WIND POWER FORECASTING USING DEEP LEARNING TECHNIQUES

A PROJECT REPORT

Submitted by

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TKM20EEPS10

to

the **APJ Abdul Kalam Technological University**

in partial fulfillment of the requirements for the award of the Degree

of

Master of Technology

In

Power Systems

DEPARTMENT OF ELECTRICAL & ELECTRONICS ENGINEERING

T.K.M COLLEGE OF ENGINEERING

KOLLAM-5

2020-2022

DEPARTMENT OF ELECTRICAL & ELECTRONICS ENGINEERING
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CERTIFICATE

This is to certify that the project report titled **'WIND POWER FORECASTING USING DEEP LEARNING TECHNIQUES'** submitted by **Ms.NAZERIN N**., to the APJ Abdul Kalam Technological University in partial fulfillment of the requirements for the award of the Degree of Master of Technology in Power Systems, Electrical & Electronics Engineering is a bonafide record of the project work carried out by her under our guidance and supervision. This report in any form has not been submitted to any other University or Institute for any purpose.

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ACKNOWLEDGEMENT

I am obediently thankful to **God Almighty**, praise and glory is to Him, for all His uncountable bounties and guidance, without which, this project would have never been a reality.

I am immensely indebted to **Dr.Sabeena Beevi K**,Associate Professor, Head of the Department, Department of Electrical and Electronics Engineering for providing me with all the necessary facilities and support.

I am grately obliged to **Prof. Shanavas T N**, Associate Professor, PG Coordinator, Department of Electrical and Electronics Engineering, for his constant support.

I am extremely grateful to **Prof.Baiju R Naina**, Professor,Project Guide, Department of Electrical and Electronics, for her constructive guidance and advices.

I am extremely grateful to my project coordinator **Prof. Jibi P Mathew**, Asst. Professor, Project coordinator, Department of Electrical and Electronics, for his constant support and technical guidance provided during the project work.

I express my sincere gratitude to Principal **Dr. T A Shahul Hameed** for providing all necessary facilities.

I show my extreme gratitude to all Faculty member and Technical staffs in Electrical and Electronics Dept. for providing all the help and necessary facilities to present this project and my deep hearted cheers to my parents and all my friends who extended their support and co-operation towards the successful presentation of the project.

NAZERIN N

ABSTRACT

The safety and stabilisation of the electricity network will be challenged as wind power's share of the grid continues to rise, which will ultimately limit the scope of wind power development. For the wind energy industry to grow sustainably, forecasting is crucial. Power system dispatching may be done with confidence thanks to high-precision wind power forecasting. Since wind energy is intermittent and occurs over a range of time scales, increased wind power generation necessitates accurate wind forecasting. Numerous models have been developed for precise wind power prediction because of its stochastic character. Here, an accurate deep learning prediction model employing the LSTM (Long Short-Term Memory) technique is suggested.The model generates a forecast of wind power after being trained with real-time data from a wind farm. Two approaches, ARIMA and Random Forest, were compared in order to ascertain this model's efficacy. The outcome demonstrates that the LSTM approach offers greater forecasting accuracy while requiring less MAPE. In Python software, the LSTM, Random Forest, and ARIMA models are implemented.

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ABBREVIATIONS

ACF	Auto Correlation Function
AI	Artificial Intelligence
ANN	Artificial Neural Network
AR	Auto Regressive
ARIMA	Auto Regressive Integrated Moving Average
IES	Intelligent Energy Storage
LSTM	Long Short Term Memory
MA	Moving Average
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MSE	Mean Squared Error
MSTAN	Multi-Source and Temporal Attention Network
NWP	Numerical Weather Prediction
PACF	Partial Auto Correlation Function

RMSE	Root Mean Square Error
RNN	Recuurent Neural Network
RWM	Reference Wind Mast
SVM	Support Vector Machine
WPF	Wind Power Forecasting

Chapter 1

INTRODUCTION

1.1 GENERAL BACKGROUND

Given the pace at which global industrialization is developing, it is now widely acknowledged that over reliance on fossil fuels will harm the environment and speed up the depletion of fossil fuel reserves. These elements will contribute to increased health risks and dangers brought on by climate change. The energy source that is now growing at the highest rate, followed by fossil fuels and nuclear power, is renewable energy. Renewable energy is defined as useable energy that can be obtained from the environment. Solar energy, wind energy, hydropower, biomass energy, waves, tides, and geothermal energy are a few examples.. The topic of renewable energy has gained attention due to its sustainability and low environmental impact, and numerous studies have recently been conducted in this area. Soon one of the biggest issues with renewable energy. The energy supply is one of the biggest obstacles facing renewable energy in the near future. The integration of renewable energy sources into current or upcoming energy supply infrastructure is known as the renewable supply. The development of renewable energy systems will be able to address key difficulties with today's energy issues, like enhancing supply reliability and resolving localised energy shortages. However, the creation of different energy sources is random and intermittent because of the high volatility and intermittent nature of renewable energy. Therefore, there is more work to be done in accurately handling the randomness of renewable energy data. The effectiveness of the energy system can be increased by high-precision energy monitoring. Technology for energy forecasting is essential for the creation, administration, and formulation of energy system policies. It is crucial to create appropriate technology to store renewable energy as methods of producing electrical energy from renewable sources expand. Numerous research have shown that different machine-learning algorithms have been used to estimate the use of renewable energy. The data-driven models do offer useful approaches for making forecasts about renewable energy. Hybrid machine-learning models were also developed to improve the predictability of renewable energy.

According to diverse aims of projections, several time intervals, such as minutes, hours, days, and weeks, were used to forecast renewable energy. Typically, forecasting efficiency and accuracy were used to assess how well machine learning models performed in making forecasts about renewable energy.A source of energy that is good for the environment is renewable energy. Such carbon-free technology is crucial as a replacement for the current petrochemical energy sources and aids in the fight against climate change. 20 sustainable energy power systems, however, face risks since renewable energy sometimes possesses a variety of properties.

The term "forecasting" mostly refers to the projection of electricity generation from wind and solar power plants in the near future. Due to the intermittent nature of wind resources, forecasting is necessary. In a system heavily populated with wind power facilities, forecasting aids in the creation of efficient power scheduling and unit commitment. It aids in improving the stability and dependability of the grid. Therefore, accurate forecasting methods are crucial for increasing the penetration of wind in the grid.Numerous requirements and purposes are met by forecast. Making logical decisions and making plans for the future can both be aided by it. For all parties involved in the electrical system, forecasting offers financial and other advantages. Forecasts improve operational effectiveness, lower overall costs, and enable the economically efficient integration of more renewable energy at the system level. Forecasts at the plant level make an owner's generation capacity more valuable and guarantee that it is used to the fullest degree possible.he erratic and nonschedulable character of the power generated by wind farms is one of the basic issues that power system operators must deal with. For the effective planning and operation of the power system, these fundamental qualities of wind power have both technical and commercial significance. The forecasting tools tell us how much wind power can be anticipated at what time in the upcoming days.

1.2 MOTIVATIONS

The goal of wind power forecasting is to precisely predict the wind power output of a wind farm over a range of time scales. Wind energy is a type of clean and secure renewable energy source, although it is not consistently produced, resulting in considerable fluctuation. Significant obstacles to integrating wind power into a grid system might arise from such fluctuation. The volatility of wind power necessitates power replacement from other sources, some of which may not be readily accessible at short notice, in order to maintain the balance between energy generation and consumption. Consequently, it is vital to analyze the wind power prediction method.

