FORECASTING MODELS FOR RENEWABLE POWER DISPATCH IN MICROGRIDS

BY

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This thesis, written by **ADIL AHMED** under the direction of his thesis adviser and approved by his thesis committee, has been presented to and accepted by the Dean of Graduate Studies, in partial fulfillment of the requirements for the degree of **MASTER OF SCIENCE IN ELECTRICAL ENGINEERING**.

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Dedicated to,
My Parents,
My Siblings,
and My Betrothed

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All praise is for Allah, Lord of the worlds, The Beneficent, the Merciful. Master of the Day of Judgment, It is You we worship and You we ask for help [Al-Fatiha (1:4)].

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THESIS ABSTRACT

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Electricity production through renewable energy (RE) resources is globally emphasized nowadays for the achievement of a cleaner planet, but the intermittencies in renewable power generation make its penetration a challenging task for researchers and power industry. This thesis work proposes to alleviate the issues caused by the uncertainty in renewable power plant output by developing accurate forecasting models and utilizing these models to optimize the economic dispatch. The work is performed in two phases; Firstly, forecasting models are developed for multi-steps ahead wind prediction using intelligent methods merged with state-of-the-art multi-step schemes. A new wind forecasting model based on functional network is proposed which is a novel concept in the field of power systems engineering. The proposed model is computationally light as compared to advanced hybrid forecast *models and is shown to outperform the well-accepted neural network model as well as the benchmark persistence model in terms of forecast accuracy. In the second phase, an economic dispatch strategy is proposed for selling energy in an optimal manner from a microgrid with wind generation and battery energy storage system (BESS). Wind power and market price forecasts are incorporated in a receding horizon optimization policy to maximize the running income and operational profits of the wind-BESS microgrid. The utilization of accurate forecast information not only enables a smooth RE power plant operation but also helps in determining an optimal size of the BESS. It is also studied that the accuracy of power and price forecasts has a significant impact on the improvement in income and profits. In this way, this thesis work has twofold benefits, on one hand, it brings the emerging ideas of artificial intelligence for technology advancement in the energy sector, and on the other hand, it can facilitate economically viable and technically feasible integration of RE resources into the electricity grid.*

ملخص الرسالة

الاسم الكامل: عادل أحمد

عنوان الرسالة: نماذج التنبؤ لتوزيع الطاقة المتجددة في الشبكات المصغرة

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يتم التأكيد في هذه الأيام على إنتاج الكهرباء من خلال مصادر الطاقة المتجددة (**RE**) على الصعيد العالمي للحصول على كوكبٍ أنظف، لكن التقطعات في توليد الطاقة المتجددة تجعل من إدخالها مهمةً صعبةً للباحثين و قطاع الطاقة. تقترح هذه الأطروحة التخفيف من المشاكل الناجمة عن عدم اليقين في إنتاج محطة الطاقة المتجددة عن طريق تطوير نماذج دقيقةٍ للتنبؤ، و الاستفادة من هذه النماذج لتحسين التوزيع الاقتصادي. يتم تنفيذ العمل على مرحلتين: أولاً، يتم تطوير نماذج التنبؤ لخطواتٍ متعددةٍ قبل التكهن بالرياح باستخدام أساليب ذكيةٍ مدمجةٍ مع المخططات متعددة الخطوة المتطورة. تم اقتراح نموذجٍ جديدٍ للتنبؤ بالرياح يعتمد على الشبكة الوظيفية، و هذا مفهومٌ جديدٌ في مجال هندسة أنظمة الطاقة. النموذج المقترح سلسٌ حسابياً بالمقارنة مع نماذج التنبؤ الهجينة المتقدمة، و يتضح أن أداءه يتفوق على نموذج الشبكةِ العصبيةِ المقبولة بشكلٍ جيدٍ بالإضافة إلى نموذج الثبات المرجعيّ من حيث دقة التنبؤ. في المرحلة الثانية، يتم اقترح استراتيجية توزيعٍ اقتصاديٍّ لبيع الطاقة بأسلوبٍ أمثل من شبكةٍ مصغرةٍ بإنتاج طاقة الرياح و نظام تخزين طاقة البطارية (**BESS**). يتم تضمين توقعات كلٍ من طاقة الرياح و سعر السوق في سياسة تحسين الأفق المنحسر لتحقيق أعلى دخل تشغيلٍ و أرباحٍ تشغيليةٍ من الشبكة المصغرة ذات نظام الرياح-البطارية. إن استخدام معلومات التنبؤ الدقيقة لا يمكّن فقط من تشغيلٍ سلسٍ لمحطة الطاقة المتجددة، بل يساعد أيضاً في تحديد الحجم الأمثل لنظام **BESS**. كما تم أيضاً التحقق من أن دقة توقعات الطاقة و السعر لها تأثيرٌ كبيرٌ على تحسين الدخل و الأرباح. و بذلك، فإن لهذه الرسالة فوائد مزدوجةً. من ناحيةٍ، فهي تجلب الأفكار الناشئة عن الذكاء الاصطناعي من أجل التقدم التقنيّ في قطاع الطاقة. و من الناحية الأخرى، فإنها تسهّل من الدمج – المجدي اقتصادياً و القابل للتطبيق تقنيّاً – لمصادر الطاقة المتجددة في شبكة الكهرباء.

CHAPTER 1

INTRODUCTION

1.1 Background and Motivation

Today, climate change is a huge area of concern for humanity and the major cause of this climate change is the excessive emission of carbon dioxide (CO_2) or greenhouse gases [1]. According to a report of the National Energy Technology Laboratory, USA, electricity production through fossil fuels is the largest source of greenhouse emissions all around the globe, contributing to more than 70% of the stationary CO_2 emitting sources. Moreover, the emerging fuel crisis in many regions of the world especially the Kingdom of Saudi Arabia is becoming a nuisance for the economy of these countries. Hence the reduction of fossil fuel dependency is vital for the environmental health of society and the economic growth of future generations [2].

All these social and economic reasons need revamping the structure of conventional power systems to utilize all forms of energy for power systems. Hence the generation of electric power from clean and Renewable Energy (RE) sources is much emphasized and is listed as the top priority of the future roadmap of the Kingdom of Saudi Arabia as well. In the light of Vision 2030, the aim is to generate 9.5 GW of electricity from renewable resources [3]. However, to harness these resources on a large scale, numerous barriers still need to be overcome by the researchers and industry [4, 5]. This poses a major challenge for research community to contribute innovatively and impactfully in this emerging field. Hence a cost-effective integration of renewable power into the existing network with optimum utilization of resources is the main motivating factor behind this research work.

One of the most swiftly growing RE technology is wind power, due to its affordability and promise of environment preservation [6, 7]. Wind energy is well-promoted throughout the world and according to Global Wind Energy Council (GWEC), it is expected to contribute up to 19% of the global power capacity by 2030 [8]. The bottleneck of large scale penetration of these RE sources into the main electrical grid is their intermittent and stochastic behavior. Many technical issues are posed into the power system by the introduction of these RE sources [9]. The most significant of these involve reliability assessment, power quality problems, generation planning, storage system capacity estimation, optimal economic dispatch etc [10, 11]. Researchers have made numerous efforts to mitigate the effect of these problems in microgrids. The proficient ways to address these problems are accurate renewable power forecasting, integration of Energy Storage System (ESS) in the electricity network and development of efficient power dispatch strategies for cost minimization [12, 13, 14, 15].

The need of forecasting arises because the irregularities in renewable power arise due the irregular behavior of their natural source of energy [16]. The prediction of these natural resources is necessary in order to correctly predict the power output of a renewable power plant. For example, a fractional error in wind speed forecast leads to a large power output deviation, hence accurate wind speed prediction is substantial for optimal integration of wind power into the main electricity grid [17]. A lot of research work is being done in this area and special attention is required in short term forecasting up to few hours ahead because it has great significance in a microgrid environment based on renewable energy for planning a profitable power dispatch strategy, assessing system reliability and ensuring optimal utilization of resources [18, 19].

The development and optimization of efficient ESSs is a thriving research topic. Several ESS technologies are available nowadays but their affordability is still an area of concern (see, e.g., [20] and references therein). Among them, Battery Energy Storage System (BESS) is considered as one of the most promising choice. The working principle of a BESS is found on storing surplus energy in the periods of excess energy production as compared to the demand and feeding power back to the grid when needed. Determining optimal BESS capacity, however, is a challenging task due to highly stochastic nature of wind power [21, 22]. However, by taking advantage of accurate forecast information related to renewable power (both wind and solar) can surely improve the optimization outcomes for operation and sizing of a BESS.

From the planning aspect of an electric power system, optimal Economic Dispatch (ED) plays a vital role. While devising an efficient ED strategy, the main aim is to provide the load demand and minimize the operating costs. This can be done by appropriate scheduling of the available generating units so as to optimize the microgrid operation, on the condition that all the system limitations and constraints are furnished. The optimal operation of a microgrid can be attained in various dimensions. These dimensions include efficient unit commitment scheduling, effective economic/environmental dispatch, optimal sizing of energy storage and profit maximization through resourceful grid interaction [23, 24]. This makes dispatch problem a large-scale highly constrained nonlinear optimization problem. Development of optimal ED algorithms has been an active area of research in the past years. Traditionally, several linear, nonlinear and mixed integer iterative optimization techniques have been used to solve this complex optimization problem. However, recent trends indicate two directions in this domain; first, the use of biologically-inspired heuristic optimization schemes and second, forecast-based predictive dispatch strategies such as Model Predictive Control (MPC) framework [25, 26].

The proposed work attempts to optimize the operation of RE power system using forecast-based energy management and dispatch strategies. In this regard, the work is divided into two phases; First, accurate forecasting models are developed with emphasis on wind energy. This is because forecasting of wind speed is considered as the most challenging problem due to the highly intermittent nature of wind with no clear seasonal/diurnal trends, as opposed to solar irradiance. In accordance with recent trends, latest Artificial Intelligence (AI) schemes optimized through heuristic techniques were probed. However, a novel forecast model has been proposed based on a relatively new AI architecture called functional network (FN). The performance of the proposed model is compared with existing standard models in terms of forecast accuracy.

The second phase of the work focuses on the development of forecast-based economic dispatch schemes and the analysis of forecast error on cost factors. These algorithms will be based on predictive dispatch framework that is able to effectively handle forecasting information from the developed models. In addition to RE resource forecasting, load and market price forecasting information will also be utilized in such framework to extend the problem for profit maximization in a grid-connected environment. The concept of using forecast information from real-world innovative forecasting models for viable economic dispatch is not well-researched yet and there is a lot of room for contribution in this emerging field. This outlines the main goal of this research work and makes it a fervent effort toward the contribution for renewable energy technology progress in the world for the welfare of the society and future generations.

1.2 Problem Description

The optimization of microgrid operation can be performed by using accurate renewable power forecasting information in the process of economic dispatch. However, most of the works in literature address the forecasting problem and the efficient economic dispatch problem independently. The former problem is dealt by only developing forecasting models and assessing their forecast accuracies while the latter focuses on the dispatch optimization problem and uses some assumption about forecast error or a pre-developed forecasting model [27]. Nowadays, the integration of both these domains is a trending phenomenon in the manner that the impact of forecast error models is studied on the economic variables of the power system. The proposed work also aims at not only developing novel multi-step forecast models but also studying the interconnection of accurate power forecasting with profitable economic dispatch.

To achieve this, a microgrid (MG) model with renewable energy sources and Battery Energy Storage System (BESS) is proposed. Figure 1.1 depicts the proposed system with a control and dispatch system at its heart. This dispatch system is based on Model Predictive Control (MPC) because of its ability to effectively handle complex nonlinear constrained optimization problems. The MG model is fitted with renewable generation units and a BESS to cater for their intermittencies. The proposed system supplies its own uncontrollable loads and is connected to the grid as well. The main aim of this system is to minimize the operating costs, nonetheless, it can operate in a deregulated market environment

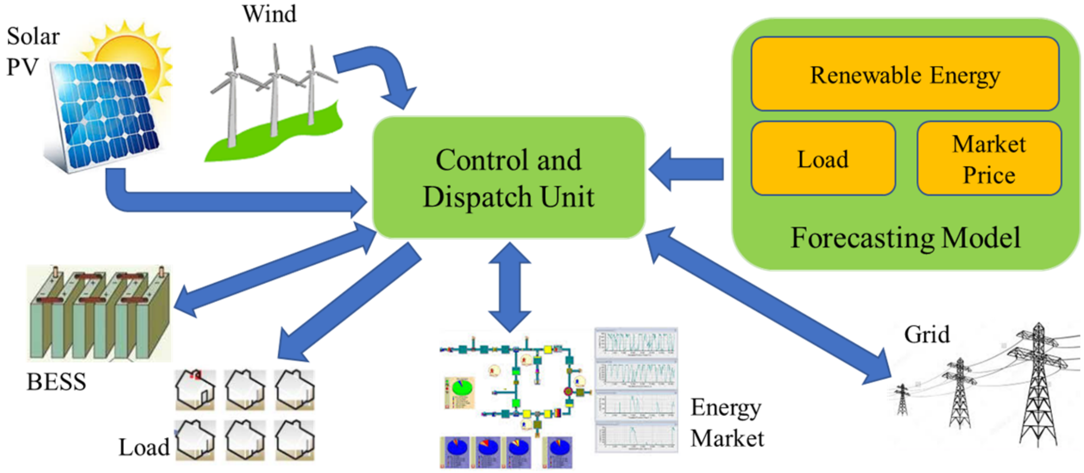

Figure 1.1: Proposed Microgrid System Model.

to communicate with the energy market efficiently in order to maximize income and profits.

The other important aspect of the proposed microgrid system is the forecasting engine. This forecasting engine is the main contribution of this thesis work and it consists of accurate and innovative forecasting models . These models are able to produce accurate forecasts for wind and solar PV power as well as load and market pricing for multi-steps ahead in future. Nonetheless, in the scope of the work, they are only used for wind speed, power and energy price forecasting. The thesis work aims at assessing the forecast accuracy of the developed models using standard procedures, benchmarks and indices. Hence our proposed problem formulation will be able to incorporate the forecast errors' information obtained from self-developed accurate forecasting models. This will allow us to study the impact of forecasting errors on the economy of the power system directly.

According to the proposed microgrid model, the work is divided into two major phases:

- Development of accurate and innovative forecasting models along with their assessment.
- Development of forecast-based economic dispatch algorithms and their sensitivity analysis with forecasting information.

The development of accurate forecast models is much emphasized in the proposed work due to the emerging concept of using forecast error information in optimizing the dispatch process [28]. This idea is well-accepted in recent literature as it not only makes the system emulations more realistic but can also help in reducing the operating costs, optimizing the reserve size and maximizing the operational profits of power system [9, 17]. This kind of system has great implications for competitive electricity markets as well for the profit of power system owners and overall social welfare [29].

1.3 Research Objectives

The main objective of the thesis work is to facilitate the cost-effective integration of renewable energy sources (especially wind energy) into electricity grid. In the light of the discussion until now, and the literature review presented in Chapter 2, this can be accomplished by completing the following sub-objectives:

- To develop innovative forecasting models for wind power prediction and evaluate their forecast accuracy.
- To develop multi-step forecasting mechanisms, integrate them with the developed models and assess the performance for a given forecast horizon.
- To develop forecast-based economic dispatch algorithms using the developed forecast models and battery energy storage system.
- To quantify the impact of power and energy price forecasting information on economic dispatch problems.

1.4 Research Methodology

Task 1: Literature Survey - The literature is surveyed extensively with a focus on recent techniques for relevant topics including renewable energy forecasting, control and dispatch algorithms and utilization of forecasting models into dispatch. In this way, recent trends in the field are identified along with the missing links, i.e., the co-ordination between forecasting models and dispatch algorithms.

Task 2: Data Collection - Real-world solar, wind, market price and load data is gathered from reliable sources and processed for conversion in a meaningful form. This data is then used for case studies in order to evaluate the performance of the developed models and algorithms. Thus, the obtained results have practical value for application in a realistic environment.

Task 3: Development of Forecasting Models for Wind Prediction - Forecasting models for wind predictions based on machine learning techniques are developed and evaluated for accuracy in terms of standard error indices. Various advanced AI models are developed and evaluated including ANN and SVM. The results of different learning algorithms including evolutionary optimization methods like PSO are also obtained. However, keeping in view the computational burden against the accuracy improvement, an ANN based model is finally selected as a base forecast model. The major contribution of this thesis work is the discovery and development of a novel wind forecasting model based on a relatively new AI paradigm, called Functional network (FN). The performance of the proposed FN model is then compared with the base model as well the benchmark. Both ANN and FN based forecast models are then utilized for the next steps in economic dispatch.

Task 4: Development and Integration of Multi-Step Forecasting Mechanisms - The second most important contribution of this work is the development of multi-step forecasting (MSF) mechanisms and their integration with the developed wind forecasting models for assessment. Three MSF schemes, namely recursive, direct, and DirRec are used throughout the work. The pros and cons of each scheme are analyzed in detail.

Task 5: Development of Forecast-Based Dispatch Algorithms - Once the forecasting models are developed for wind power and energy market price, control and dispatch algorithms ares developed that can effectually incorporate the forecasting information. The most suitable choice for this type of mechanism is the receding horizon approach based on Model Predictive Control (MPC) theory. The proposed dispatch system operates in the microgrid environment proposed in Figure 1.1. The control and dispatch framework is operated using deregulated market operating conditions as it incorporated six steps ahead forecasting of wind power and energy market price. The main optimization objective is the maximization of income and operational profit by selling optimum amount of energy while satisfying all system constraints. The developed mechanism also aids in determining the optimal size of the energy storage system.

Task 6: Analysis of Forecast Error on Dispatch - Once the proposed economic dispatch framework is established, the impact of forecast error can be analyzed and the expected outcome will be quantified in terms of system costs and operational profits. Multiple scenarios can be developed in this analysis, such as investigating the system costs with perfect forecast and with simulated and real forecast errors. Also, the results from developed forecast models and benchmark forecast models can also be compared to gauge the improvement of accurate forecasts on overall system economics.

1.5 Organization of the Thesis

The last part of Chapter 1 describes the organization of the thesis. Chapter 1 was all about background and motivation, defining the problem, stating the objectives and the proposed research methodologies to achieve those objectives. Chapter 2 presents a detailed survey of the literature for relevant topics. The survey is mainly divided into two parts; The first part covers the forecasting of renewable energy and the existing techniques as well as the introduction and application of the proposed methods. The second part mainly deals with the recent trends in power dispatch algorithms and forecast-based energy management strategies. Chapter 3, 4 and 5 contain the main research work that has been conducted for the thesis. Chapter 3 starts with the basics needed to develop a framework for wind forecasting. These include the development of ANN base model, the development and integration of MSF schemes and wind power calculation. The tools and databases needed for future case studies are also introduced in this chapter. The last section discusses the results for single step as well as multi-step forecasting with the ANN models using the selected MSF schemes. Chapter 4 is dedicated to the most innovative part of the thesis work, i.e., the development of MSF model using FNs. The chapter begins with an overview of FN, then describes the development of the proposed MSF model step-by-step, and finally elaborates the results of MSF schemes with FN as well the comparison of FN model with ANN model as well on the basis of the same case studies. Chapter 5 encompasses the utilization of the forecasting information in economic dispatch and its implications.

The chapter starts by describing the methodology for dispatch, including the problem formulation based on the MPC receding horizon principle. Then the results of the application of real-time prediction models are presented. Finally, the detailed analysis of forecast error information on the economic outcomes of power dispatch is conducted under various scenarios. The thesis is finished with the last Chapter 6 containing the concluding remarks and future recommendations.

CHAPTER 2

LITERATURE REVIEW

This research work proposes to facilitate the optimal integration of renewable energy (RE) resources in a microgrid through efficient control and dispatch algorithms based on the forecasted future information of certain inputs such as power, load and energy price. To achieve this goal, accurate and novel forecasting models are developed and their role in wind farm control and dispatch framework is investigated. Accordingly, the literature review is divided into two main sections. Section 1 deals with recent methodologies for renewable power forecasting while Section 2 surveys recent trends in power dispatch algorithms and forecast-based energy management strategies.

2.1 Forecasting Models

This section comprises of discussion on recent schemes for renewable energy forecasting from literature with focus on wind energy. The emerging trends in this domain including artificial intelligence (AI) based forecasting models are considered in detail while time series multi-step forecasting (MSF) mechanisms are also surveyed. In the end,we take a glance at the existing applications of functional network (FN), the technique behind the proposed forecasting models.

2.1.1 Renewable Energy Forecasting

One of the most useful, low cost and environment friendly renewable energy (RE) resource is wind, which is henceforth well-promoted by researchers and policy makers alike [16]. At the same time, it is considered as one of the most challenging to deal with due to the stochastic nature of wind that introduces many difficulties in power generation [7]. The forecasting of this highly intermittent source of energy is hence selected as a main goal of this thesis work. A fractional error in wind speed forecast leads to a large power output deviation, hence accurate wind speed prediction is substantial for optimal integration of wind power into the main electricity grid [6, 30]. These power forecasts are typically performed for multi steps ahead in control and dispatch framework. This kind of mechanism has wide application in time varying competitive energy markets, where the forecast accuracy plays a major role with regard to the economy and reliability of a renewable power plant [31, 32].

Due to its utmost significance, wind forecasting has been an area of keen interest for researchers over the past few decades. With respect to prediction time horizon, it can be generally divided into four categories, usually known as ultra-short term, short term, medium term and long term prediction [33]. In literature, the problem of wind speed forecasting has been tackled from various dimensions, spanning from physics (numerical weather predictions) to mathematics (statistical and probabilistic) to machine learning or a hybrid of these approaches [34].

Physical methods: Physical forecasting models are based on lower atmosphere forecasting and numerical weather predictions (NWPs). These models take into account the physical parameters of wind such as temperature, pressure, terrain and layout of wind farm etc. and thus forecast the future parameters of interest using complex meteorological models [30, 35]. This approach does not require training via historical data and its results are quite adequate for short term prediction especially. The challenge here is the acquisition and processing of physical data that requires specialized equipment as well as extensive computational power. This involves super computers and satellite technology which is very expensive and can only be used in heavily-funded projects, making this method non-feasible in many cases [36, 37].

Statistical techniques: As opposed to physical models, the statistical models are purely mathematical with a basic idea of recognizing a relationship or pattern from the acquired historical data [6]. Mostly they make use of time series models like curve fitting, the Moving average (MA) and Auto Regressive (AR) models [38]. The work in [39] presents a periodic curve fitting technique for an appreciable degree of forecast accuracy. Another research article discusses an adaptive AR model after pre-processing of data, and then periodic update through a recursive least squares curve fitting algorithm [40].

A combination of both AR and MA principles called the ARMA model is very popular for short term forecasting and has been proved successful in several cases. A very detailed analysis of four ARMA based models is given and the different conclusions are drawn for the prediction of wind speed and direction [41]. In another work, the wind speed time-series in pre-processed using wavelet theory and the ARMA model is used afterwards for forecasting. The integration of wavelet transform is reported to improve the prediction accuracy of the ARMA model [42]. Similarly, linear models making use of seasoning and diurnal historical trends are also proposed for wind speed and direction forecasting [43].

A generalization of the ARMA known as the Auto-Regressive Integrated Moving Average (ARIMA) is shown to produce promising results for short time horizon wind forecasting [44]. A fractional-ARIMA model is used to produce promising results for up to two days ahead wind speed forecasting [45]. Similarly, another work compares the results of ARIMA with an ANN model and it can be seen that the accuracy achieved by ARIMA model is quite close to the ANN model accuracy [46]. In other works, ARIMA model is mingled with other methods to form a hybrid model. The hybrid of ARIMA with wavelet decomposition is claimed to have better accuracy than a standard ANN model [47]. Other well-known methodologies include Bayesian model averaging and Grey predictor methods [48, 49]. In [48], a Bayesian inference approach is used to determine the parameters of Weibull distribution for wind speed forecasting. Similarly, a Grey Predictor system is introduced and assessed to show good forecast accuracy for wind speed in a standard manner [49].

All these techniques, in general, are easier to implement than other approaches, are economical and require less computational power. Using these methods, researchers have been able to produce acceptable results for short time horizons upto 48 hours, but the forecasting becomes very erratic for longer time periods [43, 44, 47]. Another drawback of these models is that pre-processing of time-series data is required to transform the data into standard form. In such applications, pre-processors such as independent component analysis (ICA) and wavelet transform are used [38, 42]. Sometimes the time-series model is combined with a physical inference model which recognizes the physical patterns of wind data [44]. A hybrid of these statistical models with Artificial Intelligence (AI) methods is also popular to overcome these issues [50].

Spatial correlation: This method is unique in a manner that it employs the relationship between the wind speeds of wind turbines situated at different locations by forecasting wind speed at one site based on the measurements of another site via cross correlation among them [51]. It is useful in predicting the wind speeds at certain sites where data is not available or measurement is not feasible [52]. Also, it can be employed to predict the speed for a wind farm with large number of wind turbines. It should be noted here that this correlation depends on various factors such as distance between sites, elevation and wind direction trends [53].

The usefulness of this technique is validated in numerous research works. A fuzzy model is presented which can predict wind speed using wind speed and direction data from neighbouring sites for training based on genetic algorithm (GA) [54]. Another work takes into account the interdependence of wind meteorological systems to improve the probabilistic forecasting by accurately modelling the spatial correlation of wind uncertainty [55]. The geographical correlation of wind energy is analyzed in the context of a case study for the whole Europe to enhance the power planning and trading in the region [53]. Similarly, wind power is predicted by taking observations of wind speed and direction from multiple neighbouring sites and their impact is studied [56].

Probabilistic methods: In these methods, the wind speed needs to be expressed as a generalized probability density function (PDF). The PDF which gives a good fit to wind speed profiles is Weibull Distribution [57, 58]. The Weibull distribution function can be used in many ways depending on the site and wind speed profiles. Several methods can be found in literature to estimate the Weibull parameters for forecast accuracy improvement [59]. In a related work, these parameters are estimated using five methods; namely empirical, energy pattern factor, maximum likelihood, modified maximum likelihood, and graphical method. The results are assessed on the basis of goodness of fit using standard indices [60]. There are some other probabilistic techniques which are employed not only to predict wind profile but also its expected uncertainty. These include parametric approaches and non-parametric approaches like Quantile regression, Kernel density estimation and ensemble methods [6]. But uncertainty analysis and related concepts open up another horizon and it seems out of the scope of the current research work.

2.1.2 Intelligent Forecasting Models

Machine learning or AI methods generally perform better than the other above-mentioned models since they have the ability to resourcefully make use of historical data for learning patterns and training the algorithms by finding complex relationships among variables without using complex mathematics [35]. The most prevalent of the AI techniques is the Artificial Neural Network (ANN) based model for wind speed prediction. ANNs imitate the behavior of human brain functions and exhibit the powerful ability to identify complex nonlinear relationships among variables only via training through historical data.

The idea of utilizing ANNs for wind speed prediction was introduced back in 1998 where an ANN model is shown to outperform an Auto-Regressive time series model for mean monthly and mean daily wind speed prediction [61]. Various types of ANN models are actively used but none of them can be universally claimed to be better than the other. An excellent work comparing various ANNs uses three training algorithms, namely, Levenberg-Marquardt (LM) method, Radial Basis Function (RBF) and Adaptive Linear Element to train the a Back Propagation (BP) neural network and concludes that all of them can perform better than the others in particular scenarios [62]. The use of ANNs for wind prediction can still be seen in very recent works, usually combined with other advanced techniques like wavelet decomposition or fuzzy rule base to compensate for its deficiencies and improve the prediction accuracy [63, 64].

In addition to ANN, Support Vector Machine (SVM) is an advanced neural network (NN) regression algorithm which can overcome some disadvantages of neural network, such as local minimal point, computational complexity due to overfitting etc. [65, 66]. It is based on the concept of nonlinear mapping to convert the problem into a linear regression problem. It was first used for wind prediction in 2004 and was shown to produce results better than those of Multi-Layer Perceptron (MLP) ANN [65]. Recently, some researchers have probed into the concept for short-term wind speed prediction. For instance, the implementation of SVM and optimization of its parameters via different evolutionary algorithms including GA, PSO and Cuckoo Search Algorithm (CSA) is performed to exhibit the superiority of CSA over the formers [66].

Another popular AI hybrid model known as Adaptive Neuro Fuzzy Inference System (ANFIS) is also used for wind forecasting since it combines the strength of a fuzzy model i.e. interpolating missing and inexact wind data and performing high level decision making while overcoming its feeble learning ability by combining it with an ANN [67]. Moreover, new hybrid approaches are proposed such as refining the data first using wavelet transform, then giving to ANFIS whose weights are tuned via PSO [68]. All of them improve forecast accuracy but also take a fair amount of computational time [64].

The AI or machine learning forecasting models are not only limited to wind forecasting but are also commonly used for other resources such as solar PV forecasting. [69]. Artificial Neural Network (ANN) is the most common AI model used for this purpose. In this regard, a detailed analysis of various techniques including Markov chains, Bayesian inference model, ARIMA model, k-Nearest Neighbors (k-NN) algorithm and ANN is presented, and a Multi-Layer Perceptron (MLP) based ANN is shown to outperform the others [70]. Similarly, time series prediction of solar irradiance is performed using Support Vector Machine (SVM) and Extreme Learning Machine (ELM) and are shown to be more accurate than Auto-Regressive (AR), k-NN and persistence models. Among the two AI techniques, SVM is reported to have less Mean Absolute Error (MAE) than ELM [71]. SVM and ANN are used interchangeably in recent literature and produce equivalent results. However, SVM is recommended because it is easier to use than ANN in several ways [72].

