

**Wind Speed and Power Forecasting using Advance Back
Propagation Machine Learning Mechanism**



SUPERIOR UNIVERSITY

MS ELECTRICAL ENGINEERING

BY

ZEESHAN MUJAHID

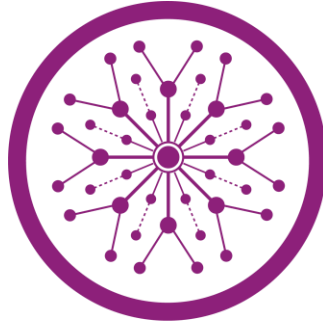
Roll No: MSEE-F21-004

SEASON 2021-2023

**DEPARTMENT OF ELECTRICAL
ENGINEERING
SUPERIOR UNIVERSITY**

Lahore, Pakistan

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SUPERVISOR Dr. Manzoor Ellahi

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Abstract

Wind energy remains as one of the most vital sources of renewable energy with attention given more specificity in the present days. Wind speed and power determination are critical factors that need to be predicted when managing the wind energy systems. This thesis aims at improving the levels of accuracy of short-term wind speed and power forecasts in Pakistan using an improved back-propagation neural network (BPNN). The method described in this paper uses ANN of a particular type, the advanced BPNN, and it deals with wind speed data of the year 2019. These are analyzed with MATLAB to evaluate and update the model as necessary using the given data. The main aim is to evaluate the effectiveness of the advanced BPNN technique in improving the forecast of the wind speed and power.

The suggested approach intends to reduce the forecast errors of wind speed and power for every month, where the mean wind speed data of every month is demanded at some locations in Pakistan where wind data are available. The outcomes of this research have the potential of enhancing the predictability of the wind speed, as well as the power output. This improvement could enhance the operation and administration of wind energy systems in in Pakistan. Therefore, this thesis proposal offers relevant data and novel ideas concerning modern approaches based on machine learning to the subject of wind energy. Analyzing our six-month dataset, we obtained the following results: The performance measurements show Root Mean Squared Error (RMSE): 0. 37069; The Mean Squared Error (MSE): 0. 13741 and mean absolute error (MAE): 0. 29662. These outcomes have the capability to reduce the sensitive factors related to generation of wind energy and enhance the overall use of renewable energy in Pakistan.

Keywords: Back-propagation neural network (BPNN), Artificial neural network (ANN), wind speed forecasting (WSF), wind power forecasting, Root Mean Squared Error (RMSE), Mean Squared Error (MSE), mean absolute error (MAE).

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Zeeshan Mujahid

Dated:

DEDICATION

I want to dedicate my thesis

To ALLAH the Almighty

&

To My Parents Teachers & Family

RESEARCH COMPLETION CERTIFICATE

The undersigned hereby certify that they have read and recommend the thesis entitled “**Wind Speed and Power Forecasting using Advance Back Propagation Machine Learning Mechanism**” by **Zeeshan Mujahid** for the degree of Master of Science in Electrical Engineering.

EXAMINATION JURY/BOARD APPROVAL

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AUTHOR’S DECLARATION

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Zeeshan Mujahid

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Abbreviations

AEDB:	The Alternate Energy Development Board
AI:	Artificial Intelligence
AML:	Advanced Machine Learning
ANN:	Artificial Neural Networks
BPNN:	Backpropagation Neural Network
EMD:	Empirical Mode Decomposition
MLPs:	Multilayer Perceptron
NWP:	Numerical Weather Prediction
NN:	Neural Networks
RE:	Renewable Energy
RBFNs:	Radial Basis Function Networks
RE:	Renewable Energy
RNNs:	Recurrent Neural Networks
SVM:	Support Vector Machine
WPF:	Wind Power Forecasting
WSF:	Wind Speed Forecasting
WP:	Wind Power

Chapter 1

1. Introduction

1.1 Background and Motivation

Wind energy forms part of the major RE sources that can generate clean and sustainable power incessantly [1]. Today wind energy is the one of the most popular source of generating RE in world. Every country in the world has realized the use of wind energy and like the other countries, Pakistan has also started investing its efforts and resources into the development of Wind Energy Projects. However, forecasting wind speed and power has proved to be vital due to variations in wind energy for system dispatch planning and apart from this the importance of the precise measurement of wind speed and power is vital when it comes to the use of wind energy [2]. Failure in forecasting may result in poor utilization of wind energy potential or, on the other hand, overstressing of the wind turbines and therefore calling for regular maintenance thus expending much of the wind turbines' useful life time.

Forecast accuracies on wind speed and power can be enhanced using the machine learning algorithms like artificial neural networks ANNs. The effectiveness of NN based schemes is attributed to the growing ability of learning and perfecting in data processing, the versatile nature to work with non-linear numbers, and its intelligent approach [3]. ANNs have widely been used in forecasting wind power since it is able to maps the non-linear relation between the independent variables and the dependent variables [4]. In predicting wind speed and power ANN models have been found useful particularly in STF applications. Based on the advancement of AI techniques, especially deep learning, it is possible to propose deep learning-based models regarding the wind speed and power prediction. This category of models is becoming famous due to enhanced capability in solving nonlinear equations. Mentioning here, the proposed applied advanced backpropagation neural network technique for estimating the wind speed and electrical power in this paper's context has the potential to enhance the previously conducted forecasts' accuracy that consequently can contain major implications on the development and integration of wind energy schemes in Pakistan. Analysing the energy consumption within Pakistan, it is possible to note some essential trends: the energy consumption has been growing rapidly in the recent years due to the processes of population growth and industrialisation [5]. The rationale for this research is to enhance the line of wind energy by implementing an enhanced and reliable forecasting system of

wind speed and power which would aid the protraction and viability of wind energy sector in Pakistan.

1.2 Overview of wind energy and its potential in Pakistan

Wind power is a distinctive cause of renewable energy that is crucial for the fulfillment of world energy needs as well as emissions reduction. Windmills are used for this purpose converting the kinetic energy of the winds into electrical energy. Relating to wind speeds potential of Wind Energy in Pakistan is also very huge, because the most part of the country is windy [5]. Reference to the information gathered from the Alternative Energy Development Board (AEDB), Pakistan has a mean estimate of wind energy potential of 50,000 MW. The estimated wind power potential of entire Pakistan is 346000 MW of which around 120000 MW are considered as realistic or potential wind power capacity. [5]. Main Potential windy zones of Pakistan are showing in Fig 1. 1.

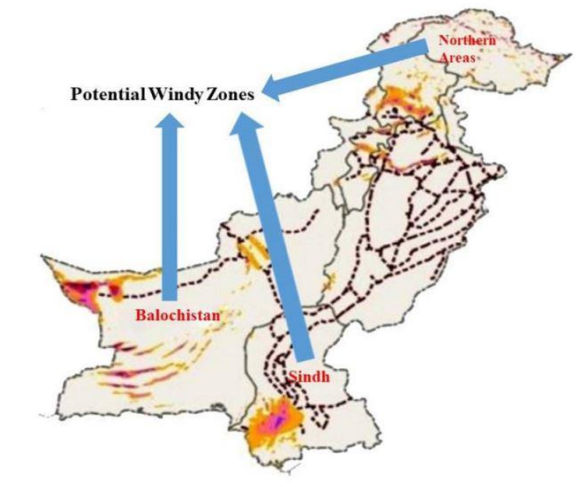


Figure 1-1: Potential windy Zones of Pakistan [5]

Pakistan has still initiated many programs to boost the development of wind energy. The AEDB of Pakistan lodges a significant role in the investment at home and abroad in the distributed Regeneration DRE [6]. The AEDB is promoting funding for the wind energy as it has unveiled its feed in tariff for wind power projects intending to generate electricity from wind power and has also identified certain areas in the country to be established as wind corridors. In this regard, an extensive emphasis should be given on the location, development strategies, funding and the life cycle of wind power plants in Pakistan [7].

Therefore, with the help of better technological methods like BPNN for wind speed and power forecasting the wind energy business in Pakistan can be promoted and can flourish. BPNN back

propagation neural networks show better feature in treating a large amount of samples and can generate more exact point forecasts, especially at the points where the wind speed increases [8]. Hence, if the wind speed and power predictions are improved with the help of the proposed BPNN model, the error rate in wind turbine power generation can be minimized, the effectiveness and profitability of wind energy projects can be maximized, and a sustainable future for Pakistan can be built..

1.3 Importance of wind speed and power forecasting

It is a requirement in wind energy systems especially when it comes to market operation to be in a position to predict the power as well as speed of the wind. Several academics have put forward a lot of forecasting methods which are deemed to enhance preciseness and reliability of wind speed predictions [9]. By using wind speed and power forecasts, the power system operators can make good conclusions in relation to more energy production and the management on the grid as well as energy trading.

Forecasting of wind speed is very crucial in managing risks associated with wind energy production since it helps to reduce risks with the nature of wind conditions [10]. Blessington wind farm has been identified as an essential component in efforts to undertake the transition from the traditional and fossil based energy sources to those that are renewable. This is depicted in figure 1. Figure 1-2 shows the projection of the total cumulative wind power capacity in the year 2022 whereby China leads other countries, then the USA and Germany and among others. The development of offshore wind sector in China also characterised an upward boost in 2016 as did the establishment of first offshore wind project in the United States in the same year [11]. However, wind energy utilization process demands the efficient evaluation of wind speed and power density. Forecasting can also be used to cut the expenses of wind energy generation like the expenses of keeping the grid in balance and the expenses of curtailment. If the wind speed and power can be predicted correctly operators could avoid contracting for backup power for their wind turbines thus the amount of energy that has to be curtailed is reduced.

Deterministic wind speed forecast and wind power forecast is essential necessary conditions for scheduling and dispatching of the power system. Thus, it can be stated that there is a need for improvement of the existing methods in wind power forecasting [12]. Therefore, development of effective models for wind speed and power forecasting by using the advanced machine learning

approaches like BPNN is very helpful for the growth of the wind energy business that leads to have a sustainable future.

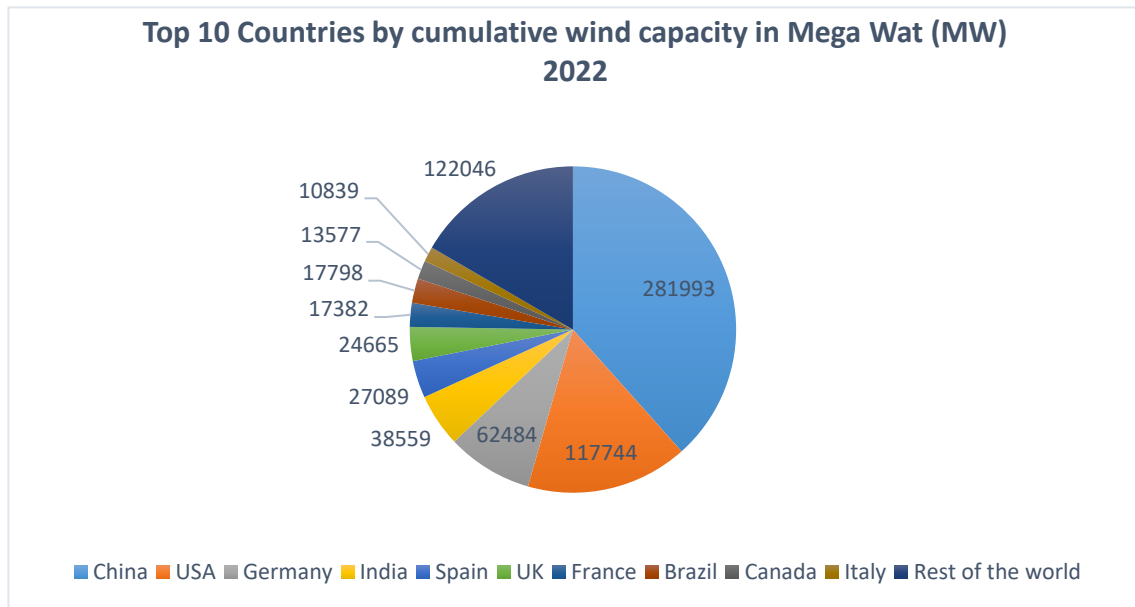


Figure 1-2: Top 10 Countries by cumulative wind capacity in Mega Wat (MW) 2022 [2]

1.4 Brief history of wind forecasting Methods

Since the development of the wind energy industry at the beginning, the wind prediction becomes one of the important research areas. Modern wind power facilities started appearing from the 1970s, while the early usage of wind forecasting was also traced to the same period. The exact prediction is vital because it provides the grid operators as well as engineers with the information to design the most optimal wind farm in order to meet the required demand of electricity [13].

In the beginning of the application of wind power, wind forecasting was done using statistical models which made its prediction depending on the past data. Physical models are used more often barely to be more unrealistic than statistical models, referred often to as algorithmic learning, data-driven or artificially intelligent models. Turbine power curve modelling is one of the recent applications of statistic approaches at turbine-level [14]. These models were linear and uncomplicated and thus suboptimal when it came to the assessment on how wind systems were structured.

