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Research Article

Estimation of wind speed by artificial intelligence method: A case study

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ABSTRACT

Wind speed changes from one region to another due to several influencing variables. In this article, a software method has been proposed to determine the future wind speed at any time and under any conditions. Neural Networks were used with engineering data regarding the method of education, training algorithms, and different activation functions between the input and output layers, each according to the nature of the data that would be generated. Back-propagation Neural was used with three variables chosen to be the inputs for the learning and training network (wind speed, humidity, and time), which are considered the most important in determining the proposed or expected speed at the relevant time and place. The hidden layer consists of 10 neurons, which are determined according to the precision of output. After comparing the measurements from the weather system with the expected values, a very tiny percentage of error was found since these readings are regarded as acceptable and aid in the problem-solving process for running companies and researchers. The error rate recorded in this work ranged between ($3 * 10^{-3}$ and $3 * 10^{-5}$), and the average number of attempts for the training and examination process reached 33 attempts, as it is known that neural networks carry out the training process based on specific mathematical functions and closed loops that depend on the lowest possible error rate.

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INTRODUCTION

The energy crisis is the biggest problem facing humanity today due to the large increase in the number of people and the increase in economic activity accompanying the increase in the population [1-3]. Energy consumption around the world increased by about 1.1% over 2022, with oil, gas, and coal continuing to cover most of the energy demand (82%), despite the record growth of renewable sources. According to the Statistical Review of World Energy issued by the Energy Institute, global primary energy consumption increased by 2.8% above 2019 levels (before the Corona pandemic), reaching 604 exajoules in 2022[4]. Electricity generation from renewable energy rose by 14% in 2022, contributing about 40.9 exajoules of total global energy consumption. Solar and wind power continued to grow rapidly in 2022, recording a record increase of 266 GW, with solar capacity accounting for 72% (192 GW) of the total [4]. Based on a 10-year average, wind and solar

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are expected to expand at rates of 15-20% each year, outpacing annual increases in the demand for power by the end of 2023 [5]. Today, engineers and researchers are trying to exploit renewable energies to fill the huge shortage in energy supplies and to address environmental pollution problems resulting from the use of conventional fuels [6, 7].

Boats and sailing ships have been using wind power for at least 5,500 years, and architects have been using wind-driven natural ventilation in buildings for similar times. The use of wind energy to generate mechanical power came later in ancient times [8]. Wind energy is one of the first types of renewable energies that were used by man, as historical evidence indicates that the Babylonians were among the first who drew attention to wind energy and harnessed it for some of their uses, and at present, the interest in wind energy has increased as a result of high oil prices and the emergence of pollution problems resulting from the use of traditional energy sources [9]. Wind energy is characterized by being clean energy, with little environmental pollution, and the absence of the need for large areas, and its disadvantage is the lack of suitable places that contain sufficient wind speeds to generate electricity [10, 11]. The past recent years have seen significant progress in the field of wind energy use due to a significant reduction in the cost of wind power plants, promising technologies, and incentive policies [12]. The cost of generating electricity from onshore and offshore wind energy has fallen by 29-55 %, respectively, over the past decade, as recorded at 0.053 $/Kw hour and 0.115 $/kW hour, respectively in 2019 [13]. Estimating the energy extracted from wind requires careful analysis and knowledge of many areas, including meteorological conditions, fluid mechanics, electrical power systems, and methods of controlling them [14, 15]. One of the most significant functions of artificial intelligence is the prediction process, which is a clever instrument with a wide range of applications. It computes values and percentages based on previously documented cases by researchers. This procedure aids researchers in designing systems and placing generators where they will either have high efficiency or not based on the neural network prediction network's indicators. The failed wind energy experiments and other economic considerations have led to focus attention on accurately estimating the available wind energy to reach high reliability that guarantees the success of wind energy projects [16]. One of the most important obstacles facing the use of wind energy is the lack of previously recorded data to determine the wind speed and direction in the location where wind energy is intended to be used. That is why researchers and scientists reported in the last five years to use of artificial intelligence methods and other statistical methods to estimate the wind speed in any area based on previous information [17]. Iraq is one of the countries that has been subjected to security operations, causing the lack of data to estimate the wind speed, and there has become an urgent need to use artificial intelligence methods to obtain an estimate of the wind speed and use it to enable specialists in the use of renewable energies, including wind energy, for electrical generation as a result of the large shortage in the supply of electric power [18]. Artificial neural networks are one of the methods of artificial intelligence and have gained great interest from researchers to solve problems and obstacles in various sciences [19, 20].

Many articles have been presented on the use of artificial neural networks in wind speed estimation in the last three years for different locations around the world [21]. For example, Yang and Wang [22] presented a novel method to estimate wind velocity depending on an artificial intelligence algorithm. A novel optimization algorithm was discussed and used to optimize the initial weights and thresholds of the backpropagation neural network using the Broyden family and wind-driven optimization. The results show that the suggested hybrid model may increase the predicting accuracy and stability using the 10 min and 30 min wind speeds from the province of Shandong, China. Cinar and Natarajan [23] used a grey wolf optimizer to estimate the wind velocity for India. This study uses an artificial neural network that has been meta-heuristically optimized to predict hourly wind speed. The hourly wind speed is predicted using a feed-forward (FF) multi-layer perceptron (MLP) artificial neural network (ANN). Thirty-eight years of hourly wind data from five cities (Ambur, Hosur, Kumbakonam, Nagapattinam, and Pudukottai) were analyzed for this study. Nine modern metaheuristic optimization strategies are used to improve the FF MLP ANN. The weights of the ANN have been optimized in this study using Artificial Bee Colony (ABC), Ant Colony Optimization (ACO), Biogeography Based Optimization (BBO), Evolutionary Strategy (ES), Genetic Algorithm (GA), Grey-Wolf-Optimizer (GWO), Population-Based Incremental Learning (PBIL), Particle Swarm Optimization (PSO), and Tree-Seed Algorithm (TSA). With a success rate ranging from about 3% to 10,000%, GWO surpasses other metaheuristic algorithms in the prediction of wind speed using an FF MLP ANN. Zhao et al. [24] reviewed the studies on big data and artificial intelligence in wind energy forecasting during the previous two decades to determine the evolution rules of these systems. The findings support the advancement of wind energy forecasting by acting as a foundation for further study. Wang et al. [25] used a neural network wind speed prediction model to predict the wind speed on the front of wind turbines in wind farms. Utilizing lidar wind measurement data from a wind farm in Xinjiang, simulation tests were carried out. Using various meteorological variables as input for multivariate time series forecasting, Nascimento et al. [26] offered a novel transformer-based deep neural network architecture linked with wavelet transform for forecasting wind speed and wind energy (power) generation for the next six hours ahead. They demonstrated that the suggested strategy performs better than the baseline model when it comes to forecasting wind speed and power generation. Results also showed that the forecast accuracy was increased by combining the transformer model with wavelet decomposition. Mahdi et al. [27] used an Artificial Neural Network technique to estimate the wind velocity in the Duhok region of northern Iraq. The researchers used weather data for Duhok City, Iraq, to predict daily average Wind velocity using Feed Forward Artificial Neural Network. MATLAB software system was utilized for this goal. Based on the results, the proposed network corrects daily wind speed data. This suggested approach aids in weather forecasting and provides an estimate of wind turbine production strength. Also, Hussain et al. [28] used the Recurrent Neural Network to predict the wind energy for Duhok in Iraq. Zhang et al. [29] used the sparrow algorithm to predicate the wind speed. The practical outcomes confirmed that the four error evaluation parameters of the Sine-SSA-BP algorithm are all smaller than the other neural networks. Bhattacharya and Sinha [30] presented neural network models to predicate the wind energy for the Bay of Bengal region. Sunil Kumar et al. [31] presented an article to discuss the venturi effect on the performance, design, and fabrication of windmills. This experimental investigation revealed that, in comparison to traditional windmills, the highest power generation was about 12% higher. Sunil Kumar and Palanisamy [2] studied the design and the performance of the blades the wind turbines for domestic uses. The results confirmed that the optimal angle of attack drops from the maximum-lift-coefficient angle of attack at the blade root to more than 80% of this value at the blade tip, according to results for a common airfoil cross-section. Also, Ofori-Ntow et al. [32] used an artificial neural method to analyze the wind prediction. Syama et al. [33] used a flight Chaotic Whale Optimization Algorithm to estimate the wind velocity. The prediction ability of the proposed model has been validated by nine other existing standard models, and the results prove the effectiveness of the proposed model and confirm the fact that WOA performance can be improved by incorporating chaotic maps and L´evy flight into the algorithm.

