COMPARISON OF THE EFFECTIVITY OF WIND SPEED FORECASTING METHODS

Diksha Kaur

A thesis submitted to
Auckland University of Technology
in fulfillment of the requirements for the degree of
Doctor of Philosophy (PhD)

2015

School of Engineering

Primary Supervisor: Tek Tjing Lie

Abstract

Environmental considerations and reducing carbon emission has accelerated the use of various renewable resources for electricity generation. Wind generation, in this context has seen sustained increases globally. Wind intermittency, its independent nature of direction, and varying speed are the best-known challenges and major barrier for accommodating very larger wind power penetration. There are several factors that can address this and help improve the attractiveness of the wind power to a utility. These may include improvements in model accuracy to decrease the forecast error, changes in the conventional plant, better storage or better load management to name a few.

Managing the wind energy intermittency for existing power system operation and control therefore becomes crucial. The issues posed in the wind speed prediction include reduction in time delay, improvement in speed prediction for short time, error reduction, model improvement for effective conversion of wind energy. However there is a lot of research being done in this field in which individual as well as hybrid forecasting techniques are being worked upon.

One effective solution is to predict the future values of wind power production, which is usually dependent on the wind speed. Precise forecasting of wind speed is vital to the effective harvesting of wind power. So, if an accurate forecasting of the wind speed from a few minutes to several hours ahead is obtained, the effective integration of larger penetration of the wind power generation can be achieved efficiently, safely and economically.

The main objective of this research is to compare the effectiveness of different techniques and to come out with a few unique hybrids that help reduce the forecasting error. The main focus lies on error reduction and improvement of model by hybridizing different techniques. It focuses on the improvement of the present forecasting methods and reduction of the forecasting error. This thesis presents a critical literature review and an up-to-date bibliography on the wind forecasting technologies. One of the objectives of this research is to develop a few novel wind speed forecasting techniques, which produce more accurate prediction.

Initially a hybrid technique, Artificial Neural Networks (ANN) along with the statistical method Ensemble Kalman Filter (EnKF) is proposed. The proposed method is used for a short-term prediction of wind speed. The well-established MATLAB software computing environment is utilized to simulate and show the effectiveness of the proposed hybrid technique. By help of past observations of wind speed, the EnKF is found to correct the output of ANN to find the best estimate of wind speed. The simulation results in MATLAB show that combination of ANN with EnKF acts as an output correction scheme.

For the next hybrid technique, the Wavelet Transform (WT) along with the Auto Regressive Moving Average (ARMA) is proposed. In the preliminary stage of the investigation, this combination is expected to give minimum Mean Absolute Percentage Error (MAPE). A simple simulation study has been conducted by comparing the forecasting results using the Wavelet-ARMA with the ANN-EnKF hybrid technique to verify the effectiveness of this new proposed hybrid method. The simulation results of the proposed WT-ARMA hybrid technique show significant improvements in the forecasting error.

The thesis has also investigated how to fully utilize Auto Regressive Moving Average (ARMA) to predict wind speed. However, the order estimation of ARMA is a very critical issue. Therefore, ANN has been used for parameter estimation, which is then combined with the Akaike Information Criteria (AIC) for order estimation. A simulation study has been conducted by comparing the proposed hybrid results with the Genetic Algorithm (GA) for parameter estimation and an exhaustive search for order estimation.

Another part of this research focuses on the Economic Dispatch (ED) problem. The stochastic nature of the wind and the highly nonlinear transformation from wind speed to electrical energy makes it more difficult to determine how to dispatch its power in order to guarantee both operational cost reduction and power system security. From a network constraint perspective in the economic dispatch problem, one of the factors to be accounted for is voltage instability, which impacts both active and/or reactive power dispatch. As a solution, an Optimal Reactive Power Dispatch (ORPD) based on Particle Swarm Optimization (PSO) using Graph Theory (GT) has been proposed to overcome the aforementioned problem. The Graph Theory has been proposed since it is very useful in cases of fault detection and isolation or to shed unbalanced nodes in case of excessive or insufficient supply. Simulation studies on the IEEE-14 Bus System have been conducted to show the effectiveness of the proposed method.

The research utilizes real time data from a few minutes to several days ahead to show the effectiveness of the proposed methods. Both synthetic data and real information from New Zealand wind resources have been used. Since the forecasting errors may vary within the time frame under consideration, different modifications have been added to the proposed hybrid techniques to get robust results from the practical data. In addition, the correlation between the forecasting error indices and the economic factors has been investigated. The Economic Dispatch problem has been identified as a major one and forecasting has been used as a solution in Graph Theory. This research may not only benefit forecasting of wind but also several other applications as well such as load forecasting or price forecasting in the future.

Table of Contents

List of Figures

List of Tables

List of Abbreviations Used

AIC	Akaike Information Criteria
ARIMA	Auto Regressive Integrated Moving Average
ARCH	Auto Regressive Conditional Heteroscedasticity
AR	Auto Regressive
ARMA	Auto Regressive Moving Average
ANFIS	Adaptive-Network-based Fuzzy Inference Systems
ANN	Artificial Neural Networks
AWNN	Adaptive Wavelet Neural Network
BJ	Box–Jenkins
CWT	Continuous Wavelet Transform
DE	Differential Evolution
DFIG	Double Fed Induction Generator
DWT	Discrete Wavelet Transform
ED	Economic Dispatch
EMD	Empirical Mode Decomposition
EMS	Energy Management System
EnKF	Ensemble Kalman Filter
ENVISAT	Environmental Satellite
EP	Evolutionary Programming

ESACF	Extended Sample Auto Correlation Function
FFNN	Feed Forward Neural Network
GA	Genetic Algorithm
GARCH	Generalized Auto Regressive Conditional Heteroscedasticity
GT	Graph Theory
GWN	Gaussian White Noise
HDE	Hybrid Differential Evolution
HIRLAM	High Resolution Limited Area Model
HMPSO	Hybrid Multi-Swarm Particle Swarm Optimization
HONN	High Order Neural Network
KF	Kalman Filter
LMBP	Levenberg–Marquardt Back Propagation
MA	Moving Average
MAE	Mean Absolute Error
MAPSO	Multi Agent Particle Swarm Optimization
MAPE	Mean Absolute Percentage Error
MATLAB	Matrix Laboratory
MCE	Maximum Co Entropy
MEE	Minimum Error Entropy
MEEF	MEE with fiducially points
MLP	Multi-Layer Perceptron

MPE	Mean Percentage Error
MERIS	Medium Resolution Imaging Spectrometer
MPSO	Modified Particle Swarm Optimization
MRA	Multi Resolution Analysis
MSPE	Mean Squared Prediction Error
NIWA	National Institute of Water and Atmospheric Research
NLP	Non-Linear Programming
NWP	Numeric Weather Prediction
OPF	Optimal Power Flow
ORPD	Optimal Reactive Power Dispatch
P	Persistence Method
PFNN	Polynomial Function Neural Network
PSO	Particle Swarm Optimization
RBf	Radial Basis Function
RMSD	Root-Mean-Square Deviation
RNN	Recurrent Neural Network
SAR	Synthetic Aperture Radar
SCIG	Squirrel Cage Induction Generator
SFLA	Shuffled Frog Leaping Algorithm
SOA	Seeker Optimization Algorithm
SSM/I	Special Sensor Microwave/Imager

STFT	Short-Time Fourier Transform
SVM	Support Vector Machine
WEP	Weather Ensemble Predictions
WT	Wavelet Transform
WTG	Wind Turbine Generators

Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

Diksha Kaur

Acknowledgements

First and Foremost, I would like to thank the Almighty, “WAHEGURU” who has always been “Gursahai”, which means that he has always been in me, around me and with me. I am truly blessed to be a “Sikh” who always has the passion to learn whatever comes their way.

I am very grateful to my primary supervisor Tek Tjing Lie from Auckland University of Technology, who gave me this opportunity to work under him. He has always helped me extensively to develop academic research skills during my study period. I really appreciate his valuable guidance and sympathetic encouragement, due to which the project has been fulfilled smoothly.

I wish to express gratitude to Nirmal C Nair, my secondary supervisor from the University of Auckland, who has generously made helpful comments, creative suggestions and contributive discussions from the first to the final level of my thesis.

I am very thankful to my co-supervisor James L Kirtley Jr. from Massachusetts Institute of Technology, who gave me the opportunity of working under him and completing the second half of my research in Boston. I really am grateful to him for investing his precious time in my study.

I must admit I cannot imagine how this thesis would look like if I did not have Brice Valles as a co-supervisor. I feel I have learnt a lot from him and I am very grateful for all the time he spent on guiding me, for his patience with me and for the continuous support he gave me. His personal kindness and scientific efforts has inspired me throughout the course of my research.

I would like to dedicate this thesis to my dear parents, Rajesh Singh and Archna Kaur who have always been there to support me through thick and thin. My father has been my source of inspiration and has helped and worked with me throughout this journey. A very special thanks to my sister, Reeti Kaur and brother in law, Manpreet Singh who were with me from the start encouraging me to take up on this opportunity. Without their blessing, this thesis would have not been possible. My heart goes out for all the kids in the family Gursahai, Neev, Arshliv, Haramrit and Japjyot whose smiles have always made things look very simple.

I would like to acknowledge and especially thank my loving, caring and supportive husband, Sunmeet Singh. His patience, love and enthusiasm over the duration, has been my pillar of strength throughout.

Many thanks are given to the data provider NIWA. NIWA is a crown-owned research and consultancy company, with a global reputation as experts in water and atmospheric research, http://www.niwa.co.nz

Last but not the least, I would like to thank the Auckland University of Technology for providing a Doctoral Scholarship for the work achieved in this research.

List of Research Outputs

1. D. Sharma, T. T. Lie (2012) Wind Speed Forecasting Using Hybrid ANN-Kalman Filter Techniques. Paper presented at the international symposium on the International Power and Energy, 14-16 Dec 2012.

2. D. Sharma, T.T. Lie, N. K. C. Nair, B. Valles (2015) Wind Speed Forecasting using ANN, ARMA and AIC hybrid to Ensure Power Grid Reliability. Paper presented at the international symposium on the Innovative Smart Grid Technologies (ISGT) Asia, 4-6 Nov 2015.

3. D. Kaur, T.T. Lie, N. K. C. Nair, B. Valles, "Wind Speed Forecasting Using Hybrid Wavelet Transform-ARMA Techniques," *AIMS Energy,* vol. 3, pp. 13-24, 2015.

Chapter 1

Introduction

1.1 Background and Rationale of the study

Environmental considerations have prompted the use of various renewable sources for electricity generation. It has led to a strong interest and an increase in the use of various renewable resources. Wind is a clean, renewable resource that may be converted into electrical power and has become very popular in recent years. With the increasing popularity and utilization of wind power technology, the cost of the new energy resources has already approached the conventional energy and thus, it has the potential ability to compete with traditional power plants [1].

Wind energy is one of the fastest growing energies and it is becoming more economically attractive causing reduction in the operating cost of any utilities. Wind speed and power predictions are beneficial for stabilization of power, matching demand and supply and power grid management [2].

But the main problem with wind is its intermittent nature that makes the output power of wind power generations difficult to control [1]. It becomes the greatest challenge while integrating wind power into the electric grid [8]. This nature of the wind results towards increasing the complexity of the existing power system regulation and reserves requirements (also known as ancillary services in electricity markets) that are used to maintain stability and reliability. Managing the intermittency of wind towards existing power system operation and control therefore becomes crucial. The intermittency of wind has a greater impact on grid security, system operation, and market economics [3].

Reference [2] shows that at wind penetrations of up to 20% of system peak load, system-operating cost, such as unit commitment cost, would increase arising from wind variability and uncertainty. The world installed capacity of wind power generation has increased from 60 GW in year 2000 to 160 GW in June 2010, and it is estimated to be 460 GW by the end of year 2015 [3]. The present total consumption of electricity from wind energy in New Zealand is close to 5% and is estimated to go up to 20% by 2030 as reported by some electricity generation and retailer companies including Genesis Energy, Meridian and Mighty River Power according to the Business and Economic Research Limited (BERL) report [4]. Because wind variability and uncertainty make the output power of wind farms difficult to control, an increase of wind penetration will result toward increasing needs for power systems regulation and reserves requirement to ensure stability and reliability.

One effective solution is to predict the future values of wind power production. The most important factor responsible for wind power generation is the local wind speed. Since wind power is a function of wind speed, forecasts of power are generally derived from forecasts of wind speed. So, if a reliable forecasting is done of wind speed/power from a few minutes to several hours ahead, the effective utilization of wind power and generation of electricity can be obtained thereby relieving the electricity network from various shortcomings and stress associated with uncertainty [6].

The increase on wind power generation requires solutions to a number of research fields including competitive market designs, real-time grid operations, interconnection standards, quality of power, ancillary service requirements and costs, capacity of transmission system and its future upgrades, stability and reliability of power system, optimal reductions in greenhouse gas emissions of entire power system (determined by optimal amount of wind penetration into system). Forecasting has become a very vital part for planning in areas where there is high concentration of wind generation and a limited transmission capacity of network. For instance, forecasting may help understand all the imbalances of the electricity market well in advance. Also, it will enable develop well-functioning hour-ahead or day-ahead markets. Another example is that even though wind energy is not dispatched, like other conventional generation, the cost of electricity may be reduced drastically if wind energy can be scheduled using accurate wind forecasting [11].

With increasing wind penetration more robust and innovative approaches are required to decrease the forecasting error and improve the generation output estimation model. Several prediction methods have been discussed in the past few years and several studies have been performed to develop the precision of wind speed prediction.

There is clearly a requirement for accurate wind forecasting in order that wind power can be integrated into the scheduling and dispatch decisions of the power system operators. Due to turbulent wind environment, wind speed and wind power vary and output power of wind turbine generator fluctuates due to the same. It can be marginally improved with changes that could improve the model and reduce some errors in the prediction.

There are several factors that can be taken care of to improve the attractiveness of wind power to a utility. These include improvements in model accuracy to decrease the error in wind forecasting, changes in the conventional plant mix such as using fast response plants, shorter start-up and ramping times for thermal plants, better storage, better load management to accommodate fluctuations [1].

As a solution, more sophisticated and innovative approaches are required. Therefore, different hybrid approaches are formed along with the traditional statistical techniques to give effective and required results. Combination of different methodologies such as mixing physical and statistical approaches or combining short-term and medium-term models, combination of alternative statistical models, to name a few, is referred to as a hybrid approach. Many types of hybrid models are utilized to predict wind power [5-6]. The aim of hybrid models is to benefit from the advantages of each model and obtain a globally optimal forecasting performance.

Among many hybrid techniques, the statistical time series and neural network methods are mostly aimed at short-term predictions. In several predictions, they use the difference between the predicted and actual wind speeds in the immediate past to tune the model parameters. Of volatility and deviation average reported error for the wind forecasting is in the order of 10%~20% of the installed power for a 24 hour horizon [11].

1.2. Problem Statement & Research Questions

1.2.1 Research Questions

To strengthen the concept, promising research questions have been identified as follows:

- Which hybrid methodology is suitable for wind speed forecasting to get the best accuracy?
- How can the proposed hybrid be extended to predict from 1 hour ahead to 6 hours ahead?
- What is the impact on the economics?

To achieve the success of this study, the following objectives will be targeted:

- Investigation and analysis of the existing methodologies and developing a new hybrid model that compensates for the forecasting error.
- Development of a method that can be extended from a few minutes to several days of forecasting and is still able to deliver an output that has minimum error.
- Investigate the correlation between forecasting error indices and the economic impacts.

1.2.2 Problem Domain

Forecasting has been performed for power systems such as load forecasting or weather forecasting. There exist various popular methods including Artificial Neural Network (ANN), Kalman Filter (KF), Auto Regressive Moving Average (ARMA), Auto Regressive Integrated Moving Average (ARIMA), Auto Regressive Conditional Heteroscedasticity (ARCH), Generalized Auto Regressive Conditional Heteroscedasticity (GARCH), Adaptive-Network-based Fuzzy Inference Systems (ANFIS), Grey Predictors just to name a few.

However, these methods are not able to decrease the forecasting error further individually so research on their hybrids variations are becoming more popular.

The advantages of these methods are different depending on what methodology is utilised. Few of these methods are very common, easy to use and easy to understand. Few methods require less statistical training whereas others require more statistical training. Most of these methods are widely used for forecasting purposes. There are others that can either fit the approximation to any time series or are able to handle missing data very efficiently. In addition, there are some methods prone to over fitting. Few of them can include random noise, which can make it very difficult to use whereas some may assume the system as a linear system.

To increase the capability of these individual methods, hybridization is usually done. It has been tried by various researchers and has also resulted in some advantages and shortcomings. The shortcomings are as follows: (i) some of the hybrids have worked well in terms of time consumption, (ii) some hybrids can be very time consuming, (iii) some hybrids have not been able to decrease the forecasting error as per the demand, (iv) few hybrids have been able to predict very short term forecasting fairly and (v) some hybrids have been tried for medium term forecasting but have not been proved as successful as required. The dire need is to take forecasting to another level and predict at least up to six hours accurately. Also, some of the methods that have been recently introduced either give large error or incur high computational time.

These advantages and pitfalls have led this research to propose a solution that is not only time efficient but also is able to decrease the forecasting error. Since the impact of better accuracy on power systems is very significant, there is a lot of interest in developing techniques that are novel.

The main problems identified include: (i) the intermittent nature of wind has to be captured by some forecasting techniques so that effective utilization of wind energy is obtained; (ii) a method is required that fits as much of the environment data and surrounding changes as possible and be flexible. The chosen method should also enable accurate estimation and be quickly computed.

1.3. Aims and Objectives of the Study

This thesis provides an insight of all the categories of wind speed prediction methods, associated with wind power and speed, their classification with respect to time horizons, different ranges, and different approaches based on numeric weather prediction (NWP), statistical approaches, artificial neural network (ANN) and hybrid techniques over different time-scales. It begins by presenting a critical literature review and an up-to-date bibliography on wind forecasting technologies. Various issues have been highlighted primarily related to wind speed and thereby power generation. From all the available methods used in prediction mentioned in the literature review, this thesis mainly focuses on the improvement of the forecasting methods and reduction of the forecasting error when applied to practical and realistic data. The choice of the wind model used amongst the various existing models is based on several performance parameters. Reference [7] gave a detailed survey of the wind speed forecasting techniques that have been provided since the past 15 years.

The first objective of this research is to critically assess two methods for wind speed forecasting namely Artificial Neural Networks (ANN) and Ensemble Kalman Filter (EnKF) followed by formulating a hybrid method and assess its performance practically using MATLAB and bring down the forecasting error to a minimum. The short-term prediction methods using hourly prediction have been done in this thesis. An ANN is normally used to map random input vector into the corresponding output vector. A surrogate is constructed based on modeling the response of large-scale model to a limited number of intelligently chosen data points. EnKF is applied on wind-wave data. It will then correct the output of the ANN to find the best estimate of the wave height. Coupling this surrogate (instead of a full model) with EnKF leads to computational efficiency. All these are tested under MATLAB developed programs to compare the individual results with the hybrid to see what effect the hybrid has. References [8-10] highlight EnKF method resulting in relatively minor errors of approximately 3.97% and therefore higher prediction precision has been obtained in this hybrid.

For the second objective, the preliminary investigation on the Wavelet Transform (WT) along with the ARMA model is proposed to form a hybrid method for better forecasting. The Wavelet analysis is a well-established technique that is being adapted in various fields for forecasting. It analyses the signal in nature and the time frequency. The WT decomposes and then reconstructs the historical wind speed data into various factors. The second method used is the ARMA model, which is a time series model. The MAPE of the ARMA has been shown to be between 7% for 1-hour up to 18% for the next six hours [11]. The aim was to decrease the MAPE to around 5% in this research.

Reference [12] shows that a combination of methods has been successful for predicting water demand of Dalian City. It combines WT, ARMA and Least Squares methods and comes out with the most accurate prediction of that area. This hybrid however, has not been tried much in the field of wind forecasting yet. Reference [13] shows the potential of this hybrid but this paper fails to justify it for a long duration of time and is very limited on experimental observations. Reference [14] shows the capability of the hybrid method by evaluating few case studies and proposing recommendation for further research. It demonstrates how pre -filtering can enhance the performance and efficiency of computation. This thesis has investigated how a hybrid method using WT and ARMA can be used towards wind speed forecasting.

The Wavelet analysis is a well-established technique used in various application areas for forecasting. It analyses the signal capturing both time and frequency resolutions. It also overcomes the drawbacks of Short-Time Fourier Transform (STFT) as it is a windowing technique that uses variable sized regions [14]. The second techniques used for the proposed hybrid is the ARMA model, which is a time series model. ARMA models are widely used because of their simplicity, cost-effectiveness and accuracy for timely forecasting. It is used to solve problems in the fields of mathematics, finance and engineering industry that deal with a large amount of observed data from history.

Another part of this research is to develop a novel wind speed forecasting technique, which produces more accurate predictions. A hybrid method composed of the Artificial Neural Network (ANN) and Akaike Information Criteria (AIC) along with the Auto Regressive Moving Average (ARMA) technique is proposed. Simulation studies were conducted to show the effectiveness of the proposed method. The simulation study results of the proposed hybrid have shown very good results through reduced forecasting error for the test data used in this thesis.

One of the main challenges is to properly determine the order of ARMA that would optimize the results. To find the optimum ARMA order, another method has to be used. Instead of the most basic Box–Jenkins (BJ) identification (which requires all calculations to be repeated when new pieces of data arrive [15]) or similar methods, this research comes out with a very novel identification method that uses ANN and AIC to determine the order of ARMA. The comparisons are made with the Genetic Algorithm (GA) method and are based on the value of the coefficients obtained. The results show that the ANN computes the coefficients of an ARMA system accurately. This part uniquely combines ANN with AIC to determine the true order of ARMA and bring down the forecasting error. Consequently, the proposed method will not only benefit the wind forecasting community but also can be adapted in the future towards load forecasting and price forecasting methods in power systems.

The third and last objective is to find the correlation between the forecasting and its application in power systems. Therefore, another problem identified with wind power i.e., the Economic Dispatch (ED) has been explored. In the modern Energy Management System (EMS), ED serves a vital functionality. Wind power may be dispatched above or below its available capacity during periods of excessive or insufficient supply. During excess generation periods, to avoid experiencing additional shutdowns and start-ups of conventional plants economic curtailment of renewable energy could be the most cost-efficient dispatch option. When there is a surplus, the extra generated wind energy should be stored otherwise would not be fully utilized. Many companies are working on utility-scale storage units that they hope will help balance intermittent renewable energy

The objective of ED is to schedule the power generation properly in order to minimize the total operational cost. It is usually quite difficult to determine how to dispatch the power in order to guarantee both operational cost reduction and power system security. Therefore, it is highly desirable to investigate how to dispatch the power in an appropriate and economic manner for the power system. So, in order to make accurate dispatch decisions it becomes crucial that the wind forecast is accurate [16].

Exact forecasting of the expected generation from a wind farm is nearly unmanageable predominantly due to the stochastic nature of the wind along with the highly nonlinear transform from wind speed to electrical energy. Due to forecasting errors, wind is not dispatched appropriately or is dispatched below the available capacity. Thus, the main problem here lies in accommodating wind energy scheduling to existing Economic Dispatch (ED) application. One of the constraints of the economic dispatch formulation is voltage stability, which depends primarily on reactive power dispatch availability. The reactive power is generally automatically available due to synchronous machine field control and transmission line characteristics. However, it affects the total generating cost by increasing the transmission losses [17]. Reactive Power Optimization is a mixed integer nonlinear programming problem where meta-heuristics techniques have proven suitable for providing optimal solutions [18]. Therefore, in order to stabilize voltage and dispatch it properly, Optimal Reactive Power Dispatch (ORPD) is required to control the regulating equipment to optimize reactive power flow, reduce active power and voltage losses, improve voltage quality and to make electric equipment work safely and reliably.

ORPD is a key instrument to achieve secure and economic operation of modern power systems [19]. Due to the complex characteristics of ORPD, heuristic optimization has become an effective solver. In this research, the Particle Swarm Optimization (PSO) approach is used to solve the ORPD problem for ED and has been tested on the IEEE-14 Bus System using Graph Theory (GT) to get the results for reactive power optimization. The objective of the proposed PSO is to minimize the total support cost from generators and reactive compensators. It is achieved by maintaining the whole system power loss as minimum thereby reducing cost allocation. The GT shows the relationship between the forecasted wind speed and its impact on the economics.

In the past decade, heuristic optimization algorithms, such as genetic algorithm (GA) [20-21], PSO [22-23], just to name a few have been applied in reactive power optimization. PSO has some advantages over other similar optimization techniques such as GA. PSO has a more effective memory capability than the GA since every particle remembers its own previous best value as well as the best neighborhood.

Moreover, PSO is easier to implement and there are fewer parameters to adjust. PSO is more efficient in maintaining the diversity of the swarm (more similar to the ideal social interaction in a community), since all the particles use the information related to the most successful particle in order to improve themselves, whereas in GA, the worse solutions are discarded and only the good ones are saved; therefore, in GA the population revolves around a subset of the best individuals [24].

GT is an important tool, which can be used in a lot of research areas of computer science such as data mining, image segmentation, clustering, image capturing, networking and others [25]. Problems of efficiently planning routes for finding the shortest path in a network, searching an element in a data, fault detection and isolation, shed unbalanced nodes may be managed very easily in GT and hence it becomes a very beneficial tool.

