into the main electrical grid depends on an accurate wind speed forecast, which is also crucial for the stability, scheduling, and planning of the power system. In order to evaluate the experiments and forecast the tentative trend of wind speed, we offer the Long Short-Term Memory (LSTM) and bidirectional LSTM algorithms (Bi-LSTM) in this study. These algorithms use various configurations and activation functions. To forecast the wind speed over Egypt's Gabal Elzayt Wind Farm, we employed both models. The used data set is a part of the MERRA-2 wind speed datasets published monthly by NASA. The LSTM network with "Sigmoid" as the gate activation function and the "SoftSign" function as the state activation function outperformed previous tests and had the lowest RMSE error. After validation, the trained model is used to forecast the wind farm's preliminary trend in wind speed for the years 2020–2022. The application of LSTM and Bi-LSTM in the field of long-term wind prediction was successful.

INTRODUCTION

Because of the growing concerns about environmental degradation and the depletion of non-renewable resources, the production of electrical energy more efficiently has received a lot of attention recently.A reliable, clean, renewable energy source is wind power. Because they are environmentally beneficial, wind energy sources have thus been contributing more and more to the electrical system recently.However, wind energy management is made difficult by the unpredictable intermittent nature of wind energy. Concerns about safety and power grid stability arise as the proportion of recently installed wind turbines in the power grid increases quickly. Therefore, the grid's operation can be improved by accurate forecasting of wind speed and relative wind power. Effective wind energy forecasting results in the grid operating more cost-effectively, efficiently, and safely. The more accurate wind, the more reliable and efficient power dispatch, energy storage systems, and effective power transmission.

EXISTING SYSTEM

Methodology based on SVM: Based on hyper plane separation, SVM is a biassed allocation that is defined. The trained data that has been tagged, which is essentially supervised data, provides an ideal hyper plane. In the suggested approach for compiling accessible data for implementation, data collecting is carried out based on a variety of distinct parameters.

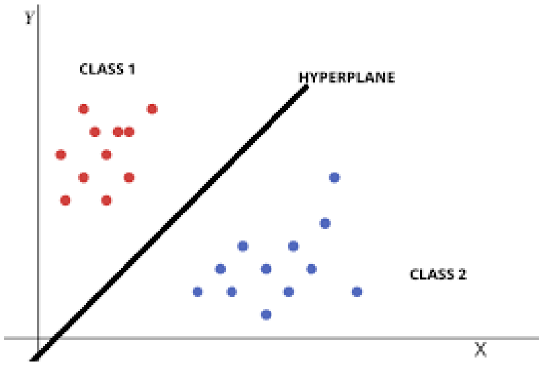

Fig.1. svm methodology

DISADVANTAGES

While LSTM (Long Short-Term Memory) models have been used successfully for wind forecast prediction in some cases, there are also some disadvantages associated with their use. Here are a few disadvantages of using LSTM for wind forecast prediction:

Data requirements: LSTM models typically require a large amount of training data to perform well. For wind forecast prediction, this means a significant historical dataset of wind data is needed. Obtaining such a dataset may be challenging, particularly if the location or time period of interest has limited data availability.

Computational complexity: LSTM models can be computationally intensive, especially if the dataset is large or if the model architecture is complex. Training and running LSTM models for wind forecast prediction may require substantial computational resources, which can be costly and time-consuming.

Over fitting: LSTM models are prone to over fitting, which occurs when the model becomes too specialized in capturing the details and noise of the training data. This can lead to poor generalization and limited accuracy when making predictions on unseen data. To mitigate overfitting, careful regularization techniques and hyperparameter tuning are required.

Interpretability: LSTM models are often regarded as black-box models, meaning they provide accurate predictions but offer limited interpretability. Understanding the reasoning behind the model's predictions and identifying the factors that contribute to the forecasted wind patterns can be challenging. This lack of interpretability may limit the model's utility in certain contexts, where explainability is crucial.