Several studies and articles on assessing the reality of winds in Iraq have been published previously. Darwish and Sayigh [34] conducted a ten-year wind data analysis for nine sites inside Iraq and six sites outside Iraq to calculate the wind energy potential in Iraq. The study showed that one-sixth of Iraq's area has an annual wind speed greater than 5.0 m/s. It can be used to establish wind farms in Iraq to generate electricity. Ahmed [35] conducted a study to assess the wind energy in Makhool Mountain (35° 7' N°, 43°25' E°) in Iraq. The average annual wind speed of the study area at a height of 10 m was 3.87 m / s, while the average annual wind speed at a height of 50 m was about 5.87 m / s. Mahmood et al. [36] confirmed an analysis for Al-Salman province, Iraq. They found that the average wind speed at a height of 50 m was 5.93 m/s. Darwish et al. [37] presented a method for improving wind energy production in Iraqi regions characterized by low wind speeds. Al-Alawy and Mohammed [38] presented a mathematical model of wind velocity for different Iraqi locations. Al-Azzawi and Zeki [39] presented a study that used wind speed data from five meteorological stations in Iraq to determine wind energy. The study outputs indicate that the average monthly and annual wind speeds range from 1.7 to 5.2 m/s and from 2.4 to 4.1 m/s, respectively. Al-Rijabo et al. [40] focused their attention on studying wind speeds in four regions of Nineveh Governorate, namely Mosul, Rabi'a, Sinjar, and Tal Afar, for the period (1980-2002). The mean monthly values, the standard deviation, the coefficient of variation and the time series for the wind speeds was studied during this period in all locations. Where ranged in Tal Afar, between (3.8-5.4 m/s) and Sinjar, the wind speed ranged between (1.9-4.5 m/s). Ibrahim and Saeed [41] studied the characteristics of winds in the Garmian region, which includes four stations for measuring winds: Kirkuk, Kalar, Khanaqin, and Tuz Khurmatu. Mishaal et al. [42] presented a study of the reality of wind energy in Iraq, and the study showed the presence of encouraging areas for the establishment of wind farms, especially in southern Iraq. The wind velocity varies from one place to another and from one season to another. Therefore, it is necessary to take into account the wind speed over several years, to reach a decision on whether or not to adopt a wind turbine. Through the forecast of turbine performance, Darwish et al. [37] created a thorough and innovative system for maximizing wind energy turbine production for low wind speed zones. Only a few methodological stages were previously documented in the literature. Due to its simplicity and clarity, the methodology is readily adaptable to a software package. For the practitioner, the concept was applied to Iraq as a low wind speed regional case study utilizing real wind speed and other data.

After 2003, Iraq suffered from serious security incidents that caused a major shortage in the supply of electricity to citizens. Therefore, the Iraqi government is trying to rely on renewable energies to replace electricity source. Also, there is a lack of wind speed data in various regions of Iraq, and it has become necessary for researchers to find ways to estimate wind speed. The wind velocity data measured for a full year will be relied upon by the meteorological system, and then a database was prepared for the smart network ANN to estimate the wind speed for subsequent years based on a specific algorithm of artificial intelligence algorithms. With this proposed method, engineers and researchers can rely on the data obtained by the artificial intelligence network in the design processes for renewable energy systems and wind turbines that are planned to be worked on the ground. This proposal can also be applied to any region and according to any data, such as pre-recorded wind speed and humidity, at any time of the year, after a simple change in the special functions and weight ratios. The proposed method proved successful compared to previous studies and corresponds to the real readings recorded from the meteorological system of the study area. Also, the article includes a study of the characteristics of wind energy in the Hawija district and the possibility of using it to generate electricity.

STUDY AREA

Hawija district (35.327 °N, 43.754 °E) is located in the western part of the Kirkuk governorate and is one of the four important districts of Kirkuk. Figure 1 shows the location of the Hawija district on the map of Iraq and the Kirkuk governorate. The district suffers from a severe shortage of electric power because of the urgent need for this energy to water crops. Artificial intelligence methods are essential to solve societal problems, especially in areas that have suffered from serious environmental problems and a lack of climate information in previous years.

