© JUL 2025 | IRE Journals | Volume 9 Issue 1 | ISSN: 2456-8880

Wind Energy Forecasting Using Hammerstein-Winer Model

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Abstract- ***Wind energy has become the world's fastest growing source of clean and renewable energy and now contributes a large proportion of total power generation. This proportion will continue to increase because of the global preference for a clean and renewable energy source. However, wind power is difficult to integrate into traditional generation and distribution systems with current technology because it is intermittent, unpredictable and volatile. Thus, it is difficult to match wind generation to energy demand, and the imbalances between demand and generation can cause adverse voltage variations. This power quality problem cannot be solved effectively only by renewable generating technology and/or power electronics. As a whole, wind power integration challenge the power quality, energy planning and power flow controls in the grid. This can be more severe in weak networks, where the whole wind power source may even be disconnected from the grid. In this case, wind energy is forecasted using Hammerstein-wiener model in MATLAB®, the waveform is obtained from the simulation result, the predicted power and the observed power are determined from the waveform. The predicted power determined is improve when it is compared to the observed power. The percentage Error which is calculated from the predicted power and the observed power described the large error associated with the system.***

I. INTRODUCTION

1.1 Background of the study

Wind power is the conversion process of kinetic energy from wind into more useful forms such as electricity by using wind turbines. Most modern wind power is generated in the form of electricity by converting the rotation of turbine blades into electrical current by means of an electrical generator. In windmills (a much older technology), wind energy is used to turn mechanical machinery to do physical work, such as pumping water. Wind power is used in large scale wind farms for national electrical grids as well as in small individual turbines for providing electricity to rural residences or grid-isolated locations like in Sweden. Wind energy is plentiful, renewable, widely distributed, cleans, and reduces toxic atmospheric and greenhouse gas emissions if used to replace fossil-fuel-derived electricity.

1.2 Wind Energy

Wind Energy has played a significant role in power production during the last decade. It is currently booming and it has become one of the fastest growing markets in the world today [4–8]. Wind Energy provides clean and cheap opportunities for future power generation and many countries around the world have fostered ambitious goals for wind power development [9]. Wind Energy has become mature, and can now be considered as a valuable supplement to conventional energy sources. The fuel is free, but its variability poses challenges to wind powers continued growth and effective integration into the power grid. A large-scale introduction of wind power causes a number of challenges for the electricity market and power system operators who need to deal with the variability and uncertainty in wind power generation when making their scheduling and dispatch decisions. In this thesis, we forecast the wind Energy using the wind load date to improve the fluctuation and the challenges associated with the wind power generation.

The advantages of wind energy system:

- Wind energy is very friendly to the surrounding environment.
- Wind turbines take less space than the average power station.

- Windmills only have to occupy a few square metres for the base.
- Newer technologies are making the extraction of wind energy much more efficient.
- Wind turbines are a great resource to generate energy in remote locations, such as mountain communities and the countryside.
- When combined with solar electricity, this energy source is great for developed and developing countries to provide a steady, reliable supply of electricity.

The disadvantages of wind energy system;

- The main disadvantage regarding wind power is down to the winds unreliability factor.
- A wind turbine can only support a specific population.
- Wind turbine construction can last over a year, be very expensive and costly to the surrounding nature environment during the build process.
- The noise pollution from commercial wind turbines is on a part with a small jet engine.
- Vast protests and/or petitions usually confront any proposed wind farm site.

1.2 Statement of the problem

A major obstacle to the expansion of renewable energy technologies is the variable nature of renewable sources, which does not fit well with present approaches to the network. Their intermittent nature poses a problem when trying to match energy demand curves, one that cannot be solved by improving renewable generation technology alone. Irregularities in wind power output affect both power quality and the planning of energy systems. This variability in wind power output is due to the lack of control over its input. For example, the wind speed fluctuates due to movement of air masses and meteorological phenomena. These variations affect the wind power in terms of its consistency, which causes power quality concerns when wind power is integrated into an energy system. Consequently, the intermittency of generated wind power may cause imbalances between demand and generation which in turn lead to adverse voltage or frequency variations. This power quality problem cannot be solved by power electronics. This can be more severe in weak networks, where expansion in wind power may result in undesired voltage levels and sometimes the whole wind power source may be disconnected from the grid as an extreme case. Furthermore, unwanted instabilities in the supply may also cause fluctuations in system frequency due to wind fluctuations. In addition, variation of system parameters, unpredictable power demands and fluctuating wind power cause various uncertainties in the system. Therefore, the instantaneous penetration of wind energy conversion technologies is bounded by power quality requirements.

In summary, wind power integration challenges the power quality, energy planning and power flow controls in the grid. Suppression of wind power fluctuations is therefore one of the major Challenges. Efficient methods must be developed in order to raise the penetration of renewable energy sources. Energy storage is considered to be a potential solution to the integration issues of wind power. Nowadays, non-dispatchable power sources without any storage are a key concern.

1.3 Aims and Objectives

The aim of the project is to forecast the wind energy using the wind and load data. The objectives of the project are as follows:

1. To study the potentials of wind energy from the available wind data.
2. To simulate the wind and load data using Hammerstein-Wiener model in MATLAB®
3. To investigate the error margin between the actual and the predicted load due to wind energy potentials.

1.4 Scope and Limitations of the research

The scope of this project is to predict the electrical energy from the available wind and load data using Hammerstein-Wiener model in MATLAB®.

1.5 Project Organisation

This chapter has presented the background of the study, statement of the problem, methodology, aims and objectives, finally the scope and limitations. The rest of the thesis is organised as follows:

Chapter 2 discusses a brief literature review, which are sub-divided into: wind power forecasting, wind power forecasting approaches, impact of wind power grid integration, wind energy forecasting, wind energy prediction, prediction performance measure, load curve

Chapter 3 present proposed methodology, which include: Hammerstein-wiener model, preparing data for identification and data simulation.

Chapter 4 highlights the major achievements of this work. This chapter also includes Data Analysis, simulation results and calculation of percentage Error.

Chapter 5 this form the last part of the chapter, which include summary, conclusion and recommendation

II. LITERATURE REVIEW

2.1 Introduction

Wind is one of the promising sources of obtaining energy which is renewable and abundant. No greenhouse gasses emission is produced during production of energy from wind resources. Currently, in the world, there are 83 countries that produce energy from the wind power [1]. Some countries are satisfying significant portion of their energy demand from wind resources. To cite an instance, Denmark is generating more than a quarter of their electricity needs from wind [2]. The energy obtained from wind resources constitutes more than 2.5% of the total electricity usage worldwide, and this figure is expected to increase in the near future. It is indicated that the amount of electricity produced from wind has been growing rapidly (i.e., 25% annual growth during the last 6 years), and this trend is expected to persist in the near future [3].

In recent years, many a papers have been published in many countries investigating the impacts of wind power generation on the power system. Due to different data's, tools as well as methods of integration of wind power, cost comparison is very difficult. Despite different methodology, wind power is not independent, but different elements of power system are related with it [10-11]. The conventional energy sources such as oil, coal, or nuclear are finite and generate pollution. In addition, the renewable energy sources such as wind, fuel cell, solar, biomass & geothermal etc, are green energy sources and available in nature in plenty amount. Out of these sources wind energy is a credible green energy source which is eco-friendly having zero pollution effect as associated with conventional fuels [12]. Wind power is fastest growing source of renewable energy. However, the volatile and uncontrollable nature of wind power raises difficulties for power systems from the perspective of maintaining operational reliability [13]. In order to ensure the reliability of power systems with high wind power penetration, adequate reserve power needs to be scheduled against possible wind power fluctuations [14]. For wind farm operators, understanding the importance of uncertainty for financial as well as operational reasons is required. Wind energy application in electric power systems continues to increase globally. Wind presents certain challenges to the power system planners and operators due to its natural characteristics. Wind mills functions & generate energy when it blows above threshold speed. Because of such characteristics, dispatch-ability of wind plants in a traditional sense is not there. Fast fluctuations and unpredictable behaviour of wind speed, integration of wind power in the grid causes serious threat to the stability, security and reliability of the power system. The impacts of wind power penetration on system reliability, stability, power quality and security are usually studied from two aspects such as system operation and system planning.

