Manage Wind Turbine Power Based on an Artificial Neural Network Model for Predicting Turbine Output Power*

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ABSTRACT

The relevance of wind power forecasting has been underscored by the increased rise of wind power generation in Egypt in the future. Wind power, on the other hand, is extremely difficult to model and forecast. Because of the continual variation in wind speed and direction, the power generated by the wind changes rapidly. Despite the research's that has been done in this field, more effective wind power forecasting algorithms are still needed. Wind power is forecasted using artificial neural network techniques in this article. This strategy is based on the use of real-time data from weather stations. Using a local onshore wind farm in Zafarana-Site3, Egypt. ANN model was created through MATLAB 2020a which depends on input data were wind speed, air density, and swept area, and the target data was wind power. The suggested ANN model was trained, tested, and evaluated.

Keywords : Artificial intelligence (AI), machine learning (ML), expert systems (ES), fuzzy logic (FL), genetic algorithms (GA), artificial neural networks (ANNs or NNWs), renewable energy (RE), wind energy (WE), solar energy (SE) and horizintal axis wind turbine (HAWT).

1 INTRODUCTION

WHILE it is difficult to determine when it will be widely acknowledged that fossil fuels will not be the future sources of energy, The availability of sunshine, air, and other resources on Earth must be used wisely for humanity's well-being while simultaneously safeguarding the environment and its living beings. The utilization of sunlight and air as a major renewable energy source (RE) has been a focus of study and development in recent years. Renewable energy is emerging as the most reliable option for our future, yet despite great development in some areas, there are still many obstacles to overcome. Solar and wind power are two of the most popular renewable energy sources, but they are weather-dependent and unpredictable, and we still need to invest in them [1]. Expert systems (ES), fuzzy logic (FL), genetic algorithms (GA), and artificial neural networks (ANNs or NNWs), among other AI approaches, have ushered in a new era in power electronics and power engineering. Artificial Intelligence (AI) could assist in achieving the future goals of the RE [2], [3]. This research work exploits the recent developments in AI adoption for the RE sector, especially in wind power prediction.

The main problem with renewable energy is its inconsistency in supply. There is also the uncertainty of load demand, in addition to the unknown qualities of renewable energy supply. When compared to traditional power generation, uncertainty is defined as the variability in the timing and magnitude of renewable power output generation [4], [5]. Variability is defined as continuous power that varies depending on a major renewable fuel source, such as solar radiation or wind [6], [7].

Artificial Intelligence (AI) offers nowadays humanity a huge opportunity to tourney its needs. Its extensive use has many interests, including the capacity to anticipate and generalize at rapid rates, pliability, clarification abilities, and figurative thinking [8], [9]. Given climate sets an increasing press on energy sources, it's not amazing that RE has reached the top of the energy networks as a result of humankind's wish to administrate energy supplies. Cost and the environment are concerns for consumers, producers, and governments alike in these situations, solutions must be sought. RE is suitable more abundant, and the issue is to get a practice to manage it to subtend the worldwide demand for clean, reasonably priced energy [10]. Today, machine learning and artificial intelligence (AI) provide energy companies and investors a valuable chance to implement more effective and productive processes to increase investment returns and promote the energy transition. While the potential for ML to accelerate positive change in the energy industry and sector decarbonization is already significant, it is the potential to accelerate positive change in the energy sector and sector decarbonization that is now becoming a greater focus. AI can use several techniques such as design, development, administration, and estimation [11], [12].

2 INTELLIGENT WIND POWER FORECAST TECHNOLOGY

The production of wind energy is steadily increasing. The amount of wind energy available is determined by the various wind speed. Because the schedule of wind-power availability is not known in advance, this causes complexity in system planning and energy forecasting for wind-farm operators. The importance of wind power prediction has been highlighted considering the increased growth of wind power generation that will be established in Egypt in the coming years. Despite the research that has been done in this field, more effective wind power forecasting algorithms are still needed [13], [14]. This section will go through the methodology behind the intelligent wind power forecast technology. An AI is used in this method (ANN).