This research is tested on a standard IEEE-14 bus system on GT where double fed induction generator (DFIG) wind turbines are used. DFIG are used typically for high power wind generation systems (>1.5 MW) in several countries. DFIG have the distinct advantage of being able to generate controllable power by reduced rated power converters in comparison with other wind generator technologies for the same power [26-27]. DFIG based system is more suitable to integrate into power system for wind power generation than Squirrel Cage Induction Generator (SCIG) system from viewpoint of power system small signal stability.

1.4. Organization of the Thesis

This thesis consists of seven chapters. Chapter 1 provides an overview of the background of the study, followed by the problem statement, research questions, significance of the study, and finally organization of the thesis.

Chapter 2 provides an extensive review of literature related to the concepts of this study, namely: types of errors, traditional techniques, and state of the art methods. It describes the literature analysis giving the main areas of intersection of ANN-EnKF, ARMA-WT and ARMA-ANN-AIC hybrids respectively.

Chapter 3 covers the research approach for the ANN-EnKF hybrid. This includes research philosophy, research method of the hybrid technique and its effectiveness. It also discusses the results in detail.

Chapter 4 explains the ARMA-WT hybrid in detail. It comes out with a unique hybrid equation that combines the main mathematical equation of both the individual methods. It also explains the results that have been tested on MATLAB.

Chapter 5 focuses on the ARMA-ANN-AIC hybrid which is used to determine the parameters estimation to find the true order for ARMA. It also gives the methodologies and results.

Chapter 6 provides a detailed discussion of the economic dispatch problem. It starts with an overview of the inductive approach and follows with a discussion of ORPD implemented on PSO in GT.

Chapter 7 summarizes the study with a recapitulation of what has been achieved, an overall discussion of the findings, discussions of the study's implications and of its limitations, and provides suggestions for future study.

Chapter 2

Literature Review

2.1 Introduction

This Chapter presents a critical literature review analysis on wind forecasting methods and related topics. The review covers a wide range of recent literature in the problem domain and is classified based on forecasting errors, hybrid methods, forecasting approaches just to name a few.

2.2 Different types of forecasting errors

A forecast error is the difference between the actual or real and the predicted or forecast value of a time series or any other phenomenon of interest. There are various types of errors such as the mean percentage error (MPE), root-mean-square deviation (RMSD), mean squared prediction error (MSPE), mean absolute error (MAE), Mean Absolute Percentage Error (MAPE), and so on. Reference [28] explains the errors, their relevance, different types of forecasting techniques and the latest developments in the ANEMOS report.

The mean percentage error (MPE) is the computed average of percentage errors by which forecasts of a model differ from actual values of the quantity being forecasted. A disadvantage of this measure is that it is undefined whenever a single actual value is zero. The MPE gives an indication of how good a measurement is relatively to the size of the thing being measured [29]

$$MPE = \frac{100\%}{n}\sum_{t=1}^{n}\frac{f_t - a_t}{a_t} \tag{2.1}$$

where a_t is the actual value of the quantity being forecasted, f_t is the forecast, and n is the number of different times for which the variable is forecasted.

The root-mean-square deviation (RMSD) or root-mean-square error (RMSE) is a frequently used measure of the differences between values predicted by a model or an estimator and the values actually observed. These individual differences are called residuals when the calculations are performed over the data sample that are used for estimation, and are called prediction errors when computed out-of-sample. The RMSD serves to aggregate the magnitudes of the errors in predictions for various times into a single measure of predictive power. RMSD is a good measure of accuracy, but only to compare forecasting errors of different models for a particular variable and not between variables, as it is scale-dependent [3]. For an unbiased estimator, the RMSD is the square root of the variance, known as the standard error. The RMSD of predicted values $\hat{y}_t$ for times t of a regression's dependent variable y is computed for n different predictions as the square root of the mean of the squares of the deviations:

$$RMSD = \sqrt{\frac{\sum_{t=1}^{n} (y_t - \hat{y}_t)^2}{n}} \tag{2.2}$$

The mean squared prediction error (MSPE) of a smoothing or curve fitting procedure is the expected value of the squared difference between the fitted values $\hat{g}$ and the (unobservable) function g. If the smoothing procedure has operator matrix L, then

$$MSPE\ (L) = E\ [(g(x_i) - \hat{g}\ (x_i))^2\ ] \tag{2.3}$$

The mean absolute error (MAE) is a quantity used to measure how close forecasts or predictions are to the eventual outcomes [30-31]. It is the average of the absolute errors, where f_i is the prediction and y_i the true value.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|f_i - y_i| \tag{2.4}$$

The MAPE is a measure of accuracy in fitted time series value. The absolute values of all errors are summed and the average is computed. It expresses accuracy as a percentage. It has the same units as the original data. It can take a range of values between zero to infinity [1, 32]. This is the reason why it has been largely used in wind speed forecasting by various researchers. MAPE stems from the law governing that wind farm owners who want to participate in the electricity market have to predict their own power. Deviations from the declared schedule are punished according to this error measurement [28]. This thesis also uses MAPE to forecast wind speed due to its accuracy.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \tag{2.5}$$

where A_t is the actual value and F_t is the forecast value.

Review of wind speed forecasting techniques has been done on the basis of time scale, design issues and types of forecasting techniques in the following section.

2.3 Wind Speed Forecasting Techniques

This section describes different forecasting techniques based on time-scales, design issues, individual and hybrid methods.

2.3.1 Very-Short Term Forecasting

Very short term is defined as the prediction from a few seconds to half an hour. This is because the deregulated markets are cleared almost every 5 min and settlements are done every 30 min. This is shown in [33] and [34] for 5 to 15 minutes timeframe. Tests are conducted and wind power data are smoothed for 30 sec resolution to match the resolution of the wind speed. Results show that wind power variation somewhat matches that of wind speed.

The Ensemble Kalman Filter (EnKF) method is explained in [35]. Reference [36] uses it to predict 10 min ahead wind speed. The ARMA model is used as the state function of the EnKF and perturbed initial wind data are taken into consideration to generate the ensemble.

The comparison between the methods shows that the EnKF is suitable for wind speed prediction and improve grid integration of wind energy and gives a MPE of about 5.06% but only for 10 min ahead forecasts.

The most common method used is the Prediction Method whereas others include ANN, ARMA, Auto Regressive Integrated Moving Average (ARIMA), Adaptive-Network-based Fuzzy Inference Systems (ANFIS) and so on. These are all used individually. A few papers are available for very-short term forecasting timeframe. Linear prediction model of the ARMA is shown in [34] where the output is a combination of past and present values. At low frequency wind speed is filtered from a low pass filter and results from 1s to 5s are reported. The time frame taken in this paper is not very big and few results have been shown.

2.3.2 Short Term Forecasting

Short term forecasting refers to the prediction from half an hour to six hours. Most research on wind forecasting has been done for this time scale. If we are able to predict the next 6 hours accurately it becomes very helpful in proper utilization of wind energy. There are numerous combinations tried in this timescale but even then there is still a lot of scope left since the error is still relatively significant.

The term wind pattern as proposed by [33] and [34] characterizes different types of trends of wind and different time duration. The trends are combined with the ARMA with only historical generation data for 1-hour advance parameters. A wind speed pattern is identified and its model is established. Wind speed data of a wind farm in Inner Mongolia, verifies it giving a small MAPE but for small time scale of up to one hour. Reference [32] shows similar results where the Auto Regressive (AR) method is used to predict only the next one-hour and a small MAE is obtained.

A hybrid between the ARMA model and the ARCH (Auto Regressive Conditional Heteroscedasticity) is used by [31] in which comparison is done with the classic Persistence model. Due to volatility clustering, variance changes over time and the advantage of the ARCH has been utilized. The results show high MAE of up to 29.37% though. However, when the Wavelet Theory is combined with the neural network it shows very good results [36]. The original wind speed is decomposed here during the wavelet theory and then the output is fed to Levenberg–Marquardt Back Propagation (LMBP) neural networks. These are built for the forecasting of every component respectively thus obtaining good results. The WT with a forecasting method based on empirical mode decomposition (EMD) shows 4.53% MAPE [1]. Thus, this method may be reliable when combined with other methods yielding favorable results.

The Grey Model is a time series model and is used by [37] to predict for the next 3 hours. There is a little documented research and this paper is the only one presenting a pilot study about it. The case study corresponds to a wind farm located in Penghu, Taiwan, to verify the feasibility of Grey Model and satisfactory results are obtained.

2.3.3 Medium Term Forecasting

Medium term forecasting is the prediction between 6 hours to one day ahead. Most of the methods developed for this time-period are based on ANN approaches, physical weather models, and hybrid models combining both of these or some new techniques. These include fuzzy logic, wavelet transform, ensemble predictions, and spatial correlation. These new methods when combined with the existing approaches are expected to give promising results.

Reference [3] uses a two-stage forecasting method up to 30 hours ahead. First the decomposition of wind is performed and then ANN is applied to each signal. Then, predicted wind speed is used to forecast wind power output through nonlinear input–output mapping using Feed Forward Neural Network (FFNN). The RMSE obtained is 7.081% for 30 look-ahead hour giving satisfactory results.

Support vector regression model is developed by [38] using three years data of wind speed, temperature, barometric pressure, wind gust, wind direction, humidity on an hourly average basis to predict hourly wind speed. It is observed that the MAPE is around 7% with a correlation coefficient close to 1.

Spatial correlation is suggested by [30] in which local and spatial relations of the wind speed are considered so as to improve the efficiency of short and long range forecasting. This method is used to test the timeframe from a few minutes to several hours thus investigating the method for a large timescale. Investigations are supported by measurements at several terrains during a whole year. An Artificial Neural Network model is used to forecast wind speeds and the associated electrical power for a few minutes up to a few hours ahead leading to MAE 20- 40 % better than the persistent ones.

2.3.4 Long Term Forecasting

Long-term forecasting is prediction from 1 day to 1 week ahead or more. It is very important in well-run electricity markets where long-term scenarios are taken into consideration.

A new type of physical method to predict probability density functions of wind power generation for 1-to-10 days ahead by 'weather ensemble predictions' (WEP) is developed by [39]. The model is calibrated and smoothened at five U.K. wind farm locations to accurately predict the uncertainty in weather conditions. Comparison of results with the ARMA model and Generalized Auto Regressive Conditional Heteroscedasticity (GARCH) show WEP giving more accurate results over a period of a week. It is disappointing to see that beyond two days ahead, this method is matched by the simplistic approach that uses the mean of the actual wind power for the same day in each of the previous five years.

Reference [40] deals with long-term of up to 72 hours wind speed and power forecasting based on meteorological information. Two novel and optimal schemes are suggested for the update of the recurrent network's weights based on the recursive prediction error algorithm. Based on the data and network chosen an exhaustive set of experiments is carried out. Results show that Recurrent Neural Network (RNNs) improve over persistence method by as much as 50% and may still be improved if additional 'node' predictions are included. This is done in [41] where RNN forecasts in lesser time and without too much data. They forecast for each month separately and results are more accurate than Feed-Forward Neural Network (FNNs) for several hours to day-ahead forecasts.

For non-Gaussian error distribution, decreasing the entropy minimizes the error [42]. Minimum Error Entropy (MEE), Maximum Co Entropy (MCE) or MEE with fiducially points (MEEF) are decreased instead of decreasing the variance (known as MSE criterion) and hence prove more suitable for training of forecast models. Tests based on MCE and MEEF criteria against minimizing its variance (MSE) criterion were conducted on FNNs that had one hidden layer of nine neurons for 72-hour ahead forecasts in half hour intervals. This has immense scope when integrated into more powerful wind prediction systems.

Table 2.1: Time Scale and Error Classification for Different Technique

Time Horizon	Range	Methods	MAPE Error	Scope
Short-Term	Very short term- Few seconds to 30 minutes ahead	Persistence (P)	30%	- Not many comparison papers available -30 min ahead forecast require models still
		EnKF	5.06%	
		ARMA	7% for 1 hour	
		ARIMA	18% for 6 hours	
		ANN	<1%	
		Grey Predictor	27% better than P	
	Short term- 30 minutes to 6 hours ahead	EMD	4.53%	
		ARCH	29.37%	
		Grey Model	Average is good	
Medium-Term	6 hours to 1 day ahead	FNN	12% better than P	-Complex Statistics (Huge Scope)
		Spatial Correlation	40% better than P	
		Support Vector Machine	7%	
Long-term	1 day to 1 week Or more ahead	RNN	Better than FNN	-Non-Gaussian Error Distribution Function and Entropy Based Criteria (New)
		WEP	Not mentioned	
		GARCH	27%	

Table 2.1 summarizes wind speed prediction methods for different time scales. It shows the classification of the main methods that fall under different time scales. Also, it shows the MAPE error or the error comparison with the Persistence Model along with the scope of the methods for respective time division.

2.3.5 Data Preprocessing

Wind speed forecasting is a very involved and specialized area. Generally, the forecast method developed for one site or wind farm does not suit other due to a variety of reasons like change in terrain, different wind speed patterns, different atmospheric factors such as temperature, pressure, humidity. But 'generalization capability' of forecast model can be improved by considering the design issues.

Generally, we feed data as input but it is sometimes directly fed into the forecast model such as ANN, time series. Reference [43] shows that various differences are evaluated in the output when these data are fed directly and are not preprocessed. Preprocessing means to divide input so that a 'local' model may be designed for each subclass [44]. The standard properties are extracted: standard deviation, mean, variance and slope from the input data. The irregularities in data are filtered and the model becomes simpler.

2.3.6 Design and training of forecast models

Wind power forecasting models are studied and tested for one location and usually cannot be applied to any other site. Developing a generalized, portable and easy-to-operate model is a big challenge. Such a method is presented in [45] that has strong robustness and can be easily modified for different wind farms with minimum effort. The results are 40% better than the Persistence model and MAPE from 9.9% to 13.64% are reported.

Excessive training is not encouraged by some researchers and should be avoided or else models tend to over-parameterize or over fit the input data. This applies to ANNs and time-series models such as ARMA. This ends up with 'poor' forecasts in test data set. Reference [44] shows that over fitting is a result of excessive complexity and lack of clear guidelines on how many parameters in a model should be taken, for a given sample size. Many researchers avoid this problem by reducing the weight of the number of neurons.

2.3.7 Selection of number of input nodes and output

Selection of the right numbers of input and output nodes is imperative because redundant input data slows the process when including pressure and temperature [6]. To avoid this, mostly inclusion of various weather variables is a prerequisite for accurate forecasts. Also, if too old past values are used, they would be inappropriate to recent patterns, i.e., low auto-correlation will weaken forecast functioning and should be avoided.

2.3.8 Implementation and Validation of forecast models

Implementation of a forecast model means to determine its parameters. Selecting optimal number of model parameters is challenging and techniques like trial and error method, and Box method [44] have been used widely for models using ARCH, ANN or fuzzy system techniques. This is especially difficult for ANNs or fuzzy systems, as selecting good design and electing proper rule base is vital otherwise the results are affected.

2.3.9 Persistence Method

Several methods are used for wind forecasting but the Persistence model is the benchmark method. The simplest methods are based on climatology or averages of past production values. The most popular and simplest form to forecast the wind is the Persistence method. It is also known as 'Naïve Predictor'. It uses the simple assumption that the wind speed at time $t+x$ is the same as it was at time t. In other words it states that the future wind values will be the same as the last measurement. Unbelievably, it is more accurate than most of the physical and statistical methods for very short to short-term forecasts. Therefore the MAPE of each method is obtained and compared with the Persistence method. But as expected the accuracy lessens with increasing time [2, 11]

A case study from Tasmania, Australia is shown in [46] for very- short term forecasting. They use the ANFIS to forecast wind vectors rather than wind speed or power. In this paper more importance is given to wind direction rather than wind speed. The model is trained for 21 month time series in steps of 2.5 minutes. Results show that the ANFIS produced less than 4% MAPE compared to approximately 30% for the Persistence model.

2.3.10 Physical Approach

Physical systems use parameterizations based on a thorough physical depiction of the atmosphere. Usually, at the location of the wind farm, wind speed given by the meteorological experts is downscaled to the onsite situations.

Several physical models have been developed based on using weather data and the topography for wind speed and wind power forecasts. Numeric Weather Prediction (NWP) models solve complex mathematical equations using weather data such as temperature, pressure, surface roughness, hindrance, effects of orography, scaling of the local wind speed within wind farms and their layouts and wind turbines power curves. NWPs require super computers, as they are highly computationally demanding. NWPs run at most 1 or 2 times a day. Therefore, these are used for up to 6 hour ahead forecasts and show better results when weather conditions are stable. NWPs include global forecasting systems [41] or HIRLAM (High Resolution Limited Area Model) [47] for instance.

These methods provide wind speed estimates for a grid of adjacent points around the wind generators. These forecasts use a meso-scale or micro-scale model for the downscaling, which interpolate the level of wind speed forecasts to that of the wind generators [48]. A detailed description of the environment surrounding the wind generators is essential to run the downscaling models. This is one of the main difficulties in the implementation of physical models.

Reference [47] uses synthetic aperture radar (SAR) and medium resolution imaging spectrometer (MERIS) onboard the environmental satellite (ENVISAT) in synergy to analyze severe weather systems. Maximum wind speeds of up to 25 m/s were measured by SAR and confirmed by the models. Significant differences were observed in the location of the maxima. HIRLAM showed differences in meso-scale turbulent behavior and coastal shadowing. Meso-scale features, e.g., downburst due to cloud patterns with a diameter of up to 15 km, were not detected by HIRLAM.

2.3.11 Statistical Approach (ANN and Time series models)

This approach includes two main types namely ANN and Time series models. They train the measured data and then use the difference between the predicted and the actual wind speeds in immediate past to tune the model parameters [49]. It is easy to model, inexpensive, and provides timely predictions. It is not based on any predefined mathematical model and is rather based on patterns. Errors are minimized when patterns match with historical ones. Sub- classification of this approach is: time-series based models and neural network (NN) based methods.

Some of the most popular techniques include ARMA models, ARIMA, seasonal- and fractional-ARIMA, grey predictors, linear predictions and exponential smoothing. The ANNs may also be trained using past data taken over a long time frame to learn the relationship between input data and output wind-speeds. ANNs have an input layer, where historical data are fed for learning, hidden layer(s), and an output layer providing forecast results. Models such as FNNs, multi-layer perceptron (MLP), RNNs, radial basis function (RBf) NNs, Adaline networks are all examples of the ANN models.

The method by [50] uses a new statistical approach that combines artificial intelligence and fuzzy logic techniques. It provides a preliminary forecasting of wind power based on Radial Basis Function (RBf) network that enhances its performance and estimates the quality of the forecasts using fuzzy rules. Results obtained with the proposed method for an actual wind farm show the applicability of the method and the improvement over other methods.

A wind power forecasting is carried out in two stages by [3]. First, a multi-resolution analysis-based forecasting using Adaptive Wavelet Neural Network (AWNN) is developed and then a feed-forward neural network (FFNN) is used for nonlinear mapping between wind speed and wind power output for predicting wind speed up to 30 hour ahead. It shows that with the discontinuous wind power series FFNN is better suited than AWNN.

Other statistical methods give comparatively efficient forecasting models that do not require any data beyond historical wind power generation data. However, the accuracy of the prediction from these models decreases remarkably as the time horizon is increased.

Reference [51] uses stochastic simulation models. They remove the annual and daily periodicities of the measured data and modeled transformed hourly average wind speeds, taking into account autocorrelation, non-Gaussian distribution and diurnal non-stationary and fit an ARMA process to wind speed data. It was observed that this model would be useful only for a short time range and not beyond two hours. Reference [52] uses an ARMA model to forecast hourly average wind speeds for five sites in Navarra, Northern Spain. They used site and month specific parameters for the ARMA model. The ARMA model usually outperformed the persistence method for the 1-hour forecast, and was better in RMSE and MAE for higher horizons up to 5 hours ahead.

Reference [53] found an ARMA (p, q) process suitable for both wind speed simulation and forecasting. The inclusion of the diurnal variation was deemed important since the (mainly thermally driven) climate of Pakistan exhibited quite strong uniformity especially in the summer months. Errors have not been calculated and only comparisons of actual and predicted data values have been shown in this paper. Reference [54] uses the differences of wind speeds from the moving averages (differenced pattern method) and found this technique to be superior to the wind speed normally used as input. They achieved improvements of up to 13% over the persistence method, while for the same time series the standard neural network approach yielded only 9.5% improvement.

Reference [55] found that wind power and especially wind power variability from large offshore wind farms (Horns Rev and Nysted) occur in certain regimes, and therefore tested "regime-switching approaches relying on observable (i.e. based on recent wind power production) or non-observable (i.e. a hidden Markov chain) regime sequences" for a one-step forecast of 1-min, 5-min and 10-min power data. It is shown that the regime-switching approach outperforms those based on observable regime sequences. The reduction in one-step ahead RMSE ranges from 19% to 32% depending on the wind farm and time resolution considered.

2.3.12 Hybrid Approach

Combination of different approaches such as short-term and medium-term models, physical and statistical approaches or mixing alternative statistical models are referred to as a hybrid approach. The aim of hybrid models is to benefit from the advantages of each model and obtain a globally optimal forecasting performance.

For example, a semi empirical model is developed that recovers wind direction and improves wind speeds from Special Sensor Microwave/Imager (SSM/I) measurements. It uses radiative transfer and ANN techniques combined with Special Sensor Microwave/Imager (SSM/I) to get ocean surface wind speeds and direction [5]. Results show that this combination can considerably improve the impact of these data in NWPs compared to using SSM/I.

Some techniques have become very popular in recent years, for instance the Spatial Correlation, Fuzzy logic, Wavelet transform, Ensemble Predictions and so on. Reference [30] uses the spatial correlation of wind speeds. The wind speed time-series of local point and its neighboring sites are employed to predict the wind speed by ANNs or adaptive neuro-fuzzy networks. Only historical data of the site under consideration is used, and no values related to the physical phenomena, such as pressure profiles, terrain shape or wind speed at different sites. This is probably the reason why their accuracy is limited.

Reference [6] presents a fuzzy model with two premise variables–the wind speed and its direction. It uses a genetic algorithm to determine model parameters. It trains data measured at various stations in and around the wind park. Thus, the autocorrelation and cross-correlation between local and remote wind speed time series are exploited to improve the error from a few minutes to several hours ahead.

Table 2.2 classifies different types of wind speed forecasting methods. It further categorizes them into different kinds. It also gives some common examples that have been studied in this research and provides a few remarks.

The following hybrid techniques have been researched in this thesis and are reviewed as follows:

2.3.12.1 ANN-EnKF Hybrid

This section covers two major areas of predicting wind speed. They are Artificial Neural Networks and Kalman Filter. Combination of ANN and EnKF acts as an output correction scheme. With observations, the EnKF will correct the output of an ANN to find the best estimate of the wind speed.

Artificial Neural Networks (ANN) have been a good selection to model and forecast time series. ANN models can represent a complex nonlinear relationship and extract the dependence between variables through the training and learning process. They are simpler to construct and require shorter development time. One just needs to identify correct inputs, set up the network structure and then model a training algorithm, which gives the best prediction

Table 2.2: Basic Wind Forecasting Methods

Forecasting Methods	Subclass	Examples	Remarks
Persistence Methods / Naive Predictor	-	P (t+k) = P (t)	- Benchmark approach -Very Accurate for very Short and short term.
Physical Approach	Numeric Weather Predictor (NWP)	- Global Forecasting System -HIRLAM, etc.	-Use of meteorological data such as wind speed and direction, pressure, temperature, humidity, terrain structure etc. - Accurate for long term
Statistical Approach	Artificial Neural Network (ANN)	- FNN -MLP -AWNN - Radial Basis Function -ADALINE, etc.	- Accurate for short term -Their Hybrid structures are useful for medium to long term forecasts - Usually, outperform time-series models
	Time-series Models	- ARMA - ARIMA - Grey Predictors - Linear Predictions -Exponential Smoothing, etc.	- Accurate for short term - Some very good time-series models supersede ANN structures
Some New Techniques	-	- Spatial Correlation -Fuzzy logic - Wavelet transform - Ensemble Predictions, etc.	- Spatial Correlation is good for short term - Entropy based training of models improves performance
Hybrid Structures	–	- Radiative Transfer +ANN -Spatial Correlation + ANN -Fuzzy+ Genetic Algorithm, etc.	- Radiative Transfer +ANN Structure are very accurate for medium and long-term forecasts.

results. References [56-58] proposed different wind prediction methods using ANN models. They perform a non-linear mapping between inputs and outputs and provide an alternative approach for wind prediction. References [59-60] showed genetic algorithm ANN that reduce workload, improve efficiency, and also improve forecasting accuracy

Sequential methods such as optimal interpolation and Kalman Filter belong to the second family of methods. In these methods, observations are used as soon as they are available to correct the present state of the model. The KF is an excellent technique for data assimilation as it takes maximum advantage of observations. On the other hand this method has a few practical problems when it is used in operational applications for large non-linear models. In these situations the computation of the forecast error covariance matrix and Kalman gain can become enormous job both in computer power and computer storage.

A Kalman filter is a linear estimator. It is used to estimate the state of a linear dynamic system by using measurements linearly related to the state of the system but corrupted with noise. A Kalman filter is a recursive data processing algorithm. It is a tool that does not require all previous data to be kept in memory. Finally this type of filter is optimal: it calculates the best possible estimate (minimum variance) for the state of the system. This research uses the Ensemble Kalman Filter for non-linear systems. References [61-62] used EnKF and the results gave a 10-30% reduction in RMS error. Reference [63] showed that High Order Neural Network (HONN) trained with an extended Kalman filter gave absolute errors to be very low around 1.23 %. References [64-65] had a new wind estimation method in which a Kalman filter was used to produce high quality wind estimate.