Some more advanced but complex techniques sporadically used in literature are regression trees and random forest approach. It is depicted in a research work that regression decision tree approach performs better than classical regression analysis tools and even ANNs and reduces the number of significant factors affecting energy consumption [73]. Sometimes combining the boons of two or more techniques does a better job than a single method. Such a case is presented by forming a hybrid Recurrent Neural Network (RNN) with wavelet activation functions and improvement in the forecast accuracy is shown over simple Back Propagation

(BP) neural network [74]. Another proposed hybrid forecasting model uses GA to optimize the AI model selection and is reported to outperform several advanced AI models [75].

From the literature survey on AI forecast models, we find out that the future contribution lies in developing and testing novel AI approaches. The forecasting models based on ANN have certain drawbacks such as local minimal point, over-fitting problems etc. [66]. These can be overcome by the advanced hybrid AI models like SVM, ELM and ANFIS, that are reported to show good performance as far as the forecast accuracy is concerned [68, 76]. However, the computational requirement of most of these models becomes a hassle, especially if training through an optimization technique is involved [77]. Thus, making them practically inapplicable for real applications such as competitive energy markets, where the bidding process is very rapid with a large number of contenders [17, 29]. Therefore, in such scenarios, accuracy with swiftness of predictions wins the day and computationally expensive methods are not preferred. This work fills the research gap by proposing innovative forecast models based on a modern AI paradigm called Functional Network (FN).

2.1.3 Multi Step Forecasting

The first phase of this research work is one-step ahead forecasting but the main interest is on multi-step forecasting (MSF). This kind of forecasting has wide application in predictive control and dispatch framework in competitive energy markets to help power system owners in planning a profitable strategy for power dispatch [9, 78]. Furthermore, reliability of a power system can be evaluated correctly on the basis of precise power predictions [17]. Therefore, MSF of renewable energy has been an active area of research recently and can be done through different models. The most important of them are Direct, Recursive, DirRec, MIMO and DIRMIMO [79, 80]. A recent review of time series models applied to wind forecasting is presented in [18] and their pros and cons are described. Another recent work has used machine learning methods for six-step ahead prediction and the prediction results are obtained for several case studies [81]. Similarly, two most common schemes, Recursive and Direct are analyzed with ANN model for wind power forecasts [79]. There is not much work found in literature for MSF as compared to single-step forecasting, hence it is still an active domain which demands contribution.

2.1.4 Functional Networks and Their Applications

Functional Networks are a generalized advanced form of neural networks instigated by E. Castillo et al. to overcome many issues present in ANN based models [82]. Since the advent of functional networks, they have been applied to show superior performance as compared to ANNs in many engineering and scientific applications. The applications in which FNs have already been used include nonlinear regression and classification , time series modelling and predictions, and modelling of differential equations [83]. Using FNs, the discovery of adequate transformations in multiple regression problems is presented. The parameters of a heteroscedastic linear model can also be estimated using FNs. Furthermore, the classification of large datasets also becomes possible with the flexible design of FN [84]. The modelling of practical systems such as stress on a beam through differential equations is also simpler using an FN based model. The modelling of such a beam subject to vertical forces in horizontal as well as vertical direction are presented and validated through real-time simulations [82].

The applicability of functional networks has been found in many practical engineering problems. In a navigation satellite, high precision prediction of on-board atomic clocks is needed [85]. A functional network model is used to improve the prediction error of these atomic clocks. Finally, the prediction accuracy is validated through real-time GPS satellite data [86]. Another emerging domain of application for functional network is petroleum engineering where FN based models are used to predict the petroleum reservoir properties. One such work uses an FN based model to predict the porosity and permeability of real site locations of petroleum reservoirs [87]. A general framework for the utility of functional network models for time-series modelling and prediction is discussed in literature [83, 88]. However, it is a novel concept in the field of power systems engineering has not been applied before to address the problem of multi-step wind forecasting.

2.2 Renewable Power Dispatch

The planning of an electric power system based on renewable energy resources depends largely on an optimal economic dispatch. The basic objective of this process is to schedule the committed generating unit outputs so as to meet the load demand at minimum operating cost, while satisfying all unit and system equality and inequality constraints. This makes the Economic Dispatch (ED) problem a large-scale highly constrained nonlinear optimization problem [89].

2.2.1 Recent Trends in Power Dispatch

Due to the challenging nature of power dispatch problem, it has been a center of attraction for researchers over the past years. The orthodox methodology for such complex nonlinear optimization problems are mathematical programming-based schemes such as dynamic programming (DP) and mixed integer programming [90]. In the setting of a smart grid, a decentralized approach is presented in which only local communication among neighbouring agents is required. According to the authors, the most suitable candidate for solving such a problem is a distributed DP method that works on asynchronous communication principles [91]. Another advanced programming technique is mixed integer quadratic programming (MIQP) which is used to solve a dynamic ED problem. The overall formulation is multi-step consisting of a pre-processor and post-processor to enhance the effectiveness of the proposed approach [92].

In recent years, however, due to the popularity of biologically-inspired heuristic optimization algorithms, they have been used widely for ED problems as well. Heuristic optimization techniques are inspired by various biological processes and have been used extensively for economic dispatch algorithms over the past few years [93]. In this regard, a comprehensive review summarizes the application of Differential Evolution Algorithm (DEA) and its advanced variants such as Hybrid DEA and Multi objective DEA on various economic load dispatch problems [94]. A novel hybrid GA and Bacterial Foraging algorithm is proposed which shows the best results in terms of cost minimization as compared to many other evolutionary methods from literature [95]. In another heuristic-based work, a multi objective optimization problem is formulated for maximizing profits and minimizing pollutant emission simultaneously. This problem is solved using Artificial Bee Colony (ABC) algorithm with its search process enhanced by the principles of Tabu Search (TS) algorithm [96].

The evolutionary algorithms are also applied on Combined Heat and Power (CHP) units for optimal dispatch. For instance, two types of ED strategies, i.e., dynamic dispatch and day-ahead dispatch are developed using a hybrid two-stage heuristic method consisting of sequential quadratic programming and Genetic Algorithm (GA) [97]. A significant contribution in the context of hybrid evolutionary optimization methods is an integration of three such algorithms to solve the problem of ED for a multi-generation system [98]. Another novel concept is the minimization of overall operating costs by optimizing the demand response. In such a work, the optimal dispatch problem is formulated taking into account the solar, wind and load forecast errors while GA is used as the load optimization algorithm. This work recommends using a more suitable power forecasting model which comes in the scope of the proposed work [99]. However, the main drawbacks of heuristic approaches include the possibility of sub-optimal solution and the exponential increase in computational complexity on increasing the size of problem such as the number of generation and customer units involved in economic dispatch [100].

Another important development in this regard is to consider the dispatch problem in a control framework using model predictive control. This approach is commonly known in literature as predictive dispatch [28]. In addition to economic dispatch, the scope of the problem is increased in a more practical manner taking into account the environmental effects such as reduction in CO_2 emissions. Such a problem is usually formulated as a multi-objective optimization problem with conflicting objectives and termed as economic/environmental power dispatch [94, 100].

2.2.2 Forecast-Based Dispatch

This type of framework is used to make dispatch decision based on the estimation of future events and values of parameters. Thus it effectively takes into account the RE source and load forecast error information for economic dispatch problems. In a review of predictive power management strategies, the importance of load forecasting, optimal sizing of power system components and renewable power prediction is elaborated while remarking in the end that economic dispatch can be made highly efficient with accurate forecasting of RE resources [101]. Among the predictive dispatch mechanisms, Model Predictive Control (MPC) framework is the most widely accepted method in literature.

Model predictive control is an optimal control method based on the principles of receding horizon philosophy. It is able to control the dynamics of the system by converting an infinite long open-loop optimization into a limited long closed-loop optimization at each sample time [102]. The main advantages of MPC are its ability to tackle large complex optimization problems, systematic handling of constraints, and prediction of performance over the future horizon, and effective utilization of future forecasted information, make it theoretically a perfect real-time optimal control paradigm [103]. Continuing on MPC, a Unit Commitment (UC) and ED combined problem is formulated in the presence of wind energy generation only. The stochastic nature of wind is compensated by developing an ARIMA forecasting model. Considering the highly nonlinear and non-convex nature of UC/ED problem, swarm optimization is used with MPC since both these methods complement each other and produce good results [103].

An excellent work in this regard makes use of MPC framework which can take into consideration the RE resource forecasts to solve a multi objective optimization problem for the minimization of generation costs and emissions. The modeling of forecast error is performed via normal distribution as white noise [100]. In another paper, a practical model of a microgrid is considered and optimized in many aspects including UC, ED, energy storage and grid interaction. The model is developed using an MPC control framework while the optimization problem is solved using Mixed Integer Linear Programming (MILP). The compensation for forecast errors and other inevitable disturbances has also been incorporated into the MPC framework. The renewable power forecast model is based on Support Vector Machine (SVM) [26]. An article about Combined Cooling, Heating and Power (CCHP) system gives the idea of utilizing the information of prediction error in RE resources and load via developing a two-stage MPC based dispatch algorithm for operation cost minimization. The first step is the rolling horizon part while the second step is the feedback correction to balance the difference between predicted and actual values. For wind and solar PV generation forecasting, a Kalman filter based algorithm is used in this work [102].

In the context of wind power dispatchability for a BESS connected microgrid, a stochastic MPC controller is developed that can incorporate wind power forecasts with non-Gaussian uncertainties via a probabilistic prediction model [104]. A recent work develops a framework for assessing the value of forecast-based dispatch on islanded microgrid operation costs. A predictive dispatch algorithm is developed for this purpose but a real model for load and RE resource forecasting is not considered. On the contrary, the reference forecasted values are taken from a case study and then different scenarios are synthesized using that reference [28]. However, all these works reiterate that forecast-based dispatch strategies are very effective in bringing down running costs of a microgrid and optimizing various operational and economic aspects [26, 102]. Hence developing real forecasting models for RE sources and loads to be used with predictive dispatch strategies is well-supported in the light of literature.

2.2.3 Analysis of Forecasting in Dispatch

A major contribution of this thesis work is the analysis of forecast error on dispatch in terms of cost-benefit analysis. Similar attempts can be seen in very recent works. In a detailed analysis, the impact of wind power forecast and its improvement is quantified through a UC problem formulation in terms of annual cost reduction and related cost factors. The reliability of the system is also examined in multiple scenarios with wind forecast improvements. NWP based ready-made forecast models are used for wind forecasting [9]. Another work has used wind power probabilistic quantile-based forecasting along with demand dispatch to estimate the operating reserve requirements for efficient operation of energy markets in UC and ED [17]. Various statistical descriptions of wind power forecast error are discussed in [19] and a novel statistical model is proposed. The model is assessed through a probabilistic reserve sizing problem to study the effect of forecast error on system size and reliability of the output.

A recent work has presented the forecast-based strategy as an alternative to minimize the operational costs for off-grid microgrids. A relationship has been made to show how the load and renewable power forecast quality can bring about cost savings. The authors also show that forecast-based strategy is able to improve the share of RE generation by adequate sizing of microgrid components [28]. In another research work, the influence of solar and wind forecast uncertainties is analyzed using the benchmark persistence model for forecasts. The effect is quantified in terms of renewable generation absorption improvement in a microgrid [99]. A very important article from the perspective of energy market outcomes is published for the European electricity market where a policy has been devised to make the aggregate wind forecasts public. According to the article, the study on the impact of wind forecasts can potentially affect energy and reserve market pricing, profits of participating power producers and the social welfare at large [29]. This realization supports our claim for the vitality of the current study and why it is important for social and economic benefits of the society and industry.

2.3 Summary of the Literature Gaps

The literature review reveals that there are missing links in both parts of the literature, i.e., the development of new forecast models as well as their application in power dispatch framework.

Various kinds of existing forecasting techniques are surveyed, however, most of them are easily beaten by the intelligent forecasting models. The numerical weather forecast models are still accurate for many weather variables but their cost is not affordable for small-scale projects like power system producers. There are some problems with basic intelligent forecast models like ANN which makes them less accurate as compared to advanced AI and hybrid models. These hybrid models tend to be extremely computationally extensive, especially if an iterative training scheme is involved such as evolutionary algorithms. The proposed Functional Network multi-step forecast model fills this research gap as it is more accurate than conventional ANN with less computational expense than advanced hybrid models and hence affordable for power industry.

The second missing link is found with the analysis of forecast error on power dispatch using wind power and market price information from real forecasting models. Most of the works in literature address the forecasting problem and the efficient economic dispatch problem independently. The former problem is dealt by only developing forecasting models and assessing their forecast accuracies while the latter focuses on the dispatch optimization problem and uses some assumption about forecast error or a pre-developed forecasting model [27]. Nowadays, the integration of both these domains is a trending phenomenon in the manner that the impact of forecast error models is studied in terms of power system economics. The proposed work also aims at not only developing novel multi-step forecast models but also studying the interconnection of accurate power forecasting with profitable economic dispatch and thus makes an effort to contribute innovatively in this emerging field.

CHAPTER 3

DEVELOPMENT OF FORECASTING MODELS

This chapter provides an introduction to the forecasting of wind as a physical quantity. The most important aspect of wind energy is the speed as it is related to the power output of a wind turbine through a nonlinear cubic relationship. Hence accurate forecasting of wind speed ensures accurate wind power forecasting. This chapter first describes the development of a wind speed forecasting model using a basic AI technique, the Artificial Neural Network (ANN), which will then be used as a basis for comparing the advanced proposed AI models. Then the multi-step forecasting (MSF) schemes used throughout this work are described. Then the wind power curve is explained followed by the description of case study databases and performance indices used for forecasting analysis. Finally, the results of the developed ANN forecast models are given for single step and MSF using the case studies.

3.1 Artificial Neural Network Forecasting Model

The problem of wind speed (v) forecasting is formulated by composing a wind speed time series $[v_1, \ldots, v_N]$ using N historical observations, that is used to forecast the wind speed for H steps (hours) ahead. The forecasted time-series is given as $[v_{N+1}, \ldots, v_{N+H}]$, where $H > 1$ denotes the absolute forecasting horizon. The basis of any forecasting strategy is that the predicted speeds $\hat{v}$ can be represented as a function of past values (v).

Numerous Artificial Intelligence (AI) methods have been employed by researchers for wind forecasting problem. The most popular of them include Artificial Neural Networks (ANNs), Support Vector Machine (SVM) and Adaptive Neuro-Fuzzy Inference System (ANFIS). In this chapter, the development of ANN forecast model is described. The type of ANN used in this work for MSF is called Nonlinear Auto-Regressive Neural Network (NARNN). The architecture of such a network is Multilayer Feedforward Neural Network (MFNN) which is typically arranged in three or more layers. These consist of an input layer, an output layer and hidden layers in between. It has been observed that only one hidden layer is enough for most applications provided it has adequate number of neurons [68]. The hidden layer consists of neurons (n) which sum up the all input signals (d) along with their respective weights to produce an activation pattern. The number of neurons can be taken as the integer number close to $log(K)$, where K is the number of training vectors [62]. In this study, the number of training vectors is based on calendar year data with 8760 samples, hence $n = 4$. Moreover, it was

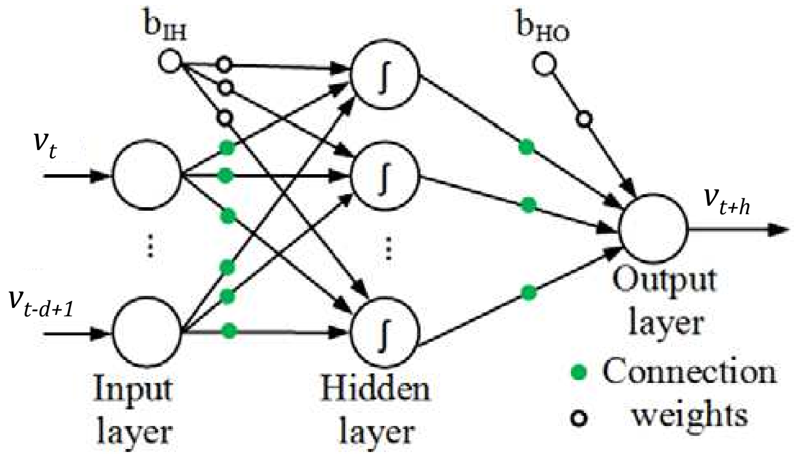

Figure 3.1: A typical BP ANN structure for time series forecasting.

also observed that varying it did not have a significant effect.

The type of neural network is defined by its training algorithm which in this case is the Back Propagation (BP) network. This proposed structure of ANN is depicted in Figure 3.1. In BP, the activation signal of each hidden layer neuron is the weighted sum of the inputs. The output of j^{th} neuron of hidden layer is given mathematically as,

$$nn_j = \sum_{i=0}^{d} w_{ij} v_i \quad (\forall i = 0, 1, \ldots, d; \forall j = 1, 2, \ldots, n) \tag{3.1}$$

where, w_{ij} is the connection weight from input node i to hidden node j, v_i is the input with v_0 being the bias b_{IH}(with weight $w_{0j} = 1$).

The activation value of each neuron from (3.1) is passed through an activation function. The most common activation function is the sigmoid, say $f_H(x)$. Hence the output z of j^{th} neuron is found to be,

$$z_j = f_H(nn_j) \quad (\forall j = 1, 2, \ldots, n) \tag{3.2}$$

These outputs are fed to the single neuron of the output layer to produce the final output as,

$$\hat{v} = f_O(\sum_{j=0}^{n} w_{jk} z_j) \quad (\forall j = 0, 1, 2, \ldots, n) \tag{3.3}$$

where, f_O is a line function used for output layer activation, w_{jk} is the connection weight from hidden node j to output node k (here $k = 1$) and z_0 is the bias b_{HO}(with weight $w_{0k} = 1$). During the training phase, all the biases and weights are assigned random values initially, then the obtained output from (3.3) is compared with the already available actual measured value of the predicted time-stamp $(t + h)$ to compute the global error (E) as,

$$E = \frac{1}{2} \sum (\hat{v}_{t+h} - v_{t+h})^2 \tag{3.4}$$

This error has to be minimized using an optimization algorithm. Traditionally, back propagation is optimized using least squares optimization [105] , but Levenberg-Marquardt (LM) algorithm is employed in our work because it produces quite accurate results at a fast speed [68, 62, 106].

3.2 Multi-Step Forecasting Schemes

Wind speed (v) historical data is used to forecast the wind speed for H steps (hours) ahead, given as $[v_{N+1}, \ldots, v_{N+H}]$. The basis of any forecasting strategy is that the predicted speeds $\hat{v}$ can be represented as a function of past values (v). The mathematical formulation of the forecasting mechanisms used in this paper described in the following subsections.

3.2.1 Recursive Forecasting

In this forecasting method, first a single model f is trained to perform a *one-step ahead* forecast, i.e.

$$v_{t+1} = F(v_t, \ldots, v_{t-d+1}) + w \tag{3.5}$$

where, $t \in [d, \ldots, N-1]$, d is the number of previous inputs of the series and w is the bias. For H step ahead forecasting, the first step is predicted by applying the model in (3.5). Afterwards, the forecasted value is included as the latest entry of the input series to predict the next step using the same trained model from (3.5). This procedure is repeated for the entire forecasting horizon. Mathematically, recursive forecasting can be defined as a piecewise function with respect to h and d as follows:

$$\hat{v}_{N+h} = \begin{cases} F(v_N, \ldots, v_{N-d+1}) & \text{if } h = 1 \\ \\ F(\hat{v}_{N+h-1}, \ldots, v_N, \ldots, v_{N-d+h}) & \text{if } h \in [2, \ldots, d] \\ \\ F(\hat{v}_{N+h-1}, \ldots, \hat{v}_{N-d+h}) & \text{if } h \in [d+1, ..., H] \end{cases} \tag{3.6}$$

For very long term forecasts, recursive mechanism may be potentially inaccurate because of the accumulation of forecast error with each forecasted value [18, 80]. Training of the neural network is performed only once for the recursive method of forecasting using one-step ahead setting, i.e., target output being the next hour value (v_{t+1}) from the known training set.

3.2.2 Direct Forecasting

The direct forecasting methodology is based on the principle of forecasting each step independently from the others. Hence a separate function model F_h is trained for each forecasting horizon (h), with the target output as the $h^t h$ future value (v_{t+h}) from the training dataset. Each of them is given as,

$$v_{t+h} = F_h(v_t, \ldots, v_{t-d+1}) + w \tag{3.7}$$

where, $t \in [d, \ldots, N - H]$ and $h \in [1, \ldots, H]$. A forecast is performed for the h^{th} step without including any previous predicted value but only considering d previous values using the learned model from (3.7) as,

$$\hat{v}_{N+h} = F_h(v_N, \ldots, v_{N-d+1}) \tag{3.8}$$

This implies that the direct strategy is immune to prediction error accumulation, however, it is more computationally expensive as compared to the recursive method. In recursive scheme, model training is performed only once for the first step, then the forecasted values for each step are included in the input vector for following forecasts. On the contrary, in direct scheme, model training is needed for every forecast step with same input vector but h^{th} following value as the target, hence H models are learned. Due to the independent choice of targets, it may also yield uncorrelated results for MSF in some cases [18, 80].

3.2.3 Dir-Rec Forecasting

A hybrid of the Direct and Recursive strategies called the Dir-Rec strategy is based on the principle of combining the good aspects of both these methods. In this forecasting mechanism, different forecasting models F_h are computed for each forecasting horizon (h), like the direct method. However, each forecasted step is included as the latest entry of the input series for next step prediction, which is consistent with the recursive method. It should be noted here that in doing so, the d increases for each step of prediction. Mathematically, the training function of Dir-Rec model is given as,

$$v_{t+h} = F_h(v_{t+h-1}, \ldots, v_{t-d+1}) + w \tag{3.9}$$

where, $t \in [d, \ldots, N-H]$ and $h \in [1, \ldots, H]$. In this manner, the H learned models for each forecasting horizon can be used to obtain the forecasts as follows:

$$\hat{v}_{N+h} = \begin{cases} F_h(v_N, \ldots, v_{N-d+1}) & \text{if } h = 1 \\ \\ F_h(\hat{v}_{N+h-1}, \ldots, v_N, \ldots, v_{N-d+1}) & \text{if } h \in [2, \ldots, H] \end{cases} \quad (3.10)$$

This strategy is usually anticipated to perform better than the direct and recursive methods but the result depends on the nature of data in the time series [107]. This technique has been probed for only a few cases by researchers, so this work further evaluates this scheme for the selected problem [80].

3.3 Wind Power Calculation

Once the wind speed is predicted, it can be used to estimate output power of wind turbine of rated capacity (P_r) using the typical power curve of a wind turbine as shown in Figure 3.2 [108]. The cut-in speed (v_{ci}) is the starting threshold of a wind turbine and is typically between $3 - 5m/s$. There is a limit to every wind generator output, which is called the rated power output (P_r) and the wind speed at which it is reached is called the rated output wind speed (v_r). Most wind turbines are designed so that the rated wind speed typically lies somewhere between $12-17m/s$. At higher wind speeds, the design of the turbine is arranged to limit the power to this maximum level usually by adjusting the blade angles so as to to keep the power at the constant level or some other technique [108].

At speeds between the v_{ci} and v_r, the power output is expressed by a non-linear curve. Finally, there is a maximum limit called cut-out speed (v_{co}) (around

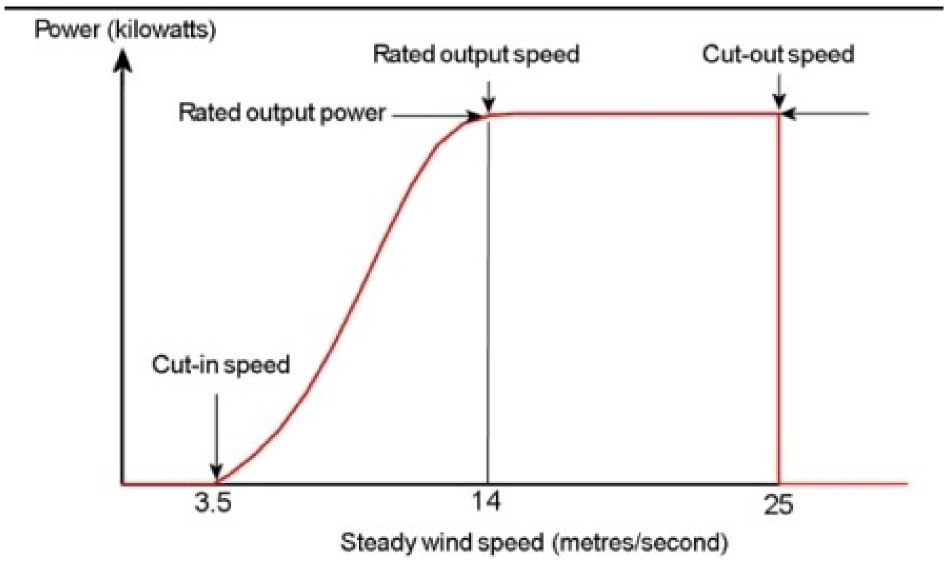

Figure 3.2: Typical power curve of a wind turbine.

$25m/s$), after which there is a risk if damage to wind turbine, hence a braking system is employed and the power output is forced to zero [108]. This phenomenon is depicted in Figure 3.2 and mathematically it can be expressed as given in (3.11) [109]:

$$P(kW) = \begin{cases} 0 & v < v_{ci} \\ \frac{1}{2} k C_p \rho v^3 \pi \frac{d^2}{4} & v_{ci} \leq v \leq v_r \\ P_r & v_r \leq v \leq v_{co} \\ 0 & v > v_{co} \end{cases} \tag{3.11}$$

where,

$v(m/s)$	:	Wind speed of particular hour
$v_{ci}(m/s)$	:	Cut in wind speed
$v_{co}(m/s)$	:	Cut out wind speed
$v_r(m/s)$	:	Rated wind speed
$P(kW)$	:	Output power of that particular hour
$P_r(kW)$	:	Rated power of wind turbine
k	:	Conversion constant for power output in kW (k = 0.000133)
C_p	:	Maximum power coefficient, ranging from 0.25 to 0.45 (theoretical maximum = 0.59)
$\rho(kg/m^3)$	:	Air density
$d(m)$	:	Diameter (twice of blade length)

3.4 Case Studies

The performance of the proposed techniques is assessed via case studies using wind speed data from real sites, while performance is compared with a benchmark model in terms of standard indices, as explained in the following subsections:

3.4.1 Databases

Two sets of data from different sites are considered in the form of hourly wind speed recorded for one calendar year 2014. The sites for wind speed data are

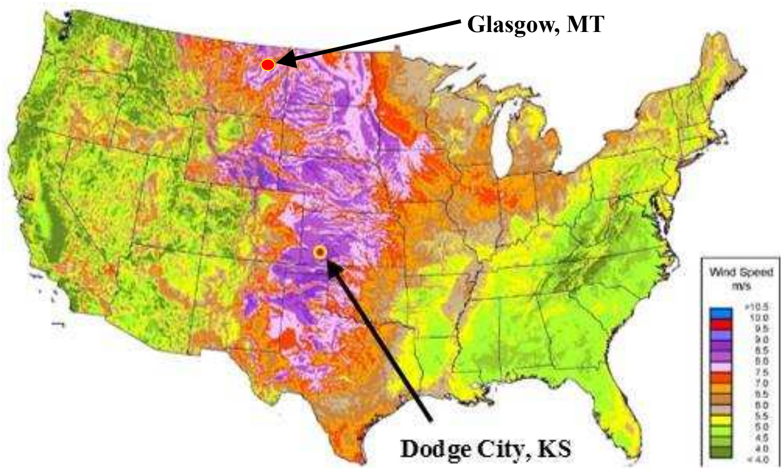

Figure 3.3: Wind speed map of the US showing sites under study (recorded at 30m).

chosen on the basis of feasibility for wind generation, i.e. having enough wind speeds for being able to run small wind turbines at the least. The targeted region is the Great Planes region, USA which has good average wind speeds and hence is suitable for wind power generation. A wind speed map is shown in Figure 3.3 where the approx. locations of data collection in the states of *Montana (MT)* and *Kansas (KS)* are shown with red markings while the region of interest is shown by the vertical strip in the middle [110].

Dataset-1 represents wind speed profile recorded by a weather station run by *Agrimet* in the region of *Glasgow, MT* [111]. This area has an average wind speed of about 5.5mph which is only suitable for small wind turbines. *Dataset-2* is collected from *Iowa Environmental Mesonet (IEM)* which collects environmental data and airport data from several networks [112]. Wind speed data of a windy region is sought and the selected site is *Dodge City, Kansas*. The available data is recorded at *Dodge City Municipal Airport* and the average wind speed for this area is quite high i.e. about 12-13mph. Table 3.1 lists down the average and maximum wind speeds for both regions over a period of six years.

Table 3.1: Six-year Average and Max. Wind Speeds of Study Sites

Years	Average wind speed (m/s)		Max wind speed (m/s)	
	Dataset-1	Dataset-2	Dataset-1	Dataset-2
2010	2.36	5.49	13.34	19.04
2011	2.61	5.88	13.07	20.07
2012	2.47	5.43	12.52	19.04
2013	2.38	5.72	11.70	21.10
2014	2.46	5.86	12.26	19.54
2015	2.37	5.52	11.59	16.45

The historical wind data is divided into three parts randomly; 80% for training, 10% for validation and 10% for testing the neural network model. For training purpose, the data is arranged in the form of time series with d hours as input and the next hour wind speed as target used to calculate the forecast error. In this way, random sets of input-target data from one year profile are picked up for training the network.

3.4.2 Persistence - The Benchmark Model

The persistence model is a widely-used benchmark for time series and is based on the assumption that the predicted variable (wind speed) will remain the same as the measured value at the time when the prediction is made. In other words, it relates the present measured value (v_N) and the future predicted value (v_{N+h}) via a linear equation as follows:

$$\hat{v}_{N+h} = v_N \tag{3.12}$$

where, N is the length of time-series and h is the forecasted step.

