ESTIMATION OF WIND SPEED USING ARTIFICIAL NEURAL NETWORKS CASE STUDY – LIBYA

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Shaker Salem A. ABUZAWAIDA

ABSTRACT

M. Sc. Thesis

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The Department of Electrical and Electronic Engineering

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Worldwide, electrical power is recognized as the main factor behind improving living standards. Therefore, the safe operation of electrical energy is required for national energy management. For this purpose, accurate estimates are needed to assess electricity demand. Before the wind power plant installation, it is necessary to determine the appropriate locations for the turbine location in feasibility studies and to measure the wind speed in the relevant region. These studies can be done with simulation and wind speed estimation. Within the scope of this study, wind speed estimation has been made for Tajora city in Libya using ANN (artificial neural network) with Levenberg-Marquardt (LM) learning algorithm. A portion of the total one-year data consisting of hourly data obtained from Libya Meteorology Center has been used for the training of ANN, test and validation. ANN structure has been tested using 10, 20, 30, 40 and 50 neurons, and the number of neurons required for the best prediction has been determined.

The accuracy analysis of the estimation made by using the estimation results obtained by the Levenberg-Marquardt algorithm (LMA), mean square error (MSE), and determination coefficient (R^2) have been performed. According to the obtained results, the model with the best performance is the Levenberg-Marquardt algorithm with 10 neurons and the R^2 and MSE values of the model are 0.99980 and 0.000243, respectively. Therefore, the wind velocity estimation values made at the specified location with the limited meteorological data used can be obtained very close to the measured values and it has been shown that the wind speed can be estimated within acceptable limits.

Keywords : Wind Speed Estimation, Artificial Neural Network, Levenberg-Marquardt, Electrical Power.

Science Code : 90554

ÖZET

Yüksek Lisans Tezi

YAPAY SINIR AĞLARI KULLANARAK RÜZGAR HIZININ TAHMİNİ VAKA ÇALIŞMASI – LİBYA

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Karabük Üniversitesi
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Dünya genelinde elektriksel güç, yaşam standartlarının iyileştirilmesinin arkasındaki temel faktör olarak kabul edilmektedir. Dolayısıyla ulusal enerji yönetimi için elektrik enerjisinin güvenli bir şekilde işletilmesi gerekmektedir. Bu amaçla, elektrik talebini değerlendirmek için doğru tahminlere ihtiyaç vardır. Rüzgar santral kurulumundan önce fizibilite çalışmalarında türbin konumu için uygun yerlerin belirlenmesi ve ilgili bölgede rüzgar hızının ölçülmesi gereklidir. Bu çalışmaların ise simülasyon ve rüzgar hız tahmini ile yapılması mümkündür. Bu çalışma kapsamında Levenberg-Marquardt (LM) öğrenme algoritmasına sahip YSA (yapay sinir ağı) kullanılarak Libya'da bulunan Tajora şehri için rüzgar hız kestirimi yapılmıştır. Libya Meteoroloji Merkezi'nden alınan ve saatlik verilerden oluşan toplam bir yıllık verinin bir kısmı YSA'nın eğitimi, bir kısmı test edilmesi ve kalan kısmı doğrulanması amacıyla kullanılmıştır. YSA yapısı; 10, 20, 30, 40 ve 50 nöron kullanılarak test edilmiş ve en iyi kestirim için gerekli olan nöron sayısı belirlenmiştir. Kullanılan Levenberg-Marquardt algoritması (LMA) ile elde edilen tahmin sonuçları, ortalama hata karesi (MSE) ve belirleme katsayısı (R^2) kullanılarak yapılan kestirimin doğruluk analizi yapılmıştır. Elde edilen sonuçlara göre en iyi performansa sahip model, 10 nöronlu Levenberg-Marquardt algoritmasıdır ve modelin R^2 ve MSE değerleri sırasıyla 0.99980 ve 0.000243'tür. Dolayısıyla kullanılan sınırlı meteorolojik veriler ile belirtilen konumda yapılan rüzgar hız kestirim değerleri, ölçülen değerlere oldukça yakın olarak elde edilebilmiş ve rüzgar hızının kabul edilebilir sınırlar içinde tahmin edilebileceğini gösterilmiştir.

Anahtar Kelimeler : Rüzgar Hızı,Yapay Sinir Ağrları, Levenberg-Marquardt, Elektriksel Güç.

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CO_2	:	Carbon dioxide
CSP	:	Concentrated solar power
PV	:	Photovoltaic
IGA	:	International Geothermal Association
WES	:	Wind Energy Systems
BPA	:	Back Propagation Algorithm
ANN	:	Artificial Neural Network
NWF	:	Numerical Weather Forecast
RNN	:	Recurrent Neural Network
MLP	:	Multilayer Perceptrons
FPGA	:	Field Programmable Gate Array
TS	:	Taboo Search (TS)
SVM:	:	Support Vector Machine
PSO	:	Particle Swarm Optimization
ARIMA-NN	:	An Autoregressive Integrated Moving Average - neural networks
ARIMA-SVM	:	An Autoregressive Integrated Moving Average -Support Vector Machines
RVM	:	Relevance Vector Machine
EMD	:	Empirical Mode Decomposition
MSE	:	Mean Square Error
OLS	:	Orthogonal Least Squares
AI	:	Artificial Intelligence
PCSV	:	Point Cumulative Semi-Variogram
RBFN	:	Radial Basis Function Neural
BP	:	Back-Propagation
RH		Relative Humidity

LM	:	Levenberg-Marquardt Algorithm
(R^2)	:	Coefficient of Determination
NNs	:	Neural Networks

PART 1

INTRODUCTION

In today's world, energy is an important parameter that determines the quality of life and performance of an economy of a country. The world is currently facing a big challenge, which is finding sustainable, clean and suitable fossil fuel replacements. [1]. Since the time, the quality of life increased, there has been a massive increase in the energy demand around the world. As a result of this, the fossil fuel consumption has tremendously increased during the last few years. Since fossil fuels are not sustainable in the long-run, and they cause serious environmental issues, including climate change and pollution besides creating political and economic issues, security issues, and some political issues, which specifically affect the countries, which export fossil fuels [1].

1.1. ELECTRICAL ENERGY RESOURCES

Three main categories of electrical energy sources are given below:

1. Nuclear resource: Currently, more than 440 nuclear power generation plants are operating worldwide, supplying electricity to 31 user countries. The total capacity exceeds 390 GW, while about 60 reactors are still under construction. Together, such nuclear units provide about 11.5% of the world's electricity demand. The main advantages of this type of energy matrix are: a) continuous and reliable load without oscillations; b) no greenhouse gas emissions; c) the waste generated has negligible volumes and, due to radiation risks, it is confined and monitored in a way that does not generate pollution to the environment; d) nuclear power plants occupy much smaller areas as compared to hydroelectric plants, wind farms, and photovoltaic cells.

There are a number of controversial points that have contributed to the mistrust among the public regarding nuclear energy: a) high reactor costs, expensive auxiliary facilities, and high safety and operational costs; b) possibility of severe nuclear accidents, which might result in extremely harmful radiation emissions; and c) wastage of time and high license costs [2].

2. Fossil fuel resources: All fossil fuels form through very slow natural processes, and they have high carbon percentage. They include petroleum, natural gas and coal. Some of them are low-carbon volatile materials. They have different hydrogen ratios, which are different in fuels like liquid petroleum and methane. Some nonvolatile fossil fuels are mostly pure carbon, such as anthracite coal. Almost all the fossil fuels are important because of their combustion property and production of significant energy for every unit of their mass. Their main issue is dangerous greenhouse gas emissions, specifically carbon dioxide, which has a direct impact on climate change [3].
3. Renewable energy sources: They are based on renewable energy technologies, which are encouraged because they counter the negative effects mentioned above, which are caused when fossil fuels are used. It is a futuristic energy that would meet the world's power generation requirement. The energy pie charts are given in Figure 1.1 [4].

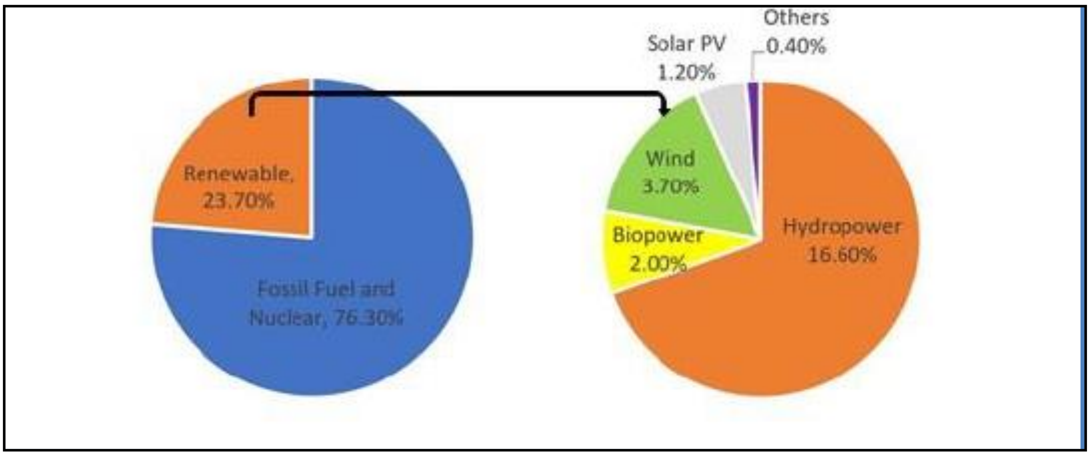

Figure 1.1. Renewable energy share in global energy in 2015 [4].

1.2. RENEWABLE ENERGY SOURCES

High electric power demands in the current era urged researchers and engineers to find alternative energy sources. In many countries, utilizing renewable energy to meet the energy needs is a high priority and focus of national energy management policies. Growing electrical energy demands and global warming have created a concern among the communities living around the world about carbon dioxide emissions. People are also facing high fossil fuel prices, which have urged governments to shift their focus towards new energy sources. In the past, disasters at nuclear power plants and their impact has resulted in debates to eliminate nuclear power generation from several countries' energy policies [5, 6]. According to International Energy Agency, the main requirements for renewable energy are natural occurrences like wind, sunlight, plant growth, geothermal heat and tides [7]. It is possible to classify the renewable energies as follows:

1. Solar energy: In principle, it comprises two main power generation types, and they are used with grid power. The first one is photovoltaic (PV) power. Concentrated solar power (CSP) generation, and the generated power is like traditional thermal power generation, through which, steam is used to generate electricity. The other form uses photovoltaic (PV) solar panels, which do not use solar radiation for thermal power generation but create a 'Photovoltaic effect' for directly generating DC power [8]. Then, it is transformed into AC, with the help of inverters, which is later transferred to the main grid. As mentioned before, PV systems do not produce/store thermal energy because they generate electricity, which is not easy to store, specifically at larger levels of power. Concentrated solar power systems (CSPs) use thermal energy storage technologies to store energy. This type of thermal energy storage will revolutionize the power generation industry because it overcomes storage problems of the PV systems; therefore, CSP systems are viable for large-scale power generation [9].
2. Hydro energy: It uses hydraulic energy, which is obtained when water falls down with a certain velocity. The changes in the falling water's pressure, angular momentum, or both run the turbine through a rotary motion. When water is used as

a working fluid, it is not consumed in a hydropower system; so, it is usable. To generate power or power machinery, hydropower is extensively used [10].