A lot of research has been done on the various methods individually and also in hybrid form but the combination of ANN and Kalman Filter remains an unexplored area of research. This research is an attempt to come out with a new technique based on the hybrid of these two techniques.

2.3.12.2 ARMA-WT hybrid

Wind speed forecasting is a very involved task and generally the forecast method developed for one site or wind farm does not suit the other due to a variety of reasons like change in terrain, and different wind speed patterns just to name a few. A lot of research is being done in order to decrease the forecasting error but there is still scope to develop methods for short term forecasting.

The Ensemble Kalman Filter (EnKF) method is explained in [35]. Reference [36] uses EnKF to predict 10 min ahead wind speed that gives an error of about 5.06%. Linear prediction model of the ARMA is shown in [34] where results from 1s to 5s only are reported. A hybrid between the ARMA model and the ARCH (Auto Regressive Conditional Heteroscedasticity) is used in [31] where comparisons are drawn with the classic Persistence model. The results however show high MAE (Mean Absolute Error), up to 29.37%. The mean absolute error (MAE) is a quantity used to measure how closely the forecasts or predictions follow to the eventual outcomes. When the Wavelet Theory is combined with the neural network it shows satisfactory results [36]. Reference [1] shows a similar result when the WT is combined with an empirical mode decomposition (EMD) showing 4.53% Mean Absolute Prediction Error (MAPE).

The Grey Model is a time series model and is used in [37] to predict the next 3 hours. Since there is very little research about this method, a pilot study has been done in this paper, which gives significant forecast errors. Developing a generalized, portable and easy-to-operate model is therefore a big challenge. Such a method is presented in [45] that has strong robustness giving 40% better results than the Persistence model.

Reference [44] shows that over fitting is a result of excessive complexity and lack of clear guidelines for the number of parameters to be chosen while modelling a given sample size. A case study from Tasmania, Australia is shown in [46] for very-short term forecasting in which more importance is given to wind direction rather than wind speed. Numeric Weather Prediction (NWP) models are used for up to 6 hour ahead forecast and show better results when weather conditions are stable. NWPs include global forecasting systems [41] or High Resolution Limited Area Model (HIRLAM) [47] for instance. The method in [50] uses a new statistical approach that combines artificial intelligence and fuzzy logic techniques.

Reference [66] shows different approaches of ARMA for short term forecasting of wind speed. The effectiveness of ARMA-GARCH is reported in [67]. It also demonstrates different GARCH approaches consistently improving the modelling sufficiency of the mean wind speed. However, the output prediction decreases with increase in the height, which is a drawback.

Reference [68] shows the impact of wind speed forecasting on the dynamic response of wind turbine. It calculates rotor speed and aerodynamic torque to estimate the effectiveness of wind speed by an inversion of a static aerodynamic model and hence shows that this may also be helpful for wind turbine response. Wind speed prediction is not only a problem for wind power prediction but also for aqueducts in China that still withstand wind loads constantly [69]. These wind loads shorten aqueducts fatigue life along with large amplitude sloshing of water and further leading to structural resonance. Another application can be seen in [70] where variable-speed wind turbine generators (WTGs) employ anemometers to measure wind speed so that the desired optimal shaft speed can be derived. Results show that the wind speed was accurately estimated and hence proved useful.

A lot of research has been done to forecast wind speed but still work needs to be done to develop methods to realize robust and more accurate predictions. Some hybrid methods have gotten satisfactory results and smaller MAPE but they have not been tested for more than one-hour prediction. The ARMA model on the other hand has shown good results for long term forecasting. In this thesis, ARMA is combined with the WT, given the complementary strengths of both techniques, to assess their forecasting accuracy.

2.3.12.3 ARMA-ANN-AIC hybrid

Wind speed forecasting is a very active and specialized research and development area. Generally, the forecast method developed for one site or wind farm does not suit another due to several factors, e.g., change in terrain and different wind speed patterns. Extensive research has been reported to decrease error but there is still a lot of scope to improve the short term forecasting techniques.

Reference [71] shows a GA fitness value relying on the deviation between the actual plant output, with or without an additive noise, and the estimated plant output. Simulation results show in detail the efficiency of the proposed approach however it does not directly tell us the best order. Reference [72] combines the effectiveness of the Multi Model Partitioning theory with the robustness of Evolutionary Algorithms but gives a bit complicated approach with a 10% error.

Reference [73] uses Artificial Neural network (ANN) technique and compares it with some known and widely acceptable techniques. The comparisons are entirely based on the value of the coefficients obtained. The results show that the use of ANN also gives an accurate computation of the coefficients of an ARMA system. But it only stops to the determination of the parameters and not the true order.

Reference [74] shows that the ARMA model based on System Identification Toolbox of MATLAB is valid to forecast wind signal and can reflect the future characteristics of the signal. The average relative error of the model is found to be 6.9%, which can be drastically reduced. Reference [46] uses ANN but fails to give any explanation on the analysis of the algorithm used. Reference [75] proposes to utilize ANN for order identification that uses Extended Sample Auto Correlation Function (ESACF) method to determine the order of ARMA. However, the proposed method finds it hard to estimate the proper order when the p and q values become too great. In addition, it takes a long learning time. The present work proposes to combine ANN with AIC and the simulation studies are conducted to show that the proposed hybrid method gives better satisfactory results. The gaps in these papers are filled with the proposed hybrid.

There are several publications that report to predict ARMA and its true order but the combination of ANN- Akaike Information Criteria has not been used for order estimation. Therefore, in this research the ARMA model is combined with the ANN and AIC to give good and accurate results.

2.3.12.4 ORPD-PSO-GT hybrid solution for the Economic Dispatch problem

In the last decades, many useful studies [76-79] based on classical techniques for solving ORPD problems have been carried out. These include Newton and quadratic techniques nonlinear programming (NLP), successive linear programming, and mixed integer programming just to name a few. These approaches are broadly categorized as constrained optimization techniques. There are still a number of issues to be addressed with regarding practical power systems. One is when a local minimum is returned instead of a unique global minimum or the other is the inherent integer nature of the problem among the few crucial problems. This means that most control devices have pre-specified discrete values. Thus irrespective of the accuracy of the continuous solution, it is impossible, without making some reasonable approximations, to assign these values directly to the physical control devices.

A lot of attention has been given to the computational intelligence-based, heuristics methods over the years such as GA [80], PSO [81] and differential evolution (DE) [82] since they have been giving better results as compared to the classical methods [83]. GA's are stochastic search techniques based on the mechanism of natural selection and survival of the fittest. Reference [84] shows how to correct abnormal bus voltages to prescribed limits for the Nigerian Grid. Reference [85] describes the basics of PSO, different kinds, and few hybrids including GA-PSO techniques, and its applications in power systems. It shows that the PSO algorithm is one of swarm intelligence techniques based on simulating the food-searching behavior of birds, and has been widely used in power systems. These techniques have shown effectiveness in overcoming the disadvantages of classical algorithms such as slow speed since they lack the potential to finding good solutions. To the contrary, PSO and DE have received great attention from researchers because of their speed, novelty and searching power.

Reference [86] presents a PSO for reactive power and voltage control (Volt/Var Control) considering voltage security assessment. It shows that PSO only requires less than 50 iterations for obtaining sub-optimal solutions even for large-scale systems. Reference [87] explains PSO as a tool for loss reduction of optimal power flow (OPF) problem. Reference [88] compares three new PSO with the state of the art PSO algorithms for the optimal steady-state performance of power systems, namely, the reactive power and voltage control. It proves Coordinated Aggregation based PSO to be better over others. Reference [89] shows a modified particle swarm optimization (MPSO) method to realize ORPD considering voltage stability improvement. It shows decrease in system loss by 11.4%. Although these papers have considered PSO as a good technique there is no research that uses this in conjunction with the GT.

DE, however, is not completely free from the problems of slow and/or premature convergence as shown in [90]. It describes a family of improved variants of the DE/target-to-best/1/bin scheme, which utilizes the concept of the neighborhood of each population member and tries to overcome the disadvantages of becoming stagnant. Reference [91] tries to overcome the problem of voltage instability of ORPD by employing a new algorithm named shuffled frog leaping algorithm (SFLA). It calculates active power losses to be very low. Reference [92] compares the evolutionary programming (EP), PSO, DE and the proposed hybrid differential evolution (HDE) algorithms. The HDE proves to be the best for calculation of fuel cost. Reference [93] explains the reactive power dispatch problem in detail and compares the solution with PSO and DE algorithms. Hybrid multi swarm PSO gives the minimum transmission losses.

Reference [94] presents a solution to the reactive power dispatch problem with a novel particle swarm optimization approach based on multi agent systems (MAPSO). An agent in MAPSO represents a particle to PSO and a candidate solution to the optimization problem. The computational time taken by MAPSO is found to be very high where almost 70% of the total computing time is spent on the load flow algorithm. Reference [95] proposes different HDE algorithms, which tend to take a larger average convergence time than the single optimization scheme since two sub-optimization processes are executed in a single simulation run.

Several papers have used different algorithms to come out with a solution of ORPD but they seem to be complex. Reference [96] uses a seeker optimization algorithm (SOA)-based reactive power dispatch method, which is a novel heuristic stochastic optimization algorithm, based on simulating the act of human searching. It shows that the basic form of the proposed SOA algorithm can only handle continuous variables. Reference [97] proposes hybrid multi-swarm particle swarm optimization (HMPSO) algorithm to solve the ORPD problem where only the control variables are adjusted and compared with different algorithms to make the solution better. It comes out to be more complex as compared with PSO and DE algorithm and requires more computing time.

Some researchers have been working on GT in power systems to identify faults in the electric system. However, there is not much that has been done in wind generation and dispatch. Reference [98] shows how GT can be used to number different nodes and how positive direction of current should be taken. Reference [99] introduces tie-set GT that uses loops to realize distributed control in local units. It shows the application of GT to smart grid by breaking the graph into various required and not required sections. Reference [100] develops a polynomial time algorithm to decompose a graph but this paper lacks the means to identify the elements of a set and also the order of the largest graph in the set. Reference [101] presents an electrical network graph partitioning technique that divides power networks into zones and then tests it on the IEEE 39-bus and IEEE 118-bus. It shows the capability of GT for model reduction of complex power systems.

2.4 Summary

A lot of research has been done to forecast wind speed but still work needs to be done to develop methods to realize robust and more accurate predictions. Some hybrid methods have got satisfactory results and smaller MAPE but they have not been applied for more than one-hour prediction. The ARMA model on the other hand has shown good results for long term forecasting. Also, results from 1 hour ahead to 50 hours ahead can be obtained accurately. The WT is chosen for this combination since wavelets allow complex information such as music, speech, images and patterns to be decomposed into elementary forms at different positions and scales and subsequently reconstructed with high precision. Therefore, ARMA is combined with the WT, given the complementary strengths of both techniques, to assess their forecasting accuracy

Moreover, there has been research on the various forecasting methods but the combination of ANN and Kalman Filter remains an unexplored area of research. This research has explored this hybrid to come out with a new technique. ANNs are simpler to construct and require shorter development time whereas KF is an excellent technique for data assimilation as it takes maximum advantage of observations.

A number of factors determine the economics of utility-scale wind energy and its competitiveness in the energy marketplace. It includes the cost of wind energy that varies widely depending upon the wind speed at a given project site, improvements in turbine design bring down costs, optimal configuration of the turbines, cost of financing affects, transmission, tax, environmental, and other policies also affect the economics of wind. The potential economic benefits arise in the system-wide generation cost savings and in the ancillary service cost savings. The results from the new wind-forecasting model may be implemented into a power system economic dispatch model, which may take into account both spatial and temporal wind speed correlations. This, in turn, will lead to an overall more cost-effective scheduling of system-wide wind generation portfolio. Reference [102] shows a model to study how changes in the trading arrangement or changing the imbalance pricing system would affect different players in the electricity market. Reference [103] analyzes different market scenarios and has estimated to decrease MAPE to 3.7% for wind power forecast until 2020.

A lot of work still needs to be done to develop methods to realize robust and more accurate solutions. This research proposes PSO as a solution of OPRD using GT to analyse the relationship between the forecast wind speed and the ED problem. Some hybrid methods have got satisfactory results and small transmission losses but they have not been tested outside their range. The PSO technique can generate high-quality solutions within shorter calculation time and have more stable convergence characteristic than other stochastic methods. Although the PSO seems to be sensitive to the tuning of some weights or parameters, research is still in progress to prove its potential in solving complex power system problems.

Chapter 3

ANN-EnKF Hybrid

3.1 Introduction

This Chapter focuses on the ANN-EnKF hybrid. A surrogate of ANN has been built and has been shown with the help of a schematic diagram. Also, EnKF has been discussed and the mathematical equations are shown in the next section. The reason for choosing ANN and EnKF has been justified in Section 2.6. ANN has been combined with EnKF with the help of a mathematical matrix equation to come out with a hybrid to act as an output correction scheme. This hybrid has been tested on MATLAB for Auckland, New Zealand for 3 hourly and 6 hourly data. This hybrid proves to be beneficial for this short term forecasting and hence, this research proves to be useful for wind speed forecasting.

3.2 Surrogate of ANN

Surrogate models are approximate models that copy the behavior of large scale models to small scale models that makes it cost efficient. It is constructed using data driven models and choosing appropriate data points placed together. ANN maps the input vector into corresponding output vector while other values need not be known makes it imperative. This makes ANN very useful to mimic nonlinear relationships without the need of any already existing models [60].

Reference [104] showed a dynamic system in which the state at time k depends on the system state for preceding time state and wind speed. Therefore, a recurrent model is designed to develop the desired state form. In this paper the following time lagged ANN surrogate is used to map the wind model in reduced space in which F_{NN} is the surrogate model.

$$\widehat{X_S^H}\ (k+1) = F_{NN}[\hat{X}_S^H\ (k), \hat{X}_S^H(k-1), \dots \hat{X}_S^H\ (k-\tau_H), U_S\ (k), U_S\ (k-1), \dots, U_S\ (k-\tau_U)] \tag{3.1}$$

$\widehat{X_S^H}\ (k+1)$ is the predicted output of the model. So this will give one-step ahead output. τ_U and τ_H are the time index parameters.

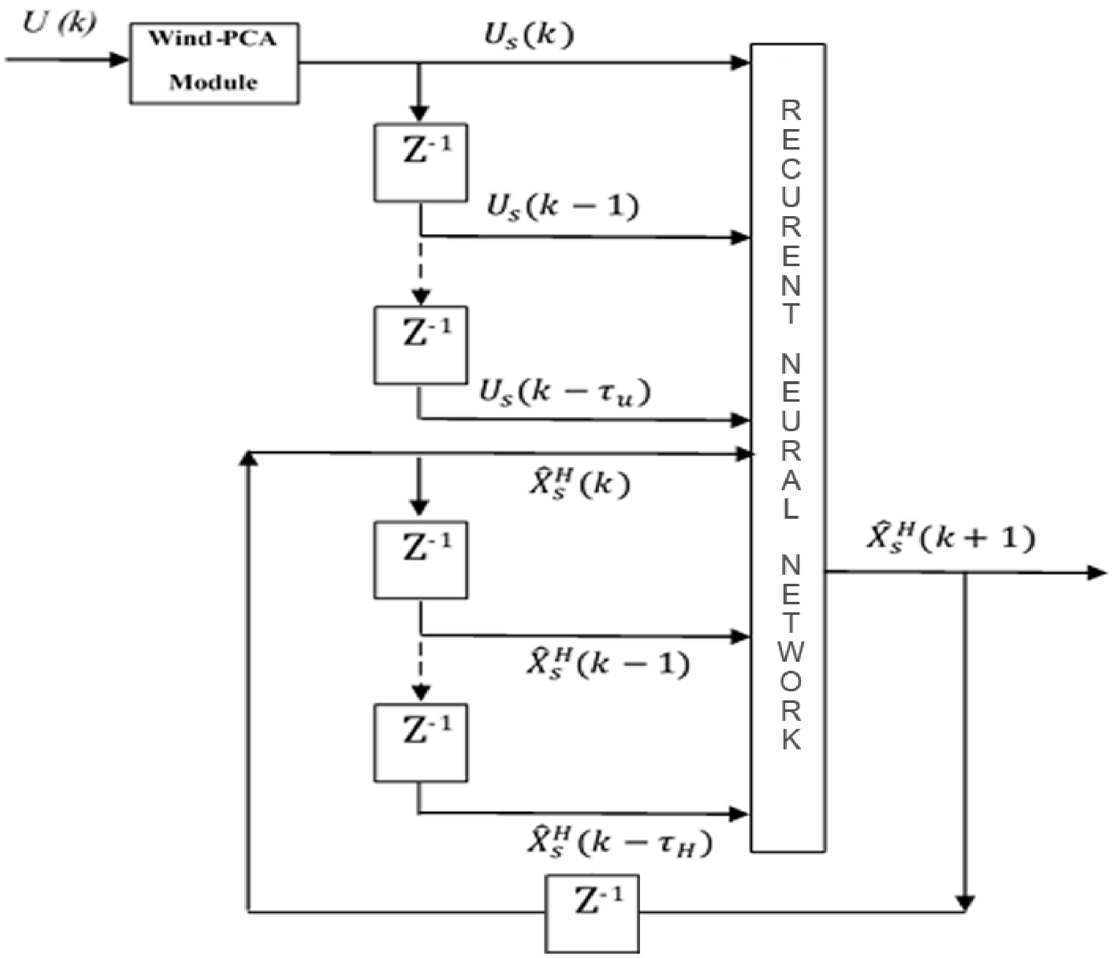

Fig 3.1. Schematic presentation of ANN surrogate

Figure 3.1 shows the dynamic recurrent network with feedback output to input in a schematic diagram. The output $\widehat{X_S^H}\ (k+1)$ is fed back through unit delay operator Z^{-1} to the input that consists of past system states.

ANN is a model approximate i.e., it is a model of a model. Its accuracy is lower than the original but can be increased by clustering of data. Being a data driven model, this model is not sensitive to type of wave model and can be set up by using the data or other generation models.

3.3 Ensemble Kalman Filter

The Kalman filter tries to estimate the state x that belongs to k_n of a discrete-time controlled process that is governed by a linear stochastic differential equation. The recursive form of a Kalman filter that is suitable for problems with a large number of variables is referred to as an ensemble Kalman filter or EnKF.

Now, our process again has a state vector, but that process is now governed by the non-linear stochastic differential equation model *M* which is

$$X^f(k) = M\ [\ X^f(k-1), U(k-1)] + w(k-1)] \tag{3.2}$$

$$y^{\circ}(k) = H\ (k)x^f\ (k) + v\ (k) \tag{3.3}$$

where $x^f(k)$ denotes forecast at time k, $U(k)$ is forcing of the system and M is one time step of the model. Reference [29] has used these equations to study the Kalman filter.

In practice, the process noise covariance and measurement noise covariance matrices are given as:

$$\begin{aligned} &p(w) \sim N(O, Q) \\ &p(v) \sim N(O, R) \end{aligned} \tag{3.4}$$

In order to obtain an optimal estimate, it is needed to combine the measurement taken from the actual system modeled by Eq. (3.2) with the information given by the system model (Eq. (3.3)). The forecast state at time *k*, denoted by x^f, is the forecast from observation time *k-1* to observation time *k*. It is given by

$$x^f(k) = M[x^a(k-1), U(k-1)] \tag{3.5}$$

where $x^a(k-1)$ is the analyzed system state. Observation $y(k)$ is updated by

$$x^a(k) = x^f(k) + K\left[y^{\circ}(k) - H(k)x^f(k)\right] \tag{3.6}$$

Also, the Kalman gain is given by

$$K(k) = P^f(k)H(k^{T)}[H(k)P^f(k)H(k^{T)} + R]^{-1} \tag{3.7}$$

It is the minimum variance gain and $P^f(k)$ is the forecast error covariance matrix. This covariance can be calculated by a finitely number of randomly generated system states [105].

3.4 Hybridizing ANN Surrogate and Kalman Filter

In the combined method, the output of the ANN will be considered as state vectors. The state vectors are provided to the EnKF. By help of the observations, the EnKF will correct the output of the ANN to determine the best estimate of the system (or analyzed state). The analyzed state will return to the inputs of the ANN for the next time step. There is a difference between inputs of network, which come from forcing or from feedback loop. To deal with the time delayed states in Eq. (3.1), the Kalman filter formulation proposed by [106] is employed and an extended vector is taken as follows

$$X^k[X_s^{H,k}, X_s^{H,k-1}, \ldots., X_s^{H,k-\tau_H}]^T \tag{3.8}$$

This new state vector expands the dynamic equation to the following equation

$$\begin{bmatrix} X_s^{H,k+1} \\ X_s^{H,k} \\ X_s^{H,k-1} \\ \vdots \\ X_s^{H,k-\tau_{H+1}} \end{bmatrix} = \begin{bmatrix} & & F_{NN(\dots)} & & \\ 1 & 0 & \dots & 0 & 0 \\ 0 & 1 & \vdots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \dots & 1 & 0 \end{bmatrix} \begin{bmatrix} X_s^{H,k} \\ X_s^{H,k-1} \\ \vdots \\ X_s^{H,k-\tau_H} \end{bmatrix} + \begin{bmatrix} W_s^k \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \quad (3.9)$$

F_{NN} is given in Eq. 3.1 and I is the identity matrix. The compact equation of this is in accordance with the general equation of Kalman filter and is

$$X^{k+1} = M_s[X^k] + W^k$$
$$W^k = [W_s^k, O, O, \dots O]^T \quad (3.10)$$

where W^k is the extended noise vector and M_s is the new dynamic operator.

The observation Eq. 3.3 can be replaced by

$$y^{\circ}(k) = H(k)\pi_{r^2}^T X_s^{H,k} + v_s \quad (3.11)$$

where $v_s(k)$ is the measurement noise in reduced space. Reference [106] gives derivation of the measurement noise in the reduced space

$$v_s(t_k) \approx H(t_k)(X^{H,k} - \pi_{r2}^H(\pi_{r2}^H)^T X^{H,k} + \mu^H) + v(t_k) \quad (3.12)$$

This corrects the underlying model.

3.5 Results and Discussion

In the present study, wind data and the input-output patterns for training of a network are taken from Auckland City, New Zealand for the year 2011 on a minute basis. The platform chosen to test the available set of data is MATLAB. The six hourly wind fields are extracted from the data from the period of January 2011 to July 2011, which means that data for 6 hours was extracted from each day's data. For this, the total number of data values selected were 1000. Wind speed data values are at an interval of 1 minute. These results are a proxy for true wave states. Levenberg-Marquardt back propagation algorithm is used for this analysis.

Since it is a comparison between the individual and the hybrid of the two methodologies, different figures have been plotted for different ensembles in MATLAB. The six hourly data were selected for the execution of wind speed model. The total number of data values taken was 1000. The wind speed results are a proxy of the true wind states. The forward run time is approximately 180s. The original wind data is shown in Figure 3.2. It shows the time index for 1000 data values and the general pattern of wind speed in that location for the particular period of time. The larger variances show large-scale patterns with slow changing amplitudes representing stability whereas the smaller variances show small-scale patterns with fast changing amplitudes representing instability.

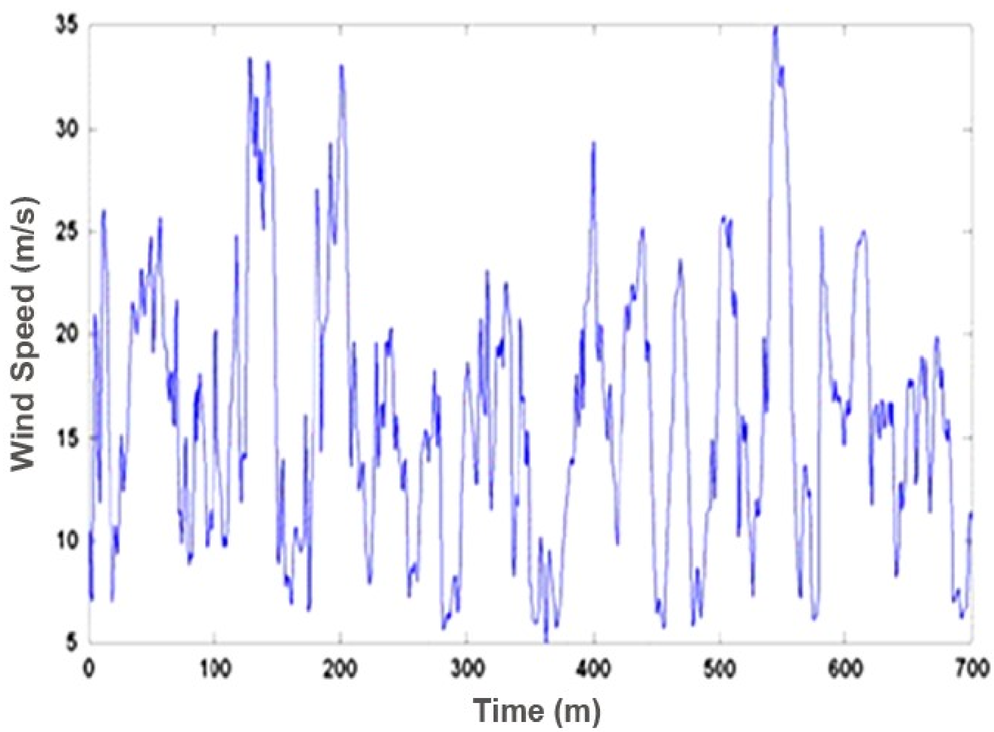

Fig. 3.2 Original Wind Data

The first and foremost step in the prediction process is data normalization. This step is done by transforming the actual wind speed data X into Normal wind speed data, Xn (i.e., Xn is a normalized Gaussian Random Variable with zero mean and unit variance). The shape of the Normal signal Xn is shifted down with negative values compared to the actual signal X due to the normalization process as done in [126]. It is noted, negative wind speed is observed throughout this thesis. This is because some wind speed is negative when the wind speed is quite slow as in [127]. Therefore, the raw data may be dealt with before considering the sampling frequency is not high if necessary.