1.3 THESIS MAIN OBJECTIVES

- Understanding how wind forecasting improves the performance of electricity systems
- To develop an intelligent computing technique for prediction of wind turbine power

1.4 ORGANIZATION OF THESIS

The entire thesis as follows:

It consists of 7 chapters. Chapter follows basic introduction,main objectives and motive of the project.Chapter 2 includes the literature review. Chapter 3 deals with the brief introduction,time outline of wind power forecasting and its methods.Chapter 4 focuses on the role of AI in renewable energy .Chapter 5 follows the mehodology and classical time series forecasting method ARIMA and Machine learning method like Random Forest. Chapter 6 deals with the proposed LSTM model and its implementation.Chapter 7 discusses the result of forecasted methods.

Chapter 2

LITERATURE REVIEW

In [1] researcher presents a deep residual network to improve the accuracy and efficiency of time-series forecasting models, especially when using considerable volumes of renewable energy sources.ReLU and SeLu are used as activaion function for 1D and dense layer respectively. A concatenated residual learning by fusing the multilevel residual network (MRN) and DenseNet is used. The technical issue will be eliminated by combining the original input, shortcuts of the residuals, and the original activated input.MSE,MAPE,MAE were used as evaluation metrics.

Machine learning techniques have been increasingly applied to renewable energy, and the bulk of predictions for solar and wind energy use artificial intelligence methods and hybrid models is suggested in [2] .Then when using machine learning models to estimate the use of renewable energy, the decomposition method is more frequently used than the other data pre-processing techniques.The peformance metrics used here is MAPE.

The SVM, Decision Tree, and Random Forest machine learning algorithms are utilised in [3]to demonstrate the accuracy of short-term wind power forecasts.Then, using their corresponding MAPE and RMSE, the predicting accuracy is evaluated. For SVM, Random Forest, and Decision Tree, the RMSE is found to be 0.039, 0.0052, and 0.0015, respectively. While the MAPE for SVM, Random Forest, and Decision Tree, respectively, is 20.834, 1.889, and 1.126. Therefore, it is evident that, RMSE, and MAPE values that the decision tree and random forest techniques provide significantly superior wind power predictions than the SVM.

In [4] author offers a novel statistical approach that enhances short-term wind-electric power projections on the basis of WPP through the identification of wind patterns and RWM data correlations with NWP. The AdaBoost algorithm is used to integrate the three independent NWP meteorological grid data inputs, and the resulting output grid wind speed and direction data are then classified using the best possible cluster number. In order to obtain a wind-to-wind correlation and localise the NWP data to the relevant WPP site via RWM measurements, each clustered wind data set is used to train a separate ANN/SVM model. To further enhance the wind-electric power projections, a wind-pattern based learning approach is developed in the literature.

Mainly concentrated on the use of WPF among system operators in the[5] . Of course, these forecasting consumers would like to see an increase in forecasting accuracy overall. The capacity to predict wind power ramping occurrences is particularly important because these could have a significant impact on how the power system operates. Additionally, it is crucial for system operators that the WPF tool be able to provide accurate estimations of forecast uncertainty. The implementation of WPF as a key component of their system and market operations is something that several ISOs/RTOs in the US are actively working on. It is evident that WPF needs to be better integrated into several operational areas, from determining operating reserve requirements through unit commitment and dispatch decisions.

For Xcel Energy, NCAR has done research and set up a Wind Power Forecasting System that combines high-resolution and ensemble modelling with AI techniques. This cutting-edge forecasting system uses specialised technology, such as a Variational Doppler Radar Analysis System and an expert system, to detect wind power ramps in the short future. Through increased reliability and cost-effective methods of reliability improvement, wind power forecasting can considerably enhance grid integration. In the energy market, forecasting errors become opportunity costs; therefore, more accurate forecasts have the potential to save the utilities and their ratepayers a sizable sum of money is discussed in [6].

The development of wind energy, a form of renewable energy, is essential to China's production of electric energy. Therefore, precise wind energy generation forecasting aids in optimising power grid dispatching, lowering system reserve capacity, and lowering system operating expenses.A hybrid LSTM model is built using data from six indexes to forecast the production of wind power in China is describes in [7] . These indexes include the gross domestic product, consumer price index, industrial added value, total imports and exports, total power generation, and hydropower generation. A hybrid WD-LSTM model is developed for forecasting the nation's wind power generation using wavelet decomposition and long short-term memory neural network techniques.

In [8] provided a review of several wind power forecasting techniques along with a number of models, including WPPT, WPFS Ver 1.0, Prediktor, Previento, etc., according to various time scales. As a result, WPMS is utilised under a statistical method for short-term wind power forecasting, whereas ANEMOS is employed under a statistical and physical approach. WPPT is the most effective method for short-term wind power prediction when using a statistical approach, while WPFS Ver. 1.0 and Sipreolico are employed when using a statistical and physical approach. Previento as well as Localpred and Regionpred approaches are employed under a statistical and physical approach when discussing long-term wind power forecasting models. The numerous forecsating techniques that are accessible were the author's area of focus.

In [9] author has been designed and put to use to determine the best values for the variety of variables connected to ARIMA/ARMA models, such as the length of the training period and the model orders. The effectiveness of the models was evaluated by comparing their one-hour projections to the Persistence model, which served as a baseline. A 14-week training period was used to balance computing time and relative error using the AIC criteria. The researcher conveys ,as wind energy's contribution to the system's power output rises and forecasting production of this erratic energy source becomes more important to its growth with rising wind power installed capacity, the enhanced forecasting findings are helpful.

Chapter 3

WIND POWER FORECASTING

3.1 INTRODUCTION

This chapter focuses on the basic introduction of wind power forecasting and its methods

3.2 WPF

In contrast to the conventional generation system, wind generation is directly influenced by wind speed and is more difficult to dispatch. Variations in wind generation so deserve good attention. According to different timelines or methodologies, there are several ways to anticipate wind power. Different descriptions in the literature use different time scales to describe wind power forecasting techniques.

The location of the wind farm, the height of the windmills, the direction and speed of the wind, the temperature, the pressure, the humidity, etc. are some of the variables that affect wind power. A wind turbine's output is correlated with its speed (v) (m/s), sweep area (A) (m2), and wind power (P) (W) as follows

$\mathrm{P} = 1/2\rho \mathrm{A} v^3$

Here, the thickness of the air is ρ (kg/m3), which relies upon temperature just as air pressure.

Forecasting precise wind power is becoming more important due to the stochastic nature and uncertainty of the power generated by the wind, which have caused various notable issues in the operation and planning of power systems. Numerous forecasting techniques for wind energy, such as probabilistic forecasting techniques and point forecasting techniques, have recently been proposed. Wind power is becoming more and more prevalent, and as a result, WPF is swiftly becoming a significant problem for the electric power business. The efforts to create forecasting models that are better, more dependable, more accurate are supported by system operators (SOs), generating businesses (GENCOs), and regulators.Better wind power forecasts help wind farm owners and operators compete in the electricity markets against more reliable and dispatchable energy sources. WPF can generally be used for a variety of tasks, including planning for generation and transmission maintenance, determining operating reserve needs, unit commitment, economic dispatch, and optimising energy storage (such as pumped hydro storage) and energy trading.

3.3 TIME OUTLINES

A forecasting system's time horizon, or the future time period for which the wind generation will be anticipated, is what distinguishes it from other forecasting methods (e.g., the next day). The forecasting system is classified based on its time horizon in various power system forecasting issues, such as load forecasting: extremely short term, short term, medium term, or long term. The WPF can generally be divided into three categories:

3.3.1 Very Short Term

A few hours is the range for the time horizon, however there is disagreement over how many hours it should be. For a time horizon of this length, the value is 9 hours with a 4 hour upper limit. The owner of a wind farm can use this time horizon WPF, but how they do so depends on the market laws. For instance, trading intraday markets may be possible using these projections. The use of these forecasts for the SO is dependent on how the power system's ancillary services are managed.