2.1 Zafarana Onshore Windfarm

This study belongs to the location of "Zafarana" onshore windfarm, which has a capacity of 550MW. With each turbine able to produce a capacity of between 500KW and 2MW, this is equivalent to one-third of the Nasser High Dam's output. The Zafarana project is east Africa's second-largest power plant, behind the Gabal El Zeit farm, which generates 580MW [15], [16]. The "Zafarana" site is in the Suez Gulf, roughly 200 kilometers southeast of Cairo, near the southern boundary of N 27° 40' 5° and E 33° 11' 31.4" / N 28 ° 12' 1.5". Zafarana winfarm was divided into five sites. In this research we selected Site.3 which is a windfarm with a configuration of 46 WT, each turbine type HAWT-Upwind with three blades from model Vestas (V47-660/200kW) with rated power is 660 KW, the total capacity to site.3 was 30MW.

2.2 Wind Turbine Specification

The collected wind power and wind speed are generally available in time series format, in which each data point represents an average over-short intervals of time, such as a month. It contains data from January to December. The turbine specifications, which are shown in (Table.1) and (fig.1) show the power curve for the mentioned wind turbine.

TABLE 1
WIND TURBINE SPECIFICATION USED IN THIS STUDY [17].

Wind Turbine Specification	
Manufacturer	Vestas
Type	V-47 660/200 kW
Rated Power	660 kW
Number of blades	3
Cut-in Wind Speed	4.0 m/s
Cut-out Wind Speed	25.0 m/s
Rated Wind Speed	16 m/s
Rotor Speed	28.5 rpm
Hub Height	45 m
Diameter	47 m
Swept area	1,735.0 m²

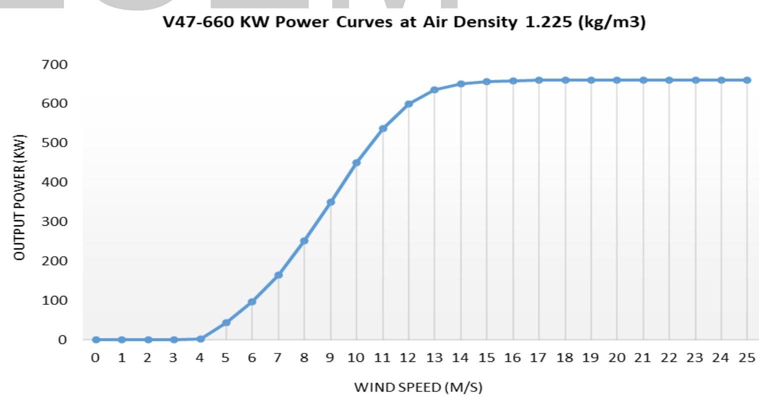


Figure 1 Wind power curve for Vestas - V-47 660 kW [18].

2.3 Characteristics of Wind Power Generation

There are 46 turbines in the "Zafarana-site3" wind farm with meteorological instrument equipment. regarding meteorological data collected from meteorological towers, such as wind speed readings, it was fairly difficult. An average reading was chosen as input data, so the input signal to the model was clearly understood by the data source. The following section offers detailed information on wind power, wind speed, and capacity, as well as a prediction of turbine energy production. The entire quantity of energy produced by the wind farm is used to calculate the power output by all the wind turbines. This research examines the features of wind turbine power generation and forecasts wind power using a feed-forward neural network [19], [20]. The energy carried by the wind is used in the creation of wind turbine power. The wind power density, or area's power per unit normal to wind azimuth, is an essential unit for calculating the amount of energy delivered by the wind. the horizontal component of mean free-flowing wind velocity is denoted by v (m/s), A is an area (m^2).

P is wind power (W/m^2), and ρ is air density (kg/m^3), as in “(1).

$$P = 1/2\ \rho A v^3 \qquad (1)$$

The density of the air and wind speed, on the other hand, are rarely constant, resulting in significant fluctuating power output via a turbine. There are two elements to this property of dynamic power production. For example, from a temporal and geographic standpoint, the power outputs for turbines are determined by the wind farm's location, The turbine's power produced is proportional to the wind speed at the hub height, according to established criteria. [21], [22]. The turbine hub height of the "Zafarana-site3" wind farm is 45 meters above the ground. This connection proves that the velocity at the hub height remains constant and is well understood. Despite this, due to the varied topography, turbines on the wind farm are spread out over a large area, whereas the meteorological tower has a lesser number of turbines. The real wind velocity of each turbine is usually different from that measured by unknown meteorological towers. Because wind speeds observed over time from various meteorological towers vary, turbine power generation from various turbines varies as well [23].