There are two groups of data taken to prepare the surrogate model. The first one contains 1000 data values for training of network whereas the second group contains 100 data values for testing of network. Levenberg-Marquardt back propagation algorithm is used for this training of network. Initially 20 numbers of hidden neurons were taken to check the performance and were increased up to a number where significant changes were not observed. It was seen that with 53 hidden neurons there was no requirement of any further improvement.

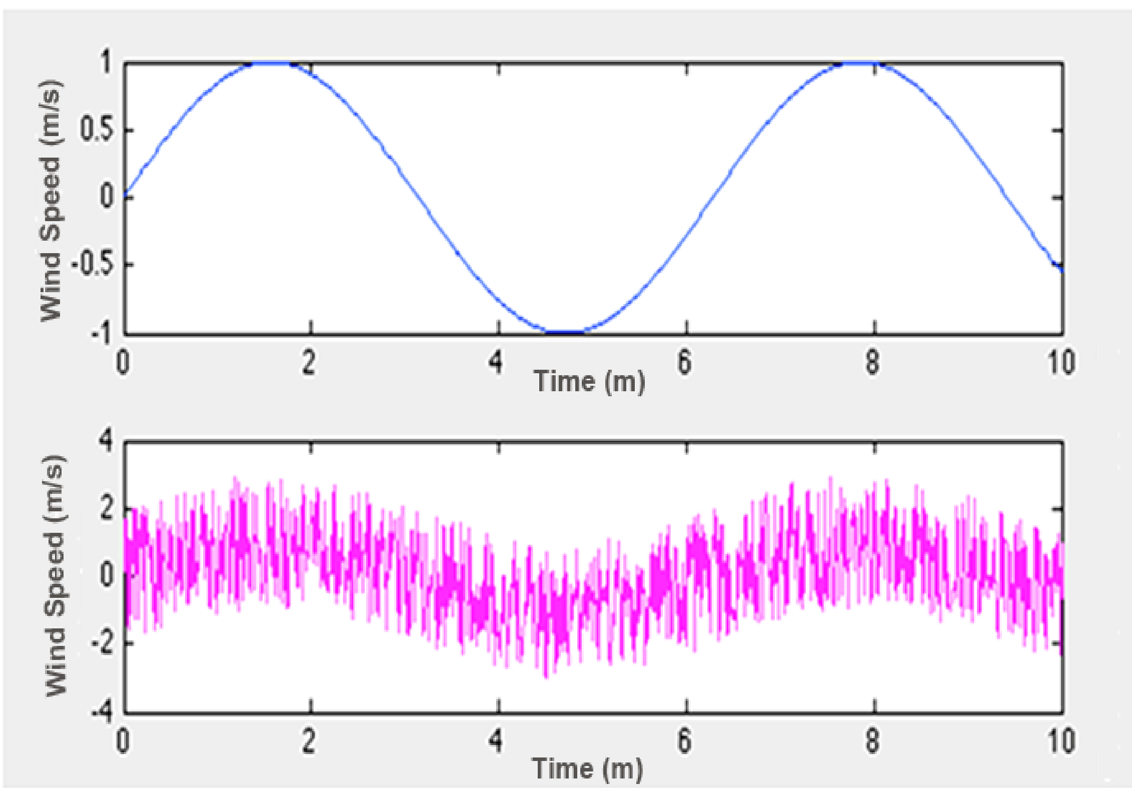

Fig 3.3 Output of ANN fed with original wind data

Figure 3.3 shows the output of ANN when fed with the original wind data. The first graph in blue shows the original wind data. When it is fed to ANN, the second graph in pink is obtained. The bottom graph in the following figure shows the ANN output, and the top graph shows the original wind data. Data has been normalized here as done in [126].

The test data includes 100 data values that are not included in the training of network. In spite of well-trained data the surrogate alone could not predict the exact wind speed in the test period. This surrogate has both simulation and reconstruction errors.

As a solution, a hybrid of the surrogate with the Ensemble Kalman Filter is combined to reduce the error. As this is a comparison of the individual and the hybrid techniques the graph for the Ensemble Kalman filter is plotted which is shown in Figure 3.4. Three models are plotted that include the reduced space model (red), which is used because of the surrogate model. This field is projected into the reduced space and it can be re-embedded to full space to reconstruct the original wave field. The wind model (green) is the one that is depicted in such a way so as to see the variation of the wind model. The surrogate model of ANN (blue) is the approximate model that copies the behavior of large-scale models to small-scale models. These models are plotted for the Ensemble Kalman Filter. The effects can be noticed when the same models are plotted for the ANN-EnKF hybrid. This shows the much-improved result when the surrogate is coupled with the Kalman Filter. It gives much finer and accurate prediction for the surrogate model.

This estimates the original wind speed to the closest prediction and proves to be beneficial for the forecasting of the wind speed.

The same three models are now plotted for the ANN-EnKF hybrid and effect can be seen in Figure 3.5. The ensemble size is chosen to be 100. It showed decreasing error with increasing number of ensembles. The results are much improved when the surrogate of ANN is coupled with the Ensemble Kalman Filter. It gives much finer and accurate prediction for the surrogate model. This estimates the original wind speed to the closest prediction and proves to be beneficial for the forecasting of the wind speed.

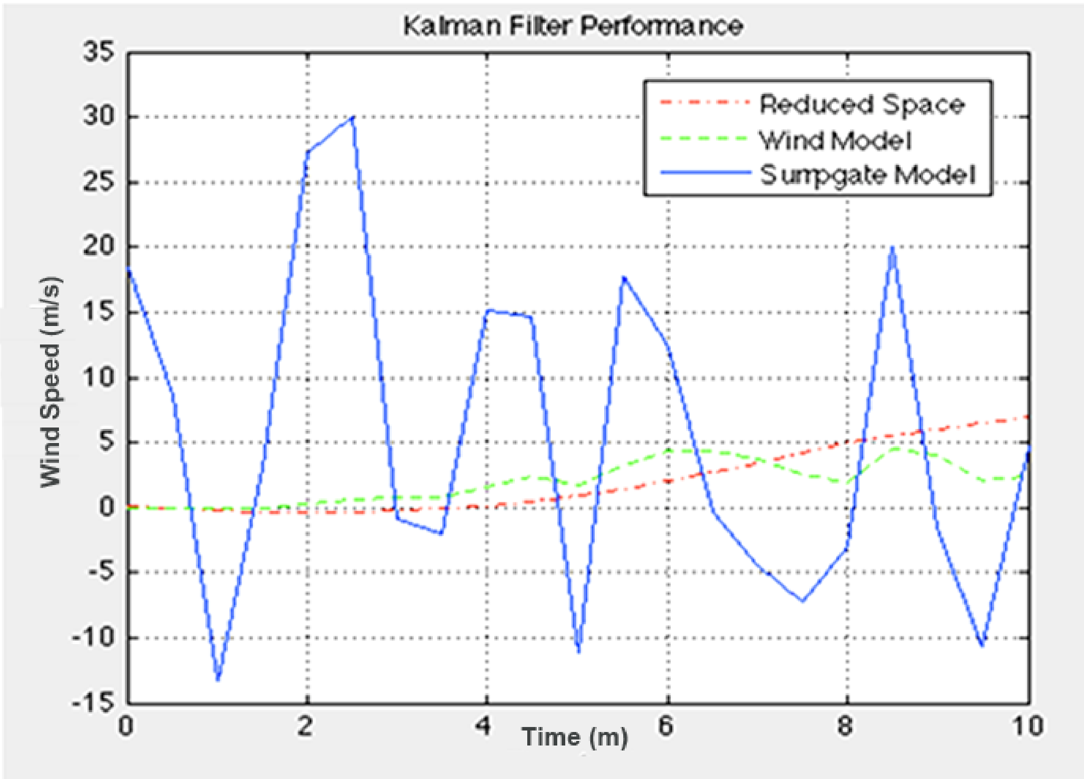

Fig. 3.4 Output of Ensemble Kalman Filter

The results show the MAPE to be 6.57%. The difference between the actual wind speed and the one obtained from the hybrid is shown in Figure 3.6. The error is minimum thereby confirming that this hybrid acts as an output correction scheme. There is not much difference in the actual data gathered and the one obtained from the graph that proves the accuracy.

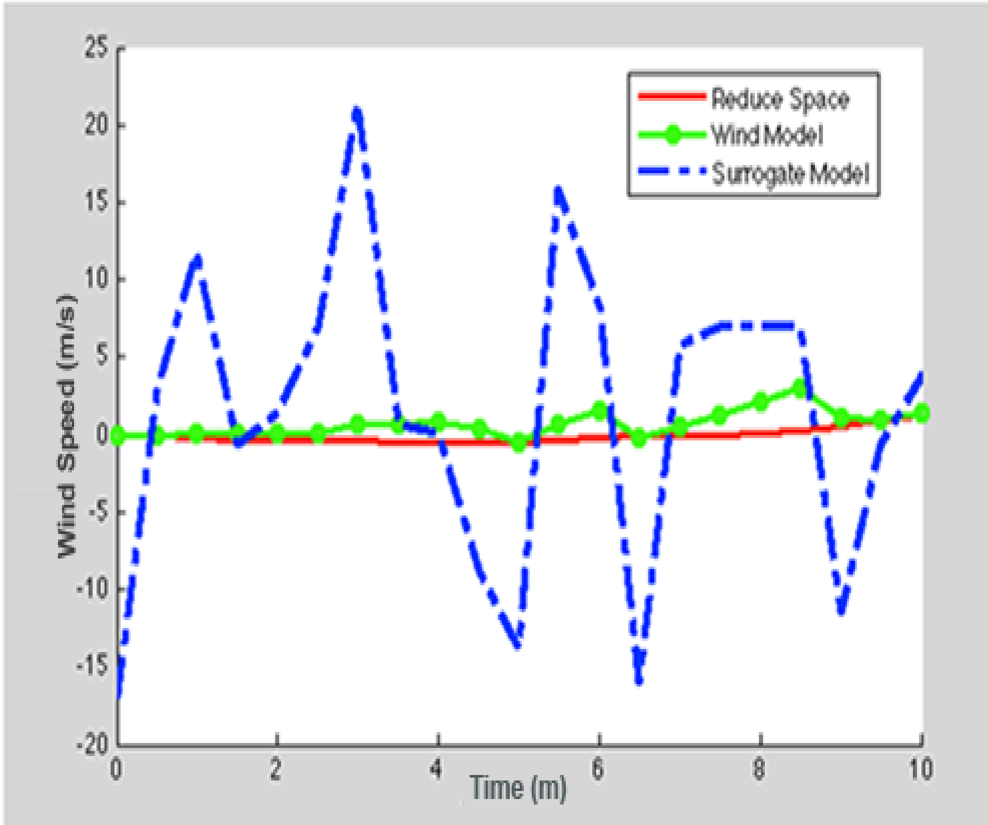

Fig. 3.5 Output for the hybrid of ANN and EnKF.

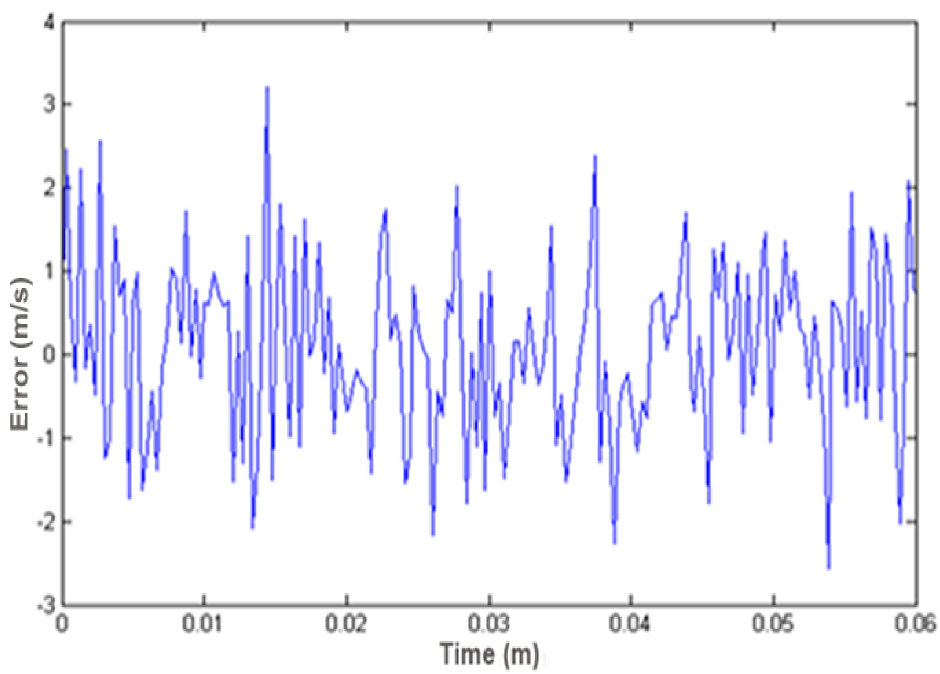

Fig. 3.6 Error Graph for ANN-EnKF Hybrid

The root mean square errors of the surrogate alone and the reconstructed hybrid are also calculated and the results are shown in Figure 3.7.

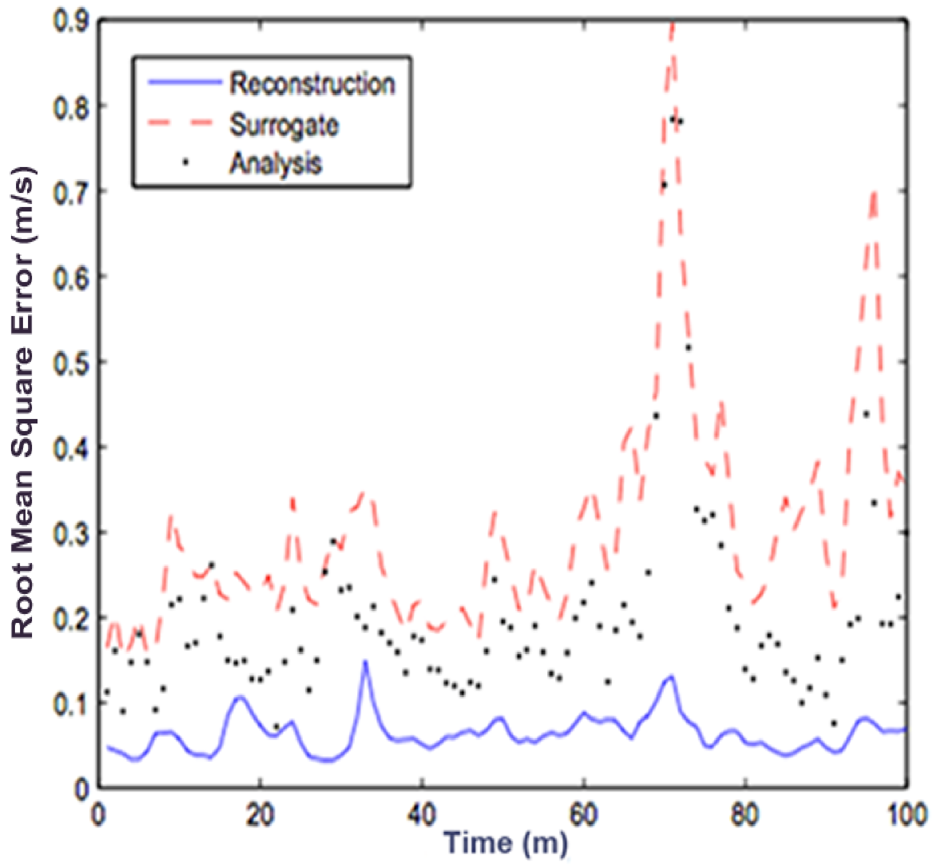

Fig. 3.7 Root Mean Square Error for various wind speeds.

Table 3.1. Root mean square errors for different wave ensembles.

Ensemble Members	Root Mean Square Error (m/s)
5	1.387
50	0.126
100	0.110

Table 3.1 shows that with the increasing number of ensembles the root mean square error decreases. Hence, the underlying model acts as an output correction scheme.

3.6 Summary

This chapter presents the critical assessment of a unique combination of ANN and EnKF methodologies. The mathematical equations of both the individual methods and the combination have been presented. The proposed hybrid technique was applied on three hourly data and six hourly data in MATLAB. First, the original wind data were shown. Second, the changes from ANN and EnKF methods individually to the hybrid were shown with different graphs. Finally, the RMS errors were calculated for different number of ensemble sizes. The error decreases as the ensemble size increases. Therefore, the proposed hybrid technique proves to be effective for very short term wind speed forecasting.

Chapter 4

WT-ARMA Hybrid

4.1 Introduction

In this Chapter, the Wavelet Transform (WT) along with the ARMA is chosen to form a hybrid. These methods have been preferred since the proposed hybrid has a very high potential for producing more accurate forecasting results. The Wavelet analysis is a novel technique that is being adapted in various fields for forecasting purposes. The second method used is the ARMA model, a time series model. The MAPE of the ARMA has been proved to be between 7% for 1-hour up to 18% for the next six hours [11]. In this study, these two methods have been combined to form a hybrid.

The ARMA model has been chosen in this research because it is suitable for high frequency data. They produce accurate forecasts based on the historical patterns of the time series data. They belong to the class of linear models and can represent both stationary and non-stationary data. They do not involve the dependent variable; instead they make use of information in the series to generate the series itself.

The ARMA model when compared to other conventional models is more robust in terms of forecast accuracy as it takes seasonality into consideration. If the original series do not exhibit season, non-seasonal ARMA shall be fitted. The ARMA models outperform conventional time series models like moving average and other smoothing models in terms of degree of forecast accuracy, treating seasonality and long term forecasts.

The disadvantage of the ARMA model is that it is tedious to build manually without the aid of Statistical software.. Moreover, there are situations where the final model may not fit the requirements due to error terms with non-constant variance. This is known as heteroskedasticity, and may be treated separately using ARCH and GARCH techniques. Another disadvantage of the ARMA compared to other conventional models is that forecasts are unreliable with data series having less than 50 data points. The ARMA models are more sensitive to outliers present in the original series. However, if the degree of accuracy is not of great concern, conventional time series models can be employed that is simple and less time consuming.

The proposed hybrid model (WT-ARMA) works as follows. The WT decomposes highly nonlinear wind speed time series into several approximate stationary time series. The decomposed time series are fed to different ARMA models established respectively, and then the outputs of each ARMA model are combined to get the forecasting results. This is shown in Figure 4.1. In order to see the effectiveness of the proposed approach, actual wind speed data from a weather station are used to establish forecasting model. The results indicate that the wavelet theory is a useful tool in wind speed forecasting and when combined with the ARMA model brings significant improvement to reduce forecasting errors.

4.2 Wavelet Analysis

Wavelet means a small wave or a pulse of short duration with finite energy that integrates to zero. The Wavelet Transform divides the data into components of different frequency and then matches resolution of each component to its scale. The WT breaks the original signal into projections of translated and scaled versions of the original mother wavelet. The basis function of the Wavelet Analysis is the mother wavelet function (ψ) [107-108].

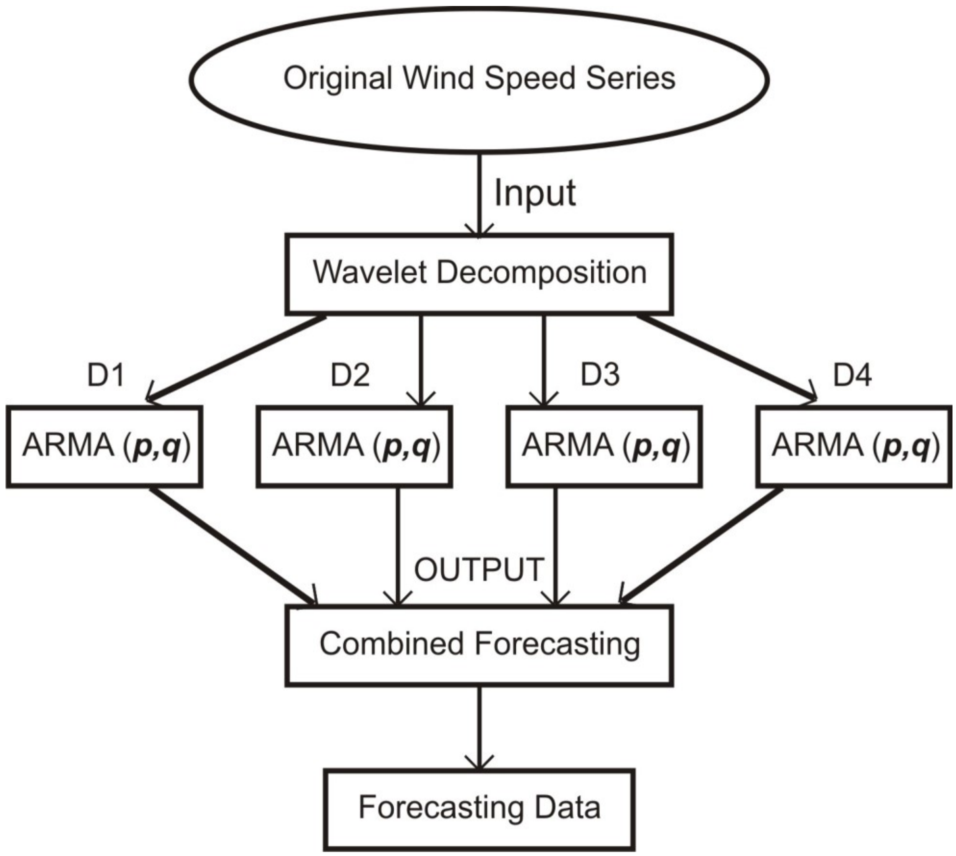

Fig. 4.1 Procedure of Wind Speed Forecasting using WT-ARMA

The roots of the Wavelet Analysis have been derived from the very famous Fourier analysis that mathematically transforms a stationary signal from time domain to frequency domain. Although having a lot of advantages, the Fourier analysis has a serious drawback. When transforming to the frequency domain, time information is lost and when transforming to the time domain, frequency information is lost. That means both frequency domain and time domain do not support and counter confirm each other's data.

Reference [109] uses the WT to avoid this problem and improve the results for Fourier transform. In this only a small section of the signal at a time is analyzed. This is called windowing. The technique that maps a signal into a two-dimensional function of time and frequency is known as Short-Time Fourier Transform (STFT). It balances the time and frequency based views of a signal. So, it gives information about what time and frequencies a signal event occurs but with limited precision.

Another limitation of STFT is that once a particular size for the time window is selected it remains the same for all frequencies. Many signals demand for a more flexible approach where changing the size of the window gives more accurate particular characteristics. The wavelet transform gives better results and overcomes this deficiency, as it gives the option of variable sized windows. Usage of long time intervals is allowed in the wavelet analysis.

Unlike Fourier Transform, the Wavelet transforms do not have a single set of basic functions. The Fourier transform breaks the original signal into sine and cosine functions waves of several frequencies whereas the wavelet transform breaks the signal into projections of translated and scaled versions of the original mother wavelet. Thus, the wavelet analysis provides immediate access to information that can be obscured by other time-frequency methods. It generally has two categories as described in the following sub-sections.

4.2.1 Continuous Wavelet Transform (CWT)

The continuous time wavelet transform of *f (t)* with respect to a wavelet *(t)* is given by

$$W\ (m,n) = \int_{-\infty}^{\infty} f\ (t)\ \frac{1}{\sqrt{|m|}}\ \Psi^*\ \left[\frac{t-m}{n}\right] dt \tag{4.1}$$

where, *m* is the scale variable, *n* is the translation variable and * denotes complex conjugate. The CWT maps the one dimensional function *f (t)* to a function *W (m, n)* having continuous real variables *m* and *n*. The coefficient of *W(m,n)* at a particular scale and translation, tells us how well the original function or signal *f (t)* matches with the scaled or translated mother wavelet. However, to recover the function we do not require all the coefficients of *W(m,n)* so CWT gives a redundant way to represent the signal [107,109].

The translated term relates to the window location that shifts through the signal. In the transform domain it corresponds to time information. High scales relate to a non-detailed global view (low frequencies) and low scale corresponds to detailed view (high frequencies).

4.2.2 Discrete Wavelet Transform (DWT) and Multi Resolution Analysis (MRA)

DWT is used to decompose a signal into different resolution levels. Compared with CWT, DWT is sufficient in decomposing and reconstructing most wind speed disturbances. It provides enough information and offers high reduction in the computational time. Multi-resolution analysis is to break a continuous real valued finite energy function into a hierarchy of approximations. It is a technique that represents a function on many different scales, which are formed by scaled and translated mother wavelet.