3.3.2 Short Term

The time horizon can be as short as the extremely short term or as long as 48 or 72 hours. Many tasks only have time boundaries of 48 hours or, occasionally, only for 36 hours. Trading in the day-ahed market makes the most sense for this time horizon. These predictions are very useful for planning maintenance, especially when the time horizon is 72 hours.They are used for dispatch planning, intelligent load shedding decisions.

3.3.3 Medium Term

The time horizon spans from a limit of seven days to the short-term limit. The forecasting mistakes rise with the time horizon. Both the UC of conventional generation (such as coal units) and the maintenance planning of conventional plants can use these forecasts as inputs. It is also possible to schedule the maintenance of electricity system lines and wind farms using these forecasts as inputs.

Presently, due to the economic relevance of forecasting, most of the commercial and research prediction systems are employed over time horizons ranging from 36 to 72 hr ahead.

Table 3.1. Classification of various forecasting methodologies according to several time aspects

Time Horizon	Range	Application
Immediate short term	Few seconds to $\frac{1}{2}$ hour ahead	Regulation Actions,market clearing
Short Term	$\frac{1}{2}$ hour to 6 hours ahead	Load increment/decrement decisions, Economic Load Dispatch Planning
Medium Term	6 hours to 1 day ahead	Generator offline/online decisions, Operational Security in the day-ahead electricity market
Long Term	1 day to 1 week or more ahead	Maintenance scheduling to obtain optimum operating cost, Reserve requirement decisions, Unit Commitment decisions

Chapter 4

THE IMPACT OF ARTIFICIAL INTELLIGENCE TECHNOLOGY ON RENEWABLE ENERGY

4.1 Introduction

Global energy demands are growing every year. And, fossil fuels won't be able to fulfill our energy needs in the future. Carbon emissions from fossil fuels have already hit an all-time high in 2018 due to increased energy consumption. On the other hand, renewable energy is emerging out as a reliable alternative to fossil fuels. It is much safer and cleaner than conventional sources. With the advancements in technology, the renewable energy sector has made significant progress in the last decade.However, there are still a few challenges in this sector that can be addressed with the help of emerging technologies. Technologies like AI and Machine Learning can analyze the past, optimize the present, and predict the future. And, AI in the renewable energy sector can resolve most of the challenges.

4.2 Issues facing the sector of renewable energy

One of the significant challenges of producing renewable energy is the unpredictability of the weather. Solar and wind are the leading sources of renewable energy, and power generation largely depends on the weather.Although we've efficient technologies in place for weather forecasting, there are going to be sudden changes in the climate that can affect the energy flow. The supply chain of renewable energy is prone to such vulnerabilities. Therefore, it needs to be smoothened enough to cope with unexpected changes.

Secondly, the recent developments in energy storage technology are quite promising. But, they are yet to be tested thoroughly. The electric grid is one of the most complex machines on Earth. However, it is evolving rapidly with the addition of variable renewable energy sources. Due to the inherent variability of wind and solar, the current grid faces many challenges in accommodating the diversity of renewable energy. The utility industry needs smart systems that can help improve the integration of renewables into the existing grid and make renewable energy an equal player in the energy supply.

AI technology has the potential to upgrade the grid as well as increase the reliability of renewable energy.

4.3 Enhanced Reliability and Safety

While managing the intermittency is the primary objective of AI in renewable energy, it can also provide increased safety, efficiency, and reliability. You can use it to determine the health of the equipment, locate energy leaks, and comprehend patterns of energy usage. For instance, the AI-powered predictive analysis can gather information from sensors on wind turbines to track wear and tear. The system will keep track of the equipment's general health and notify the operator when maintenance is required.

4.4 Improved Microgrid Integration

AI can assist in managing distributed energy and integrating microgrids. It is challenging to balance the energy flow inside the system whenever community-scale renewable energy producing units are introduced. The AI-powered control system can be quite helpful in addressing the difficulties with quality and congestion.

4.5 Increase Market Size

By offering new service models and promoting greater involvement, the integration of AI can aid suppliers of renewable energy in expanding the market. The AI-powered systems will have the ability to examine energy collection data and offer perceptions on energy consumption. Suppliers could establish new service models and optimise their current offerings with the use of this data. A new consumer market can be targeted by retail providers with its assistance.

4.6 Intelligent Grid and Grid Storage

Intelligent Energy Storage (IES) and artificial intelligence combined can offer a dependable and sustainable solution for the renewable energy sector. This smart grid will be able to assess a sizable amount of data gathered from several sensors and decide when to allocate energy. In addition, it will make it easier for microgrids to continue trading power with the main grid while effectively managing local energy needs.

Chapter 5

IMPLEMENTED PREDICTION MODELS

5.1 INTRODUCTION

This chapter deals with methodology and detailed descriptions of time series forecasting model such as ARIMA and Random Forest.

5.2 METHODOLOGY

Here, an ML-based approach is shown that predicts power output for the next 24 hours. everything that is utilised by Python software. The Jupyter notebook serves as a platform for forecasting. Three models will be used by us to make predictions. Without any data for the future, the fundamental ML model cannot predict future values. Therefore, we began our work with forecasting models, among which ARIMA was the most fundamental. A statsmodels library issue was preventing accurate prediction.

Historical data is collected from wind mill.It includes a number of characteristics, including wind power, wind speed, wind direction, and power curve.Data has been recorded from January 2018 till December 2018.Readings have been recorded at a 10 minute interval.

The Parameters in the data are:

1. Date/Time (for 10 minutes intervals)
2. LV ActivePower (kW)
3. Wind Speed (m/s)
4. TheoreticalPowerCurve (KWh)
5. Wind Direction (°)

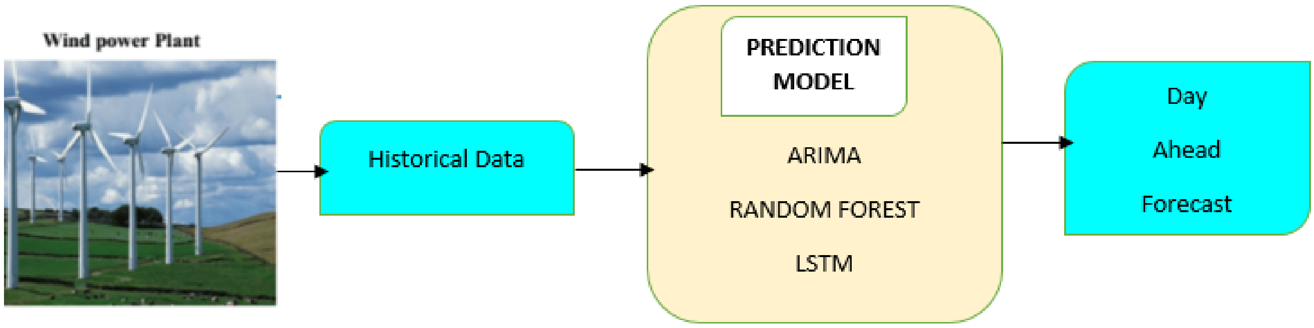

Figure 5.1. Prediction model

From Wind power plant,the historical data were collected such as wind direction, Power curve , Wind speed and Wind power.In this thesis, three models were used for prediction. The detailed description explained in below.

5.3 AUTOREGRESSIVE INTEGRATED MOVING AVERAGE

The ARIMA (Autoregressive Integrated Moving Average) model and is used to measure variables that occur over time, is one of the most significant and often used time series (statistical) models. A sequence in which a metric is determined across predictable time periods is known as a time series, and the model is used to analyze historical data and forecast future data in that series.The historical values of a time series, including its own lags and lagged prediction error, are used by this category of models to demonstrate the behaviour of the time series. In general, an ARIMA model is defined by three terms, such as p, d, and q, where p denotes the order of the AR term, q the order of the MA term, and d the number of differencings needed to make the time series stationary.The ARIMA model can be thought of as a filter that seeks to extract the signal from the background noise before specifying the signal for predictions in the future. The projections for a number of fixed periods using ARIMA's predictive statistics have residual climatic errors and inconsistencies.