Sensitivity to hyperparameters: LSTM models have several hyperparameters that need to be set appropriately to achieve good performance. Determining the optimal values for these hyperparameters can be a trial-and-error process, requiring extensive experimentation and tuning. Moreover, the optimal hyperparameter values may vary depending on the specific wind forecast prediction task and dataset, making it time-consuming and potentially suboptimal.

Handling long-term dependencies: While LSTMs are designed to capture long-term dependencies in sequential data, they can still struggle with capturing very long-term dependencies effectively. In wind forecast prediction, where the interaction between weather patterns and wind patterns can span across various time scales, the LSTM model may face challenges in accurately capturing and representing these complex dependencies.

Real-time prediction limitations: LSTM models usually require the entire input sequence to be available before making predictions. This limitation makes them less suitable for real-time wind forecast applications, where timely predictions based on incoming data are essential.

It's worth noting that while LSTM models have their disadvantages, they have also demonstrated promising results in wind forecast prediction tasks. The suitability and performance of LSTM models may vary depending on the specific dataset, problem formulation, and modeling choices.

PROPOSED SYSTEM

In proposed system, we are opting to optimize the network with minimal errors using recurrent neural network and temporal neural network i.e.., inspiration from backpropagation we want to implement a new model.

We are using LSTM model that are designed to model sequences of data by maintaining memory of past inputs.

To use an LSTM for wind speed forecasting, you would typically pre-process the data by dividing it into sequences of a fixed length, such as hourly or daily intervals, and normalize the data to improve training performance. You would then train the LSTM on the pre-processed data, using a loss function such as mean squared error to optimize the model's weights

A thorough summary of earlier studies on a subject is called a literature review. In a literature review, academic books, journal articles, and other sources that are pertinent to a certain field of study are surveyed.

Here are some of the literature surveys of wind speed forecasting project:

Current status and future advances for wind speed and power forecasting J Jung, RP Broadwater - Renewable and Sustainable Energy Reviews, 2014 - Elsevie

A review on the forecasting of wind speed and generated power M Lei, L Shiyan, J Chuanwen, L Hongling energy reviews, 2009 - Elsevier Different models of wind speed prediction; comprehensive review SM Lawan, W Abidin, WY Chai, A Baharun International Journal of 2014 Citeseer.

RMSE for the LSTM is 0.427, and for the SVM, it is 0.768. It is obvious to see that the SVM method has a higher error rate than the LSTM algorithm. SVM has a higher error rate than LSTM since it lacks LSTM's ability to remember patterns for extended periods of time.

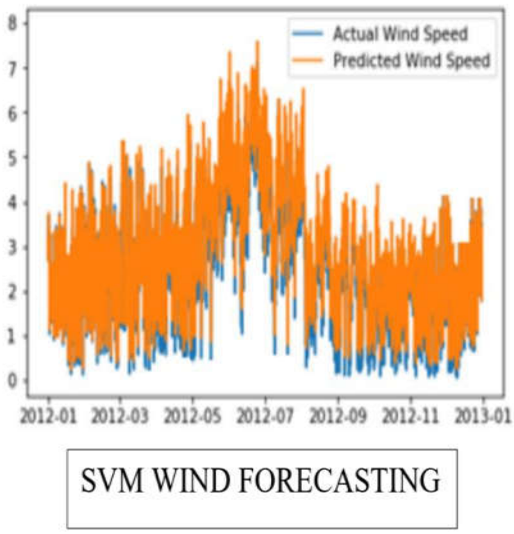

Fig.2. SVM window forecasting

PROBLEM DEFINITION

The growing usage of distributed energy sources, which are predominantly based on renewable sources, has led to the development of wind speed forecasting as a significant area of research to serve the electricity business.

In order to anticipate future wind patterns using previous wind data and other pertinent meteorological variables, Long Short-Term Memory (LSTM) neural network models are applied. Modelling sequential data with long-term dependencies is a task that is ideally suited for LSTM, a particular type of recurrent neural network (RNN).