Mathematical Relations and Data Analysis

The process of collecting data to train the neural network on a certain work or task is one of the most important processes on which the success of the proposed network depends to a very large extent. The network inputs must have real values and fixed proportions for the prediction process to be closer to reality and with the lowest error rate [43]. More than one input was selected in the training process, which is considered one of the important variables in knowing the proposed wind speed for a day or an hour. The inputs to the estimation and training network (wind speed, humidity, time, and date) are the variables that have been chosen, which in turn will predict the speed for the coming days and as required. The data was collected from a meteorological system installed in the study area, which is considered a rural area, and a large percentage of alternative energy is required from the traditional due to the presence of problems in energy transfer operations with process capacity that is not commensurate with the volume of work, whether in factories and companies or the field of agriculture, harvesting crops and processing them. The actual climate readings are for a whole year, starting in September 2021 until August 2022, which includes, in addition to wind speed (trends, humidity, temperatures, solar radiation, radiation rate, precipitation rate, etc.). All data related to wind speed (such as wind direction, humidity, temperature, and precipitation) were selected and pulled into the particular data file. There are several methods for determining suitable wind characteristics, including:

Wind speed rate method

It is one of the simplest methods, and the rate of velocity is calculated using the following equation [44]:

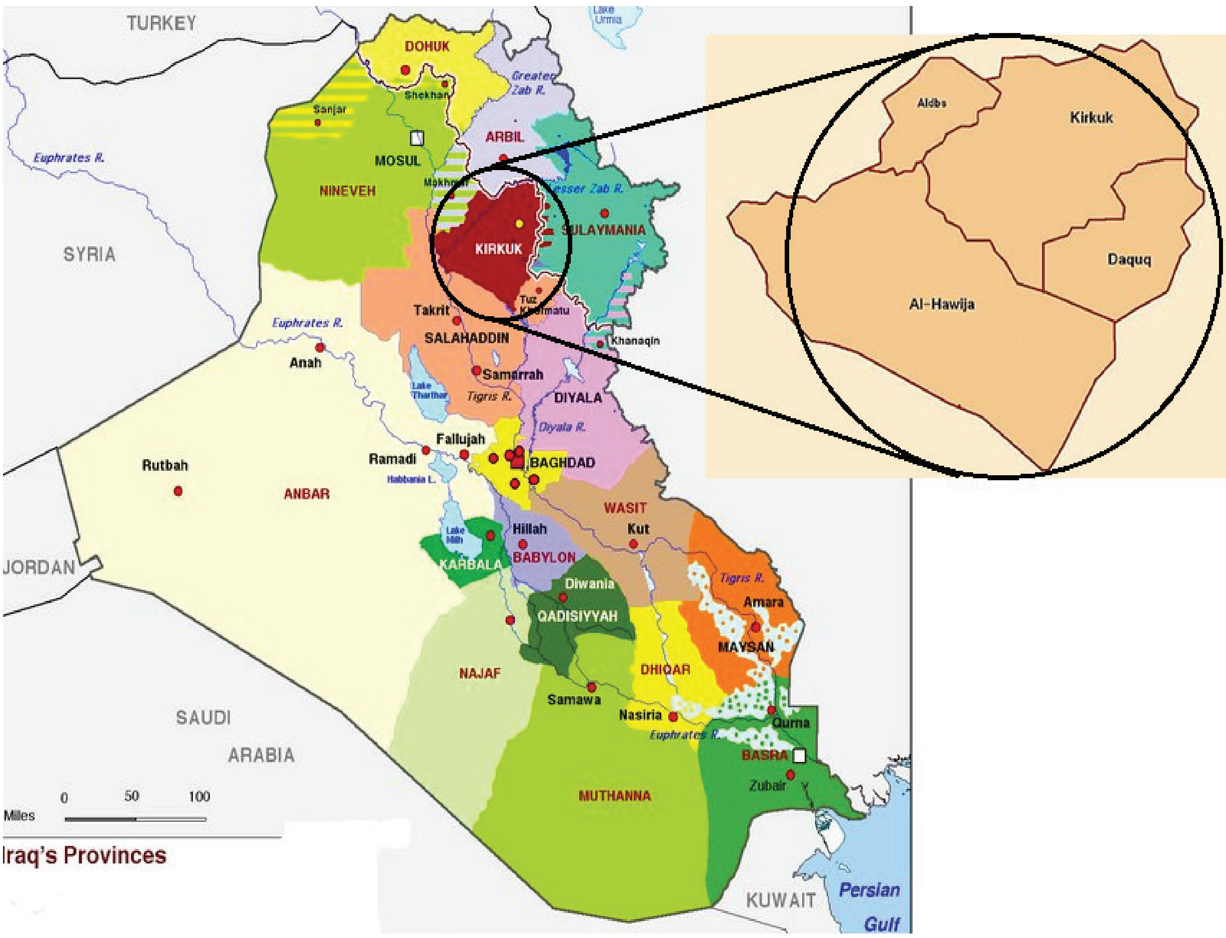


Figure 1. Hawija district map (study area).

$$v_m = \frac{1}{n}\sum_{i=1}^{n} V_i \quad (1)$$

whereas:

$\sum_{i=1}^{n} V_i$= The sum of all measured wind speeds.

n = The number of measured readings.

Wind data was collected for several years, and these data are usually taken through hourly, monthly, and annual measurements and were used in the current article to measure wind speeds. A weather station type (Davis Pro 2) was used to measure wind speeds. The wind speed at the surface of the earth differs from that at high altitudes due to the effect of friction and the roughness of the ground. The higher the altitude, the higher the wind speed, and this is understood from the following equation [44]:

$$\frac{V}{V_r} = \left[\frac{H}{H_r}\right]^{\alpha} \quad (2)$$

Whereas:

V= Wind speed at a given altitude (m/s), V_r= Wind speed at a reference height (9.1m), and H= The altitude at which the wind speed should be calculated (m).

The standard altitude at which the wind speed is measured in weather stations is Hr = (9.1 m). In addition to the effect of altitude on wind speed values, there is an effect of natural and industrial obstacles on wind speed [45]. The coefficient α, which is called the coefficient of friction or the roughness of the earth's surface, is calculated from the following equation [39]:

$$\alpha = \frac{0.37-0.0881*\ln{(V_r)}}{1-0.0881*\ln{(\frac{H_r}{10})}} \quad (3)$$

Power rate velocity method

The power produced by a wind turbine is directly proportional to the cube of the wind speed, so it was relied upon to determine the appropriate wind speed on the average energy speed as follows [46]:

$$\bar{V}_E = (\frac{\sum_{i=1}^{n} V_i^3}{n})^{1/3} \quad (4)$$

The electrical power produced per square meter is calculated according to the relation [47]:

$$\frac{P}{A} = \frac{1}{2}\rho V^3 \quad (5)$$

The maximum efficiency of wind systems, which is called the power coefficient, which is equal to the ratio of the maximum power derived from wind energy to the total wind energy, and this means that wind turbines, regardless of their efficiency, cannot convert more than 60% of the total wind energy at best. The real power of the wind turbine is calculated as follows:

$$P_{total} = \frac{1}{2} * \eta * \rho * A * V_i^3 \quad (6)$$

where η is the efficiency of the turbine ranges between (30-40%) [44].