The progresses made since the 1990's in the wind forecasting techniques include the Numerical Weather Prediction NWP models. These models based on computational formula that analyzed the

meteorological conditions so as to forecast wind velocities at specific points and at distinct levels. NWP models were able to predict the movement of air mass and thus, was good for Wind Power Forecasting (WPF) before the establishment of the wind power plant. Though NWP models were quite accurate with minuscule and precise forecasts, these were coupled with high computational costs and required a large amount of meteorological data.

Table 1-1: Describe different wind forecasting methods [4]

	Description	Advantages	Disadvantages
Persistence	Strategy was frequently used to assess the benefits of new short-term predicting techniques.	Simple and economical	May not account for sudden changes in weather patterns or wind speed
Numerical weather prediction NWP	Computer models to simulate weather patterns and predict wind speed and direction	cover longer time horizons (e.g., up to several days)	significant computational resources and may be less accurate in complex terrain or near coastal areas
Machine learning ANN	Analyzes historical wind speed and power output data and makes predictions based on patterns and trends	Effective for STF (e.g., up to several hours)	Requires large amounts of training data and may be less accurate over longer time horizon
Ensemble forecasting	Combines multiple forecasting models or methods to generate a more robust and accurate forecast	Improves forecast accuracy and reliability	Requires significant computational resources and expertise

ANN and SVM algorithms which have the capability to define the linkages between conventional input and output variables in a more complex manner and also able to learn when situation is changed over time has been recently used in structural reliability analysis [16]. As demonstrated by the above-mentioned methods there has been enhancements made on wind forecasts and these methods have gained popularity in the wind energy market.

The general development of wind forecasting methods, in particular, underlines the necessity of refining the methods and the use of more complex and elaborate approaches to wind speed and power prognostication as the systems involved become expanded. This trend is however being kept on with the emerging of AML approaches such as the BPNN to improve the efficiency of wind forecasting to benefit the wind energy sector and other stakeholders.

1.5 Problem Statement& Research Questions

- This is a quite difficult task which should be covered in the discussion as the large-scale power generation through the wind turbines necessitates the precise estimation of wind speed and the corresponding power to be generated. However, the techniques utilized generally in wind speed and power prediction have inaccuracies, which can translate to huge losses in addition to poor performance of the wind turbine system. The research questions for this thesis are: The research questions for this thesis are:
- In what way is advanced BPNN beneficial for enhancing the wind speed and power forecasting precision?
- This study aims to raise the following research question: what is the effect of using the proposed advanced BPNN on the power output of the wind turbines and the accuracy of the power forecasting?
- Is it possible to decrease the error rate of wind turbine systems with the help of the modern advanced BPNN?
- In what way can the optimization of the advanced BPNN algorithm be checked and tested to address the desired outcome?
- In this context, the current issue seeks to find out if the use of momentum item in BPNN leads to the enhancement of the convergence rate and subsequently resulting in high wind forecasting accuracy.

1.6 Objectives of the study

The valuable objective of this study is given below.

- The algorithm is applied on the wind speed data with an aim to enhance the wind speed and Power forecasting as operational results.

- In order to construct an optimized model using BPNN and decrease the error rate for wind power generation and its forecast.
- To evaluate the performance of the developed suggested BPNN model by validation and testing phases and compare the result expectance of suggested BPNN model with the other benchmark techniques to predict the wind speed and power.
- To analyse the role of momentum item in the BPNN algorithm for enhancing the rate of convergence and to modify the incorporated BPNN model further.
- To discuss possibilities of the effects of the proposed BPNN model on the economic and environmental areas of interest in wind energy industry in Pakistan and provide suggestions for the further research and development.
- Thus, the purpose of this study is to introduce and design a more enhanced method than existing AML techniques for the wind speed and power forecasting that will be beneficial for the wind energy business sector in Pakistan as well as the country's sustainable future.

1.7 Scope of the Study

Therefore, the objective of this study is to analyze the feasibility of an AML technique that is known as BPNN in a context of wind speed and power forecasting in Pakistan. Estimation of wind speed and the power data of the various locations in Pakistan where the wind data is available would form the basis of the study with large dataset of wind speed and power data to be used for the study. In this research, a proposed BPNN design will be fine-tuned and assessed with the aim of lowering the error rates of wind turbine power production. The objective of the study will also involve making discoveries on how best to enhance the rate at which the BPNN algorithm converges using the momentum item. The study will produce the findings that would discuss about the plausible economic and environmental effects of the BPNN model for wind energies in Pakistan. Nevertheless, one has to note that the study has certain drawbacks. The scope of analysis is confined up to the estimation of wind speed and power data of those places where wind data is available in Pakistan; however, the proposed BPNN model cannot be successfully implemented to other areas of different climates and geophysical environment. Also, in evaluating the performance of the proposed controller, the study relies on actual wind speed and power data and thus does not consider the effects of initial or randomness errors in the variables.

1.8 Geographic scope: regions in Pakistan with available Wind Data

The scope of this study is focused on the application of advanced BPNN algorithm for wind speed and power forecasting in places of Pakistan where wind data is available. The study will analyze past wind speed data from various locations in Pakistan where wind energy is being produced, The province of Sindh in Pakistan has a wind power making capacity of 88,460 MW, with potential sites including Hyderabad, Kotri, Jerruck, Gharo, Jhampir, Lakha, Khuttikun, and Bhambore [17]. Wind Corridor of Sindh Showing in figure 1-3.

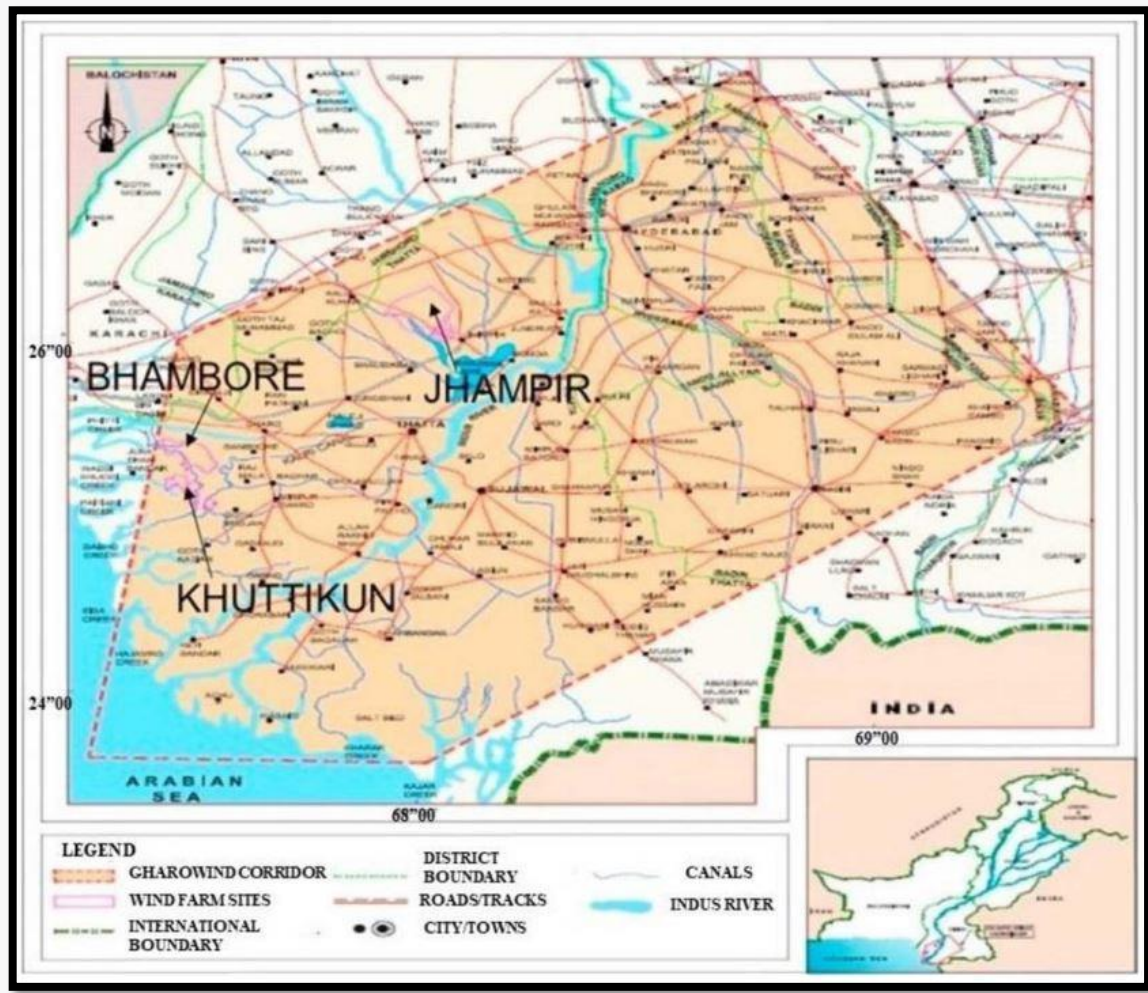


Figure 1-3: Wind corridor of Sindh Pakistan [5]

Therefore, the study will mainly concentrate on short-term wind speed and power prediction as an attempt to improve the accuracy of the forecast using the developed BPNN algorithm. This study will also investigate the fact that momentum items are applied in the BPNN to enhance the rate of wind forecasting and the convergence rate of the neural network as well.

This research work does not cover the general methods applied to wind forecasting but is restricted to the evaluation of the accuracy of BPNN algorithm for this purpose only. Further, this study doesn't contain areas where wind data is not available in Pakistan, the research depends on the areas where data was collected.

For this particular study, the broad aim is to contribute towards improving the different forms of wind forecasting for the production regions in O&M of Pakistan.

1.9 Timeframe: short-term wind speed and power forecasting

This paper is focused on the short-term wind speed and power forecasting, where empirical data on wind speed of 2019 for various places in Pakistan where electricity has been produced using wind energy. It is moreover important to mention that short-term wind forecasting takes into consideration the time horizon ranging between one and 72 hours and the main purpose of this research is to improve the existing methods of such predictions. This work will cover the period within which the advanced BPNN algorithm for wind speed and power forecasting shall have been developed and implemented. The study will also involve ensuring that the model developed in the work is correct and optimally functioning.

1.10 Methodology: Advanced Backpropagation Neural Network

The methodology of this study involves the use of an advanced BPNN algorithm for wind speed and power forecasting. BPNN is a kind of artificial neural network that is broadly used in pattern recognition and prediction in various fields, including weather forecasting. An error back-propagation algorithm-based multilayer feedforward network is called a back-propagation artificial neural network. [18]. The figure 1-4 presents the working mechanism of advanced backpropagation NNs for wind speed prediction.

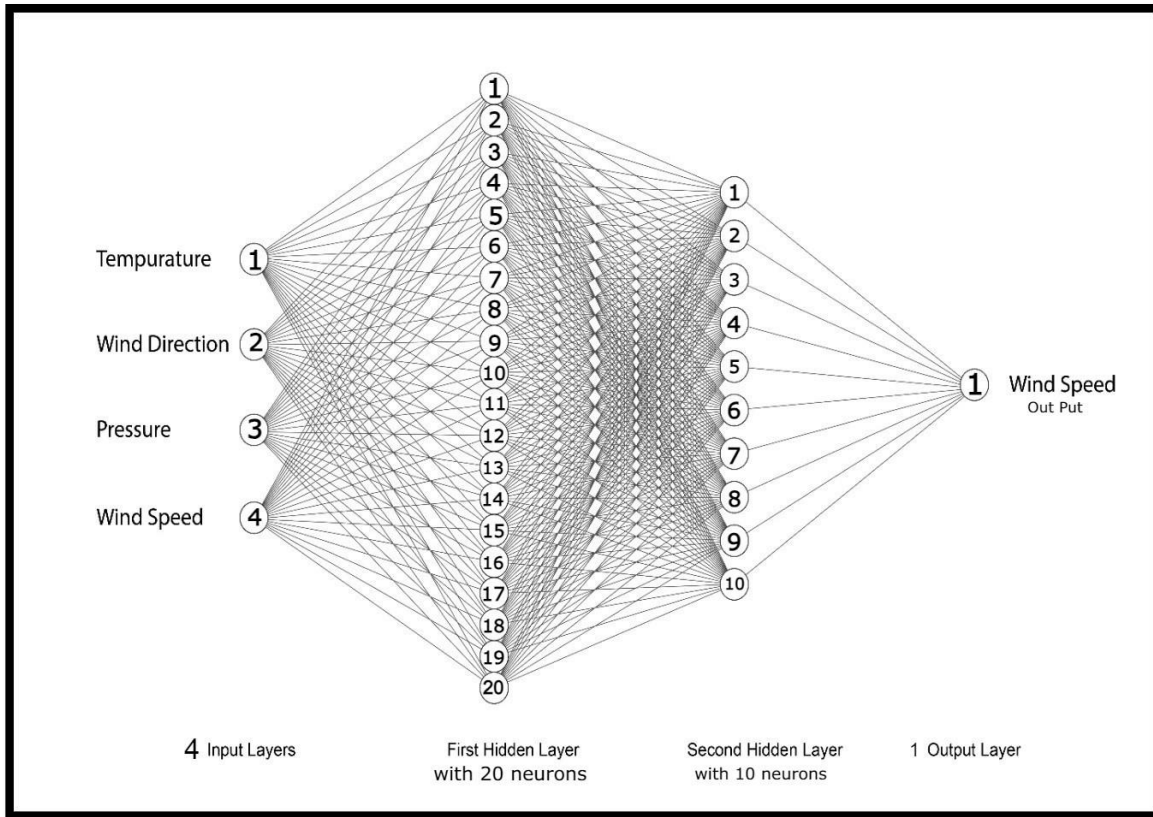


Figure 1-4: The topology structure of BP neural network [18]

Basically, there are 4 inputs, 2 hidden layers with 20 and 10 neurons, and 1 output layer in our designed BP neural network. Among its main features, one can list particularly the forward particular transmission and the error back propagation. Coming from the input layer, passing through the hidden layer into the output layer, the input signal is transmitted together with its processing. Indeed, only the next layer in the network will be affected by the neural state of that particular layer. The function will then use the back propagation method if the desired output is not achieved by the network at the output layer. , to adjust the output towards the anticipated output confusing the weight and the threshold with be changed in proportion to the degree of inaccuracy in the forecasting. The hidden layer can be further divided into two groups; single layer and multilayer depending on its construction. The usage of multiple hidden layers is more accurate and has better generality than that of the usage of single layer [18].