In wind forecast prediction, the LSTM model takes as input a sequence of past wind measurements, along with other environmental variables such as temperature, pressure, humidity, and geographical information. The

model learns from this historical data to capture the complex relationships and patterns between these variables and the corresponding wind patterns.
During the training phase, the LSTM model learns to understand the temporal dependencies and dynamics of wind patterns over time. It adjusts the weights and biases of its internal nodes to optimize its ability to predict future wind conditions based on the given inputs. The model learns to capture both short-term and long-term patterns in the data, allowing it to make accurate predictions for future time steps.

LSTM based methodology
Generally speaking, this type of methodology relies on neural network techniques to make predictions, and the neural network process is used to produce results. The nodes in neural networks are connected by directed cycles, which are a type of recurrent neural network. Back propagation is an algorithm that's utilised for training, and it shares parameters between all of its steps for better, more effective results. The first step in the proposed methodology is to compile the data that is already available for use; the criteria used to obtain this kind of data vary. Basic environmental parameters are what are being used here as parameters. The second aim of the pre-processing step is to use data visualisation to reduce the dimensionality of the data.

Data visualization's major goal is to choose the necessary parameters from the entire dataset. The newly acquired set of variables is now taught using the back propagation process of recurrent neural networks. The final step is to apply LSTM to the trained data after the data has been trained in order to produce predictions and the error rate (RMSE value).

The working of LSTM is defined briefly below.
Due to the output gradient's dependence on past values rather than only the present ones, back propagation occurs throughout time. LSTM calculates hidden states using a variety of functions. A memory cell in an LSTM consists of four major components: an input gate, a neuron, a forget gate, and an output gate. The LSTM gate is the only component required for interaction between the environment and memory cells. We must back propagate two steps in order to calculate a gradient at step 3, then we must add the gradient value.