In the latest power systems, wind power integration is one of the key issues. Wind energy is the most promising source of energy in the present modern world. Presently wind energy is fast emerging among the renewable sources. The chaotic behaviour of wind is a great challenge to the power system reliability & stability. Accurate forecast of wind power is very useful for unit commitment, economic dispatch and power system operations [5]. Wind power forecast depends on following factors-direction of wind, humidity, temperature etc. With the increase of the wind power penetration in the power system, poses a great challenge to its operation. Wind forecasting is important for power system reliability and it reduces the unit cost of the power system [6]. To convert available wind power to actual power the curve varies non-linearly as shown in power curve in Figure 2.1. The Figure 2.1 shows the relationship between wind speed (m/s) and output power curve depicts that change in wind speed causes the variation of output power. Below a minimum speed, which is called the threshold speed (around 3 m/sec), output power is zero. It is evident that output power growth of machine is only till nominal power is achieved (around 15 m/sec). Beyond this speed of 15 m/sec, the output power of machine is almost constant up to cut off speed (around 25 m /sec) [7],[8].

Wind turbine rotor produces wind energy & theoretically it is represented by

P_r=0.5 ρ π R2 Cp (λ,β) V^3 (2.1)

Where
Pr = Wind Power of the Rotor
ρ= Air density
R= Rotor Radius
V= wind speed
Cp = Rotor power Coefficient
λ = Blade Pitch angle
β = Tip speed ratio

The conversion of the available wind power into actual power for utilization varies nonlinearly, as seen in the power curve (Figure 2.1), due to the transfer functions of available generators. The power has zero output below a minimum speed i.e. threshold speed (around 3 m/s), a rapid growth in output until the wind speed is around 15 m/s and the output power is constant once the wind speed is above the cut-off level (around 25 m/s) [9].

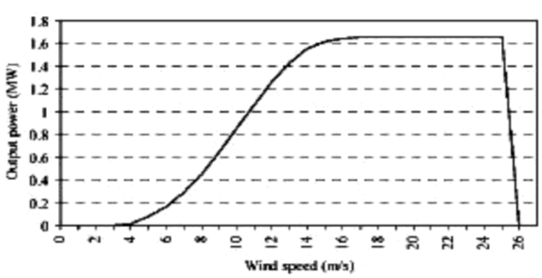

Figure 2.1 Power Curve for VESTAS V66-1.65 MW Wind Turbine [9]

Uncertainty related to inability to predict the weather and wind is always there. Figure 2.2 illustrates an example of the performance of physical prediction method which is based on Numerical Weather Prediction (NWP) as compared to time series method for a horizon larger than a few hours ahead [19]. No matter what methods are employed so far, the errors of predictions cannot be ignored.

As one of the most fundamental aspect of wind power integration, wind power forecasting accuracy is directly tied to the need for balancing energy and system security maintenance. Researchers have made significant efforts on wind power forecasting, and a number of methods are well established. State of the art wind power forecasting methodology is based on statistical models, physics-based methods, or their combination. As a stochastic process, more sophisticated methods are being proposed for the purpose of accurate wind power forecasting. The objective of this paper is to present the development of different techniques in this area.

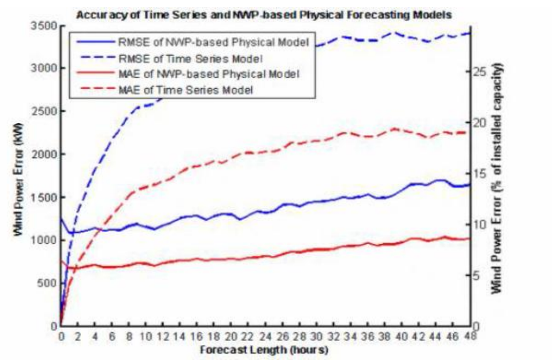

Figure 2.2 Performance of different prediction methods [19]

2.2 Wind power forecasting

2.2.1Forecast Objectives

Forecast objectives are defined by its applications. Power plant scheduling, power balancing, determination of wind speed and power, grid operation and congestion management are the applications of wind power forecast [20].

2.2.2 Forecast Horizons

An important feature of a forecasting system is its time horizon. The time horizon is defined as the time period in future for which the wind generation will be forecasted. Depending on the time horizon, wind power forecasting can be categorized into three types: very short term, short term and long term power prediction. Look-ahead periods that span from few minutes up to an hour are defined as very short term forecasting [21]. A span of 1 to 12 hours ahead is termed as short term horizon and a span of 3-84 hours ahead as long term horizon [4].

2.2.3 Forecast Data

The data required for wind power prediction are collected from wind farms with dozens of turbines. The Supervisory Control and Data Acquisition (SCADA) systems installed at each wind turbine can be used to obtain the necessary data. Data for weather forecasting can also be obtained from National Weather Service Forecast Models. Data for various locations in the neighbouring locality of the wind farm can be obtained from these models. The type of data required depends on the time horizon used for wind power forecasting. Wind speed (ms-1), wind direction (mph), air density (kg/m3),temperature difference (K), sensible heat flux at the surface(Wm-2), percentage of surface covered by vegetation (%) are some of the data required for wind forecasting [4].

2.2.4 Forecast Accuracy

The quality of a wind power forecast is determined by its accuracy. A long time period should be considered to measure the quality of a forecasting system, as the accuracy of forecast changes with time. The different metrics used to evaluate the prediction accuracy are Mean Absolute Error (MAE), Mean Square Error (MSE), Root Mean Square Error (RMSE) etc.

2.3 Wind power forecasting approaches

The wind industry is in need of accurate models for prediction of output power and health monitoring of wind farms. These models require large number of parameters and building such models is a challenging task [22]. Hence new modelling approaches are the need of the hour to cater to the high dimensional and random nature of wind. The wind power forecasting techniques are classified mainly into three main groups: Physical Approach, Statistical Approach and Learning Approach [20]. The physical approach comprises of several sub models, which translate the Numerical Weather Prediction (NWP) forecast at a certain grid point and model level, to forecast the power at the considered site and at turbine hub height. The mathematical description of the physical processes relevant to the translation is contained in each sub model. In the statistical approach, the relation between historical measurements, meteorological predictions and generation output is realized through statistical models whose parameters are estimated from the data, without taking into account any physical phenomena. The learning approach makes use of soft computing techniques like neural networks, fuzzy logic etc to learn the relationship between the forecasted wind and power output from the time series of the past [9]. The physical approach consists of a group of models of the different physical processes involved including wind conditions at the site and hub height of the turbines, wind turbine power curve etc. In statistical approach, the relationship between weather forecasts and output power production from the time series of the past is analysed and described such that it could be used in future. The models developed using Artificial Intelligence (AI) techniques learn the relationship between input data (NWP model predictions) and output data (power output), using algorithms.

2.3.1 Persistence method:

Persistence Model for wind power forecasting assumes that the wind power at a certain future time will be the same as it is when the forecast is made, i.e., $P_{t+k|t} = P_t$. At a functional level, the latest available measurements of wind power should be used, as provided by the SCADA system [9]. The persistence method is the most simplest of all forecasting methods and serves as a reference to evaluate the performance of other advanced methods. Any advanced forecasting technique is worth implementing, only if it outperforms the persistence model.