5.3.1 ARIMA Model Analysis

As a direct result of various views and errors still present in earlier steps, the ARIMA model adjusts the following step in the sequence. In order to make the sequence stand, a process known as integration combines the types of Autoregression (AR) and Moving Average (MA) with a step-by-step sequence analysis phase (I). It provides a simplified yet effective method for producing precise time forecasts by explicitly listing the most frequent time-series data formats.The sequence is first converted into a stationary sequence using the difference or integrated part. The criterion of the difference order is met when the sequence essentially keeps shifting around a particular value. The model's main elements are as follows:

a. AR (Auto Regression) : Explains how one observation and several lag observations are related in a dependent manner.

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \cdots + \beta_p Y_{t-p} + \varepsilon_1$$

The function Yt, which is a function of the lags of predicted values, is made up of the error term, the first lag value of the time series data, the coefficient of first lag value, and the constant value.

b. I (Integrated) : The process of changing the raw data in order to get the time series stationary, for as by eliminating one observation from another at an earlier time step

c. MA (Moving Average) : It is a representation of the moving average,which shows how a value observed and the residual error of lagged values from a moving average model applied to earlier observations relate to one another. Here, a moving average model creates a regression-like model utilising historical prediction mistakes rather than the past values of the forecast variables as in a regression.

$$Y_t = \alpha + \varepsilon_t + \phi_1 \varepsilon_{t-1} + \phi_2 \varepsilon_{t-2} + \cdots + \phi_p \varepsilon_{t-q}$$

where ε_t is the error term of the corresponding lags' autoregressive models.

The time series was differentiated once or twice across the whole model to make it stationary for further processing, and the AR and MA were then combined using the eqs mentioned above to produce the projected values and give the overall mathematical eq.

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \cdots + \beta_p Y_{t-p} + \phi_1 \varepsilon_{t-1} + \phi_2 \varepsilon_{t-2} + \cdots + \phi_p \varepsilon_{t-q}$$

so in general form we can denote ARIMA model using eq as:

Forecasted () is equal to Constant, Lags of Y (for lags), and the linear combination of Lagged forecast errors (for q lags)

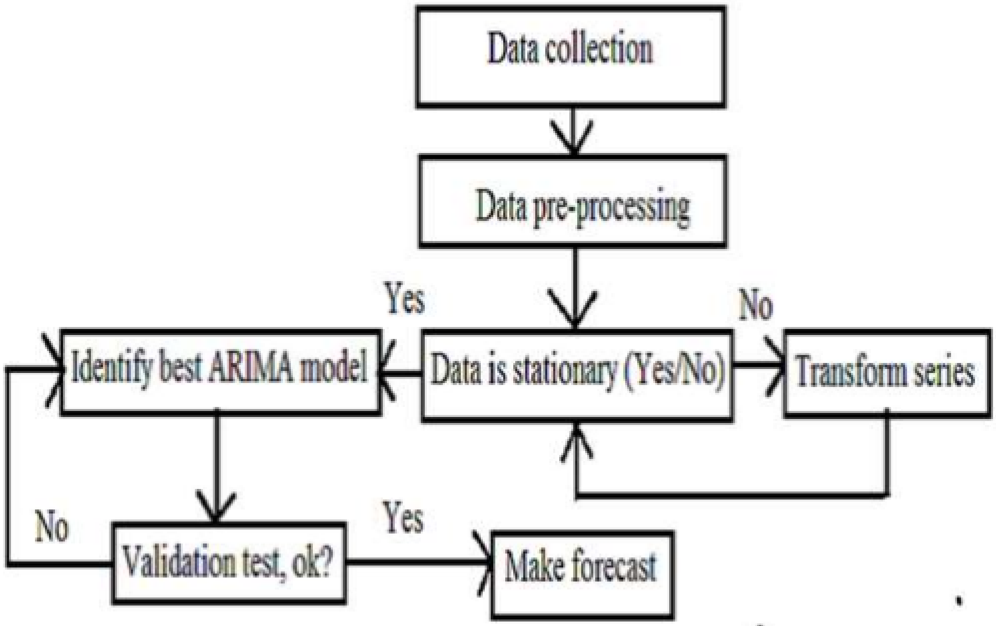

Figure 5.2. Flowchart of ARIMA model

Fig.5.1 displays the algorithm flowchart for the ARIMA model. The first phases in the procedure involve collecting the data and preparing it for processing with the ARIMA model. In order to use ARIMA for forecasting, a time series must first be made stationary if it contains a trend or seasonality component. The time series must be turned stationary but it will not be by applying differencing or by carrying out the required number of transformations. Check for stationarity after taking the first difference. Take as many variations as necessary. Select AR and MA terms, decide whether to include one or more of them using the ACF and PACF, and then develop a model to forecast to N. (depends on your needs).Then eliminate a validation sample that was utilised to confirm the accuracy of our model. To do this, divide the train test from the validation test. The model is then validated by comparing the predicted values to the actual values in the validation sample.

Table 5.1. Dickey-Fuller test

Test Statistic
-11.62646

5.3.2 Algorithm of ARIMA model

Step 1 :Database collection

Step 2 : Import libraries

Step 3 : Data Visualization

Step 4 : Filling the missing values

Step 5 : Turn categorical values into numbers

Step 6 : Testing for stationarity

Step 7 : Anlaysis of ACF and PACF

Step 8 : Build the ARIMA model

Step 9 : Calculate error

Step 10 : Final power prediction

Only after transforming the series of observations (sample data) taken into consideration for forecasting into a stationary series, the Autoregressive Integrated Moving Average model is projected. According to the stationary series, there is only a small change in the mean and variance of the observations over time. First, it is determined whether or not the sample data's sequence of observations are stationary. The suitable differencing order of the data series under consideration changes non-stationary in mean. The ADF (Augemented Dickey Fuller Unit Root Test) is obtained here to demonstrate the stationarity of the series.From Table 5.1 it is clear that series is stationary.

5.4 RANDOM FOREST

A popular algorithm for classification and regression issues is the supervised machine learning technique known as random forest. On various samples, it constructs decision trees and uses their average for classification and majority vote for regression. The Random Forest Algorithm's ability to handle data sets with both continuous variables, as in regression, and categorical variables, as in classification, is one of its most crucial qualities. For categorization issues, it produces superior results.

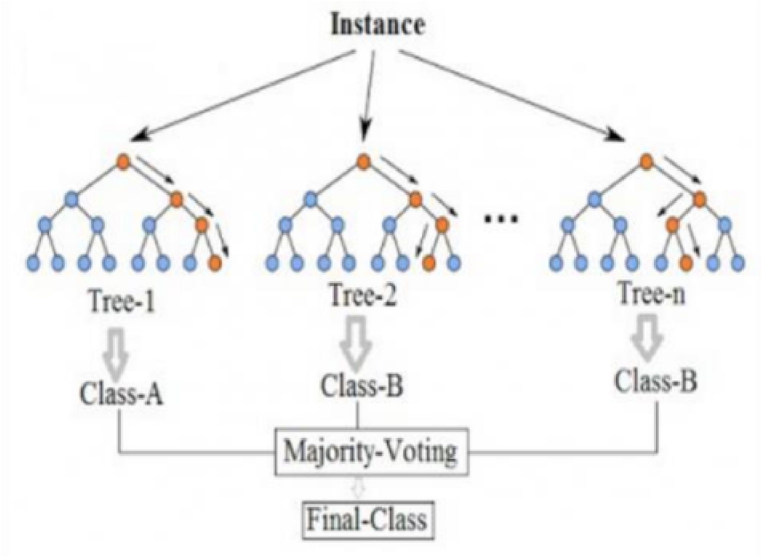

Figure 5.3. Diagrammatic representation of the working of a simple random forest

Based on the Bagging principle, Random Forest operates. The ensemble method employed by random forest is bagging, sometimes referred to as Bootstrap Aggregation. A random sample is chosen from the data set using bagging. As a result, each model is created using the samples (Bootstrap Samples) that the Original Data gave, with a replacement process known as row sampling. Bootstrap refers to this stage of row sampling with replacement. Each model is currently trained independently, producing results. After merging the output from all models, the final decision is made based on a majority vote. Aggregation is the process of aggregating all the results and producing a result based on a majority vote.