Proposed ANN Model

The deficiency of wind speed data in Iraq may be addressed, and artificial intelligence (AI) can help renewable energy projects in several ways.

a. AI systems can use existing data from neighboring regions or with comparable climates to impute missing wind speed data in Iraq. This is known as an Imputation Technique. Techniques such as extrapolation and interpolation can be used to bridge gaps in the available data.
b. Machine Learning Models: With the available data, artificial intelligence (AI) models, such as neural networks or regression algorithms, can be taught to estimate wind speeds in regions where information is lacking. With the use of historical data and weather trends, these models can identify patterns and reliably anticipate wind speeds.
c. Artificial Intelligence (AI) can employ remote sensing technology, such as radar data, LiDAR, or satellite photography, to collect data on wind patterns, topography, and atmospheric conditions in Iraq. These data sources can support or corroborate what is already known. Several neural networks were constructed in the proposed study, each with a unique learning mechanism, training method, activation functions, and weights.

The architectures of neural networks differ greatly, which has an impact on the activation functions, training procedures, and learning mechanisms. Learning with Feedforward Neural Networks (FNNs) Neural networks with mechanisms are the most basic kind and are usually employed in jobs involving supervised learning. Through forward data transmission through the network, computation of outputs, and weight adjustment depending on prediction inaccuracy, they learn. Algorithm Training To update weights and reduce errors, gradient descent-based optimization techniques (SGD, Adam, etc.) sometimes combine backpropagation. To stop overfitting, regularization strategies like dropout and L1/L2 regularization might be used. Sigmoid, ReLU, tanh, and other common activation functions may be used, depending on the issue and network depth [19].

The purpose of building more than one network is to increase the reliability of the data in the first place and then to increase the accuracy of the error rate compared to previous works. In neural networks, several things must be prepared before starting the construction and training process to avoid problems and endless loops of calculations. The overall process for this work is shown in Figure 2. The number of entries is important to know the real workings of the network, as it is supposed to include as many entries as possible related to the intended arithmetic operation. Three main inputs were chosen in the proposed work to calculate the wind speed for the following days, which are (wind speed, humidity, and time). These variables are more important for the speed prediction process for any day of the year than the training algorithm found in artificial intelligence in general and neural networks in particular. Other factors might be used as inputs in the proposed network; however, these variables were selected in order to restrict the study and take advantage of the direct effect on wind speed. The topography, temperature, precipitation, and pressure all affect wind speed differently. The number of inputs in neural networks affects the speed of reaching the optimal solution, and the results are more accurate since the work relied on more than one case in determining the output. The second stage, (after determining the number of inputs in neural networks), is the set of data for each input, the type of numbers, and their range. The data set must be limited to real numbers within certain mathematical operations or recorded from the readings of the available devices, whether electronic or weather forecast or through sensors. This set of data will be relied upon in the training and education process of the network since the resulting set of solutions will be within the set of entered data. The type of data entered into the network is variable; there are binary numbers, there are polar numbers, and there are the usual numbers known to them, while the binary numbers (0, 1) are the most used because the range is limited and the learning will be at an ideal speed and with a very small error rate. The neuron output depends on many variables, such as input and bias value (optional) and the type of activation function as mentioned (sigmoid, linear and semi-linear). The network connection for the proposed neural network is shown in Figure 3.

After determining the number of inputs and the quality of data that will be dealt with, as mentioned previously the data that will be trained on is the real data that was recorded from the weather system to ensure that the real optimal solution is reached without coding it with additional algorithms. The process of creating a network for training, as the structure of the network is the same, but the training and education algorithms are different, you need some basic things before starting anything. As it is known, neural networks need training and education. The first is called a training process, and the second is a learning algorithm. Both of them need to initialize the inputs, choose the weights, the activation function, and the target value for each output from the process, etc. which will be explained in detail. When selecting the inputs for the training network in the neural network, the activation function of the input stick must be determined. There are a lot of activation functions that can be used (linear, binary, trigonometric) and it depends on the type of data being agreed upon. Also, among the things related to the input are the weights for each stick, and they are given random values between 0 and 0.5, in order to be taken into account in the calculations, and if the feedback function is used, the weights will be updated according to the location of the stick. Weights play an important role in the education and training process, as they are included in the main calculations of the equations for the training process, and then the goal is reached with the speed and accuracy involved. In neural networks, there is more than one layer in the engineering structure that bears the names (input layer, output layer, and hidden layer).

The input layer contains the input sticks that were mentioned above. As for the output layer, it is the one that will be by the number of outputs and depends on the system to be processed in terms of the variables to be calculated. The hidden layer is considered the key to solving many programming problems and is taken into account. This layer contains many sticks that in turn take the signal from the input sticks, in addition to weights different from the weights in the input layer. The activation function in the input layer sticks is usually a sigmoid because the network data in this region is not applicable, so it can be expressed in an analogue, polar, or binary way, depending on the nature of the system. In the proposed work, the input layer was defined with ten sticks, and the activation function for each of them is (Sigmoid). Now that the most important elements of the bacilli network of the proposed work have been known, the network structure of our proposal will be built in the form of three inputs, each of which has a special activation function, which is (Step), because, in the input stage, the researcher is bound by one type of data that does not accept the interpretation. The data within the solutions group are taken from real previous readings, as the researcher must confine them within a very narrow range

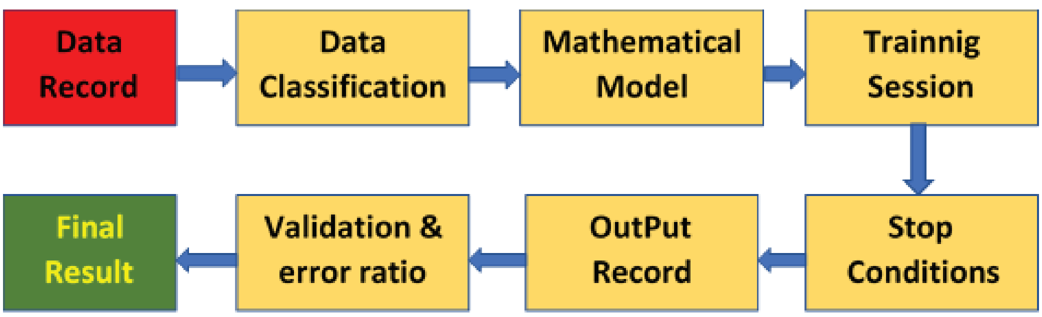


Figure 2. Proposed System for the proposed work.