In order to obtain a matrix W of wavelet coefficients for Discrete Wavelet Transform (DWT), it is possible to define w, in order to obtain a matrix W of wavelet coefficients, which results in the Discrete Wavelet Transform (DWT)

$$W = w.x \tag{4.2}$$

This matrix w in equation (4.2) can be represented as $w = [w_1,\ w_2,\ w_2, \dots\ w_J,\ v_J\ ]^T$. Similarly, we can define W such as $W = \left[W_1, W_2, ..W_J, V_J\right]^T$.Here, x being a time series defined as $x\ = [x_1,\ x_2, \dots\ x_N\ ]^T$ with N an integer multiple of $2^{\ j}$ where j is the level of resolution. For the DWT the first J sub- vectors contain all the wavelet coefficients for scale J. Each w_j column vector has $N/2\tau_j$ coefficients associated with changes on a scale of length $\tau_j\ = 2^{j-1}$, for $j = 1, 2, 3, \dots, J$. The final sub-vector v_J contains just the scaling coefficients associated with averages on a scale of length $2^{\ J}$.

The DWT decomposes the signal into an approximation (low frequency) and detail (high frequency) information and then analyzes the signal at different frequency bands with different resolutions. DWT engages two sets of functions, called scaling functions and wavelet functions, which are related with low pass and high-pass filters, respectively. By successive high-pass and low-pass filtering of the time domain signal the breakdown of the signal into different frequency bands is attained.

Multi Resolution Analysis (MRA) equation resulting from the reconstruction of the wavelet coefficients is

$$x = w^T\ .W = \sum_{j=1}^{J}(w_j^T\ \ .W_j\ ) +\ v_J^T\ .\ V_J\ \ =\ \sum_{j=1}^{J}(D_j) + A_J \tag{4.3}$$

In the MRA equation (4.3), the time series x is stated as the sum of a constant vector A_J and J other vectors, D_j, *(j=1,2,3...J),* each of which contains a time series related to variations in x at a certain scale. The D_j refer to the j^{th} wavelet detail and the A_J as the approximation. MRA is intended to give good time resolution and poor frequency resolution at high frequencies and good frequency resolution and poor time resolution at low frequencies. This methodology has proved to give good results especially when the signal has high frequency components for short durations and low frequency components for long durations.

1. The decomposition of algorithm: According to the decomposition algorithm, if A_0 is a discrete signal to be decomposed, then the equation is

$$\begin{cases} a_{j+1} = Ha_j \\ d_{j+1} = Gd_j \end{cases} \tag{4.4}$$

   where, $j= 0$ -J, J is the maximum decomposed level; H is a low-pass filter; G is a high pass filter; a_j and d_j are respectively low frequency signal and high frequency signal of the original signal in the resolution of 2^{-j} with the adjacent of the original signal in the different frequency band. Finally, a_0 is decomposed into $d_1, d_2 ... d_J$ and a_J. To make the total output data length and the length of the input data remain consistent the decomposition algorithm makes the data length half in each layer than the one before the decomposed signal [110].

2. The reconstruct algorithm: The expression of the reconstruct algorithm is

$$A_J \ = H^* a_{j+1} \ + \ G^* d_{j+1} \tag{4.5}$$

   where, $j = J-1, J-2 ... 0$; H^* and G^* are the dual operators. The decomposed wavelet increases the number of signals which are later reconstructed using the Equation 4.5. Reconstruct $d_1, d_2, ..., d_J$ and a_J separately to get $D_1, D_2, ..., D_J$ and A_J ,then X can be yielded

$$X = D_1 + D_2 \dots D_J + A_J \tag{4.6}$$

   where $D_1 = \{d_{1,1}, d_{1,2}, ...,\} ...$, $D_J = \{d_{J,1}, d_{J,2}, ..\}$ is the reconstruction of high frequency signals from the first layer to the J^{th} layer; $A_J = \{a_{J,1}, a_{J,2}, ...\}$ is the reconstruction of low frequency signals of J layer.

4.3 AUTO REGRESSIVE MOVING AVERAGE (ARMA)

Wind pattern expresses an equivalent theory in wind forecasting. A wind pattern illustrates one specific type of trend of wind process at a particular site or location, and duration of each pattern may be special for that particular region. When the traits of wind patterns are known, forecasts of wind speed become easier in the located area. The wind patterns can be used as complements to forecasts based on the ARMA, which are blind to the possible trend of wind speed variation in the following hours.

The ARMA models can be described by a series of equations. The mean-adjusted series are obtained if the time series is first reduced to zero-mean by subtracting the sample mean. Therefore, we will work with the mean-adjusted series

$$y_t = Y_t - \bar{Y},\ t = 1, \dots N \tag{4.7}$$

where Y_t is the original time series, $\bar{Y}$ is its sample mean, and y_t is the mean-adjusted series. One subset of the models is the so-called autoregressive, or AR models. This model describes a time series as a linear function of its past values. The order of the AR model signifies the number of lagged past values included. The simplest AR model is the first-order autoregressive, or AR (1), model

$$y_t + \varphi_1 y_{t-1} = a_t \tag{4.8}$$

where y_t is the mean-adjusted series in year t, y_{t-1} is the series in the previous year, φ_1 is the lag-1 autoregressive coefficient, and a_t is the noise. The noise is also known as the error, the random-shock, and the residual. The error a_t is supposed to be random in time, not auto correlated, and normally distributed. We can rewrite the equation for the AR (1) model as

$$y_t = -\varphi_1 y_{t-1} + a_t \tag{4.9}$$

This equation shows that the AR (1) model has taken the form of a regression model in which y_t is regressed on its previous value. Here, a_1 is comparable to the regression coefficient, and a_t to the regression residuals. The name autoregressive implies to the regression on self (auto). Higher-order autoregressive models include more lagged y_t terms as predictors.

The moving average (MA) model is a form of the ARMA model in which the time series is regarded as a moving average (unevenly weighted) of a random shock series a_t. The first-order moving average, or MA (1), model is given by

$$y_t = a_t + \theta_1 a_{t-1} \tag{4.10}$$

where a_t, a_{t-1} are the residuals at times t and $t-1$, and θ_1 is the first-order moving average coefficient. MA models of higher order than one include more lagged terms.

This shows that the AR model includes lagged terms on the time series itself, and that the MA model includes lagged terms on the noise or residuals. So, by taking both types of lagged terms, we arrive at what is called autoregressive-moving-average, or ARMA, model. The order of the ARMA model is included in parentheses as ARMA (p, q), where p is the autoregressive order and q the moving-average order. The simplest ARMA model is first-order autoregressive and first-order moving average, or ARMA (1,1). The ARMA model is used for stationary time series that take past values, prediction errors and a random term into account.

An ARMA (p, q) model of order p and q, with φ_j and θ_j the autocorrelation and the moving average coefficients respectively, is represented by [108]

$$y_t = \sum_{j=1}^{p} \varphi_j \; y_{t-j} + \; a_t - \; \sum_{j=1}^{q} \theta_j \; a_{t-j} \tag{4.11}$$

The process of the ARMA(p, q) is combined by the processes of AR (p) and MA (q). If $q=0$, then the equation becomes an AR model of order p. When $p=0$, the process becomes an MA model of order q. In the ARMA (p, q) model, $\{y_t\}$ is the return series of original time series and $\{a_t\}$ is the innovations noise process. In the process of constructing an ARMA model, it is imperative to confirm the orders p and q.

Equation 4.11 is put into Equation 4.3 to get the proposed hybrid formula that is

$$x = \sum_{j=1}^{J} D_j + A_J = \; \sum_{j=1}^{J} D_j + \left\{ y_t - \sum_{j=1}^{p} \varphi_j \; y_{t-j} + \sum_{j=1}^{q} \theta_j \; a_{t-j} \right\} \tag{4.12}$$

This explains the proposed hybrid. The original wind speed data are taken and put into the Wavelet Transform that first decomposes the highly non-linear data and then reconstructs it.

It is then fed into ARMA, which gives the combined forecasting data with very less errors.

In this study, an index, namely mean absolute percent error (MAPE), is used as forecasting precision measure. The index is represented as follows:

$$E_{MAPE} = \frac{1}{N} \sum_{t=1}^{N} \left| \frac{Y_t - \widehat{Y}_t}{Y_t} \right| \tag{4.13}$$

where Y_t is the actual time series value at period t, $\widehat{Y}_t$ is the forecasting time series value at period t, and N is the number of forecasting periods.

4.4 Results and Discussion

In the present study, actual wind data and the input-output patterns for training of a network are taken from Auckland City, New Zealand, for the year 2011 on a 30 seconds interval. This dataset was provided by NIWA, which is the only producer of wind speed datasets in New Zealand. Only wind speed and direction were provided therefore no other factors such as temperature are considered here. The platform chosen to test the available set of data is MATLAB. The forecasting errors are also computed using MATLAB.

A hybrid model is established on the basis of consecutive hourly mean wind speed samples, thus allowing the prediction of wind speeds at future time-steps.

Firstly, the original wind speed time series is decomposed into detailed time series at different resolutions (scales), $d_1, d_2, \ldots, d_J$ and a coarse approximation time series a_J, then we obtain Dj $(1 \leq j \leq J)$ and A_J by reconstruction. From this, the data is being filtered. If direct data are put into the ARMA model then the results will not be very accurate [108]. As a result, for different time series (Dj and A_J) of Wavelet Transform, the ARMA models are established to forecast respectively. Lastly, the hybrid approach is utilized to obtain the forecasting result. In the experiments, 250 input/output data values are used for the simulation. The first 215 data values form the training data set, whereas the others are used as checking data for validating the wavelet-ARMA model.

Figure 4.2 is plotted for WT, which is the sum of the decomposition at level 5 and reconstruction of the wavelets. The approximations for the low frequency and details for high frequency are added and the summation of both is shown in this figure. It shows the decomposed coefficients of every scale. D_1, D_2,.. D_5 are details, they reflect the detail information of every scale. A_5 is the approximation; it reflects the development trend of wind speed. The relation between A_5 and Dj $(1 \leq j \leq 5)$ meets $S=A_5+D_5+D_4+D_3+D_2+D_1$.

The characteristic of wavelet decomposition is that the more scales the original signal can be decomposed into, the better signals are, but great errors will be brought about at the same time. As a compromise the decomposed number of scales is always less than 6 [107-109]. Therefore, data were tested for $j = 1\text{-}6$ levels for the hybrid and $j = 5$ was seen to be giving the best results therefore $j = 5$ has been chosen. Table 4.1 shows the different errors (MAPE) obtained for different values of j and hence results show why $j=5$ has been chosen for testing this particular dataset in this section.

Table 4.1 Different Error for Different values of $1 \leq j \leq 6$

j	**WT-ARMA MAPE(%)**
1	3.4
2	3.2
3	3.0
4	3.0
5	**2.7**
6	2.9

Now the ARMA model is fed with the wavelet transform output and the results analysed for different p and q. The results of ARMA(1,1), ARMA(1,2), ARMA(2,1), and ARMA(2,2) are compared. However, no significant discrepancies between the results are observed. As an example, the results for ARMA(1,1) are displayed in Fig. 4.3. One of the possible reasons for not observing any difference could be due to the use of synthetic data.

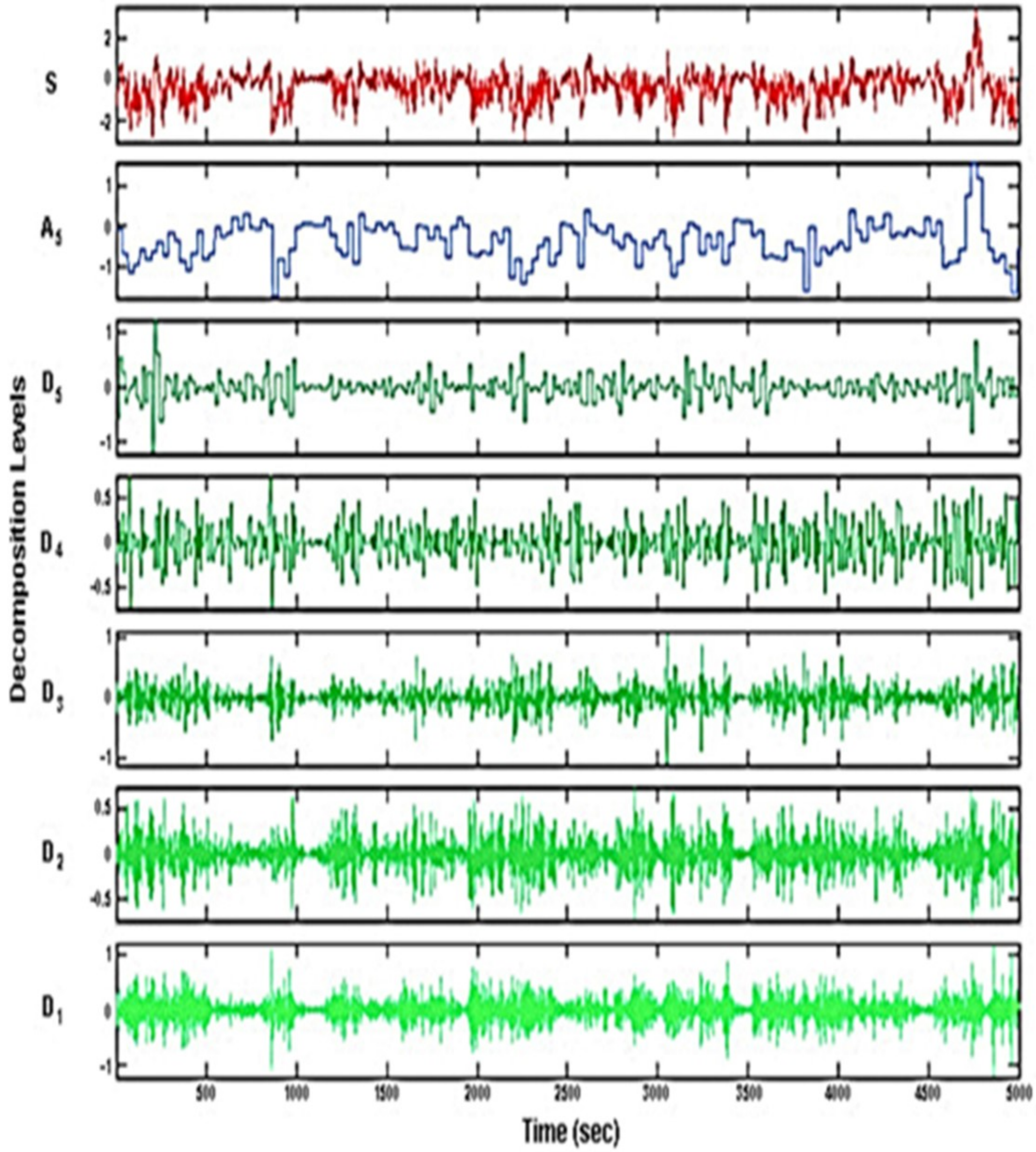

Fig. 4.2 Output of Wavelet Analysis shows approximations for the low frequency (A_5) and details for high frequency D_j ($1 \leq j \leq 5$) that are added as (S).

After the parameters are learned from the training set, the forecasting algorithm is applied as described in Section 3 to make 35 points' predictions (1-hour-ahead prediction). Figure 4.4 compares the forecasted results of WT-ARMA hybrid to the original wind. Figure 4.5 shows the Wavelet ARMA hybrid with the original wind data and gives a very good minimum error.

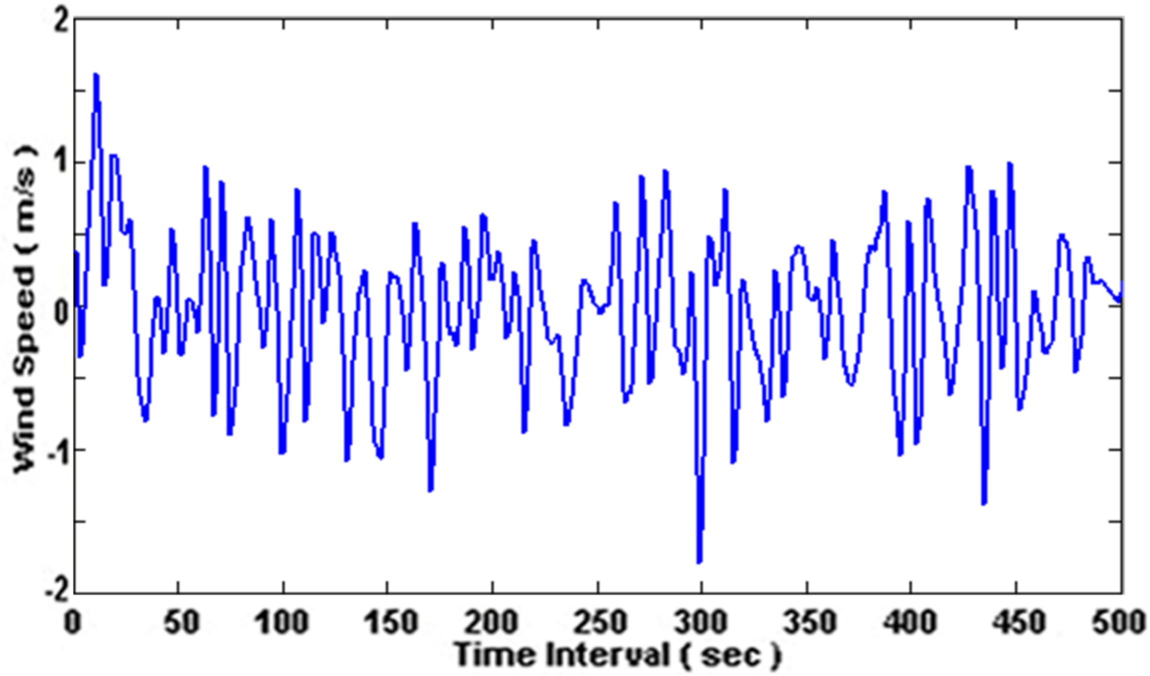

Fig. 4.3 Output of ARMA fed with Wavelet

These results have been compared with the Artificial Neural Networks (ANN) - the Ensemble Kalman Filter (EnKF) hybrid [111]. The MAPE of the ARMA has been shown to be between 7% for 1-hour [11] as shown in Table 4.2. It shows the MAPE and the computational time for ARMA, ANN-EnKF and Wavelet-ARMA techniques. It clearly shows the MAPE for the Wavelet- ARMA hybrid is the smallest and thus proving it to be an output correction scheme.

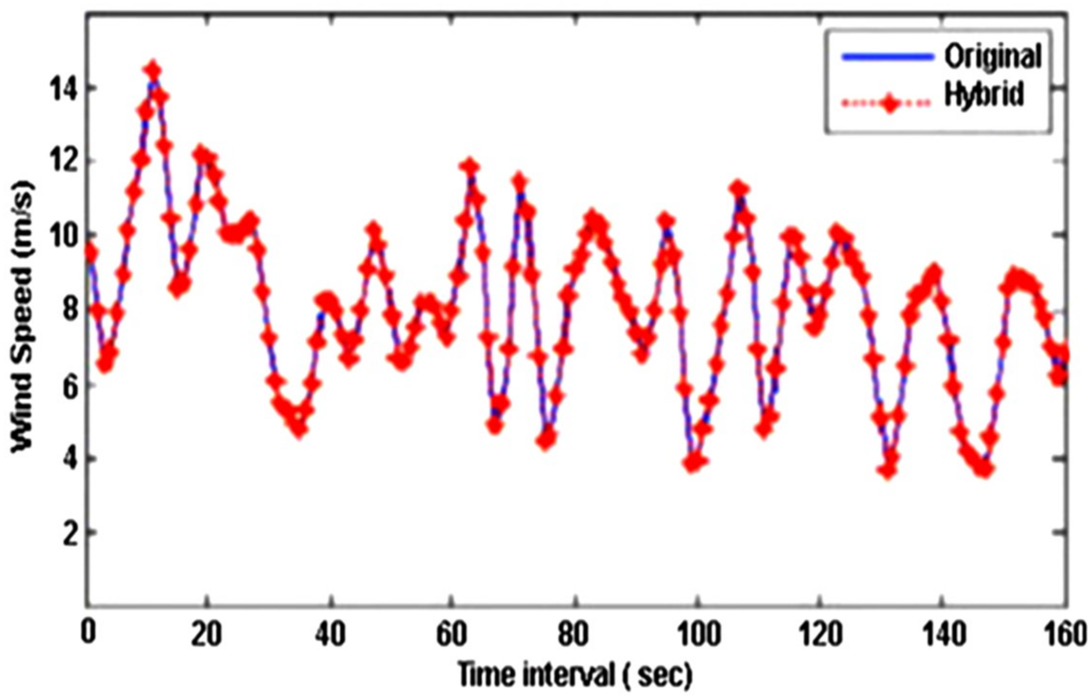

Fig. 4.4 Actual Wind Speed versus Forecasted using Hybrid Model

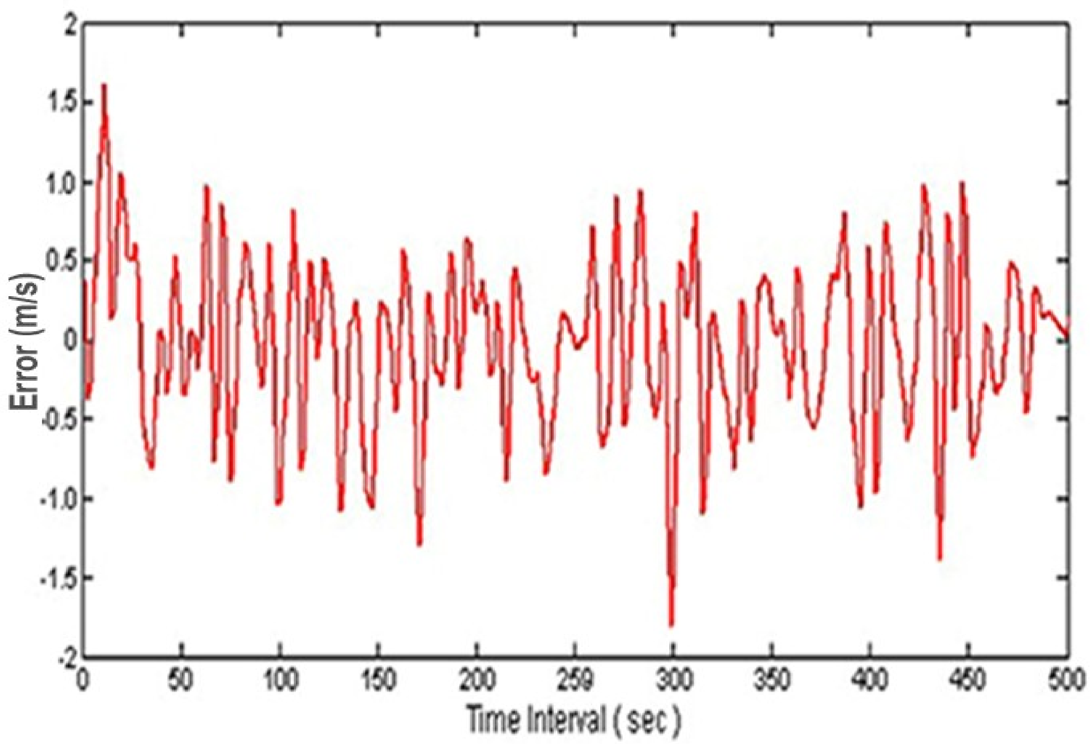

Fig. 4.5 Error graph for WT-ARMA hybrid

Table 4.2 Results Analysis

Comparison between Wavelet ARMA hybrid and ANN-KF in Wind Speed Forecasting			
Method	ARMA	ANN-KF	Wavelet –ARMA
MAPE%	7.98%	6.57%	2.7%
Computational Time	100 sec	180 sec	160 sec

Table 4.2 shows the MAPE and Computational Time of ARMA, ANN-KF and WT-ARMA. The MAPE is the least of WT-ARMA since this hybrid proves to be a better one in this research. The computational time of ARMA is the least because of less complexity as compared to the hybrids as in [128]. It can be seen that the MAPE of the Wavelet-ARMA model is 2.70%, marginally outperforming the persistence model, ARMA, ANN-EnKF model.

4.5 Summary

This chapter presents a very effective WT-ARMA hybrid forecasting technique. The nonlinear wind speed time series is seen to be decomposed which is later fed to different ARMA models which are then reconstructed to get new and improved results. A unique equation that combines both these methods is established. This hybrid has also been tested on MATLAB. In order to see the effectiveness of the proposed approach, different figures for individual as well as the proposed hybrid technique has been plotted. The results indicate that the wavelet theory when combined with the ARMA model becomes a beneficial tool in wind speed forecasting and brings a tremendous amount of improvement to reduce forecasting errors.

Chapter 5

ARMA-ANN-AIC Hybrid

5.1 Introduction

This Chapter focuses on developing a novel wind speed forecasting technique, which produces more accurate predictions. A hybrid method composed of the Artificial Neural Network (ANN) and Akaike Information Criteria (AIC) along with the Auto Regressive Moving Average (ARMA) technique is proposed. One of the main challenges is to properly determine the order of ARMA that would optimize the results. This research combines ANN with AIC to determine the true order of ARMA and bring down the forecasting error. Simulation studies have been conducted to show the effectiveness of the proposed method and have been compared to GA. The results have shown very good results in the forecasting error for the test data given in this part.

5.2 ARMA

An ARMA (p, q) model of order p and q, with φ_j and θ_j the autocorrelation and the moving average coefficients respectively, is represented by [108]

$$y_t = \sum_{j=1}^{p} \varphi_j \ y_{t-j} + \ a_t - \sum_{j=1}^{q} \theta_j \ a_{t-j} \tag{5.1}$$

The order of the ARMA model is included in parentheses as ARMA (p, q), where *p* is the autoregressive order and *q* the moving-average order. In Equation (5.1), $\{y_{(t)}\}$ is the return series of original time series. In the process of constructing an ARMA model, it is imperative to confirm the orders *p* and *q* [108].