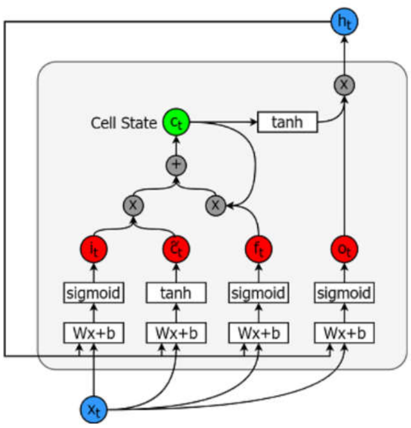

Fig.3. LSTM Cell Structure

System Architecture

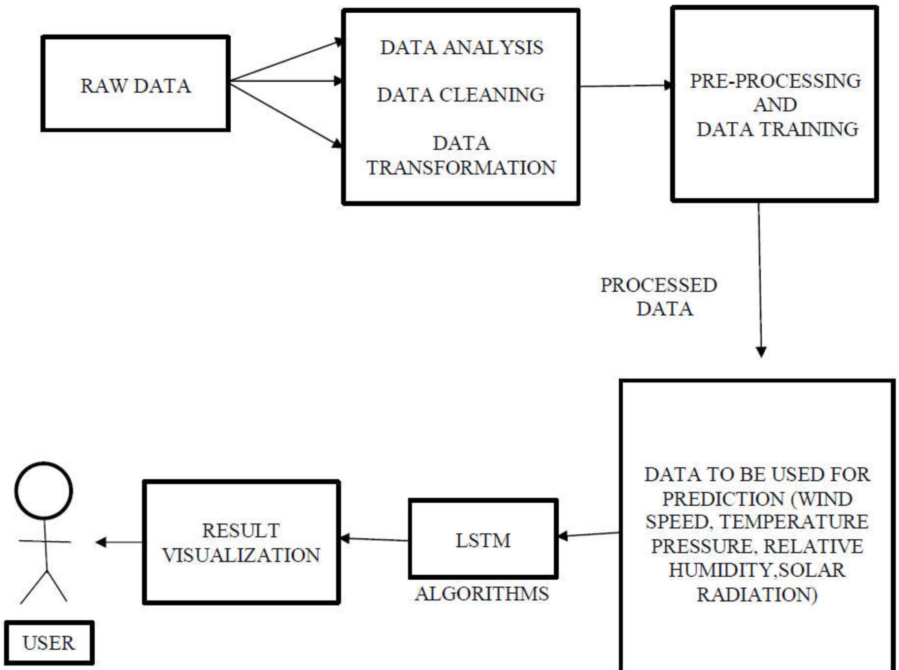

Fig.4. system architecture

The system architecture for wind forecast prediction using LSTM typically involves several components working together. Here's a high-level overview of the system architecture:

Data Collection: This component focuses on collecting wind-related data from various sources. It may involve accessing weather stations, sensors, or meteorological databases to gather historical wind measurements, as well as real-time or near-real-time data for forecasting. The collected data can include attributes such as wind speed, direction, temperature, pressure, humidity, and time stamps.

Data Preprocessing: The collected wind data needs to be preprocessed before feeding it into the LSTM model. This preprocessing component involves tasks such as data cleaning, handling missing values, normalizing the data, and possibly performing feature engineering to extract relevant features or derive new ones. Preprocessing ensures that the data is in a suitable format for training the LSTM model.

LSTM Model: The LSTM model is the core component responsible for learning and predicting wind forecasts. It consists of one or more LSTM layers, which are specialized recurrent neural network (RNN) layers capable of capturing long-term dependencies in time-series data. The LSTM layers are connected to other layers, such as Dense layers, for final output predictions. The model architecture can vary based on the specific requirements of the wind forecast problem.

Training and Validation: This component involves training the LSTM model using the preprocessed historical wind data. The training process iteratively adjusts the model's weights and biases to minimize the prediction errors. Validation is performed by evaluating the model's performance on a separate validation dataset to ensure it generalizes well to unseen data. Various evaluation metrics, such as mean squared error (MSE), mean absolute error (MAE), or root mean squared error (RMSE), can be used to assess the model's accuracy.

Prediction: Once the LSTM model is trained and validated, it can be used for wind forecast prediction. This component takes in new input data, such as recent wind measurements, and feeds it into the trained model. The LSTM model processes the input sequence and generates forecasts for future wind values. The prediction component may also include post-processing steps to transform or scale the predicted values, as well as generate visualizations or reports for easy interpretation and analysis.

Deployment and Integration: The final step is deploying the wind forecast prediction system for practical use. This component involves integrating the trained LSTM model into a production environment or system where it can receive real-time or batch inputs and generate wind forecasts accordingly. The deployment can be done through various means, such as web applications, APIs, or standalone software.

IMPLEMENTATION

LIBRARIES

Pandas

Using its potent data structures, Pandas, an open-source Python library, offers high-performance data manipulation and analysis tools. Python was mostly utilised for data preprocessing and munging. It did not make much of an impact on data analysis. Pandas figured out the solution. Regardless of the source of the data input, we may complete the five standard processes of data processing and analysis using Pandas: prepare, modify, model, and analyse. Python and Pandas are utilised in a variety of academic and professional sectors, such as finance, economics, statistics, analytics, etc.

Matplotlib

In a number of hardcopy formats and interactive settings across platforms, Matplotlib, a Python 2D plotting tool, generates figures of publishing quality. In addition to four graphical user interface toolkits, Matplotlib can be included into Python scripts, the Python and Ipython shells, the Jupyter Notebook, web application servers, and Python scripts. Easy tasks are made to seem difficult using Matplotlib, and the converse is also true. With just a few lines of code, graphs, histograms, power spectra, bar charts, error charts, scatter plots, etc. can be produced. You can see samples in the sample plots and thumbnail galleries.