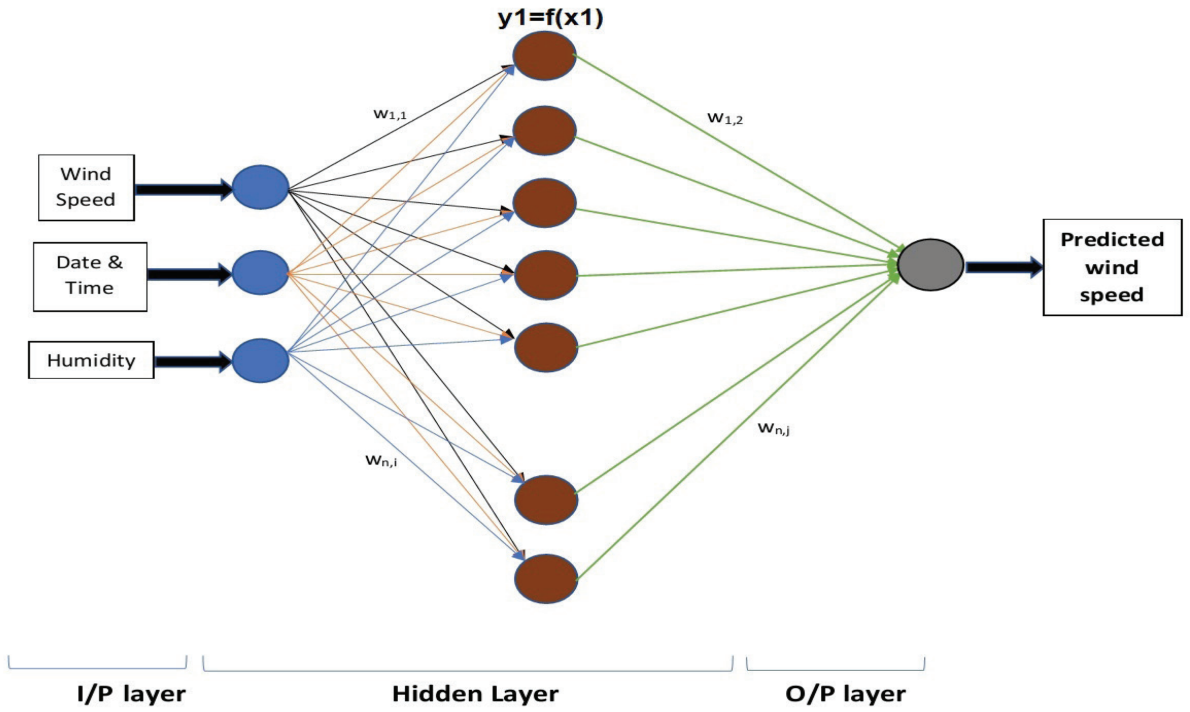


Figure 3. Proposed network for the wind speed prediction.

to reach the solutions in the least time and with the most accurate acceptance rate. The hidden layer in the proposed work was defined as a single layer with ten sticks with an activation function of the type (Sigmoid) to smooth the process of calculating variables within the network such as weights with bias elements (b) for each stick. As mentioned earlier, neural networks contain a learning method and a training algorithm for a set of available solutions to reach the intended goal. In this work, two types of algorithms were applied, namely (Backpropagation) and (Perceptron), to notice the difference in the error rate, in addition to increasing and documenting the resulting data through the achieved goals. In the feed-back algorithm, the variables are calculated in each (epoch), where the special mathematical model is applied to each stage in the forward direction, then the same operations are repeated in the back direction to adjust the weights for each stick, as well as review the type of functions for each stick.

The specific training process is as follows. Suppose S training samples are used to train the network, one of which is sample s. For sample s, the input of the nth neuron of the i^{th} layer is:

$$net_{ns}^{(i)} = \begin{cases} x_n & i = 1 \\ \sum_{J=1}^{Ni-1} w_{nj}^{(i)}\, o_{js}^{(i-1)} - \theta_n^{(i)} & i = 2,3,4 \end{cases} \quad (7)$$

where x_n is the input of the neuron n, $\theta_n^{(i)}$ is the threshold of the neuron n of the ith layer, $o_{js}^{(i-1)}$ is the output of neuron j of the $(i - 1)^{th}$ layer of sample s. The output of the nth neuron of the ith layer is:

$$O_{ns}^{(i)} = \begin{cases} net_{ns}^{(i)} & i = 1 \\ g\left(net_{ns}^{(i)}\right) & i = 2,3,4 \end{cases} \quad (8)$$

where g(.) is the activation function.

The activation function, sigmoid, can be expressed as:

$$y_{i,j} = f(x_n) = \frac{1}{1+e^{-s_k}} \quad (9)$$

Other forms of activation function can be linear or simi-linear functions:

$$y_{i,j} = f(x_n) = x \quad (10)$$

The quadratic error function for S training samples is:

$$\begin{aligned} L &= \frac{1}{2}\sum_{s=1}^{S}\sum_{n=1}^{N4}(t_{ns} - y_{ns})^2 \\ &= \frac{1}{2}\sum_{s=1}^{S}\sum_{n=1}^{N4}(t_{ns} - O_{ns}^{(4)})^2 \end{aligned} \quad (11)$$

where y_{ns} is the predictive output of the output node n of sample s, and t_{ns} is the target output of the output node n of sample s. If the learning process adjusts the weighting coefficient in the direction where L decreases the fastest.

Here the proposed algorithm was used by the neural network:

1. Read the initial data set (all the mentioned variables)
2. Set initial values for the network parameters such as: (bias, weights)

3. Compute the output for each layer and each neuron.
4. Compare the final output with the target.
5. Test the stopping conditions
6. End

The training algorithms of backpropagation comprise regularization techniques and gradient descent variations, whereas the learning processes of the technique incorporate either supervised or unsupervised learning paradigms. Activation functions are important because they influence learning speed, resolve vanishing gradient problems, and determine how expressive the network is. For neural networks to be trained effectively, the right combination of these components must be chosen, taking into account things like convergence speed, vanishing gradients, and the network's capacity to recognize intricate patterns in the data.

RESULTS AND DISCUSSION

In the Hawija area of the Kirkuk Governorate, northern Iraq, this study was conducted using meteorological data collected over four years. The data included temperatures, humidity levels, wind directions, and speeds, among many other characteristics. In order to forecast future wind speed, the neural network was trained with three of the variables as inputs.