ARMA parameters may be obtained from three-layer neural networks utilizing a polynomial representation of the activation function in the hidden units. Consider a nonlinear, time-invariant, discrete-time dynamic system represented by the following ARMA model shown in Fig. 5.1.

5.3 ANN

Figure 5.1 shows a three-layer ANN topology. Note that weights of *x* input neurons are W leads and weights of *y* input neurons are *V* leads. The coefficients are obtained from the neural network weights values and polynomial coefficients given by

$$\mathbf{a_i} = \sum_{\mathbf{j=1}}^{\mathbf{M}} \mathbf{W_{ij}}\ \mathbf{a_j}\ \mathbf{V_{ij}}\ \mathbf{y(n-i)} \tag{5.2}$$

$$\mathbf{b_i} = \sum_{\mathbf{j=1}}^{\mathbf{M}} \mathbf{W_{ij}}\ \mathbf{a_j}\ \mathbf{V_{ij}}\ \mathbf{x(n-i)} \tag{5.3}$$

where *M* is the number of hidden units, *i,* and *n* are indexes [112].

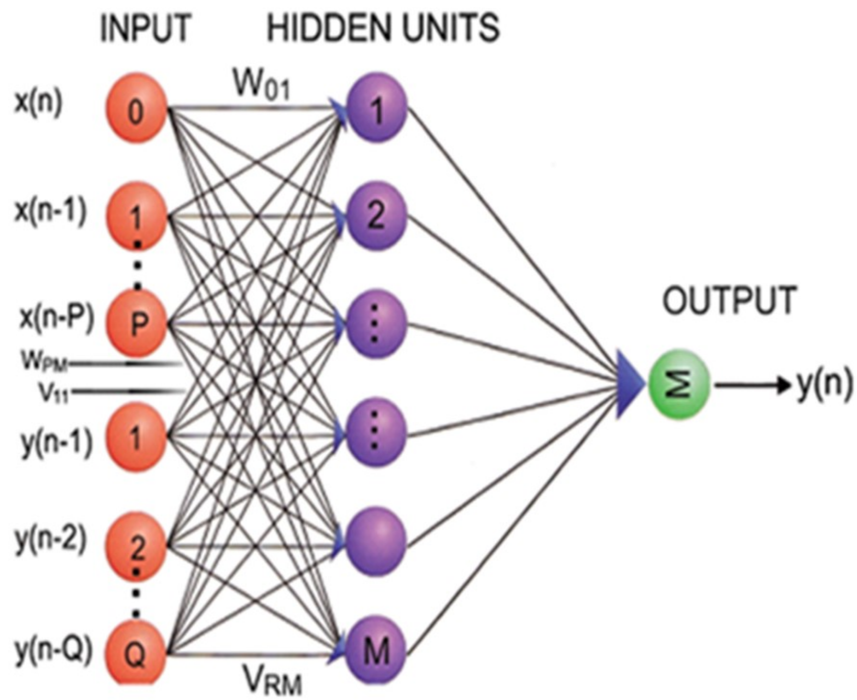

Fig. 5.1 A three layer ANN topology. Note that the weights of x input neurons are W leads and the weights of y input neurons are V leads.

These model parameters are obtained using ANN, which are then fed into the AIC to obtain the true order.

5.4 AIC

The AIC criterion can be defined as

$$\mathbf{AIC(d) = \log g[\![(\hat{\sigma}_d^2]\!]) + 2\frac{d}{N}} \tag{5.4}$$

where $\widehat{\sigma_d^2}$ is the error variance of fitted model and *N* is the number of observations estimated under the assumption that *d* is the true order [113-114].

For the ARMA (p, q) model, d is the model order where $d = p + q$. In practice, the optimal d is obtained by minimizing AIC (d) where

$$\widehat{\sigma}_d^2 = \frac{1}{N}\sum_{n=1}^{N} e(n)^2 \tag{5.5}$$

where,

$$\mathbf{e(n) = y(n) - \hat{y}(n)} \tag{5.6}$$

and $\hat{\mathbf{y}}(\mathbf{n})$ is given by

$$\hat{y}(n) = -\sum_{k=1}^{t} \widehat{a_k} y(n-k) \tag{5.7}$$

The value of AIC is obtained for different p and q. The one with the least value of AIC is considered to be the true order. It can be explained with the help of Fig. 5.2.

According to Fig. 5.2, the parameters are obtained using Equation (5.2) and (5.3) of ANN. Then these model parameters are fed into Equation (5.4) of Akaike to estimate the true order of ARMA. Then, ARMA takes the true order and forecasts wind speed data. For the sake of completion, it is imperative to account for the following steps

1) First, we fix the range of the ARMA model orders to be considered ($1 \leq p \leq p_{max}$ and $1 \leq q \leq q_{max}$)

2) Then, estimation of the model parameters by an appropriate algorithm such as ANN is done. The predicted signal $\hat{\boldsymbol{y}}(\boldsymbol{n})$ is computed keeping the error variance $\widehat{\sigma}_d^2$ equal to one mimicking what has been done in [112].

3) Evaluate AIC over $S=(1 \leq p \leq p_{max})$, and choose the value of d that minimizes AIC to find the true order of ARMA.

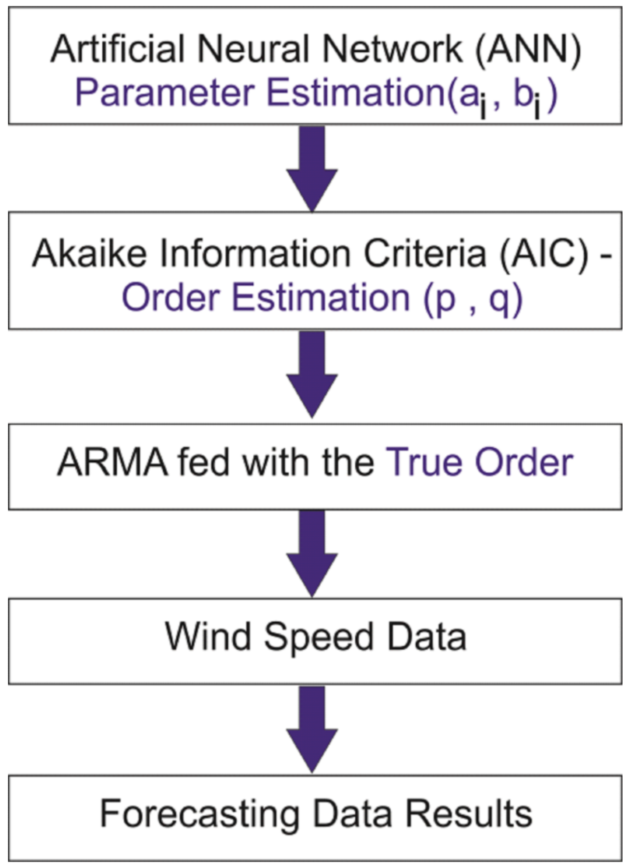

Fig. 5.2 Procedure of the ANN-ARMA-AIC hybrid

5.5 Results and Discussion

In this research, wind data and the input-output patterns for training of a network are taken from North Island, New Zealand for the year 2006 on a hourly basis at a 30 seconds interval for station number STH1, as provided by NIWA [1]. The platform chosen to test the available set of data is MATLAB. The six hourly wind fields are extracted from the data. The test data have an error of 0.8%.

During the experiments, 1500 input/output data values are employed for the simulation. The first 750 data values are used for the training (these become the training data set), while the others are used as checking data for validating the ARMA model.

---

[1] **NIWA is a Crown Research Institute of NZ.**

For the first part ANN is used to determine the model parameters. We use a polynomial function neural network (PFNN) model for training the simulated data to identify the coefficients of ARMA models. The max values of p and q have been taken equal to 6, giving a total of 36 possible combinations for p and q. The best order has been found to be $(p=3, q=2)$ as shown in Table 5.1 therefore the results for this order have been shown here. For this order the ARMA model was generated with the Moving Average (MA) excitation being uncorrelated Gaussian white noise (GWN) with a variance of one as in [130]. The following linear ARMA model was utilized:

$$y(n) = x(n) + 0.358\, x(n-1) + 0.212\, x(n-2) + 0.343\, x(n-3) + 0.201\, y(n-1) + 0.301\, y(n-2) \tag{5.8}$$

For the PFNN analysis, the input and output data pair was segmented into two 750-point data segments. The first half of the input–output data segment has been used to train the network, and the second half was used to test the predictive quality of the network. All of the simulations were carried out in this manner. Since the PFNN method utilizes a back-propagation learning algorithm, the time required to compute parameter estimates is less than GA. It should also be noted that the learning rate of the neural network is affected by the selection of the ARMA model order (or the selection of the memory length), that is, longer training of the network is required with larger ARMA model orders, and vice versa.

To examine how strongly the neural network topology depends on the assumed model order, the results obtained by the PFNN method and the Genetic Algorithm have been compared. To check the validity of the results from Equation 5.2 and 5.3, the simulations were also carried out for different combinations of $1 \leq p \leq 6$ and $1 \leq q \leq 6$. The results for the order $p=3$ and $q=2$ were chosen, corresponding to the best case as it will be shown in the latter section. Table 5.2 shows that both methods gave very similar parameter values.

Using Table 5.2, the time series were computed corresponding to the parameter values obtained for ANN and GA. The difference between the two time series is plotted in Fig. 5.3. This figure shows that there is no significant difference between the two outcomes thereby indicating the validity of the proposed approach when compared to GA.

TABLE 5.1 THE EXHAUSTIVE SEARCH RESULTS FOR DIFFERENT *p* AND *q*

q / p	1	2	3	4	5	6
1	329.3	329.4	328.9	330.0	330.3	330.4
2	328.1	329.7	329.8	328.5	330.3	331.2
3	327.1	325.9	326.5	327.3	328.9	330.3
4	333.0	331.2	333.3	334.1	332.4	337.1
5	335.2	335.4	337.5	339.1	340.1	340.5
6	340.3	342.4	341.3	344.4	343.5	346.6

TABLE 5.2 COMPARISON OF PARAMETERS USING ANN AND GA

Parameters	**Parameters for order (3,2)**				
	a1	***a2***	***a3***	***b1***	***b2***
ANN	0.3	0.21	0.34	0.2	0.3
GA	0.35	0.21	0.3	0.21	0.3

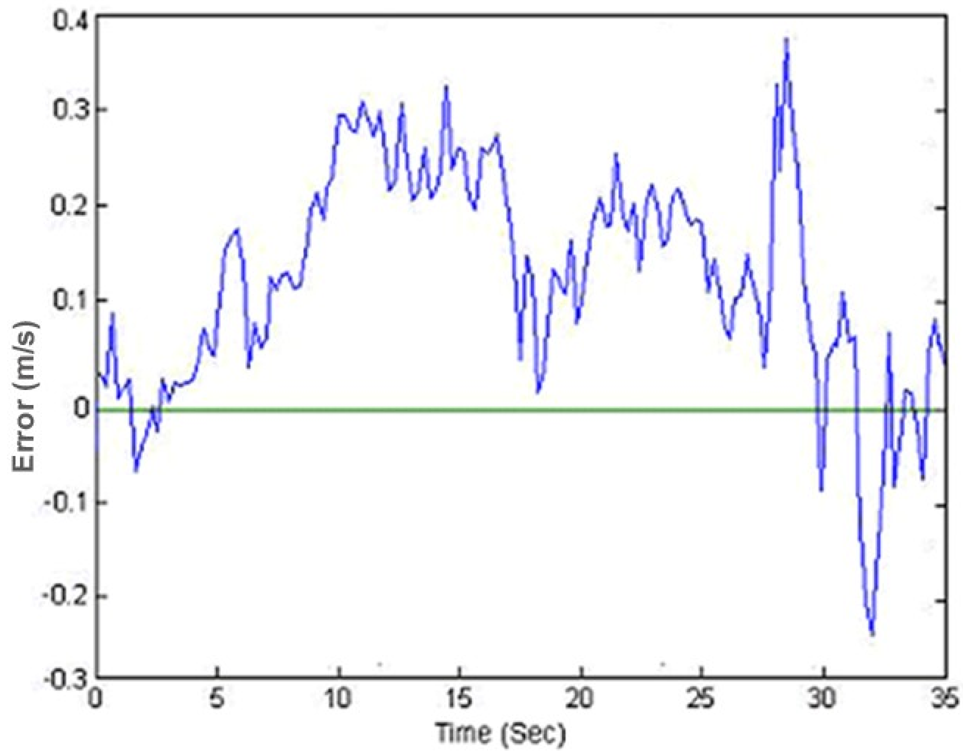

Fig. 5.3 Difference between the parameters for ANN and GA

Next, these parameter values are put in the equation of AIC to determine the true order of ARMA. An exhaustive search for different p and q has also been done to compare the results. It is shown in Table 5.1. The matrix gives the AIC values for different p and q values. It can be seen that the least values are obtained for $p = 3$ and $1 \leq q \leq 4$. The least value is obtained for $p = 3, q = 2$. The other combinations have a greater AIC value.

The procedure for true order determination by AIC is summarized as:

1. The different parameters are fed into AIC.
2. The different values of AIC are determined for different p and q orders.
3. The order that gives the least value of AIC is considered to be the best order.

The AIC values have been calculated for $1 \leq p \leq 6$ and $1 \leq q \leq 6$. The range of AIC values obtained is between 326 and 345. The best values are observed to be between $p = 3$ and $1 \leq q \leq 4$ and these AIC values are given in Table 5.3.

TABLE 5.3 AIC VALUES

Model Order	AIC for p=3, $1 \leq q \leq 4$
	AIC
(3,1)	327.1
(3,2)	325.9
(3,3)	326.5
(3,4)	327.3

When ARMA is applied to the test data of station STH1 provided by NIWA with $p = 3$ and $q = 2,$ the forecasting error is close to 0.75% which is very close to actual error provided by NIWA. If we propose a hybrid including ARMA with the correct p and q and another method then it may bring down the error even further, which opens doors for future researches.

5.6 Summary

This Chapter presents a parameter estimation problem, which is necessary for ARMA to run effectively. In order to do so, this research combines ANN-ARMA-AIC to estimate parameters properly. First, the order is estimated with the help of ANN which is later fed into AIC which estimates the true order of ARMA. The order that gives the least value of AIC is considered to be the best order. This true order is given as an input into ARMA, which makes ARMA to function effectively. The simulation studies were also carried out for different combinations of $1 \leq p \leq 6$ and $1 \leq q \leq 6$. The results for the orders $p = 3$ and $q = 2$ were chosen, corresponding to the best case. The hybrid is tested on data taken from North Island, New Zealand for the year 2006 on MATLAB. The results show a very low forecasting error, which proves the proposed hybrid, is a successful one.

Chapter 6

ORPD and PSO in GT

6.1 Introduction

The objective of this Chapter is to find the correlation between the forecasting and its application in power systems. Therefore, the Economic Dispatch (ED) is identified as another problem with wind power. Wind power may be dispatched above or below its required demand during periods of excessive or insufficient supply. When it is dispatched above its required demand, the Energy Storage System (ESS) comes into play. It stores the extra wind power, which can be used in times of insufficient supply. The ESS is used to compensate the power fluctuations from the wind farm. The ESS is commanded to supply or absorb power equal to the fluctuations between the original output of the wind power generator and the desired output of the ESS conjunction with the wind power generator in a particular regulation period.

It is usually quite difficult to determine how to dispatch the power, which should result in minimum losses. Wind energy and its forecasting may act as the most effective solution to the ED problem therefore it becomes crucial that the wind forecast is accurate. The ED problem is due to the voltage instability because when voltage fluctuates the economic dispatch is not proper [129]. Therefore, Optimal Reactive Power Dispatch (ORPD) should be used in order to reduce active power and voltage losses. This research mainly focuses on the ORPD and GT. The voltage instability is not done here it being a completely different area of research.

6.2 Optimal Reactive Power Dispatch

ORPD plays a significant role in optimal operation of electric power systems. It is a complex nonlinear optimization problem with a mixture of continuous and discrete control variables. ORPD is a sub- class of the optimal power flow (OPF) problem [92, 115]. The objective of ORPD is to minimize the transmission losses and to control the voltage profile such that the voltage deviations at the load buses for various loading conditions. ORPD plays a vital role for the secured economic performance of power systems.

This chapter describes an approach to the ORPD problem. PSO is one of the evolutionary computation technique based on swarm intelligence. It is sensitive to the tuning of its parameters and has a flexible mechanism to explore a global optimum point within a short calculation time [115]. DE and PSO are population-based optimization algorithms. Due to their excellent convergence characteristics and few control parameters, DE and PSO have been applied to obtain optimal solutions to some real value problems efficiently [116].

The following flowchart (Fig. 6.1) shows the sequence of problems that are addressed in the study. If wind energy is unable to be predicted efficiently then the ED problem arises due to voltage instability [25]. Then, ORPD comes into play for which PSO is used as a solution in this research. The input data are taken from a previous Auto Regressive Moving Average (ARMA) and Wavelet Transform (WT) hybrid [Figure 4.4] [117] and is tested on IEEE-14 Bus system in GT.

The objective of the reactive power dispatch is to minimize the active power loss in the transmission network, which can be described as follows [22, 80, 115]:

$$min \sum_{k=N_E} P_{kloss} = \sum_{k=N_E} g_k(v_i^2 + v_j^2 - 2v_i v_j \cos\theta_{ij}) \tag{6.1}$$

where k= (i, ,j); $i \in N_B$ (Total number of buses), $j \in N_i$ (No. of buses adjustment to bus i including bus i, N_E= Set of numbers of network branches, $\sum_{k=N_E} P_{kloss}$ = Total active power losses in the transmission system, g_k = conductance of branch k (p.u.), v_i, v_j = voltage magnitude (p.u.) of bus i and j resp., θ_{ij} = load angle difference between bus i and j (rad).

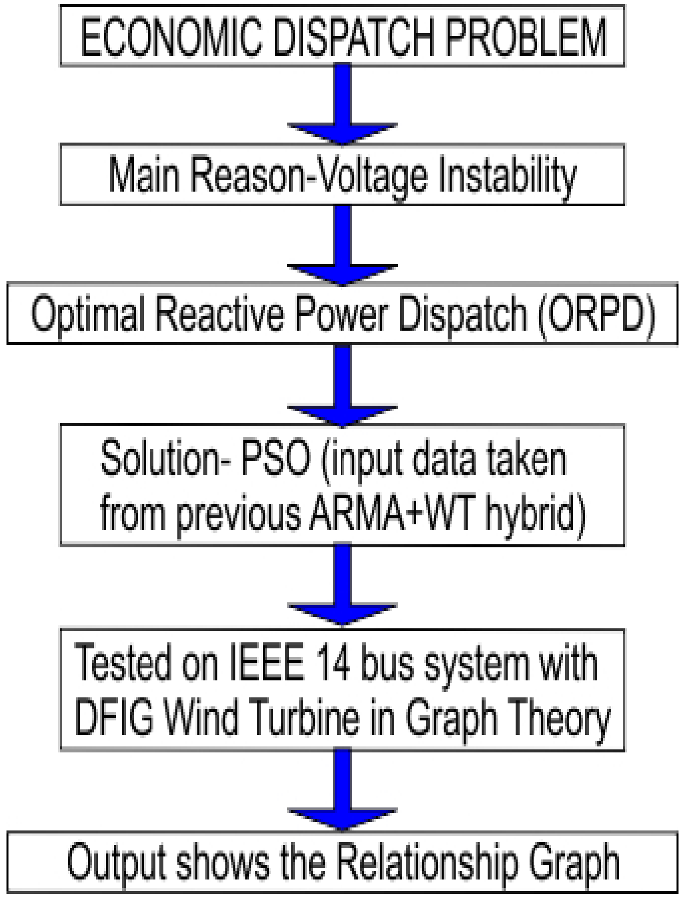

Fig. 6.1 Flowchart showing the sequence of problems in ED

Equality constraints:

Active power flow balance equations at all buses

$$P_{gi} - P_{di} - v_i \sum_{j=N_i} v_j (g_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}) = 0 \qquad (6.2)$$

where P_{gi} is the injected active power at bus i (p.u.), P_{di} is the Demanded active power at bus i (p.u.), v_i is the voltage magnitude of bus i (p.u.), g_{ij} is the Transfer conductance between bus i and j (p.u.), B_{ij} is the Transfer susceptance between bus i and j (p.u.)

Reactive power flow balance equations at all PQ buses (load buses)

$$Q_{gi} - Q_{di} - v_i \sum_{j=N_i} v_j (g_{ij} \sin\theta_{ij} + B_{ij} \cos\theta_{ij}) = 0 \tag{6.3}$$

where Q_{gi} is the Injected reactive power at bus i (p.u.), Q_{di} is the Demanded reactive power at bus i (p.u.).

Inequality constraints:

Reactive power generation limit for each generator bus

$$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max}, i \in N_g \tag{6.4}$$

Voltage magnitude limit for each bus

$$v_i^{min} \leq v_i \leq v_i^{max}, i \in N_g \tag{6.5}$$

Power flow limit constraint of each transmission line

$$s_l \leq s_l^{max} \tag{6.6}$$

where S_l is the Power flow in branch l (p.u.).

6.3 Particle Swarm Optimization (PSO)

The Particle swarm optimization (PSO) method was introduced by Kennedy and Eberhart [24]. It was described as a self-educating stochastic optimization algorithm that could be applied to any linear, nonlinear, mixed-integer optimization problems having continuous and/or discontinuous objective and constraint functions. PSO has many obvious advantages over the other evolutionary algorithms. It has a high probability of finding a global minimum. It is a fast, simple and efficient population-based optimization method. PSO does not require parameter tuning and gives a faster and tougher optimal search [16].

It is a multi-agent search technique that traces its evolution to the emergent motion of a flock of birds searching for food [115, 118]. PSO finds the optimal solution by a process motivated by the imitation of social behavior such as fish schooling and birds flocking in search of food and not by survival of the fittest. A population of random potential solutions called particles that come together to form a group known as a swarm initializes PSO. Each particle in the swarm has a certain velocity that helps it move over the search space. The velocity of each particle is influenced by the particles' own flying experience as well as its neighbors' flying experience. Every agent's position is represented along XY axis and Vx and Vy respectively represent the velocity. Each agent knows its local best value so far (p_{best}) and global best value in the group (gbest). Namely, each agent tries to modify its position using the current positions (x, y); the current velocities (Vx, Vy); the distance between the current position and pbest; the distance between the current position and gbest [26]. PSO solves a highly constrained problem as an unconstrained one by adding a suitable penalty function to the main objective function [16].

In computer science a set of randomly generated solutions propagates in the design space towards the optimal solution over a number of iterations. PSO optimizes a problem by having a population of candidate solutions, here dubbed particles, and moving these particles around in the search-space according to simple mathematical formulae over the particle's position and velocity. Each particle's movement is influenced by its local best-known position and is also guided toward the best-known positions in the search-space, which are updated as better positions are found by other particles. This is expected to move the swarm toward the best solution as shown in the following equations [17- 18].

$$v_i^{k+1} = w \times v_i^k + c_1 \times r_1 \times \left(p_{best_i} - x_i^k\right) + c_2 \times r_2 \times \left(g_{best} - x_i^k\right) \tag{6.7}$$

$$x_i^{k+1} = x_i^k + \chi \times v_i^{k+1} \tag{6.8}$$

where, v_i^{k+1} is the velocity of i^{th} particle at $(k+1)^{th}$ iteration; w is the inertia weight of the particle; v_i^k is the velocity of i^{th} particle at k^{th} iteration; c_1 and c_2 are the acceleration constants having values between [0, 2.5] on an average give better performance, and also, helps find the global optimum within a reasonable number of iterations; r_1 and r_2 are randomly generated numbers between [0, 1]; p_{best} is the best position of the i^{th} particle obtained based upon its own experience; g_{best} is the global best position of the particle in the population; x_i^{k+1} is the position of i^{th} particle at $(k+1)^{th}$ iteration; x_i^k is the position of i^{th}

particle at k^{th} iteration; χ is the Constriction factor, which is a function of c_1 and c_2 as shown below. It may help insure convergence [17].

$$\chi = \frac{2}{\left|2-c-\sqrt{c^2-4c}\right|} \tag{6.9}$$

where c = c1 + c2 and c > *4*

In general, inertia weight factor w decreases linearly from max w_1 to min w_2 according to the following equation

$$w = w_{max} - \frac{w_{max}-w_{min}}{iter_{max}} \times iter \tag{6.10}$$

Where, w_{max} is the value of inertia weight at the beginning of iterations, w_{min} is the value of inertia weight at the end of iterations, *iter* is the current iteration number and $iter_{max}$ is the maximum number of iterations.

6.4 Wavelet Transform and ARMA Hybrid

The input data for this PSO has been taken from Chapter 4, which uses the hybrid of WT and ARMA for forecasting wind speed [117]. This research is in continuation of this hybrid to see the impact of accurate forecasting on the economics. The hybrid equation used (eq 4.12) in Chapter 4 is:

$$x = \sum_{j=1}^{J} D_j + A_J = \sum\nolimits_{j=1}^{J} D_j + \left\{ y_t - \sum_{j=1}^{p} \varphi_j \; y_{t-j} + \sum_{j=1}^{q} \theta_j \; a_{t-j} \right\}$$

where the time series x is stated as the sum of a constant vector A_J and J other vectors, *Dj (j=1,2,3...J),* each of which contains a time series related to variations in x at a certain scale. The *Dj* refers to the j^{th} wavelet detail and the A_J as the approximation. In the ARMA (p, q) model, $\{y_t\}$ is the return series of original time series and $\{a_t\}$ is the innovations noise process. The order of the ARMA model is included in parentheses as ARMA (p, q), where p is the autoregressive order and q the moving-average order. Also, φ_j and θ_j are the autocorrelation and the moving average coefficients respectively.