3. Geothermal energy: It is a form of thermal energy, which is generated from the Earth and also stored in it. Geothermal energy is always in the Earth's crust but it is generated based on the planet’s original formation and the radioactive material decay. Geothermal gradient represents temperature difference between the planet’s surface and core; so, heat rises to the surface. Geothermal energy is low-cost, sustainable, reliable and good for the environment. The installed capacity of geothermal energy has gradually increased worldwide over the last decade, reaching 13.93 gigawatts in 2019. Geothermal technologies are among the growing renewable energy trend occurring across the world, as environmentally friendly technologies are sought after due to lower emissions and the use of a renewable source [11].
4. Biomass energy and Biofuels: The biomass is an organic material that is used to generate power. Organic materials, such as grass clippings, wood pellets and crops, such as corn and sugarcane are used for manufacturing biofuels. Since plants regrow, biomass is a renewable energy source [12].
5. Ocean energy: Currently, research is continued on tapping the potential of the ocean energy. Oceans cover large part of the world, which is almost three-fourth of the entire earth surface. New investigations are continued to harness the amazing potential oceans can offer [13]. Calculations are done to tap different forms of ocean energy, such as tidal power, wave power, temperature gradients and salinity gradients. The ocean energy is consistent and predictable that makes it suitable for generating power more reliably than any other renewable energy form [14]. The marine energy can be used to generate sufficient power supply for the entire world.
6. Wind energy: It is a process to use wind to generate electricity with the help of turbines, which perform using the wind motion, and they transform the kinetic energy of wind into useful mechanical energy. Generators are used to convert the mechanical power and transform it into electricity. Wind is a phenomenon, which is a result of uneven atmospheric heat because of solar, geographical and planetary variations. Wind turbines work when their rotating propellers move and run an electric generator [15].

1.3. OVERVIEW ON THE UTILIZATION OF WIND ENERGY

The wind energy use is not new. Boats sail using wind energy, and in some parts of the world, wind has been successfully used for pumping water and grinding grains. The first time, when wind was used to generate electricity, was in late 19th century. Since that was a time of steam turbines, wind turbines could not gain popularity. The renewed interest in wind power was observed after the 1970s oil crises. First, it was just used to generate low amounts of electricity to charge batteries.

In 1990s, the focus of governments shifted from onshore to offshore developments in several windy countries of Europe. First offshore wind turbines were proposed in 1930s in Germany. The first turbine was installed in 1991 in Sweden, followed by another in 1992 in Denmark. In Europe, 2.4 GW wind turbines were installed in July 2010 [16]. Until 2010, the size and power production of horizontal-axis wind turbines improved substantially [17], as Figure 1.2 shows. This kind of offshore wind energy has certain requirements:

A. Lower wind sheer
B. Lower intrinsic turbulence intensity
C. Availability of larger sites to develop
D. Higher wind speeds

It has certain drawbacks:

A. High installation and maintenance costs
B. Difficult working conditions

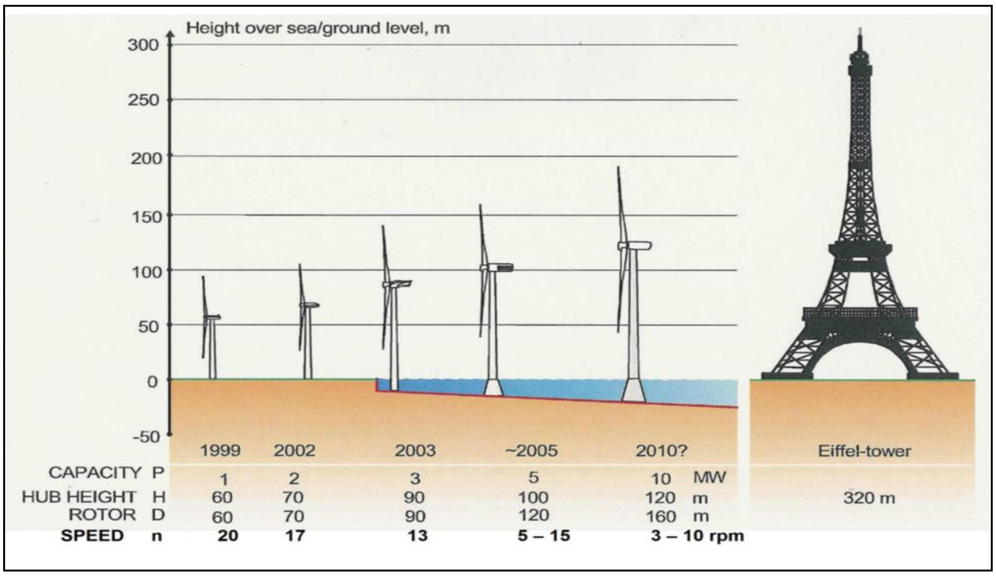

Figure 1.2. Improvement in horizontal-axis wind turbines [17].

Now, wind is a widely-recognized and feasible renewable power production source that generates economical energy in large quantities. Wind power generated approximately 420 GW power in 2016, which is likely to become more than 1000 GW in 2030 [18]. Modernization process is going on in Wind Energy System (WES) to assure efficiency in power production [19, 20]. WES is now widespread and complex; therefore, it requires new technology development initiatives to increase its reliability [21], improve its maintenance [22] and make it a less risky investment [23], which will certainly make the energy market more competitive. Since the market for wind energy is growing with a lot of untapped potential, it needs both investment and technical advancements. Efforts are focused to harness the wind energy to a higher level specifically targetting the technical aspects. Researchers addressed many issues so far, for example, wind turbines' aerodynamic optimization [24].

1.4. WIND ENERGY IN LIBYA

Libya is a North Africa country that is located 18° to 33° on the northern latitude and 9° to 25° on the eastern longitude. Since it is sufficiently windy, so wind can become an alternative power generation source. During winters, Libya gets a plenty of atmospheric winds and during summer, it has northeastern trade winds. It is exposed to Ghibli winds as well [25]. In the Libyan seashore areas, such as Tripoli, there is excessive wind energy, which can generate electricity and perform important tasks like sea water desalination. Available data resources show that yearly average wind speed is 6 m/s in Tripoli that can generate 2,303 MWh power for residential areas, which can provide the required cooling and heating [26]. Libyan wind map is available in a previous work, which is based on satellite data [27]. Until 2025 (Figure 1.3), the government has planned to expand the already initiated renewable projects for increasing the renewable energy utilization by 25% [28], which means that Libya will have to explore several renewable energy forms, and utilize them to their full potential until 2050 for satisfying the country's energy requirements, and start exporting the excessive energy. Until 2050, Libyan renewable energy use is likely to exceed its fossil energy use, which is contrary to what is happening in the country at the moment [28].

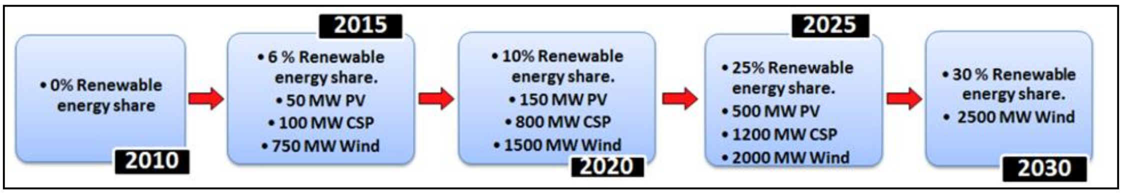

Figure 1.3. Action plan of renewable energy authority of Libya [28].

At 40 m height in Libya, the average wind speed is 6-7.5 m/s, and more specifically, an attractive location is Dernah city along the Libyan coast that has average wind speed 7.5 m/s [29]. This information shows that Libya has significant wind speed, which must be appropriately utilized to create a reliable alternative electrical power generation source. Currently, Libya consumes 20% light fuel, 42% heavy fuel, and 38% natural gas to meet the total energy requirements, but now, the country has planned to expand its renewable projects with a target to increase the renewable energy usage from 6% to 10% in the next few years [30]. With such an ambitious energy policy, the Libyan government can expect the wind energy to deliver the results it needs. Because of rising energy demands and environmental challenges pertaining to power generation, it is more useful to use wind energy as an alternative renewable energy source [31]. Since wind is a clean energy form, and besides, it is harmless and inexhaustible. Because of its environment-friendliness, it does not release Carbon dioxide (CO_2) or any other greenhouse gas, which is contrary to fossil fuels. Now, it is evident that the substantial wind energy potential needs to be evaluated. Estimating wind speed is needed for realistic production planning, maintenance and control of wind power plants; however, due to the irregular and discrete nature of wind, it is not easy to estimate the wind speed with very high accuracy. Considering the many benefits of wind power – namely, in socioeconomic and ecological terms – it has turned into a rapidly growing source of reusable tools to produce power. Across the globe, there are more chances of wind use than other sources like oil, which may quickly deplete, ecologies become polluted and climates go warmer. The countless merits of wind include being clean, economical, and highly available; in addition, there is no need to move the power source or any advanced means to make use of it. To forecast wind energy output, variety of models were used for data as a mixture of meteorology and background or past generation [34].

1.5. THE OBJECTIVE OF THE STUDY

There are many dangerous effects of climate change on the Earth's atmosphere, which include floods, violent storms, cyclones, fires, long droughts, and acid rain; therefore, several nations are making efforts for achieving sustainable economic development, which is possible through power generation through renewable resources, including water, wind, biomass, and sun. Because of its several benefits, wind power grew sharply for large-scale power generation; however, it requires continuous and persistent wind speed forecasts for avoiding investment losses and assuring operational efficiency. Several factors influence wind; so, wind speed forecasting is a challenging research issue in this era [35].

Since wind energy is a significant field, so now, forecasting wind speed and collecting data are required to install wind-based power generation systems. Atmospheric pressure, humidity data and air temperature are commonly-used parameters, which help predicting the wind speed. For this research, we used artificial neural network (ANN) that comprises intelligent neurons, which work like a human brain, and clear the input-output relationships. It also deals with linear/non-linear mathematical processes. A neural network is applied to find the input-output relation. ANN was created in a MATLAB environment and it was used to predict and assess wind speed in Tajora city, which is located in Libya.

As mentioned earlier, Libya has wind-abundance for most part of the day; therefore, wind system is a natural, practical and clean energy source. This research is based on studying wind speed applying ANN because it is a popular algorithm. This research has been conducted with a main objective to predict wind speed in Tajora city by using the ANN model. Libya has high levels of wind speed, and it has various factors, which affect it. Using such factors as inputs and wind speed as an output, ANN is used to estimate the wind speed.

Five chapters are presented in this thesis. It begins with introductory section, as given above in Part 1. Part 2 offers the literature survey that reviews previous wind speed calculations, and applying the ANN.

Part 3 explains the research methodology to represent the work in detail using flow charts and supporting steps of the work from previous literature, and also by the illustration of modeling and simulations performed in the MATLAB environment using the ANN technique. We also presented data pre-processing and sampling methods, applied forecasting techniques and discussed the designed models' properties.

Part 4 presents the results in this work and compares their performances. Part 5 is the final chapter, which includes conclusions, mentions limitations and offers future work recommendations.

PART 2

LITERATURE REVIEW

2.1. MODELS FOR FORECASTING

The wind energy produced from a farm depends directly on the wind farm composition, wind characteristics and other meteorological situations. Wind power forecasting is challenging because wind is a highly variable natural phenomenon and it depends on turbine height and terrain factors. Some weather conditions might make a wind turbine to generate zero power while certain weathers make it generate its maximum. Moreover, wind power is like other natural energy resources; therefore, it cannot be stored or directly transmitted to the users because that is inappropriate and economically unfeasible. Thus, the wind power's dependence on weather requires a highly reliable power-forecasting system. It is needed to assess the wind energy, which can be obtained from a wind farm. It is significant to anticipate how much power demand can be fulfilled by wind power and how much power a power grid can provide. Several studies are found in the literature, which focus on finding a sufficient solution for coping with variability of weather; so, researchers have documented various methods so far [36]. Considering many wind power benefits, such as social, ecological and economic advantages, it has turned into a rapidly growing source of re-usable tools to produce electrical power. Across the globe, there are more cases of wind use since other sources like oil are quickly getting depleted, ecologies are getting polluted and climates are getting warmer [37]. To forecast wind energy output, a variety of models have been used as a blend of meteorology and background or historical generation [38]. Numerous studies have tried to come up with appropriate models to forecast wind patterns, some of which are related to physical, statistical, hybrid physical-statistical, artificial intelligence (AI) and other approaches [39-40].