3 ARTIFICIAL NEURAL NETWORK MODEL DESCRPTION

ANN Algorithms are a type of algorithm that is used to solve problems. The "Zafarana-site3" wind farm's output power was predicted using a feedforward artificial neural network model that was constructed by training neural networks based on historical data [24], [25]. The ANN models were built based on three primary aspects in the area that directly affect power generation: an input layer that receives data, an output layer that sends computed information, and a hidden layer that connects the input and output layers. The model development's governing equation is stated generation.

$$\text{Power} = F\ (\text{wind speed, air density, and swept area}). \qquad (2)$$

With Feed-Forward backpropagation, the average wind power value in the "Zafarana-site3” wind farm has been forecasted in this study. the wind farm has an in-house meteorological station, the monthly climatic data were acquired from there. Typically, the Levenberg-Marquardt algorithm is employed to train the dataset. The ANN design for this study was created using MATLAB R2020a. Because the model comprises three individual parameter variables, as stated in “(2), a single hidden layer was placed just on the modeling process to complete the conceptualization and design of the ANN. The ANN was trained on 70% of the given dataset, while a calibrated step was undertaken to improve the validation data percentage for verifying the network. For 15% of the samples, 15% of the data is utilized to generalize and halt training before overfitting. The remaining 15% of data is utilized for an official test of network generalization. (fig.2) Block Diagram of inner Structure of ANN, which are consists of three main layers were input layers, hidden layers, and output layers. Also, the same figure depicts the design of mentioned neural network which has three inputs data in the input layer wind speed, air density, and swept area which passes through hidden layers before coming to the output layer which is representative output power. The Levenberg-Marquard technique was used to train this network.

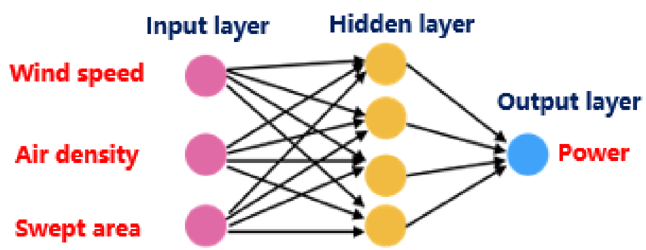


Figure 2 Block diagram of the inner structure of ANN (a).

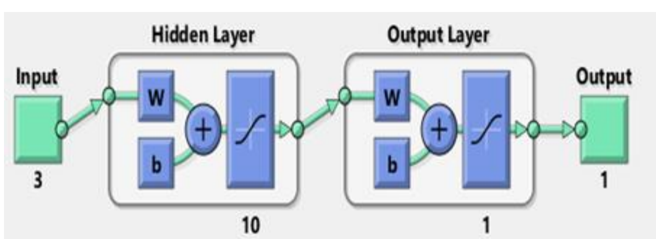
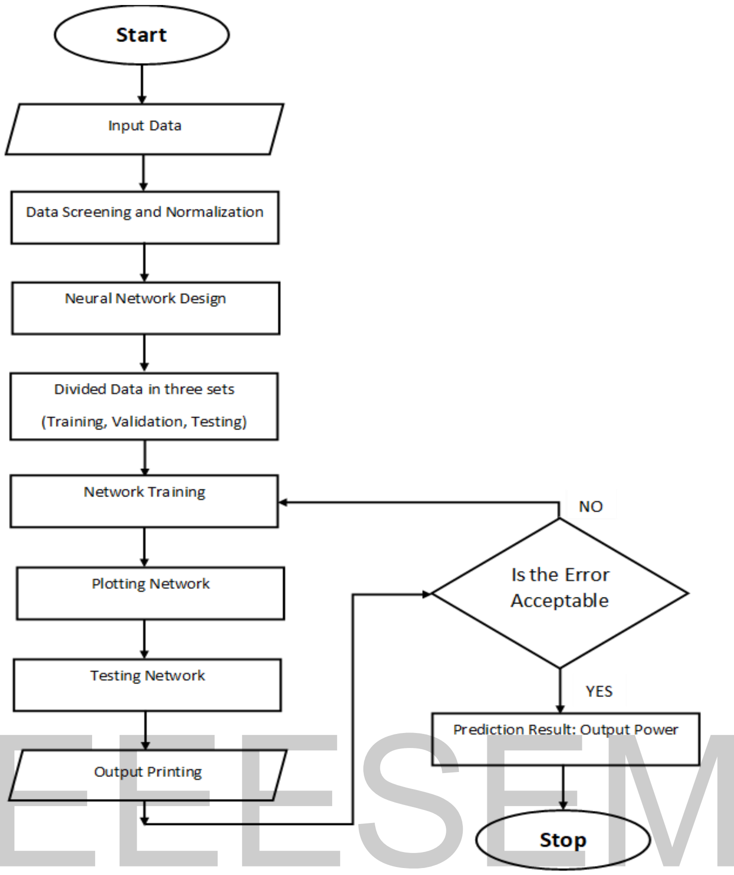