6.5 Graph Theory (GT)

A GT has an excellent capability to simplify large power networks. The GT can solve a number of things such as shortest path algorithm in a network, finding a minimum spanning tree, finding graph planarity, algorithms to find adjacency matrices, algorithms to find the connectedness just to name a few. It also helps to detect and isolate faults. When a node fault is detected, the corresponding row is eliminated corresponding to the fault-node(s) and the columns that correspond to the edges that connect these nodes. The edges surrounding the fault-node(s) are detected and are placed into a row matrix in order to be returned by the function and later disconnected. One can also shed unbalanced loads. If the generators capacity is not enough to supply all of loads the algorithm will disconnect the loads with lower priorities [25].

A number of power systems properties can be appropriately defined by means of a diagram consisting of a set of vertices together with a set of edges that may be joined together.

A graph may be directed or undirected. An undirected graph is one in which there is no distinction between the two vertices associated with each edge. A directed graph shows a flow network from node to node where each edge acts as an input or output for the flow of current, voltage etc. The amount of flow on an edge cannot exceed the capacity of the edge. The amount of flow entering into a node should equal the amount of flow out of that node [119]. This type of graph may be used to manage fluid in pipe or currents in an electrical circuit for instance [120]. It is also known as a network, the vertices are called nodes and the edges are called arcs. The following are few types of graphs-

1. **Directed Graph:** is represented as $G=(N, E)$, consists of a set N of nodes (or vertex) and a set E of directed arcs (or edges) whose elements are ordered pairs of distinct nodes
2. **Node-Edge Incidence matrix:** is represented as an nxm matrix, which contains one row for each node of the directed graph and one column for each edge. The column

corresponding to arc *(i, j)* has only two nonzero elements, -1 in the row corresponding to node *i* and +1 in the row corresponding to node *j*

3. **Network:** A network is a graph or digraph with weights assigned to each edge. These numbers might represent distance, capacity, resistance, etc., depending on the context.

4. **Net flow:** In an arc *(i, j),* a **net flow** is a real-valued function *f (i, j),* which may be thought of as an amount of some commodity that can arrive to j from i per unit time, this could be positive or negative. A conservation criterion at each node must be satisfied i.e., the total flow into a node must be equal to the total flow out of the node, unless the node is a *source*, which has more outgoing flow, or *sink,* which has more incoming flow.

5. **Capacitated Network:** Is a network in which some arcs are assigned nonnegative capacities, which define the maximum allowable flow in those arcs. The capacity of an arc *(i, j)* is denoted k_{ij}, and this capacity is indicated on the graph by placing the number k_{ij} adjacent to the arc.

6. **Residual Network**: Given a flow network, the residual network consists of arcs that can admit more net flow. The amount of available capacity of an arc *(i, j)* is the *residual capacity* and is given by $kr_{ij} = k_{ij} - f_{ij}$.

A directed graph has been used in this research. In the graph **G**, the elements $v_i \in V$, $i = 1,2,...,n_b$, and $e_{ij} \in E \subseteq V \times V$, $i, j = 1,2,...,n_b$, denote the set of nodes and edges, respectively. The sets **V** and **E** represent the buses and branches in the power system, respectively. This may be used for the evaluation in a wind farm where there is a path joining every turbine in the wind farm (which produces electricity) with the reference node, thus making it relatively easy. If there is a possible path it means that the energy produced by the turbine can be dispatched to the electrical system, otherwise that energy is lost [121-122].

6.6 Results and Discussion

MATLAB has become a popular tool for scientific computing and is well suited for the numerical computation typical of steady-state power system simulations. This thesis uses MATPOWER, an open-source MATLAB power system simulation package [123-124]. It is used widely in research and education for AC and DC power flow and OPF simulations. MATPOWER consists of a set of MATLAB M-files designed to give the best performance possible while keeping the code simple to understand and customize. It combines a high-level language ideal for matrix and vector computations, a cross-platform runtime with robust mathematical libraries, an integrated development environment and GUI with excellent visualization capabilities, and an active community of users and developers [116].

This research has been tested on the IEEE 14 bus system, which is a standard grid system, used for testing any power unit or fault of any power system components. Simulation of the modified IEEE 14 bus system has been built as follows. At bus number 3, Doubly Fed Induction Generator wind turbines are connected as shown in Fig. 6.2. Bus number 3 has been chosen randomly since at any bus the results may be the same. Very less power is lost via the converter, which makes DFIG very popular in improving system performance. In this system, there are four Generators that act as a source. They are located at Bus 1, 2, 6 and 8 respectively. PV (Active Power and Voltage) bus at Bus 2 is the bus where voltage is being controlled. There are three condensers at Bus 3, 6, 8. TG refers to the Turbine Governor at Bus 2. It controls the flow rate of steam turbine so as to maintain its speed of rotation as constant. AVR refers to the Automatic Voltage Regulators that help in regulating voltage. Also, there are four transformers connected between Bus 4-9, 4-7, 5-6, and 7-8. The slack bus, which is the reference bus, is taken to be Bus 1 in this research. The losses in Table 6.1 are calculated with respect to this slack bus. These combined together form the IEEE-14 Bus System used in this study.

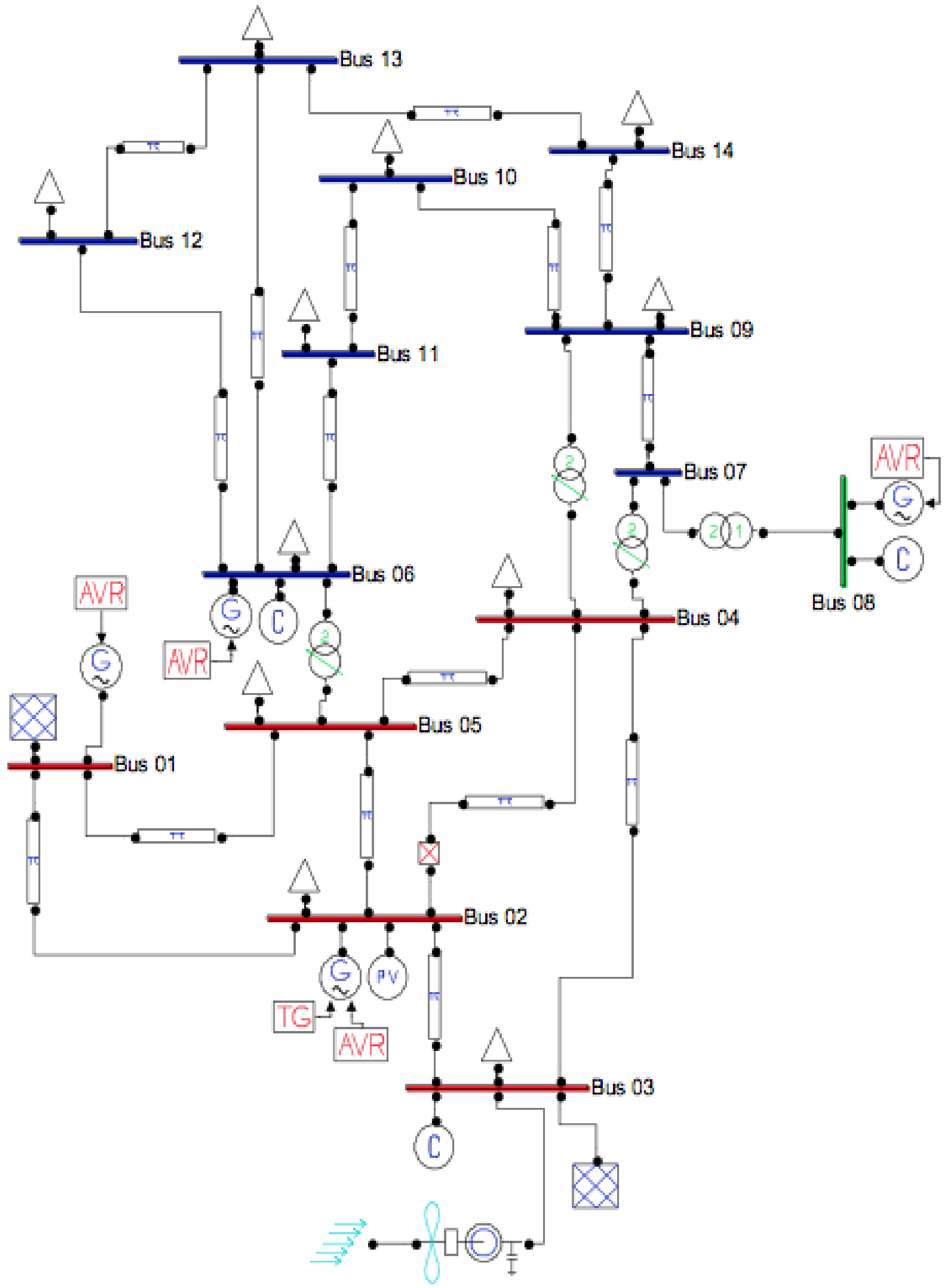

Fig. 6.2 Standard IEEE- 14 bus system with DFIG at Bus 3

The corresponding graph is shown in Fig. 6.3 where each bus corresponds to a node. It shows the relationship between nodes thus showing that the data may flow unidirectionally. Also, since the network is designed to be redundant, it makes use of the unidirectional ability to cope with failure. As node property, each node has input ports and output ports, so the flow entering a loop should be equal to the flow exiting a loop.

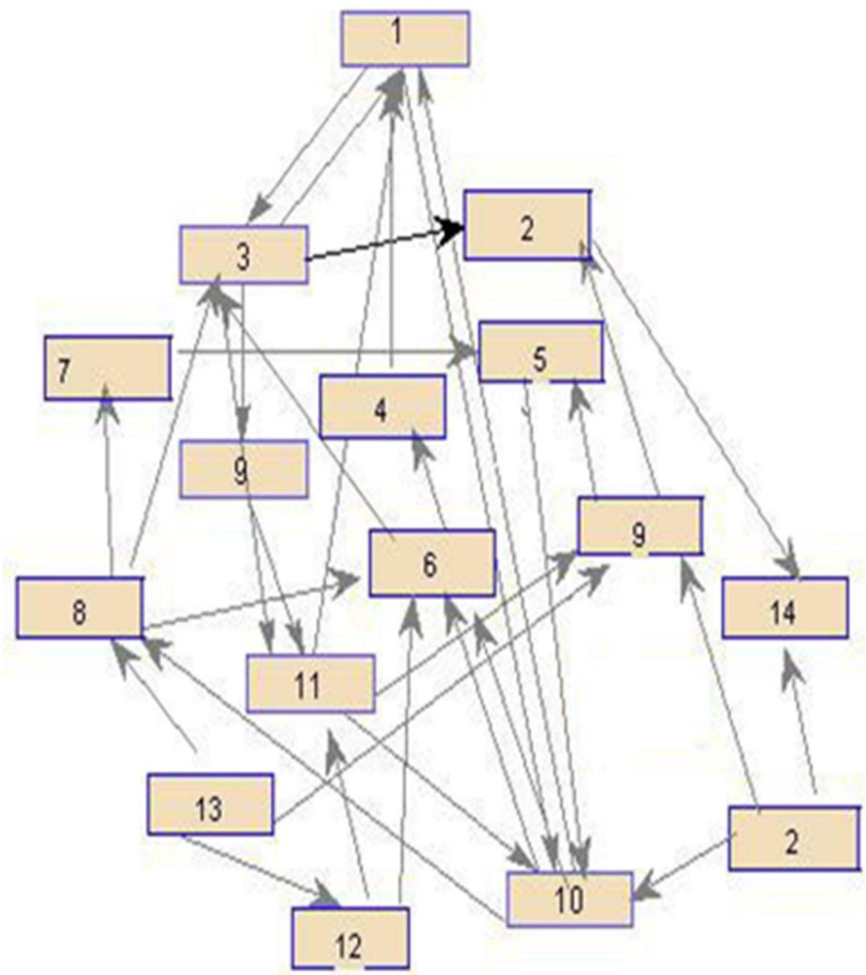

Fig. 6.3 Graph showing the relationship of Power Flow

This graph is making three things very simple. Firstly, it provides easy communication, where information in the form of electric signals is taking place in both directions. Secondly, there can be a Reduction of Loss of Electricity since finding the shortest path can shorten the distance of transfer of electricity. For instance, if node 13 is acting like the input node and 14 as the output node, then the shortest path may be from 13->9->2->14. This will help reduce electricity loss. Thirdly, if any node or Bus is out of service then, that node can be isolated and the fault may be avoided. Suppose, if node 7 stops working then isolate it and still continue with 13->9->2->14 to find and work with the shortest path.

To calculate the losses, PSO has been used where the input data are taken from the results of the ARMA and WT hybrid shown in Fig. 4.4 from Chapter 4 [117].

The output of the forecasted results of Fig. 4.4 has been used as an input to PSO to see the effect on the economics part [120]. The results are shown in Fig. 6.4. It shows the total reactive power losses for 30 iterations.

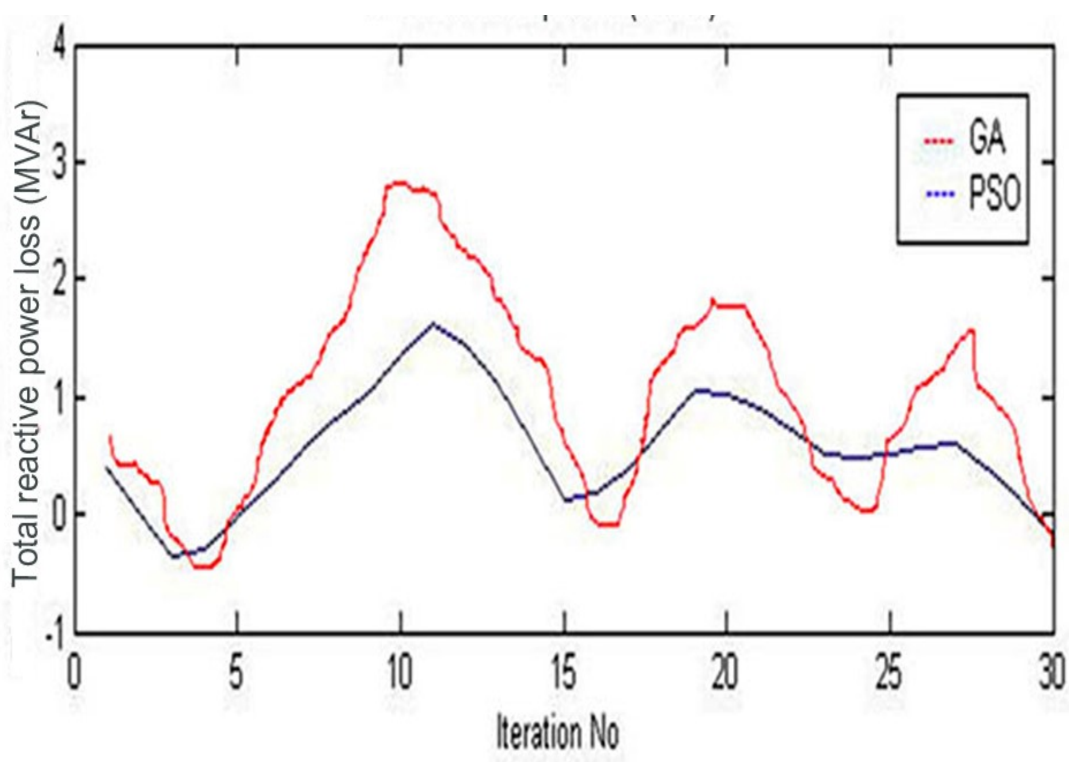

Fig. 6.4 Total Reactive Power Losses

Since PSO and GA are two of the most popular intelligent techniques that have been given a lot of attention in recent years, the proposed PSO method has been compared to GA method [125]. Both methods have been tested on the IEEE-14 Bus System. Table 6.1 shows the total reactive power losses in PSO and GA. It shows that with the combination of ARMA, WT and PSO the losses are quite low and it clearly shows that PSO proves useful towards the economic dispatch problem in comparison to the GA.

TABLE 6.1 REACTIVE LOSSES

Methodologies	Reactive Power Losses with respect to Slack Bus (MVAr)
PSO	0.86
GA	2.25

6.7 Summary

The motivation of this research is to put into application wind forecasting studied in the previous chapters. To do so, the ED problem has been identified as a crucial problem for which forecasting can be used as a solution to make better dispatch solutions. For this, PSO has been used in GT to come up with a result, which shows the relationship between various buses of the IEEE- 14 bus system. The total reactive losses have been calculated and compared with GA and the results show that PSO is better than GA. Hence, ORPD acts as a solution for the ED problem that is proved in GT.

Chapter 7

Summary and Future Research Recommendations

7.1 Summary

The demand for using various renewable resources arises from changing environment. This research uses wind as a renewable resource for better integration of wind power into the electric grid. Intermittency of wind is the greatest challenge and managing it becomes crucial. The effective solution is to predict the future values of wind power production, which is totally dependent on wind speed. Changing the prediction model to decrease the forecast error is one way and has been chosen in this study. There is a need for a hybrid method that can accurately predict wind speed from a few minutes to several hours.

The types of error have been studied and then a critical literature review and an up-to-date bibliography on wind forecasting technologies have been done. Review of wind speed forecasting techniques based on time scale, design issues and types of techniques have been done in detail. An approach to wind wave forecasting is presented.

It is based on two techniques namely Artificial Neural Networks which are simpler to construct and have shorter development time and the Ensemble Kalman Filter which is an excellent technique for data assimilation as it takes maximum advantage of observations. A fast surrogate is built to train the data for short-term prediction. Therefore, the approach of EnKF that requires the evolution of the dynamics of the system for large number of ensembles becomes feasible. Then, their hybrid is constructed and hence proved on

MATLAB. Combination of ANN and EnKF acts as an output correction scheme. Wind data is taken on an hourly basis for six hours. The data driven prediction is updated as soon as they are available using new observations. The analyzed or corrected states can be used for the next forecast if required. The experiments show that the error can be reduced and a very good accuracy can be obtained if we use this hybrid for the prediction of the wind speed as the error is significantly reduced. This corrects the underlying model.

The need arises to come up with a hybrid that can accurately predict wind speed from a few minutes to several hours. Therefore the ARMA model has been chosen which has proved to be very accurate for long term forecasting in load forecasting and price forecasting. Simple input data can be fed into the ARMA but if preprocessed data are fed into it then much better results can be obtained. The Wavelet Transform has been chosen for this since it decomposes the data and then reconstructs it. The proposed hybrid is tested with synthetic data for one hour ahead prediction on MATLAB. Different results are plotted for the WT and the ARMA model. The WT-ARMA hybrid graph is plotted with the original wind speed graph to show the forecast error. Comparisons have been done with the ANN-EnKF hybrid developed in this research. Results show that the WT-ARMA hybrid has comparatively less errors and less computational time than the ANN-EnKF hybrid.

Also, order estimation of ARMA is of utmost importance. Therefore, ANN has been chosen and has been combined with AIC to estimate the ARMA true order. The proposed ANN-ARMA-AIC hybrid has been tested on real data from NIWA on MATLAB. An exhaustive search has been carried out for different combinations of $1 \leq p \leq 6$ and $1 \leq q \leq 6$. The results have been compared with the Genetic Algorithm that shows no significant difference between the parameter estimation of ANN and GA thus validating the results. We showed that the time required to compute estimates of the parameters is less than GA. The results also showed that if a proper sequence is followed then ANN can be used to estimate the parameters and in turn AIC can be used to identify the model order correctly. This research may not only benefit forecasting of wind but also several other applications as well such as load forecasting or flood forecasting for instance.

The ED problem has been a serious issue in the past and still needs a lot of attention whose main concern lies in the voltage instability issue. The economic dispatch in the context of large scale wind generation needs to be reconsidered especially in the context of ensuring overall voltage stability to system operation. In times of excessive or limited generation periods the dispatch should not be affected. Here the forecast of wind energy becomes very imperative and might result in the most cost-efficient dispatch option but could be insecure from voltage security viewpoint. In this research, an ORPD based on PSO has been proposed to overcome the aforementioned problem. The output of accurately forecasted wind energy has been used as an input for PSO. The results have been tested on the IEEE 14 bus system in GT to see the relationship between the forecasted wind speed and its effect on the economics. The transmission losses are quite low thus proving the amalgamation of these techniques to be good.

7.2 Future Research Recommendations

The future scope lies in combining ARMA, WT, EnKF and GT with some other techniques, which are able to remedy the long term forecasting problem. Upcoming new methods like Support Vector Machine (SVM) that has been tested for few hours' forecasts can be combined with these methods to predict day ahead forecast to reduce the forecasting error even further [110]. This research can also be extended to predict several hours ahead wind speed and can be improved for medium or long term forecast. This work may not only benefit forecasting of wind but also several other applications as well such as load forecasting or flood forecasting. If wind is forecasted properly then wind power production due to wind energy will increase. Optimization errors can also be decreased when this research is taken onto another level.

References

1. Liu D, Li H, and Ma Z, "One hour ahead prediction of wind speed based on data mining," *Proceedings of the 2nd international symposium on the Advanced Computer Control*, 29 March 2010

2. Wu, Y-K., and Hong, J-S., "A literature review of wind forecasting technology in the world," *Proc. of the IEEE Power Technology*, Lausanne, 1-5 July 2007.

3. Bhaskar, K. and Singh, S. N., "AWNN-Assisted Wind Power Forecasting Using Feed-Forward Neural Network," *IEEE Transactions on Sustainable Energy, 2012, 3*(2), 306-315.

4. Wai, J. L. and Generosa, A. , "*Economic Benefits of Wind Farms in New Zealand*," The BERL Report, 2011.

5. Chang, P. S. and Li, L. , "Ocean surface wind speed and direction retrievals from the SSM/I," *IEEE Transactions on Geoscience and Remote Sensing, 1998, 36*(6), 1866-1871.

6. Damousis, I. G., Alexiadis, M. C., Theocharis, J. B. and Dokopoulos, P. S., "A fuzzy model for wind speed prediction and power generation in wind parks using spatial correlation," *IEEE Transactions on Energy Conversion, 2004, 19*(2), 352-361.

7. Bhaskar, M., Jain, A. et al., "Wind speed forecasting: Present status," *Proc of Power System Technology* , 2010.

8. Lydia, M. and Kumar, S. S. "A comprehensive overview on wind power forecasting," *Proc of the International Power Engineering Conference (IPEC)*, 2010.

9. Amjady, N., Keynia, F. et al., "Wind Power Prediction by a New Forecast Engine Composed of Modified Hybrid Neural Networks and Enhanced Particle Swarm Optimization," *IEEE Trans. On Sustainable Energy*, 2011, 99, 1-1.

10. Zhang, W. and Wang, W., “Wind speed forecasting via ensemble Kalman Filter,” *Proc of the Advanced Computer Control (ICACC)*, 2010.

11. Soman S S, Zareipour H, Malik O, Mandal P., “A review of wind power and wind speed forecasting methods with different time horizons,” *Porc. of the 3rd international symposium on the North American Power*, 26-28 Sept. 2010.

12. Huang, L., Zhang, C., Peng, Y. and Zhou, H., “Application of a Combination Model Based on Wavelet Transform and KPLS-ARMA for Urban Annual Water Demand,” *J. Water Resour. Plann. Manage*, 2014, 140(8), 04014013

13. Ling, L. L, Li, J. H., He, P. J. and Wang, C. S. ,”The Use of Wavelet Theory and ARMA Model in Wind Speed Prediction,” *Proc. of the 1st international symposium on Electric Power Equipment*, 23-27 October 2011.

14. Faria, D. L., Castro, R., Philippart, C., Gusmao, A., “Wavelets pre-filtering in wind speed prediction,” *Proc. of the international symposium on the Power Engineering, Energy and Electrical Drives*, 18-20 March 2009.

15. Chatterjee, S. and Bard, J. F. “A comparison of Box-Jenkins time series models with autoregressive processes,” *IEEE Transactions on Systems, Man and Cybernetics, 15*(2) 252-259, 1985.

16. Pappala, V. S., Wilch, M., Singh, S. N. and Erlich, I., "Reactive Power Management in Offshore Wind Farms by Adaptive PSO," *Proc of the International Conference on Intelligent Systems Applications to Power Systems, 2007*, pp. 1-8.

17. Shrawane, S. S., Diagavane, M. and Bawane, N., "Optimal reactive power dispatch by furnishing UPFC using multi-objective hybrid GAPSO approach for transmission

loss minimisation and voltage stability," *Proc of the international Conference on Nascent Technologies in the Engineering Field (ICNTE), 2015*, pp. 1-6.

18. Ali, M. Y. and Raahemifar, K., "Reactive power optimization based on hybrid particle swarm optimization algorithm," *Proc of the 25th IEEE Canadian Conference on Electrical & Computer Engineering (CCECE), 2012*, pp. 1-5.

19. Khorsandi, A., Alimardani, A., Vahidi, B. and Hosseinian, S. H., "Hybrid shuffled frog leaping algorithm and Nelder-Mead simplex search for optimal reactive power dispatch," *IET: Generation, Transmission & Distribution,* vol. 5, pp. 249-256, 2011.

20. Tyagi, B. and Srivastava, S. C. "A method for optimal placement of reactive sources : reactive power procurement in competitive electricity markets," Proc of the IEEE *Power India Conference,* 2006, pp. 6.