2.3.2 Physical Approach

All the wind power forecast models depend on the weather forecasts from NWP models as their essential input. A model chain of various hierarchical levels with different NWP models is used. Meteorological observations carried out by meteorologists, weather monitoring stations, satellites etc. throughout the world, mark the starting point of the model chain. A global NWP model, which models the atmosphere of mother earth, is established using the data available as input. Using the physical laws governing the weather, state of the atmosphere in future is predicted by the developed NWP

2.3.3 Statistical Approach

Statistical methods are easy to model and economical in comparison with the others. Statistical methods use the previous history of wind data to forecast the next few hours. It is good for the short time period. The disadvantage of the Statistical method is that error increases with the increase of prediction period. Statistical time series models are used to predict wind power output up to six hours in advance. The auto regressive moving average (ARMA) is a well-known time series statistical model. It is based on time series analysis [32].

This model shows the good forecasting results within 1 to 2 hours. Auto regressive integrated moving average (ARIMA) models have three components as auto regressive, integrated, and moving average. Once the integration term is absent then the model is known as ARMA mode. Statistical approach consists of a single step which involves the direct transformation of the input variables into wind generation. The inputs of speed, direction, etc. from various NWP models are combined together with the online measurements of wind speed, direction, power and others in the statistical block.

A direct approximation of the regional wind power from the input parameters is made possible in a single step [9]. This approach involves the application of statistical methods such as Auto Regression (AR), Auto Regressive Moving Average (ARMA) method, linear prediction, probability density function, Gaussian distribution function etc. An overview of few statistical approaches implemented for wind power forecasting is presented here. A linear time varying AR process to model and forecast wind speed, considering its non-stationary nature was proposed by Huang and Chalabi in [23]. Smoothed integrated random walk processes were used to model the time varying parameters of the AR model. A technique for wind power forecasting based on ARMA modelling was developed by Rajagopalan and Santoso in [33]. The relationship between the accuracy of the forecast and the variability of wind power was also studied. The model coefficients were determined using Burg and Shanks algorithms. Accurate forecasts were obtained for a look-ahead period of one hour, but the accuracy declined further ahead in time. Wind speed on the day-ahead (24 hours) and two-day-ahead (48 hours) horizons have been modelled and forecasted using fractional-ARIMA (Auto Regressive Integrated Moving Average) or f-ARIMA models in [24]. The forecasting accuracy of the developed model was significantly higher than the persistence method. Short-term wind speed forecasting using a new kernel machine method was presented by H. Mori and E. Kutara in [25]. The prediction model was constructed using Gaussian Process (GP) with Bayesian estimation. The developed model reduced the average error of Multi-Layer Perception (MLP) and Radial Basis Function Network (RBFN) by 27% and 12% and the maximum error by 13% and 7.8% respectively.

A method to calculate wind power forecast in a particular area employing an aggregate prediction method was proposed by M.G. Lobo and I. Sanchez in [26]. This method used the distances between wind speed forecasts for a set of selected coordinates and its accuracy was also tested in comparison with other methods and found to be significantly higher.

A comprehensive evaluation of a well-designed power model, including the description of the method and its comparative performance with a standard power model is provided in Reference [27]. The impact of short-term wind power forecasting in Romania has been presented in [28]. The prediction of wind speed signals using linear prediction with Finite Impulse Response (FIR) and Infinite Impulse Response (IIR) filtering has been developed in [29]. The speed signals are transformed from Weibull to Normal Probability Density

The prediction of wind power output using probabilistic forecasting is one of the recent areas of research. The prediction error approach and the direct approach are the two main approaches to probabilistic wind power forecasting. The probabilistic forecast of the errors of an existing deterministic forecasting model is provided by the first approach, whereas the second approach provides the probabilistic predictions of a particular variable under consideration directly. Reference [30] details on a method for producing the complete predictive Probability Density Function (PDF) based on Kernel Density Estimation (KDE) techniques. Spot forecasts, quartile forecasts and interval forecasts could be derived from the complete predictive distribution computed by the model. The performance of these derived forecasts was significantly better than other forecasting models. In order to enhance the participation of wind farm operators into short-term electricity markets, a risk-based decision-making method was developed in [31]. Integration of the uncertainty associated to the wind power and the market regulation price forecasts was the basis of this work.

2.3.4 Hybrid / Combination Approach

In general, combination of different approaches such as physical and statistical approaches or combining short term & medium term models, etc, is referred to as a hybrid approach. Below Figure 2.3 shows the pictorial view of Hybrid/Combination Approach.

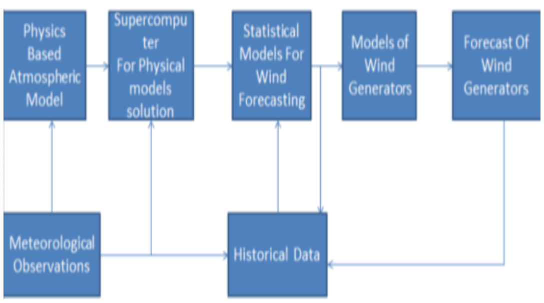

Figure 2.3. Hybrid Approach of Wind Power Forecasting

2.3.5 Learning Approach

Artificial Neural Networks (ANN) do not use explicit derivation of model equation but they learn using input output mapping of variables. They are used in various areas of research including pattern recognition, prediction and forecasting, optimization and control. Mohandes et.al., introduced a neural network based technique for prediction of wind speed and compared its performance with an Auto-Regressive (AR) model [34]. The RMSE was used as performance indicator and the ANN technique performed better than the AR model. A neural network based technique for the forecasting on mean hourly wind speed time analysis has been presented by Steftos in [35]. The method was based on the fact that, when the averaging interval lies within an interval of 10 minutes, the wind speed was more predictable. A locally recurrent neural network for prediction of wind speed using spatial correlation was developed by Barbounis and Theocharis [36]. This technique outperformed the performance of previously used methods. Mabel and Fernandez developed an ANN architecture for wind speed prediction [37]. The monthly average wind speed, relative humidity and monthly generation hours were used as input to the ANN model and the output variable was the wind energy output of wind farms (Figure 2.4). The MSE and MAE were calculated both for the training and testing data sets. The predicted wind energy output showed good coherence with the actual values. Accurate prediction of wind speed using two structures of neural network banks was proposed in [38]. This technique showed remarkable improvement in the performance of the hybrid physical-statistical wind speed forecasting models, better than those that used single neural network structures. Generally, the ANN based methods of wind speed prediction outperformed the statistical models.

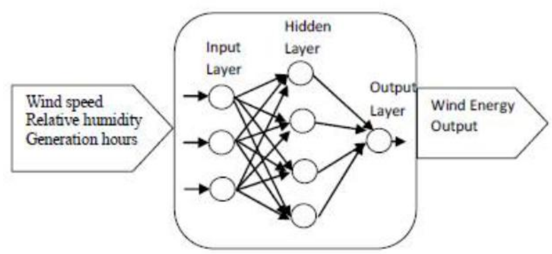

Figure 2.4. ANN Architecture

Support Vector Machines (SVM) are a set of related supervised methods used for classification and regression. Neural Network models for short term wind speed prediction were compared with SVM models by Sreelakshmi and Ramkantha kumar [39]. They observed that SVM models compute faster and give better accuracies than the ANN models.

Principles Fuzzy logic is based on of approximate reasoning and computational intelligence. A genetic algorithm based learning scheme was used to train the input data which consisted of wind speed and direction data. The fuzzy model could predict wind speed from 30 min to 2 hours ahead and it outperformed the persistent method. The spatial correlation that existed among the wind speed time series data of various measuring stations was exploited by the fuzzy expert system developed by Damousis and Dokopoulos for wind power prediction [41].