In case of physical ones like Numerical Weather Forecast (NWF) and mesoscale models [25], they often prove to be effective as they merged together many such factors in the form of autoregressive integrated moving-average models to determine the connection in the estimated wind speed time series [41, 42]. There are some latest AI-based approaches, such as multilayer perceptron, ANN [43,44], radial basis functions [45], repetitive neural networks [46,47], and fuzzy logic [48,49]. The basic estimation of local speed is possible using time series analysis and statistics [50]. Oztopal et al. [51] applied neural networks to estimate velocity and interpolation. Kalogirou et al. [52] suggested that it is necessary for the sector to forecast different fluctuations in terms of weather factors like the velocity of wind, average moisture, radiation from the sun, overall temperature, and others to accurately set the aim, analyze operations, and estimate the expenditure associated with renewable energy. Sahin and Sen [53] developed a system to determine wind velocity in the west of Turkey based on normal distribution graphics.

Sirdas et al. [54] proposes a time series for the sea location in Marmara, again in Turkey, to predict wind with Fourier analysis. There is a grouping based on topography mentioned in Sen’s study [55], which ends up with various clusters. To make local estimates, cumulative semi-variogram, point cumulative semi-variogram (PCSV), and semi-variogram are among the other techniques suggested by Krige [56] and Sen [57]. Sen and Sahin [58,59] studied the Turkish Marmara region for wind velocity using the PCSV approach to determine the spatial dependence function. Wherever there is any shortage of data, experts might have to arrange inventories of wind power accessibility. Under such circumstances, the ANN method can be a good solution. Apart from this, statistical stability, presence of wind, seasonal changes and speed estimates are needed [60].

2.2. ANN APPLICATION

Neural networks comprise plain elements, which function in parallel and they are based on biological nervous systems. Similar to the natural world, the network function can be arranged to a large extent using the connections among different elements. Neural networks are possible to be trained so as to do a given task by arranging the connection values (weights). Neural networks are generally trained/adjusted so as to make certain input yield a desired output. Figure 2.1 shows an example, in which, a network is adjusted keeping in view the target output and the current output and the adjustment helps the network output match the target. Countless input-target output combinations are commonly applied for training a network. In this respect, weight and bias-changes set is used for batch training according to an entire set (or batch as the name implies) of input vectors. The network biases and weights can be changed with incremental training once required for each single input vector. Such training is also called "adaptive" or "online" training that helps neural networks to carry out multi-level functions in many different fields such as for identification, pattern recognition, speech, vision, control systems and classification. Presently, these networks deal with problems, which are otherwise challenging for humans or conventional computing devices [61].

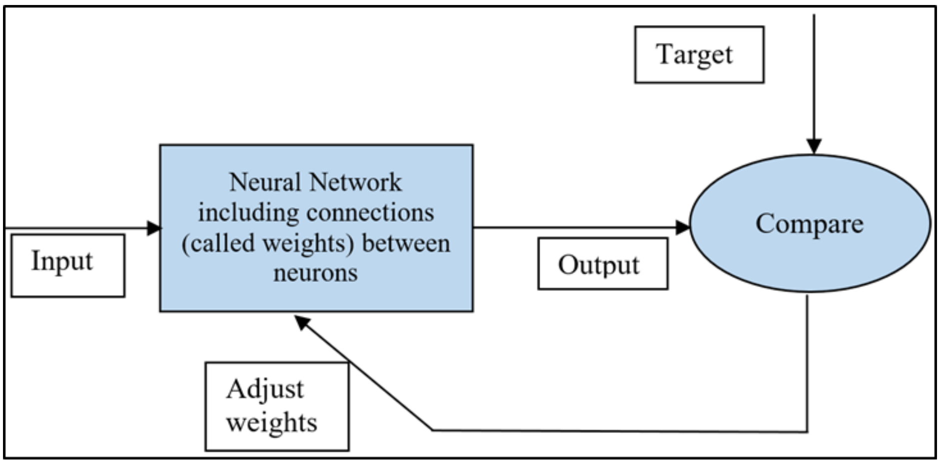

Figure 2.1. Basic principles of artifical neural network [61].

One form of the network, feed forward ANN, is a system that comprises neurons, which are in layers. It is possible to have one or more layers hidden between the input and output layers. In each of these layers, the neurons are linked with neurons of the next layer via a weight w, which is adjustable while training. The data pattern that has values x_i in its input layer i propagates towards the first hidden layer j through the network. Every hidden neuron takes the preceding layer's weighted outputs $w_{ji}x_i$, and all of them are added for obtaining a net value, which in turn changes into the output value when an activation function is applied [62].

Owing to the 'black box' character of nonparametric models such as ANNs determined parameters, which do not hold any reference to physical parameters, and it is an issue that can always create problems during the interpretation of a model [61]. Another advantage of ANNs is that one can simply relate input and output variables. A drawback, though, can be that no information may be available on how various parameters influence the wind speed; therefore, the main focus is directed towards the use of the statistical approach to forecasting the interactive impacts of the combined variables of weather conditions on the wind speed applying the ANN approach to modeling. ANN comprises three layers: hidden, output, and input. Here, h_1, h_2... h_n represent hidden layer neurons, input layer neurons are represented by x_1, x_2... x_n and O_1, O_2....O_n represent output layer neurons. A major historical development in ANN's occurred when back-propagation learning algorithms were introduced, thus rekindling scientific and engineering field specialists' interests to model and process numerous quantitative phenomena with the help of neural networks. In multilayered feed-forward networks, the learning algorithm is used with processing elements, which have both differentiable and continuous activation functions. This type of networks with back-propagation learning algorithms are called as 'backpropagation networks' which are equipped with an input-output pairs' training set. In a back-propagation network, the algorithm offers a procedure, which accurately classifies given input patterns and modifies the weights. The gradient descent method provides the foundation for such weight update algorithm that has differentiable neurons and it is used for simple perceptron. In two flow phases, the back-propagation algorithm performs to obtain a required input-output pair: Initially, an input pattern propagates from input to output layer and based on such forward data flow, it creates a real output. After that, the error signals propagate backwards from the output layer to previous layers. Such error signals are formed because of difference between the actual output and the output pattern [62].

2.3. RELATED WORK

This thesis has been designed with a key objective to develop the ANN model, to place the hidden neurons in a hidden layer of the neuron models, and use the developed model to correctly predict the speed of wind. It is based on detailed analyses, which were conducted in the earlier studies and it is presented in the current section:

Wind speed estimation is required for more realistic production planning, maintenance and control of wind power plants so the wind speed prediction helps enhancing the generated power [63]. Artificial neural network models have been applied for various prediction applications over several years [64]. ANN is an intelligent computational technique that works like a human neural network. The top neural network characteristics include adaptability, non-linearity, nature of generalization and the ability to handle large data. The neural network is effective due to these inbuilt features, and it accurately predicts wind speed using the given input parameters. In numerous fields, neural networks have been applied for recognition, prediction, classification, image processing, control and association. Different wind speed prediction approaches [65-67] are applied to accurately predict the wind speed, which include statistical and physical methods. Simple and higher-order equations are used in the physical method, which involves an actual system's physical quantities. The relation between the forecasted and existing outputs is highlighted in the statistical approaches, in which, available data is used to estimate the parameters [68]. Statistical methods apply to both non-linear and linear models. Normally, the wind speed rapidly varies because of its non-linearity. Being an effective and flexible tool, ANN has been employed in the current thesis to predict the selected wind prediction system's nonlinear behavior. Since the neural networks are nature-inspired and based on the human brain's biological functioning; the artificial neuron is its fundamental element [69]. Mathematical models or equations are not needed in the ANN; however, it automatically minimizes the error based on available input and output knowledge. In the wind speed prediction literature, numerous methods have been reported with time series, physical approaches, machine learning approaches and statistical methods. A wind power generation process employs Back Propagation Algorithm (BPA), which was originally developed for minimizing the error and more accurately predicting the wind patterns [70]. A Recurrent Neural Network (RNN) model has been designed with below 10% average prediction error during wind speed forecasting [71]. Giebel modeled an online software platform to predict the wind speed [72]. Jayaraj et al. proposed a wind speed prediction from 1 hour to 48 hours using Elman network and multilayer perceptrons (MLP) [73]. For predicting wind speed 20 minutes earlier, a BPA model has been developed [74]. Silva et al. employed a Radial Basis Function Neural (RBFN) network [75] to predict wind speed, which outperforms as compared to MLP. Zhang and Li applied ANN for hybridization using Field Programmable Gate Array (FPGA) network [76] with the help of a state machine. For 72-hour long-term wind speed prediction, Barbounis et al. applied RNN in their research [77]. For predicting the wind speed at Zaragoza, two models of the MLP network were employed: spatial expert and time expert [78]. Adaptive Neuro Fuzzy Inference System, Taboo Search (TS) algorithm and Recurrent Fuzzy Neural Network were used to predict wind speed, enhance prediction accuracy and reduce the computation duration [79–82]. Chen et al. developed a prediction system [83] that employed Orthogonal Least Squares (OLS) algorithm to measure RBFN-based hidden nodes. They used this model for predicting average hourly wind speed an hour earlier. Wu et al. used a back-propagation network (BPN) [84] to predict wind speed using previously noted values. Monfared et al. used a fuzzy-based ANN model [85] to forecast wind speed, which is based on fuzzy logic and it provides a fuzzy associative memory table besides employing a faster learning process for a neural network. Soman et al. proposed three models for prediction application, including BPN, Adaptive Linear Network (Adaline), and hybrid network [86]. For wind speed prediction, Han et al. [87] based their model on the improved neural network by adding the wind direction factor as an input vector, and analyzed the relation between the wind speed and wind direction. In a review, Bhaskar et al. analyzed the present status of wind speed prediction [88] using Support Vector Machine (SVM), Particle Swarm Optimization (PSO), and ANN. Their work helped the owners of wind farms to understand the current model of wind prediction and its capabilities. Fesharaki et al. used ANN and employing adaptive weighted PSO [89] and proposed a wind speed prediction model. They predicted wind speed using Rough Set Theory-based genetic ANN, which Guo et al. had introduced [90]. An MLP-based and RBFN-based multiple architecture system is developed to predict wind speed [91]. In their new hybrid model, Terzi et al. used BPN and ANFIS to predict wind speed [92]. Sajedi et al. used ANFIS to predict wind speed in the short-term and employed persistence method and RBFN in their hybrid model for wind speed forecasting [93]. Wu et al. developed Grubbs test using the RBFN model [94]. In their hybrid forecasting model, Shi et al. [95] used autoregressive integrated moving average - support vector machines (ARIMA-SVM) and autoregressive integrated moving average - neural networks (ARIMA-NN). Cao et al. proposed an RNN-based model [96] using five different wind mill heights. In their model, Xinrong et al. [97] used a Relevance Vector Machine (RVM) and presented an Empirical Mode Decomposition (EMD) based wind speed forecasting model. For short-term wind predictions and overcoming the limitations of the clustering based approach, Hu et al. proposed a pattern based approach [98]. Zhang et al. used intelligent optimized algorithm for hybrid wind speed forecasting [99]. In MATLAB, two main tools are used to implement the algorithms [100]:

- Nntool is an open-network/data manager that implements single-layer and multi-layer algorithms.
- Nftool is a neural network fitting tool that implements a back propagation algorithm (BPA). It has the least Mean Square Error (MSE) when the graph is plotted between the targeted and predicted values.

PART 3

MATERIALS AND METHODS

3.1. DEVELOPING ANN APPROACH

The ANN and ANN-based methods are arranged exactly according to the modeling of the learning patterns of humans, with neurons at their core and positioned within repeated layers as a hidden layer, an output layer, and an input layer. The input layer receives the data, which passes through the hidden one, and moves on to the output. This mechanism helps in modeling the patterns of structures with noisy and incomplete data [52], which can be otherwise too complicated to set up algorithms, as well as to select a certain structure from within the available data. Learning through examples characterizes the neural network processes as they are not programmable for certain jobs. Practically, the system comprises statistical information, which is non-linear with algorithms, among which, back-propagation (BP) is the most commonly applied to keep errors minimum between the output and expected values upon adjusting the neuron weights [61]. The ANN approach is used to determine wind velocity using BP algorithm and a feed-forward neural network with the help of the MATLAB toolbox [61]. Input factors are chosen for the network as the hourly average relative humidity, hourly average atmospheric pressure and hourly average atmospheric temperature. The output factor is the hourly average wind speed at the location.