Figure 2 Block diagram of the inner structure of ANN (b).

3.1 ANN Model Flow Chart



4 RESULTS AND DICUSSION

4.1 Total Actual Wind Power Collected for Each Month

Monthly power generation data (MW) for the mentioned year were obtained from the wind farm authorities. (Table.2) and (fig.3) are shown the variance in produced power over a year. The greatest power generating rate is approximately 12548 megawatts. Peak electricity generated occurs in June, July, August, and September when most of the "Zafarana-site3" areas experience strong winds.

TABLE 2
TOTAL ACTUAL WIND POWER/MONTH.

Month	Total Actual Power
Jan	2647.3
Feb	4209.6
Mar	4892
Apr	8675.1
May	8587.1
Jun	11513.6
Jul	12548.4
Aug	10352.8
Sep	11798.2
Oct	9662.5
Nov	7602.8
Dec	5319.8

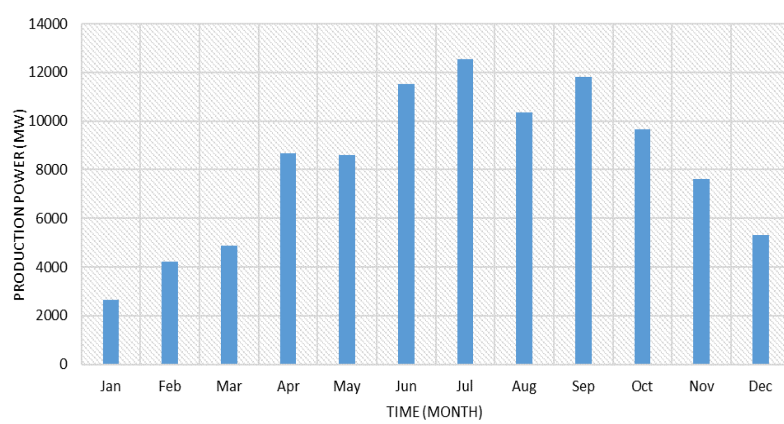


Figure 3 Total actual production power diagram/month.

4.2 Average Wind Speed for Each Month

The fluctuation in average wind speed throughout the past year's months is seen in (fig.4) and (Table.3). The summer season has the highest wind speeds, with values of 8.5, 8.7, 8.3, and 8.4 in June, July, August, and September, respectively. The lowest wind speed occurs in the winter, with readings of 5.2, 5.4, and 5.5 in January, February, and March, respectively.

TABLE 3
AVERAGE WIND SPEED/MONTH.