This means that the persistence model requires the measurement of only one present value to predict the future value as the same. Then, when the actual measurement is available, it predicts the preceding hour and so on. Considering the nature of wind speed, this model often proves to be more accurate than many complex techniques, especially for very-short term forecasting [21], hence performing better than persistence benchmark is considered an important feature for the effectiveness of forecasting method. To evaluate the performance of the proposed model, the same metrics are applied on the benchmark persistence model.

3.4.3 Performance Indices

Accuracy of forecasting models is assessed based on forecast error (e_k) which is the difference between measured wind speed (v) and forecasted wind speed ($\hat{v}$) for k^{th} forecast,

$$e_k = v_{N+h} - \hat{v}_{N+h} \tag{3.13}$$

The performance metrics used to evaluate the prediction accuracy in this study are Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Symmetric Mean Absolute Percentage Error (SMAPE). If N is the total number of forecasts made, then these errors can be computed as follows:

$$MAE = \frac{1}{N}\sum_{k=1}^{N}|e_k| \tag{3.14}$$

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{N}\sum_{k=1}^{N}{e_k}^2} \tag{3.15}$$

$$SMAPE = \frac{1}{N}\sum_{k=1}^{N}\frac{|e_k|}{|v|+|\hat{v}|}\% \tag{3.16}$$

3.5 Results and Discussions

3.5.1 Single-Step Forecasting

This historical wind data is divided into three parts randomly; 80% for training, 10% for validation and 10% for testing the neural network model. For training purpose, the data is arranged in the form of time series with d hours as input and the next hour wind speed as target used to calculate the error through (3.13). In this way, random sets of input-target data from one year profile are picked up for training the network.

Dataset-1 from *Glasgow, MT* is considered first and neural network is trained using data of 2014 while testing of the trained network is performed using one-week data of 2015 (1-7 Jan). A smaller testing data set is used as this is just a preliminary test for single-step forecasting, and the length of the testing set will increase up to three months for the next set of results. Error analysis for the said period is compiled in Table 3.2. Three cases have been tested while varying the input length (d). For each case, the developed NN model named NARNN is compared with persistence benchmark in terms of MAE, SMAPE and RMSE. It can be observed that, in all cases, NARNN performs better than Persistence with a maximum improvement of 0.02 MAE, 1.53% SMAPE and 0.04 RMSE. Slight improvement is recorded with increasing input vector size but this trend is not followed when the same model is tested on other periods of the year. Hence varying the number of time series inputs has no significant effect on the error performance.

Table 3.2: Single Step Forecasting for Dataset-1

Errors	Persistence	NARNN		
		n=4, d=2	n=4, d=4	n=4, d=6
MAE	0.6168	0.5948	0.5895	0.5826
RMSE	0.8154	0.7755	0.7619	0.7542
SMAPE	16.9567	15.5101	15.4634	15.2461

In addition to error analysis, a pictorial idea about the forecasting accuracy is given in Figure 3.4 where the measured and forecasted wind speed profiles are plotted for a random day (1st Jan 2015) of the testing set. This is just a small representative portion of the whole testing set shown for the purpose of visibility, otherwise for longer dataset, the plot would look cluttered. It can be observed that the predicted output follows the actual wind speed in quite good manner, however, there is a lag of one time period which is expected due to autoregressive nature of the network.

Dataset-2 from *Dodge City, KS* is considered while training and testing of neural network is performed in the same way as *Dataset-1*. Similarly, error analysis

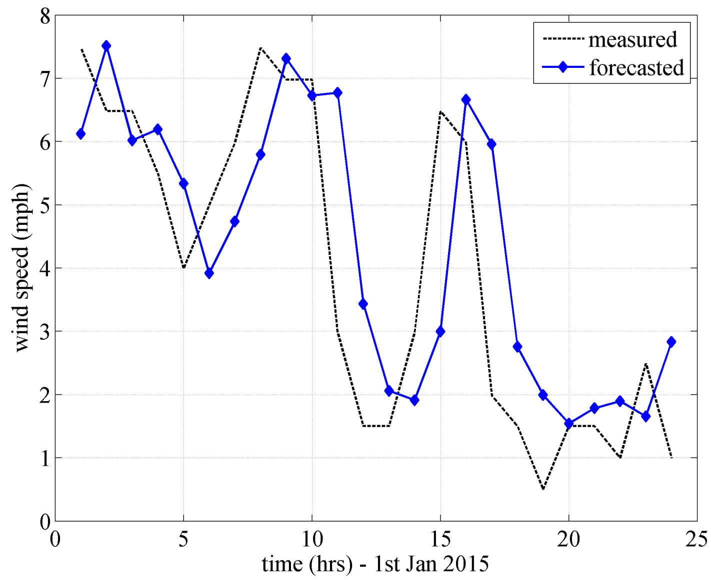

Figure 3.4: Comparison 24h forecast Glasgow, MT.

for *Dataset-2* is compiled in Table 3.3. It can be observed that, in all cases, again NARNN shows improvement of 0.04 MAE, 0.9% SMAPE and 0.07 RMSE over persistence. The values of MAE and RMSE are almost double to that of *Dataset-1* which was expected here due to higher wind speeds for *Dataset-2* as can be noted from Table 3.1. However, the improvement in these indices over persistence is also double or even more as compared to *Dataset-1*.

Table 3.3: Single Step Forecasting for Dataset-2

Errors	Persistence	NARNN		
		n=4, d=2	n=4, d=4	n=4, d=6
MAE	1.2454	1.1994	1.2039	1.2002
RMSE	1.7721	1.6982	1.7039	1.6999
SMAPE	16.8639	15.9711	16.0402	16.1440

The insignificance of varying the number of time series inputs (d) on the error

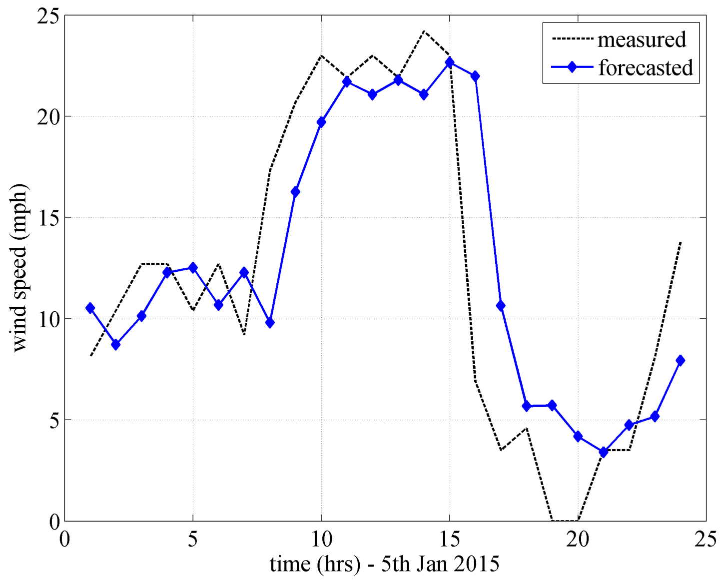

Figure 3.5: Comparison 24h forecast Dodge City, KS.

performance can be observed very clearly since the error either increases with increasing d in case of SMAPE, or follows no particular trend in case of MAE and RMSE. A graphical depiction of the developed forecast model for *Dataset-2* is shown in Figure 3.5 as a 24-h wind speed profile for a random day (5th Jan 2015) of the testing set. Despite abrupt variations in the actual wind speed, the forecast remains reasonably close to it which represents the robustness of the developed model in the face of sudden disturbances.

3.5.2 Multi-Step Forecasting

Multi-step forecasting (MSF) is carried on *Dataset-2* only which represents wind data from *Dodge City, Kansas*. The training dataset comprises of wind speed values from calendar year 2014 while testing dataset is based on three months of 2015 (Jan-March). Detailed error analysis for the said period is performed in terms of three error indices as mentioned before, i.e., MAE, SMAPE and RMSE. The simulation results are summarized in Table 3.4. As it can be observed, all three forecasting methods, i.e., Direct, Recursive and Dir-Rec are compared with benchmark persistence model for one to six steps ahead prediction. In terms of all performance indices, these techniques outperform the persistence benchmark. The improvement becomes more significant at large forecast horizons.

Quantitatively, the direct method shows an improvement of 0.02 m/s in MAE, 0.05 m/s in RMSE and 1.54% in SMAPE over persistence at step-1 which increases to 0.31 m/s in MAE, 0.53 m/s in RMSE and 4.05% in SMAPE at step-6. Similarly, the improvement of recursive method over persistence rises from 0.02 m/s to 0.36 m/s in MAE, from 0.05 m/s to 0.51 m/s in RMSE and from 1.54% to 4.44% in SMAPE as the forecast horizon goes from step-1 to step-6. For Dir-Rec method, this difference over persistence improves from 0.01 m/s to 0.36 m/s in MAE, from 0.05 m/s to 0.53 m/s in RMSE and from 1.52% to 4.46% in SMAPE at the whole range of forecast horizons. Comparing the performance of the strategies among themselves, it can be observed that there is very small difference in accuracy in terms of results from Table 3.4 and the improvement over persistence given in the preceding paragraph. This small deviation can be specific to the dataset under consideration and it may vary from this pattern for another case study.

In addition to tabular error analysis, the pictorial depiction of MSF scenario is provided in Figures 3.6, 3.7 and 3.8. Here each of the errors, i.e. MAE, SMAPE and RMSE are plotted against the six forecasting steps. In each case, it is clear

Table 3.4: Artificial Neural Network MSF Error Analysis

Errors	Steps	Persistence	Direct	Recursive	DirRec
MAE	1-step	1.08	1.06	1.06	1.06
	2-step	1.44	1.37	1.36	1.36
	3-step	1.76	1.63	1.61	1.60
	4-step	1.99	1.80	1.79	1.79
	5-step	2.22	2.00	1.95	1.94
	6-step	2.43	2.12	2.07	2.07
RMSE	1-step	1.47	1.42	1.42	1.42
	2-step	1.95	1.84	1.84	1.84
	3-step	2.37	2.18	2.17	2.16
	4-step	2.70	2.40	2.41	2.41
	5-step	3.02	2.62	2.62	2.60
	6-step	3.28	2.75	2.76	2.75
SMAPE	1-step	13.96	12.42	12.42	12.42
	2-step	17.34	15.05	14.94	14.88
	3-step	19.82	16.98	16.79	16.74
	4-step	21.53	18.29	18.13	18.10
	5-step	23.20	19.74	19.30	19.27
	6-step	24.75	20.70	20.30	20.28

that the error increases quite significantly with each step ahead forecast. However, the error value is more in persistence method as compared to the developed MSF schemes as was observed previously. The errors of DirRec method are smaller than those of direct and recursive method but the increment pattern is approximately the same. Another interesting aspect to note here is the increment ratio, i.e., the measure of increment in a particular type of error along with the forecast horizon. In all types of error, it can be observed that the increment pattern for persistence and proposed techniques is quite different. The results for increment ratio are given in Table 3.5 for all error indices. It can be seen that the increment ratio for persistence is much more as compared to all other methods which shows the effectiveness of these methods for large forecasting horizons.

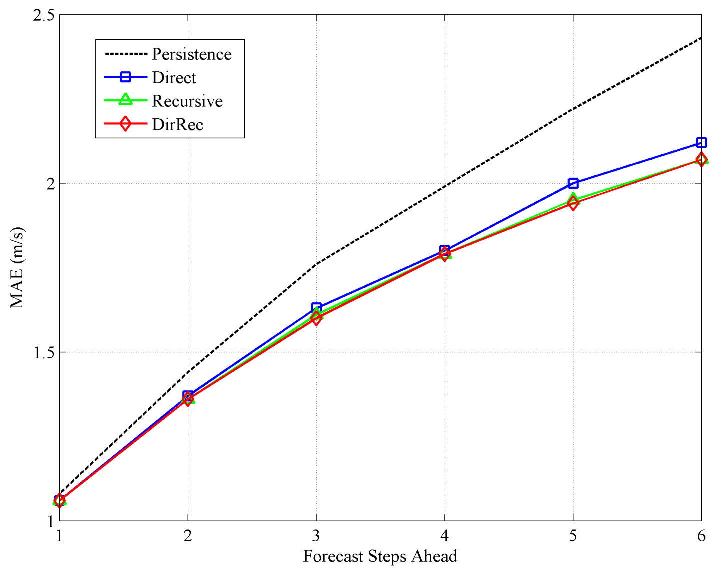

Figure 3.6: Variation in MAE for all forecast models over prediction horizon.

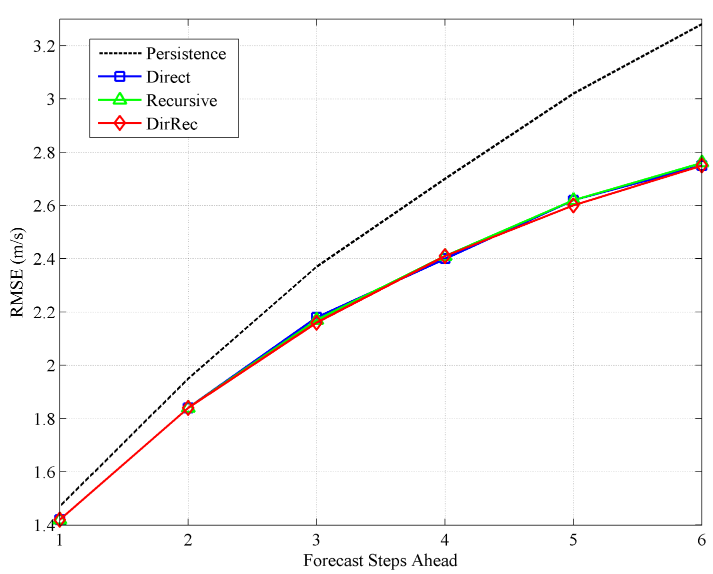

Figure 3.7: Variation in RMSE for all forecast models over prediction horizon.

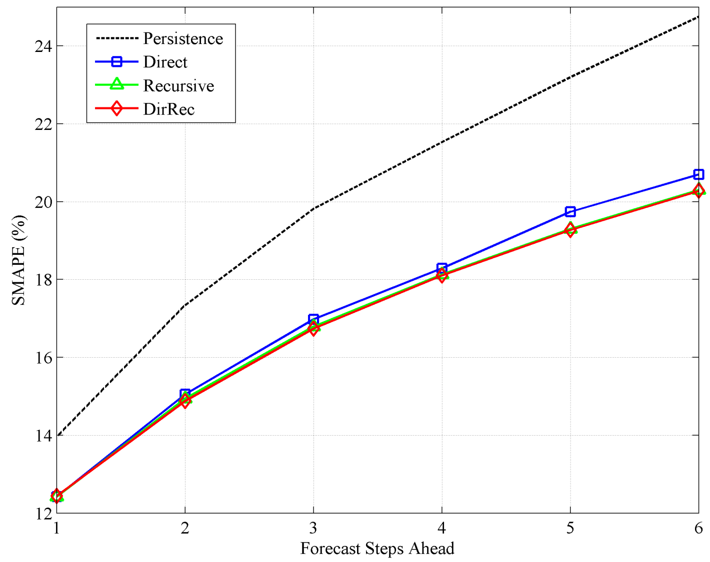

Figure 3.8: Variation in SMAPE for all forecast models over prediction horizon.

Table 3.5: Increment ratio (IR) of errors for six steps

Errors	Persistence	Direct	Recursive	DirRec
IR-MAE	1.35	1.06	1.01	1.00
IR-SMAPE	10.79	8.28	7.89	7.84
IR-RMSE	1.81	1.33	1.35	1.33

Another view to the obtained results is provided in Figure 3.9 using a bar-graph representation of each method on every step of prediction in terms of percentage error, i.e., SMAPE, since it is the most universal. This graph shows the superiority of the proposed MSF methods over persistence benchmark. Also, this concept is reiterated again that these methods not only perform better than persistence for each step, but also error difference keeps increasing with the forecast horizon, which is clear from the prominent height difference in bars for persistence as compared to both of others in every next step. Another minor conclusion that can be drawn from here is that the difference between recursive and the other two schemes' RMSE reduces gradually with increasing forecast horizon due to the use of forecasted values for higher step prediction in the recursive method which causes superposition of prediction error.

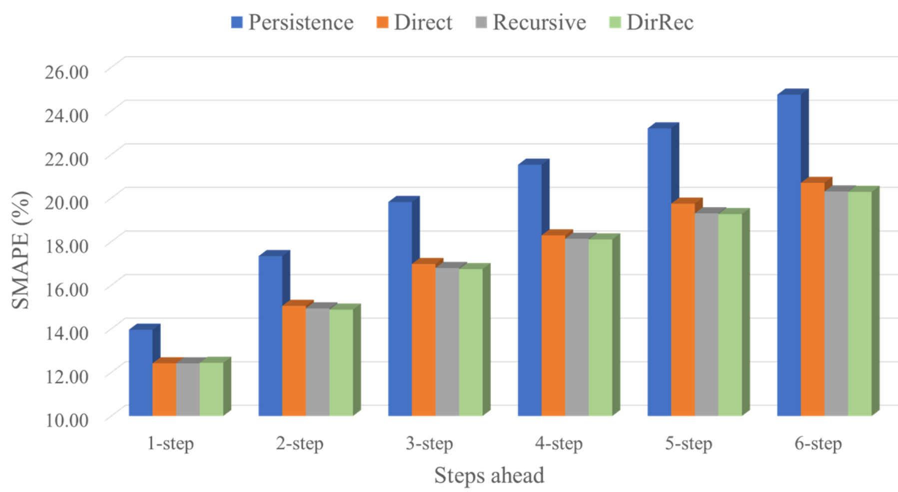

Figure 3.9: Improvement of Developed Forecast Models over Persistence - SMAPE Bar Graph.

CHAPTER 4

FUNCTIONAL NETWORK FORECASTING MODEL

The forecasting models presented in the previous chapter are based on ANN with certain drawbacks such as local minimal point, over-fitting problems etc. [66]. These can be overcome by the advanced hybrid AI models like SVM, ELM and ANFIS, that are reported to show good performance as far as the forecast accuracy is concerned [68, 76]. However, the computational requirement of most of these models becomes a hassle, especially if training through an optimization technique is involved [77]. Thus, making them practically inapplicable for real applications such as competitive energy markets, where the bidding process is very rapid with a large number of contenders [17, 29]. Therefore, in such scenarios, accuracy with swiftness of predictions wins the day and computationally expensive methods are not preferred. This work fills the research gap by proposing innovative forecast models based on a modern AI paradigm called Functional Network (FN).

A step-by-step procedure for the development of wind forecast models with the proposed scheme is illustrated for better understanding. Three state-of-the-art MSF mechanisms, namely, recursive, direct, and DirRec are developed for six steps ahead forecasts. A benchmark persistence model for time series is used to evaluate the performance of the FN model with all three techniques, while they are also compared among each other to draw conclusions about their benefits and applicability. Forecast accuracy is gauged on the basis of standard error indices. The efficacy of the proposed FN based approach for wind forecasting is further validated by drafting a comparison with a benchmark nave model and standard ANN model. Wind data from a real location is used for all simulations. The significant improvement in forecast accuracy with low computational burden verifies the effectiveness and applicability of the proposed FN model for the wind forecasting problem in practical situations.

In the light of the above discussion, the aim of this chapter can be briefly stated as:

To develop and analyze forecasting models using functional networks - a novel AI paradigm - for multi-step wind forecasting and compare them with existing standard forecasting models to help the wind power producers in devising quick and profitable power system planning and dispatch strategies.

4.1 Functional Network - An Overview

Functional Networks are a generalized advanced form of neural networks first developed by E. Castillo et al. to overcome many issues present in ANN based models [82]. Since the advent of functional networks, they have been applied to show superior performance as compared to ANNs in many engineering and scientific applications [83]. The applications in which FNs have already been used include nonlinear regression and classification [84], time series modelling and predictions [88], and differential equations modelling like beam stress modelling [82]. The applicability of functional has been found in many practical engineering problems like error prediction of navigation satellite clock [86] and for model parameter predictions in petroleum reservoir applications [87]. A general framework for the utility of functional network models for time-series modelling and prediction is discussed in literature [83, 88]. However, it is a novel concept in the field of power systems engineering has not been applied before to address the problem of multi-step wind forecasting.

Functional Networks (FN) are a generalized form of neural networks that can be applied to show superior performance as compared to ANNs in many engineering applications. Some of the advantages of FNs are listed below:

- ANN models have generalized topologies, whereas, the topology design of functional networks can be derived from the analytical structure of the problem.
- In functional networks, the neural functions themselves are learned from the data, as opposed to neural networks, where function coefficients and connection

weights are trained for given neural functions.

- The forms of all neural functions in ANNs are identical, i.e., the weighted sum of inputs. In contrast, the neural functions can have various multi-dimensional structures chosen from one or more basis families.

- In functional networks, the outputs of multiple neurons can be forced to coincide using an intermediate layer, that can simplify the initial network, which is not possible in classical neural networks.

4.2 Development of Forecasting Model with Functional Network

The development of a typical functional network begins with a problem-driven network topology design, followed by parametric learning of neural functions, optimal model selection and finally, testing of the developed model.

4.2.1 Parametric Learning

As already discussed, the topology of a functional network is usually problem-driven, i.e., it is based on functional equations derived from the known problem structure, leading to a unique design of functional network. However, assuming we have a wind speed time series with no known information or analytical structure, just the historical data. In such cases, the neural functions are approximated based on the given time-series data. This process is called *Approximate Learning*, as opposed to *Exact Learning* which is performed using the functions that are solutions of the functional equations when dealing with a system with known analytical structure.

To model the wind speed time series using functional networks, a set of embedding inputs $(v_N, \ldots, v_{N-d+1})$ and required output steps to be predicted are specified in the form of approximate functions, just like the training phase in neural networks. This can be represented by (4.1):

$$\hat{v}_{N+h} = F_h(v_N, \ldots, v_{N-d+1}) = \sum_{i=1}^{r} c_i f_i(v_N, \ldots, v_{N-d+1}) \tag{4.1}$$

where, c_i are model parameters obtained for each neural function after training. N is the sample size and h is the prediction horizon. The functions $f_i(v_N, \ldots, v_{N-d+1})$ can be represented by a functional basis containing a family of known functions. This basis can be in the form of polynomial functions, Fourier trigonometric functions or a combination of these [82]. For the problem at hand, a polynomial basis of the form $1, x, x^2, \ldots, x^k$ is chosen, where k is the degree of the polynomial basis. This choice is made for simplicity for now, however, in future, a combination of polynomial and Fourier trigonometric functions can be developed and investigated.

The choice of these functions for parametric learning is also flexible as it can be linear or nonlinear [83]. In linear method, we develop a separable functional network in which the system is attempted to be represented by linearly independent functions. The effect of each input is represented through separate functions and this kind of functional network can be optimized by solving a system of linear equations for parameter estimation. On the other hand, to represent complex nonlinear systems like wind speed time-series, we need to consider a set of nonlinear functions. In these functions, the inputs can have interactions with each other and the resulting network is termed as interacting functional network.

4.2.2 Model Selection

After the parametric learning process, various sets of linear, nonlinear functions are obtained to approximate the neuron functions of the functional network for the selected problem. Considering the complex nonlinear nature of wind speed time-series, a set of nonlinear neural functions is needed to reflect the information contained in it. This is initially a large set of functions approximated based on the selected degree of the model. At this point, a *Model Selection* method is applied to optimally select the set of functions with best performance. There are various choices for this model-selection method including exhaustive search, forward-backward, backward-forward, or backward elimination methods.

The selected method for model selection is *Backward Elimination*, a regression technique which involves the elimination of unfit or redundant elements from the population [113]. We start with all candidate variables, or in our case, functions, and test the deletion of each function based on a chosen optimal selection criterion. The function (if any) whose loss does not a have a statistically significant deterioration on the model fitness is deleted and the process is repeated until no further functions can be deleted. This results in a minimal set of functions that give the specified model fitness.

The fitness criterion for model selection process is chosen to be *Minimum Description Length (MDL)*. This is a concept from information theory which makes the optimal choice not only on the basis of prediction error but also takes into account information required to store the given dataset using the model. Hence it puts a penalty on the number of model parameters to minimize the model complexity along with the accuracy of results. Mathematically, the MDL measure is given as,

$$MDL = \frac{p \log N}{2} + \frac{N}{2} \log RMSE^2 \tag{4.2}$$

where, p is the number of functions in the optimal set (number or parameters), N is the length of the training dataset, and $RMSE$ is the root mean square error. In essence, the first term in (4.2) is a penalty for model complexity to reduce the number of functions to a minimum possible value, while the second term is a measure of accuracy to gauge the error between the target and predicted output.

A systematic flow diagram of the proposed functional network model development is exhibited in Figure 4.1. This flow diagram is divided into three parts showing three important phases of the methodology; Parametric learning, Model selection and Model testing phase. At some stages, where one of the available choices has to be selected, the opted one is shown with green. The inputs are wind training dataset in the training phase and testing dataset in the testing phase. The output of the training phase is an optimally trained functional net-

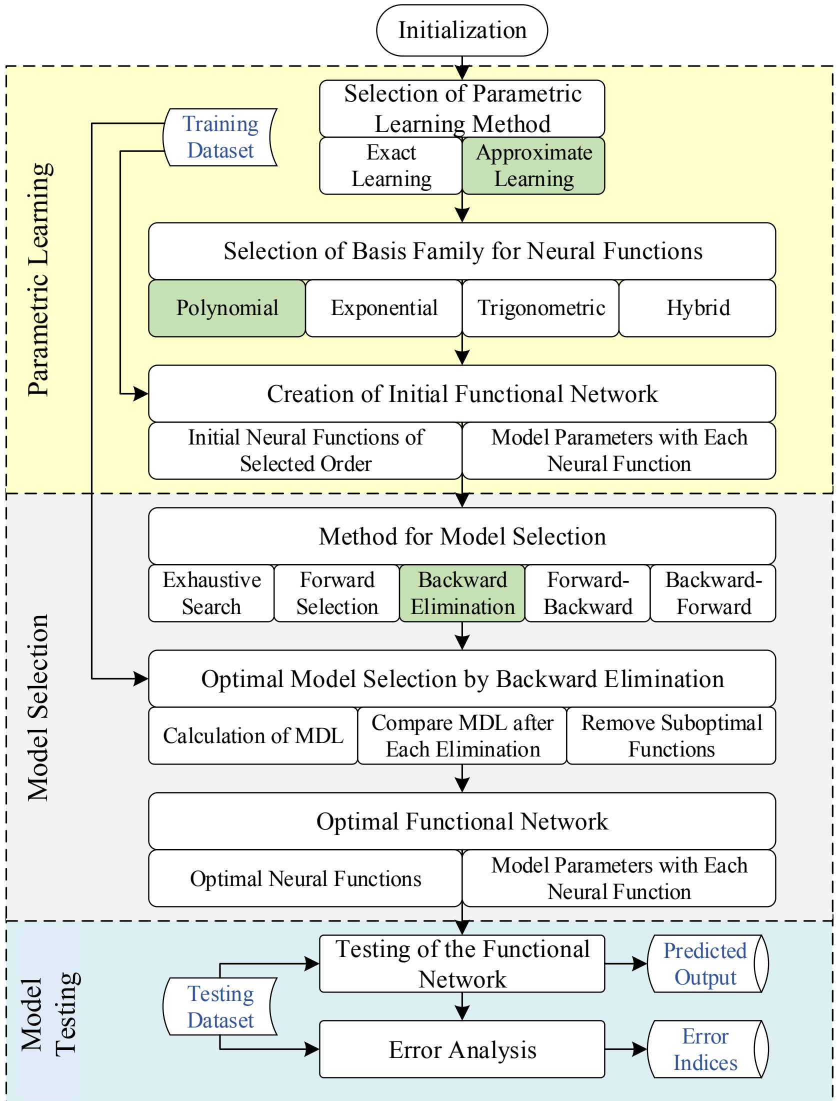

Figure 4.1: A flow diagram for the proposed functional network methodology.

work while the outputs of testing phase and error analysis are predicted wind speed and error indices.

4.2.3 An Illustrative Example

For illustrative purposes, a typical functional network developed for time series prediction is depicted in Figure 4.2. This network consists of 4 time-series inputs

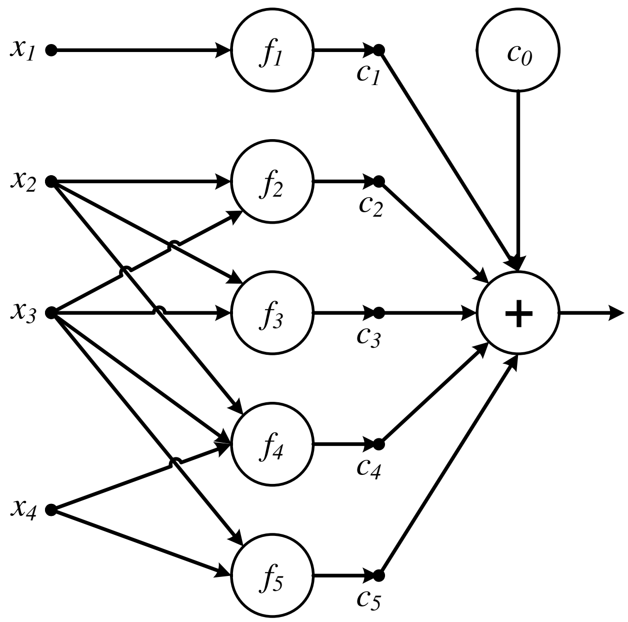

Figure 4.2: A typical functional network structure.

such that,

$$v_N = x_1; \quad v_{N-1} = x_2; \quad v_{N-2} = x_3; \quad v_{N-3} = x_4 \tag{4.3}$$

whereas, the output $\hat{v}_{N+1} = \hat{x}$ is given as,

$$\hat{x} = \sum_{i=0}^{5} c_i f_i \tag{4.4}$$

In this functional network, the initial bias c_0 is for the initial condition ($f_0 = 1$), while the other weights are optimized for each neural function. Unlike neural networks, the neural functions ($f_1, \ldots, f_5$) do not have identical structure but are chosen optimally from a polynomial family with $k = 3$. A nonlinear parametric learning process is carried out as is evident from Figure 4.2 that some of the inputs interact with each other to generate neural functions [82], such as $f_4(x_2, x_3, x_4)$. However, it is not a necessary condition because some neural functions may remain univariate, such as in this case $f_1(x_1)$. Model-selection is performed through Backward Elimination algorithm that gives an optimal size $p = 6$.