Hence for the study, historical wind speed data of 2019 will be utilized to train the BPNN where wind energy is being generated in different regions of Pakistan. The stored data will then be preprocessed to into suitable format to be fed into the machine learning model. Momentum item will be used in the BPNN model to increase the convergence rate as well as the perfection in the wind speed and power forecasting.

After the establishment of the BPNN model and the determination of the optimum parameters, the model which will be used for wind speed data validation and testing will be obtained from the available wind speed data. The validation and testing phase will be carried out by comparing the output data of the BPNN model against the actual wind speed figures.

In general, the framework of this work is founded on the BPNN algorithm for the prediction of wind speed and power employing the historical wind speed records of 2019 in different areas in Pakistan in which wind energy is being generated. The following are the outputs of the model that will be conducted as well as validation and testing to check its efficiency: Weights decay & Dropout Weight decay and dropout are the other techniques that will be applied to the model to enhance the optimization of the model while the validation and testing will confirm its efficiency.

1.11 Significance of the study

The suggested study for wind speed and power forecast dealing with AML technique known as BPNN has great importance in various ways. Consequently, the prospective research's main objectives are to advance the state of practice for better wind speed and power forecasting techniques. These enhanced approaches for the forecasting of wind speed and direction can promote and enhance the development of this sector, that is the wind energy sector in Pakistan. This proposed BPNN model in this paper makes the feature of improving the wind energy projects' profitability by cut down the error rates in the wind turbine power generation. This in turn can and often does, contribute a great deal towards promotion of an eco-friendlier existence.

Secondly, the conducted study can indicate an appropriate set of AML methodologies that can be useful for tackling important issues in the energy field. BPNN model proposed here can be extended for the other regions and domains for better accuracy of the forecast like the solar power generation, energy demand etc. Thirdly, the study could help to progress the field of scientific research and development within machine learning category and in general in the framework of neural networks. Since the study focuses on optimizing the momentum item in the given BPNN algorithm to enhance the convergence rate the proposed work would contribute to the existing literature regarding the functioning of neural network algorithms.

In general, the study can include policy considerations for policy-makers as well as pertinent stakeholders as pertains energy. These findings and recommendations can be beneficial, in devising the policies and plans, for utilization of RE sources in Pakistan and other similar regions. As a whole, all the concepts and the suggested study on wind speed and power forecasting enlisting the

usage of AML techniques would contribute to the enhancement of knowledge and practical application associated with the usage of renewable power sources in large scopes.

1.12 Potential contributions to wind energy sector in Pakistan

The major implications of this study are relevant to augmenting the existing knowledge base in the domain of wind energy in Pakistan. At the present time, the wind energy constitutes a small portion of the total energy consumed in Pakistan while showing a large prospect for development. Hence, the establishment of improved methods for wind speed and power models for forecasting can make a significant effect in the growth and advancement of wind power.

By developing and implementing an advanced BPNN algorithm for wind power and speed forecasting, this research can contribute to the following areas: By developing and implementing an advanced BPNN algorithm for wind power and speed forecasting, this research can contribute to the following areas:

Increased energy production: Improving the capacity as well as precision in predicting the wind flow and its velocities.

may be followed by more production of energy because wind turbines can be used optimally and productivity can be enhanced.

Reduced costs: It also means that accurate forecast can also assist in cutting the cost relating to wind energy generation such as in the areas of maintenance and unpredicted downtimes.

Improved grid stability: When wind resource is forecasted more accurately and precisely potential of wind energy can be incorporated smoothly with the national grid leading to more stabilized and reliable grid system.

Technology transfer and knowledge sharing: Similarly, an enhanced algorithm involving the above said elements of BPNN and its implementation for wind speed and power forecasting in Pakistan may also be helpful for technology transfer and diffusion of knowledge among the scientific community, professionals working in wind energy, as well as policy makers.

In conclusion, it can be said that this research has major implications for the wind industry of Pakistan and can play a vital for the development of wind energy sector in the country.

1.13 Summary

Chapter 1 contains a comprehensive description of the literature review embracing the background study, purpose, and importance of wind speed and power forecasting for wind energy industry of Pakistan. The chapter also shows that forecasting is one of the most important requirements for optimizing the performance of wind turbines as well as reducing costs and how the use of state of the art approaches, particularly the BPNN model, can greatly improve the forecast accuracy. The chapter additionally discusses the feasible wind power in Pakistan, actions performed to developed wind power in Pakistan, and working of Alternative Energy Development Board (AEDB). The author also gives a brief on the history of wind forecasting approaches beginning with statistical methods, then classical numerical weather prediction approached and finally leading to the use of machine learning approach specifically artificial neural networks. This paper presents the research questions, objectives of the study, and its scope, methodology, and importance to this sector of wind energy production in Pakistan: enhanced production, cost reduction, better grid conditions, and dissemination of findings.

Chapter 2

2. Literature Review

WP is one of the primary forms of RE; therefore, its incorporation into existing Electricity grids is among the essential skills that need to be forecasted accurately. In the literature, two approaches are commonly used to perform WP forecasting: two methods: the direct WP forecasting based on historical data of WP and the indirect WP forecasting by predetermining wind speed (WS) and applying wind power curve [2]. Consequently, the research focus has been transposed towards WS and WP prediction. Many software application have been developed using the combination of various forecasting methods, the advanced AI techniques like NNs and physical models [19]. Indeed, this literature review will discuss the latest literature concerning WS & WP forecasting, especially with reference to NN methods. Furthermore, the course of the review of the current literature on fault detection and diagnosis of WT NNs will include some of the recent studies.

2.1 Wind Power Forecasting Techniques and Software Programs

Wind Power (WP) forecasting stands as a pivotal technology for integrating wind power into diverse electricity grids [2]. In the existing literature, two fundamental methods are prevalent for performing WP forecasting. The first approach involves forecasting wind speed (WS) initially and then constructing WP forecasts based on a wind power curve. Alternatively, the second method entails forecasting WP directly using previous WP data. The literature has extensively examined both techniques to improve the precision of wind power forecasts. This curve displays the power that can be produced at various WS values. As a result, researchers have focused on both WS and WP forecasting. The wind industry has developed various Wind Power (WP) forecasting software programs by integrating different forecasting methodologies. One such program is Predictor, designed by the Danish Ris National Laboratory, functioning as a physical WP prediction system. Another notable software is WindForTM, initially known as the Wind Power Prediction Tool and invented by the Technical University of Denmark. WindForTM combines physical models with cutting-edge Artificial Intelligence (AI) techniques, constituting a self-learning and self-adjusting WP forecasting system [20]. Through hundreds of runs, the model's parameters are rigorously tested with an emphasis on algorithms based on various cluster segments, numbers of neurons, hidden layers, and trained functions in order to improve the model's accuracy and performance. Additionally, hybrid models for Wind Power Forecasting (WPF) have been suggested, incorporating techniques such as AdaBoost-extreme learning and other machine learning methods

[19]. Overall, advanced techniques and software program have been created for this goal, and WP forecasting is a crucial instrument for attaining a more dependable and effective integration of Wind Power into existing electrical networks.

2.2 Direct Wind Power Forecasting Techniques and Challenges

Direct Wind Power WPF is one of the two main methods applied to WP forecasting, in which actual WP data to directly forecast future WP production [10]. This technique has been researched a lot in the literature, and there are various forecasting techniques developed for this very idea. For instance, the neural networks – Backpropagation Neural Networks BPNN with Multilayer Perceptron's (MLPs) have widely adopted in the literature because of the ability of modeling complex nonlinear relationship existing in the variable of input and output [22]. However, the use of direct WP forecasting is dependent on some factors like the amount as well as availability of past data, choice of input variables and the type of model to be employed. In conclusion, direct WP forecasting, despite its simplicity, could be considered as an effective technique for generating rather accurate and reliable WP forecasts, so further investigations could be of great importance for enhancing the efficiency of the given method.

2.3 Indirect Wind Power Forecasting through Wind Speed Prediction

One more direction is the technique called Indirect WP Forecasting – one more variety of WP forecasting. This method entails extrapolation of future wind speed initially and then using the power curve of the wind turbine to arrive at a forecast on the wind power generation [23]. Output of wind power is component of speed and is used in making curves. Turbines are the structures that receive the wind energy, and transform it into mechanical energy[24]. WS forecasting techniques are also available such as machine learning algorithms physical models. Indirect WP forecasting has been established to be a useful approach of realizing accurate WP forecasting mainly in cases whereby the main power system that experiences efficient distribution is wind turbines [25]. The wind industry has developed many of the software applications with several of the methodologies for forecasting. One example of such a usage is Prediktor, a method for the prediction of physical WP developed at the Danish Ris National Laboratory [20]. Another piece of software was developed by the Technical College of Denmark, and is known as WindForTM or formerly the Wind Power Prediction Tool. It is a WP prediction system that self learns and self adjusts with the help of strong Artificial Intelligence (AI) methods interfaced with physical models. This software tool does numerous tests to most of the model parameters in a bid to enhance the performance of

the model as well as precision. It is to note that all these tests are performed in terms of concrete algorithms, and the variety of cluster segments; neurons; hidden layers and learned functions is taken into consideration. Research has also proposed combination forecasts for the Wind Speed (WS) variable. These integrated models using methods of machine learning for regression and selection of features use multi-layer perceptron's, support vector machine and linear regression [2]. In a special work, Yue's [s34] used a combination of WP decomposition and AdaBoost extreme learning machine for WP forecasting [26]. Despite the occurrence of these WP forecasting software programs, there is still a need to carry out further researches in order to enhance the efficiency and accuracy of the WP forecasting to enable their incorporation with existing electrical networks of different sizes.

2.4 Development and Challenges of Wind Power Forecasting Software Programs

The use of Neural Networks (NNs) has become increasingly favored in the area of Wind Power WP forecasting. Multilayer perceptron's (MLPs) within a neural network are commonly used for forecasting and prediction of various data sets [27]. Backpropagation neural networks BPNNs are a popular type of NN technique, as they can more easily determine a loss function's gradient concerning all of the network weights. However, some studies have found that even with the maximum number of training epochs, the training procedure was unable to converge on the training objective, leading to greater prediction errors [28]. Researchers have employed momentum BP and GA-BP to increase the precision and convergence rate of BPNNs [29].

2.5 Neural Networks in Wind Power Forecasting

An entire family of learning algorithms, called "neural networks" (NNs), is derived from the efforts to mimic real neurons. NNs consist of artificial neurons or processing nodes connected hierarchically to perform pattern recognition and correlation analysis on the data [30]. The most commonly applied type of NN used in WPF is the backpropagation neural network BPNN which ushers MLPs to develop forecasts. BPNN also may be trained with historical values and is able to model nonlinear relationship between input and output variables [31]. Two more other NN types that have been deployed in the WPF industry are RBFNs and RNNs [32]. In general, it can be noted that consideration of NNs has a positive impact on increasing the accuracy of WPF models.

Enhancement methodologies for achieving higher levels of accuracy and precision to the Neural Networks in WPF needs the best of trainings and optimization skills. It is a training method known as backpropagation the weights and biases of the network are constantly tweaked to minimise the difference between expected and actual output. [33]. In an attempt to increase the convergence rate while avoiding cases of over fitting, there has been proposed some optimization methods, which include the momentum-based optimization and the genetic algorithms [34].

2.6 Literature Review and Related Work

The prominent contributions made by the researchers in the field of wind resource and power forecasting are given in the table below,

Table 2-1: Prominent Contributions by the Researchers

Wind Power Forecasting Techniques		
NO	Author	Contribution
1	L. Ziavaka, S. Misak [10].	Yet again, this paper tends to develop a method for direct WPF through the differentiation of the generalized DE into polynomial functions. The authors prove that applying this approach results in fairly good seven, 12, 18 and 24-hour ahead wind power forecasts. The focus of the study is on the necessity of accurate WPF in terms of the integration of wind energy into the system. The limitation is that the study focuses on short-term forecasts but does not address long-term wind power forecasting or its broader integration challenges.
2	C. Wan, Z. Xu [35].	The approach described in this work enables the direct interval forecasting of wind energy to acquaint the power system with wind power integration. The allegedly proposed strategy is inspired by the use of a quantile regression neural network accompanied by the Gaussian process regression. The authors show that the suggested approach enables generating of interval forecasts with adequate investment for up to 48 hours ahead with greater accuracy than other approaches. Interval forecasts are highlighted in the study as useful for enhancing decision-making in electricity market compared with the detailed descriptions of the confusion regarding forecasts of wind power. The limitation is that the study does not address long-term forecasting or the accuracy of detailed wind power predictions.