Particularly when used in conjunction with IPython, the pyplot package offers a MATLAB-like interface for basic plotting. For the power user, there are two options for controlling line styles, font settings, axis properties, etc.: an object-oriented interface or a set of MATLAB-friendly functions.

Numpy

NumPy is a fundamental Python library for numerical computing. It stands for "Numerical Python." NumPy provides a powerful array object called **ndarray** (N-dimensional array), along with a wide range of functions and operations that allow efficient manipulation of large, multi-dimensional arrays and matrices.

NumPy is widely used in various domains, including data analysis, machine learning, image processing, signal processing, simulation, and scientific research. Its efficient array operations and mathematical functions make it a crucial library for handling large datasets, performing numerical computations, and building complex data processing pipelines in Python.

This allows you to access NumPy functions and objects using the ‘**np** ‘namespace prefix, such as creating arrays, performing operations, or applying mathematical functions.

Scikit learn

The popular Python module Scikit-learn is used for machine learning tasks. It offers a comprehensive array of tools and methods for feature extraction, model selection, and model evaluation. A strong and comprehensive Python machine learning package, Scikit-learn is developed on top of NumPy, SciPy, and Matplotlib.

Windrose

In Python, the wind rose library provides functionality to create wind roses, also known as polar bar plots, to visualize wind direction and speed data. Wind roses are commonly used in meteorology and climatology to represent wind patterns and frequencies.

ALGORITHMS

Obtain past wind information for a certain area. Data elements including wind speed, direction, temperature, humidity, pressure, and any other pertinent variables should be included. Create training and test sets from the data.

Normalize the input data to improve the training process and ensure that all features are on a similar scale. You can use techniques like min-max scaling or standardization.

Convert the normalized data into sequences of fixed length. Each sequence will contain a series of consecutive data points. The length of the sequence will depend on the characteristics of your data and the forecast horizon you want to predict.

Divide the sequences into input (X) and output (y) components. The input sequences will be used to predict the output values, which are typically the wind speed or direction for the next time step.

Create an LSTM model using a deep learning framework such as TensorFlow or Keras. The model should consist of one or more LSTM layers followed by one or more fully connected (dense) layers. Experiment with different architectures and hyperparameters to find the optimal configuration.

Train the LSTM model using the training data. During training, the model learns to capture temporal patterns and dependencies in the data. Adjust the number of epochs and batch size to avoid overfitting or underfitting.Use the trained LSTM model to make wind speed or direction predictions on new, unseen data. Preprocess the new data in the same way as the training data, create sequences, and feed back to their them into the model to obtain the predictions.

If necessary, apply inverse transformations to the predicted values to bring them original scale. This step is important if you normalized the data during preprocessing.

Visualize the predicted wind values along with the actual values to assess the model's performance. You can use line plots, scatter plots, or other appropriate visualization techniques.Refine your model by adjusting hyperparameters, architecture, or preprocessing techniques based on the performance and feedback. Iterate on the process to improve the accuracy of the wind forecasts.