The selected functions and their weights are summarized in Table 4.1. From this illustration, the functional network based wind prediction model is described in a step-by-step fashion, which clearly shows its differences as compared with the neural networks, that,

- The topology of a FN is not fixed.
- Not only the weights, but mainly the neural functions are optimized during the training phase.
- The neural functions do not necessarily have univariate and identical structure but can be multidimensional and variable for every FN.

It is worth mentioning here that the network shown in Figure 4.2 and the functions in Table 4.1 are only given for illustrative purposes. The actual trained model neural functions and weights used in the results may be different from this model, even for same dataset. Moreover, the development is easily extendable to any time-series prediction problem using functional networks.

4.3 Results and Discussions

The case study is carried out in a similar fashion as explained in Section 4.2.3. During the parametric learning process, the dataset used for training and cross-validation of the FN model comprises of historical wind data for Jan-Mar 2014,

Neural Functions	Weights
$f_0 = 1$	2.05005
$f_1 = x_1$	0.85569
$f_2 = x_2 {x_3}^2$	-0.00116
$f_3 = {x_2}^2 x_3$	0.00105
$f_4 = x_2 x_3 x_4$	-0.00123
$f_5 = {x_3}^2 x_4$	0.00135

Table 4.1: Optimized Neural Functions and Weights.

divided randomly with a ratio of 70% and 30% respectively. The number of functional network inputs is determined by the embedding length (d) for time series forecasting, which should be kept at a minimal value to avoid model complexity and computational burden during the training phase. The optimal value of d is determined through testing of the network with various d starting from $d = 1$. The forecast error improved with increasing d but it was observed that there was no significant improvement after $d = 6$, hence this value is chosen for basic FN model.

The parametric learning process results in a different functional network structure (neural functions and weights) for different prediction horizons and various MSF mechanisms. It is very tedious to depict all these FN models in this section in a pictorial or tabular form. The neural functions for all cases are chosen from a family of polynomial basis functions with a polynomial degree $k = 3$.

Once the trained FN model is developed, it is tested on another dataset of future values. The testing dataset is composed of wind speed data for Jan-March 2015 from the same geographical site. First, a profile of the measured and pre-

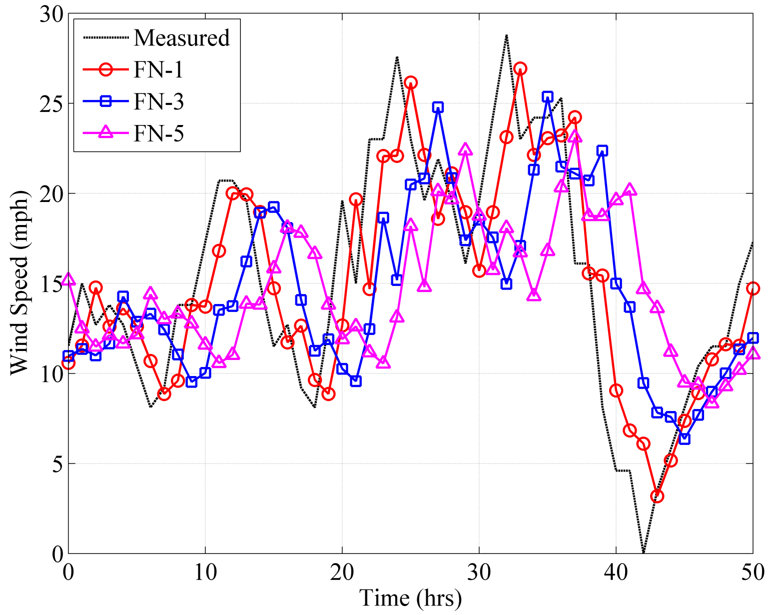

Figure 4.3: Measured vs. predicted wind speed for 1st, 3rd and 5th forecast step.

dicted wind speed is depicted for various forecast horizons in Figure 4.3. The actual testing data set with about 2156 samples is not completely represented here, but only a selected 50 samples for clarity of presentation.

As a characteristic of all forecast models that are based on random walk, it can be seen that the predicted output lags behind the measured wind speed and the lag is proportional to the increasing forecast horizon. In addition to this, the correlation also diminishes with forecast horizon due to under-prediction of the FN forecast model. This amounts to the amplifying error, but it is still less than other forecast models as will be depicted by the detailed error analysis in the coming subsections.

During the testing phase, it is observed that a unique functional structure with different number of neural functions and weights is obtained due to the randomness in training data, even if all conditions and variables are kept the same. However, the error performance of these distinct FN models under similar conditions does not vary a great deal in terms of the standard error indices. Thus, the simulation scheme is as follows: For each prediction horizon and MSF mechanism, the model is trained 10 times and the best obtained results in terms of performance indices, MAE, RMSE and SMAPE are reported.

4.3.1 Multi-Step Wind Forecasting with Functional Network

There are two major sets of results; the first set is concerned with a detailed error analysis of the proposed functional network model with the three proposed MSF mechanisms, namely, Recursive, Direct and hybrid DirRec. Six steps ahead forecasts are obtained with each scheme, due to it special significance for time-varying competitive energy markets [114]. The results of each scheme are summarized with the benchmark persistence model at every forecast horizon in Table 4.2.

Table 4.2 clearly shows that proposed FN model performs significantly better the benchmark model in terms of all error indices. Figure 4.4, Figure 4.5 and Figure 4.6 are a pictorial depiction of Table 4.2. It can be clearly observed from these figures that all MSF schemes start at the same point at the first step (which is essentially the same), however, with the increase of prediction horizon, the direct and DirRec schemes show much better error performance as compared to the recursive model.

Table 4.2: Functional Network MSF Error Analysis

Errors	Steps	Persistence	Recursive	Direct	DirRec
MAE	1-step	1.08	1.05	1.05	1.05
	2-step	1.44	1.40	1.14	1.11
	3-step	1.76	1.65	1.23	1.19
	4-step	1.99	1.84	1.38	1.29
	5-step	2.22	2.00	1.56	1.43
	6-step	2.43	2.13	1.75	1.58
RMSE	1-step	1.47	1.41	1.41	1.41
	2-step	1.95	1.87	1.49	1.46
	3-step	2.37	2.18	1.58	1.53
	4-step	2.70	2.40	1.75	1.64
	5-step	3.02	2.59	1.91	1.79
	6-step	3.28	2.72	2.14	1.95
SMAPE	1-step	13.96	11.52	11.52	11.52
	2-step	17.34	15.18	13.13	12.93
	3-step	19.82	17.15	14.05	13.71
	4-step	21.53	18.61	15.32	14.68
	5-step	23.20	19.89	16.92	15.91
	6-step	24.75	20.90	18.44	17.10

The performance of recursive FN model deteriorates because it is trained only once for the single step and afterwards the prediction error accumulates with the prediction horizon. Still the errors indices are much less as compared to the persistence model and this scheme can be utilized in situations when model training is not possible for every step. The DirRec scheme trains the model at each step like direct scheme and it keeps a correlation with the previous steps by including the forecast from each step into the next like the recursive scheme. Thus it can be observed from Figure 4.4, Figure 4.5 and Figure 4.6 that hybridization of good features from both schemes makes it superior to both models. Another observation from these results is that the error performance enhances for greater prediction horizons.

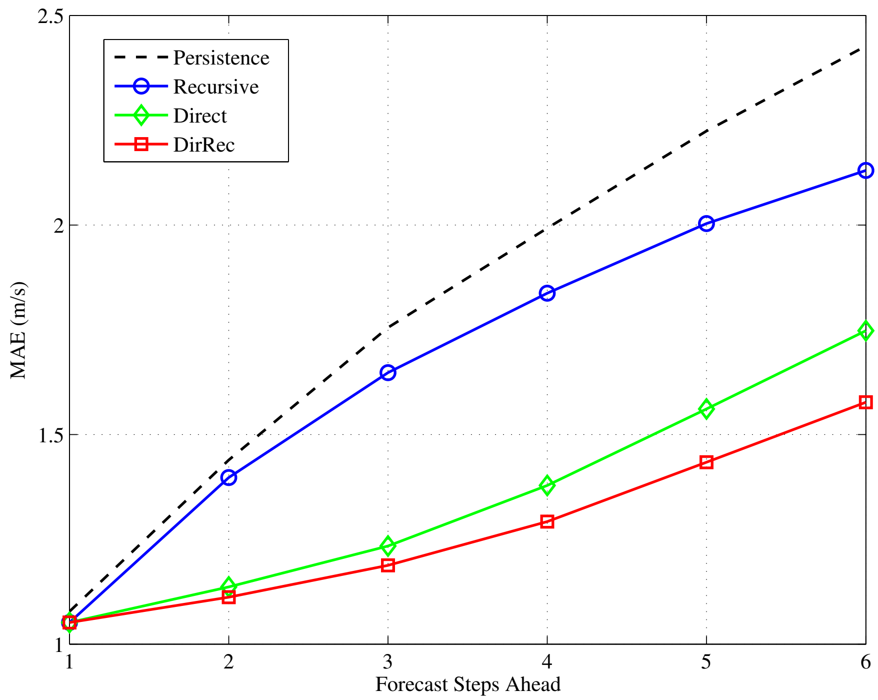

Figure 4.4: MSF schemes and persistence over prediction horizon - MAE.

The significant improvement of FN model over persistence especially for large forecast horizons can be gauged by percentage improvement of each FN based MSF scheme over persistence model. Table 4.3 records the max percentage improvement in terms of both error indices. It should be noted that these maximum improvements are achieved at longer forecast horizons, i.e., at 4^{th}, 5^{th} and 6^{th} steps. The improvement achieved by the recursive scheme is comparatively less than the direct and DirRec models. From Table 4.3, it is clear that FN-DirRec has the largest improvements over persistence, going over 40% in terms of RMSE, hence it can be termed as the best in terms of all error indices, especially over

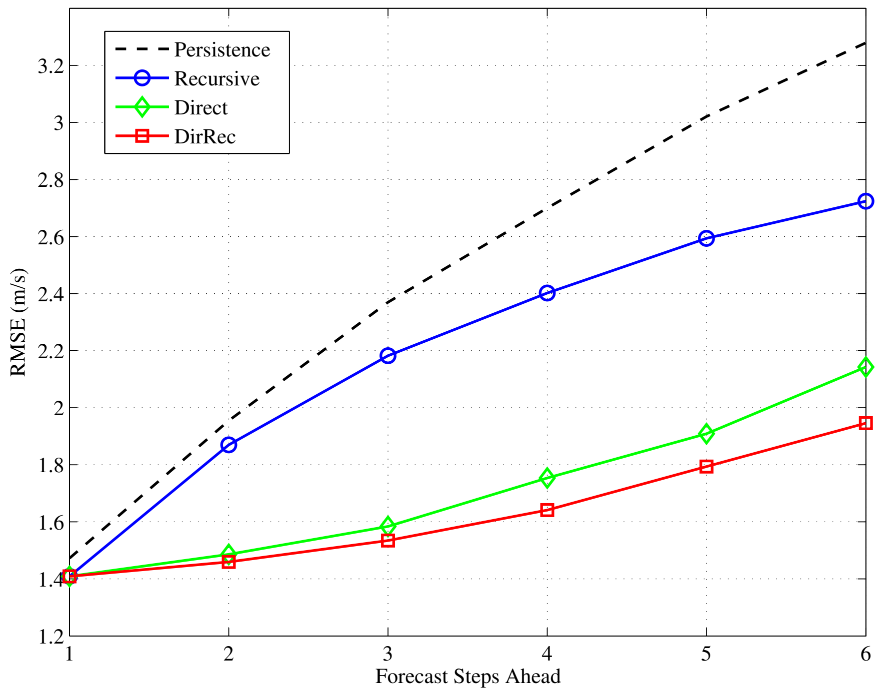

Figure 4.5: MSF schemes and persistence over prediction horizon - RMSE.

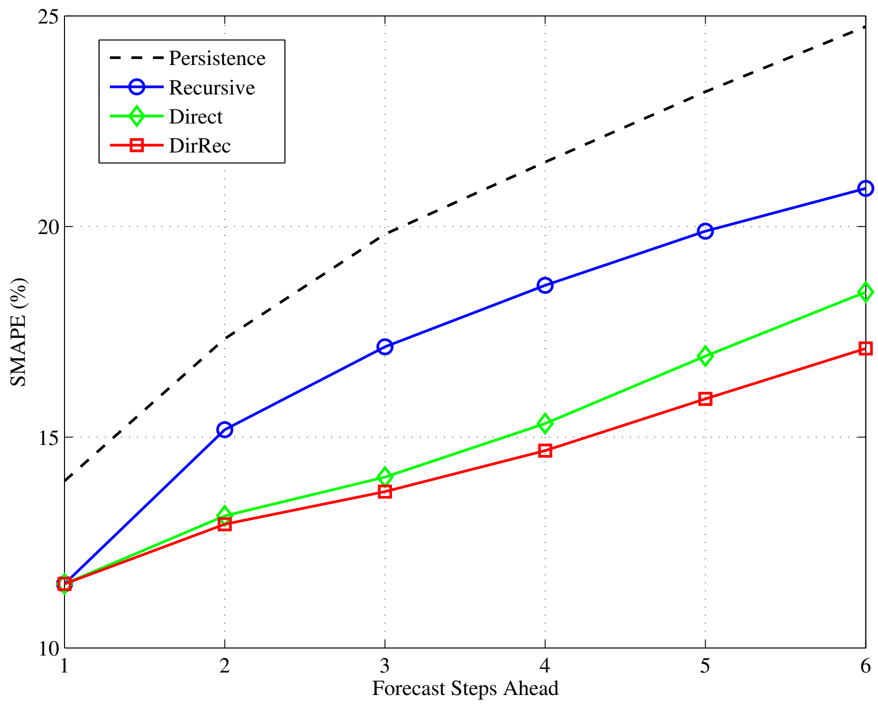

Figure 4.6: MSF schemes and persistence over prediction horizon - SMAPE.

large forecast horizons.

Table 4.3: Max Improvements (%) of MSF Schemes over Persistence

Errors	Recursive	Direct	DirRec
MAE	12.23	30.80	35.54
RMSE	16.93	36.81	40.65
SMAPE	15.53	29.10	31.82

4.3.2 Comparative Analysis - Functional Network and Neural Network

The second set of results presents a comparative analysis of the proposed FN forecasting model with a standard ANN model. The ANN forecast model is subject to the same conditions for comparison on an equal footing. These conditions include: Training and cross-validation wind data for first three months (Jan-Mar) of the calendar year 2014; Testing data for first three months (Jan-Mar) of the calendar year 2015; and embedding length $d = 6$. In this case also, six steps ahead forecasts are obtained. The MSF scheme used for this set of results is Direct forecasting. Percentage error improvement of the proposed FN model is measured at each forecast step in comparison with ANN model as well as persistence model to exhibit the superiority of the FN model.

This set of results is compiled in Table 4.4 where comparison of FN model is drawn with persistence benchmark and ANN model for six steps ahead predictions. These results exhibit that FN outperforms other models in terms of all indices at

Table 4.4: Comparative Analysis (FN, ANN, Persistence)

Errors	Steps	Persistence	ANN	FN
MAE	1-step	1.08	1.06	1.05
	2-step	1.44	1.37	1.14
	3-step	1.76	1.63	1.23
	4-step	1.99	1.83	1.38
	5-step	2.22	1.95	1.56
	6-step	2.43	2.12	1.75
RMSE	1-step	1.47	1.42	1.41
	2-step	1.95	1.84	1.49
	3-step	2.37	2.18	1.58
	4-step	2.70	2.41	1.75
	5-step	3.02	2.61	1.91
	6-step	3.28	2.76	2.14
SMAPE	1-step	13.96	12.46	11.52
	2-step	17.34	14.99	13.13
	3-step	19.82	17.01	14.05
	4-step	21.53	18.53	15.32
	5-step	23.20	19.39	16.92
	6-step	24.75	20.67	18.44

all forecast horizons. Nevertheless, the performance enhancement is comparatively better at longer forecast horizons. The comparative analysis can also be pictorially seen in Figure 4.7, Figure 4.8 and Figure 4.9 in terms of MAE, RMSE and SMAPE respectively. Although ANN shows quite good improvement over persistence, but the FN model offers approx. 3 times better performance as compared to ANN as measured in Figure 4.7 and Figure 4.8. As for SMAPE, the FN based model can be seen to perform at least twice as better than the ANN model (see Figure 4.9).

A more quantitative approach to support our claim is the percentage improve-

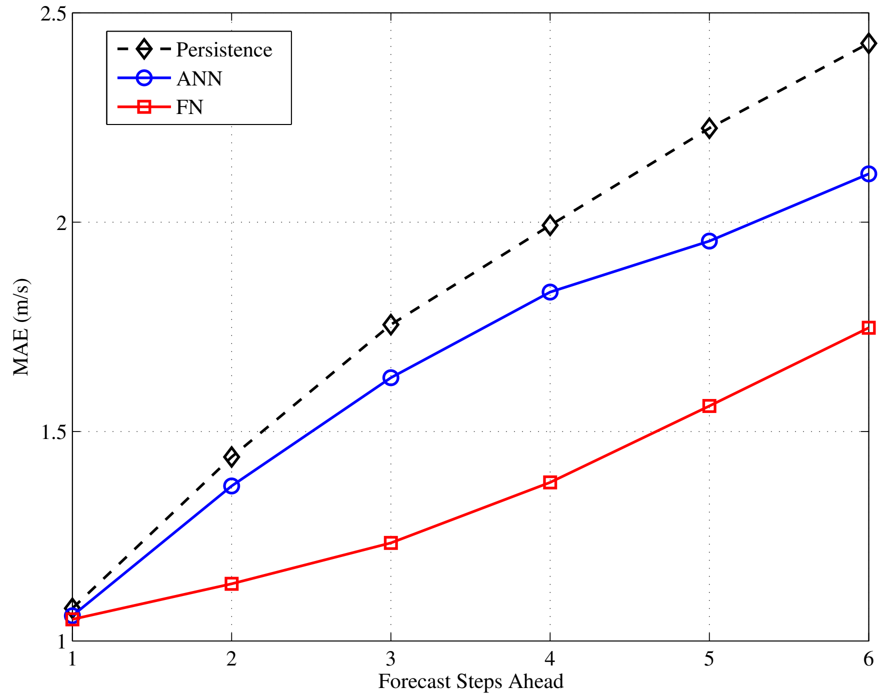

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Figure 4.7: Comparative analysis (FN, ANN, and Persistence) in terms of MAE.

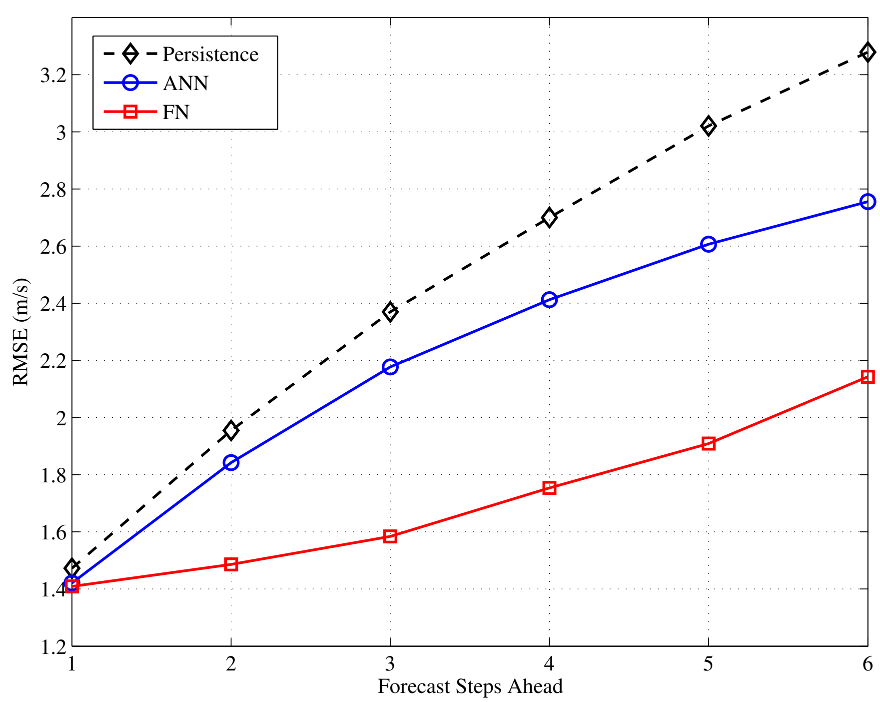

Figure 4.8: Comparative analysis (FN, ANN, and Persistence) in terms of RMSE.

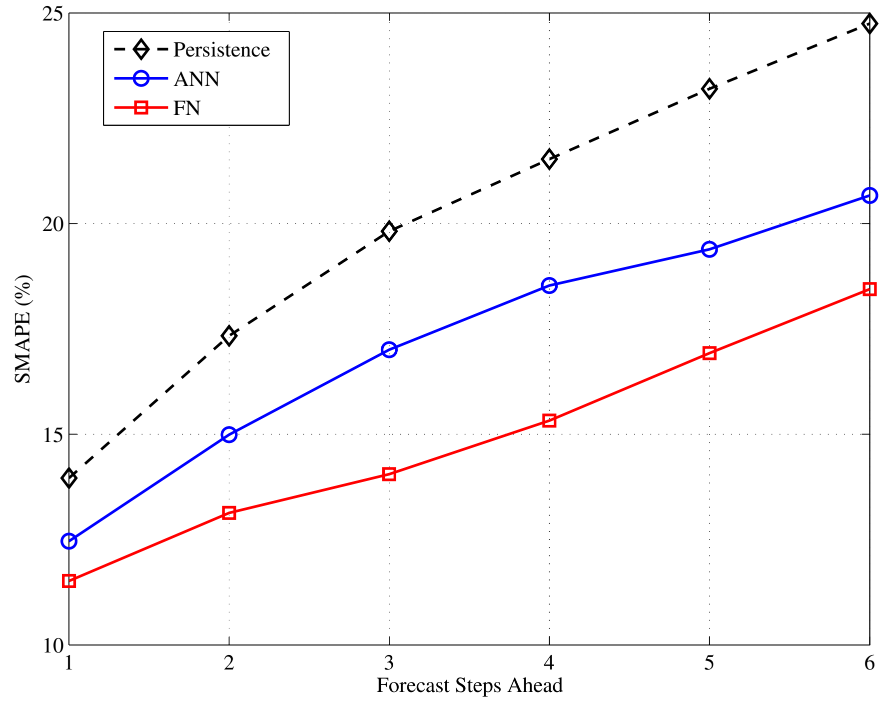

Figure 4.9: Comparative analysis (FN, ANN, and Persistence) in terms of SMAPE.

ment of FN over persistence and ANN models, as depicted in Table 4.5. We have already seen a notable 40% improvement of FN over persistence. Similarly, improvement of FN over ANN goes as much as 27%, which shows its dominance. Hence, it can be said that FN model is not only a novel technique, but it is also very effective as validated by a comparative analysis with popular MSF models in a standard manner.

Table 4.5: Max Improvements (%) of FN over Other Models

Errors	Persistence	ANN
MAE	30.80	24.79
RMSE	36.81	27.31
SMAPE	29.10	17.38

CHAPTER 5

FORECAST-BASED POWER DISPATCH

This chapter targets at the application of the forecasting models developed in the previous chapters in profitable power dispatch and the study of the impact of forecast error for energy management in terms of system costs and profits. Specifically, a grid-connected wind power plant (WPP) is considered in this chapter which is operated to sell the energy output to the grid. The selling strategy strives on maximizing the plant income and operational profit by optimizing the amount of energy to be sold using the information of energy market price.

The major issues in devising such a strategy for economically profitable dispatch is the uncertainty in WPP output. Also, in competitive energy markets, the energy prices are not known for the future. Hence it becomes difficult to determine how much energy will be available for selling and also what will be the optimum period of selling the energy according to the market price. This is where our developed forecasting models come into play which enable us to forecast the wind power output as well as the energy market prices based on the historical trends of these data. Using the wind energy and market price forecasts, we can plan our energy selling strategy for few steps ahead in future. We will analyze from the results obtained that the accuracy of these forecasts have a direct impact on tangible cost benefits achieved from energy trading.

The WPP is also attached with battery energy storage system (BESS) which can be used as a backup. The BESS is another agent to make up for the intermittencies in WPP output and ensuring maximum income. Since we can not get constant power output from the WPP, hence it is possible that we cannot deliver enough energy to increase our profits at the time of peaking market rates. Under such circumstances, the BESS can supply the required energy, according to its physical constraints. Similarly, we can utilize the surplus energy in charging the BESS in those time periods when market prices are lower and we couldn't gain much profit from selling the energy. We will also conduct a scenario-based analysis for various BESS energy and power capacities which will help us finding out an optimal BESS size as well.

5.1 Methodology for Dispatch

The discussed goals can be achieved by making use of a receding horizon approach based on the Model Predictive Control (MPC) theory. The strength of this approach is that it is simpler to formulate, it can directly handle realistic system constraints, and it can easily incorporate multi-step forecasts. The inputs of the proposed optimization model are six steps ahead wind energy and market price forecasts along with system and BESS constraints. The output is obtained in the form of an optimal control sequence for energy which is selected on the basis of receding horizon principle. The optimization is performed using well-established Linear Programming (LP) optimization. Enhanced economic benefits and operational features can be obtained from the proposed strategy through the coordinated action of wind power and energy price forecasts within an integrated Wind-BESS system.

5.1.1 Problem Formulation

A WPP connected to the grid and associated with a BESS is taken into account for wind power dispatch problem formulation. For formulating such a problem, a relationship is developed between BESS capacity and percent revenue improvement over a trivial strategy (without energy storage). Realistic and physical constraints concerning battery and market regulations are also included in setting up the problem. For a given wind farm, a problem formulated in such a manner can help in optimal sizing of the BESS and estimation of the amount of adequate investment required for profit maximization.

In the scenario under consideration, a BESS is attached to a wind farm. As depicted in Figure 5.1, the energy output of the wind farm at k^{th} instant is $p(k) \in \mathbb{R}$, and the amount of energy sold to the grid through the market at k^{th} instant is $g(k) \in \mathbb{R}$. In this situation, $g(k)$ should be greater than or equal to zero, i.e.,

$$g(k) \geq 0, \quad \forall k \geq 0. \tag{5.1}$$

Moreover, the difference $e(k)$ between the energy produced and sold is given as,

$$e(k) = p(k) - g(k), \tag{5.2}$$

This energy is stored in the BESS assuming lossless conversion stages. Clearly, $e(k) > 0$ in the BESS charging cycle, while $e(k) < 0$ when the BESS is discharged. Additionally, let the the market energy price at k^{th} instant be $m(k) \in \mathbb{R}$. Hence the income of the wind farm at k^{th} instant is given by $m(k)g(k)$.

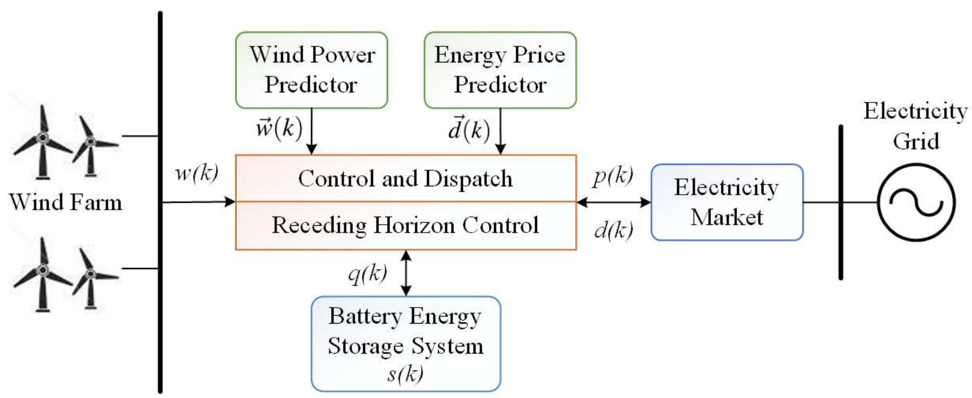

Figure 5.1: Signal flow diagram in the proposed configuration.

If the the amount of energy in the battery at k^{th} instant is denoted by $x(k) \in \mathbb{R}$, then the following difference equation is satisfied:

$$x(k+1) = x(k) + p(k) - g(k). \tag{5.3}$$

If we define the maximum charge rate and maximum discharge rate to be $r_c > 0$ and $r_d > 0$ respectively, then the difference in two consecutive states of the battery has the following constraint,

$$r_d \leq x(k+1) - x(k) \leq r_c, \quad \forall k \geq 0. \tag{5.4}$$

Let the capacity of the BESS be $C > 0$ while $0 < \alpha_m < \alpha_M < 1$ be given constants, then the life of the battery can be prolonged and the cost of the BESS can be reduced by setting up the following limitation,

$$\alpha_m C \leq x(k) \leq \alpha_M C, \quad \forall k \geq 0. \tag{5.5}$$

Hence it can be said that the discrete time system (5.3) has to satisfy constraints (5.1), (5.4) and (5.5).