Neural Networks and Fuzzy Systems complement each other. An Adaptive Neuro-Fuzzy Inference System (ANFIS) can incorporate fuzzy if-then rules and also the fine tune the membership functions. It is basically a neural.

Network at par with the fuzzy inference model functionally. A comparison of various forecasting approaches like the Box- Jenkins approach, Feed-Forward NN, Radial basis function network and ANFIS models on mean hourly wind speed data using time series analysis was performed by Steftos [42]. He concluded that the models based on artificial intelligence outperformed the respective linear ones. An ANFIS-based method for very short-term wind prediction technique for power generation was introduced by Potter and Negnevitsky [21]. The wind prediction system was designed to forecast wind vectors 2.5 minutes ahead. The ANFIS model was compared with a persistence model and the mean absolute percentage error was found to be 4% and 30%. A locally recurrent fuzzy neural network with application to wind speed prediction using spatial correlation was developed by Barbounis and Theocharis [43]. Wind speed is estimated for 15 min to 3hours ahead by using the NN developed model. A technique based on the combination of neural network and fuzzy logic was used to increase the accuracy of the estimated wind speed and to reduce the computation time. In the proposed model using the fuzzy logic requires a lesser number of neurons. Thus, the prediction models based on ANFIS, exploit the advantages of both neural networks and fuzzy logic. Though they appear complicated, they perform better and obtain good prediction accuracies

The process of extracting information from bulk of data is called as data mining. It is the task of discovering interesting pattern from bulk data's stored in databases, data warehouses or other information repositories. Different data mining models including linear and non-linear models were studied and their advantages and drawbacks compared in [44]. These models comprised of neural networks, random forests and support vector machines. Algorithms for developing monitoring models used for computing wind farm power were proposed in [22]. The algorithms were developed in four different domains, namely data mining, evolutionary computation, principal component analysis and statistical process control. An evolutionary strategy algorithm was used to construct a nonlinear parametric model of the wind turbine power curve, which was used to monitor the online performance of the wind farm. Kusiak A., Zheng H., and Song Z., used the data mining approach to build time series models for the prediction of wind farm power over short (10-70 minutes) and long (1-4 hours) horizons [45,4]. The various wind farm datasets were tested using five different data mining algorithms, out of which two algorithms performed very well. Zheng and Kusiak built models to predict the power ramp rates of a wind farm using data mining algorithms, which would be of importance to the electric grid [46]. A data driven approach for maximization of power produced by wind turbines was developed in [47]. The optimal control settings of wind turbines were computed using data mining and evolutionary computation. Hence data mining is a promising approach to model wind farm performance. The models developed based on data mining algorithms can be easily updated and expanded.

2.4 Impact of wind power grid integration

Wind power integration to the grid will have significant impact on reliability, security and stability of power system due to fast fluctuation and unpredictable characteristics of wind speed. Large quantity of wind farms integration can have either positive or negative impacts on the performance of power system reliability. The impacts of wind power penetration on system reliability, stability, power quality and security are usually studied from two aspects point of View-system operation and system planning [48]. Wind energy has several effects on power system which may lead to reverse power flow [49].

2.4.1 Power Quality
Power quality is related to voltage variation and harmonic distortion in the network. The integration of wind power in the system affects the quality of the supplied voltage to the end user. To minimize the affect these days, variable speed wind turbines equipped with power electronics are extensively used in the wind power plants. Power electronics increase power quality because they control the harmonic distortion.

2.4.2 Protection System
Protection system is also affected by wind farms since the incorporation of wind power injection changes the direction of power flow so that normal protection system might fail under fault situations. Power network is passive which maintains stability in majority situations. This statement is no longer valid if considering an increase of wind energy penetration. Now a days, requirement for wind units have been designed in order to keep the power system stability within limit in severe condition like low voltage ride through capability [51].

2.4.3 Transient Stability
Traditional generators try to meet the fluctuating load demand to minimize voltage & frequency fluctuations. During fault which causes the voltage dips, generators accelerates to bridge the gap between mechanical and electrical powers. When the fault is cleared they absorb reactive power lowering the network voltage, if not enough reactive power is supplied a voltage depression is must. Exciters of synchronous generators enhance the reactive power output during low voltages and thus support voltage restoration. Whereas induction generators try to impede voltage recovery. If the penetration of wind generation is more and it gets disconnected at small voltage depression it can lead to a large generation deficit, to prevent this wind farms are needed to ensure sufficient compensation fault ride through capability [52].

2.4.4 Voltage Control
Power system nodal voltage is permitted to fluctuate from ±5% to up to ±7%. Synchronous generator and other devices used as compensator to regulate the nodal voltage by supplying or absorbing reactive power. In contrast induction generators absorb reactive power and have no direct control over reactive power flows. Even variable-speed wind turbines are also not capable to keep the voltage within limit at the instant of connection, because the wind farm network is predominantly capacitive [53]. The voltage variation issue results from the wind velocity and generator torque. The voltage variation is straight way related with the changes to real and reactive power.

The voltage variation is commonly classified as under [54]:

- Voltage Sag/Voltage Dips
- Voltage Surge
- Short Interruptions
- Long duration voltage variation

The voltage flicker issue indicates dynamic changes in the network resulted due to wind turbine or by varying loads. Thus the power fluctuation from the wind turbines develops due to continuous operation. The amplitude of voltage fluctuation depends on grid strength, network impedance, and phase angle and power factor of the wind turbines. It is defined as a fluctuation of voltage in a frequency 10-35 Hz.

2.4.5 Frequency control
Increasing wind power penetration especially in non interconnected systems is changing gradually the way grid frequency control is achieved. In the power system, frequency is the variable indicating the status of generation and demand. Frequency is around the nominal value once operation is normal and there is no mismatch between demand and supply. Figure 7 illustrates the frequency variation owing to primary response as well as secondary response. Primary control and secondary control in this regard is described here under:-

- Primary Control: Subsequent to event leading to frequency deviation, during initial 30-40 sec the rotational energy stored in large synchronous machine is used to maintain the equilibrium between production and consumption through the deceleration of the rotors. Such units (often called as primary control units) generation is thus increased until the frequency is stabilized by restoring the power balance.

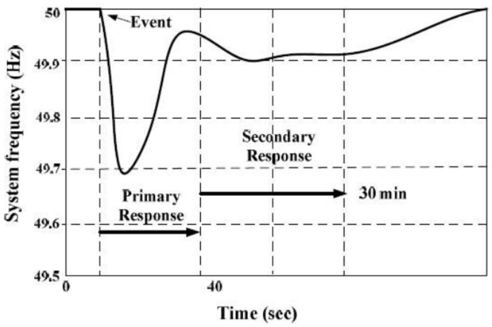

Figure 2.5. Definitions of frequency control in power systems

- Secondary control: Post the primary response of the unit, a slow supplementary control function is activated in order to restore the frequency to its normal. The generators connected to the system are ordered to change their production through Automatic Generation Control (AGC) scheme or through manual request by the system operator.

2.5 Wind energy forecasting

The forecast of wind power production is traditionally predicted to foretell the available energy that the wind can produce. This knowledge store is not fully understood in processes that affect future events. Therefore, it is important to provide a method to evaluate the accuracy of these estimates by pointing out more points about wind power generation in days [4]. By present practice, uncertainty is expressed in the form of predictable predictions or common predictions. Some decisions related to wind direction and business-related sales have been proven to be more optimistic when determining concrete forecasts. Examples of business applications, studies show that realistic forecasts of aviation fields, advanced marketing methods. Other studies of this type involve optimal dynamic quantification of reserves requirements, including optimal operation of a combined wind system, or multi-zone multi-level regulation. Such studies include better integrated ventilation schemes, or better backup interventions at multiple multi-level monitoring sites. Wind energy prediction researches helps to plan the future, help manage the power system in a robust and economical way, help plan wind farm maintenance in the next few days, plan power exchange/flow and fuel planning consumption with neighboring systems.