Month	Average Wind Speed (m/s)
Jan	5.2
Feb	5.4
Mar	5.5
Apr	7.6
May	7.8
Jun	8.5
Jul	8.7
Aug	8.3
Sep	8.4
Oct	8.2
Nov	6.8
Dec	5.6

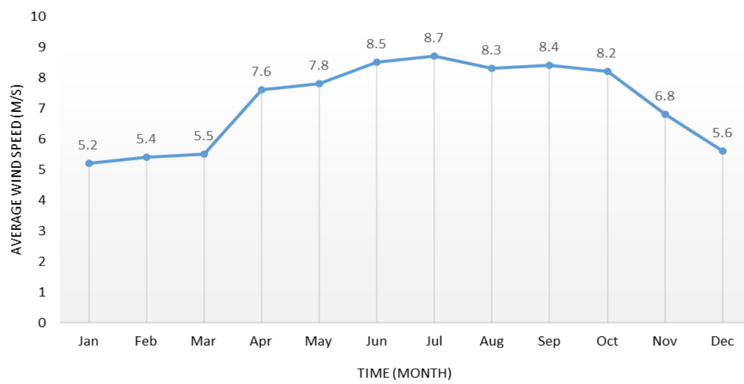


Figure 4 Average monthly wind speed over the year in the site.

4.3 Wind Power Prediction Consequence through ANN Model

The highest accuracy performance is shown in (fig.5), which was created through MATLAB R2020 and delineates the network's performance job that has been significantly improved by training. The data analysis simplifies the information in the form of validity, test, training, and curve. the neural network will be accurate and have good output results when the total values of the Coefficient of Correlation (R) for test and validation and training values are close to 1, as an overall result for training, validation and test results in the mentioned ANN have R equal to 0.99945 this value is very close to 1 It demonstrates a quite fascinating fitness for the neural network.

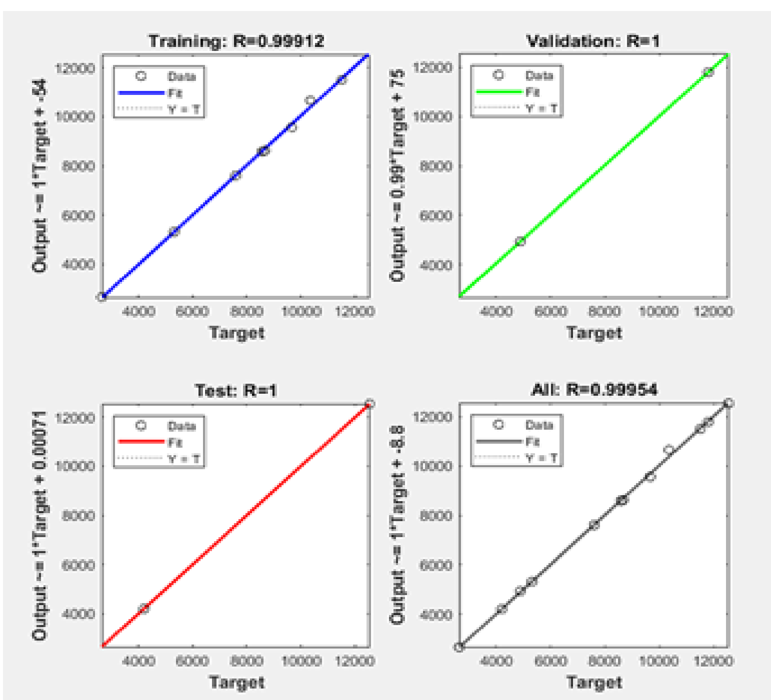


Figure 5 The LM algorithms predictive power vs Actual power: training, validation, test, and overall.

4.4 Wind Power Predicted through ANN Model

Exhibits in (Table.4) the variation of average wind power prediction for each month, The greatest power generating rate is about 12537MW. The peak months for electricity production are June, July, August, and September, which coincide with the peak months for real power production., (Table.5) exhibits the output predicted power value very close to the actual value.

TABLE 4
WIND POWER PREDICTION.

Month	Total Prediction Power
Jan	2648.21
Feb	4098.58
Mar	4958.06
Apr	8675.16
May	8587.04
Jun	11741.97
Jul	12537.70
Aug	10305.28
Sep	11524.02
Oct	9226.69
Nov	7599.04
Dec	5273.39

TABLE 5
ACTUAL WIND POWER VS PREDICTION WIND POWER.