5.1.2 Receding Horizon Approach

To derive an optimal wind power dispatch strategy, an optimization methodology based on MPC is proposed. In this methodology, first the economic function which needs to be maximized is considered with $H > 0$ being the forecast horizon as:

$$V_H = \sum_{j=0}^{H-1} \hat{m}(j)\hat{g}(j), \tag{5.6}$$

where, $\hat{m}(j)$ stands for the predicted future value of the energy price and $\hat{m}(0) = m(k)$, i.e., the current energy price is known. Additionally, the tentative control actions are contained in the vector $\vec{g}(k)$. This vector is defined over the whole range of H as,

$$\vec{g}(k) = \{\hat{g}(0), \hat{g}(1), \ldots, \hat{g}(H-1)\}. \tag{5.7}$$

As a result, the optimization problem for the current states is setup via MPC as follows:

$$V_H^{op} = \max_{\vec{g}} \left\{ \sum_{j=0}^{H-1} \hat{m}(j)\hat{g}(j) \right\}, \tag{5.8}$$

subject to:

$$\hat{x}(j+1) = \hat{x}(j) + \hat{p}(j) - \hat{g}(j), \tag{5.9}$$

$$\hat{g}(j) \geq 0 \tag{5.10}$$

$$\alpha_m C \leq \hat{x}(j) \leq \alpha_M C \tag{5.11}$$

$$r_d \leq \hat{x}(j+1) - \hat{x}(j) \leq r_c \tag{5.12}$$

for all $j \in \{0, \ldots, H-1\}$, where $\hat{x}(0) = x(k)$ and $\hat{p}(0) = p(k)$, i.e., the current battery state and wind power are known.

Hence cost function is maximized by the optimal input sequence $\vec{g}^{op}(k)$, i.e.,

$$\vec{g}^{op}(k) \triangleq \arg \left\{ \max_{\vec{g}} \sum_{j=0}^{H-1} \hat{m}(j)\hat{g}(j) \right\}. \tag{5.13}$$

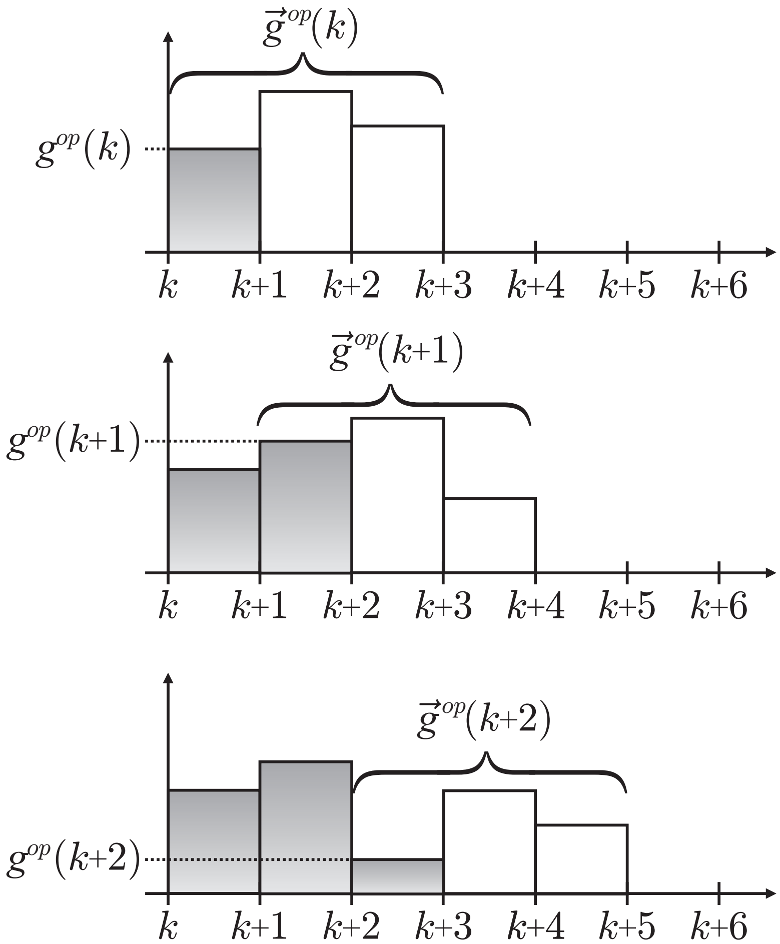

Figure 5.2: Moving horizon principle with horizon ($H = 3$ for illustration): the shaded rectangles represent the actual inputs applied to the system.

The optimal input control sequence is of the form given as follows:

$$\vec{g}^{op}(k) = \{g^{op}(0), g^{op}(1), \ldots, g^{op}(H-1)\}\,. \tag{5.14}$$

The resulting optimal control sequence, $\vec{g}^{op}(k)$ in (5.14), lies at an extremum of the control signal set in the admissible range. This kind of control strategy is commonly known as bang-bang control.

One key aspect of MPC is the receding or moving horizon principle [115] which states that after obtaining the optimal input sequence in (5.14), only the first element, $g^{op}(0)$, is applied to the system, discarding the remaining elements of $\vec{g}^{op}(k)$. Then the optimization process is repeated at the next sampling instant using new predicted values for $\hat{m}$ and $\hat{p}$ to obtain a new optimal input sequence, $\vec{g}^{op}(k+1)$. The moving horizon principle is illustrated briefly in Figure 5.2 for the case $H = 3$. Thus the solution of the optimal control problem $\mathbb{P}_H(x)$ yields the following control law

$$g^{op}(k) = g^{op}(0). \tag{5.15}$$

Therefore, the resulting MPC closed-loop system can be represented for each sampling instant as:

$$x(k+1) = x(k) + p(k) - g^{op}(k). \tag{5.16}$$

The final wind power dispatch strategy is summarized in Algorithm 1. Here, the functions m-PRED($\cdot$) and p-PRED($\cdot$) represent the predictors used to forecast the electricity market price and the wind power for $H = 6$ steps ahead.

5.1.3 Optimization Method

The optimal control problem $\mathbb{P}_H(x)$, presented in (5.8), is formulated (in both cost function and constraints) by linear relationships. Therefore, this can be solved by any linear programming (LP) algorithm such as interior-point, simplex, etc. [116]. The standard Linear Programming (LP) optimization formulation, which minimizes a linear function of the state, $f^T\bar{\boldsymbol{x}}$, subject to constraints, is typically

Algorithm 1 Optimal Power Dispatch Strategy

Initialization: $k \leftarrow 0$**,** $H \leftarrow 6$
while (1) **do**
- **Energy Price Predictor**
  $m(0) \leftarrow m(k)$
  $\vec{m}(k) = \textbf{m-PRED}(\cdot)$
  $\vec{m}(k) \leftarrow \big\{m(0) \quad \hat{m}(1) \quad \ldots \quad \hat{m}(H-1)\big\}$
- **Wind Power Predictor**
  $p(0) \leftarrow p(k)$
  $\vec{p}(k) = \textbf{p-PRED}(\cdot)$
  $\vec{p}(k) \leftarrow \big\{p(0) \quad \hat{p}(1) \quad \ldots \quad \hat{p}(H-1)\big\}$
- **Optimization**
  $\hat{x}(0) \leftarrow x(k)$
  $\vec{g}^{op}(k) = \textbf{OPT}(\hat{x}(0), \vec{m}(k), \vec{p}(k), H, \alpha_m c, \alpha_M c, r_d, r_c)$
  $\vec{g}^{op}(k) \leftarrow \big\{g^{op}(0) \quad g^{op}(1) \quad \ldots \quad g^{op}(H-1)\big\}$

  $g(k) \leftarrow g^{op}(0)$ ▷ **Receding Horizon Policy**
  $x(k+1) \leftarrow x(k) + p(k) - g(k)$
  $k \leftarrow k+1$
end while

defined as:

$$\min_{\bar{\boldsymbol{x}}} f^T \bar{\boldsymbol{x}} \;\text{ such that} \begin{cases} \bar{A}\bar{\boldsymbol{x}} \leq \bar{b} \\ \bar{A}_{eq}\bar{\boldsymbol{x}} = \bar{b}_{eq} \\ lb \leq ub \end{cases} \tag{5.17}$$

Thus, the problem under consideration can be written in standard form for LP such that the objective function from (5.13) and constraints given in (5.9)–(5.12) become:

$$\vec{g}^{op}(k) = \arg\left\{\max_{\vec{g}} \vec{m}^T \vec{g}\right\} \tag{5.18}$$

$$\text{s.t.} \qquad A\vec{g} \leq b \tag{5.19}$$

where the vector $\vec{m} = \begin{Bmatrix} \hat{m}(0) & \dots & \hat{m}(H) \end{Bmatrix}^T$ contains the market price predictions, and

$$A = \begin{bmatrix} -\mathrm{I} \\ \Phi \\ -\Phi \\ \mathrm{I} \\ -\mathrm{I} \end{bmatrix}, \quad b = \begin{bmatrix} 0 \\ (x(k) - \alpha_m c)\Gamma + \Phi\vec{p} \\ -(x(k) - \alpha_M c)\Gamma - \Phi\vec{p} \\ \vec{p} + r_d\Gamma \\ -\vec{p} + r_c\Gamma \end{bmatrix} \tag{5.20}$$

$$\Phi = \begin{bmatrix} 1 & 0 & \cdots & 0 & 0 \\ 1 & 1 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 1 & 1 & \cdots & 1 & 0 \\ 1 & 1 & \cdots & 1 & 1 \end{bmatrix}, \qquad \Gamma = \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \\ 1 \end{bmatrix} \tag{5.21}$$

where $\vec{p} = \begin{Bmatrix} \hat{p}(0) & \dots & \hat{p}(H) \end{Bmatrix}^T$ are the wind energy predictions.

5.1.4 Databases

To validate the developed dispatch system and to study the impact of forecast error, a case study is carried out. Wind power data is obtained from a wind farm at Roaring 40s Woolnorth, Tasmania, Australia (shown in Figure 5.3). Australian electricity market operator is chosen for electricity market price data acquisition. The typical time interval for power dispatching in the Australian National Electricity Market (NEM) is 5-min [117]. Hence the resolution of obtained data is also the same. The rated power of the wind turbine used here is 65 MW. The simulations consists of 288 intervals of 5-min which correspond to a single calendar day of 24 hours.

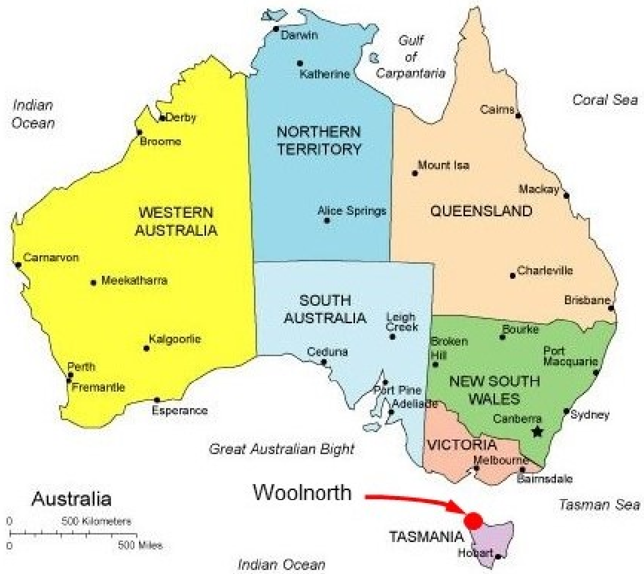

Figure 5.3: Real location of wind farm for case study, Woolnorth, Australia.

5.2 Application of Real-Time Forecasting Models in Dispatch

This section gives the results of the wind power dispatch strategy to maximize income and profit from selling wind power using future-predicted power and price information using a real-time predictor based on functional network (FN) developed in the previous chapter.

In most of the cases, integrated Wind-BESS plants require a large storage BESS where the storage capacity is calculated using power and energy ratings, while the cost of BESS is characterized by power (in kW or MW) and energy (in kWh or MWh) capacities [118, 119]. The operational revenues of a wind power plant can be increased by optimizing the size of associated BESS coupled with its optimal operation under feasible constraints. Therefore, the selling strategy is assessed for a range of realistic BESS power and energy ratings, and percent income improvement (II) has been calculated as follows:

$$\%\ \mathrm{II} = \frac{\mathrm{MI\ -\ TI}}{\mathrm{TI}} \quad \times 100 \tag{5.22}$$

where MI is the model income and TI is trivial income calculated over a given period T as follows:

$$\mathrm{MI} = m(k) \times \vec{g}^{op}(k)T \tag{5.23}$$

$$\mathrm{TI} = m(k) \times p(k)T \tag{5.24}$$

First of all, the wind power and market price profile considered in this work is shown in Figures 5.4 and 5.5. These profiles are based on 288 samples which represent the data of a single day (24 hours) with a resolution of 5-min. After running optimization algorithm formulated in the previous section, the state of BESS can be observed as computed from the optimal output power sold. This state of charge (SOC) of the BESS is shown in Figure 5.6 for a 20MWh capacity. As it can be observed, it remains within the defined constraints of upper and lower capacity of 80% and 20% as specified in the formulation. The BESS is used most at the times of peaking market prices and lower wind power available while the

SOC remains at higher levels and BESS is charged in the opposite scenario.

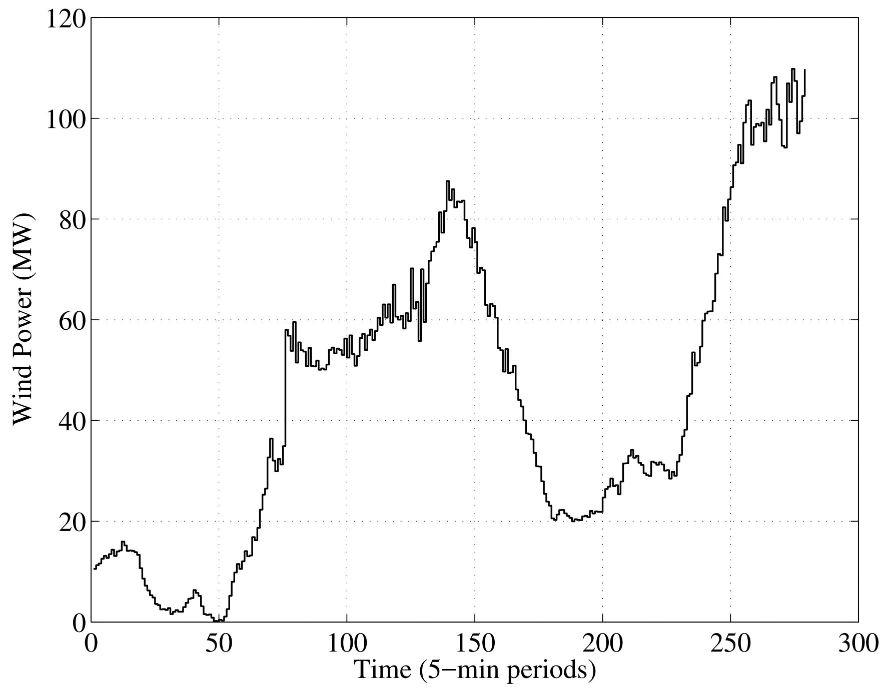

Figure 5.4: Wind Power Profile for a single day.

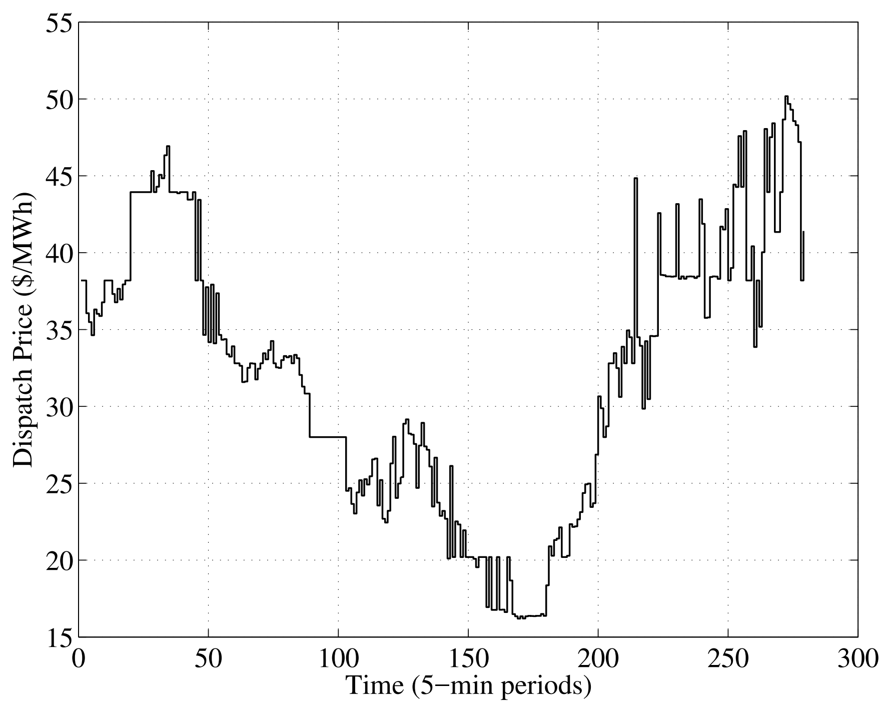

Figure 5.5: Market Price Profile for a single day.

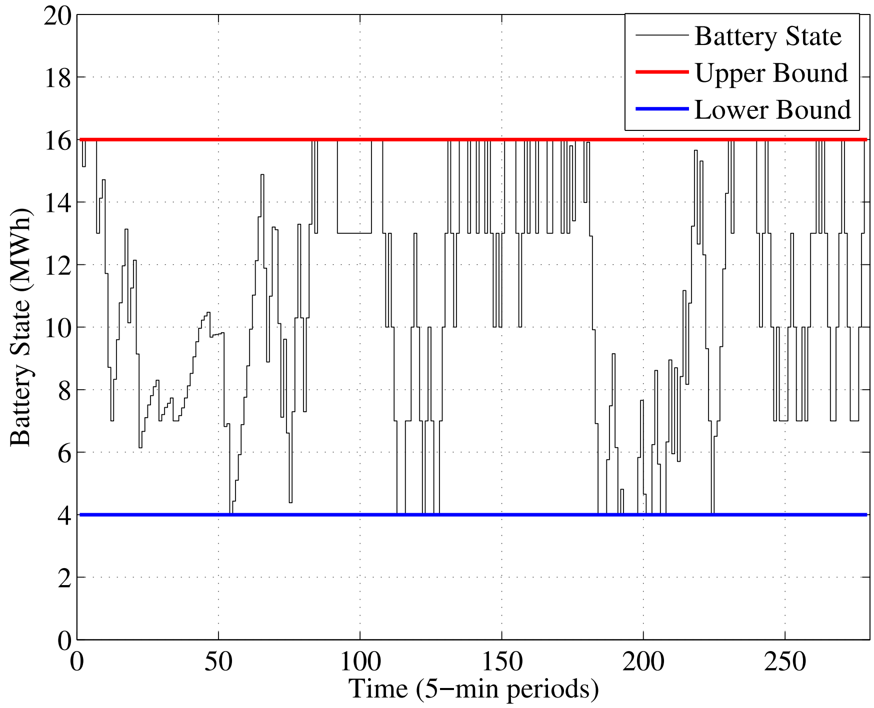

Figure 5.6: Battery State of Charge for a 20MWh BESS during Dispatch.

A further in-depth view of the optimization process can be observed from Figure 5.7 where the wind energy calculated from the generated output of the wind turbine is shown along with optimal output sold to the grid at every 5-min interval. The SOC of the BESS is also shown using the right y-axis to exhibit the charging/discharging action of the BESS. Figure 5.7 is basically a depiction of equation (5.16), hence it shows that the future SOC of the battery is changed as the sum of the current SOC and wind output minus the optimal plant output. In other words, the optimal output is above the wind turbine output by the amount of energy discharged from the BESS or it is below the wind turbine output by the amount used to charge the BESS. It should be noted that this decision is based on the optimal output to maximize the income according to the market price, which is not shown in this plot due to scaling limitations.

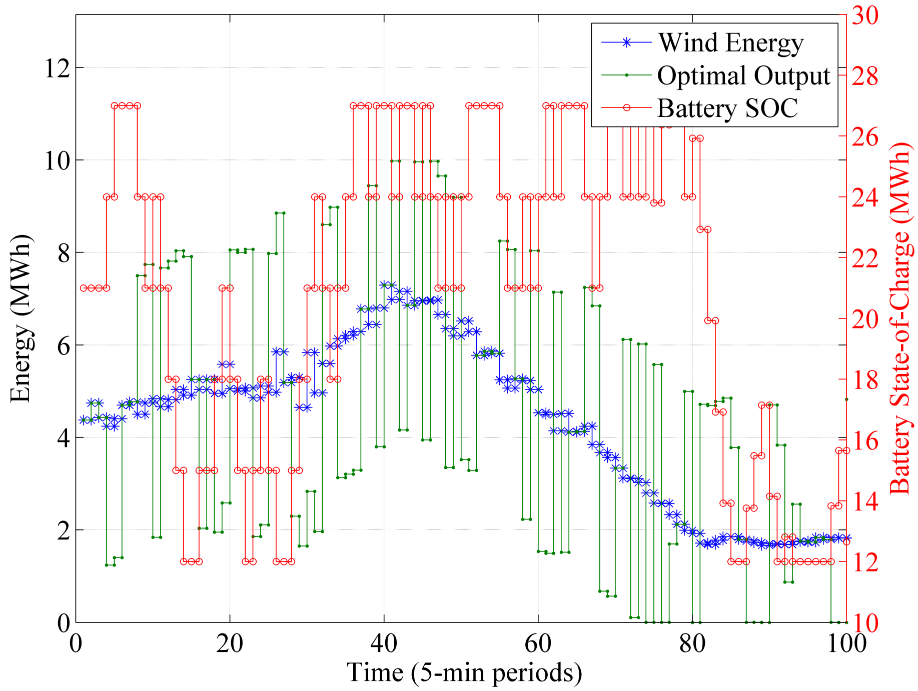

Figure 5.7: Wind generation, battery SOC and optimal plant output sold to the grid.

Figure 5.8 is a representation of the income improvement (II) percentage over a range of BESS energy capacity while considering different power capacities. The range of BESS energy capacity is varied from 0-300MWh while the values of 2, 3, 4, 5, 6 and 8MW power capacities are considered. It is clear from Figure 5.8 that for a BESS with particular power capacity, the daily II reaches a saturation level after which it cannot be improved despite enlarging the energy storage capacity of the BESS. The saturation point or optimum point is greater for greater BESS power capacities obviously. This can help us in determining the optimal combination of BESS power and energy capacity. From this figure, for instance, the optimal BESS capacity is about 50MWh for a 2MW/5min power BESS and so on.

In order to analyze the investment return, we have also calculated daily oper-

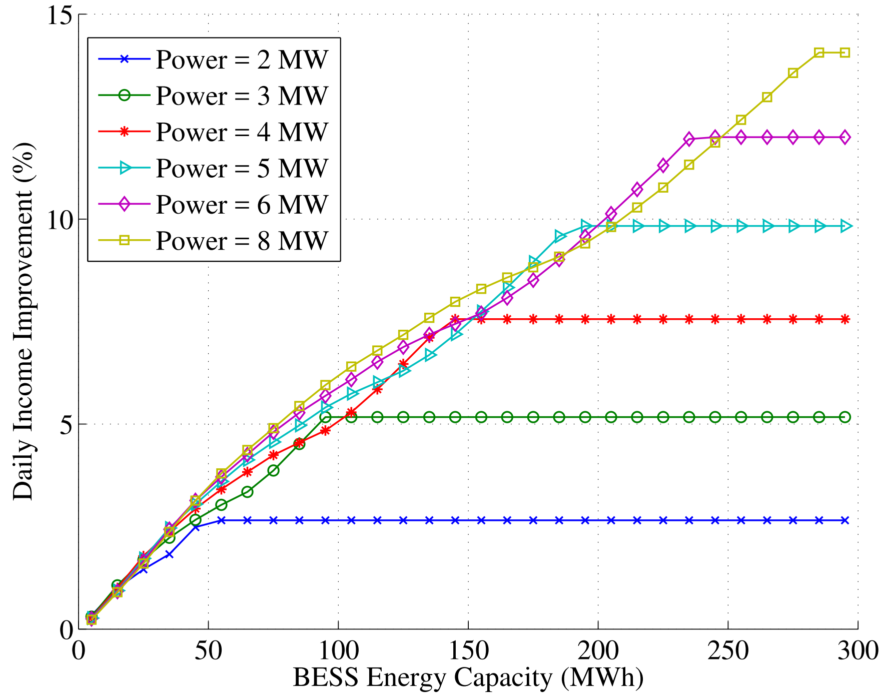

Figure 5.8: Daily Income Improvement vs. Energy Capacity.

ational profit (OP) for each BESS. The OP is calculated by subtracting the daily MI from daily BESS cost as follows:

$$\text{Daily OP} = \text{Daily MI} - \text{Daily BESS Cost} \tag{5.25}$$

where Daily MI and Daily BESS cost are expressed in dollars.

It should be noted that daily OP has been calculated based on chosen short-term daily cycle, otherwise, the battery cost is distributed over many years, typically 20 years. In such case, many other cost factors such as operational and maintenance costs, battery degradation and chemistry, and converter technology must be considered to find the OP accurately for a longer period which is out of the scope of our research currently. However, it is important to notice that the operational and maintenance costs are minimized by the inherent property of the proposed algorithm, for example, controlled operation of battery within operational limits avoids over/under-charging and prolong the lifetime of battery which consequently reduces the maintenance cost. Similarly, as we are using actual battery model, with charging and discharging efficiencies, rate of charge and discharge; power in and out from the battery is automatically adjusted and hence all practical aspects of the battery are automatically incorporated in the calculations.

Figure 5.9 expresses OP for different BESSs with a few selected power ratings. In Figure 5.9, the Daily BESS cost is shown to be linearly increasing with BESS energy capacity. For each power rating, the Daily OP shows similar behavior, i.e., it goes to a maximum value at a certain BESS capacity, termed as Optimal Capacity, after which the profit degrades. The optimal capacity is less for lower BESS power ratings and increases for higher power ratings. This is because large energy capacity at smaller power ratings doesn't improve the income but the cost of BESS keeps increasing. This result is very useful from the aspect of power system planning, as it can help the planners to install optimum BESS capacity for given BESS power rating to maximize their operational profits.

A similar analysis is performed over the range of BESS power capacity from 2MW to 36MW with various cases of BESS power capacity to show the daily II and operational profit. In Figure 5.10, the values of BESS energy capacity are 60-100MWh with a step of 10MWh. It can be observed that the income improves

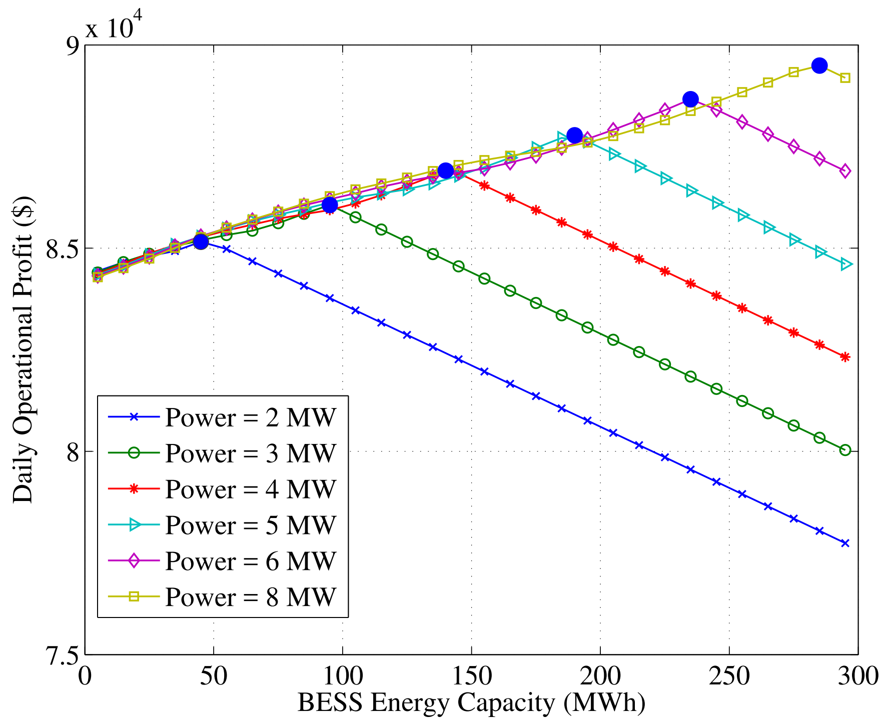

Figure 5.9: Daily Operational Profit vs. Energy Capacity.

by increasing the energy capacity for sure, but increasing the power capacity while keeping the energy capacity same is not fruitful after a certain value. This can help us in determining the optimal combination of BESS power and energy capacity. From this figure, for instance, the optimal BESS power capacity is about 2.5MW/5min for a 100MWh BESS which gives an II of about 5.2%. Similarly, optimal combinations can be found for various cases.