2..5.1 Categorization of wind energy forecasts based on Time-Scales

Methods distributed based on time or methods can be used for prediction of wind speed. Over time, the wind speed forecast methods below is shown.

1 Ultra short-term forecast from the first a few minutes to 1 hour.
2 Short term forecasts range from hours to hours.
3 The medium-term forecast one day to a week.
4 Long-term predictions range from 1 week to 1 year or longer.

2.6 Wind energy prediction

Island, Greece, using historical wind data from the island and from other neighbouring islands as input; the same method was improved later in [48] for a different location in Greece. In [46], the Author used two models based on NN to predict the wind speed for a time horizon of one hour. The first model used the last known values of the hourly wind speed as inputs. The second improved model used wind speed time series with 10 min intervals as inputs in addition to using the NN. In addition, [36] evaluated a persistence model, ARIMA models, NN, and neuro-fuzzy systems and gave performance comparisons. A different approach based on the frequency domain was also proposed in [53] and [54].

In [55], a new technique was presented to predict hourly wind speeds based on the Grey predictor model. The predicted wind speed was converted to wind power using a manufacturer's power curve. In [41], the author presented a fractional-ARIMA (f-ARIMA) model to predict wind speed. The predicted wind speed was also converted to wind power by using a manufacturer's power curve. An Adaptive Neural Fuzzy Inference System (ANFIS) [56] was used to predict the wind speed for a 2.5 min prediction horizon. In [57], the author presented the idea of using more than one model to predict the wind speed. In [40], five ARMA models were presented to predict the hourly average wind speed for a time horizon of 10 hr in five different locations with different characteristics. Four NN configurations were tested in [47] for hourly wind speed predictions. In [58], the author described an approach that used the last six measured values as inputs to predict wind speed for the following minutes. The results were good when compared with the persistence for time horizons below 10 min of averaged data. In [59], a Kalman filter based method was demonstrated for short-term wind prediction. In [60], a Kalman filter was used to control a variable-speed wind turbine as well. In [61], a hybrid statistical method was presented to predict wind speed and wind power. In [62], the author presented a method for the analysis and forecasting of wind velocity in Chetumal. In [39], several tests were performed to select AR models for wind power prediction. In [63], the author described two approaches for local polynomial regression with particular emphasis on data quality. A hybrid statistical–physical approach was described in [64]. Hybrid approaches like ANFIS were also used for wind power prediction [65] and [66]. The techniques based on physical models use the weather data for wind power predictions (see, e.g., [67–69]. These models have been reported to be inefficient for short-term predictions and are very expensive and complicated as well. Extensive prediction techniques and algorithms exist in the literature. A complete list is quite large and could continue further; but the need of improvement is, in fact, always there. In this thesis, prediction is based on combining NWP data with data from multiple observation points from close neighbouring sites to improve the prediction at the given point, i.e., prediction at the turbine level is improved using information from nearby turbines in the wind farm. The relevant literature, discussions and comparison with similar techniques are given in the wind power prediction chapter of this thesis.

Secondly, as wind power is a function of wind direction, many studies have concluded that the prediction of wind direction is a prerequisite for effective operation of wind turbines [19,70]. Approaches found in the literature focused on the prediction of wind speed, direction or power individually. We particularly focus on the simultaneous prediction of both wind speed and direction and consequently the power, i.e., the research in this thesis is based on prediction of wind vectors, and consequently the prediction of wind power is achieved simultaneously using the observations. In addition, owing to wind direction variability, the concept of direction dependence is utilised to achieve the final wind power prediction.

2.7 Prediction performance measures

The following standard error measures are commonly used to compare the performance of prediction models.

2.7.1 Prediction Error

In general, the difference or deviation between predicted and measured quantity is called the prediction error. For wind power prediction, the prediction error observed at a given time t +k for a prediction made at time origin t, is defined as the difference between the value of wind power that is actually measured at t +k, and the value of predicted wind power at t +k that was originally predicted at t, i.e.

$$e_{t+k|t} = P_{t+k} - \hat{}P_{t+k|t}$$

Where e_(t+k|t) is the error corresponding to time t +k for the prediction made at time t, P_(t+k) is the measured power at time t +k, and 〖^P〗_(t+k|t)is the power prediction for time t+k made at time t.

2.7.2 Normalised Prediction Error

It is often convenient to use the normalised prediction error, which can be obtained by dividing the prediction error by the installed capacity, as follows:

$$e_{t+1|t} = \frac{1}{Pinst}[Pt + k - \hat{}Pt + k|t]$$

where P_inst is the wind farm's installed capacity. Normalised prediction errors are useful because these allow wind farm to be compared, regardless of their rated capacity. This produces results that do not depend on wind farm size. In our study, P_inst refers to the rated power of the given turbine since our research is based on the individual turbines in a given wind farm site.

2.7.3 Mean Squared Error

The mean squared error (MSE) is a measure of prediction accuracy. The lower the mean square error, the more accurate the predictions. It is a common error measure to identify the contribution of both positive and negative errors to a prediction method's lack of accuracy, which consists of the average of the squared errors over the test set, i.e.

$$MSE = \frac{1}{N}\sum_{t=1}^{N} \cdot e_{t+1|t}^{2}$$

2.7.4 Mean Absolute Error

The mean absolute error (MAE) is a quantity used to measure how close predictions are to the eventual outcomes. The mean absolute error is given by

$$MAE = \frac{1}{N}\sum_{t=1}^{N} \cdot e_{t+1|t}$$

where all errors receive a weighting directly proportional to their amplitude in contributing to this error measure. The MAE divided by the installed capacity or the average production of the wind farm, is called Normalised Mean Absolute Error (NMAE). In our study, MAE is normalised by the rated power of the given turbine and the numerical results are presented as a percentage of the rated power.

2.7.5 Root Mean Square Error

Root mean square error (RMSE) is the square root of the mean square error and is given as

$$RMSE = \sqrt{\frac{1}{N} e_{t+1|t}^{2}}$$

Since the errors are squared before they are averaged, larger errors are penalised more than smaller errors in contributing to this error measure. This means the RMSE is most useful when large errors are particularly undesirable. The RMSE, divided by the installed capacity or the average production of the wind farm, is called Normalised Root Mean Square Error (NRMSE). In this study, RMSE is normalised by the rated power of the given turbine and the numerical results are presented as a percentage of the rated power.

2.8 Variable load on wind power station

The load on a power station varies from time to time due to uncertain demands of the consumers and is known as variable load on the station. A power station is designed to meet the load requirements of the consumers. An ideal load on the station, from stand point of equipment needed and operating routine, would be one of constant magnitude and steady duration. However, such a steady load on the station is never realised in actual practice. The consumers require their small or large block of power in accordance with the demands of their activities. Thus the load demand of one consumer at any time may be different from that of the other consumer. The result is that load on the power station varies from time to time.

2.8.1 Effects of variable load.

The variable load on a power station introduces many perplexities in its operation. Some of the important effects of variable load on a power station are:

(i) Need of additional equipment.

The variable load on a power station necessitates to have additional equipment. By way of illustration, consider a steam power station. Air, coal and water are the raw materials for this plant. In order to produce variable power, the supply of these materials will be required to be varied correspondingly. For instance, if the power demand on the plant increases, it must be followed by the increased flow of coal, air and water to the boiler in order to meet the increased demand. Therefore, additional equipment has to be installed to accomplish this job. As a matter of fact, in a modern power plant, there is much equipment devoted entirely to adjust the rates of supply of raw materials in accordance with the power demand made on the plant.

(ii) Increase in production cost.