3	González-Sopena B. Ghosh [36].	The paper provides an overview of the outcome measures utilised in the performance assessment of short-term WPF. The authors discuss traditional and develop new measures for assessing the accuracy of forecasts and their uncertainty. The study also brings out the features of performance measurement emphasizing the need to get the measures right in order to enable the organization to make the right decisions. The limitation is that the study focuses solely on short-term forecast performance measures and does not address long-term forecasting accuracy.
4	Wang a, W. L. Xue [37].	In the actual physical access control system, a probabilistic WPF model based on spiking neural networks is introduced. The authors prove that the aforesaid model's application is capable of making accurate predictions of wind power generation as well as expressing the degree of uncertainty of said predictions. It demonstrates that probabilistic forecasting is a crucial concept in decision-making for power industry because it contains more information concerning possible risks in connection with different decisions. Incorporating spiking neural networks in WPF is quite unique and thus it could lead to better forecasting because of enhanced accuracy and dependability. The limitation is that the study does not evaluate the model's performance in practical, real-world scenarios or across different geographic locations.
5	Y. Lin, M. Yang, C. Wan, J. Wang, Y. Song [38].	According to this research, probabilistic WPF can be improved by using this novel three-model combined strategy for modeling. Lending significance to multiplicity of models and probabilistic forecasting, the study stress on how to make accurate decisions in the electricity business. It helps in expanding the theoretical foundations of the WPF community in particular and the field in general. The limitation is that the study does not address the practical implementation challenges or scalability of the combined strategy in real-world applications.
Wind Speed Forecasting Techniques		
6	Aasim, S.N. Singh, A. Mohapatra [39].	This paper has adopted the transform based ARIMA for very short-term (WSF). It is more effective in giving forecasts than the regular ARIMA models and stresses the need to have

		accurate WSF for proper incorporation of wind energy. Thus, the study has a significant value added by presenting a new method to enhance the accuracy of the forecast. The limitation is that the study focuses only on very short-term forecasts and does not explore the method's effectiveness for longer-term wind speed forecasting.
7	M. Santhosh, C. Venkaiah, D. V. Kumar [40].	To improve the performance of RE integration, therefore, this research surveys recent advances and techniques in wind speed and WPF. The authors compare different forecasting models that they use to articulate the importance of accurate forecasting techniques like probabilistic forecasting. The paper also highlights the issues that can be associated with the use of WPF and the suggestions for further studies. The limitation is that the study focuses only on very short-term forecasts and does not explore the method's effectiveness for longer-term wind speed forecasting.
8	S. R. Moreno, V. C. Mariani, L. S. Coelho [41].	Consequently, this paper is an attempt to adopt, first, multi-stage decomposition associated, second, with the application of a parametric model for WSF in the Brazilian Northeast. The approach yields a better forecast as compared to ARIMA model and emphasized that suitable decomposition of the data and the models to be applied has to take into account the characteristics of wind speed data, which is highly variable and dynamic in nature. The limitation is the model's regional specificity and lack of generalizability.
9	Hamed H.H. Aly [42].	In this article, first, the development of a Recurrent Kalman Filter-Wavelet-Time Series hybrid model for WSF is described. It provides more accurate predictions compared to the traditional models and focuses on the importance of selection of the right models that take into account the dynamic characteristics of wind speeds data. It is necessary to underline that the paper has a strong focus and makes a valuable input to the WSF discipline. The limitation is that it does not address the model's performance in diverse wind speed conditions or its general applicability.

10	J. Wang, P. Du, C. Wu, X. Chen, and W. Yang [43].	The implication advocated in this paper involves using system based on multi- objective optimization incorporated with artificial neural network and support vector regression model for WSF. Comparing to the traditional and single models, it proves enhanced forecasting effectiveness and suggests the need of having the proper choice of the models together with adjustment of the parameters.
Wind Power forecasting based on a wind power curve		
11	H. Demolli, A. S. Dokuz, A. Ecemis, and M. Gokcek [1].	The article to be reviewed is known as “WPF based on daily wind speed data using machine learning algorithms,” which essentially presents a model for Wind Power Forecasting (WPF). The research compares the accuracy of four machine learning algorithms and proves that the proposed approach is better than the conventional one. In particular, the Gradient Boosting Regressor (GBR) shows the greatest efficacy in the context of the discussed research. Vitiello and Giuliani’s paper is able to confirm that there is potential that machine learning algorithms can help in enhancing the Wind Power Forecasting accuracy.
12	M. Collu, Z. Lin, and X. Liu [44].	The research study is named as “Wind power prediction based on high-frequency SCADA data along with isolation forest and deep learning neural networks” and uses three components to formulate a model for wind power prediction. This study proposal aims to discuss the blending of isolation forests with deep learning neural network for wind power prediction and ascertain that with the help of the proposed model the portrayal of wind power will have better accuracy than the previous techniques.
13	J. Yan, and T. Ouyang [45].	The paper by the name of ‘Advanced wind power prediction based on data-driven fault correction’ presents the method of wind power forecasting enhanced by a data-driven fault correction approach. The study proves that by correcting the errors in the output of standard methods of wind power prediction, the suggested methodology can significantly enhance the reliability of wind power predictions. To support the suggested strategy, real data from a wind farm located in

		Germany is used, based on machine learning approaches. In light of the results obtained in the context of the study, it can be established that implementation of the proposed approach can produce substantial improvements in wind power estimation, thus, having noteworthy consequences for wind power integration with the grid.
14	Y. Wang, Q. Hu, D. Srinivasan, and Z. Wang [46].	The paper introduces a new approach to the problems of wind power curve modeling, as well as Wind Power Forecasting (WPF) using data with uncertainty. The suggested approach comprises two steps: first, the wind power curve is obtained from the historical data, and then based on this obtained wind power curve, WPF is practiced. Thus, according to the findings presented in the study, this method improves the reliability of WPF even when it works with such data. Empirical data from a wind farm in china is used in the validation of the results of the study. The proposed method has vast implications in the actualization of desirable grid integration of wind power.
15	X. Shen, X. Fu, C. Zhou [47].	In the context of the research, the use of power curves for wind turbines and their cleaning is offered to carry out in two stages. This aberrant data is detected and removed by using qualitative and change point grouping algorithms of a program. This paper's findings affirm that this method is useful in characterizing and eliminating outliers from the power curve, using actual data harvested from a wind farm in China. Altogether, the presented innovative technique increases the accuracy of Wind Power Forecasting (WPF) by a large margin, as it was identified by the research. The limitation is that the method's effectiveness is demonstrated only with data from a single wind farm and may not be applicable universally.
BPNN for wind speed and wind power prediction.		
16	N. Bokde, A. Feijóo, D. Villanueva, K. Kulat [48].	The paper also looks into the use of empirical mode decomposition (EMD) in conjunction with the BPNN. The application of EMD instrument is established in the aspect of enlarging the accurate rate of the prediction through the combination of BPNN with EMD by decomposing the data. The benefits of such an integration are explained in this paper as well

		<p>as the proposed architecture of the BPNN models, their training, and the ways of choosing the most suitable input features. In conclusion, the proposed hybrid EMD-BPNN model shows the better results in the prediction of wind speed and wind power. The limitation is that the paper does not address the model's performance across varying data sets or real-world conditions.</p>
17	<p>R. Cai, B. Wang, R. Yang, and Y. He [49].</p>	<p>Therefore, concerning the forecast of export and import of services, this paper has put forward a WSF model by using a Backpropagation Neural Networks BPNN. The proposed BPNN model is compared to the traditional methods and it indicates the higher efficiency in wind speed prediction. It has been established that how features are chosen and the tuning of parameters of the used BPNN model are critical success factors. In conclusion, this paper puts great importance on the use of BPNN for enhancing the integration of RE in WSF.</p>
18	<p>G. Chen, L. Li, Z. Zhang, and S. Li [50].</p>	<p>In order to develop a short-term model for WSF, the paper introduces a Principle-Subordinate Predictor relying on an improved BPNN. The basic BPNN model undergoes modifications in terms of activation function and weight initialization to boost the learning ability and convergence performances. The performance evaluation shows that BPNN is suitable in estimating wind speed for better integration and planning of RE specifically into the grid.</p>
19	<p>W. Ding, F. Meng [51].</p>	<p>The paper presents a approach to WSF operated by linear component extraction. As the present paper is not entirely devoted to Backpropagation Neural Networks BPNN, it reveals possible advantages associated with the linear component extraction in the context of the wind speed forecast. Thus, the proposed method increases efficiency and accuracy since the linear trend and residuals from historical wind speed data are identified. This paper derives point and interval forecasting models from these factors to enhance the analytical decision-making in the RE integration planning. The limitation is the incomplete exploration of BPNN benefits and lack of comparison with advanced techniques.</p>

20	Y. Shang, L. Miao, Y. Shan, K. R. Gnyawali [52].	In this paper, a new WSF methodology named as hybrid, CEEMDAN and GA-BPNN has been proposed. Even though, the employment of BPNN is contained in this study while developing the hybrid strategy as one of the methods of analysis, others are also considered. For improving the accuracy of forecasted wind speed, the hybrid technique uses decomposition integrated with GA-BPNN optimization. The limitation is that the study does not evaluate the hybrid methodology's effectiveness compared to other advanced forecasting techniques.
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2.7 Summary

Summarizing the literature-review given in this chapter, it can be pointed the important advance achieved concerning wind speed and WPF. As it can be seen from the findings above, the use of sophisticated methods like the neural networks has enhanced the WPF's precision and general ability to diagnose defects within wind turbines. Nevertheless, there are obstacles the application of which is still problematic, including the quality of input data, the model complexity, and the availability of the results' explanation. Insights for future work can be summarized in the following points: Further enhancing the performance of such models and incorporating additional data, more effective methods need to be identified in order to approach such issues in a better way. Furthermore, there is a need to pay more effort in the development and enhancement of decision support systems that correspond to the operators and maintenance squads in accordance to what the models present.

Chapter 3

3. Methodology

3.1 Introduction

Section III outlined the procedure used in the prediction of wind speed and power using the developed BPNN model on MATLAB comprising of Chapter 3. The structure of the developed neural network, the data pre-processing, training algorithm and the cross-validation methods are defined. In addition, the results achieved from training and cross validation are presented and discussed and have offered means to draw conclusions about the accuracy and the efficiency of the suggested BPNN model for the analysis of the wind speed and wind power.

3.2 Pseudocode

The pseudocode of the NN based implementation for wind forecasting mechanism is shared below,

Table 3-1: Pseudocode of NN based Implementation

```
1  Initialize x as the transpose of Input data.
2      Initialize t as the transpose of Output data.
3          Set num Folds as 5.
4              Set trainFcn as 'trainlm'.
5                  Initialize an array performance with zeros of size numFolds.
6                      For fold in range from 1 to numFolds:
7                          Initialize hidden Layer Size as [20, 10].
8                              Create a neural network net with `fitnet` function and hidden Layer Size using train.
9                                  Set net's division parameters for training, validation, and testing data ratios.
10                                     Set weight Decay as 0.001.
11                                         Enable weight decay regularization in the network.
```


3.3 Block Diagram

This block diagram shown in fig 3. 1 is depicting the process of training and testing of a neural network model through cross validation and through three measures of performance. The algorithm first sets up input data pointed to by x and target data pointed to by t , then deciding the number of cross validation and the training function. Several actions are executed for each fold, such as the construction of a neural network with a certain architecture and learning schedule, the definition of data splits, and the application of omission, among others, in order to calculate the predicted outputs. The performance of different models on each of the folds is computed and saved. Finally this mean performance is computed after all the folds and printed.

Additional output results, MSE, MAE, RMSE as well as R-squared are computed and depicted alongside the network architecture. Last, the means of the actual vs. predicted values and the residual values and plots are presented to evaluate the model's performance. The block diagram shows a system approach to the problem's solution and describes the sequence of actions and their relationships to each other, starting from initialization and ending with evaluation.