21. Sharma, T. and Srivastava, L. "Evolutionary Computing Techniques for Optimal Reactive Power Dispatch: An Overview and Key Issues," *Proc . of the Fourth International Conference on Communication Systems and Network Technologies (CSNT),* 2014, pp. 507-511.

22. Amrane, Y. and Boudour, M., "Optimal reactive power dispatch based on particle swarm optimization approach applied to the Algerian electric power system," Proc of the *11th International Multi-Conference on Systems, Signals and Devices (SSD),* 2014, pp. 1-6.

23. Zhang, Yujiao and Song, Yanguang, "Comparison of multiobjective particle swarm optimization and evolutionary algorithms for optimal reactive power dispatch problem," *Proc of the IEEE Congress on Evolutionary Computation (CEC),* 2014, pp. 258-265.

24. del Valle, Y., Venayagamoorthy, G. K., Mohagheghi, S., Hernandez, J. C. and Harley, R. G., "Particle Swarm Optimization: Basic Concepts, Variants and

Applications in Power Systems," *IEEE Transactions on Evolutionary Computation, 2008,* vol. 12, pp. 171-195.

25. Riaz, F. and Ali, K. M., "Applications of Graph Theory in Computer Science," *Proc of the Third International Conference on Computational Intelligence, Communication Systems and Networks (CICSyN),* 2011, pp. 142-145.

26. Ling, P., Liu, Yongdong, and Francois, B., "Modeling and control of doubly fed induction generator wind turbines by using Causal Ordering Graph during voltage dips," *Proc. Of the International Conference on Electrical Machines and Systems, 2008*, pp. 2412-2417.

27. Chandra, D. R., Kumari, M. S., Sydulu, M., Grimaccia, F., Mussetta, M., Leva*, S., et al.*, "Small signal stability of power system with SCIG, DFIG wind turbines," *Proc. Of the Annual IEEE India Conference (INDICON),* 2014, pp. 1-6.

28. Giebel, G., Badger. J., MartiI., Louka, P., “The State-Of-The-Art in Short-Term Prediction of Wind Power-the results of the ANEMOS project,” Retrieved on May 30, 2013, from, *http://www.prediktor.dk/publ/GGiebelEtAl*

29. Zhang, W., and Wang, W., “Wind speed forecasting via ensemble Kalman Filter,” *Proc of the 2nd International Conference on Advanced Computer Control (ICACC)*, 27-29 March 2010.

30. Alexiadis, M. C., Dokopoulos, P. S., and Sahsamanoglou, H. S., “Wind speed and power forecasting based on spatial correlation models,” *IEEE Transactions on Energy Conversion, 1999, 14*(3), 836-842.

31. Gao, S, He, Yu, and Chen, H., “Wind speed forecast for wind farms based on ARMA-ARCH model,” *Proc of the International Symposium on the Sustainable Power Generation and Supply*, 6-7 April 2009.

32. Zhang, W-Y., Zhao, Z.-B., Han, T-T. and Kong, L-B., “Short Term Wind Speed Forecasting for Wind Farms Using an Improved Autoregression Method,” *Proc of the International Conference on Information Technology, Computer Engineering and Management Sciences (ICM)*, 24-25 Sept. 2011.

33. Wang, C., Lu, Z., and Qiao, Y., “Modeling of wind pattern and its application in wind speed forecasting,” *Proc. Of the International Conference on Sustainable Power Generation and Supply*, 6-7 April 2009.

34. Negnevitsky, M., Johnson, P., Santoso, S., “Short term wind power forecasting using hybrid intelligent systems,” *Proc of the IEEE Power Engineering Society General Meeting*, 24-28 June 2007.

35. Evensen, G., *Data Assimilation : The Ensemble Kalman Filter*. Berlin: Springer Verlag, 2007.

36. Wei, W., Wu, G., Yang, M., Zhang, Y., Qiu, S. and Sun, A., “Short-term forecasting for wind speed based on wavelet decomposition and LMBP neural network,” *Proc of the 4th international symposium on Electric Utility Deregulation and Restructuring and Power Technologies*, 6-9 July 2011.

37. Huang, C. Y., Liu, Y. W., Tzeng, W. C. and Wang, P. Y., “Short Term Wind Speed Predictions by Using the Grey Prediction Model Based Forecast Method,” *Proc of the international symposium on the Green Technologies*, 14-15 April 2011.

38. Sangita, P. and Deshmukh, S. R., “Use of support vector machine for wind speed prediction,” *Proc of the International Conference on Power and Energy Systems (ICPS)*, 22-24 Dec. 2011.

39. Taylor, J. W., McSharry, P. E., and Buizza, R., “Wind Power Density Forecasting Using Ensemble Predictions and Time Series Models,” *IEEE Transactions on Energy Conversion, 2009, 24*(3), 775-782.

40. Barbounis, T. G., Theocharis, J. B., Alexiadis, M. C., and Dokopoulos, P. S., "Long-term wind speed and power forecasting using local recurrent neural network models," *IEEE Transactions on Energy Conversion, 2006, 21*(1), 273-284.

41. Senjyu, T., Yona, A., Urasaki, N., and Funabashi, T. , "Application of Recurrent Neural Network to Long-Term-Ahead Generating Power Forecasting for Wind Power Generator," Proc of the IEEE PES Power Systems and Exposition, 29 Oct- 1 Nov 2006.

42. Bessa, R. J., Miranda, V., and Gama, J., "Entropy and Correntropy Against Minimum Square Error in Offline and Online Three-Day Ahead Wind Power Forecasting," *IEEE Transactions on Power Systems, 2009, 24*(4), 1657-1666.

43. Haque, A. U., Mandal, P., Meng, J., Kaye, M. E., and Liuchen, C. , "A new strategy for wind speed forecasting using hybrid intelligent models," *Proc. Of the 25th IEEE Canadian Conference on the Electrical and Computer Engineering (CCECE)*, April 29 - May 2, 2012.

44. Hippert, H. S., Pedreira, C. E., and Souza, R. C., "Neural networks for short-term load forecasting: a review and evaluation," *IEEE Trans. On Power Systems*, 2001, 16(1): 44-55.

45. Fan, S., Liao, J. R., Yokoyama, R., Chen, L. and Lee, W. J., "Forecasting the Wind Generation Using a Two-Stage Network Based on Meteorological Information," *IEEE Trans on Energy Conversion,* 2009, 24(2): 474-482.

46. Potter, C. and Negnevitsky, M. "Very short-term wind forecasting for Tasmanian power generation," Proc of *the IEEE Power Engineering Society*, 2006.

47. Brusch, S., Lehner, S. and Schulz-Stellenfleth, J., "Synergetic Use of Radar and Optical Satellite Images to Support Severe Storm Prediction for Offshore Wind Farming," *J. Applied Earth Observations and Remote Sensing, 2008,* 1(1):57-66.

48. Candy, B., English, S. J., and Keogh, S. J., "A Comparison of the Impact of QuikScat and WindSat Wind Vector Products on Met Office Analyses and Forecasts," *IEEE Transactions on Geoscience and Remote Sensing, 2009, 47*(6), 1632-1640.

49. Lange, M., and Focken, U., "New developments in wind energy forecasting," *Proc of the IEEE Power and Energy Society General Meeting - Conversion and Delivery of Electrical Energy in the 21st Century*, 20-24 July 2008.

50. Sideratos, G. and Hatziargyriou, N. D., "An Advanced Statistical Method for Wind Power Forecasting," *IEEE Trans. on Power Systems*, 2007, 22(1): 258-265.

51. Daniel, A. R., and Chen, A. A., "Stochastic simulation and forecasting of hourly average wind speed sequences in Jamaica," *Solar Energy, 1991, 46*(1), 1-11.

52. Torres, J. L., Garc, A., De Blas, M., and De Francisco, A., "Forecast of hourly average wind speed with ARMA models in Navarre (Spain)," *Solar Energy, 2005, 79*(1), 65-77.

53. Kamal, L. and Jafri, Y. Z., "Time series models to simulate and forecast hourly averaged wind speed in Quetta, Pakistan," *Solar Energy, 1997, 61*(1), 23-32.

54. Alexiadis, M. C., Dokopoulos, P. S., Sahsamanoglou, H. S., and Manousaridis, I. M., "Short-term forecasting of wind speed and related electrical power," *Solar Energy, 1998, 63*(1), 61-68.

55. Pinson, P., Christensen, L. E. A., Madsen, H., Srensen, P. E., Donovan, M. H., and Jensen, L. E., "Regime-switching modelling of the fluctuations of offshore wind generation," *Journal of Wind Engineering and Industrial Aerodynamics, 2008, 96*(12), 2327-2347.

56. Yuan-Kang, W. and H. Jing-Shan, "A literature review of wind forecasting technology in the world," *Proc of the IEEE Power Tech*, 2007, Lausanne.

57. de Aquino, R. R. B., M. M. S. Lira, et al., "Application of wavelet and neural network models for wind speed and power generation forecasting in a Brazilian experimental wind park," *Proc of International Joint Conference on Neural Networks*, 2009.

58. Kolhe, M., L. Tzu Chao, et al., "GA-ANN for Short-Term Wind Energy Prediction," Proc of the Asia Pacific Power and Energy Engineering Conference (APPEEC), 2011.

59. Shifan, G., L. Yansong, et al., "Wind speed forecasting of genetic neural model based on rough set theory," *Proc of the 5th international symposium on Critical Infrastructure (CRIS)*, 2010.

60. Kani, S. A. P. and Riahy, G. H., "A new ANN-based methodology for very short-term wind speed prediction using Markov chain approach," *Prof of the IEEE Canada Electric Power Conference, EPEC*, 2008.

61. Sanz, S. S., A. B. Perez, et al., "Short-Term Wind Speed Prediction by Hybridizing Global and Mesoscale Forecasting Models with Artificial Neural Networks," *Proc of the 8th international symposium on Hybrid Intelligent Systems*, 2008.

62. Donald, E. G. and William, H. L., "Applications of estimation theory to inverse problems in meteorology," *Proc of the 17th international symposium on Decision and Control including the 17th Symposium on Adaptive Processes*, 1978.

63. Alanis, A. Y., Ricalde, L. J., et al., "High Order Neural Networks for wind speed time series prediction," *Proc of the International Joint Conference on Neural Networks,* 2009.

64. Delahaye, D. and Puechmorel, S. "TAS and wind estimation from radar data," *Proc of the Digital Avionics Systems Conference*, 2009.

65. Li, S., “Wind power prediction using recurrent multilayer perceptron neural networks,” *Proc. Of the IEEE Power Engineering Society General Meeting*, 2003.

66. Erdem, E., and Shi, J., "ARMA based approaches for forecasting the tuple of wind speed and direction," *J. Applied Energy*, 88(4), 1405-1414.

67. Liu, H., Erdem, E., and Shi, J., "Comprehensive evaluation of ARMA-GARCH approaches for modeling the mean and volatility of wind speed,” *J. Applied Energy*, 88, 724–732.

68. Pstergaard, K. Z., Brath, P. and Stoustrup, J., “Estimation of effective wind speed,” *Journal of Physics: Conference Series 2007*. 75(1):012082.

69. Zhang, H., Sun, H., Liu, L., and Dong, M., “Resonance mechanism of wind-induced isolated aqueduct–water coupling system,” *J. Engineering Structures 2013*. 57(0): 73-86.

70. Wei, Q., Zhou, W., Aller, J. M. and Harley, R. G., “Wind Speed Estimation Based Sensorless Output Maximization Control for a Wind Turbine Driving a DFIG,” *IEEE Transactions on Power Electronics,* 2008. 23(3), 1156-1169.

71. Akramizadeh, A., Farjami, A. A. and Khaloozadeh, H. “Nonlinear Hammerstein model identification using genetic algorithm,” *Proc of the Artificial Intelligence Systems*, 2002.

72. Beligiannis, G. N., Likothanassis, S. D., Demiris, E. N. “A robust hybrid evolutionary method for ARMA model identification,” *Proc of the Image and Signal Processing and Analysis, 2001*.

73. Chon, K. H., Cohen, R. J. “Linear and nonlinear ARMA model parameter estimation using an artificial neural network,” *IEEE Transactions on Biomedical Engineering,* 1997, *44*(3), 168-174.

74. Shiqiong, Z., Jixuan, Y., Zhumei, S., Jun, T. and Longyun, K. "Wind Signal Forecasting Based on System Identification Toolbox of MATLAB," *Proc of the Intelligent System Design and Engineering Applications (ISDEA*), 2013.

75. Wang, L. and Libert, G. A. "Combining pattern recognition techniques with Akaike's information criteria for identifying ARMA models," Signal models," *IEEE Transactions on Signal Processing,* 1994, 42(6), 1388-1396.

76. Zhao, B., Guo, C. X. and Cao, Y. J., "A multiagent-based particle swarm optimization approach for optimal reactive power dispatch,"*IEEE Transactions on Power Systems, 2005,* vol. 20, pp. 1070-1078.

77. Maharana, M. K. and Swarup, K. S., "Graph theory based corrective control strategy during single line contingency," *Proc of the International Conference on Power Systems, 2009,* pp. 1-6.

78. Zimmerman, R. D., Murillo, S., Sanchez, C. E. and Thomas, R. J., "MATPOWER: Steady-State Operations, Planning, and Analysis Tools for Power Systems Research and Education," *IEEE Transactions on Power Systems, 2011,* vol. 26, pp. 12-19.

79. Yong-jun, Z. and Zhen, R., "Optimal Reactive Power Dispatch Considering Costs of Adjusting the Control Devices," *IEEE Transactions on Power Systems, 2005,* vol. 20, pp. 1349-1356.

80. Sharma, T. and Srivastava, L., "Evolutionary Computing Techniques for Optimal Reactive Power Dispatch: An Overview and Key Issues," *Proc of the Fourth International Conference on Communication Systems and Network Technologies (CSNT),* 2014, pp. 507-511

81. Y. Amrane, Y. and M. Boudour, M., "Optimal reactive power dispatch based on particle swarm optimization approach applied to the Algerian electric power system," Proc of the *11th International Multi-Conference on Systems, Signals and Devices (SSD),* 2014, pp. 1-6.

82. Das, S., Abraham, A., Chakraborty, U. K. and Konar, A., "Differential Evolution Using a Neighborhood-Based Mutation Operator," *IEEE Transactions on Evolutionary Computation, 2009,* vol. 13, pp. 526-553.

83. Li, Y., Jiang, L., Wu, Q. H., Jiang, Q. Y. and Cao, Y. J., "Distributed optimal reactive power dispatch based on parallel particle swarm optimisation algorithm," *Proc of the 43rd International Universities Power Engineering Conference, 2008,* pp. 1-5.

84. Bakare, G. A., Venayagamoorthy, G. K. and Aliyu, U. O., "Reactive power and voltage control of the Nigerian grid system using micro-genetic algorithm," *Proc of the IEEE Power Engineering Society General Meeting, 2005. Vol 2,* pp. 1916-1922.

85. del Valle, Y., Venayagamoorthy, G. K., Mohagheghi, S., Hernandez, J. C. and Harley, R. G., "Particle Swarm Optimization: Basic Concepts, Variants and Applications in Power Systems," *IEEE Transactions on Evolutionary Computation, 2008,* vol. 12, pp. 171-195.

86. Yoshida, H., Kawata, K., Fukuyama, Y., Takayama, S. and Nakanishi, Y., "A particle swarm optimization for reactive power and voltage control considering voltage security assessment," *IEEE Transactions on Power Systems, 2000,* vol. 15, pp. 1232-1239.

87. Esmin, A. A. A., Lambert-Torres, G. and de Souza, A. C. Z., "A hybrid particle swarm optimization applied to loss power minimization," *IEEE Transactions on Power Systems, 2005,* vol. 20, pp. 859-866.

88. Vlachogiannis, J. G. and Lee, K. Y., "A Comparative Study on Particle Swarm Optimization for Optimal Steady-State Performance of Power Systems," *IEEE Transactions on Power Systems, 2006,* vol. 21, pp. 1718-1728.

89. Guanglin, C., Zhen, R. and Tao, Y., "Optimal Reactive Power Dispatch Based on Modified Particle Swarm Optimization Considering Voltage Stability," *Proc of the IEEE Power Engineering Society General Meeting, 2007,* pp. 1-5.

90. Das, S., Abraham, A., Chakraborty, U. K. and Konar, A., "Differential Evolution Using a Neighborhood-Based Mutation Operator," *IEEE Transactions on Evolutionary Computation, 2009,* vol. 13, pp. 526-553.

91. Khorsandi, A., Alimardani, A., Vahidi, B. and Hosseinian, S. H., "Hybrid shuffled frog leaping algorithm and Nelder-Mead simplex search for optimal reactive power dispatch," *IET Proc*: *Generation, Transmission & Distribution, 2011,* vol. 5, pp. 249-256.

92. Nakawiro, W., Erlich, I. and Rueda, J. L., "A novel optimization algorithm for optimal reactive power dispatch: A comparative study," *Proc of the International Conference on Electric Utility Deregulation and Restructuring and Power Technologies (DRPT),* 2011, pp. 1555-1561.

93. Shrawane, S. S., Diagavane, M. and Bawane, N., "Optimal reactive power dispatch by furnishing UPFC using multi-objective hybrid GAPSO approach for transmission loss minimisation and voltage stability," *Proc of the 2015 International Conference on Nascent Technologies in the Engineering Field (ICNTE),* 2015, pp. 1-6.

94. Li, Han-lin and Jiang, Jin-liang, "Notice of Retraction
Optimal reactive power dispatch based on dynamic readjusting cost," *Proc of the 2011 IEEE Power Engineering and Automation Conference (PEAM),* 2011, pp. 508-511.

95. Huang, C. M., Chen, S. J., Huang, Y. C. and Yang, H. T., "Comparative study of evolutionary computation methods for active-reactive power dispatch," *IET Proc: Generation, Transmission & Distribution, 2012,* vol. 6, pp. 636-645.

96. Ding, Chaohua, Chen, Weirong, Zhang, Yunfang, and Zhao, Xuexia, "Seeker Optimization Algorithm for Optimal Reactive Power Dispatch," *IEEE Transactions on Power Systems, 2009,* vol. 24, pp. 1218-1231.

97. Srivastava, L. and Singh, H., "Hybrid multi-swarm particle swarm optimisation based multi-objective reactive power dispatch," *IET Proc: Generation, Transmission & Distribution, 2015,* vol. 9, pp. 727-739.

98. Oepomo, T. S., "A step-by-step method for Z-loop construction using graph theory and topology for power system studies," *Proc of the IEEE Region 8 International Conference on Computational Technologies in Electrical and Electronics Engineering, 2008*, pp. 186-191.

99. Nakayama, K. and Shinomiya, N., "Distributed control based on tie-set graph theory for smart grid networks," *Proc of the 2010 International Congress on Ultra Modern Telecommunications and Control Systems and Workshops (ICUMT),* 2010, pp. 957-964.

100. Demaine, E. D., Hajiaghayi, M. and Kawarabayashi, K., "Algorithmic graph minor theory: Decomposition, approximation, and coloring," *Proc of the 46th Annual IEEE Symposium on Foundations of Computer Science,* 2005, pp. 637-646.

101. Quiros-Tortos and Terzija, V. "A graph theory based new approach for power system restoration," *Proc of the IEEE Power Tech (POWERTECH), Grenoble*, 2013, pp. 1-6.

102. Amelin, M., “Simulation of Trading Arrangements Impact on Wind Power Imbalance Costs,” *Proc of the 10th International Conference on the Probabilistic Methods Applied to Power Systems*, 25-29 May 2008.

103. Jaehnert, S., Aigner, T., Doorman, G., and Gjengedal, T., “Impact of large scale wind integration on power system balancing,” *Proc of the IEEE PowerTech*, Trondheim, 19-23 June 2011.

104. Fonte, P. M., G. X. Silva, et al., "Wind speed prediction using artificial neural networks," *WSEAS Transactions on Systems*. 2005, 4(4): 379-383

105. Aanonsen, S. I., Nœvdal, G., et al., "The ensemble Kalman filter in reservoir engineering-A Review," *SPE Journal*, 2009, 14(3): 393-412.

106. Li, S., "Wind power prediction using recurrent multilayer perceptron neural networks," *Proc of the IEEE Power Engineering Society General Meeting*, 2003.

107. Khan, A. A. and Shahidehpour, M., "One day ahead wind speed forecasting using wavelets," *Proc of IEEE PES Power Systems and Exposition*, 15-18 March 2009.

108. Cao, L. and Li, R., "Short-term wind speed forecasting model for wind farm based on wavelet decomposition," *Proc of the 3rd international symposium on the Electric Utility Deregulation and Restructuring and Power Technologies*, 6-9 April, 2008.

109. Faria, D. L., Castro, R., Philippart, C., and Gusmao, A., "Wavelets pre-filtering in wind speed prediction," *Proc of the International Conference on Power Engineering, Energy and Electrical Drives*, 18-20 March 2009.

110. Han, X., Zhang, X., Chen, F., Song, Z., and Wang, C., "Short-term wind speed prediction method based on time series combined with LS-SVM," *Proc of the 31st Chinese Control Conference (CCC)*, 25-27 July 2012.

111. Sharma, D. and Lie, T. T., "Wind Speed Forecasting Using Hybrid ANN-Kalman Filter Techniques," *Proc of the International Power and Energy Conference*, 14-16 Dec 2012.

112. Chon, K. H. and Cohen, R. J., "Linear and nonlinear ARMA model parameter estimation using an artificial neural network," *IEEE Transactions on Biomedical Engineering,* 1997, *44*(3), 168-174.

113. Aksasse, B. and Radouane, L., “Two-dimensional autoregressive (2-D AR) model order estimation,” *IEEE Transactions on Signal Processing,* 1999, *47*(7) 2072-2077.

114. Wang, L. and Libert, G. A., “Combining pattern recognition techniques with Akaike's information criteria for identifying ARMA models,” *IEEE Transactions on Signal Processing,* 1994, 42(6), 1388-1396.

115. Zhao, B., Guo, C. X. and Cao, Y. J., "A multiagent-based particle swarm optimization approach for optimal reactive power dispatch," *IEEE Transactions on Power Systems, 2005,* vol. 20, pp. 1070-1078.

116. Maharana, M. K. and Swarup, K. S., "Graph theory based corrective control strategy during single line contingency," *Proc of the International Conference on Power Systems, 2009*, pp. 1-6.

117. Kaur, D., Lie, T.T., Nair, N. K. C., and Valles, B., “Wind Speed Forecasting Using Hybrid Wavelet Transform-ARMA Techniques,” *AIMS Energy, 2015,* vol. 3, pp. 13-24.

118. Sahli, Z., Hamouda, A., Bekrar, A. and Trentesaux, D., "Hybrid PSO-tabu search for the optimal reactive power dispatch problem," *Proc of the 40th Annual Conference of the IEEE Industrial Electronics Society,* 2014, pp. 3536-3542.

119. Certuche-Alzate, J. P. and Velez-Reyes, M., "A reconfiguration algorithm for a DC Zonal Electric Distribution System based on graph theory methods," *Proc of the IEEE Electric Ship Technologies Symposium,* 2009, pp. 235-241.

120. Ali. M. Y. and Raahemifar, K., "Reactive power optimization based on hybrid particle swarm optimization algorithm," Proc of the *25th IEEE Canadian Conference on Electrical & Computer Engineering (CCECE),* 2012, pp. 1-5.

121. Jiang, Xiaoming, Zhang, Cong, Chen, Haoyong, and Xie, Xuanhao, "Optimal reactive power dispatch considering wind turbines," Proc of the *2014 IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC),* 2014, pp. 1-5

122. Minguez, R., Martinez, J. M., Castellanos, O. F. and Guanche, R., "Component failure simulation tool for optimal electrical configuration and repair strategy design of off-shore wind farms," *Proc of the IEEE OCEANS, 2011 Spain*, pp. 1-10.

123. Zimmerman, R. D., Murillo, S., Sanchez, C. E. and Thomas, R. J., "MATPOWER: Steady-State Operations, Planning, and Analysis Tools for Power Systems Research and Education," *IEEE Transactions on Power Systems, 2011,* vol. 26, pp. 12-19.

124. Dung Anh, L. and Dieu Ngoc, V., "Optimal reactive power dispatch by pseudo-gradient guided particle swarm optimization," *Proc of the International Power Engineering Conference*, 2012, pp. 7-12.

125. Bakare, G. A., Venayagamoorthy, G. K. and Aliyu, U. O., "Reactive power and voltage control of the Nigerian grid system using micro-genetic algorithm," *Proc of the IEEE Power Engineering Society General Meeting, 2005, vol 2,* pp. 1916-1922.

126. Abdel-Karim, N., Ilic, M. and Small, M., "*Modeling wind speed for power system applications*," ed: Carnegie Mellon University, USA, Technical Report, 2011

127. Mi, Sibei, "Short-Term Forecasting of Wind Speed and Wind Power Based on BP and Adaboost_BP" (2014). *Theses and Dissertations.* Paper 505.

128. Song, Youqiang, Wang, Rujing, Song, Bingyu, Liu, Wenbo, and Jiang, Feng, "Prediction about time series based on updated prediction ARMA model," Proc of the *2013 10th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD),* 2013, pp. 680-684.

129. Dutta, P. and Sinha, A. K., "Environmental Economic Dispatch constrained by voltage stability using PSO," Proc of the *IEEE International Conference on Industrial Technology,* 2006, pp. 1879-1884.

130. Tan, H. Z. and Chow, T. W. S., "Recursive scheme for ARMA coefficient and order estimation with noisy input-output data," *IEE Proceedings - Vision, Image and Signal Processing, 1999,* vol. 146, pp. 65-71.