The variable load on the plant increases the cost of the production of electrical energy. An alternator operates at maximum efficiency near its rated capacity. If a single alternator is used, it will have poor efficiency during periods of light loads on the plant. Therefore, in actual practice, a number of alternators of different capacities are installed so that most of the alternators can be operated at nearly full load capacity. However, the use of a number of generating units increases the initial cost per kW of the plant capacity as well as floor area required. This leads to the increase in production cost of energy.

2.9 Load curve

The curve showing the variation of load on the power station with respect to (w.r.t) time is known as a load curve. The load on a power station is never constant; it varies from time to time. These load variations during the whole day (i.e., 24 hours) are recorded half-hourly or hourly and are plotted against time on the graph. The curve thus obtained is known as daily load curve as it shows the variations of load w.r.t. time during the day. Figure 2.6. Shows a typical daily load curve of a power station. It is clear that load on the power station is varying, being maximum at 6P.M. in this case. It may be seen that load curve indicates at a glance the general character of the load that is being imposed on the plant. Such a clear representation cannot be obtained from tabulated figures. The monthly load curve can be obtained from the daily load curves of that month. For this purpose, average values of power over a month at different times of the day are calculated and then plotted on the graph. The monthly load curve is generally used to fix the rates of energy. The yearly load curve is obtained by considering the monthly load curves of that particular year. The yearly load curve is generally used to determine the annual load factor.

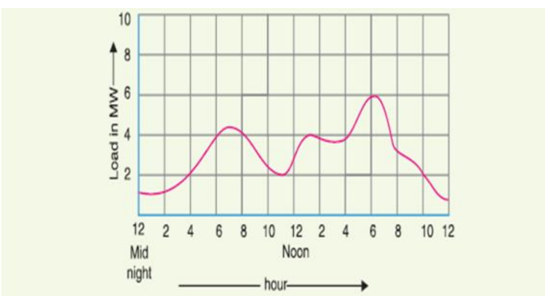

Figure 2.6: load curve of a power station

2.9.1 Importance of load curve
The daily load curves have attained a great importance in generation as they supply the following information readily:

(i)The daily load curve shows the variations of load on the power station during different hours of the day.
(ii)The area under the daily load curve gives the number of units generated in the day. Units generated/day = Area (in kWh) under daily load curve.
(iii) The highest point on the daily load curve represents the maximum demand on the station on that day.
(iv)The load curve helps in selecting the size and number of generating units.
(v)The load curve helps in preparing the operation schedule of the station.

2.10 Load duration curve
When the load elements of a load curve are arranged in the order of descending magnitudes, the curve thus obtained is called a load duration curve.

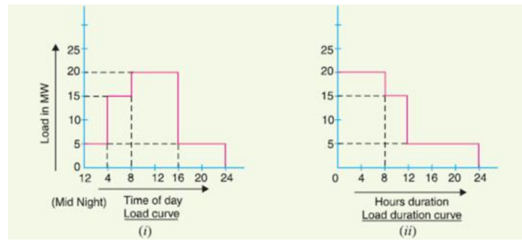

Figure 2.7

The load duration curve is obtained from the same data as the load curve but the ordinates are arranged in the order of descending magnitudes. In other words, the maximum load is represented to the left and decreasing loads are represented to the right in the descending order. Hence the area under the load duration curve and the area under the load curve are equal. Figure 2.7 (i) shows the daily load curve. The daily load duration curve can be readily obtained from it. It is clear from daily load curve [See Figure 2.7. (i)], that load elements in order of descending magnitude are : 20 MW for 8 hours; 15 MW for 4 hours and 5 MW for 12 hours. Plotting these loads in order of descending magnitude, we get the daily load duration curve as shown in Figure 4.2 (ii).

The following points may be noted about load duration curve:

(i) The load duration curve gives the data in a more presentable form. In other words, it readily shows the number of hours during which the given load has prevailed.
(ii) The area under the load duration curve is equal to that of the corresponding load curve. Obviously, area under daily load duration curve (in kWh) will give the units generated on that day.
(iii) The load duration curve can be extended to include any period of time. By laying out the abscissa from 0 hour to 8760 hours, the variation and distribution of demand for an entire year can be summarised in one curve. The curve thus obtained is called the annual load duration curve.

2.10.1 Types of Loads

A device which taps electrical energy from the electric power system is called a load on the system. The load may be resistive (e.g., electric lamp), inductive (e.g., induction motor), capacitive or some combination of them. The various types of loads on the power system are:

(i) Domestic load. Domestic load consists of lights, fans, refrigerators, heaters, television, small motors for pumping water etc. Most of the residential load occurs only for some hours during the day (i.e., 24 hours) e.g., lighting load occurs during night time and domestic appliance load occurs for only a few hours. For this reason, the load factor is low (10% to 12%).

(ii) Commercial load. Commercial load consists of lighting for shops, fans and electric appliances used in restaurants etc. This class of load occurs for more hours during the day as compared to the domestic load. The commercial load has seasonal variations due to the extensive use of air conditioners and space heaters.

(iii) Industrial load. Industrial load consists of load demand by industries. The magnitude of industrial load depends upon the type of industry. Thus small scale industry requires load up to 25 kW, medium scale industry between 25kW and 100 kW and large-scale industry requires load above 500 kW. Industrial loads are generally not weather dependent.

(iv) Municipal load. Municipal load consists of street lighting, power required for water supply and drainage purposes. Street lighting load is practically constant throughout the hours of the night. For water supply, water is pumped to overhead tanks by pumps driven by electric motors. Pumping is carried out during the off-peak period, usually occurring during the night. This helps to improve the load factor of the power system.

(v) Irrigation load. This type of load is the electric power needed for pumps driven by motors to supply water to fields. Generally this type of load is supplied for 12 hours during night.

(vi) Traction load. This type of load includes tram cars, trolley buses, railways etc. This class of load has wide variation. During the morning hour, it reaches peak value because people have to go to their work place. After morning hours, the load starts decreasing and again rises during evening since the people start coming to their homes.

2.11 Load curves and selections of generating units

The load on a power station is seldom constant; it varies from time to time. Obviously, a single generating unit (i.e., alternator) will not be an economical proposition to meet this varying load. It is because a single unit will have very poor efficiency during the periods of light loads on the power station. Therefore, in actual practice, a number of generating units of different sizes are installed in a power station. The selection of the number and sizes of the units is decided from the annual load curve of the station. The number and size of the units are selected in such a way that they correctly fit the station load curve. Once this underlying principle is adhered to, it becomes possible to operate the generating units at or near the point of maximum efficiency.

2.11.1 Illustration of load curve

The principle of selection of number and sizes of generating units with the help of load curve is illustrated in Figure 2.8. In Figure 2.8 (i), the annual load curve of the station is shown. It is clear form the curve that load on the station has wide variations; the minimum load being somewhat near 50 kW and maximum load reaching the value of 500 kW. It hardly needs any mention that use of a single unit to meet this varying load will be highly uneconomical.

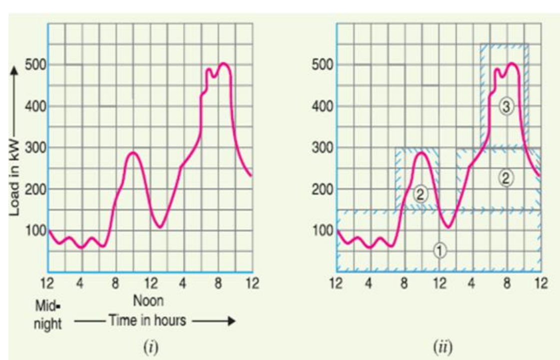

Figure 2.8 Load curve Illustration

As discussed earlier, the total plant capacity is divided into several generating units of different sizes to fit the load curve. This is illustrated in Fig. 2.8 (ii) where the plant capacity is divided into three units numbered as 1, 2 and 3. The cyan colour outlines shows the units capacity being used. The three units employed have different capacities and are used according to the demand on the station. In this case, the operating schedule can be as presented in Table 2.2.