3.2. TAJURA CITY

We obtained a data set of observations in Tajora, Libya. This was provided by the Libyan State Meteorological Service and it comprises 8761 data points, which correspond to a whole year of hourly averaged measurements. They were taken 10 meters above the ground level from 1 January, 2015 to 30 December, 2015. The Permission from the officials of the institution of Solar Energy Research and Studies

Center http://www.csers.ly/en/ [101] was taken to obtain data from their archives and used it for this research (Appendix 1). The selected input factors were hourly average atmospheric pressure, (RH), hourly average atmospheric temperature T (^{0}C), and P (mbar) while the outputs include hourly average wind speed (WS) at the location.

3.3. ANN APPLICATION TO PREDICT WIND SPEED

At this point, the model was applied with a hidden layer network to measure wind speeds on different occasions. Figure 3.1 highlights the schematic diagram for the network structure; the output layer is a linear activation function while the hidden layers are logarithmic sigmoid functions.

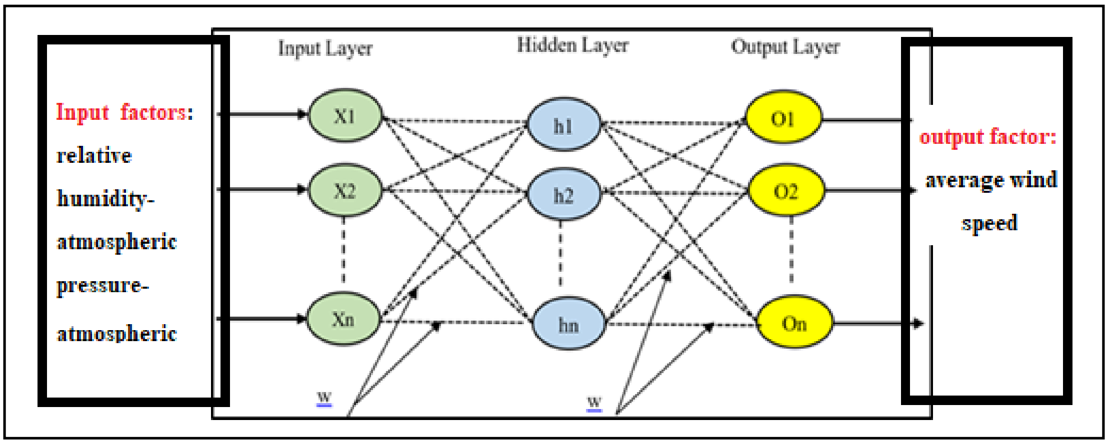

Figure 3.1. Schematic diagram for the network structure.

3.4. ANN IN MATLAB

Algorithms, applications and functions are available in Neural Network Toolbox™ and applications for developing, training, monitoring, and modeling Neural Networks (NNs) take place by means of algorithms and other instruments for grouping, pattern identification, clustering, regression, time series, active systems, and deep learning [102,103]. The steps involved in NN design are given below:

1) Collect data,
2) Create a network,
3) Configure the created network,

4) Initialize weight and bias,
5) Train the network,
6) Validate the network, and
7) Network application.

Certain stages may be carried out automatically with default values and settings in MATLAB; yet, intervention and personalized settings are also possible. The toolbox comprises four design levels for software application. GUI represents the first level, which offers instant access related to issues like clustering, pattern recognition, time series analysis and function fitting. Besides, the MATLAB script may be produced using optional details that duplicate the conditions intended for the research.

At the next level, fundamental command processes take place, in which, line functions apply a basic series of arguments with smart default settings as parameters. In this way, one can skip the entire default stage and add to both efficiency and functionality. The third stage comprises customization, a higher-order alternative to tailor-made NNs while resuming full access to functionality. In the fourth level, users may change the code files since all computational components are inscribed in MATLAB code and, hence, available in their entirety.

3.5. REGRESSION ANN IN MATLAB

Regression (fit data) is available by means of GUI or command-line functions. In principle, GUIs are applicable for designing and developing the network [51]:

1) Neural Network Tool (nntool): It is a common NN instrument with complete control over settings and allows one to create any NN, which is not just regression ANN.
2) Neural Fitting Tool (nftool): A feature guiding how to handle data fitting scenarios using a double-layered feed-forward network developed using either scale conjugate gradient BP or Levenberg-Marquardt. The alternatives, though, may be few, but one can choose MATLAB workspace data or choose featured datasets for application. After network development, its performance and

functionality were tested with regression analysis and mean square error. Next, the obtained outcomes were analyzed with visualization, namely regression fit or error histograms. Lastly, the performance may be evaluated using regression to validate performance.

3.6. TRAINING A NEURAL NETWORK

For application, development and trials of NN, we used the MATLAB nftool applying the basic feed forward network, which has a series of neurons in a hidden layer. They are trained applying the Levenberg-Marquardt algorithm (LM), which is the fastest training algorithm for moderate-sized networks [104]; so, it is applied below. For wind-based system in Tajora city, we proposed ANN as a feed-forward back-propagation network model that has a tangent sigmoid transfer (tansig) function at a hidden layer with a range of functions and neurons for linear transfer (purelin) at the output node. We used the following embedded MATLAB codes for this purpose:

```
% Solve an Input-Output Fitting problem with a Neural Network
% Script generated by Neural Fitting app
% Created 10-Oct-2020 00:36:07
% This script assumes these variables are defined:
%   Input - input data.
%   Output - target data.
R=load('lmb.dat');
x = Input' = [R(1:8761,1:3)];
t= Output'=[R(1:8761,4)];
% Choose a Training Function
% For a list of all training functions type: help nntrain
% 'trainlm' is usually fastest.
% 'trainbr' takes longer but may be better for challenging problems.
% 'transact' uses less memory. Suitable in low memory situations.
trainFcn = 'trainlm';  % Levenberg-Marquardt backpropagation.
% Create a Fitting Network
   hiddenLayerSize = 10;
```

```
% hiddenLayerSize = 20;
% hiddenLayerSize = 30;
% hiddenLayerSize = 40;
% hiddenLayerSize = 50;
net = fitnet(hiddenLayerSize,trainFcn);
% Choose Input and Output Pre/Post-Processing Functions
% For a list of all processing functions type: help nnprocess
net.input.processFcns = {'removeconstantrows','mapminmax'};
net.output.processFcns = {'removeconstantrows','mapminmax'};
% Setup Division of Data for Training, Validation, Testing
% For a list of all data division functions type: help nndivide
net.divideFcn = 'dividerand';  % Divide data randomly
net. divide Mode = 'sample’; % Divide up every sample
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;
% Train the Network
[net, tr] = train (net, x, t) ;
% Test the Network
y = net(x);
e = gsubtract(t,y);
Performance = perform(net,t,y)
% View the Network
view(net)
% Plots
% Uncomment these lines to enable various plots.
%figure, plotperform(tr)
%figure, plottrainstate(tr)
%figure, ploterrhist(e)
%figure, plotregression (t, y)
%figure, plotfit (net, x, t)
```

PART 4

RESULTS AND DISCUSSION

Three different layers exist in ANNs, as mentioned earlier, the hidden layer, the output layer, and the input layer. The multilayered ANN helps generating models utilizing non-linear input variables' combinations. For conceptualizing and constructing a neural network model, the following measures must be taken: We should record the sample data sets with data training, verification and design, input, and output of the neural network. For two cities of Libya, two pairs of input-output data sets were used.A dataset is divided randomly into testing subsets, for example, training 70%, validation 15% and 15% for network test. In this study, the proposed ANN is a back propagation feed-forward network model that has a tangent sigmoid transfer (tansig) function in the hidden layer that has a range of neurons as well as a linear transfer (purelin) function at the output node while embedded MATLAB code is used. A MATLAB code was generated using neural fitting (nftool) five times using Levenberg–Marquardt algorithm to train a neural network in the single hidden layer using 10, 20, 30, 40, and 50 neurons, respectively. Each set had 15% original data in the validation and test data sets for selected neurons, as displayed in Figure 4.1.

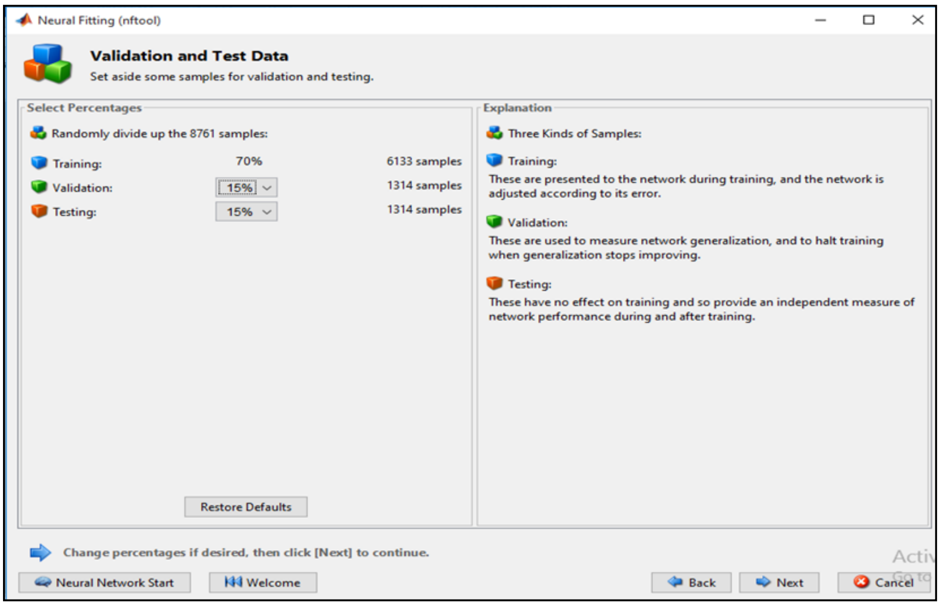

Figure 4.1. Setup the data distribution for training.

As displayed in Figure 4.2-4.6, after running MATLAB code, training carried on to the point when the validation error can no longer be reduced (validation stop). As displayed in Figure 4.2, when the validation error increased for three iterations, this training stopped at iteration 360.

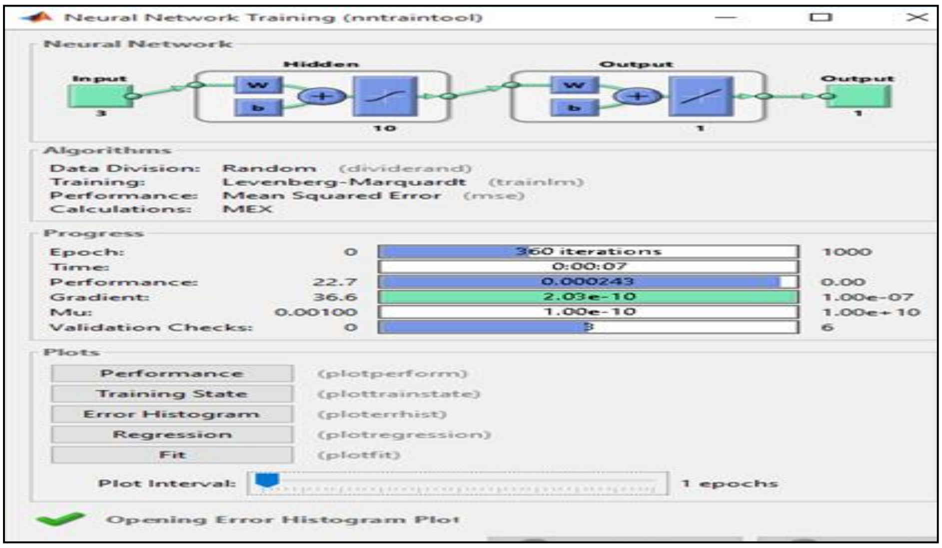

Figure 4.2. Training performance of neural network using Levenberg-Marquardt Algorithm at 10 neurons.