Figure 5.11 expresses OP for BESS power ratings with a few selected capacities. It can be observed that although the operational profit improves by increasing the energy capacity, but increasing the power capacity while keeping the energy capacity same is not fruitful after a certain value. This is because large energy capacity at smaller power ratings doesn't improve the income but the cost of

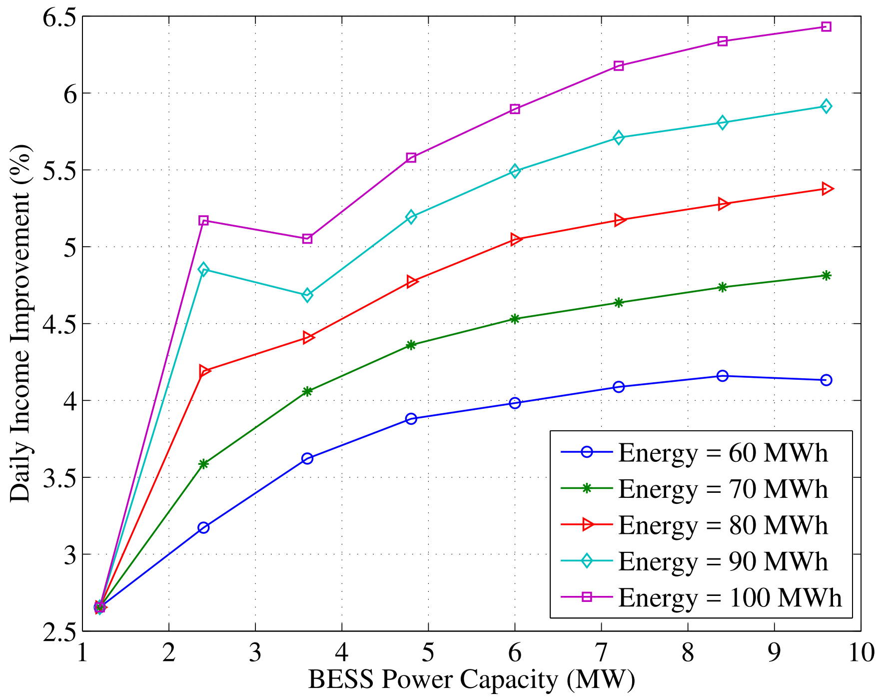

Figure 5.10: Daily Income Improvement vs. Power Capacity.

BESS keeps increasing. These results can help us in determining the optimal combination of BESS power and energy capacity. From this figure, for instance, the optimal BESS power capacity is about 2.5MW/5min for a 90MWh BESS which gives an OP of about $86,000. Similarly, optimal combinations can be found for various cases. This result is very useful from the aspect of power system planning, as it can help the planners to install optimum BESS capacity for given BESS power rating to maximize their operational profits.

5.3 Forecast Error Analysis on Dispatch

Wind power and market price is forecasted for six-steps ahead prediction horizon. Then these forecasts are used in the MPC receding horizon framework to deter-

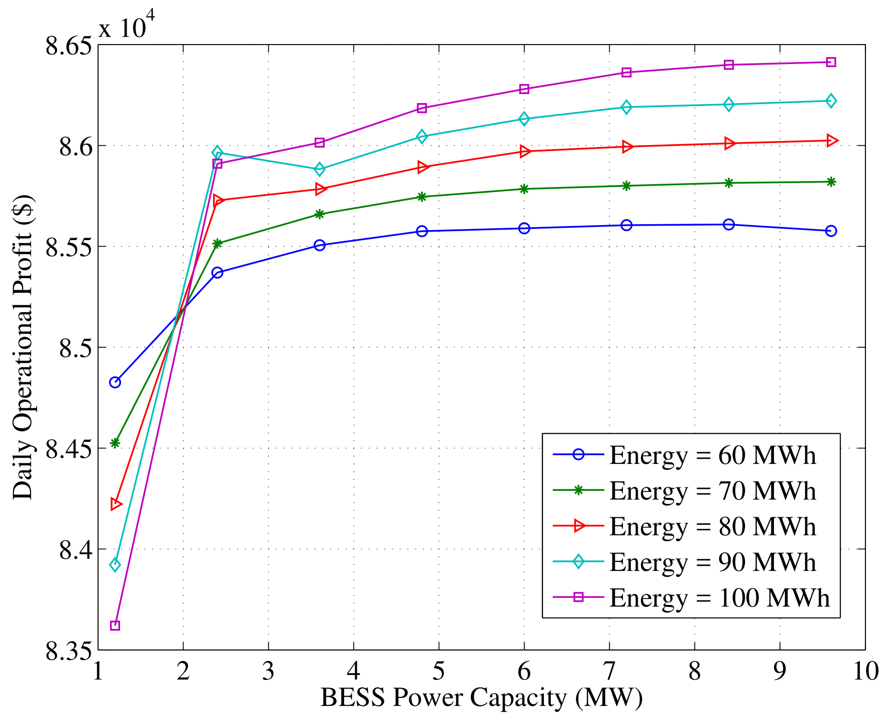

Figure 5.11: Daily Operational Profit vs. Power Capacity.

mine the optimal sequence of energy ready to be sold. The system carries along according to the receding horizon policy. In this setting, an error in wind power and price forecasts does impact the resulting control sequence, hence influencing the income and operational profit gained from selling the energy. This section is dedicated to analyze and quantify the impact of the forecast error upon these cost metrics.

Artificial intelligence based real forecast models have been developed and examined in the previous chapters. These include artificial neural network (ANN) model and functional network (FN) model. In addition to these real-time models, some simulated error models have also been introduced in this section for the sake of comparison. These simulated models include *random error* and *ramping error*.

The random error model generates an error with predefined limit (say ±10%), using a random distribution (like uniform distribution). This is a generic model and does not reflect the actual error dynamics of a multi-step forecasting system where the overall error increases with every step. To model this behavior, a better alternative is a ramping error which ramps up with every step in the prediction horizon. Thus, if we have a ramping error of 5%, it means it will be a 5% error in the first step but then it will ramp up with every step using a pre-defined slope. The next sub-sections analyze the impact of forecast errors from these real and simulated models from various perspectives.

5.3.1 Analysis of Functional Network Forecasting Model

In this subsection, the effect of the proposed FN prediction model is presented in terms of daily income improvement (II) and operational profit (OP). Three simulated models are used here including a random error model with 15% max. error, which means there is a deviation of $-15\% < 0 < 15\%$ from the actual value of wind power and market price. The ramping error models consist of 5% ramping error (starting from 5% and a ramp of 5% with each step) and 15% ramping error (starting from 15% and a ramp of 5% with each step).

The first result in this regard is shown in Figure 5.12, where a comparison is drawn between the FN predictor and three simulated error models in terms of II over a range of BESS power ratings. It can be observed that the II shows a decreasing trend in the beginning, but after about 7MW, the trend of II starts to ramp up for FN predictor as well as 15% random error model. The good performance of random error model is due to the fact that its error does not enlarge with increasing forecast horizon. Despite this effect in FN predictor, it still takes a clear lead over random error model and ends up with an II of about 8.6% over the trivial model at 36MW, whereas the II of random error model at the same point is about 7.3%. As for the ramping error models, they are unable to show good performance as their II deteriorates over increasing BESS power ratings. The 5% ramping models shows some increase and goes up to approx. 3.5% II at 10MW BESS rating, but after that, it continuously ramps down identical to the 15% ramping error model. This result shows the importance of accurate wind power and market price forecasting as the adverse effect of ramping error is clearly depicted by the depreciation in income despite increasing the BESS power capacity.

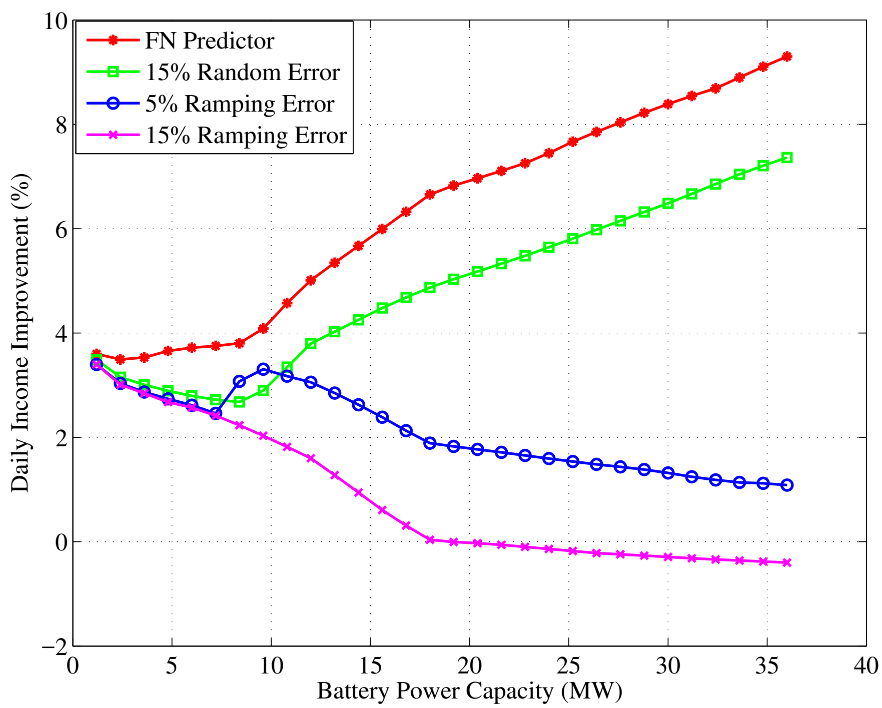

Figure 5.12: Daily Income Improvement for various forecast error models.

Another way of comparing the impact of forecast error is by running a similar optimization algorithm and analysis assuming there is no forecast error at all. This is an impossible situation as we cannot know the future exactly, however, it is just used as a reference to gauge the depreciation in performance of the proposed prediction models. The prediction model with least depreciation will be considered as the best. The II comparison results for FN predictor are depicted in Figure 5.13. It can be seen that for the case without error the II increases with almost a constant rate which is not the case with prediction error. There is a difference of about 10% improvement in income for the FN predictor while the other error models are worse.

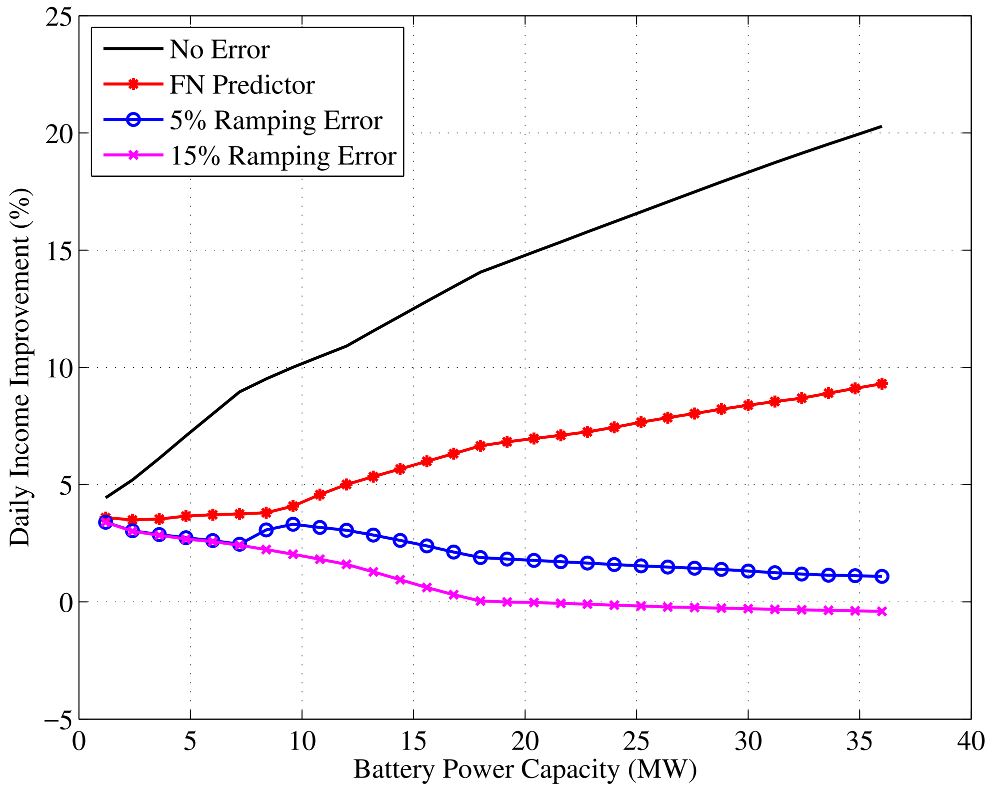

Figure 5.13: Daily Income Improvement of forecast error models vs. zero error reference.

A similar analysis is performed for FN predictor and three simulated error models in terms of OP over a range of BESS power ratings in Figures 5.14 and 5.15. Similar to II plot, the OP also shows a decreasing trend in the beginning, but after about 8MW, the trend of OP starts to ramp up for FN predictor as well as 15% random error model. FN model shows a max. improvement of $70 daily over random error model and of $400 to $500 over ramping error models. This result shows the importance of accurate wind power and market price forecasting as the adverse effect of ramping error is clearly depicted by the depreciation in OP despite increasing the BESS power capacity. Similarly, the max. deterioration of the FN prediction model from the OP with no forecasting error is about $350 as shown in Figure 5.15.

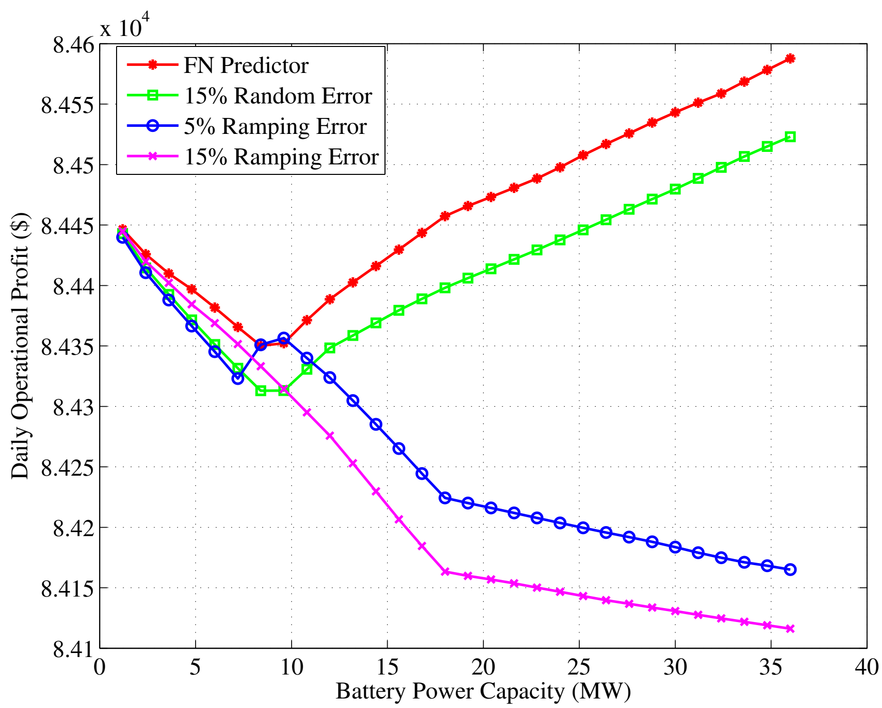

Figure 5.14: Daily Operational Profit for various forecast error models.

In the last part of this subsection, the impact of forecast error is analyzed from

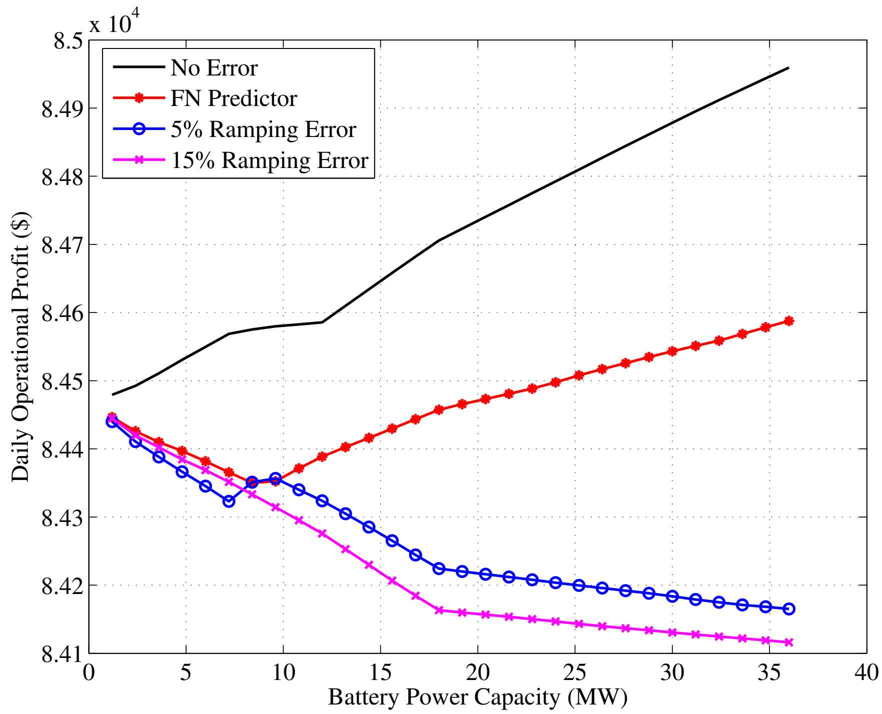

Figure 5.15: Daily Operational Profit of forecast error models vs. zero error reference.

a different perspective over a range of BESS energy capacities, while the power capacity is kept fixed. In this regard, the daily II and OP are shown against the BESS capacities varying from 0-300MWh for a suitable power capacity of 6MW. In Figure 5.16, the daily II of FN prediction model is compared with real-value model results with zero prediction error. It can be seen that there is a max. depreciation of 0.5% in II, which shows the efficacy of the predictor that the income is not deteriorated with forecast error. Moreover, the gap keeps closing as the BESS capacity is increased and finally II from both models coincides at an optimum level after which there is no improvement even for no forecast error. The optimum value for this particular power capacity (6MW/5min) is around 280MWh. The reason behind this minimal impact of forecast error is inherent that BESS capacity basically caters for the intermittencies in renewable power generation, hence increasing the capacity almost eliminates the impact of forecast error after the optimum point.

A similar analysis is performed in terms of daily OP in Figure 5.17 and similar results have been obtained with a max. profit depreciation of around $200 which keeps improving and finally coincides at the optimum point which is obtained at the same capacity of 280MWh. The only difference is after the optimum since the income becomes constant but further increasing the capacity still increases the capacity cost, so the OP begins to drop after that point.

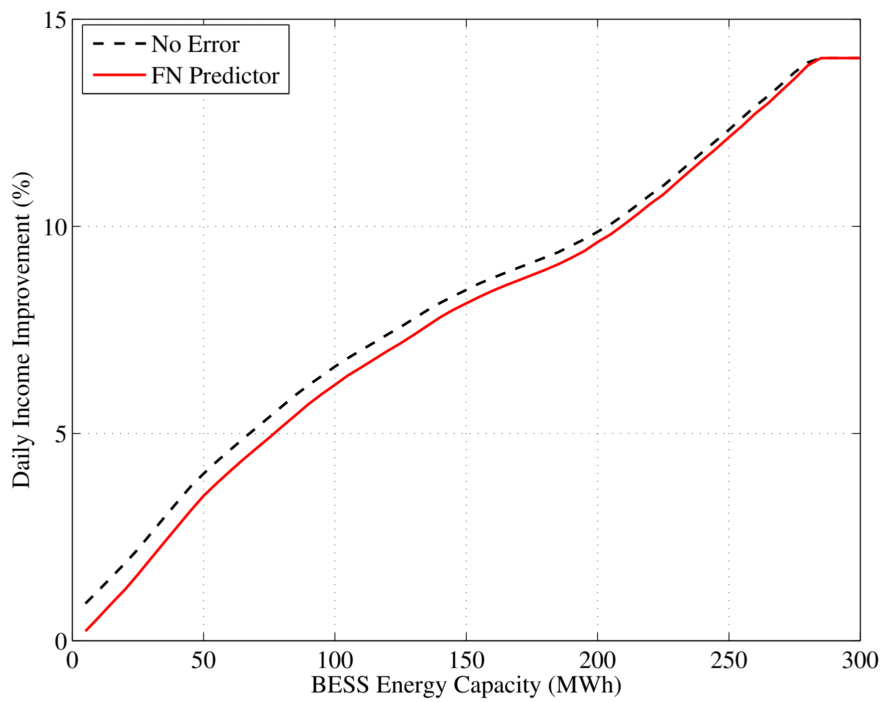

Figure 5.16: Daily Income Improvement of FN Prediction model vs. zero error reference.

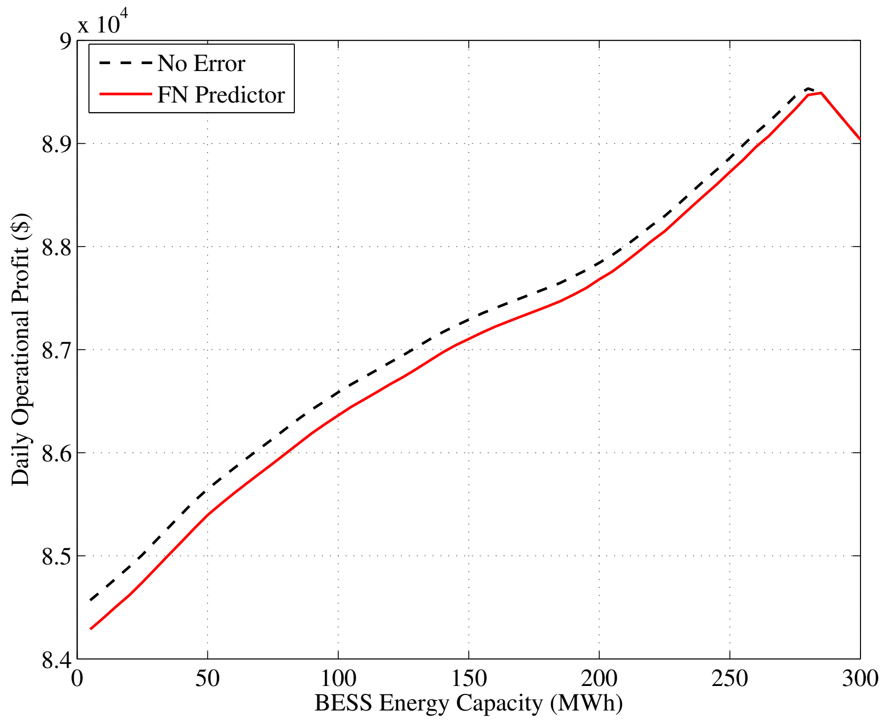

Figure 5.17: Daily Operational Profit of FN Prediction model vs. zero error reference.

5.3.2 Analysis of Real-Time Model Results

The focus of this sub-section is to present the comparison between both developed prediction models in this thesis work in terms of income and operational profit after power dispatch. As already discussed, these two models are FN predictor and ANN predictor. Figure 5.18 shows the comparison of both these predictors over BESS power ratings that although the performance of both these models does not have a huge difference, FN model still gives a little bit better II as expected. The FN model poses about 1-1.5% better II than ANN model over the whole range of Figure 5.18. As compared to zero error reference which is not possible in reality the II drop is shown in Figure 5.19.

In a similar way, the comparison between the two real-time predictors is de-

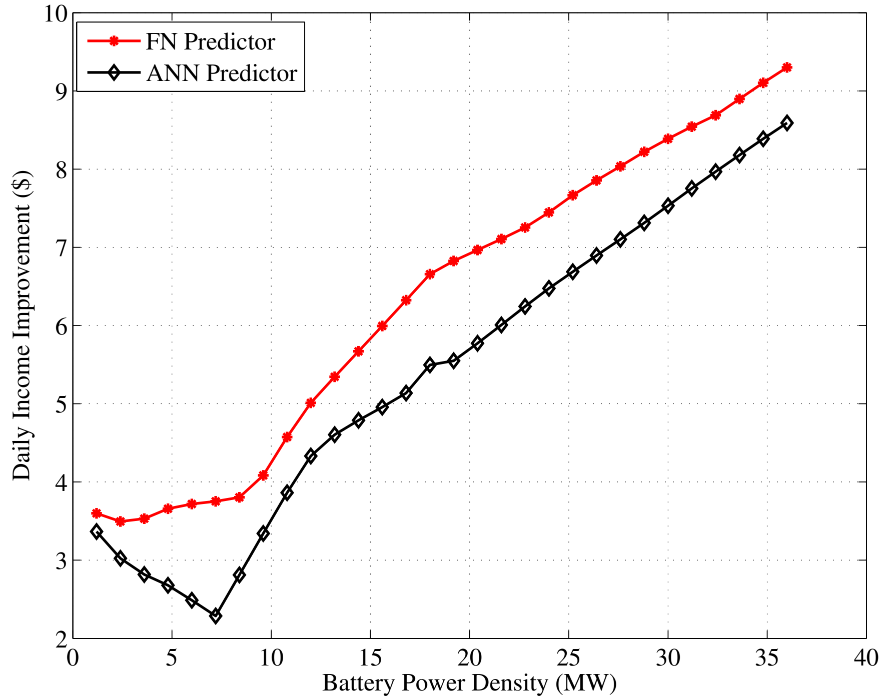

Figure 5.18: Daily Income Improvement for FN and ANN forecast models.

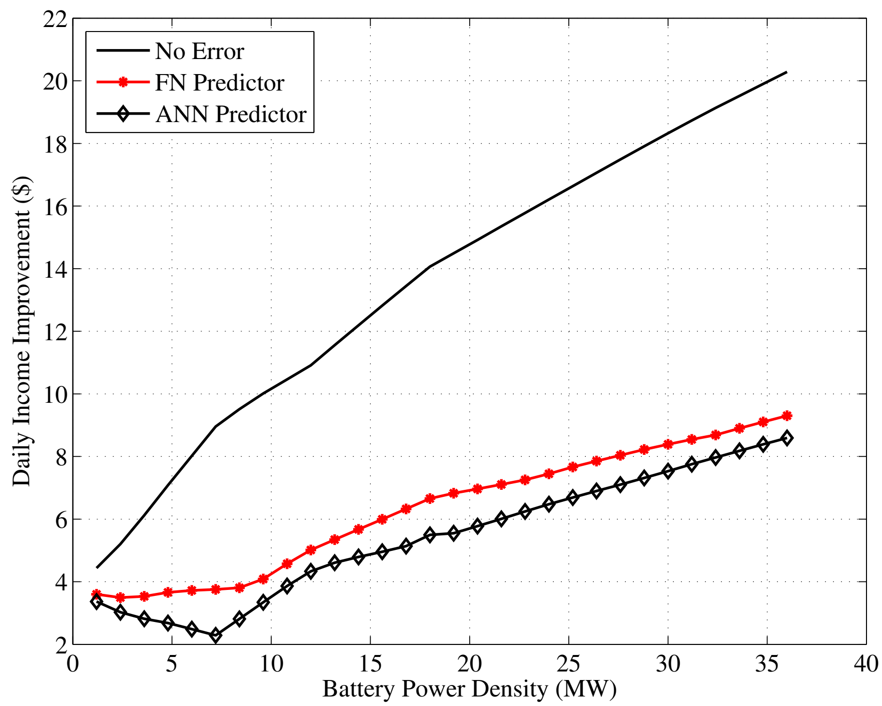

Figure 5.19: Daily Income Improvement for FN and ANN forecast models vs. zero error reference.

picted in terms of OP in Figures 5.20 and 5.21. The OP sloped down at the beginning of BESS power capacity range until 7-10MW where it hits a low value of \$84,280 for ANN model and \$84,350 for FN after which OP trend ramps up for both models while keeping a margin of around \$40 for the whole range. From the zero error reference, the ANN model has a depreciation of about \$370 maximum which is a bit more than that of FN model.

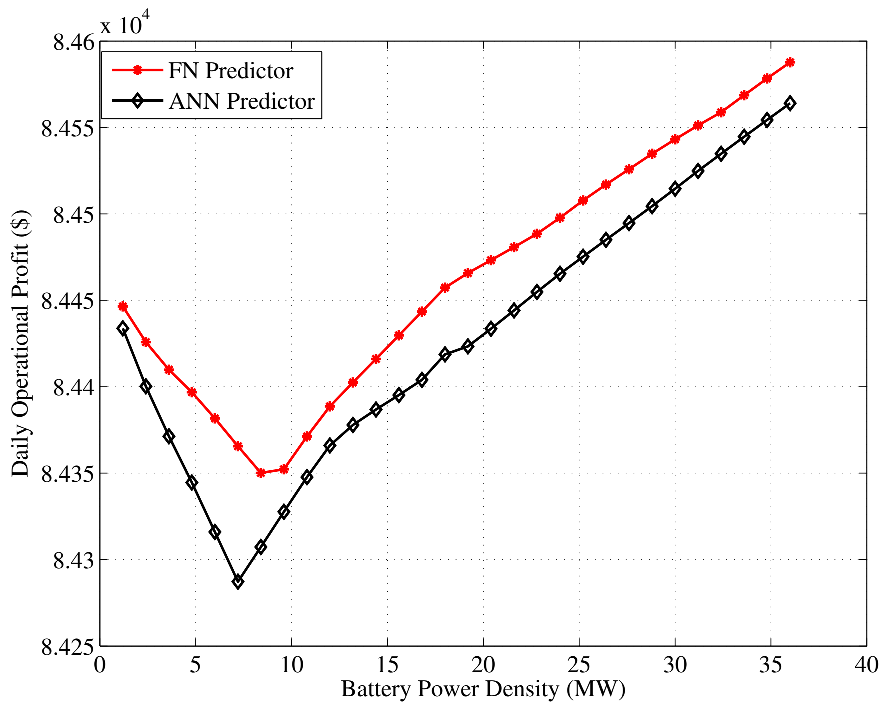

Figure 5.20: Daily Operational Profit for FN and ANN forecast models.