Thus by selecting the proper number and sizes of units, the generating units can be made to operate near maximum efficiency. This results in the overall reduction in the cost of production of electrical energy

2.11.2 Important Points in the Selection of Units

While making the selection of number and sizes of the generating units, the following points should be kept in view:

(i) The number and sizes of the units should be so selected that they approximately fit the annual load curve of the station.

(ii) The units should be preferably of different capacities to meet the load requirements. Although use of identical units (i.e., having same capacity) ensures saving in cost, they often do not meet the load requirement.

(iii) The capacity of the plant should be made 15% to 20% more than the maximum demand to meet the future load requirements.

(iv) There should be a spare generating unit so that repairs and overhauling of the working units can be carried out.

The tendency to select a large number of units of smaller capacity in order to fit the load curve very accurately should be avoided. It is because the investment cost per kW of capacity increases as the size of the units decreases.

Table 2.2: Load operation

Time	Units in operation
From 12 midnight to 7 A.M. From 7 A.M. to 12.00 noon	Only unit no.1 is put in operation. Unit no. 2 is also started so that both units 1 and 2 are in operation.
From 12.00 noon to 2 P.M. From 2 P.M. to 5 P.M.	Unit no. 2 is stopped and only unit 1operates. Unit no. 2 is again started. Now units 1 and 2 are in Operation.
From 5 P.M. to 10.30 P.M. From 10. 30 P.M. to 12.00 midnight	Units 1, 2 and 3 are put in operation. Units 1 and 2 are put in operation.

2.11.3 Base Load and Peak Load on Power Station

The changing load on the power station makes its load curve of variable nature. Figure 2.9. Shows the typical load curve of a power station. It is clear that load on the power station varies from time to time. However, a close look at the load curve reveals that load on the power station can be considered in two parts, namely;

(i) Base load: The unvarying load which occurs almost the whole day on the station is known as base load. Referring to the load curve of Figure 4.4, it is clear that 20 MW of load has to be supplied by the station at all times of day and night i.e. throughout 24 hours. Therefore, 20 MW is the base load of the station. As base load on the station is almost of constant nature, therefore, it can be suitably supplied (as discussed in the next Article) without facing the problems of variable load.

(ii) Peak load: The various peak demands of load over and above the base load of the station is known as peak load. Referring to the load curve of Figure 2.9, it is clear that there are peak demands of load excluding base load. These peak demands of the station generally form a small part of the total load and may occur throughout the day.

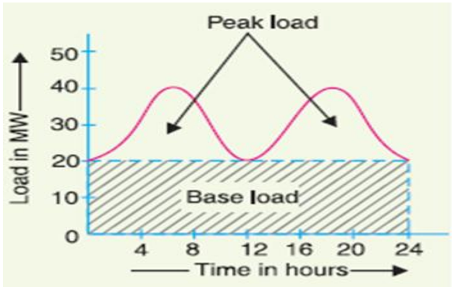

Fig 2.9: load curve of a power station

III. RESEARCH METHODOLOGY

3.1 Introduction

The project's methodology consists of several approaches and steps. The procedures that had been taken are referred from literature review through many journals, report papers and articles founded about the wind energy forecasting from many sources like internet and library. A suitable model has been selected for this research. The Hammerstein-wiener model is used to forecast and simulate the wind load data. As discussed in the literature review, there are some projects that have been done before but they uses other model to forecast the data. This project will extend the previous work by using MATLAB® to improve the fluctuation in wind Energy, because it is user friendly and had the entire component for the simulation of result.

3.2 Hammerstein-wiener model

Hammerstein-Weiner models were described as dynamic systems using one or two static nonlinear blocks in series with a linear block. The linear block is a discrete transfer function and represents the dynamic component of the model. In this paper, this structure is chosen as the best fitting model for nonlinear real-time ranges. Figure 3.1 shows the structure of NLHW which represents the dynamic system using input and output static nonlinear blocks in between dynamic linear blocks which is distorted by static nonlinearities [5]. Hammerstein-Weiner structure is then used to capture the physical nonlinear effects in the system that will affect the input and output of the linear system.

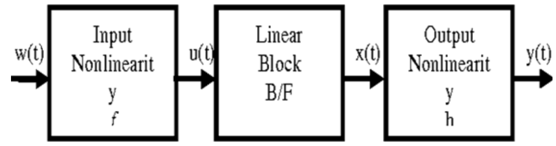

Figure 3.1: Structure of Hammerstein-wiener model

The applications of NLHW model depend on its inputs. If the output of a system depends nonlinearly on its inputs, it can be decompose the input-output relationship into two or more interconnected elements. This system is preferred because they have a convenient block representation, transparent relationship to linear systems, and easier to be implement than heavy-duty nonlinear models. In this paper, it is present an algorithm to identify Single-Input Single-Output (SISO) HW systems.

3.3 preparing Data for identification

You can use only uniformly sampled time-domain input-output data for estimating Hammerstein-wiener models. Your data can have one or more input and output channels. You cannot used time series data (output only) or frequency domain data for estimation.

To prepare data for model estimation, import your data into MATLAB® workspace, and do one of the following:

- In the system identification app- import data into the app, as described in represent data
- At the command line- Represent your data as an iddata object

After importing the data, you can analyse data quality and pre-process data by interpolating missing values, filtering to emphasize a specific frequency range, or resampling using a different sample time. For most applications, you do not need to remove offsets and linear trends for from the data before nonlinear modelling. However, data detrending can be useful in some cases, such as before modelling the relationship between the change in input and output about an operating point. After preparing your estimation data, you can configure your model structure, loss function, and estimate the model using the estimation data.

3.4 Data Simulation

After getting the data, the next procedure is to import the data on MATLAB, because it has the model that can be used for the simulation. Identify the Hammerstein-Wiener model, at the command line use sim to simulate the model output. Wind Energy can be forecasted using different model, after understanding the previous model used, then try to developed your own model to forecast the wind energy

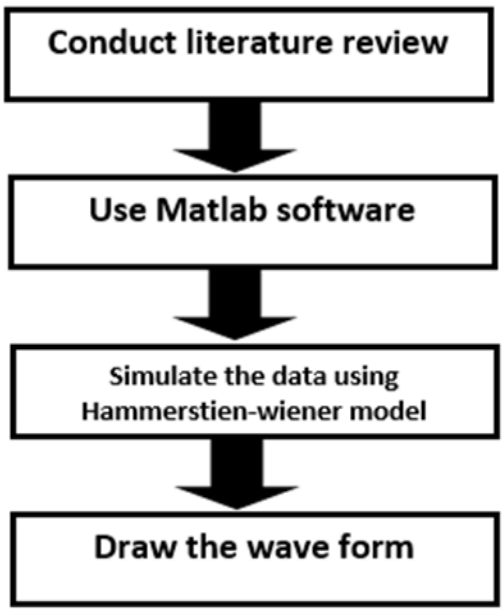

Fig 3.2 Simulation flow

IV. RESULTS AND DISCUSSION

4.1 Wind data

The wind load data cover a period form first of January to thirty first of January, the data comprises of time, relative humidity, temperature, wind direction, wind speed and load, which are used for the simulation of result, the input used for the simulation are temperature, wind direction and wind speed while the output is load. The wind speed and wind direction were discussed in the previous chapters, the load and the variation of load on power station will be discussed fully in section 4.2, 4.3, 4.4, 4.5.

4.2 Data Analysis

MATLAB® is going to be used here to get the data output of power produced by the various data of wind power plant. From this data, the output will beanalysed whether this system can give enough energy to supply our home low power equipment without using supply from TNB and then, at the same time can reduce our electricity bill every month. The output results also will decide where are the potential places the power can be apply. The amount of energy that can be captured from the wind is exponentially proportional to the speed of the wind. The power generated is calculated using equation 2.1.