The current article relied on the data from the weather station, which was installed in the Renewable Energy Research Unit of the Technical Institute-Hawija. The measured data was relied on for the period from 2010 to 2013, then data recording stopped for the period from 2014 to 2020 as a result of ISIS events, and then data recording began again in 2021 till now. The results as:

Wind Properties and Rates

Table 1 shows the change in wind speed at a height of 10 m, where it is noted that the wind speed, in general, is less than the wind speed suitable for generating electric power, which should not be less than (3.5 m/s) [44]. It is also clear that the wind speed increases during the summer and then begins to slow towards the winter months. The three

Table 1. Average monthly wind speed values for the study area

Date	Average Wind Speed (m/s)	Max Wind Speed (m/s)	Date	Average Wind Speed (m/s)	Max Wind Speed (m/s)
Aug. 2010	2.3	10.3	Dec. 2012	1.1	6.7
Sep. 2010	2.7	16.5	Jan. 2013	1	6.5
Oct. 2010	2.3	17.4	Feb. 2013	1.1	9.8
Nov. 2010	1.7	9.4	Mar. 2013	2.4	20
Dec. 2010	2.1	15.2	Apr. 2013	3.2	23.2
Jan. 2011	1.8	14.3	May. 2013	3.5	19.2
Feb. 2011	1.7	16.1	Jun. 2013	3.6	16.1
Mar. 2011	2.1	21	Aug. 2021	2.20	9.8
Apr. 2011	2.8	29.5	Sep. 2021	2.30	10.7
May. 2011	2.7	16.1	Oct. 2021	1.80	14.3
Jun. 2011	3.7	19.2	Nov. 2021	1.70	12.1
Jul. 2011	3.3	17.4	Dec. 2021	1.70	11.6
Aug. 2011	3.1	13.9	Jan. 2022	1.61	12.5
Sep. 2011	2.2	14.8	Feb. 2022	1.86	13.4
Oct. 2011	2.1	19.2	Mar. 2022	2.15	18.3
Nov. 2011	1.8	15.2	Apr. 2022	2.15	17
Dec. 2011	1.3	12.5	May. 2022	2.28	15.6
Jan. 2012	1.233	10.3	Jun. 2022	2.71	17.4
Apr. 2012	2.1	12.1	Jul. 2022	2.67	12.5
May. 2012	2.6	19.2	Aug. 2022	2.60	13
Jun. 2012	3.3	21.5	Sep. 2022	2.30	6.3
Jul. 2012	2.5	16.1	Oct. 2022	1.79	11.6
Aug. 2012	2.3	20.1	Nov. 2022	1.65	11.2
Sep. 2012	1.70	14.30	Dec. 2022	1.68	12.5
Oct. 2012	1.4	24.6	Jan. 2023	2.30	13.4
Nov. 2012	1.3	13.9	Feb. 2023	3.10	17.9

Table 2. Average annual wind speed values for the study area

Year	Yearly average velocity (m/s)	Yearly expected velocity (m/s)
First year (August 2010 to July 2011)	2.43	2.3947
Second year (August 2011 to July 2012)	2.22	2.2088
Third year (August 2012 to July 2013)	2.15	2.1539
Fourth year (August 2021 to July 2022)	2.10	2.1308
Average wind speed for four years	2.225	2.22205

Table 3. Surface roughness coefficient for the study area

Year	Surface roughness coefficient (α)
First year (August 2010 to July 2011)	0.339
Second year (August 2011 to July 2012)	0.349
Third year (August 2012 to July 2013)	0.352
Fourth year (August 2021 to July 2022)	0.374
The average coefficient of friction	0.346

summer months (June, July and August) recorded the highest rates of speed Figure 4. This behavior was repeated every year, and the reason for the high wind speed rates during this time of the year is due to the prevalence of atmospheric instability accompanying the movement of air depressions and the heterogeneous heating process in the upper layers of the atmosphere, and this is a valuable result because the high of these rates coincides with the peak energy demand in these months due to the urgent need to irrigate the

Table 4. Comparison of average wind speed (m/s) at heights of 10 m and 50 m

Date	Average speed at a height of (10 m)	Average speed at a height of (50 m)	Date	Average speed at a height of (10 m)	Average speed at a height of (50 m)
Aug. 2010	2.3	4.15	Dec. 2012	1.1	1.99
Sep. 2010	2.7	4.88	Jan. 2013	1	1.81
Oct. 2010	2.3	4.15	Feb. 2013	1.1	1.99
Nov. 2010	1.7	3.07	Mar. 2013	2.4	4.33
Dec. 2010	2.1	3.79	Apr. 2013	3.2	5.78
Jan. 2011	1.8	3.25	May. 2013	3.5	6.32
Feb. 2011	1.7	3.07	Jun. 2013	3.6	6.50
Mar. 2011	2.1	3.79	Aug. 2021	2.20	3.1
Apr. 2011	2.8	5.06	Sep. 2021	2.30	4.2
May. 2011	2.7	4.88	Oct. 2021	1.80	3.4
Jun. 2011	3.7	6.68	Nov. 2021	1.70	3.5
Jul. 2011	3.3	5.96	Dec. 2021	1.70	3.3
Aug. 2011	3.1	5.60	Jan. 2022	1.61	3.5
Sep. 2011	2.2	3.97	Feb. 2022	1.86	3.4
Oct. 2011	2.1	3.79	Mar. 2022	2.15	4.5
Nov. 2011	1.8	3.25	Apr. 2022	2.15	3.4
Dec. 2011	1.3	2.35	May. 2022	2.28	3.8
Jan. 2012	1.233	2.23	Jun. 2022	2.71	4.2
Apr. 2012	2.1	3.79	Jul. 2022	2.67	4.8
May. 2012	2.6	4.70	Aug. 2022	2.60	4.7
Jun. 2012	3.3	5.96	Sep. 2022	2.30	4.2
Jul. 2012	2.5	4.52	Oct. 2022	1.79	3.4
Aug. 2012	2.3	4.15	Nov. 2022	1.65	3.5
Sep. 2012	1.70	3.07	Dec. 2022	1.68	3.3
Oct. 2012	1.4	2.53	Jan. 2023	2.30	4.4
Nov. 2012	1.3	2.35	Feb. 2023	3.10	6.2

agricultural land. Table 2 represents a comparison of the average annual wind speed for four different years. It is noted that the average wind speed for the first year (August 2010 to July 2011) is the highest. It is noted that the wind speed values in the northern region of Iraq, including the Hawija region, are lower than the rest of the other regions of Iraq. The reason for the decrease in wind velocity rates in the northern region is the effect of mountain heights on wind movement. The highest recorded wind velocity was 29.5 m/s in April 2011, and the lowest recorded wind velocity was 6.5 m/s in January 2013. It is also noted that there is no clear correlation between the values of the highest velocity with the hot months of the year, but the lowest values for the highest velocity were during the winter months, and this indicates that there is no economic feasibility for using wind to generate electricity in the winter season and to confirm the accuracy of this conclusion, readings must be taken at an altitude of 50 m to reach good reliability of this result [35, 48]. From equation (3), the ground surface roughness coefficient (α) is calculated for the four years shown in Table 3. Using the roughness coefficient in equation (3), it has been gotten the wind speed for the different months of the year at a height of 50 m Table 4, and it is clear from this table that the wind speed at a height of 50 m is suitable for generating electricity as it is higher than (3.5 m/s) in different months of the year and average wind speed during the year (4.12 m/s). From the analysis of wind speed trends, it was found that the highest percentage of wind direction is found in the northwest winds (27.29%), then the southeast winds (17.31%), while the lowest percentage is found in the south winds by (2.84%). These results coincided with the [40], who attributed the reason for the recurrence of this trend to the nature of the surface slope towards the east and the nature of the pressure slope from the atmospheric high on the Mediterranean Sea, which gives dominance to this direction, and this leads to the need to set up wind turbines in a direction perpendicular to the direction of the prevailing winds.