Next we present a major comparison among all the developed and simulated forecast models as shown in Figures 5.22 and 5.23 in terms of daily II and OP respectively. It can be observed that the II shows a decreasing trend in the beginning, but after about 7MW, the trend of II starts to ramp up for both real-time predictors as well as 15% random error model. The FN predictor, takes a clear lead over other models and ends up with an II of about 9.2% over the trivial

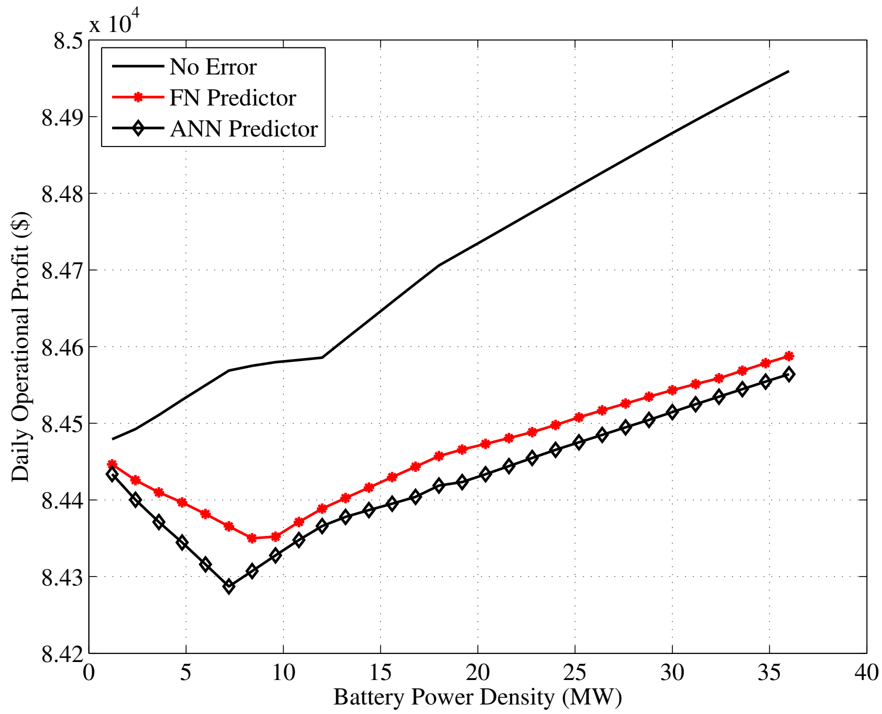

Figure 5.21: Daily Operational Profit for FN and ANN forecast models vs. zero error reference.

model at 36MW, whereas the II of ANN model at the same point is about 8.6%. As for the ramping error models, they are unable to show good performance as their II deteriorates over increasing BESS power ratings. The 5% ramping models shows some increase and goes up to approx. 3.5% II at 10MW BESS rating, but after that, it continuously ramps down identical to the 15% ramping error model. This result shows the importance of accurate wind power and market price forecasting as the adverse effect of ramping error is clearly depicted by the depreciation in income despite increasing the BESS power capacity.

A similar analysis is performed for real-time predictors and three simulated error models in terms of OP over a range of BESS power ratings in Figure 5.23. Similar to II plot, the OP also shows a decreasing trend in the beginning, but after about 7MW, the trend of OP starts to ramp up for both developed predictors as well as 15% random error model. FN model shows an improvement of about \$80 daily over random error model and of \$400 to \$500 over ramping error models.

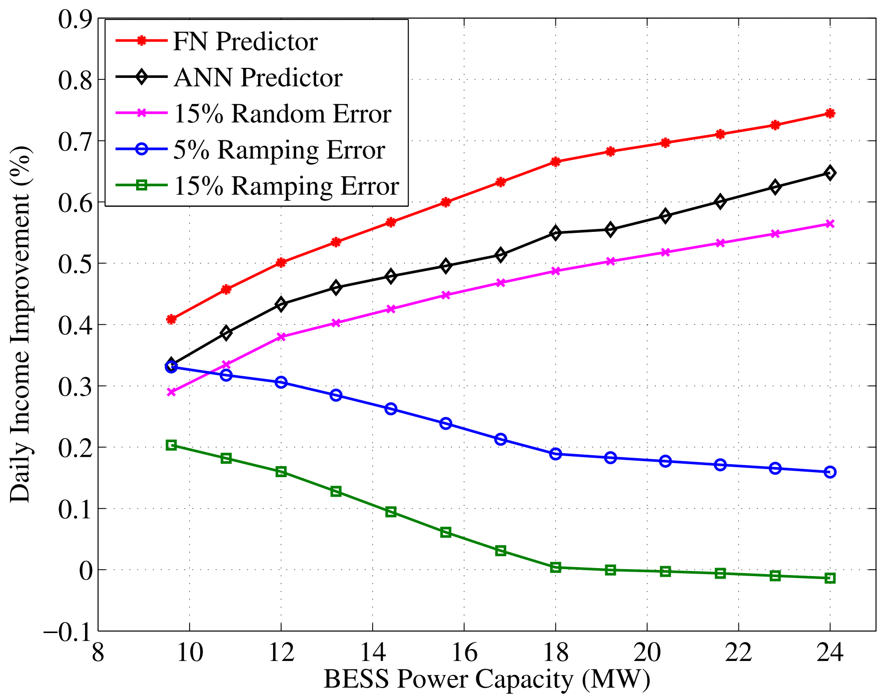

Figure 5.22: Daily Income Improvement for various forecast models.

The case of zero forecast error is compared to study the drop in II and OP due to forecast error as well for all developed and simulated forecast models. The II comparison results for FN predictor are depicted in Figure 5.24. It can be seen that for the case without error the II increases with almost a constant rate which is not the case with prediction error. There is a difference of about 10% improvement in income for the FN predictor and about 12% for the ANN predictor while the other simulated error models are worse. Similarly, it is shown in Figure 5.25 that the max. deterioration of the FN prediction model from the OP with no forecasting error is about \$360 while for ANN model it is about \$400. The

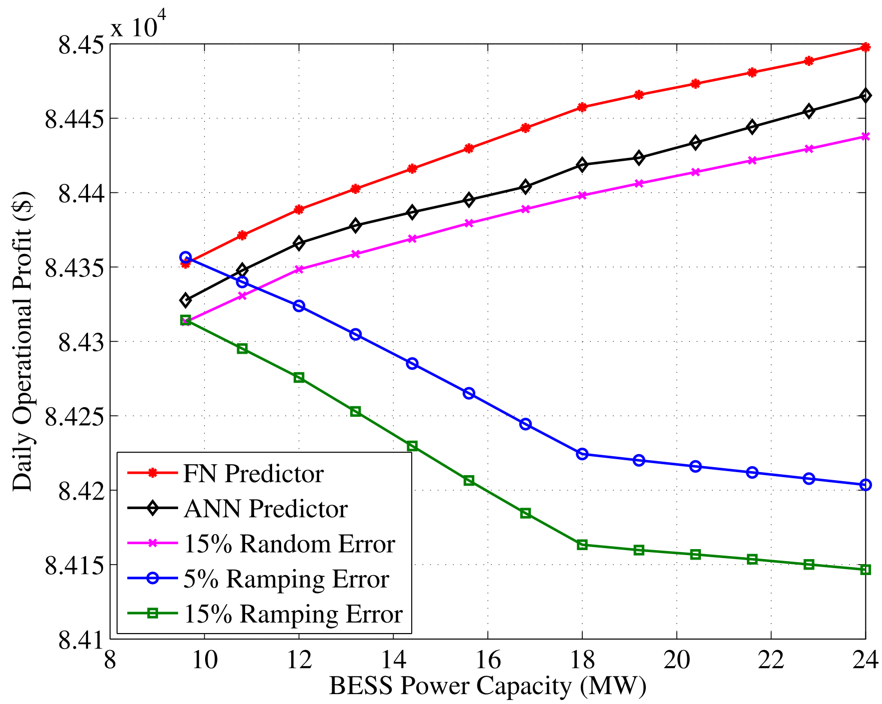

Figure 5.23: Daily Operational Profit for various forecast models.

simulated ramping error models show a drop of up to $800 daily which show the direct benefit of better forecast accuracy if the developed forecast models.

In the last part of this subsection, the impact of forecast error for both developed forecast models is analyzed from a different perspective over a range of BESS energy capacities, while the power capacity is kept fixed. In this regard, the daily II and OP are shown against the BESS capacities varying from 0-300MWh for a suitable power capacity of 6MW. In Figure 5.26, the daily II of both FN and ANN prediction models is compared with real-value model results with zero prediction error. It can be seen that both the models show almost similar performance while the comparison with zero error reference is already discussed in Section 5.3.1. Similarly, it is shown in Figure 5.27 that the developed models show identical performance in terms of OP as well. In essence, two conclusion can be drawn

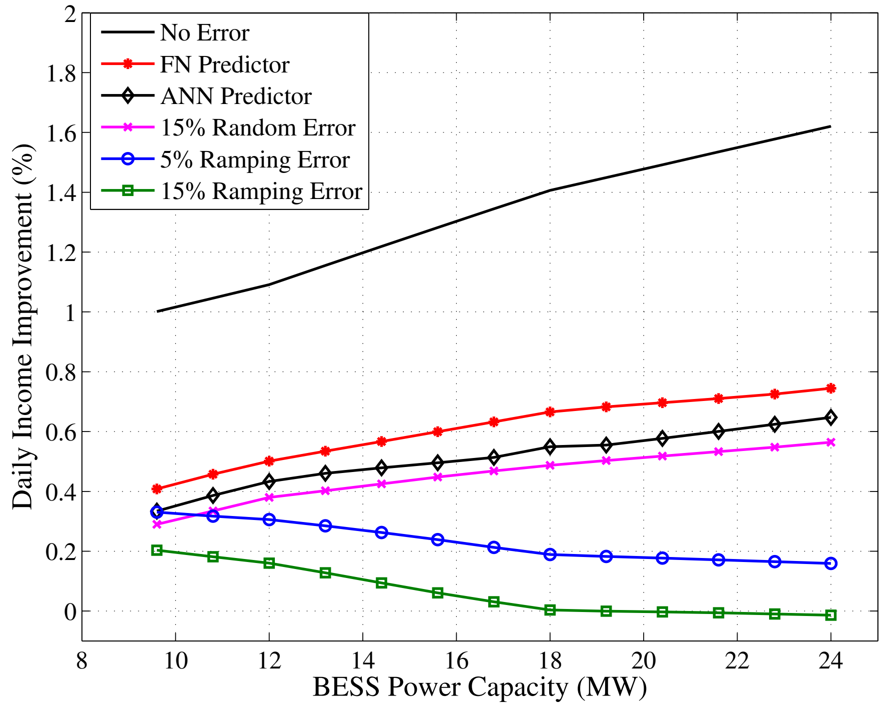

Figure 5.24: Daily Income Improvement for various forecast models vs. zero error reference.

from these results, 1) There is no significant impact of forecast error performance over the range of BESS capacities as both models give similar results and they are not much deteriorated from the zero error case either. 2) This analysis can help us in determining the optimal BESS capacity at a particular power rating after which no more profit can be earned.

5.3.3 Analysis at High Energy Capacity

In this subsection, the effect of forecast error is analyzed at high BESS capacities. For this purpose, the daily II and daily OP are plotted against various power capacities of the BESS as done in previous sections. The improvement in daily income at a high BESS capacity of 240 MWh is shown in Figure 5.28 for various

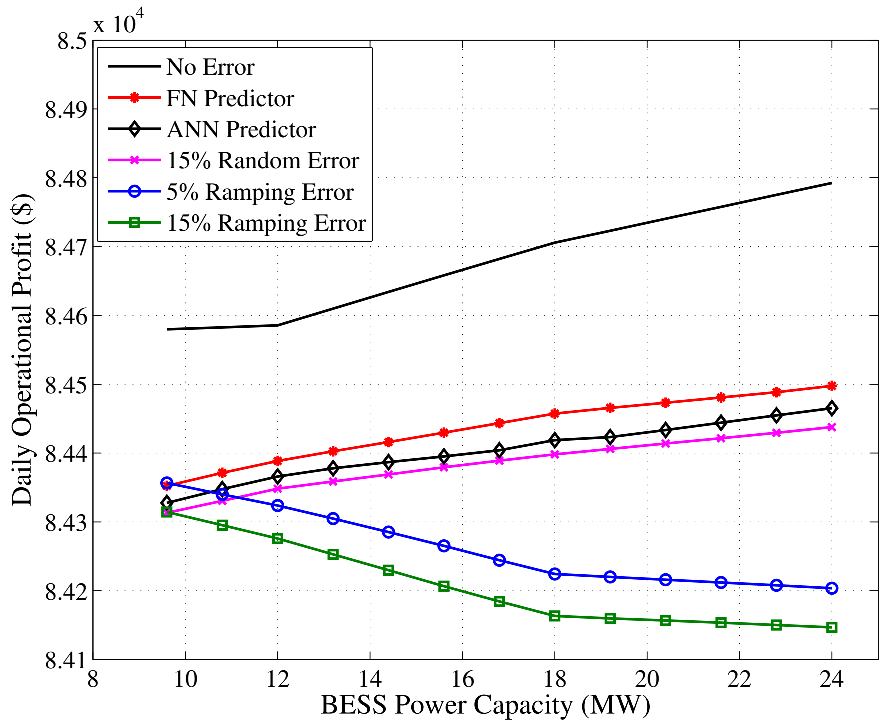

Figure 5.25: Daily Operational Profit for various forecast models vs. zero error reference.

real and simulated forecast error models. It can be observed in this plot that unlike previous results at smaller BESS energy capacities, the II for all models is almost similar, whereas the II of FN predictor shows an improvement of approx. 1.5% over other models. In comparison to the reference zero error II, the behavior of FN predictor is almost similar at lower BESS power capacities until 10MW but afterwards the performance deteriorates due to forecast error and goes up to a fall of 2% in II at highest BESS power capacity under consideration, i.e., 36MW, whereas the other forecast models show a decrement of about 3-3.5%. Furthermore, the optimum value of II is 11.5% which is achieved only at 6MW Power capacity and it coincides with the zero error case, which shows the supremacy of FN predictor as this is not achieved in case of other predictors.

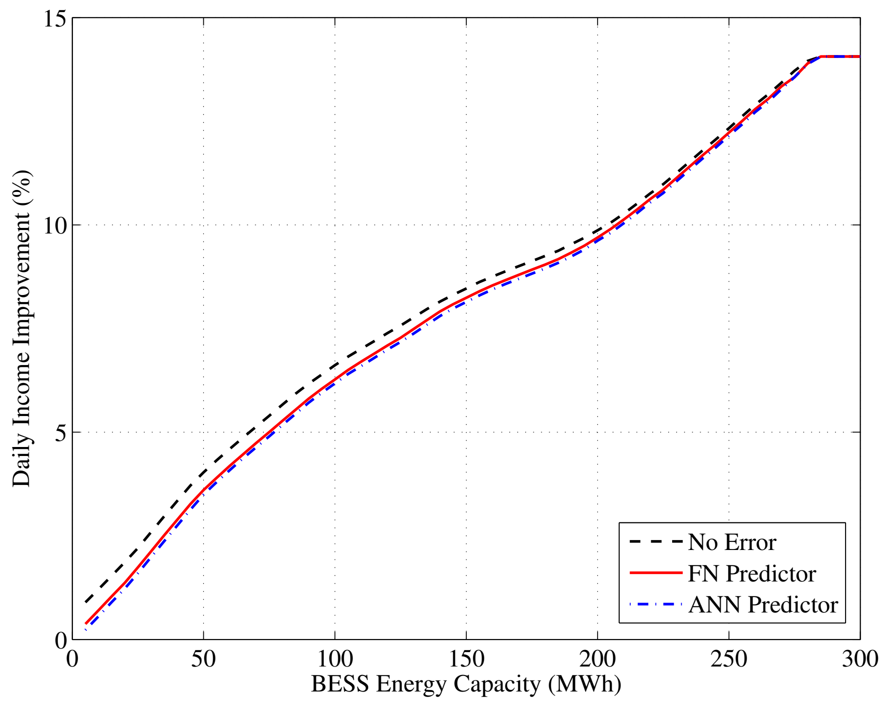

Figure 5.26: Daily Income Improvement of Real Prediction models vs. zero error reference over BESS Capacity.

Similarly, the daily OP trend is analyzed at high BESS capacity of 180 MWh in Figure 5.29. For OP as well the trends are identical to the income. The OP of FN predictor is same as the zero error reference until the optimum $87,600 at a BESS power capacity of 5MW but it shows a decrease of about $1200 at higher power rating of 36MW. The other prediction models do not coincide with the optimum and show about $500 less than the FN predictor.

Finally, the forecast error analysis is shown at much higher capacities of around 300 MWh in Figures 5.30 and 5.31 for daily II and OP respectively. These results depict that the impact of forecast error is minimized at this much high BESS capacity. There is a deterioration of only about 2% max. II from the reference real market price and wind power. In a similar fashion, Figure 5.31 shows the

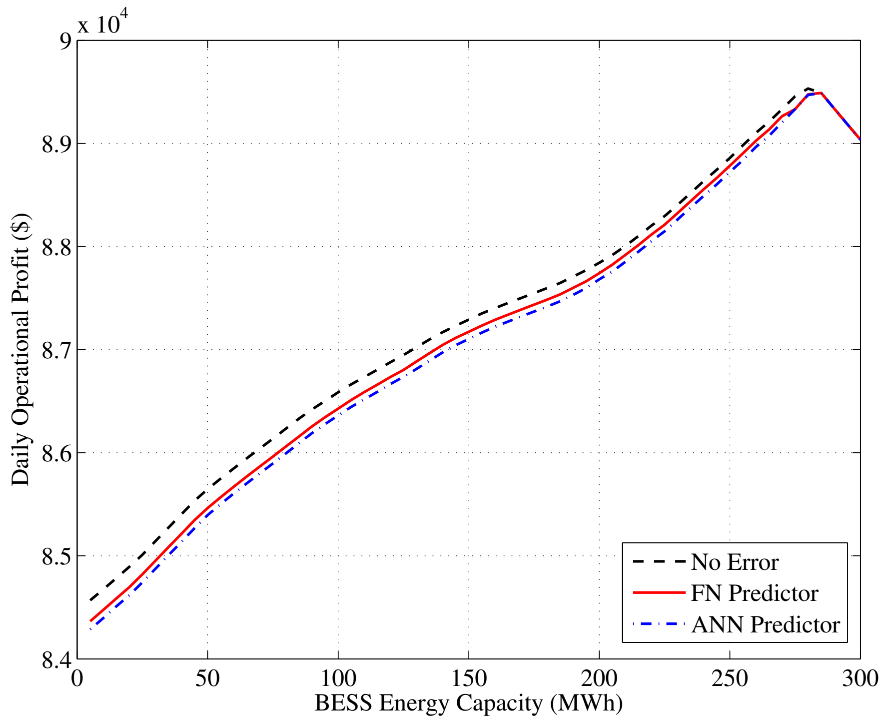

Figure 5.27: Daily Operational Profit of Real Prediction models vs. zero error reference over BESS Capacity.

minimality of forecast error impact at this high capacity such that there is a max. drop of \$1000 in OP for all forecast models with respect to real reference. Furthermore, an optimal small value of BESS power capacity can be found as 7MW after which there is only a profit of approx. \$1000 in going up to 32MW.

Hence, we can say that the impact of wind power and market price forecast error on income and profit of power dispatch is diminished as the BESS capacity goes higher. Furthermore, the analysis at higher BESS capacities helped us pointing out a minimum optimal value of BESS power capacity which gives maximum improvement in income and operational profit daily.

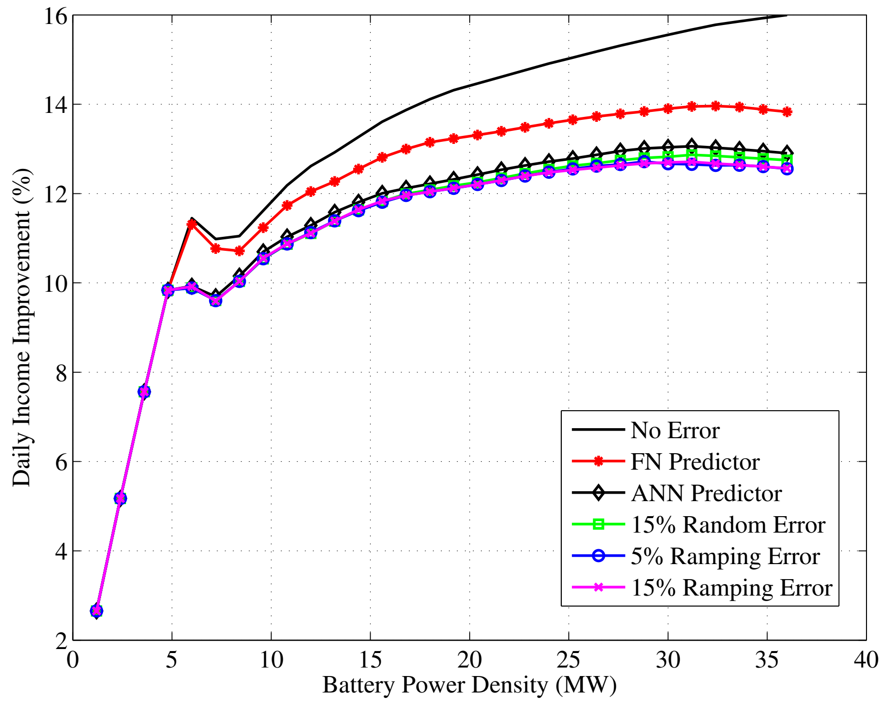

Figure 5.28: Daily Income Improvement of various Prediction models at higher BESS Capacities.

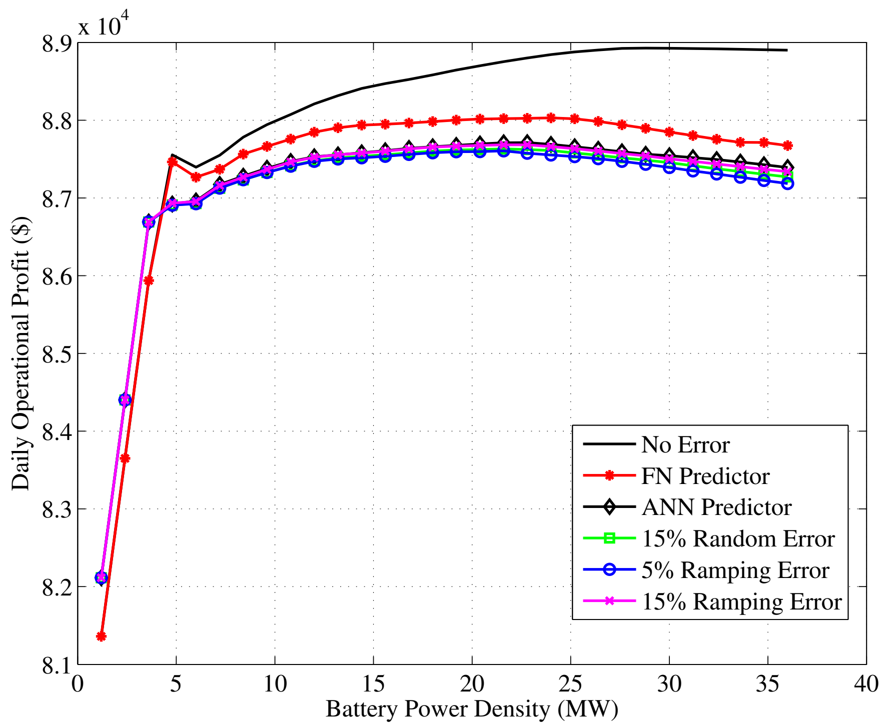

Figure 5.29: Daily Operational Profit of various Prediction models at higher BESS Capacities.

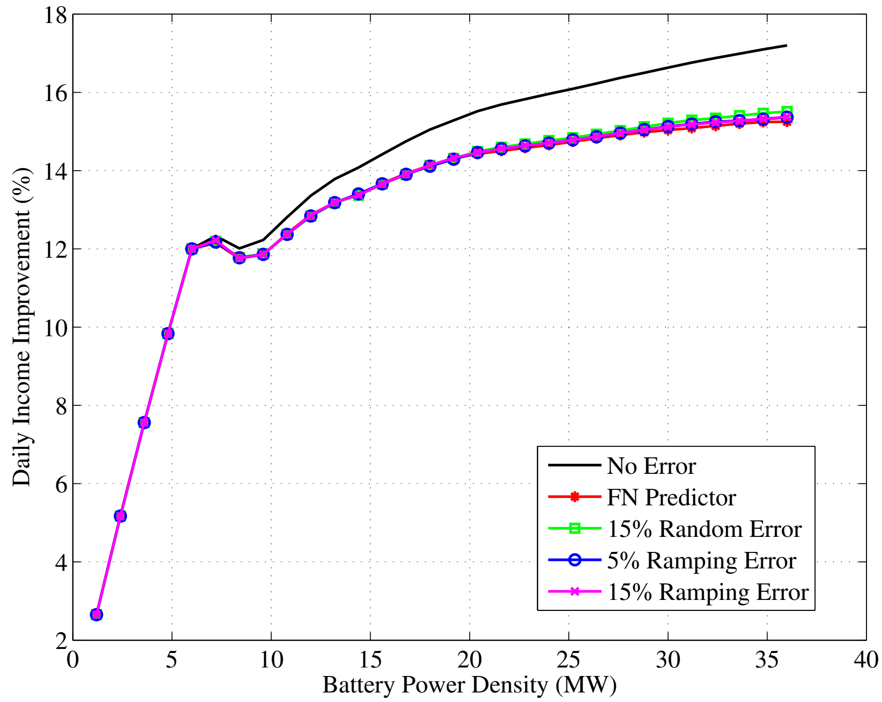

Figure 5.30: Daily Income Improvement of various Prediction models at high BESS Capacity (300MWh).

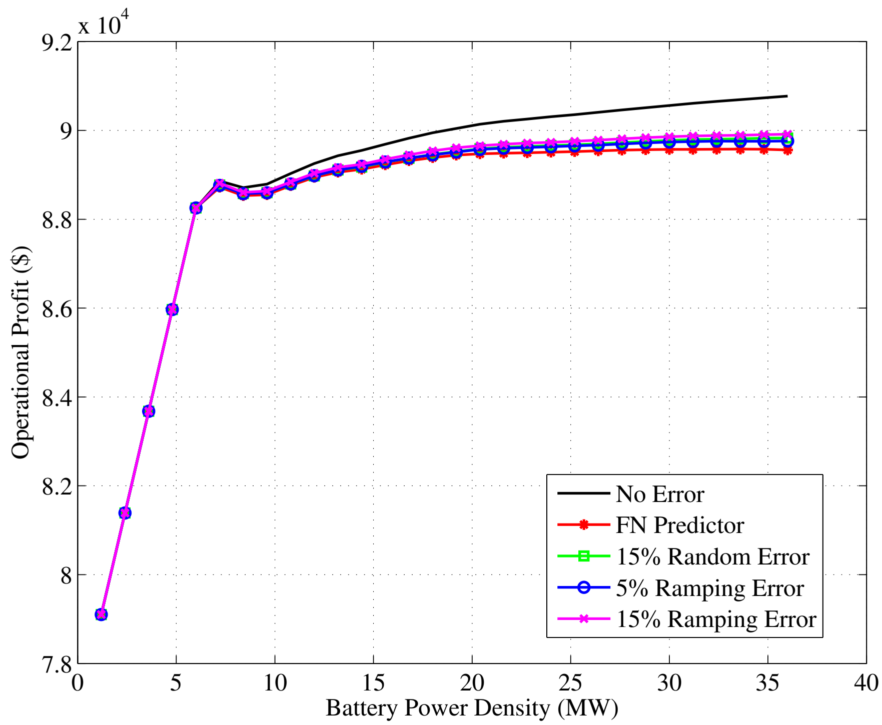

Figure 5.31: Daily Operational Profit of various Prediction models at high BESS Capacity (300MWh).

CHAPTER 6

CONCLUSION

In this thesis work, forecasting models are proposed and developed using AI techniques for multi-step ahead predictions via three forecasting schemes including recursive, direct and DirRec forecasting. The base AI model used to predict wind speed is based on ANN. A novel wind forecast model using FN is proposed and is shown to be better than the ANN model. The developed six-step ahead forecast models are applied to a dispatch strategy based on receding horizon MPC theory. The dispatch mechanism is intended to sell the wind energy at optimal intervals using forecasted market price information as well. Finally, the analysis of forecast error depicts the income improvement and operational profit benefits of the proposed real-time prediction model as compared to other real and simulated forecast error models.

6.1 Major Conclusions

The major conclusions that can be drawn from the described work are listed as under:

- The ANN wind forecasting model performs better than the benchmark persistence model in terms of all forecast error indices, and the trend shows that accuracy improvement of ANN over persistence is larger at longer forecast horizons.

- For the ANN multi-step forecast (MSF) model, the accuracy obtained by all three MSF schemes is very close to each other, hence none can be termed to be better than the other, however, recursive is preferred for its simplicity and less computational requirement.

- The proposed FN wind forecast model is not only innovative, but it is also very effective since it is more accurate than the benchmark and ANN MSF models, while less computationally expensive as compared to advanced hybrid AI models.

- The FN wind prediction model shows a max. improvement of 41% from persistence and 27% from the developed ANN model for MSF at longer forecast horizons.

- For FN MSF model, the forecast accuracy of the MSF schemes can be clearly ranked as (DirRec > Direct > Recursive), which is a logical outcome and reflects the benefit of the superior training method of FN.

- The application of real-time six-step FN prediction model in a microgrid helps in optimizing the dispatch process and the amount of wind energy that can be sold at various BESS capacities and power ratings.

- The scenario-based analysis for a range of BESS capacities and power ratings helps in determining the optimal BESS size after which no significant improvement in daily income and operational profit (OP) can be achieved.

- The forecast error analysis depicts that FN based prediction being the most accurate, shows better income improvement (II) and OP after optimization as compared to other simulated forecast error models as well as the developed ANN model over a range of BESS power capacities.

- Variation in BESS energy capacity does not have a significant effect on the obtained II and OP from different forecasting models, while the effect of forecast error is negligible at a fairly large BESS capacity.

It should be noted that all conclusion are deduced from the obtained results for the case studies under consideration. Hence some of them may not be generic and may vary for other case studies.