4.3 Simulation result

The simulation of the result is done using the wind load data, where temperature, wind speed and wind direction are used as the input, while the load is used as the output. The figure 4.5 show the simulation command in the MATLAP command window and the Wind Load Data

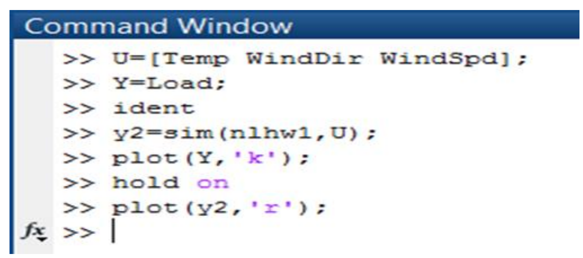

Figure 4.5 simulation command

Table 4.1: Wind Load Data

S/N	Temp	Rel Hum	Wind Dir	Wind Spd	Load
1	-9.6	88	36	8	1,643.40
2	-9.2	91	34	6	1,620.40
3	-8.3	92	36	6	1,577.70
4	-9.7	91	36	7	1,555.90
5	-11	90	36	8	1,556.40
6	-10.4	88	36	10	1,576.70
7	-11	86	34	9	1,609.90
8	-10.3	88	35	11	1,579.30
9	-9.5	89	35	12	1,619.30
10	-5.6	66	32	33	1,654.30
11	-4.1	62	32	31	1,673.70
12	-3.8	59	32	33	1,686.70

13	-3.7	59	31	33	1,696.20
14	-3.4	60	30	34	1,675.00
15	-4	63	30	33	1,671.20
16	-5	69	31	25	1,686.90
17	-5.3	72	32	22	1,778.30
18	-5.9	74	33	14	1,897.00
19	-5.8	85	33	9	1,875.00
20	-5.9	90	35	8	1,854.80
21	-4.3	73	32	29	1,827.50
22	-3.7	68	31	36	1,819.40
23	-5.1	68	33	24	1,721.70
24	-5.4	65	33	23	1,642.30
25	-5.9	60	32	32	1,593.40
26	-6.9	62	34	20	1,533.10
27	-8.1	64	34	19	1,504.40
28	-9.5	68	34	16	1,517.60
29	-10.7	70	35	12	1,553.70
30	-11.6	73	36	12	1,628.00
31	-12.5	77	36	13	1,751.80

The simulation result for a day (24 hours) and for a month data (January) is shown in figure 4.6

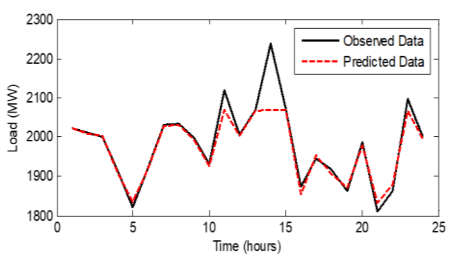

Figure 4.6(a): simulation result for 24 hours

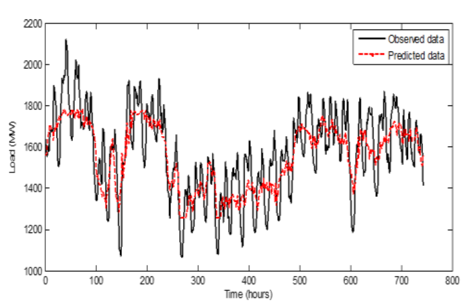

Figure 4.6 (b): simulation result for a month

4.4 Calculation of percentage Error

The percentage error is the difference between the predicted power and observed power divide by observed power. The percentage error for 4weeks is calculated from Fig 4.5(c) as shown above, where the predicted power and observed power are determined from the graph.

- For Week 1, 168hours
  Power (observed) = 1200MW
  Power (predicted) = 1300MW
  Error (%) = [(1300 – 1200)/1200] × 100 = 8.3%

- For Week 2, 336hours
  Power (observed) = 1220MW
  Power (predicted) = 1320MW
  Error (%) = [(1320 – 1220)/1220] × 100 = 8.2%

- For week 3, 504hours
  Power (observed) = 1640MW
  Power (predicted) = 1720MW
  Error (%) = [(1720 – 1640)/1640] × 100 = 4.9%

- For week 4(One month), 672hours
  Power (observed) = 1520MW
  Power (predicted) = 1700MW
  Error (%) = [(1700 – 1520)/1520] × 100 = 11.8%

4.5 Simulation results and calculation of percentage Error.

The results gotten from the simulation was observed for both the observed power and predicted power, and their corresponding values for some specified period of time were recorded and filled in the Table 4.2

Table 4.2: Simulation result and calculation Error

S/NO.	Week	Time (hours)	Power (observed) (MW)	Power (predicted) (MW)	Error (%)
1	1	168	1200	1300	8.3
2	2	336	1220	1320	8.2
3	3	504	1640	1720	4.9
4	4	673	1520	1700	11.8

4.6 Calculation of prediction performance measure
The following standard error measures are commonly used to compare the performance of prediction models.

1. Mean Squared Error
The mean squared error (MSE) has the general formula
MSE=1/N ∑_(t=1)^N▒.e_(t+1|t)^2
MSE=(68.89+67.24+24.01+139.24)/4=79.4%

2. Mean Absolute Error
The mean absolute error is given by
MAE =1/N ∑_(t=1)^N▒.e_(t+1|t)^.
MAE =(8.3+8.2+4.9+11.8)/4=8.3%

3. Root Mean Square Error
Root mean square error (RMSE) is the square root of the mean square error and is given as

RMSE $=\sqrt{\frac{1}{N}\,e_{t+1|t}^{2}}$

RMSE =√79.4=8.9%

4.7 Discussion
The waveform shown in figure 4.6(b) are used to obtained the observed power and predicted power at the same period of time, the value obtained undergoes further processing by calculating the percentage error which is known as the normalised prediction error, which is the difference between the predicted power and the observed power divided by the observed power. The normalised error for different weeks (4 weeks) was calculated and recorded for comparison as shown in table 4.2, from table 4.2 it was observed that the predicted power was improve when it is compared to the observed power, that is to say the forecasting was impressive. And finally, it was also observed that the fourth week seems to have the highest error simply because there are some undesirable error associated to the system during the fourth week, the performance was also computed for better Accuracy, the Mean Squared Error (MSE) which is used to measure the prediction accuracy has a higher value, that is to say the prediction accuracy is low, which implies that they are large error is associated to the predicted outcome. To improve the error the Root Mean Squared Error (RMSE) is calculated, from the value calculated from the RMSE, the prediction accuracy is improve and the error is minimise.

V. CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction
The wind power provides clean and cheap opportunity for the production of power. The fuel is free and there are some challenges associated with wind power. These challenges affect the electricity market and the power operation. To overcome these challenges the wind Energy is forecasted using Hammerstein-Wiener Model, to improved the challenges associated with the wind energy.

5.2 Conclusion
From the forecast result, it was concluded that the idea of the proposed approach is based on the use of multiple observation points and the incorporation of meteorological forecasts, which led to an improvement in the performance when the observed power is compared with the predicted power. The model used was analyzed to improve the prediction performance in a given wind farm using the wind load data. This model is flexible enough to incorporate more information and can be extended to an entire wind farm.

5.3 Recommendations
There is some recommendation for further work in order to improve this work. Firstly, try to design and analysea circuit using PSCAD software since the software is related to power system. Other recommendation is that more complex model can be used to forecast the wind energy to get more accurate output. Lastly, it is recommended to use more and most update wind loaddata from other places to find out which places are most suitable to practice this wind system.

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