As displayed in Figure 4.3, when the validation error increased for two iterations, the training stopped, and that happened at iteration 135.

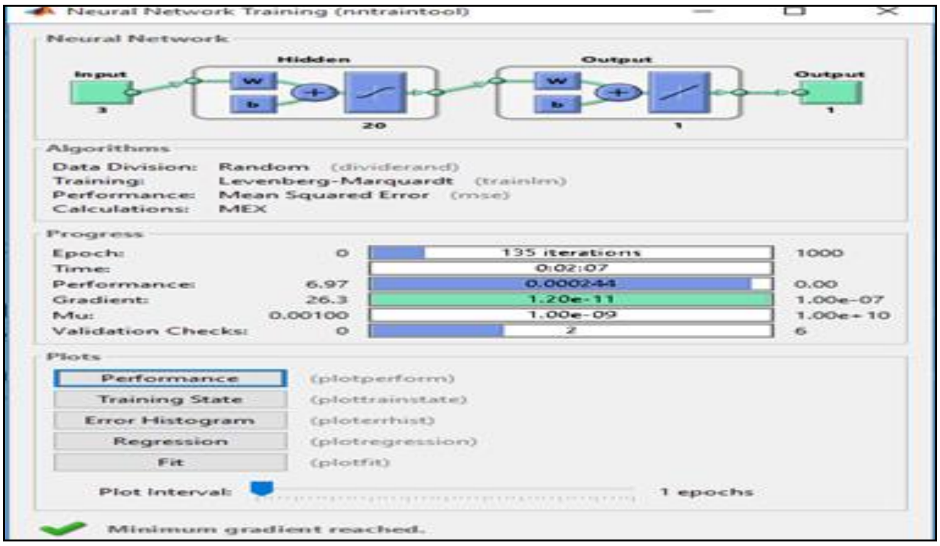

Figure 4.3. Training performance of neural network using Levenberg-Marquardt Algorithm at 20 neurons.

As displayed in Figure 4.4, as the validation error increased for one iteration, the training stopped, and that happened at iteration 67.

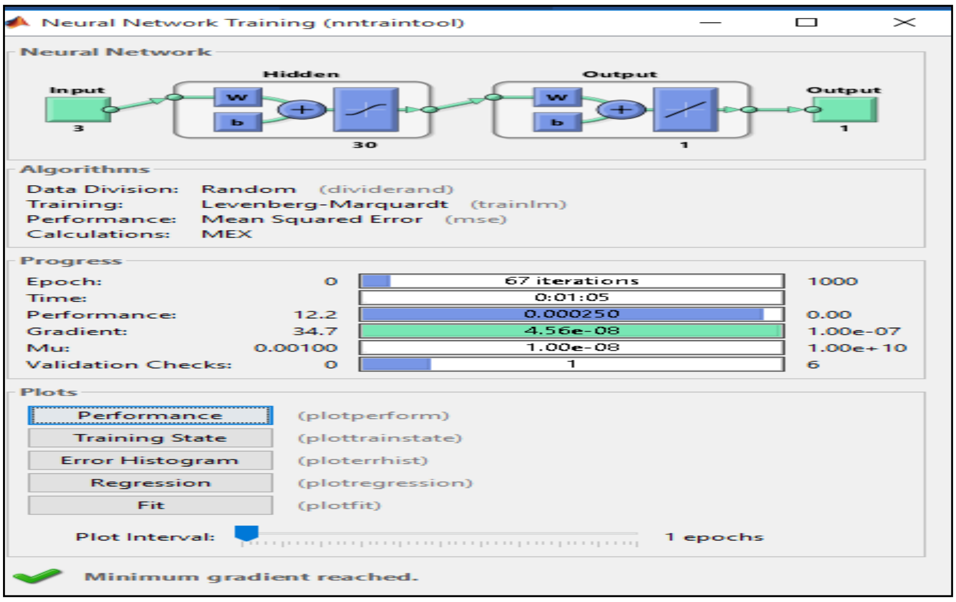

Figure 4.4. Training performance of the neural network using Levenberg-Marquardt Algorithm at 30 neurons.

As displayed in Figure 4.5, this training stopped when the validation error occurred at iteration 41.

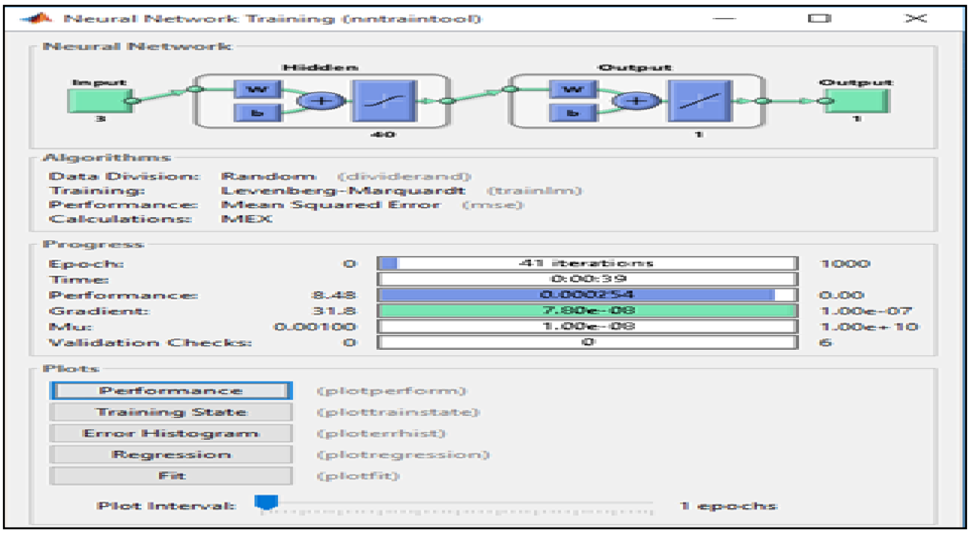

Figure 4.5. Training performance of the neural network using Levenberg-Marquardt Algorithm at 40 neurons.

Figure 4.6 shows that when the validation error increased for two iterations, the training stopped and that happened at iteration 24.

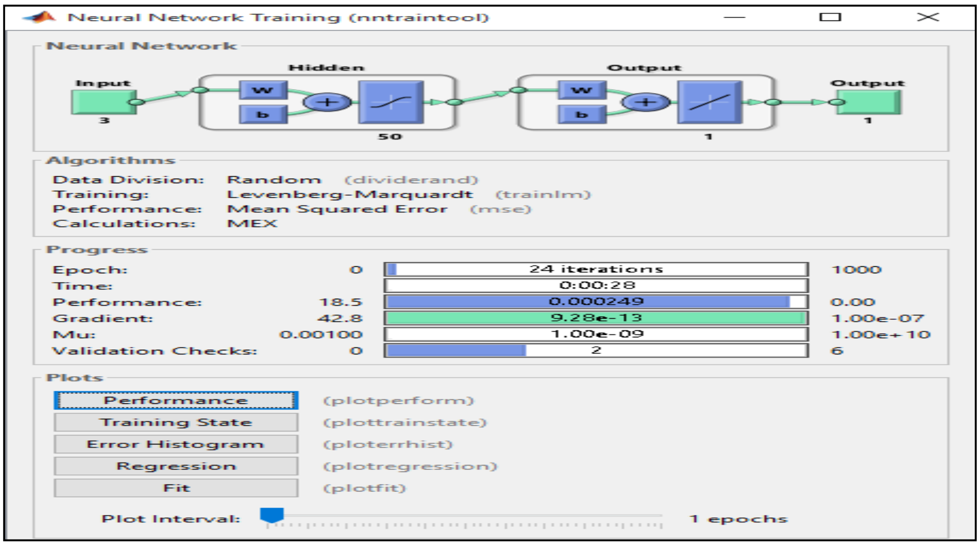

Figure 4.6. Training performance of neural network using Levenberg-Marquardt Algorithm at 50 neurons.

The Levenberg-Marquardt algorithm was tested with the range of neurons after the comparison of predicted results versus the target data based on the coefficient of determination (R^2) and mean square error (MSE). As displayed in Figure 4.7 – 4.11, the network outputs are demonstrated in terms of training, validation, and test set objectives. To achieve full fitting, the data has to overlap at 45 degrees because that represents equal outputs and targets. In all cases, there is a satisfactory fit in all sets at R^2 values. Figure 4.7 shows that there is satisfactory fitting in the validation, test set, and training with R^2 0.99977, 0.9998 and 0.99978 for 10 neurons, respectively.

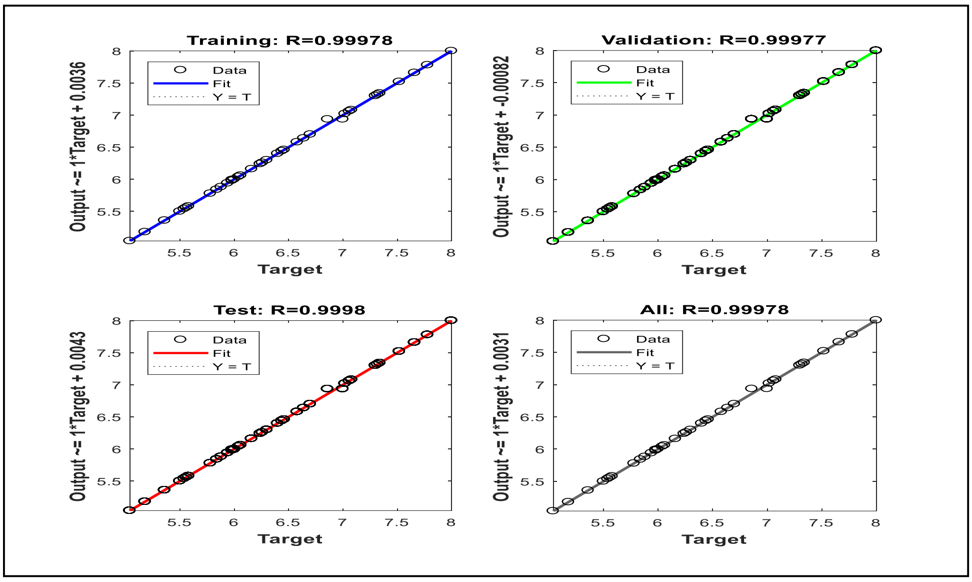

Figure 4.7. Regression plot of neural network using Levenberg-Marquardt Algorithm at 10 neurons.

Figure 4.8 shows that there is satisfactory fitting in the validation, test set, and training with R2 0.99982, 0.99975 and 0.99978, for 20 neurons respectively.

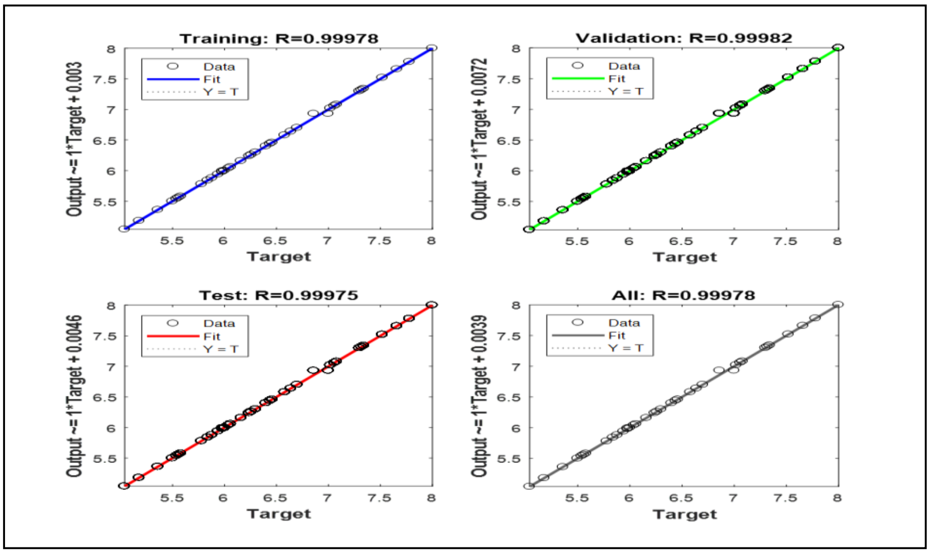

Figure 4.8. Regression plot of neural network using Levenberg-Marquardt Algorithm at 20 neurons.