6.2 Recommendations for Future Research

Some recommendations and possible directions for future research in the same domain are given as under:

- The developed forecast models are generic and can be used for various applications in power systems such as solar irradiance and power forecasting, load forecasting and even for time-series forecasting applications other than power systems.
- This work targets at the basic concept of functional network model, however, many advancements can be made in the basic model. These advancements may include a different functional basis for neural functions which may consist of trigonometric functions to improve the forecast accuracy. Furthermore, a more advanced model-selection method such as forward-backward or backward-forward method may bring computational benefits.
- In recent works, the FN based model is seen to be combined with other advanced AI models such as ANN and ELM for other applications. The same can be tried for the problem of time-series forecasting.
- The developed models can be applied to diversified dispatch applications including a complex load profile which needs to be forecasted or a case of hybrid generation with many types of generation which can all be predicted using these models.
- The analysis of forecast error can be performed from various other angles by

considering a multi-objective optimization scenario in which we have an environmental objective or BESS life cycle maximization objective. The impact of forecast error on these objectives is also expected to produce publishable outcomes.

6.3 Closing Remarks

The development of accurate and innovative AI based forecast models is a much emphasized domain, firstly due to the rise of intelligent systems in this era. Secondly, the proposed work has immense implications due to the emerging concept of forecast-based control and optimization mechanisms in power dispatch process. This idea is well-accepted in recent literature as it not only makes the system more realistic but can also help in reducing the operating costs, optimizing the reserve and energy storage size and maximizing the operational profits in competitive energy markets. All in all, it is a fervent effort to attain profound technical and economic benefits for renewable energy technology to make progress toward the goal of cleaner environment for the welfare of the community and future generations.

REFERENCES

[1] M. I. Hoffert, K. Caldeira, G. Benford, D. R. Criswell, C. Green, H. Herzog, A. K. Jain, H. S. Kheshgi, K. S. Lackner, J. S. Lewis *et al.*, "Advanced technology paths to global climate stability: Energy for a greenhouse planet," *Science*, vol. 298, no. 5595, pp. 981–987, 2002.

[2] J. K. Kaldellis and D. Zafirakis, "The wind energy (r) evolution: A short review of a long history," *Renewable Energy*, vol. 36, no. 7, pp. 1887–1901, 2011.

[3] R. Shamseddine, "Saudi arabia targets 9.5 GW of renewable by 2030," Reuters, Tech. Rep., April 2016.

[4] N. Nguyen and J. Mitra, "Reliability of power system with high wind penetration under frequency stability constraint," *IEEE Transactions on Power Systems*, 2017.

[5] H. Holttinen, "Wind integration: experience, issues, and challenges," *Wiley Interdisciplinary Reviews: Energy and Environment*, vol. 1, no. 3, pp. 243–255, 2012.

[6] J. Jung and R. P. Broadwater, "Current status and future advances for wind speed and power forecasting," *Renewable and Sustainable Energy Reviews*, vol. 31, pp. 762–777, 2014.

[7] I. Okumus and A. Dinler, "Current status of wind energy forecasting and a hybrid method for hourly predictions," *Energy Conversion and Management*, vol. 123, pp. 362–371, 2016.

[8] L. Fried, S. Shukla, S. Sawyer, and S. Teske, "Global wind energy outlook," Global Wind Energy Council and Greenpeace International, Tech. Rep., 2016.

[9] Q. Wang, C. B. Martinez-Anido, H. Wu, A. R. Florita, and B.-M. Hodge, "Quantifying the economic and grid reliability impacts of improved wind power forecasting," *IEEE Transactions on Sustainable Energy*, vol. 7, no. 4, pp. 1525–1537, 2016.

[10] J. O. Dabiri, J. R. Greer, J. R. Koseff, P. Moin, and J. Peng, "A new approach to wind energy: opportunities and challenges," in *AIP Conference Proceedings*, vol. 1652, no. 1. AIP, 2015, pp. 51–57.

[11] G. Ren, J. Liu, J. Wan, Y. Guo, and D. Yu, "Overview of wind power intermittency: Impacts, measurements, and mitigation solutions," *Applied Energy*, vol. 204, pp. 47–65, 2017.

[12] L. Xie, Y. Gu, X. Zhu, and M. G. Genton, "Short-term spatio-temporal wind power forecast in robust look-ahead power system dispatch," *IEEE Transactions on Smart Grid*, vol. 5, no. 1, pp. 511–520, 2014.

[13] H. Bitaraf, S. Rahman, and M. Pipattanasomporn, "Sizing energy storage to mitigate wind power forecast error impacts by signal processing techniques," *IEEE Transactions on Sustainable Energy*, vol. 6, no. 4, pp. 1457–1465, 2015.

[14] M. A. Abido, "Multiobjective evolutionary algorithms for electric power dispatch problem," *IEEE transactions on evolutionary computation*, vol. 10, no. 3, pp. 315–329, 2006.

[15] D. McLarty, C. C. Sabate, J. Brouwer, and F. Jabbari, "Micro-grid energy dispatch optimization and predictive control algorithms; a uc irvine case study," *International Journal of Electrical Power & Energy Systems*, vol. 65, pp. 179–190, 2015.

[16] M. R. Patel, *Wind and solar power systems: design, analysis, and operation.* CRC press, 2005.

[17] A. Botterud, Z. Zhou, J. Wang, J. Sumaili, H. Keko, J. Mendes, R. J. Bessa, and V. Miranda, "Demand dispatch and probabilistic wind power forecasting in unit commitment and economic dispatch: A case study of illinois," *IEEE Transactions on Sustainable Energy*, vol. 4, no. 1, pp. 250–261, 2013.

[18] J. Wang, Y. Song, F. Liu, and R. Hou, "Analysis and application of forecasting models in wind power integration: A review of multi-step-ahead wind speed forecasting models," *Renewable and Sustainable Energy Reviews*, vol. 60, pp. 960–981, 2016.

[19] K. Bruninx and E. Delarue, "A statistical description of the error on wind power forecasts for probabilistic reserve sizing," *IEEE Transactions on Sustainable Energy*, vol. 5, no. 3, pp. 995–1002, 2014.

[20] H. Zhao, Q. Wu, S. Hu, H. Xu, and C. N. Rasmussen, "Review of energy storage system for wind power integration support," *Applied Energy*, vol. 137, pp. 545–553, 2015.

[21] P. Harsha and M. Dahleh, "Optimal management and sizing of energy storage under dynamic pricing for the efficient integration of renewable energy," *IEEE Transactions on Power Systems*, vol. 30, no. 3, pp. 1164–1181, 2015.

[22] M. Khalid and A. V. Savkin, "Minimization and control of battery energy storage for wind power smoothing: Aggregated, distributed and semi-distributed storage," *Renewable Energy*, vol. 64, pp. 105–112, 2014.

[23] M. Khalid, A. Ahmadi, A. V. Savkin, and V. G. Agelidis, "Minimizing the energy cost for microgrids integrated with renewable energy resources and conventional generation using controlled battery energy storage," *Renewable Energy*, vol. 97, pp. 646–655, 2016.

[24] S. Chen, H. B. Gooi, and M. Wang, "Sizing of energy storage for microgrids," *IEEE Transactions on Smart Grid*, vol. 3, no. 1, pp. 142–151, 2012.

[25] L. Ciabattoni, F. Ferracuti, G. Ippoliti, and S. Longhi, "Artificial bee colonies based optimal sizing of microgrid components: a profit maximization approach," in *Evolutionary Computation (CEC), 2016 IEEE Congress on*. IEEE, 2016, pp. 2036–2042.

[26] A. Parisio, E. Rikos, G. Tzamalis, and L. Glielmo, "Use of model predictive control for experimental microgrid optimization," *Applied Energy*, vol. 115, pp. 37–46, 2014.

[27] A. Khatamianfar, M. Khalid, A. V. Savkin, and V. G. Agelidis, "Improving wind farm dispatch in the Australian electricity market with battery energy storage using model predictive control," *IEEE Transactions on Sustainable Energy*, vol. 4, no. 3, pp. 745–755, 2013.

[28] S. Mazzola, C. Vergara, M. Astolfi, V. Li, I. Perez-Arriaga, and E. Macchi, "Assessing the value of forecast-based dispatch in the operation of off-grid rural microgrids," *Renewable Energy*, vol. 108, pp. 116–125, 2017.

[29] L. Exizidis, J. Kazempour, P. Pinson, Z. De Greve, and F. Vallee, "Impact of public aggregate wind forecasts on electricity market outcomes," *IEEE Transactions on Sustainable Energy*, 2017.

[30] S. Singh and N. Kumar, "Wind power forecasting: A survey," *Int. J. Eng. Res. Gen. Sci*, vol. 4, pp. 802–806, 2016.

[31] M. Liu, F. L. Quilumba, and W.-J. Lee, "Dispatch scheduling for a wind farm with hybrid energy storage based on wind and lmp forecasting," *IEEE Transactions on Industry Applications*, vol. 51, no. 3, pp. 1970–1977, 2015.

[32] G. Sideratos and N. D. Hatziargyriou, "An advanced statistical method for wind power forecasting," *IEEE Transactions on power systems*, vol. 22, no. 1, pp. 258–265, 2007.

[33] W.-Y. Chang, "A literature review of wind forecasting methods," *Journal of Power and Energy Engineering*, vol. 2, no. 4, 2014.

[34] J. Yan, K. Li, E.-W. Bai, J. Deng, and A. M. Foley, "Hybrid probabilistic wind power forecasting using temporally local gaussian process," *IEEE Transactions on Sustainable Energy*, vol. 7, no. 1, pp. 87–95, 2016.

[35] S. Lawan, W. Abidin, W. Chai, A. Baharun, and T. Masri, "Different models of wind speed prediction; a comprehensive review," *International Journal of Scientific and Engineering Research*, vol. 5, no. 1, pp. 1760–1768, 2014.

[36] K. Orwig, C. Clark, J. Cline, S. Benjamin, J. Wilczak, M. Marquis, C. Finley, A. Stern, and J. Freedman, "Enhanced short-term wind power forecasting and value to grid operations," in *11th Annual Int. Workshop on Large-Scale Integration of Wind Power into Power Systems*, 2012.

[37] V. Lara-Fanego, J. Ruiz-Arias, A. Pozo-Vázquez, C. Gueymard, and J. Tovar-Pescador, "Evaluation of DNI forecast based on the WRF mesoscale

atmospheric model for CPV applications," in *AIP Conference Proceedings*, vol. 1477, no. 1. AIP, 2012, pp. 317–322.

[38] U. Firat, S. N. Engin, M. Saraclar, and A. B. Ertuzun, "Wind speed forecasting based on second order blind identification and autoregressive model," in *Machine Learning and Applications (ICMLA), 2010 Ninth International Conference on*. IEEE, 2010, pp. 686–691.

[39] M. A. Kulkarni, S. Patil, G. Rama, and P. Sen, "Wind speed prediction using statistical regression and neural network," *Journal of Earth System Science*, vol. 117, no. 4, pp. 457–463, 2008.

[40] X. Zhang, J. Zhang, Y. Li, and R. Zhang, "Short-term forecasting of wind speed based on recursive least squares," in *Electrical and Control Engineering (ICECE), 2011 International Conference on*. IEEE, 2011, pp. 367–370.

[41] E. Erdem and J. Shi, "Arma based approaches for forecasting the tuple of wind speed and direction," *Applied Energy*, vol. 88, no. 4, pp. 1405–1414, 2011.

[42] L. Ling-ling, J.-H. Li, P.-J. He, and C.-S. Wang, "The use of wavelet theory and arma model in wind speed prediction," in *Electric Power Equipment-Switching Technology (ICEPE-ST), 2011 1st International Conference on*. IEEE, 2011, pp. 395–398.

[43] T. H. El-Fouly, E. F. El-Saadany, and M. M. Salama, "One day ahead prediction of wind speed and direction," *IEEE Transactions on Energy Conversion*, vol. 23, no. 1, pp. 191–201, 2008.

[44] M.-D. Wang, Q.-R. Qiu, and B.-W. Cui, "Short-term wind speed forecasting combined time series method and arch model," in *Machine Learning and Cybernetics (ICMLC), 2012 International Conference on*, vol. 3. IEEE, 2012, pp. 924–927.

[45] R. G. Kavasseri and K. Seetharaman, "Day-ahead wind speed forecasting using f-arima models," *Renewable Energy*, vol. 34, no. 5, pp. 1388–1393, 2009.

[46] E. Cadenas, W. Rivera, R. Campos-Amezcua, and C. Heard, "Wind speed prediction using a univariate arima model and a multivariate narx model," *Energies*, vol. 9, no. 2, p. 109, 2016.

[47] H. Liu, H.-Q. Tian, C. Chen, and Y.-f. Li, "A hybrid statistical method to predict wind speed and wind power," *Renewable energy*, vol. 35, no. 8, pp. 1857–1861, 2010.

[48] A. Bracale and P. De Falco, "An advanced bayesian method for short-term probabilistic forecasting of the generation of wind power," *Energies*, vol. 8, no. 9, pp. 10 293–10 314, 2015.

[49] C.-Y. Huang, Y.-W. Liu, W.-C. Tzeng, and P.-Y. Wang, "Short term wind speed predictions by using the grey prediction model based forecast

method," in *Green Technologies Conference (IEEE-Green), 2011 IEEE.* IEEE, 2011, pp. 1–5.

[50] H. B. Azad, S. Mekhilef, and V. G. Ganapathy, "Long-term wind speed forecasting and general pattern recognition using neural networks," *IEEE Transactions on Sustainable Energy*, vol. 5, no. 2, pp. 546–553, 2014.

[51] M. Lei, L. Shiyan, J. Chuanwen, L. Hongling, and Z. Yan, "A review on the forecasting of wind speed and generated power," *Renewable and Sustainable Energy Reviews*, vol. 13, no. 4, pp. 915–920, 2009.

[52] M. Alexiadis, P. Dokopoulos, and H. Sahsamanoglou, "Wind speed and power forecasting based on spatial correlation models," *IEEE Transactions on Energy Conversion*, vol. 14, no. 3, pp. 836–842, 1999.

[53] A. Malvaldi, S. Weiss, D. Infield, J. Browell, P. Leahy, and A. M. Foley, "A spatial and temporal correlation analysis of aggregate wind power in an ideally interconnected europe," *Wind Energy*, vol. 20, no. 8, pp. 1315–1329, 2017.

[54] I. G. Damousis, M. C. Alexiadis, J. B. Theocharis, and P. S. Dokopoulos, "A fuzzy model for wind speed prediction and power generation in wind parks using spatial correlation," *IEEE Transactions on Energy Conversion*, vol. 19, no. 2, pp. 352–361, 2004.

[55] G. Papaefthymiou and P. Pinson, "Modeling of spatial dependence in wind power forecast uncertainty," in *Probabilistic Methods Applied to Power Sys-*

tems, 2008. PMAPS'08. Proceedings of the 10th International Conference on. IEEE, 2008, pp. 1–9.

[56] M. Khalid and A. V. Savkin, "A method for short-term wind power prediction with multiple observation points," *IEEE Transactions on Power Systems*, vol. 27, no. 2, pp. 579–586, 2012.

[57] S. A. Arefifar, Y. A.-R. I. Mohamed, and T. H. El-Fouly, "Supply-adequacy-based optimal construction of microgrids in smart distribution systems," *IEEE transactions on smart grid*, vol. 3, no. 3, pp. 1491–1502, 2012.

[58] D. Villanueva and A. Feijóo, "Wind power distributions: A review of their applications," *Renewable and Sustainable Energy Reviews*, vol. 14, no. 5, pp. 1490–1495, 2010.

[59] Y. Atwa, E. El-Saadany, M. Salama, and R. Seethapathy, "Optimal renewable resources mix for distribution system energy loss minimization," *IEEE Transactions on Power Systems*, vol. 25, no. 1, pp. 360–370, 2010.

[60] W. Werapun, Y. Tirawanichakul, and J. Waewsak, "Comparative study of five methods to estimate weibull parameters for wind speed on phangan island, thailand," *Energy Procedia*, vol. 79, pp. 976–981, 2015.

[61] M. A. Mohandes, S. Rehman, and T. O. Halawani, "A neural networks approach for wind speed prediction," *Renewable Energy*, vol. 13, no. 3, pp. 345–354, 1998.

[62] G. Li and J. Shi, "On comparing three artificial neural networks for wind speed forecasting," *Applied Energy*, vol. 87, no. 7, pp. 2313–2320, 2010.

[63] B. Doucoure, K. Agbossou, and A. Cardenas, "Time series prediction using artificial wavelet neural network and multi-resolution analysis: Application to wind speed data," *Renewable Energy*, vol. 92, pp. 202–211, 2016.

[64] A. E. Saleh, M. S. Moustafa, K. M. Abo-Al-Ez, and A. A. Abdullah, "A hybrid neuro-fuzzy power prediction system for wind energy generation," *International Journal of Electrical Power & Energy Systems*, vol. 74, pp. 384–395, 2016.

[65] M. A. Mohandes, T. O. Halawani, S. Rehman, and A. A. Hussain, "Support vector machines for wind speed prediction," *Renewable Energy*, vol. 29, no. 6, pp. 939–947, 2004.

[66] J. Wang, Q. Zhou, H. Jiang, and R. Hou, "Short-term wind speed forecasting using support vector regression optimized by cuckoo optimization algorithm," *Mathematical Problems in Engineering*, vol. 2015, 2015.

[67] Z. Yang, Y. Liu, and C. Li, "Interpolation of missing wind data based on anfis," *Renewable Energy*, vol. 36, no. 3, pp. 993–998, 2011.

[68] J. Catalao, H. Pousinho, and V. Mendes, "Hybrid Wavelet-PSO-ANFIS approach for short-term wind power forecasting in Portugal," *IEEE Transactions on Sustainable Energy*, vol. 2, no. 1, pp. 50–59, 2011.

[69] R. H. Inman, H. T. Pedro, and C. F. Coimbra, "Solar forecasting methods for renewable energy integration," *Progress in energy and combustion science*, vol. 39, no. 6, pp. 535–576, 2013.

[70] C. Paoli, C. Voyant, M. Muselli, and M.-L. Nivet, "Forecasting of preprocessed daily solar radiation time series using neural networks," *Solar Energy*, vol. 84, no. 12, pp. 2146–2160, 2010.

[71] M. Lazzaroni, S. Ferrari, V. Piuri, A. Salman, L. Cristaldi, and M. Faifer, "Models for solar radiation prediction based on different measurement sites," *Measurement*, vol. 63, pp. 346–363, 2015.

[72] C. Voyant, G. Notton, S. Kalogirou, M.-L. Nivet, C. Paoli, F. Motte, and A. Fouilloy, "Machine learning methods for solar radiation forecasting: A review," *Renewable Energy*, vol. 105, pp. 569–582, 2017.

[73] G. K. Tso and K. K. Yau, "Predicting electricity energy consumption: A comparison of regression analysis, decision tree and neural networks," *Energy*, vol. 32, no. 9, pp. 1761–1768, 2007.

[74] J. Cao and X. Lin, "Study of hourly and daily solar irradiation forecast using diagonal recurrent wavelet neural networks," *Energy Conversion and Management*, vol. 49, no. 6, pp. 1396–1406, 2008.

[75] Y.-K. Wu, C.-R. Chen, and H. Abdul Rahman, "A novel hybrid model for short-term forecasting in pv power generation," *International Journal of Photoenergy*, vol. 2014, 2014.

[76] L. Yang, M. He, J. Zhang, and V. Vittal, "Support-vector-machine-enhanced markov model for short-term wind power forecast," *IEEE Transactions on Sustainable Energy*, vol. 6, no. 3, pp. 791–799, 2015.

[77] N. Amjady, F. Keynia, and H. Zareipour, "Wind power prediction by a new forecast engine composed of modified hybrid neural network and enhanced particle swarm optimization," *IEEE transactions on sustainable energy*, vol. 2, no. 3, pp. 265–276, 2011.

[78] J. Wu, T. Ji, M. Li, P. Wu, and Q. Wu, "Multistep wind power forecast using mean trend detector and mathematical morphology-based local predictor," *IEEE Transactions on Sustainable Energy*, vol. 6, no. 4, pp. 1216–1223, 2015.

[79] A. Ahmed and M. Khalid, "Multi-step ahead wind forecasting using nonlinear autoregressive neural networks," *Energy Procedia*, vol. 134, pp. 192–204, 2017.

[80] S. B. Taieb, G. Bontempi, A. F. Atiya, and A. Sorjamaa, "A review and comparison of strategies for multi-step ahead time series forecasting based on the nn5 forecasting competition," *Expert systems with applications*, vol. 39, no. 8, pp. 7067–7083, 2012.

[81] Z. Chi, W. Haikun, Z. Tingting, Z. Kanjian, and L. Tianhong, "Comparison of two multi-step ahead forecasting mechanisms for wind speed based on ma-

chine learning models," in *Control Conference (CCC), 2015 34th Chinese*. IEEE, 2015, pp. 8183–8187.

[82] E. Castillo, A. Cobo, J. A. Gutierrez, and R. E. Pruneda, *Functional networks with applications: A neural-based paradigm.* Springer Science & Business Media, 2012, vol. 473.

[83] E. Castillo, J. M. Gutiérrez, A. S. Hadi, and B. Lacruz, "Some applications of functional networks in statistics and engineering," *Technometrics*, vol. 43, no. 1, pp. 10–24, 2001.

[84] B. Lacruz, A. Pérez-Palomares, and R. E. Pruneda, "Functional networks for classification and regression problems," in *International conference on mathematical and statistical modeling*, 2006.

[85] Y. Wang and B. Xu, "Improving prediction precision of navigation satellite clocks with functional network," in *Nature and Biologically Inspired Computing (NaBIC), 2011 Third World Congress on.* IEEE, 2011, pp. 119–124.

[86] B. Xu, Y. Wang, and X. Yang, "Navigation satellite clock error prediction based on functional network," *Neural processing letters*, vol. 38, no. 2, pp. 305–320, 2013.

[87] F. Anifowose, J. Labadin, and A. Abdulraheem, "A least-square-driven functional networks type-2 fuzzy logic hybrid model for efficient petroleum reservoir properties prediction," *Neural Computing and Applications*, vol. 23, no. 1, pp. 179–190, 2013.

[88] E. Castillo and J. Gutiérrez, "Nonlinear time series modeling and prediction using functional networks. extracting information masked by chaos," *Physics Letters A*, vol. 244, no. 1-3, pp. 71–84, 1998.

[89] M. A. Abido, "Environmental/economic power dispatch using multiobjective evolutionary algorithms," *IEEE Transactions on Power Systems*, vol. 18, no. 4, pp. 1529–1537, 2003.

[90] Y.-K. Wu, G.-T. Ye, T.-Y. Hsieh, and B.-S. Jan, "Economic dispatch in an offshore island system with high wind power penetration," in *Power and Energy Engineering Conference (APPEEC), 2016 IEEE PES Asia-Pacific*. IEEE, 2016, pp. 374–378.

[91] Y. Xu, W. Zhang, and W. Liu, "Distributed dynamic programming-based approach for economic dispatch in smart grids," *IEEE Transactions on Industrial Informatics*, vol. 11, no. 1, pp. 166–175, 2015.

[92] M. Wang, H. B. Gooi, S. Chen, and S. Lu, "A mixed integer quadratic programming for dynamic economic dispatch with valve point effect," *IEEE Transactions on Power Systems*, vol. 29, no. 5, pp. 2097–2106, 2014.

[93] M. Zaman, S. M. Elsayed, T. Ray, and R. A. Sarker, "Evolutionary algorithms for dynamic economic dispatch problems," *IEEE Transactions on Power Systems*, vol. 31, no. 2, pp. 1486–1495, 2016.

[94] L. Jebaraj, C. Venkatesan, I. Soubache, and C. C. A. Rajan, "Application of differential evolution algorithm in static and dynamic economic or emission

dispatch problem: A review," *Renewable and Sustainable Energy Reviews*, 2017.

[95] E. E. Elattar, "A hybrid genetic algorithm and bacterial foraging approach for dynamic economic dispatch problem," *International Journal of Electrical Power & Energy Systems*, vol. 69, pp. 18–26, 2015.

[96] C. S. Sundaram, M. Sudhakaran, and P. A.-D.-V. Raj, "Tabu search-enhanced artificial bee colony algorithm to solve profit-based unit commitment problem with emission limitations in deregulated electricity market," *International Journal of Metaheuristics*, vol. 6, no. 1-2, pp. 107–132, 2017.

[97] C. Wu, P. Jiang, Y. Sun, C. Zhang, and W. Gu, "Economic dispatch with chp and wind power using probabilistic sequence theory and hybrid heuristic algorithm," *Journal of Renewable and Sustainable Energy*, vol. 9, no. 1, p. 013303, 2017.

[98] T. Sen and H. D. Mathur, "A new approach to solve economic dispatch problem using a hybrid aco–abc–hs optimization algorithm," *International Journal of Electrical Power & Energy Systems*, vol. 78, pp. 735–744, 2016.

[99] D. Neves, M. C. Brito, and C. A. Silva, "Impact of solar and wind forecast uncertainties on demand response of isolated microgrids," *Renewable Energy*, vol. 87, pp. 1003–1015, 2016.

[100] J. Alejandro, A. Arce, and C. Bordons, "Combined environmental and economic dispatch of smart grids using distributed model predictive control,"

International Journal of Electrical Power & Energy Systems, vol. 54, pp. 65–76, 2014.

[101] V. Prema and K. U. Rao, "Predictive models for power management of a hybrid microgrida review," in *Advances in Energy Conversion Technologies (ICAECT), 2014 International Conference on.* IEEE, 2014, pp. 7–12.

[102] W. Gu, Z. Wang, Z. Wu, Z. Luo, Y. Tang, and J. Wang, "An online optimal dispatch schedule for cchp microgrids based on model predictive control," *IEEE transactions on smart grid*, 2017.

[103] S. S. Kaddah, K. M. Abo-Al-Ez, and T. F. Megahed, "Application of nonlinear model predictive control based on swarm optimization in power systems optimal operation with wind resources," *Electric Power Systems Research*, vol. 143, pp. 415–430, 2017.

[104] P. Kou, F. Gao, and X. Guan, "Stochastic predictive control of battery energy storage for wind farm dispatching: Using probabilistic wind power forecasts," *Renewable Energy*, vol. 80, pp. 286–300, 2015.

[105] W.-Y. Chang, "Application of back propagation neural network for wind power generation forecasting," *International Journal of Digital Content Technology and Its Applications*, vol. 7, no. 4, p. 502, 2013.

[106] A. Sfetsos, "A comparison of various forecasting techniques applied to mean hourly wind speed time series," *Renewable Energy*, vol. 21, no. 1, pp. 23–35, 2000.

[107] A. Sorjamaa and A. Lendasse, “Time series prediction using dirrec strategy,” 2006.

[108] W. Program, “Wind turbine power curves,” http://www.wind-power-program.com/turbine_characteristics.htm, [Online; accessed 12-Dec-2016].

[109] L.-B. Fang and J.-D. Cai, “Reliability assessment of microgrid using sequential monte carlo simulation,” *Journal of Electronic Science and Technology*, vol. 9, no. 1, pp. 31–34, 2011.

[110] NREL, “NREL: Dynamic Maps, GIS Data, and Analysis Tools - Wind Maps,” http://www.nrel.gov/gis/wind.html, [Online; accessed 01-Jan-2017].

[111] B. of Reclamation, “Great Plains Region,” https://www.usbr.gov/gp/index.html, [Online; accessed 25-Dec-2016].

[112] D. H. Akrherz, “IEM:: Download ASOS/AWOS/METAR Data,” https://mesonet.agron.iastate.edu/request/download.phtml?network=KS_ASOS, [Online; accessed 21-Dec-2016].

[113] I. Guyon and A. Elisseeff, “An introduction to variable and feature selection,” *Journal of machine learning research*, vol. 3, no. Mar, pp. 1157–1182, 2003.

[114] P. Oribe, “Operating procedure dispatch,” Australian Electricity Market Operator, Tech. Rep., 2011.

[115] G. Goodwin, S. Graebe, and M. Salgado, *Control System Design.* New Jersey: Prentice Hall, 2001.

[116] E. K. Chong and S. H. Zak, *An introduction to optimization.* John Wiley & Sons, 2013, vol. 76.

[117] R. Gillett, "Pre-dispatch process description," A report, Document No. 140-0033, v 3.1, 2010.

[118] B. Zakeri and S. Syri, "Electrical energy storage systems: A comparative life cycle cost analysis," *Renewable and Sustainable Energy Reviews*, vol. 42, pp. 569–596, 2015.

[119] M. Obi, S. Jensen, J. B. Ferris, and R. B. Bass, "Calculation of levelized costs of electricity for various electrical energy storage systems," *Renewable and Sustainable Energy Reviews*, vol. 67, pp. 908–920, 2017.

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Research Publications

- A. Ahmed and M. Khalid, "Multi-Step Ahead Wind Forecasting using Nonlinear Autoregressive Neural Networks," Energy Procedia, vol. 134, pp. 192-204, 2017.
- A. Ahmed and M. Khalid, "An Intelligent Framework for Short-Term Multi-Step Wind Speed Forecasting Based on Functional Networks," Applied Energy (accepted).

- A. Ahmed and M. Khalid, “A Review on the Selected Applications of Forecasting Models in Renewable Power Systems,” Renewable and Sustainable Energy Reviews (under review).
- A. Ahmed and M. Khalid, “A Nonlinear Autoregressive Neural Network Model for Short-Term Wind Forecasting,” in The 9th IEEE GCC Conference and Exhibition, Manama, Bahrain, May 2017.
- A. Ahmed and M. Khalid, “Multi-step Ahead Wind Forecasting Using Nonlinear Autoregressive Neural Networks,” in KES International Conference on Sustainability in Energy and Buildings: SEB-17, Chania, Greece, July 2017.
- A. Ahmed and M. Khalid, “Economic Dispatch Using Functional Network Forecast Model for Wind Power and Energy Market Price,” accepted in The 27th International Symposium on Industrial Electronics, Cairns, Australia, June 2018.