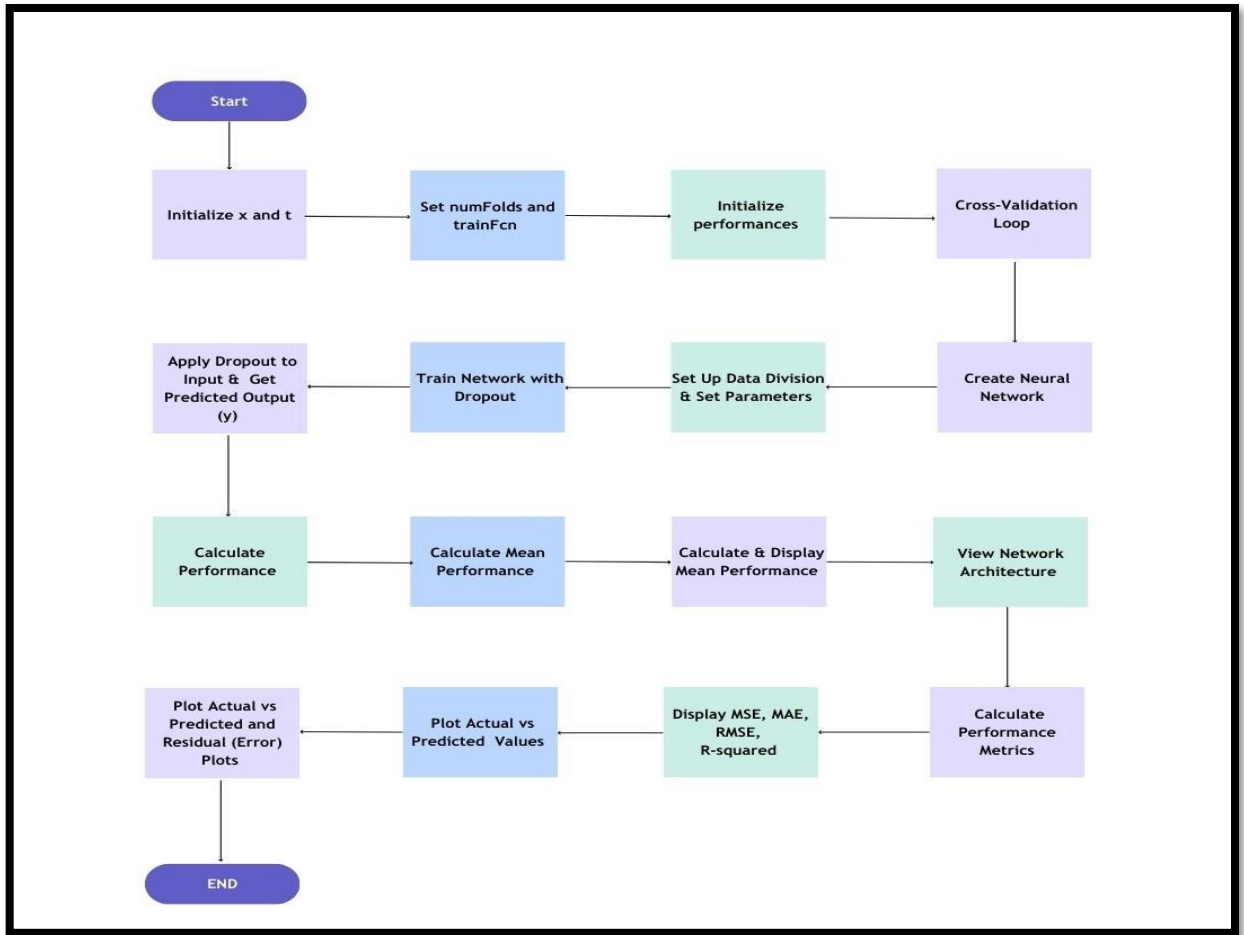


Figure 3-1: Algorithm Block Diagram

3.4 Flow Chart

The process begins by setting the number of folds for cross-validation. A training function is then chosen, followed by the creation of performance metrics. The flow then moves to the cross-validation step, where a loop is established. Within this loop, a fitting network is created, or if the cross-validation loop ends, the process proceeds. Subsequently, the network is trained, and after training, it is tested. Post-testing, performance calculations are conducted twice. Figure 3-2 shows the preprocessing steps, including normalization and data partitioning, facilitated the effective training and evaluation of the BPNN model for wind speed prediction using the specified dataset from Keti Bandar, Pakistan.

The mean performance is displayed, offering an overview of the network's effectiveness. Additionally, there's an option to view the network's structure and calculate performance again if needed. The final steps involve displaying metrics and concluding the process.

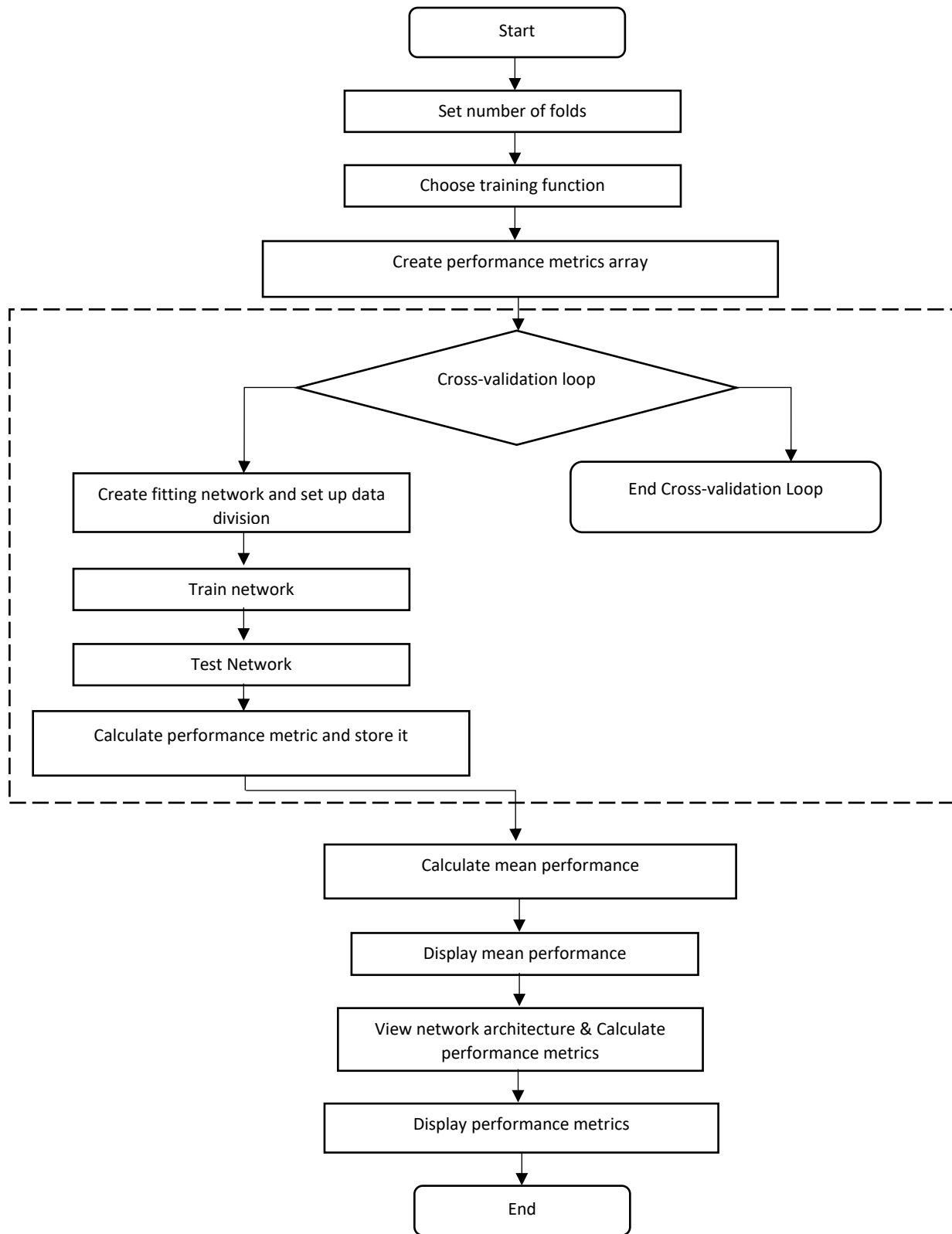


Figure 3-2: Flow Chart of Algorithm

3.5 Data Preprocessing

In this case, one year data of Keti Bandar, Pakistan, was collected for this research. The variables and input features used in the learning process incorporated the temperature, wind direction, and pressure, while the target feature of interest was the wind speed. Before the training of the proposed BPNN model, some pre-processings were performed on the data. For normalization, Data Cleaner app in MATLAB was applied.

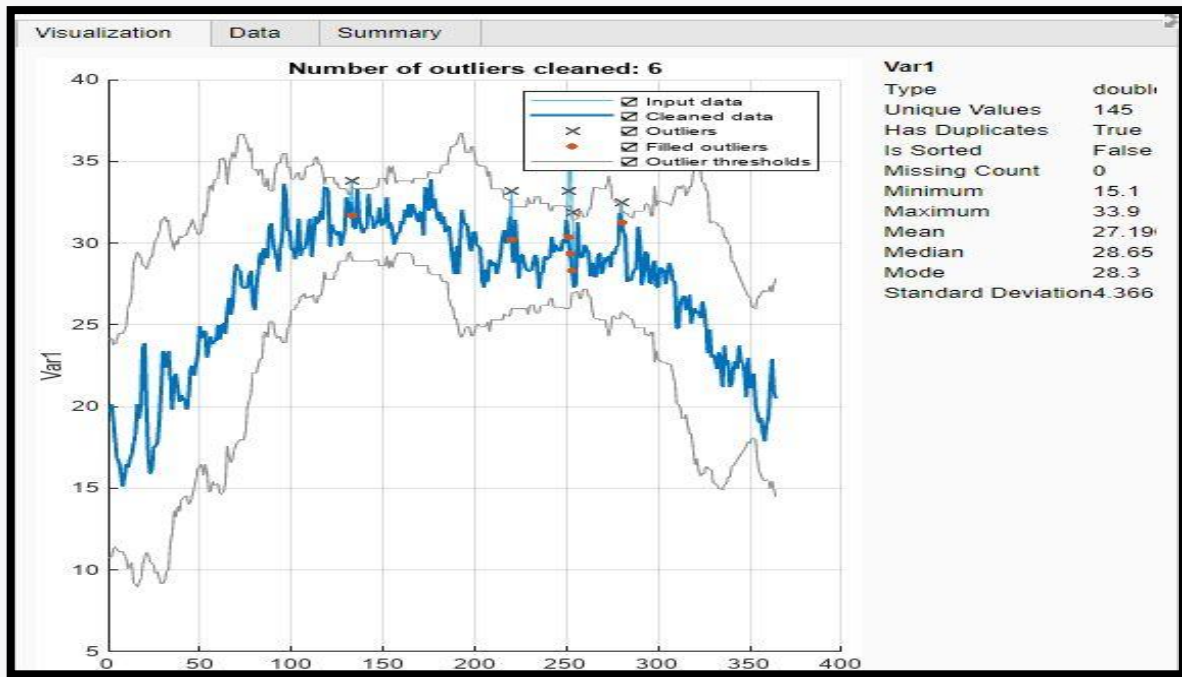


Figure 3-3: Data Preprocessing using Data cleaner app on MATLAB

This step was important as to avoid a situation where some of the input variables are much larger than other leading to a dominance in the training process. Moreover, the data arisen was splitted into 70% for training and 30% for testing purpose. It also meant that training of the model could be done on a larger portion of the data and another part could be selected for use in testing the model's fidelity.

3.6 Neural Network Architecture

Figure 3-4 presents the architecture of the BPNN used in this research for forecasting of wind speed since it is designed to model the non-linear relationship between the input variables and the wind speed responses. The structure of the network mainly covers the initial input layer, one or several hidden layer(s), and the final output layer.

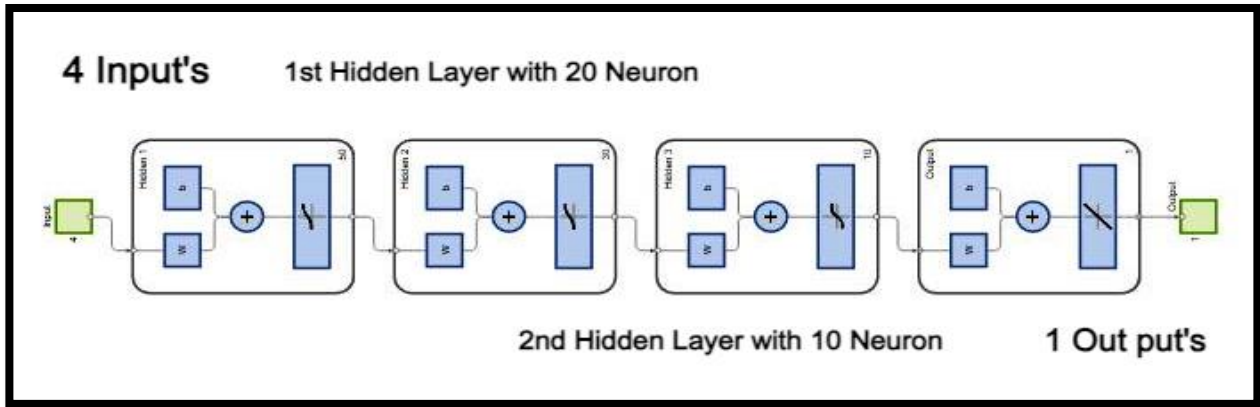


Figure 3-4: Network Diagram of back Propagation Neural network

The size and structure of the hidden layers and neurons of the network also determines how well the neural network will learn by generalizing from the training data. As for the hidden layers, one first hidden layer is used that contains 20 neurons, while the second hidden layer contains ten neurons. Thus, the choice of this architecture is to make the network more complex and to provide it with more representations to consider the wind speed data non-linear characteristics and interactions between them.