Figure 4.9 shows that there is satisfactory fitting in the training, validation, and test set with R^2 of 0.99978, 0.99979 and 0.99977 for 30 neurons respectively.

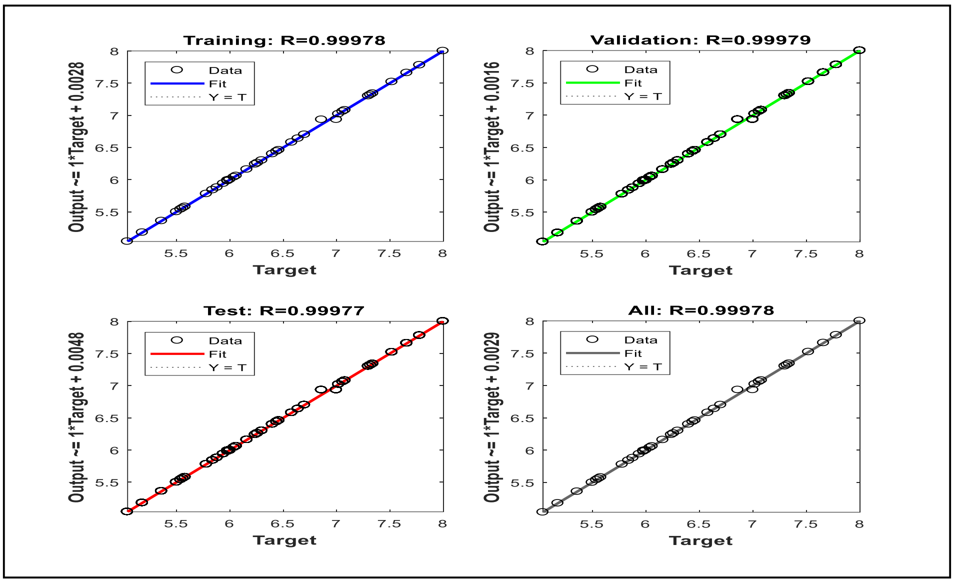

Figure 4.9. Regression plot of neural network using Levenberg-Marquardt Algorithm at 30 neurons.

Figure 4.10 shows that there is satisfactory fitting in the validation, test set, and training with R^2 of 0.9998, 0.99982 and 0.99977 for 40 neurons, respectively.

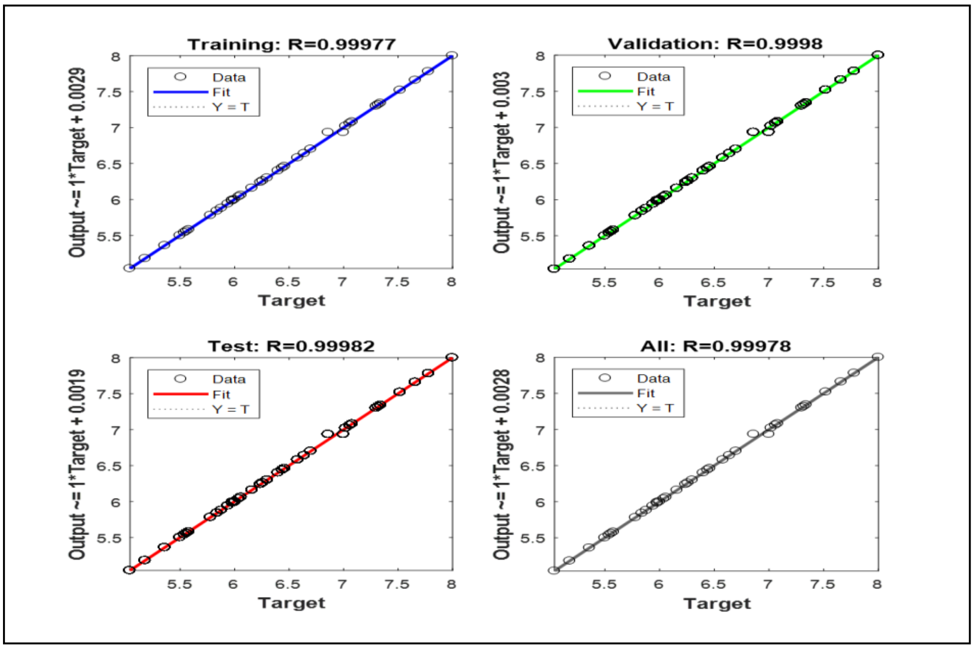

Figure 4.10. Regression plot of neural network using Levenberg-Marquardt Algorithm at 40 neurons.

Figure 4.11 shows that there is satisfactory fitting in the validation, test set, and training with R^2 0.99977, 0.99976 and 0.99979 for 50 neurons, respectively.

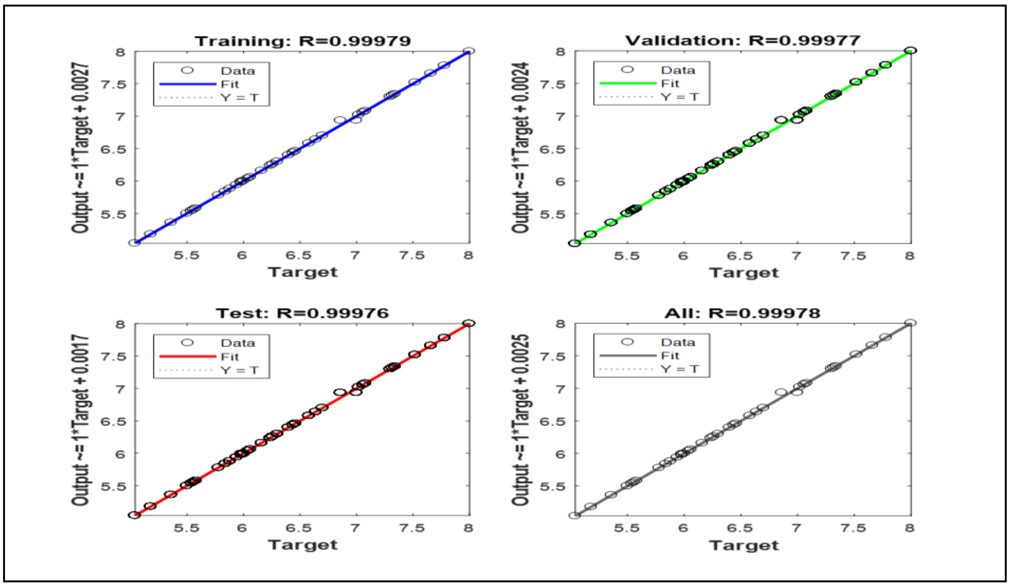

Figure 4.11. Regression plot of neural network using Levenberg-Marquardt Algorithm at 50 neurons.

Figure 4.12–4.16 shows that the Levenberg-Marquardt algorithm was tested with the range of neurons after comparison of predicted results versus the target data based on the MSE. Figure 4.12 highlights the MSE of developed ANN model using the training, testing, and validation results to forecast wind speed at 10 neurons. Evidently, LM shows lower MSE for training, testing and validation. Henceforth, LM is the ideal training algorithm with average performance 0.000243. Furthermore, the lowest MSE in validation occurs at epoch 357 measured at 0.00025289 with 10 neurons as the best validation.

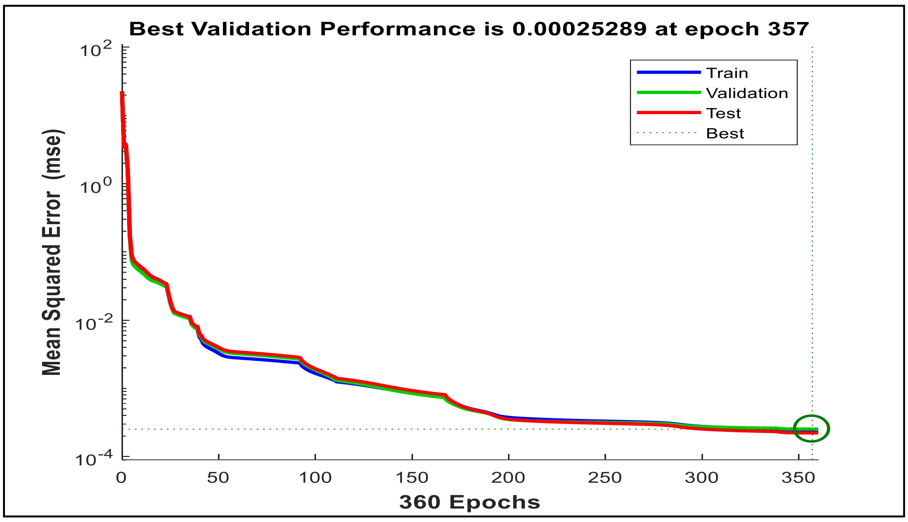

Figure 4.12. Training performance result plotting at 10 neurons.

Figure 4.13 highlights the MSE of developed ANN model using the training, testing, and validation results to forecast wind speed at 20 neurons. Evidently, LM shows lower MSE for training, testing and validation. Henceforth, LM is the ideal training algorithm with the average performance 0.000244. Furthermore, the lowest MSE in validation occurs at epoch 133 measured at 0.00020307 with 20 neurons as the best validation.

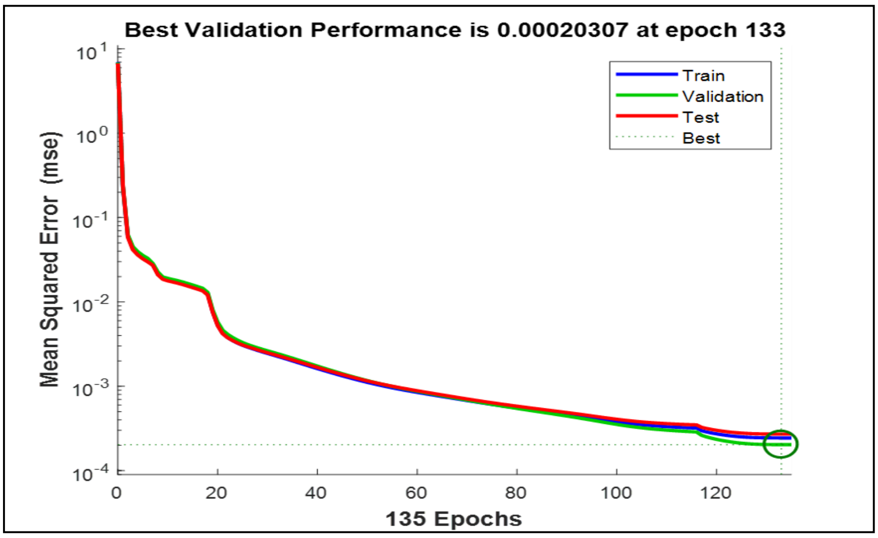

Figure 4.13. Training performance result plotting at 20 neurons.

Figure 4.14 highlights the MSE of developed ANN model using the training, testing, and validation results to forecast wind speed at 30 neurons. Evidently, LM shows lower MSE for training, testing and validation. Henceforth, LM is the ideal training algorithm with the average performance 0.000250. Furthermore, the lowest MSE in validation occurs at epoch 66 measured at 0.00021126 with 30 neurons as the best validation.