The Results of the Predictions Model

Figure 5 represents a comparison of the practically measured values that were predicted using the proposed model for the year 2022, where we see that during the months (June, July, August), there is a relative increase in wind speed compared to other months of the year. The prediction itself is at the appropriate level with a difference that is either bigger or smaller. The figure shows the percentage of disagreement between the two readings (error), which is sometimes

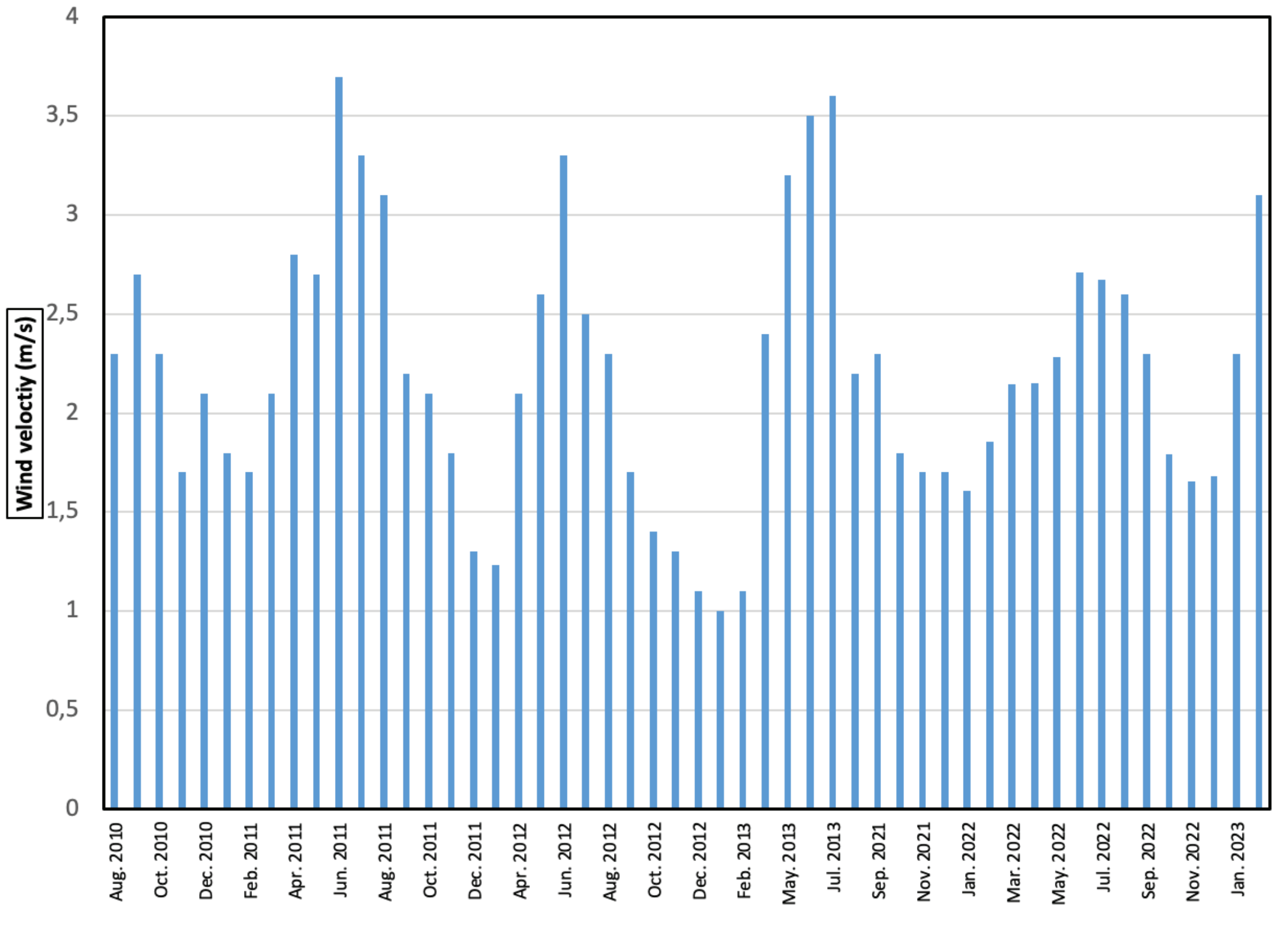


Figure 4. Average monthly wind speed values for the study area.