RESULTS

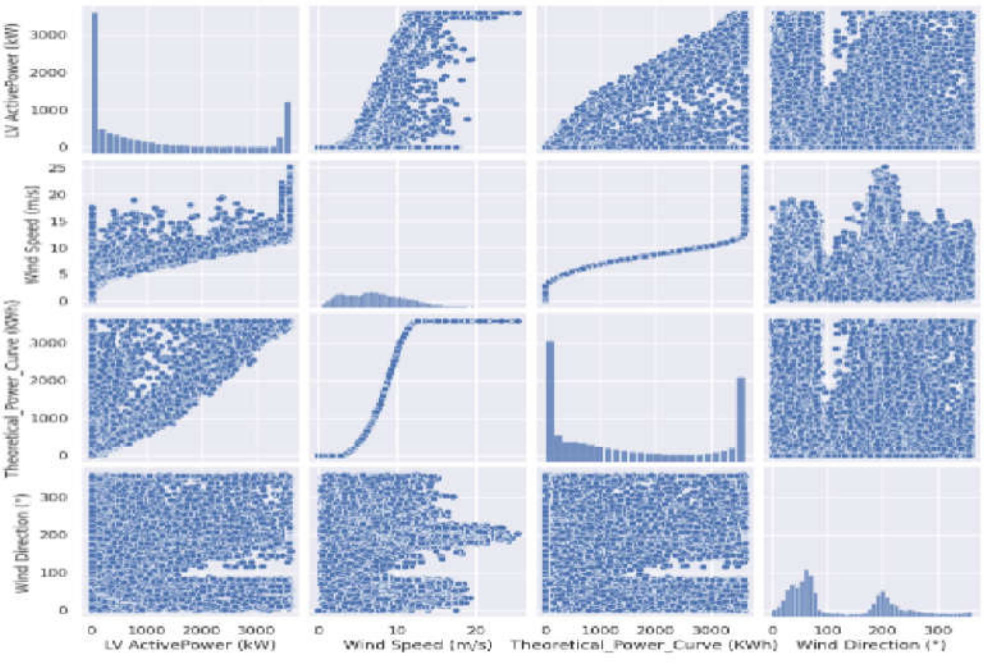

Fig.5. SNS PAIRPLOT

Fig.6.Correlation between the values

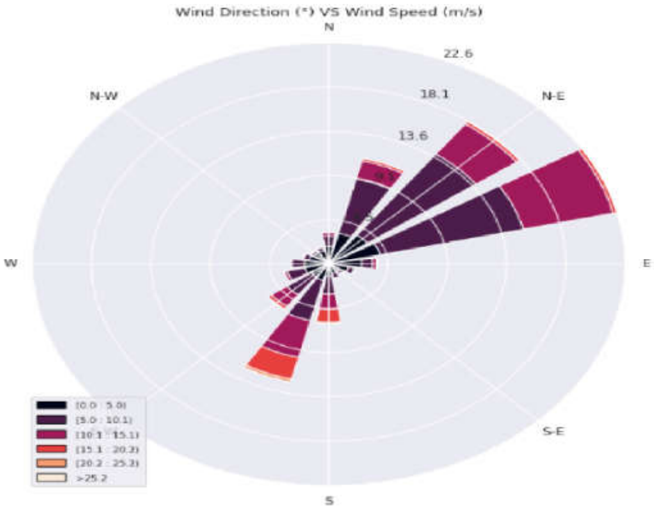

Fig.7. wind direction vs wind speed

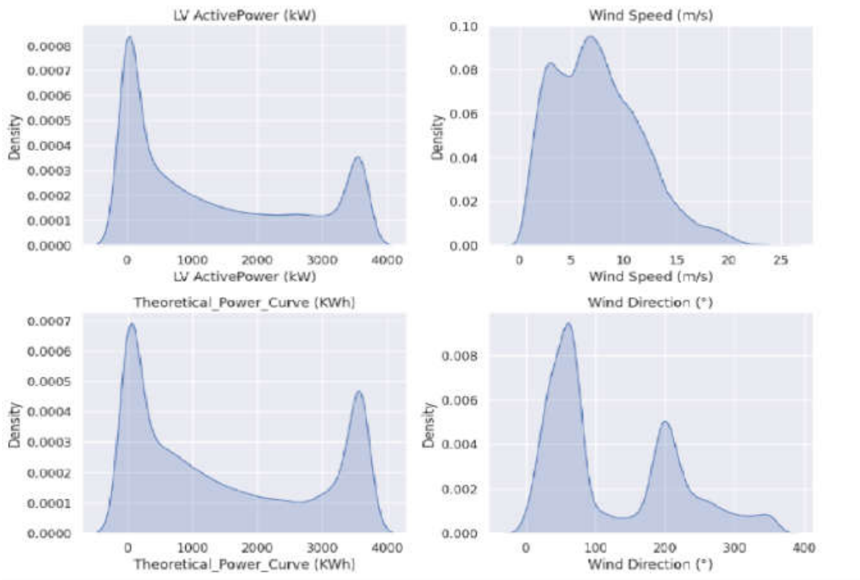

Fig.8. DATA DISTRIBUTION

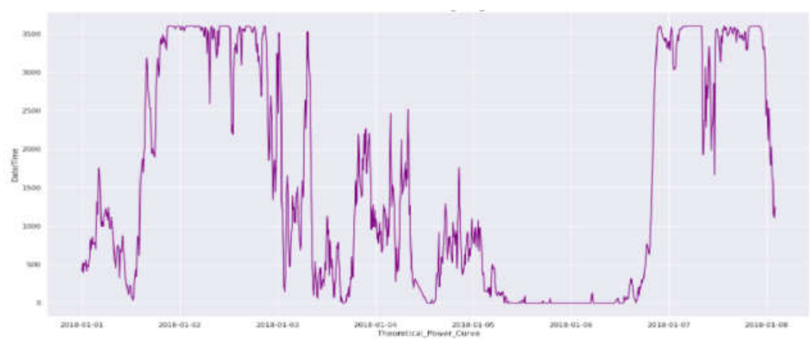

Fig.9. DATE/TIME VS THEORETICAL POWER CURVE

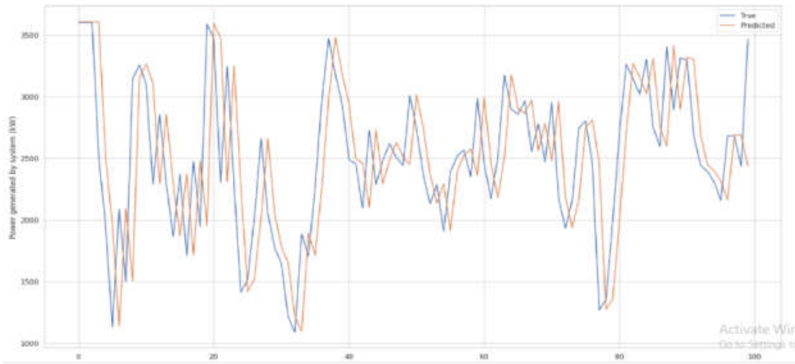

Fig.10. FINAL PREDICTION CURVE

CONCLUSIONS

After carefully examining the outcomes of both approaches, it can be said that the LSTM is more efficient than the SVM.Since LSTM has a lower error rate than the alternative, it can be applied more frequently in forecasting techniques.Because LSTM with deep learning has the virtue of pattern recall for longer periods of time, it can be used to achieve more effective results in predicting systems.Other models can be hybridised with LSTM to provide more precise models with effective prediction.As a result, LSTMs with the ability of pattern remembrance can be further applied to bigger data sets to generate extremely accurate results, which can then be used by organisations to anticipate weather conditions more accurately and effectively.

FUTURE SCOPE

The potential of Long Short-Term Memory (LSTM) neural networks for wind forecast prediction is quite high. For time series forecasting applications, including wind forecasting, LSTM is a form of recurrent neural network (RNN). Here are some potential improvements and future directions for LSTM-based wind forecast prediction:.

Improved Accuracy: Researchers and data scientists can continue to refine LSTM models by experimenting with various architectural modifications, hyper parameter tuning, and data preprocessing techniques. This can lead to improved accuracy and more reliable wind forecasts.

Overall, the future scope of wind forecast prediction using LSTM involves continuous advancements in model architecture, data handling techniques, uncertainty quantification, real-time forecasting, scalability, and integration with other technologies. These advancements can significantly improve the accuracy and reliability of wind forecasts, enabling better decision-making in various industries and sectors.

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