To train the ABPNN, Levenberg-Marquardt backpropagation algorithm (trainlm) is used in this present research. This means that this training algorithm is efficient and effective in its essence of making the network weights to get closer to the optimal values whereby the wind speed values estimates made by the network are as close as possible to the actual wind speed targets. The Levenberg-Marquardt algorithm is a variation of both the gradient descent or backpropagation and the Gauss-Newton method, thus is fit for applying to neural networks, particularly for regression analysis such as wind speed prediction.

Table 3-2: Neural Network Training Progress

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	4	1000
Elapsed Time	-	00:00:00	-
Performance	317	0.107	1
Gradient	1.41e+03	28.9	1e-07
Mu	0.001	1e-05	1e+10
Validation Checks	0	0	6

This complex structure implies that the network is capable of learning the non-linearity of the wind speed data, or patterns that exist in the data set. The Levenberg-Marquardt algorithm helps in easy optimization of weight; thereby, increasing the accuracy and the speed of convergence in neural networks. These factors make the above selection of BPNN architecture for wind speed prediction appropriate as it gives the enhancement of the accuracy of wind energy systems' forecasting. The network training progress is as follow, ****Table 3-2****

3. 7 Weight allocation criteria

The weights allocation and regularization directly depend on the several parameters and settings as follows. Architecture of the network is initialized having two hidden layers, and the specified number of neurons for each layer. Hyper-tuning of the network is done using the following configurations: The 'logsig' activation function is used for the hidden layers and the learning rate is 0. 01. The regularization in form of weight decay is employed and is applied to all weights with a strength of 0. 01. The parameters involving training which includes the number of epochs, and the training goal (mean squared error) will be pegged at 1000 and 1. 00, respectively. The data is divided into three subsets: training set, validation set, and test set in the proportion that is specified. Moreover, due to the concepts of dropout, the dropout rates of 0. 3 and 0. 2 are implemented manually during the training of model. These settings together determine the weights allocation and the regulation method of the weights in the neural networks, offer the power of managing training process of the network and reduce the overfitting problem. It is noteworthy that these parameters can be tuned depending on the features of the corresponding dataset and the nature of the problems solved.

3.8 Error-Reducing Techniques

3.8.1 Weight Decay

Thereby, weight decay parameter is set to 0. 001 and the weight decay is turned on through weight Decay. It is a form of regularization technique that discourages large weights in the network through addition of penalty term with the loss function hence reduce cases of overfitting.

3. 8. 2 Dropout

The code also incorporate dropout into the training procedure. It establishes Dropout Ratio at 0. 2 which translates to a dropout rate, It helps in creating dropout ratio (dropout Ratio) of 0. 2. Dropout is similar to the below function that randomly drops out units from the network with the help of

dropout indices multiplying the input data with x . This technique assist in stabilizing the network because it reduces the level of interconnection between the remaining units which requires it to learn more of independent and more robust features. It is mandatory to generate a dropout ratio %

When applying weight decay as well as Dropout on the model the figure 3-5 reveals that the residual error plot is displayed in wave form.

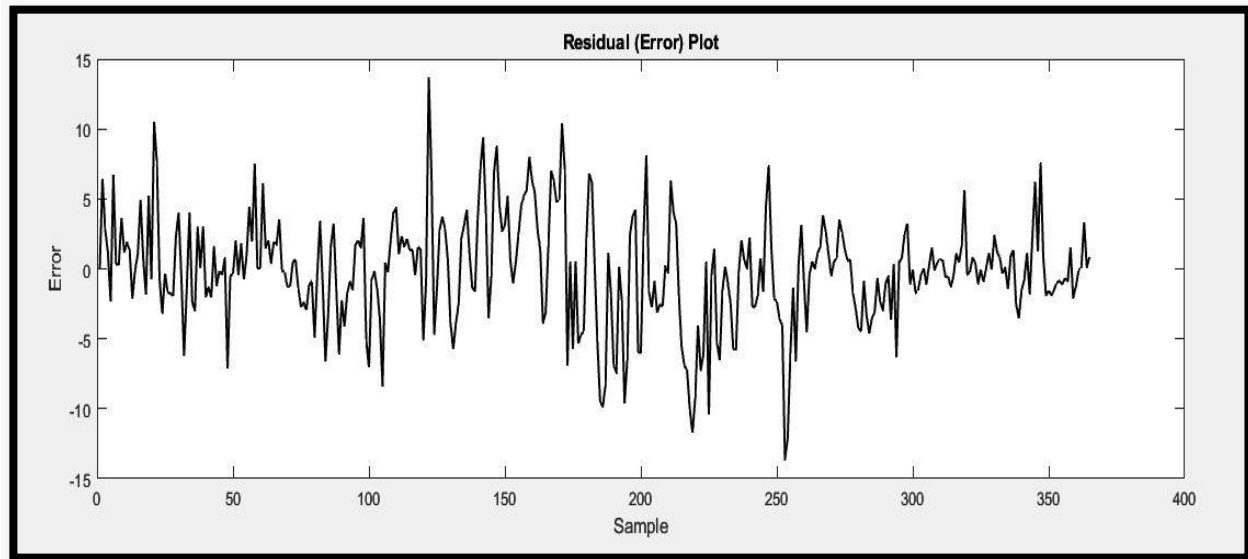


Figure 3-5: Residual Error Plot Diagram of one year wind data

3.8 Equations related to Error Reducing Rate

The criteria for comparing forecast results include MAE, RMSE, and MRE. According to the described approach, the MRE is most useful when evaluating actual forecasts against time series data of different orders of magnitude. The equations for these evaluation metrics are as follows: The equations for these evaluation metrics are as follows:

3. 8. 1 Mean Absolute Error (MAE).

Equation 1 will give Mean Absolute Error (MAE) which represent an average absolute difference between the look-up table values and the values reconstructed by the model in the dataset. MAE provides model performance assessment that is unambiguous and simple, with lower scores indicating higher accuracy of the model's predictions. However, MAE being resistant to outliers it is preferred over MSE as a measure of accuracy in a predictive model.

$$\text{MAE}(N) = \frac{1}{N} \sum_{t=1}^N |Y_t - Y_t^*| \quad (1)$$

3.8.2 Root Mean Squared Error (RMSE)

Mean Squared Error or MSE as shown in (2) is a variation of RMSE or also referred to as mean of the squares of the deviations. RMSE average the squared difference of the actual value and the predicted value and then take the square root of the average. RMSE is commonly applied in cases where there is a requirement of representing the prediction errors in terms of the target variable. Also reminiscent of MSE, RMSE scores represent the model performance and the lower the scores the better the model performs. Another strength of the RMSE is that it gives the measure of error in the original unit of the data which in turn makes it easier to compare the error with the true value.

$$\text{RMSE}(N) = \sqrt{\frac{\sum_{t=1}^n (Y_t - Y_t^*)^2}{N}} \quad (2)$$

3.8.3 Mean Relative Error (MRE)

Mean Relative Error (MRE) represented in Equation 3 is a statistic utilized to measure the relative accuracy of a model's prediction. It computes the mean standardised difference between observed and forecasted values simplified by finding the average of the absolute percentage differences of the former over the latter. Relative error is more advantageous than absolute error when expressing the errors as a percentage of the actual values and is more interpretable when highlighting this relative disparity in light of the data's scale, given by MRE. MRE of assessed quantities is lower for better prediction accuracy and, in its ideal case, approaches zero value..

$$\text{MRE}(N) = \frac{1}{N} \sum_{t=1}^N \left| \frac{Y_t - Y_t^*}{Y_t} \right| \quad (3)$$

3.8.4 Mean Squared Error (MSE)

The equation (4) is MSE and it presents the average of squared the differences between actual and predicted values. It is a means of measuring the extent of total error and is applied frequently in

regression plus artificial intelligence. As a result of the squaring operation, MSE is more influenced by the outliers and more so, it penalized large errors more than mean.

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (Y_t - Y_i)^2 \quad (4)$$

3.9 Summary

This paper specifically focuses on overall procedure for the BPNN model of wind velocity and wind energy potential assessment in MATLAB and each step was well elaborated and analyzed in this chapter. It started with a distinct data cleaning step, both for clearing wind speed data and for outlier detection and treatment, together with missing values handling which assures cleanliness of the available dataset.

Regarding the model training, a BPNN architecture was chosen with two hidden layers containing 20 neurons in the first layer, and 10 neurons in the second one. Areas: Crucial decisions in choosing appropriate training functions were found to be important in determining the enhancement of the learning process of the neural network. The Levenberg-Marquardt backpropagation algorithm was used due to the optimization of the prediction errors of the model and an increase in the overall accuracy of the output.

Thus, the cross-validation with different folds was applied for the model synthesis in order to test its efficiency. MSE is Equated with 4 and MSE measures the average of the squared differences of the actual value and the predicted value. It is commonly used in regression and machine learning and represents an indication of the error totals. This is due to the process of squaring that has been applied in the formulation of MSE, and as results MSE punishes large errors more when compared to ME. Unlike the training set, the model performance on cross-validation set gave an idea of true ability of the model and also helped in overcoming common issue of overfitting in machine learning applications.

Moreover, the applied methodology incorporated powerful error-preventing methods such as weight decay and dropout. When a time dimension is introduced to the loss function and weight decay was applied to prevent over-fitting and discourage the building of overly complicated models. This regularization method in particular was instrumental in the process of increasing the model's ability to generalize to unseen data and improving its performance on such data. Dropout, another method that was applied, was a technique of deliberately setting some of the neurons under training into a state of inactivity, which in essence ensured that there was no mutual learning among the

neurons and prohibited overfitting to provide the best BPNN model. Dropout, on the other hand, desires trained the nodes or neurons at arbitrary times during the training, and thus the formation of a stronger network that can work well with different type and pattern of data. The assessment of the model was carried out thoroughly and emphasized on the aspects such as MSE and MAE. The calculated MSE and MAE were impressively low and this also reflected the low variation of the real and predicted wind speeds data. Further, in order to assess the average size of the prediction errors, RMSE was computed and the results proved the reliability of the formulated model. The significant R-squared value that was obtained, whereby this is a statistic that determines the extent to which the dependent variable is explained by the model, supported the provided results and enhanced the model's validity.

In conclusion this chapter introduced a complex BPNN model for wind speed forecasting, as. Additionally it focused on every careful step to pre-process the data, to train the constructed model, and finally to validate its performance and to provide a profound analysis of the obtained results. With the enhancement of several features like weight decay & dropout along with the application of Levenberg-Marquardt backpropagation algorithm, it was possible to build a reliable & precise framework of prediction of wind speed. It is envisaged that application of this methodology offers great potential to create a sea change in wind energy forecasting and open up new vistas in the realm of renewable energy system in Pakistan.

Chapter 4

4. Results and Discussions

This chapter contains the result of the constructed model for wind speed prediction using back propagation neural networks, prepared with the assistance of the MATLAB neural network toolbox. The aim of this study was to examine the way, how the model functions using different data length; thus, six months, one year and two years of wind speed data were used. We evaluated the model's performance using three widely accepted error metrics: Root Mean Squared Error (RMSE), Mean Squared Error (MSE) and Absolute Mean Error (MAE). These parameters give insights into the efficiency of how our prediction model's reliability and accuracy increases or decreases with the size of the dataset in consideration.

4.1 Outputs & Results

4.1.1 Performance

Other metrics for the trained neural network are computed in the code as follows Members of the commercial banking and operations team train the neural network with the input data used in the current study and other datasets. It calculates the value of coefficient of correlation namely R-squared, mean squared error, average absolute error, root mean square error and mean squared error. These parameters characterize the network's performance when anticipating the precision and predictability of the output with regard to the actual target values. The type of testing is called Performance Validation, which is illustrated in the following figure 4-1.