5.4.1 Algorithm of Random Forest model

Step 1: From a data set with k records, n random records are selected at random and used in the Random Forest algorithm.

Step 2: For each sample, a unique decision tree is built.

Step 3: An output will be produced by each decision tree.

Step 4: For regression, the final result is evaluated using an average.

Here, the training size is 67%, from this records the number of decision trees are built.In random forest, the hyperparameters are either used to speed up the model or to improve its ability to forecast. The first hyperparameter is n_estimators, which simply specifies how many trees the algorithm creates the average of the forecasts. In general, additional trees improve speed and make predictions more reliable, but they also slow down computation.So, the value of n_estimators is 350.Next is max_depth means the depth of the tree,it is 25.Then, min_samples_split specifies the minimum number of observations needed at a given node for a decision tree in a random forest to split it,the value is 2.After splitting a node, this Random Forest hyperparameter sets the minimum amount of samples that must be present in the leaf node, that is min_samples_leaf is 1.

Chapter 6

PROPOSED MODEL

6.1 INTRODUCTION

In this chapter, to overcome the limitations of a ARIMA model and Random Forest based model outlined in the previous section, we suggest a Long Short Term Memory Network (LSTM) that can be trained using all input data that is accessible for both the past and the future of a certain time frame.

6.2 LONG SHORT TERM MEMORY

The long-short term memory is a useful tool for dealing with time series prediction (LSTM). Recurrent neural networks (RNNs), which are common cyclic neural networks, come in a number of forms. The hidden state, which retains some knowledge or previous conditions about the sequence, is the most important aspect of RNNs. At its base, LSTM uses a hidden state to maintain data from inputs that have already been processed by it. It links numerous RNN units or memory blocks, each of which includes three gate units and one recurrently connected memory cell.It builds gated cells that respond to input by blocking or passing information depending on the importance of the data element in order to address the increasing gradient problem.

Information travels via many of these LSTM units in an LSTM network. An LSTM unit is made up of three basic parts. The recurrent neural networks (RNNs), which are the ancestors of the long-term and short-term memory network (LSTM), are able to maintain learning data over the course of learning. Fig. 6.1 depicts the LSTM's internal organisation and basic operation.

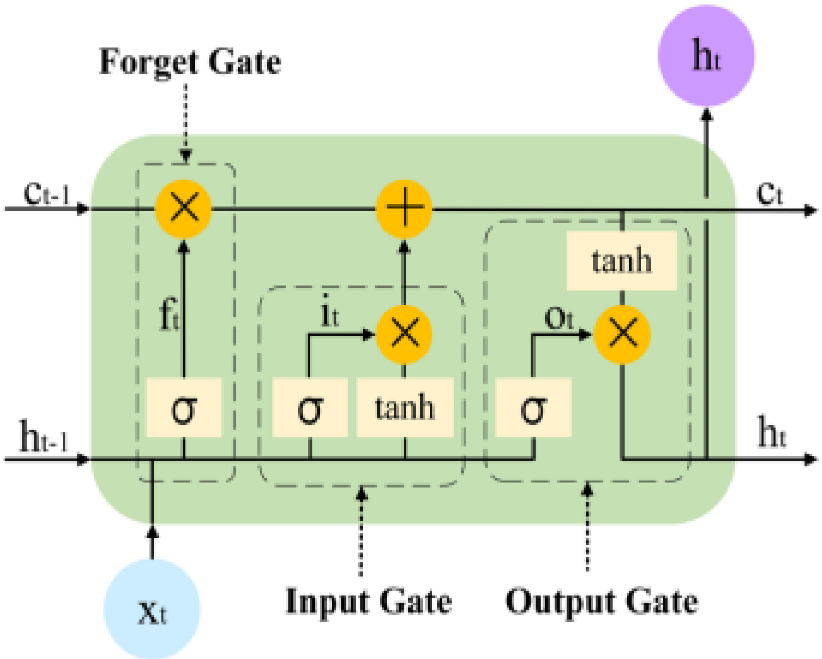

Figure 6.1. Architecture of LSTM

6.2.1 Principle of LSTM model

The recurrent neural networks (RNNs), from which the long-term and short-term memory network (LSTM) originally derived, are capable of preserving learning data throughout the learning process.

6.2.2 Forget Gate

$$\mathrm{f_t} = \sigma\left(\mathrm{W_f} \times [h_{t-1}, \mathrm{x_t}] + b_f\right)$$

where, t = time step

f_t= forget gate at t

x_t= current input

h_{t-1} = previous hidden state

w_f= weight matrix between the forget gate and the input gate

b_c= connection bias at t

Which information requires attention and which can be disregarded is determined by the forget gate. The hidden state h_{t-1} and the current input x_t are both subjected to the sigmoid function. Values between 0 and 1 are produced by Sigmoid. It draws a conclusion regarding the necessity of the old output's portion (by giving the output closer to 1). The cell will later use this value of f_t for point-by-point multiplication.

6.2.3 Input Gate

$$\mathrm{i_t} = \sigma\left(\mathrm{W_i} \times [h_{t-1}, \mathrm{x_t}] + b_i\right)$$

$$\bar{\mathrm{c}}_\mathrm{t} = \tanh\left(\mathrm{W_c} \times [h_{t-1}, \mathrm{x_t}] + b_c\right)$$

where, t = time step

i_t = input gate

W_i = sigmoid operator weight matrix between the input gate and output gate

b_i = bias vector

$\bar{\mathrm{c}}_\mathrm{t}$= the value produced by the tanh function

W_f=tanh operator's weight matrix between network output and cell state data

b_c= bias vector at t w.r.t W_f

The input gate modifies the following values to update the cell status. The starting inputs to the second sigmoid function are the current state,x_t, and the previously hidden state,h_{t-1}.The values are changed from 0 for important to 1 for unimportant. The tanh function will then receive the identical data from the hidden state and current state. For network control, the tanh operator will offer a vector ct with each possible value between -1 and 1. The activation functions prepare the output values they create to multiply numbers point-by-point.

6.2.4 Cell State

$$\mathrm{c_t} = \mathrm{f_t} \times \mathrm{c_{t-1}} + \mathrm{i_t} \times \bar{\mathrm{c}}_\mathrm{t}$$

where, t = time step

c_t= cell state information

f_t = forget gate at t

c_{t-1} = previous cell state at t-1

The input gate and forget gate have provided the network with sufficient data. The decision-making process and the storing of the data from the new state in the cell state come next. The forgets vector f_t multiplies the previous cell state c_{t-1}. Values will be removed from the cell state if the result is 0. The network then executes point-by-point addition on the output value of the input vector i_t, updating the cell state and creating a new cell state c_t.