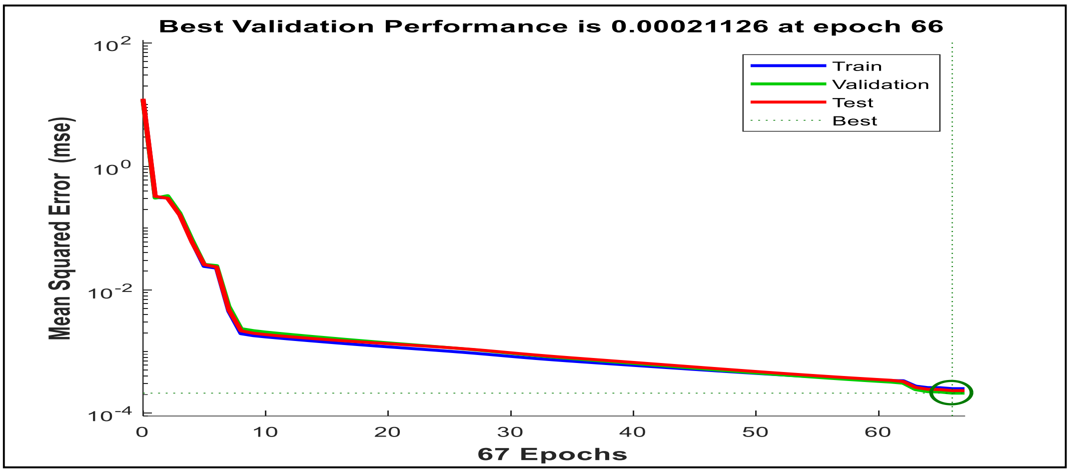

Figure 4.14. Training performance result plotting at 30 neurons.

Figure 4.15 highlights the MSE of developed ANN model using the training, testing, and validation results to forecast wind speed at 40 neurons. Evidently, LM shows lower MSE for training, testing and validation. Henceforth, LM is the ideal training algorithm with the average performance 0.000250. Furthermore, the lowest MSE in validation occurs at epoch 41 measured at 0.00022958 with 40 neurons as the best validation.

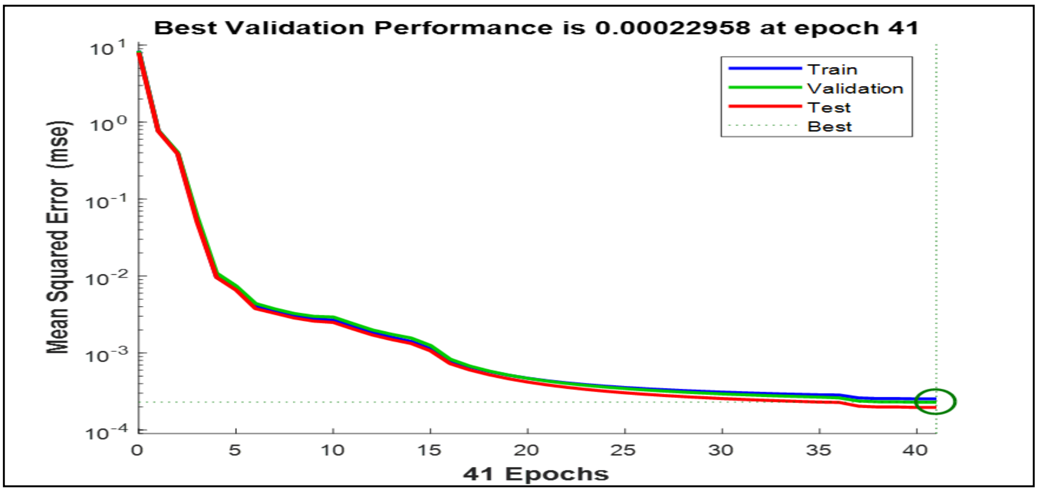

Figure 4.15. Training performance result plots at 40 neurons.

Figure 4.16 highlights the MSE of developed ANN model using the training, testing, and validation results to forecast wind speed at 50 neurons. Evidently, LM shows lower MSE for training, testing and validation. Henceforth, LM is the ideal training algorithm with the average performance 0.000249. Furthermore, the lowest MSE in validation occurs at epoch 41 measured at 0.00023788 with 50 neurons as the best validation.

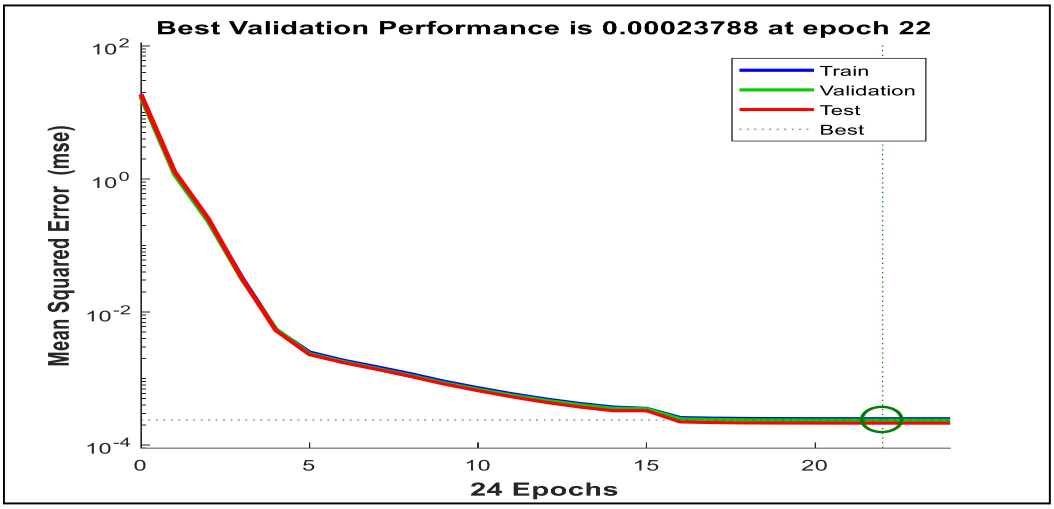

Figure 4.16. Training performance result plotting at 50 neurons.

To improve performance verification, error histogram is used to obtain the errors between the predicted and targeted values, which happens after a feed-forward neural network training. As shown in Figure 4.17-4.21, it is evident from the error values how the predicted values differ from the targeted values. An error histogram shows errors between the predicted and targeted values after a feedforward neural network training. These error values show how predicted values differ from the targeted values; therefore, they might be negative. The vertical bars are called bins, which are observable on the graph. Figure 4.17 indicates that at 10 neurons, the total error range subdivides into 20 small bins. The number of samples from the dataset are shown on the Y-axis in a specific bin. In the middle part of the plot, a bin corresponds to the error value -0.00217 while that bin has below 6000 height for the training dataset and the height for test data and validation lies between 6000 and 8000. It means that the error of many samples exists within the mentioned range. On the error axis (i.e. X-axis), zero error line corresponds to the zero error value; so, in this case, the point of zero error falls under the bin with center at -0.00217.

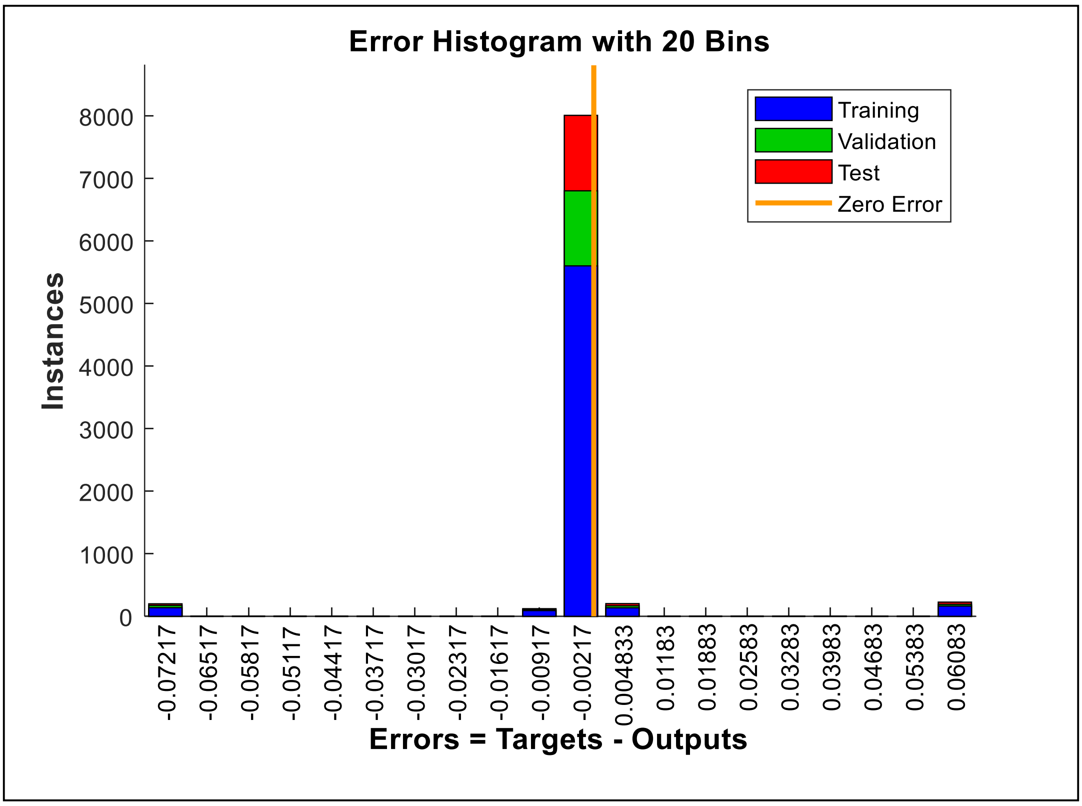

Figure 4.17. Verification of network performance at 10 neurons.

Figure 4.18 indicates that at 20 neurons, the total error range subdivides into 20 small bins. The number of samples from the dataset are shown on the Y-axis in a specific bin. In the middle part of the plot, a bin corresponds to the error value -1.2×10^{-5} while that bin has below 6000 heights for the training dataset and the height for test data and validation lies between 6000 and 8000. It means that the error of many samples exists within the mentioned range. On the error axis (i.e. X-axis), zero error line corresponds to the zero error value; so, in this case, the point of zero error falls under the bin with center at -1.2×10^{-5}.

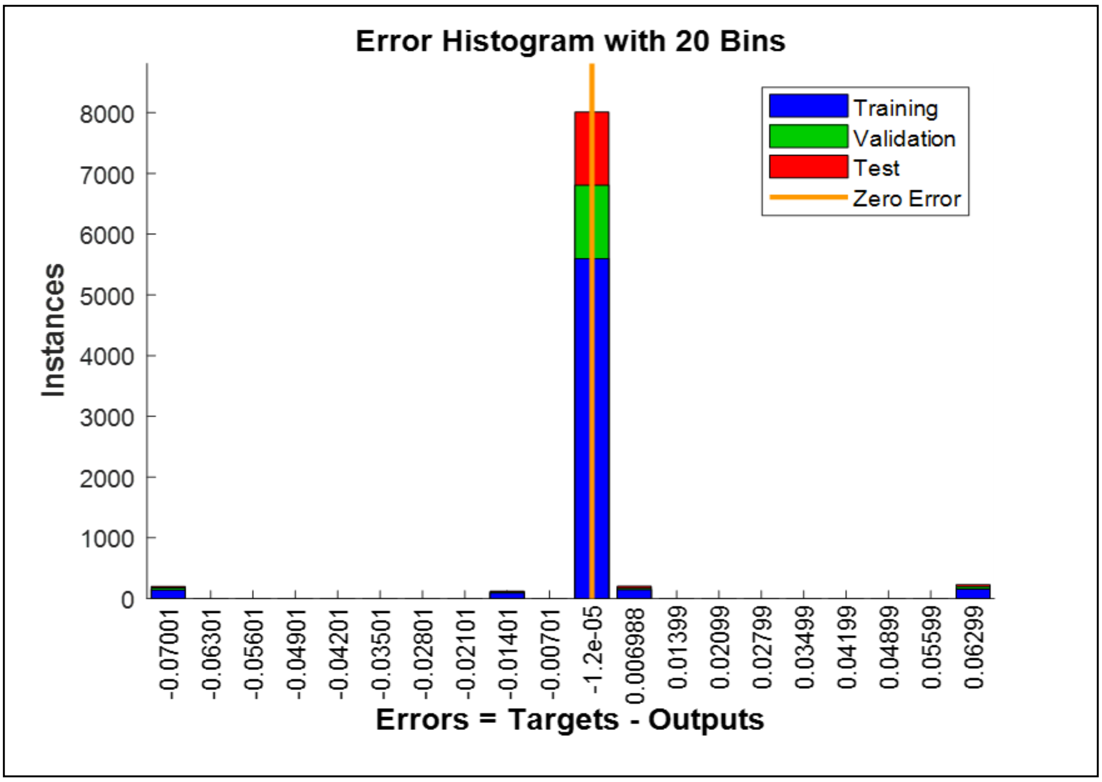

Figure 4.18. Verification of network performance at 20 neurons.