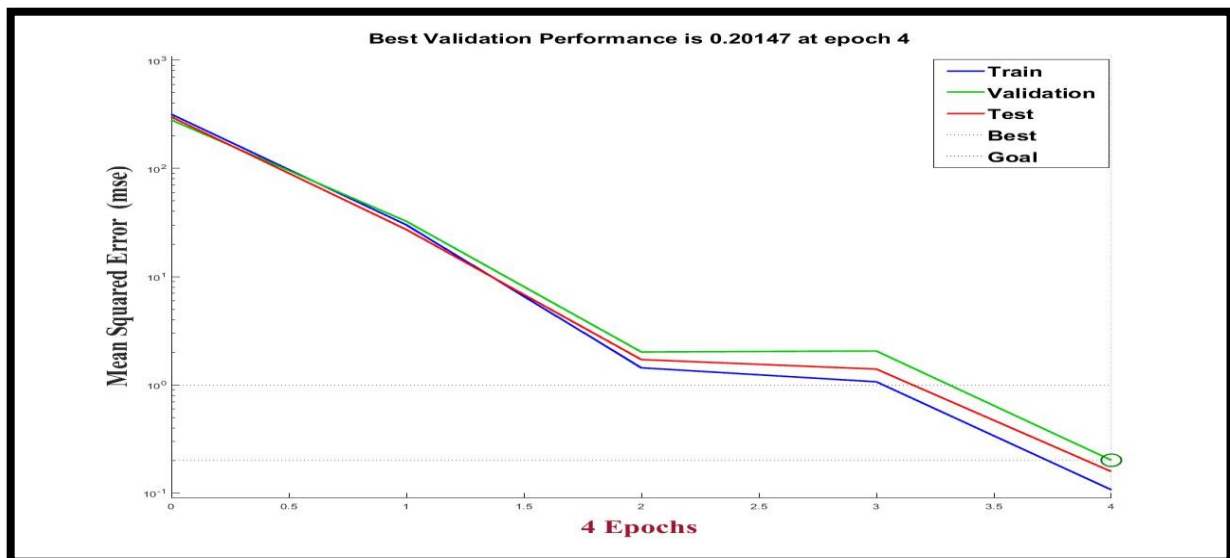


Figure 4-1: Performance Validation performance is 0.20147 at epoch 4

4.2 Training Status

The code carry out cross-validation, which implies that the neural network is trained several times on portions of the data. It then uses all the learned folds to come up with the mean performance which is a representation of the performance of the trained network. Also, the code prints the mean performance value and enables you to visualize the architecture of the network with the `view` function. Training status as shows in the following figure 4-2 below.

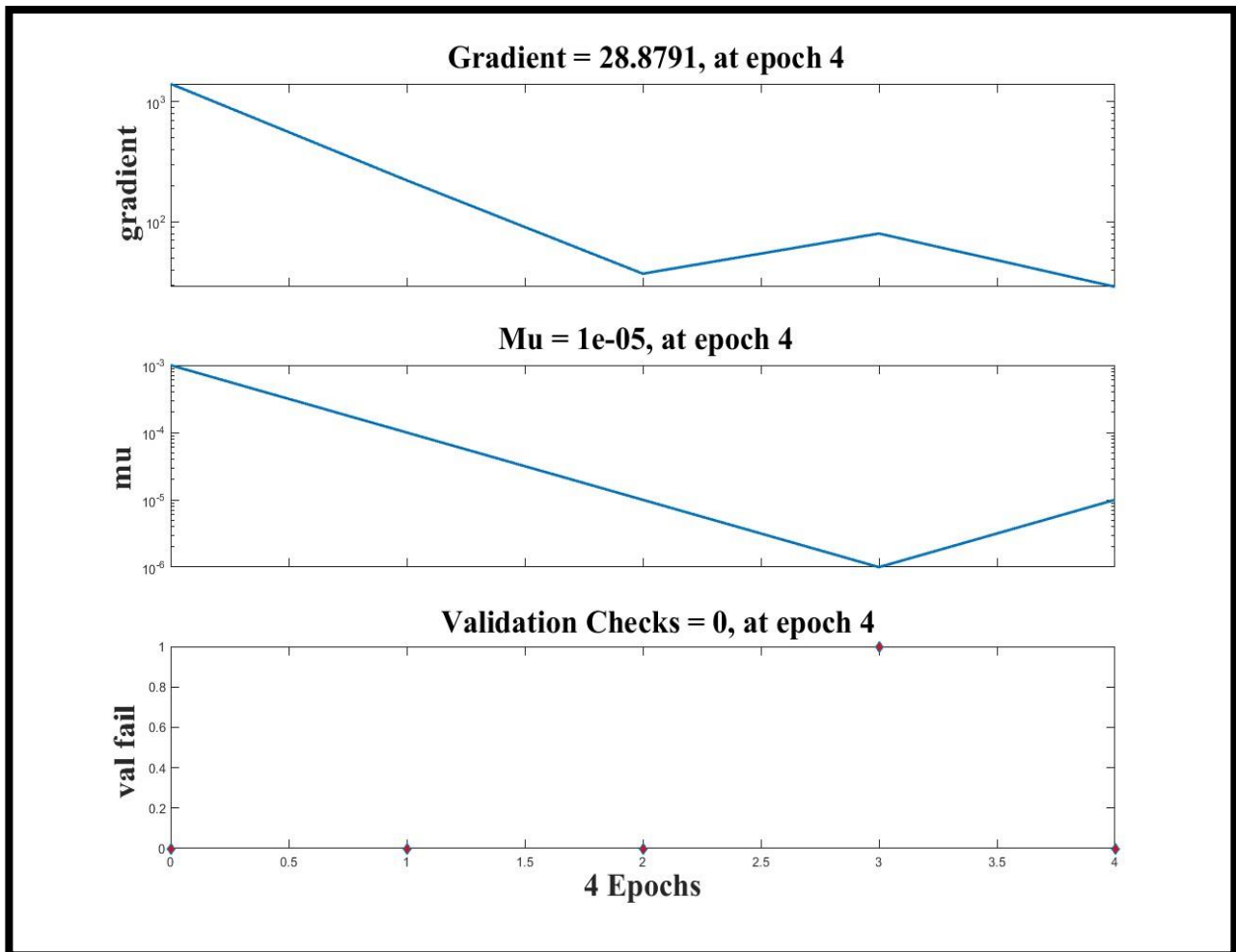


Figure 4-2: Training Status of neural network

4.3 Error Histogram

The code does not include functions of an error histogram. But it determines other error statistics involving MSE, MAE, RMSE, which inform the deviation of the predicted values from the real values. From these error metrics, one can derive statistics of the errors of the network such as the distribution and the scale of errors. Error Histogram as was demonstrated in the figure 4-3 below,

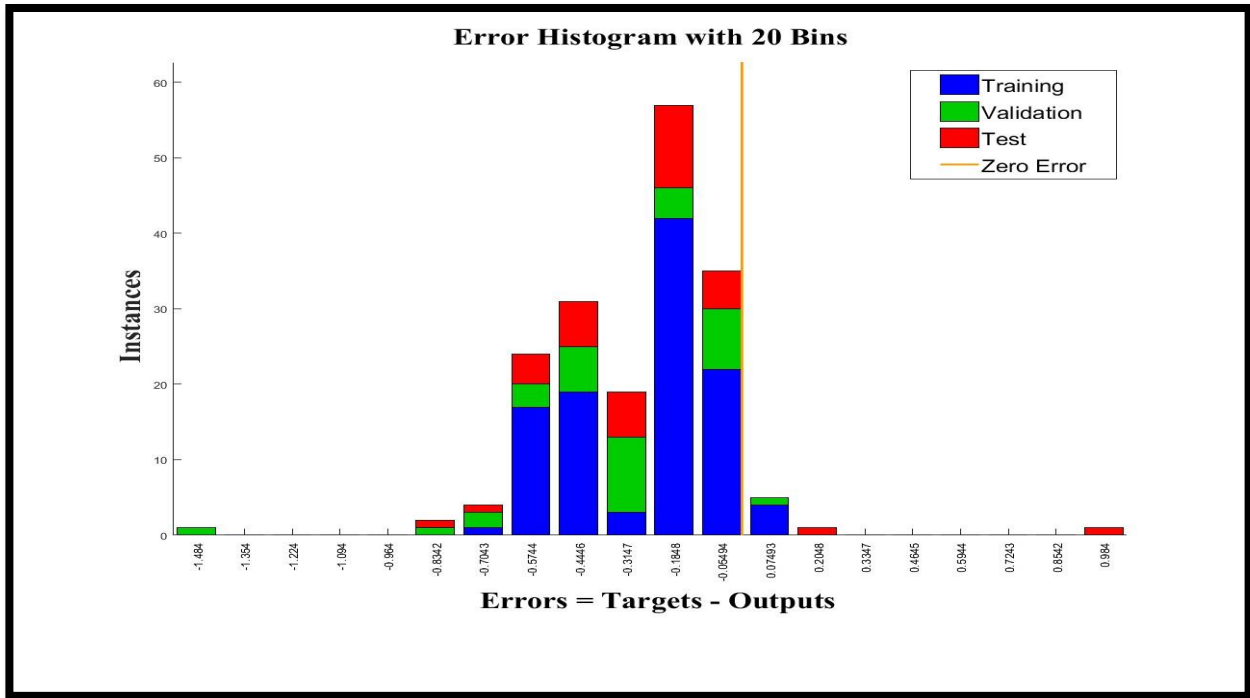


Figure 4-3: Error Histogram with 20 bins

4.5 Model Performance Using Six Months of Data

The performance of models is specified in the Table 4-1 where initially, when trained these neural networks with Six Months of wind speed Data, promising results were obtained. The RMSE of elements for this structure was 0.3028, which means that the model had a margin of error in the wind speed estimated at about 0.3028 of a unit from the real values. The MSE in the same sense was 0.0917 and the MAE was 0.2622. These relatively low error values prove that the particular model was effective when worked with a shorter period of time and succeeded in determining wind speed tendencies in the given period.

Table 4-1: Performance Using Six Months of Data

Performance Using Six Months of Data	
Root Mean Squared Error (RMSE)	0.3028
Mean Absolute Error (MAE)	0.2622
Mean Squared Error (MSE)	0.0917
Approximation error	28.6549 %
Model Accuracy	71.3451 %

Figure 4-4 depicts the actual vs predicted wind speed in which one year of wind data from January to June is used in the training of the NN as well as data from July to December is used for the purpose of result comparison the performance metrics gives a brief on how efficiently the neural network model has carried out the task. The RMSE of 0. 37069 conveys the fact of mean squared prediction errors, and the smaller value refers to the better average prediction accuracy. Hence, the Mean Absolute Error (MAE) calculated is 0. 29662 which gives average difference of absolute errors between the actual values and predicted values. When providing an average of errors, the batch progress MSE of 0. 13741 gives attention to larger errors in Mean Squared Error (MSE).

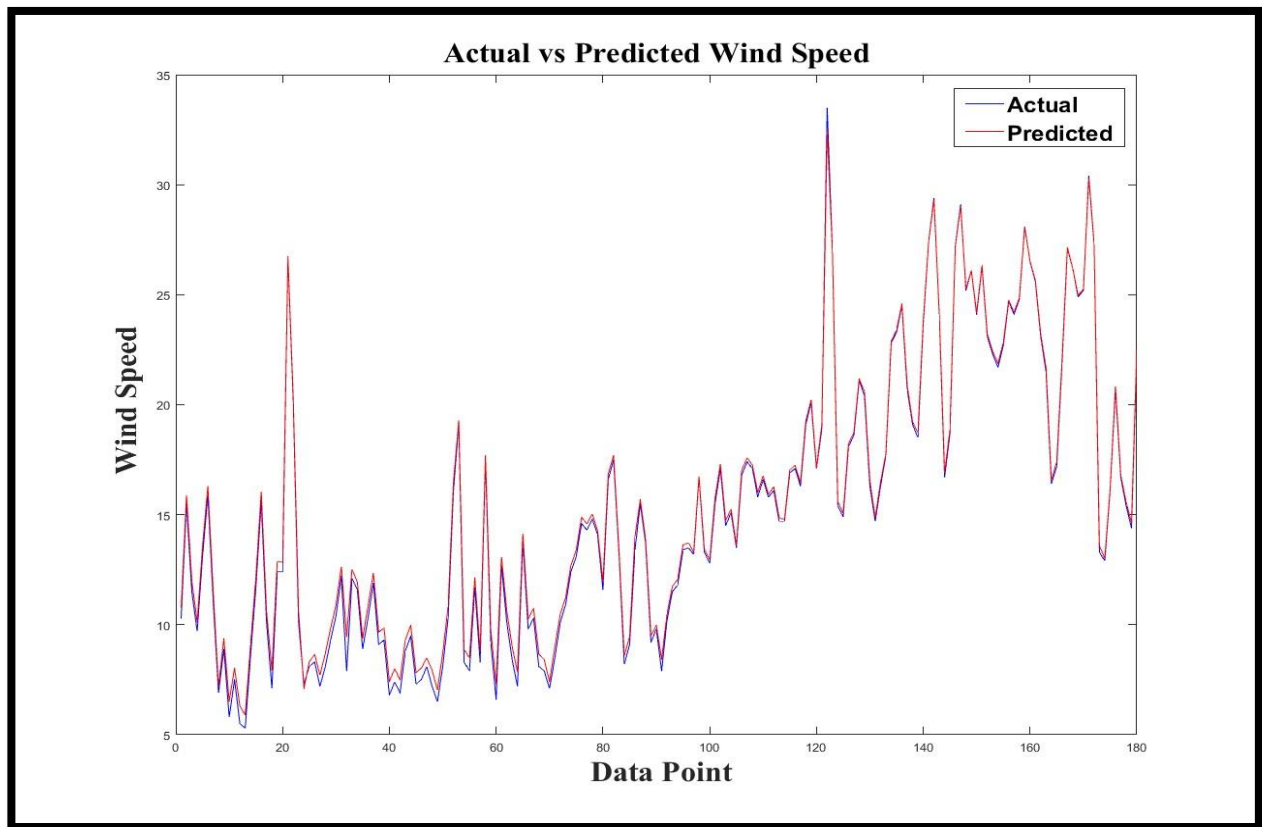


Figure 4 Actual vs Predicted wind speed using one year wind data

These metrics are summed up to capture the model's degree of fit with the target variable, with low numbers preferred. Mean Absolute Error or MAE of 2914,000 measures the actual difference of each observation, while the Approximation Error of 29. 5746% indicates how much the predicted and actual values differ in relative terms, giving the big picture of the model's effectiveness. Here it indicates that the scale of error, on average, ranges approximately 29. 57 percent from the actual values. It would be possible to proceed with additional analysis and comparison with the baseline

models or other approaches to better understand the practical meaning of these metrics in the given context of the solved problem.