6.2.5 Output Gate

$$\mathrm{o_t} = \sigma\left(\mathrm{W_o} \times [h_{t-1}, \mathrm{x_t}] + b_o\right)$$

$$\mathrm{h_t} = \mathrm{o_t} \times tanh\left(\mathrm{c_t}\right)$$

where o_t = output gate at t

W_o= Weight matrix of output gate

b_o= bias vector w.r.t W_o

h_t= LSTM output

The output gate determines the value of the next hidden state. This state contains details about earlier inputs. The values of the current state and the previous hidden state are passed to the third sigmoid function before to being called. Next, the newly formed cell state that was derived from the initial cell state is subjected to the tanh function. These two results are multiplied one by one. The network decides which information the hidden state should convey based on the final value. Next, the new cell state and hidden state are carried over to the subsequent time step eq. The forget gate selects which relevant information from the earlier processes is required to conclude. The output gates complete the next hidden state, while the input gate determines what key info can be supplied from the current stage.

6.2.6 TRAINING IN LSTM NETWORK

Because of its distinctive architecture, LSTM can forget irrelevant information. The sigmoid layer determines which components of the old output should be deleted from the inputs x_t and (by outputting a 0).This gate is known as Forget Gate f_t. $f_t * c_{t-1}$ is the output of this gate. The decision-making and storing of data from the new input x_t the cell state comes next. A Sigmoid layer determines whether of the new bits of information should be updated or ignored. A tanh layer takes the new input and constructs a vector with every conceivable value. To update the new cell state, these two are multiplied. The old memory c_{t-1} is then combined with this recent memory to create c_t.

6.2.7 Algorithm of LSTM model

Step 1 : Database Collection

Step 2 : Reading data from CSV file

Step 3 : Data visualization using Matplotlib

Step 4 : Removing null values from the data

Step 5 : Transform data to be supervised learning

Step 6 : Splitting data for training and testing

Step 7 : Build the LSTM model

Step 8 : Fit the model

Step 9 : Calculate error

Step 10 : Final Power prediction

6.3 FLOWCHART OF LSTM MODEL

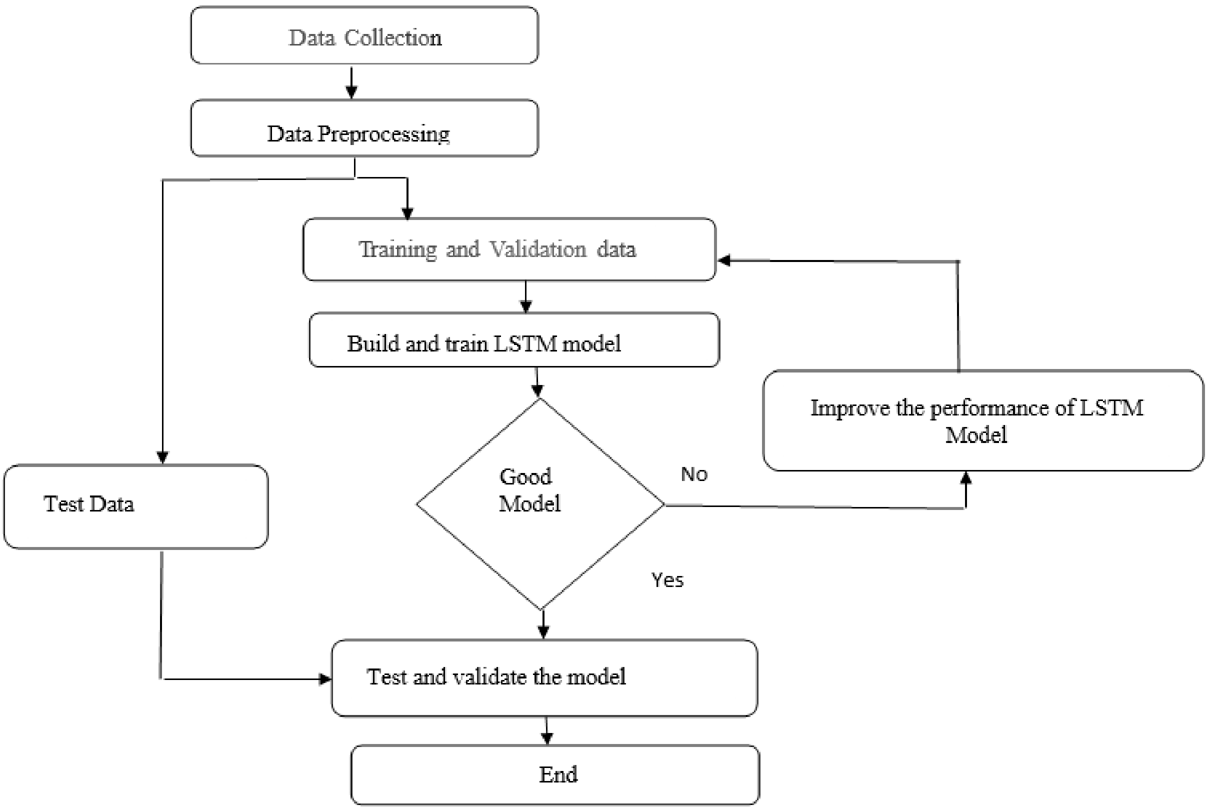

Figure 6.2. Flowchart of forecasting model based on LSTM

The major steps are outlined in the flowchart. The suggested strategy consists of 4 crucial components. Gather information from the wind system. Then, normalise the original data after pre-processing it by removing outliers and imputed missing values. Next, develop, verify, and test the LSTM model.For Preprocessing,historical data is collected from wind mill.It includes a number of characteristics, including wind power, wind speed, wind direction, and power curve.Data has been recorded from January 2018 till December 2018.Readings have been recorded at a 10 minute interval. The dataset shows 50530 observations for 5 features but some of the features have significant periods of missing data.There is need to discard some periods and fill in the missing periods, otherwise the LSTM model will not converge.Then scale the observations using Minmax Scalar.After preprocessing,create the X presictors and Y targets for training.Split 75% for training and 25% for testing.Then next step is to build LSTM network.There are three levels in an LSTM, including an input layer, a hidden layer, a cell state, and an output layer.Input layer consist of data which contains wind speed,wind power,wind direction.This input is fed to the hidden layer which is implemented with 32 neurons.The output layer predicts the output according to input.The cell state is used for updation.After building,train and validate the model .The time step is set to 24.Adam optimizer is used in implementing the model.The confusion matrix of the LSTM model is shown in fig.6.3

Figure 6.3. Confusion Matrix

Chapter 7

RESULTS AND DISCUSSION

7.1 INTRODUCTION

This chapter compares the accuracy and efficiency of each distinct time series forecasting technique used to predict the value of wind power.