Figure 4.19 indicates that at 30 neurons, the total error range subdivides into 20 small bins. The number of samples from dataset are shown on the Y-axis in a specific bin. In the middle part of the plot, a bin corresponds to the error value -0.000267 while that bin has below 6000 height for the training dataset and the height for test data and validation lies between 6000 and 8000. It means that the error of many samples exists within the mentioned range. On the error axis (i.e. X-axis), zero error line corresponds to the zero error value; so, in this case, the point of zero error falls under the bin with centre at -0.000267.

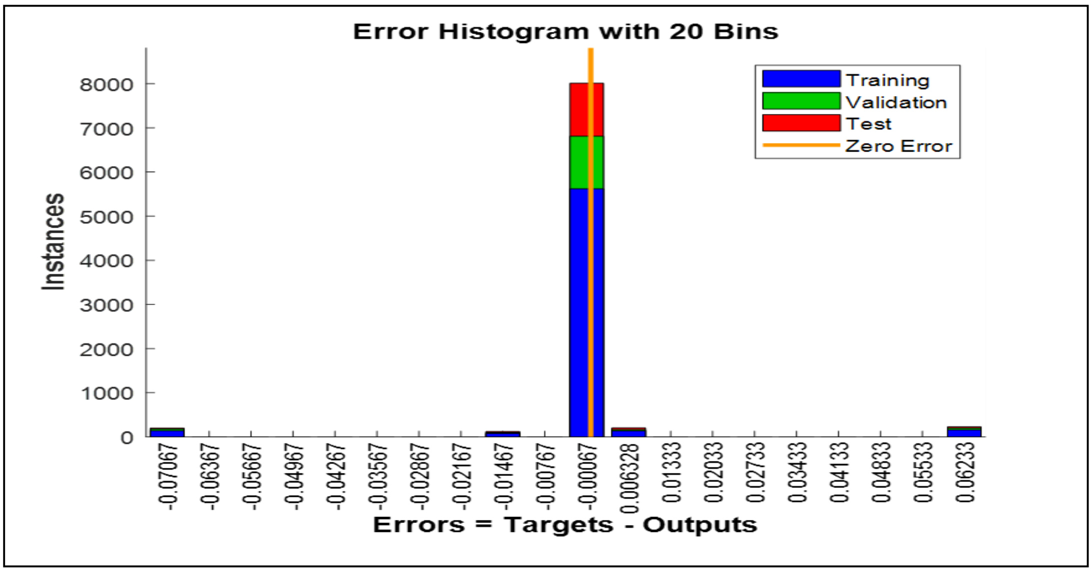

Figure 4.19. Verification of network performance at 30 neurons.

Figure 4.20 indicates that at 40 neurons, the total error range subdivides into 20 small bins. The number of samples from the dataset are shown on the Y-axis in a specific bin. In the middle part of the plot, a bin corresponds to the error value -0.00051 while that bin has below 6000 height for the training dataset and the height for test data and validation lies between 6000 and 8000. It means that the error of many samples exists within the mentioned range. On the error axis (i.e. X-axis), zero error line corresponds to the zero error value; so, in this case, the point of zero error falls under the bin with center at - 0.00051.

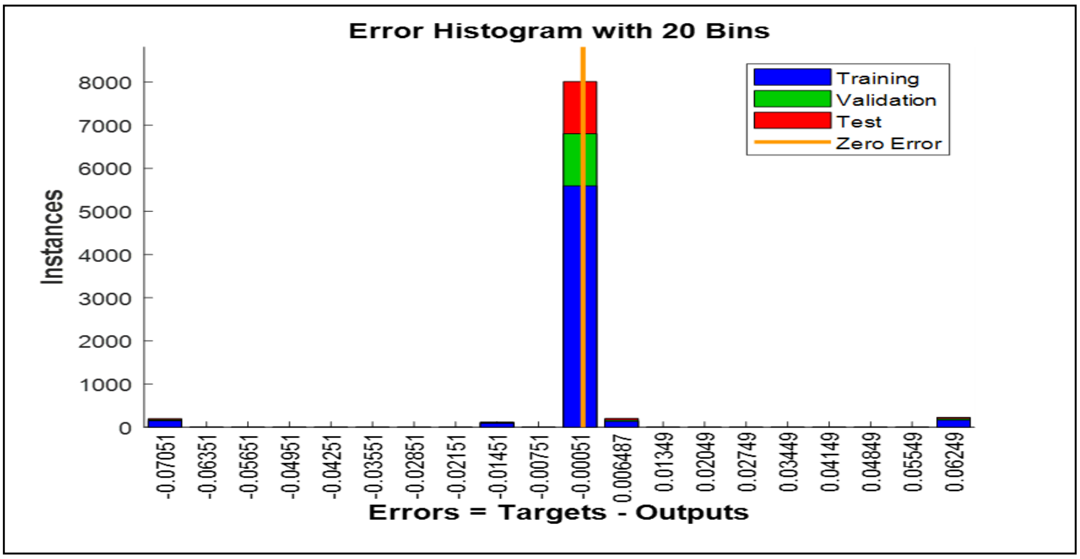

Figure 4.20. Verification of network performance at 40 neurons.

Figure 4.21 indicates that at 50 neurons, the total error range subdivides into 20 small bins. The number of samples from the dataset are shown on the Y-axis in a specific bin. In the middle part of the plot, a bin corresponds to the error value 0.00166 while that bin has below 6000 height for the training dataset and the height for test data and validation lies between 6000 and 8000. It means that the error of many samples exists within the mentioned range. On the error axis (i.e. X-axis), zero error line corresponds to the zero error value; so, in this case, the point of zero error falls under the bin with center at 0.00166.

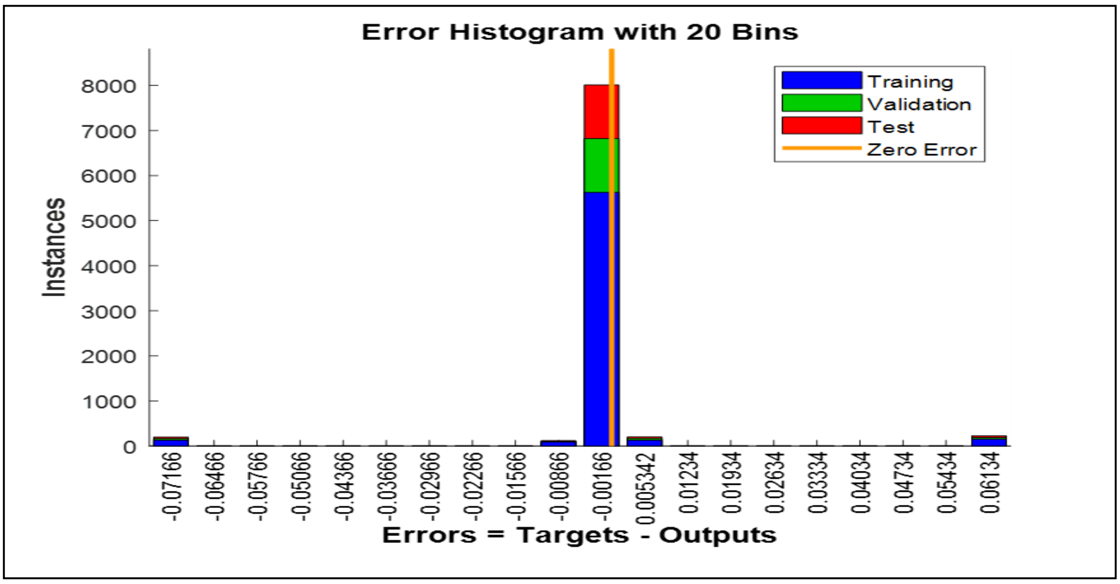

Figure 4.21. Verification of network performance at 50 neurons.

The following Table 4.1 shows comparison among different neurons according to Test-R^2 values and the MSE indicator.

Table 4.1. The results of the comparison among different neurons.

Training data set				
Type of Algorithm	Training Function	Neurons (H)	Test-R^2 values	MSE values
Levenberg Marquardt	Trainlm	10	0.99980	0.000243
		20	0.99975	0.000244
		30	0.99977	0.000250
		40	0.99978	0.000254
		50	0.99976	0.000249

The network with 10 neurons has the best R^2 performance and acceptable MSE values 0.99980 and 0.000243, respectively. It implies that for all the data sets, the ANN wind velocity values were quite closer to the actually measured values. For research purposes, different neurons' outcomes are satisfactory bearing in mind that:

- There is a negligible final mean-square error.
- Both validation set error and test set error bear identical features; and no major overfitting occurs, which means that the best validation performance occurs here.

PART 5

CONCLUSION

The ANN offers effective sets of alternatives to analyze sensor data, identify errors, determine processes and perform process monitoring. The present study employs, in its core, simulation for ANN and applies it to wind energy production. The modeling proved to be successful for WES in particular; however, the present work takes into account certain nonlinear systems as well. With the goal of preventing financial burdens, improving WES regulation, and boosting operational efficiency by means of better decision-making, the ANN approach is also employed here to compare the output with the set targets in accordance to the data obtained from the Libya Meteorological Center. The trial-and-error approach with MATLAB's neural network fitting tool (nftool) was chosen to identify the optimum settings and functions for the intended ANN. Based on the data from the Libya Meteorological Center obtained using different variables, the ultimate objective was to devise a unique model to determine wind velocity with maximum accuracy. The proposed model is a feed-forward BP system, which has a tangent sigmoid transfer (tansig) function between the hidden layer and the input layer that has a neuron range in a hidden layer and a linear transfer (purelin) function at the output node applying MATLAB's neural network fitting tool (nftool). These parameters have been checked using a training function at 10, 20, 30, 40, and 50 neurons (which were in a hidden layer). The LM algorithm was tried with a series of neurons after comparing the forecast outcomes with those received from the Libya Meteorological Center. According to the results, the LM algorithm performed as the best back propagation algorithms with negligible MSE at 10 neurons for Tajora city. When Test-R^2 values and the MSE performance were examined, the network with 10 neurons has the best R^2 performance and acceptable MSE value with values 0.99980 and 0.000243, respectively.

It implies that the ANN wind velocity values were quite close to the actual values for every data set. In conclusion, we can fairly state that the ANN model presented in this thesis is helpful for predicting wind velocity; therefore, it contributes to power generation. It must also be noted that theoretical architectures with ANN are essential for identifying an optimum modeling process to achieve the best outcomes.

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APPENDIX A.

RECORDER WEATHER DATA SUPPORT

State of Libya
Government of National Accord
Ministry of Education
Authority of Natural Science Research and Technology
Center for Solar Energy Research and Studies

دولة ليبيا
حكومة الوفاق الوطني
وزارة التعليم
هيئة أبحاث العلوم الطبيعية والتكنولوجيا
مركز بحوث ودراسات الطاقة الشمسية

التاريخ: ....
الموافق: 2020/12/15

الرقم الإشاري: م ب د ط ش/2/282

To Whom it may concern

This is to certify that the recorded weather data of Tajoura city-Libya for the year 2015 is given to the Mr. Shaker Salem A. ABUZAWAIDA for the purpose to be used for his M.Sc. program at Department of Electrical and Electronic Engineering, Karabuk University.

This letter is given upon his request to be used for legal purposes

Kind Regards

2020-12-9

Dr. Mohammad Abdunnabi
Genteral Director
Center for Solar Energy Research and Studies
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RESUME

Shaker Salem A. ABUZAWAIDA was born in Tajura in 1977 and graduated primary, elementary, and high school in the same city. After that, he started an undergraduate program at The Higher Institute for the Preparation of Tripoli Trainer. Then in 2018, he started studies at Karabuk University Electrical and Electronic Engineering to complete his M.Sc.

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