Table 4. 2 presents the results of model performance for the OAD system while using one-year historical wind speed data. Thus, to test the model’s ability and effectiveness to handle a larger dataset, we expanded the training data to one year. We took 180 values for training and in second part we compared our values with remaining 180 days values, but the results show a distinguishable increase in the error. Due to more fluctuation and dispersion, the RMSE was 0. 37069 which is considered higher for efficiency and deviated from actual wind speeds significantly. For the best model, the MSE raised to 0. 13741, while the MAE approached 0. 29662. When this value is 29. 5746% or even lower, it will comprise the Approximation Error of the section, which is a more generalized representation of the model in question as it will cover the general breadth of the predicted and actual results offered by the chosen model.

Table 4-2: Performance Using One Year of Data

Performance Using One Year of Data	
Root Mean Squared Error (RMSE)	0.37069
Mean Absolute Error (MAE)	0.29662
Mean Squared Error (MSE)	0.13741
Approximation error	29.5746 %
Model Accuracy	70.4254%

4.7 Using Two Years of Data Final Performance with comparison

Table 4-3: HOS model performance using two years of historical wind speed data Ongoing the study, the training data was enriched by using two years of wind speed data in order to check how that would influence the model’s performance. Surprisingly, there was an increase in the performance compared to when data was restricted to one year. The RMSE reduced to 0. 37069; this means that the Mean Square Error reduced and the prediction errors lessened. The MSE also reduced to 0. 13741 while the MAE reduced to 0. 29662. From these results, it can be concluded that the model suits the consideration of the expanded timeframe as regards the evaluation of the long-term characteristics of wind speed.

Table 4-3: Using Two Years of Data Final Performance with Comparison

Using Two Years of Data Final Performance with comparison				
	Our Results	Zhenyu Song et.al	Wei Sun et.al	Yan bin Cui et.al
RMSE	0.8013	4.4800	1.1375	0.9005
MAE	0.6628	6.6800	18.3203	0.6547
MSE	1.1247	1.9900	0.7696	-

4.8 Actual vs Predicted Waveforms.

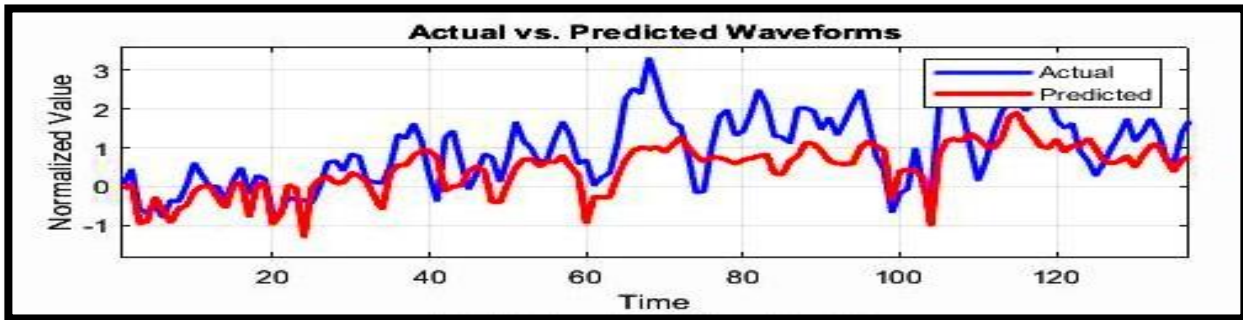


Figure 4-5 Sample of Actual vs Predicted Value with Two Years Data

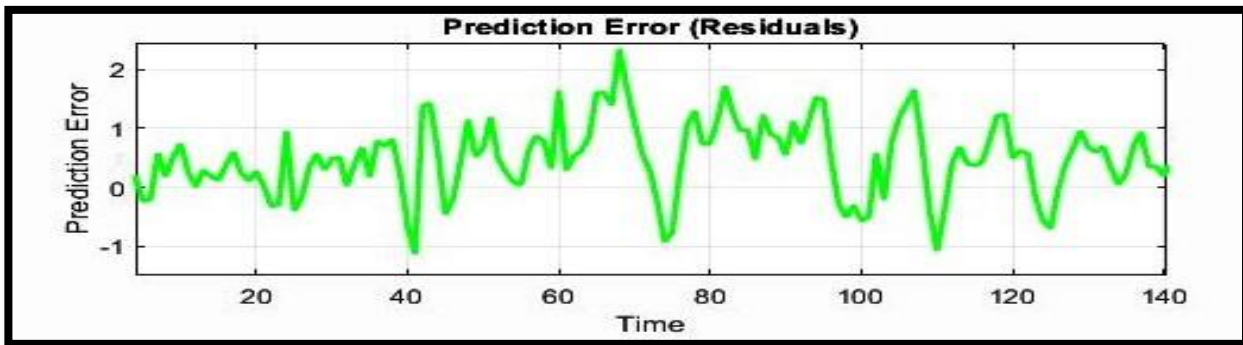


Figure 4-6 Sample of Prediction error with Two Years Data

The Actual vs. Predicted Waveform is self-explanatory and the pictorial representation is shown in Figures 4-5 and 4-6 wherein we have used Two Years data in the context of our Results. This figure is the best way to convey the effectiveness of our predictive model’s performance. The X-axis being a normalized history gives an easy to interpret comparative view of the predicted and actual results that helps in understanding the efficiency of the constructed model. On the other hand, the Y-axis is used to present time in presentation form in 20 minutes’ intervals, providing for a thorough

temporal evaluation. This plot is not only a visual representation of model outputs against actuals but also helps to look at the patterns and variations involved in the data which is critical while arriving at conclusions in our work.

4. 9 Discussion

Limitations of our model is that is trained on the data based on Pakistan weather and conditions, it could be deduced from the results presented that temporal characteristics of the training data have an effect on the performance of the neural network model in wind speed prediction. Whereas for the case of six months of data, the model gave good results, with one year of data, the model results were somehow poorer probably due to the increase in complexity. But, the, the model regained its accuracy with the use of a two-year training period hence showing the potential sides of a longer training timeframe towards improving upon the accuracy of the model.

These results can be used to prove the fact that when developing the neural network models for wind speed prediction the selection of the training dataset duration should be proper. Thus, for defining the parameters for wind energy application, necessary for creating precise predictions, researchers and specialists of the industry should consider the value between the accuracy and the length of the prediction's time period. Future studies may be required to identify the best practices and model structures that can alleviate the difficulties encountered in the longer datasets yet ensure the best prediction rates.

Chapter 5

5. Conclusion

Thus, this thesis proposal focused on enhancing the accuracy of wind speed and power forecasting in Pakistan using an enhanced back-propagation neural network (BPNN). Proof of the improvement in the accuracy was established through depicting of the decreased quantitative values as indicated by the meta RMSE, MAE, and MSE standards compared with other methods. These findings are very useful for Pakistan to cater its increased demand of energy through the renewable resources. Professionally accurate wind predictions are instrumental for the effective and efficient control and handling of wind power and energy systems thus promoting the use of renewable sources of energy and less reliance on the non-renewable sources of energy. Still, the outlook could be brighter as there are possibilities for further enhancement in the following aspects when it comes to this study. Some suggestions for future work are the aspect of complexity issue of feature selection, further hyperparameter optimization, the use of ensembles, augmented data, different architectures of neural networks, and the incorporation of spatial data. Such endeavours have the capability to increase the levels of prediction in the wind speed and wind power to the highest level possible. Not only does this thesis enrich the academic knowledge stock, but it also has practical value for government officials and energy-related industry staff. Using superior analytical methods of machine learning and future research, In Pakistan and across the globe there is the potential that outlines the chances of a bright and illuminated future rich with improved power generation and profitability.

Chapter 6

6.1 Future Work

The findings produced from the study are positive and can be used as a starting point; however, the paper has a few directions to which the further research should be addressed in order to enhance the Wind speed and power forecasting as well as to enhance the effectiveness of applied methods based on advanced machine learning techniques. Here are some potential directions for future work: Here are some potential directions for future work:

6. 2 FEATURE ENGINEERING AND SELECTION

Try one or more new subsets of the input data elements. Further, it is required to investigate other effects into the additional weather factors related to wind power and its speed like temperature, humidity, air pressure etc. It is still possible to enhance the speed and reliability of the used model, for example by applying more feature selection methods such as the Principal Component Analysis (PCA) or the Recursive Feature Elimination (RFE) that can help in the search for the most significant features.

6. 3 Hyperparameter Tuning

The result of the research also stated that the accuracy of advanced BPNN model can be highly enhanced by varying the parameters of the model. To enhance the models as well as to find out the right set of hyperparameters one can apply into the two ways like the grid search or random search.

6. 4 Ensemble Methods

In general, look at other techniques including the bagging and boosting techniques that incorporate many models to make their predictions. Ensemble forecasts are likely to have less variance than individual method due to techniques such as bagging and k-nearest neighbors, as well as less bias in terms of over prediction since methods such as boost could minimize prediction errors.

6. 5 Data Augmentation

Expand the current dataset with the help of such operations as mirroring, rotation, or adding noise. A larger and a more diverse dataset can better help the model adapt to the unseen data and hence the model's capability to predict correctly is enhanced.

6. 6: New and improved structures of neural networks

Try deep and more complex structures of a Neural Network like LSTM networks or GRU. The reason for this is that these architectures are designed to work with sequential data, so, potentially they are better suited for capturing the temporal patterns of power and wind speed.

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Appendices

Appendix 1: Sample of 1 month Wind data

Table A-1: Wind Parameters Data

Temperature	Wind Direction	Pressure	Wind Speed
18.6	38	1020.5	10.3
19.7	36	1018.9	15.5
20.1	50	1017.1	11.5
19	43	1016.5	9.7
17.8	57	1014.7	6
16.8	66	1014.2	15.9
16.6	22	1014.1	11.1
16	315	1015.9	6.9
15.1	45	1017.4	8.9
15.7	23	1018.3	5.8
16.5	42	1019.6	7.5
16.3	3	1018.5	5.5
16.8	31	1017.2	5.3
17.1	44	1018	8.6
18.3	37	1018.7	11.7
20.1	46	1018.5	15.6
19.3	41	1019.2	10
20.1	35	1018.7	7
23.6	290	1015.4	12.4
23.9	260	1011	12.5
20	255	1008.1	26.4
16.9	300	1008.5	20.1
15.9	315	1012.6	10.1
16.2	60	1014.2	7.3
17.5	2	1015.5	8.1
17.6	54	1015.8	8.3
17.8	11	1017.3	7.2

19.2	260	1017.3	8.1
21	310	1016.2	9.3

Appendix 2: Pseudocode of Dropout Technique in Matlab Code

```
# Create and train the BPNN model with dropout using manual dropout layers
```

```
# Set the number of hidden units and dropout rate
```

```
hidden_units = [20, 10] # Adjust the number of hidden units as needed
```

```
dropoutRate = 0.5
```

```
# Create layers
```

```
layers = [
```

```
    fullyConnectedLayer(hidden_units(1))
```

```
    fullyConnectedLayer(hidden_units(2))
```

```
    dropoutLayer(dropoutRate)
```

```
    dropoutLayer(dropoutRate)
```

```
    fullyConnectedLayer(1)
```

```
    regressionLayer
```

```
]
```

```
# Create a neural network
```

```
net = feedforwardnet(hidden_units)
```

```
# Add dropout layers
```

```
net.layers = [net.layers; layers(3:4)]
```

Appendix 3: Pseudocode of Weight decay Technique in Matlab Code

```
# Set weight decay
```

```
net.trainParam.weightRegularization = weightDecay
```

```
# Set training options
```

```
options = trainingOptions('adam', ...
```

```
    'MaxEpochs', 100, ...
```

```
    'MiniBatchSize', 32, ...
```

```
    'ValidationData', {X_test, y_test}, ...
```

```
    'ValidationFrequency', 10, ...
```

```
    'Verbose', false, ...
```

```
    'Plots', 'training-progress', ...
```

```
    'LearnRateSchedule', 'piecewise', ...
```

```
    'LearnRateDropFactor', 0.1, ...
```

```
    'LearnRateDropPeriod', 30, ...
```

```
    'Shuffle', 'every-epoch')
```

Appendix 4 : Pseudocode of Evaluation metrics Calculation in Matlab Code

```
rmse = sqrt(mean((testOutput - predictedOutput).^2));
```

```
mse = mean((testOutput - predictedOutput).^2);
```

```
mae = mean(abs(testOutput - predictedOutput));
```

```
fprintf('RMSE: %.4f\n', rmse);
```

```
fprintf('MSE: %.4f\n', mse);
```

```
fprintf('MAE: %.4f\n', mae);
```