7.2 Plotting of data

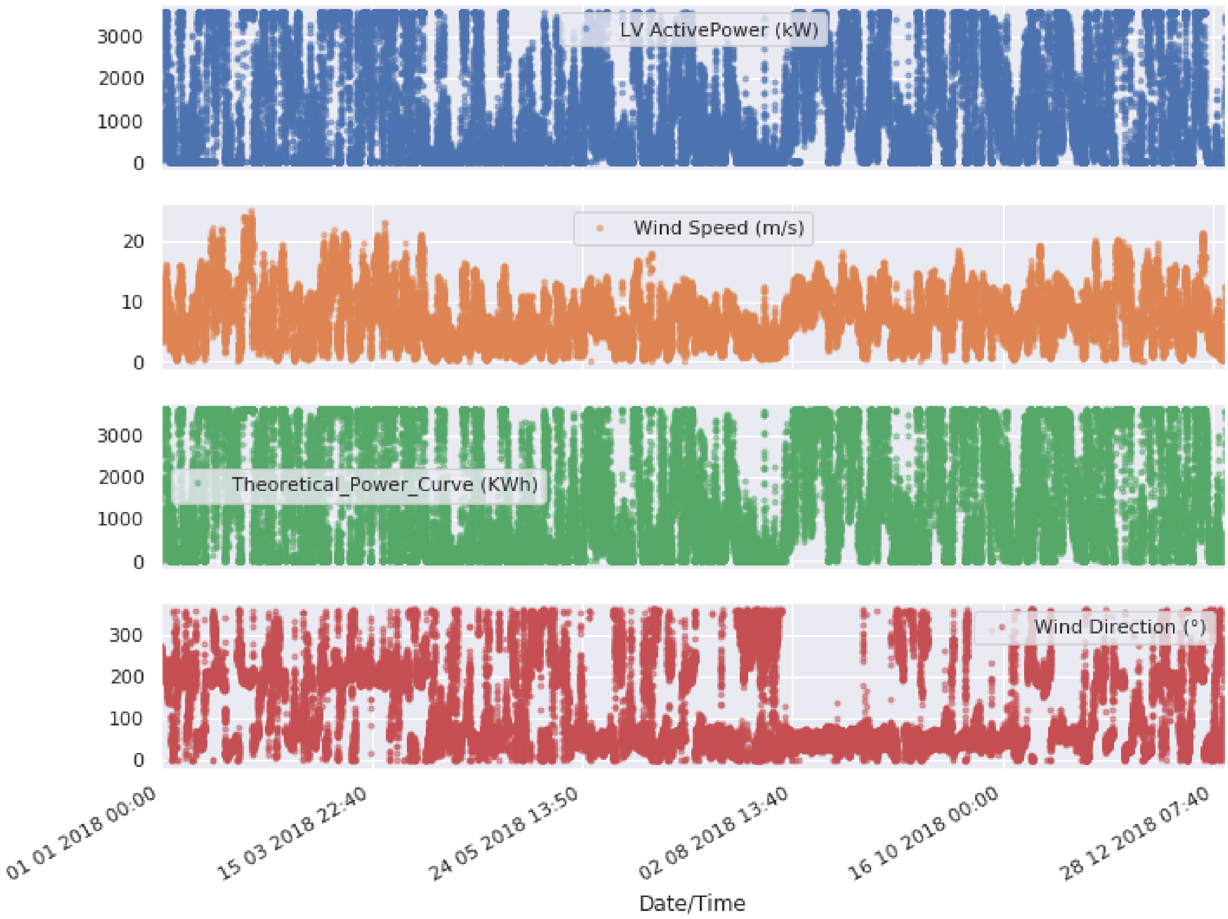

Figure 7.1. Data plotting

7.3 FORECASTED RESULTS

The wind power prediction results using ARIMA are shown in Fig.7.1, along with a comparison of the actual and predicted values. The prediction results for the same on the Random Forest Regressor are displayed in Fig.7.2, along with a comparison of the predicted and actual values. The prediction results for the same on LSTM are shown in Fig.7.3 along with a comparison of the actual and forecasted values.