Month	Average Wind Speed	Actual Power	Prediction Power
Jan	5.2	2647.3	2648.21
Feb	5.4	4209.6	4098.58
Mar	5.5	4892	4958.06
Apr	7.6	8675.1	8675.16
May	7.8	8587.1	8587.04
Jun	8.5	11513.6	11741.97
Jul	8.7	12548.4	12537.70
Aug	8.3	10352.8	10305.28
Sep	8.4	11798.2	11524.02
Oct	8.2	9662.5	9226.69
Nov	6.8	7602.8	7599.04
Dec	5.6	5319.8	5273.39

4.5 Juxtaposition of Actual Power and Prediction Power Concerning Time and Average Wind Speed

Illustrate in (fig.6) the juxtaposition between the two powers, predicted and actual output power for a wind farm. the curve shows the symmetric values for these two powers concerning the time and (fig.7) illustrated the juxtaposition between actual and predicted outputs of the wind power generation concerning average wind speed.

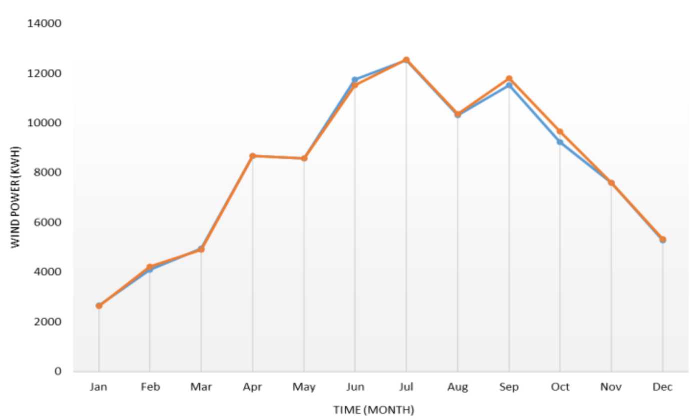


Figure 6 Actual and predicted wind power concerning the time.

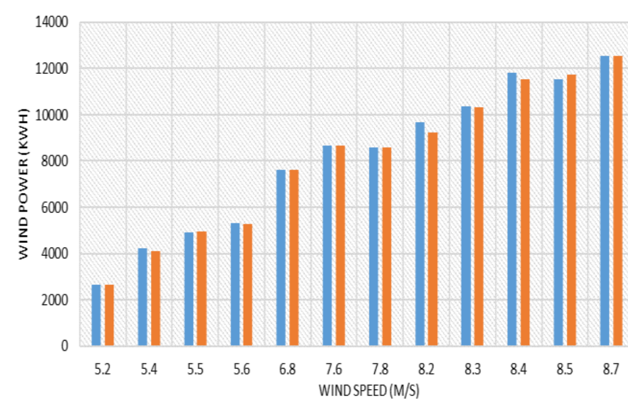


Figure 7 Actual and predicted wind power concerning average WS.

5 CONCLUSION

The study provides a wind power prediction by using an ANN that was created to anticipate wind power generated in the “Zafarana-site3“the wind farm in the Suez Gulf. With the use of the average wind speed, air density, and swept area, the model produces time-based wind power prediction results based on freely available wind data from a nearby representative measuring site. The graphical findings show that the proposed ANN approach for forecasting wind power is extremely accurate. As a result, the performance of research network models is shown to be quite near to the actual value. Consequently, utilizing anticipated meteorological conditions, the LM-based ANN model is presented for predicting potential wind power generation in future years. Wind power prediction is an effective and relatively inexpensive tool for improving the level of integration of the wind power sustainable operation, which can greatly assist in lowering costs and improving the stability of wind power by reducing undesirable output power degradation and forecasting the demand for the coming year, which gives chance to handle maintenance schedules and reduction wind turbine and grid downtime. Consequently, the study's findings bring in a new era for Egypt's wind energy generation in terms of forecasting future energy demand and supply. Egypt, as a developing country, may benefit from this development to achieve its low-cost renewable energy generating targets. Furthermore, the findings may be extrapolated to similar meteorological areas throughout the country to illustrate the feasibility and economic worth of wind power potential.

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