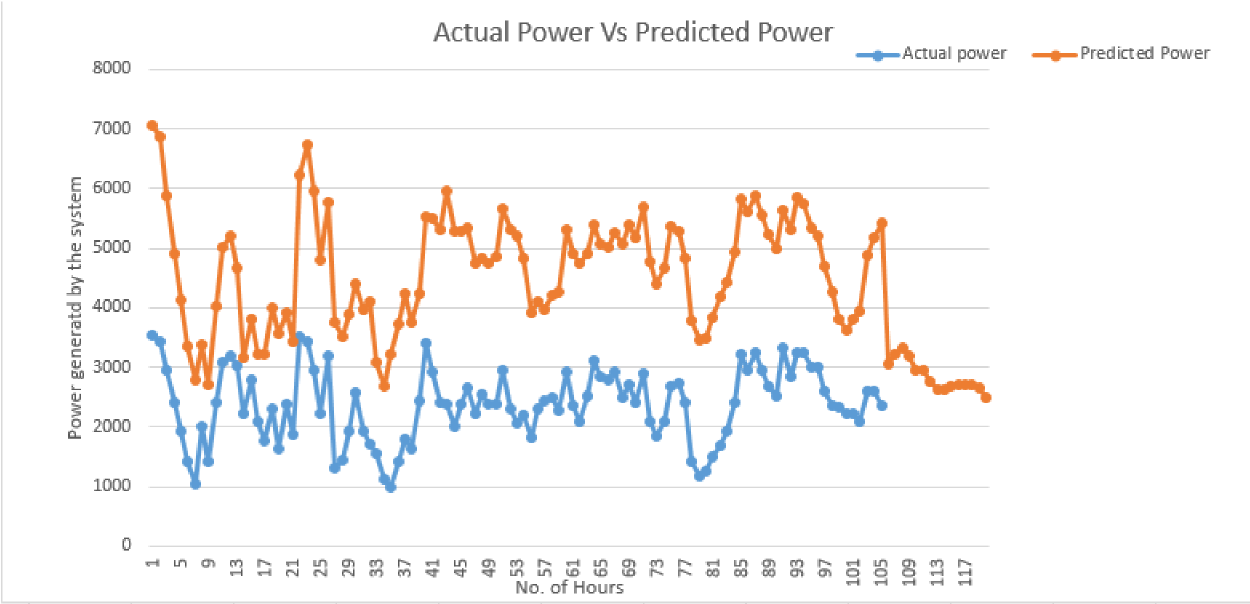

Figure 7.2. Prediction Plot of ARIMA

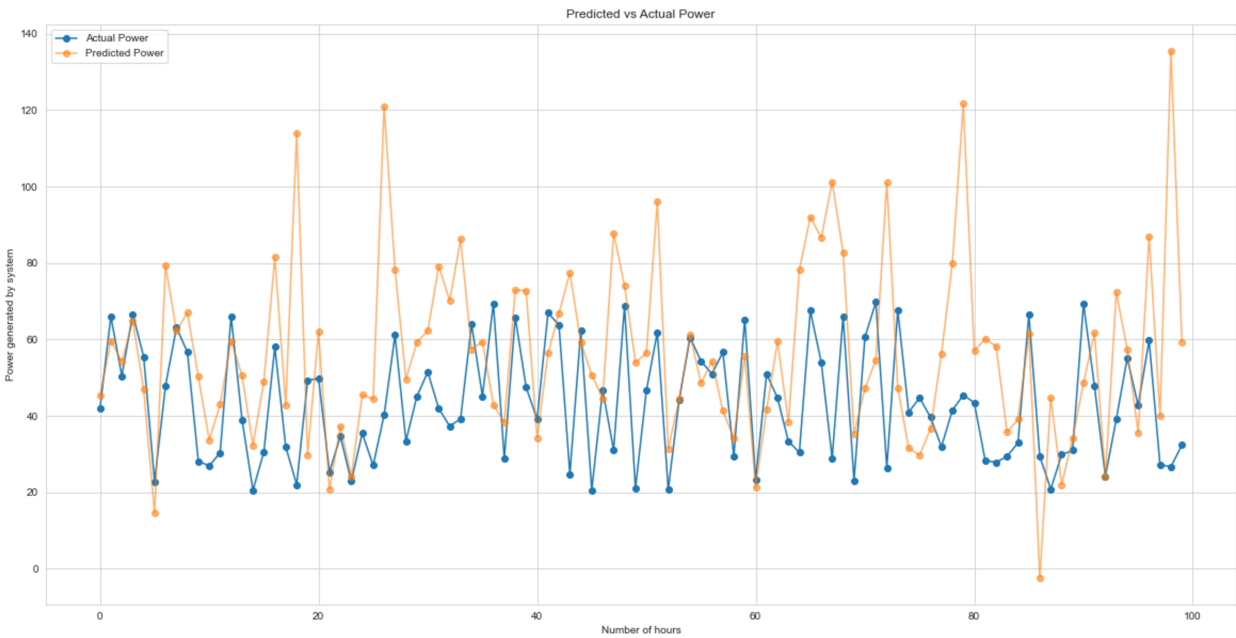

Figure 7.3. Prediction Plot of Random Forest Regressor

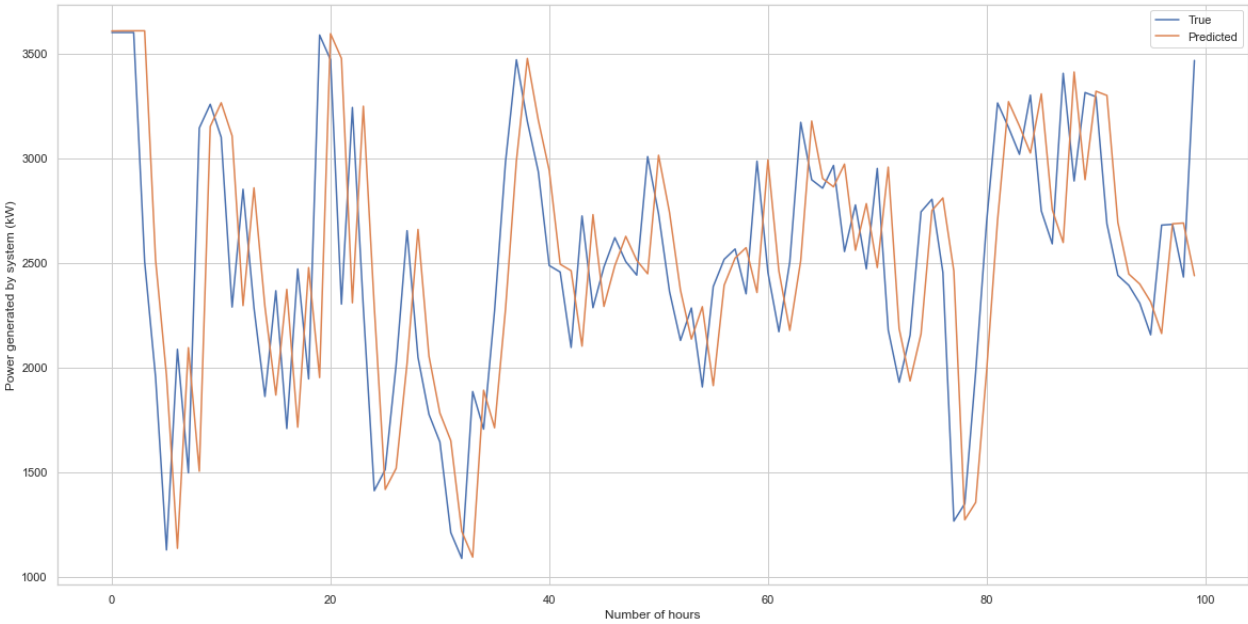

Figure 7.4. Prediction Plot of LSTM

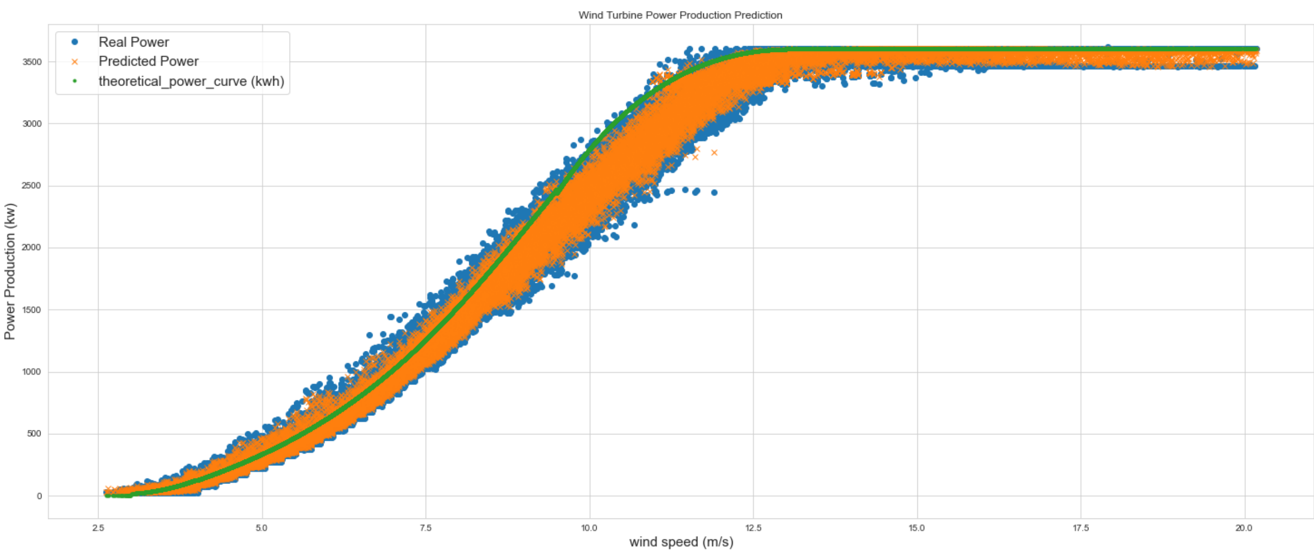

Figure 7.5. Power Curve

Each comparison plot of actual and predicted power in Fig. 6.1, Fig. 6.2, and Fig 6.3 shows the deviation level of its predicted values. By the analysis of plot it is clear that the deviation of the curve is lesser in case of LSTM model than ARIMA and Random Forest.

Table 7.1. Error comparison for all forecasting models

Name	MAPE	RMSE
AAApt¡ -Apt¿ MA R I	17.564	275.08
Random Forest	1.652	116.20
LSTM	1.374	65.75

Since deviation is very less in using proposed method, we can conclude that the prediction accuracy of LSTM is higher than classical regression method or AI forecasting models

7.4 RESULT ANALYSIS

This project captures the historical Wind turbine data from 01/01/2018 to 31/12/2018 to conduct the study. 50530 data samples in total were used. Root Mean Square Error (RMSE) and mean absolute percentage error (MAPE) were the operational metrics used in the test to evaluate the performance and accuracy of the data or to evaluate how well the predicted model represents the data itself. The RMSE MAPE should be close to zero for better predictions.

The RMSE is given by the formula:

$$\sqrt{\frac{\sum_{i=0}^{n}(Ai-Pi)^2}{n}}$$

The following formula provides the MAPE:

$$\frac{\sum_{i=0}^{n}\frac{|Ai-Pi|}{Ai}}{n}\times 100$$

Where A_i represents the final outcome

P_i represents the expected outcome.

And, n represents the number of passing hours.

Table.7.1 shows the comparison of RMSE values and MAPE for all the forecasted and actual values using each forecasting method.For LSTM, the RMSE and MAPE percentages are 65.75 and 1.374 percent, respectively. It is evident from Table.7.1 that the LSTM method's root mean square error is lower than that of the linear regression ARIMA model and Random Forest. As a result, it is clear that using LSTM to predict wind power offers a high degree of reliability and dependability.

Chapter 8

CONCLUSION

Wind energy generation is an important source of renewable energy for the production of electricity. Therefore, precise wind energy generation forecasting aids in optimising power grid dispatching, lowering system reserve capacity, and lowering system operating expenses. Deep learning techniques have the advantage of learning from data and possessing the ability for generalisation above classical learning techniques. The LSTM prediction model is chosen to forecast the production of wind energy. In this project, for the prediction of time series power data, we compared the performance of the LSTM deep learning method with that of conventional forecasting techniques like (ARIMA) and Random Forest. Then the prediction accuracy of all the models was analyzed and comparative study of all models was done, and each method's drawbacks were found out.The outcomes demonstrated that LSTM networks performed better in terms of data prediction for wind power. The outcomes also demonstrated deep learning's advantage over shallow neural networks. Overall, both short-term and long-term forecasts performed and converged better using LSTM networks.

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