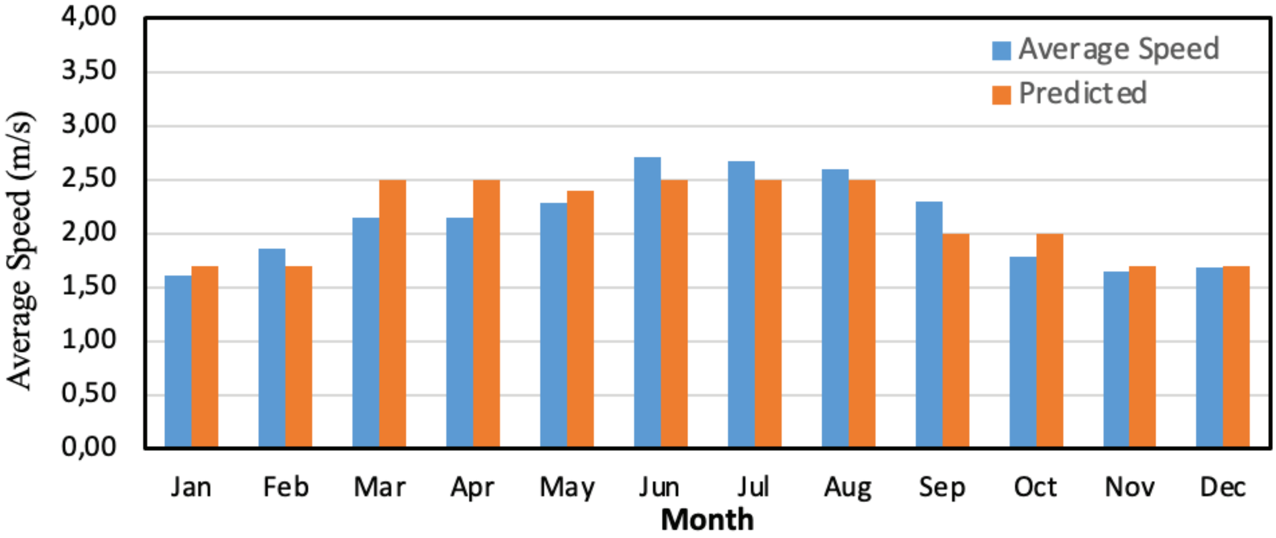
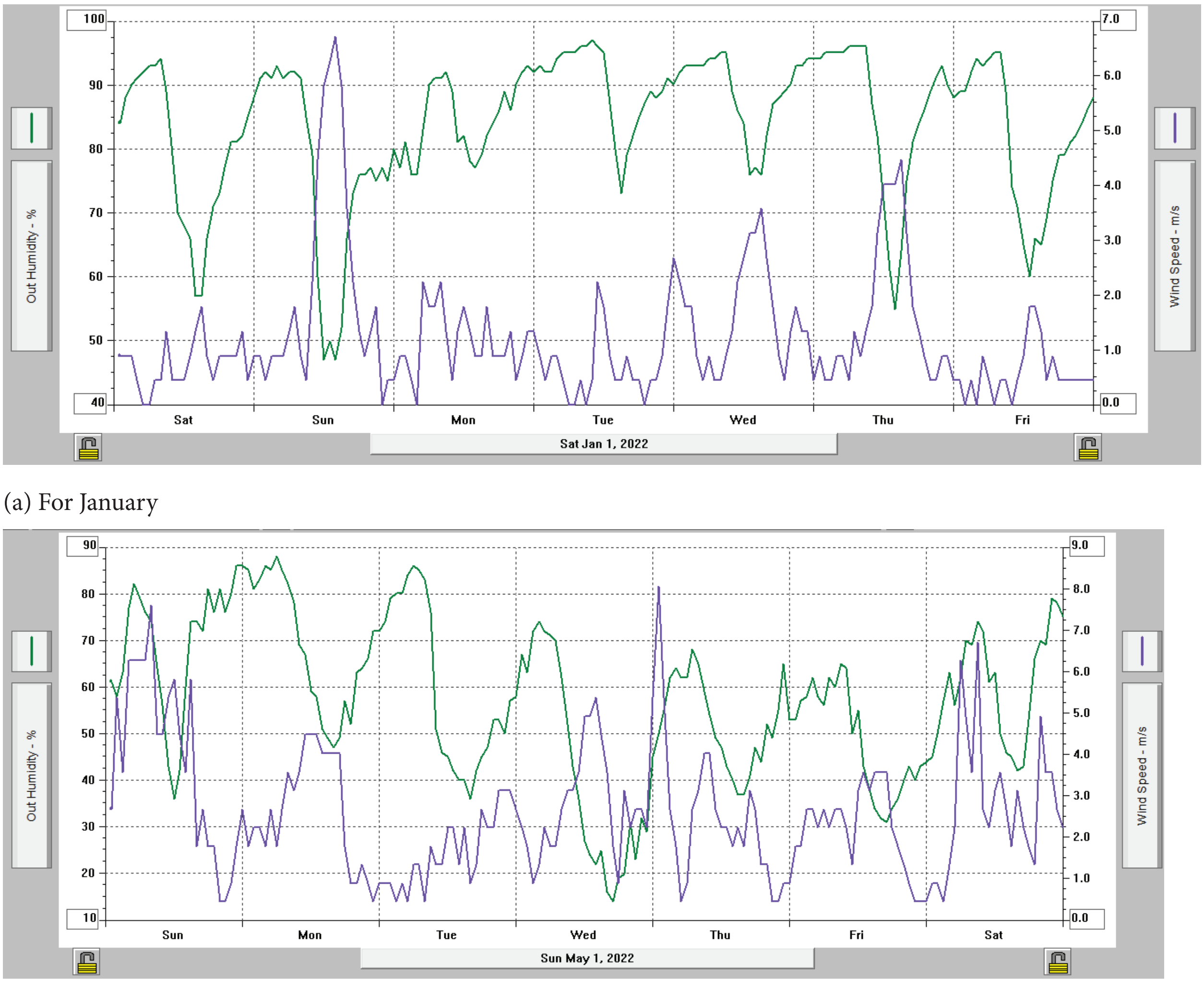


Figure 5. Recorded and predicted Average wind speed for one year.



(a) For January

(b) For May

Figure 6. The relationship between wind speed and relative humidity.

positive and sometimes negative. Humidity is an important factor in wind speed, which is evident from these results, as humidity is considered to be somewhat lacking in previous months. The speed at which air flows over the surface of water affects the rate of evaporation. Humidity depends upon the amount of vapor present in the air. so, the higher wind speed causes minimum evaporation of water and low humidity, while lower wind speed causes maximum evaporation of water and high humidity. Figure 6 represents the relationship between recorded wind velocity and relative humidity for January and May. Generally, it is noted that high wind velocity is associated with low relative humidity, and vice versa. It is also noted that the results were close between the practical readings and the results of the proposed model. The readings recorded from the proposed system are higher or lower than those readings recorded from the weather system, and this is a natural matter that must be proven because the forecasting system gives results close to the truth see Figure 5. Figure 7 also shows a comparison of the practical results and the proposed model for May 15, 2022, and there was a great convergence between the two models. The results of our wind speed prediction model show that there is a discrepancy between the proposed values and the original values in some cases.

In particular, it has been found that some predicted values were lower, and some were greater than the matching original values. This gap can be attributable to various things, such as flaws in the model's predictions, restrictions on the data used to train and test the model, and variability in the actual wind speed readings. It has examined the distribution of errors in the model's predictions to learn more about the causes of this disparity. It has been discovered that the errors were typically regularly distributed near zero, suggesting that the model's predictions were subject to random error. It has been seen some bias in the inaccuracies, though, with the model generally underestimating wind speed numbers in some scenarios while overestimating them in others. It has been suggested additional research into the underlying patterns and sources of variability in the wind speed data, as well as an examination of various model architectures and parameters, in order to address these disparities and enhance the precision of forecasts.

However, it is crucial to keep in mind that our model for predicting wind speed still offers useful insights and can be used successfully in a variety of applications despite these differences. You might wish to look at the distribution of the errors to better comprehend these errors. Calculating the difference between the actual and anticipated wind speed numbers for each observation in the dataset is one technique to accomplish this. The error values can then be plotted as a histogram so that everyone can see how they are spread. If your model is making random errors and the errors are usually distributed around zero, you may want to think about changing the model's parameters or adding new data to increase its accuracy. On the other hand, if the mistakes are skewed toward over- or under-predicting wind speed, you might need to change the model's design or look at several neural network architectures that might better capture the underlying patterns in the data. It's also crucial to think about how these mistakes may affect your forecasts for wind speed. The inaccuracies might not be a major problem if they are minimal and the forecasts can still be applied. However, it can be necessary to deal with the errors more directly if they are considerable and have a significant impact on the accuracy of forecasts. Using the backpropagation algorithm, the predicted data are shown in Figure 8

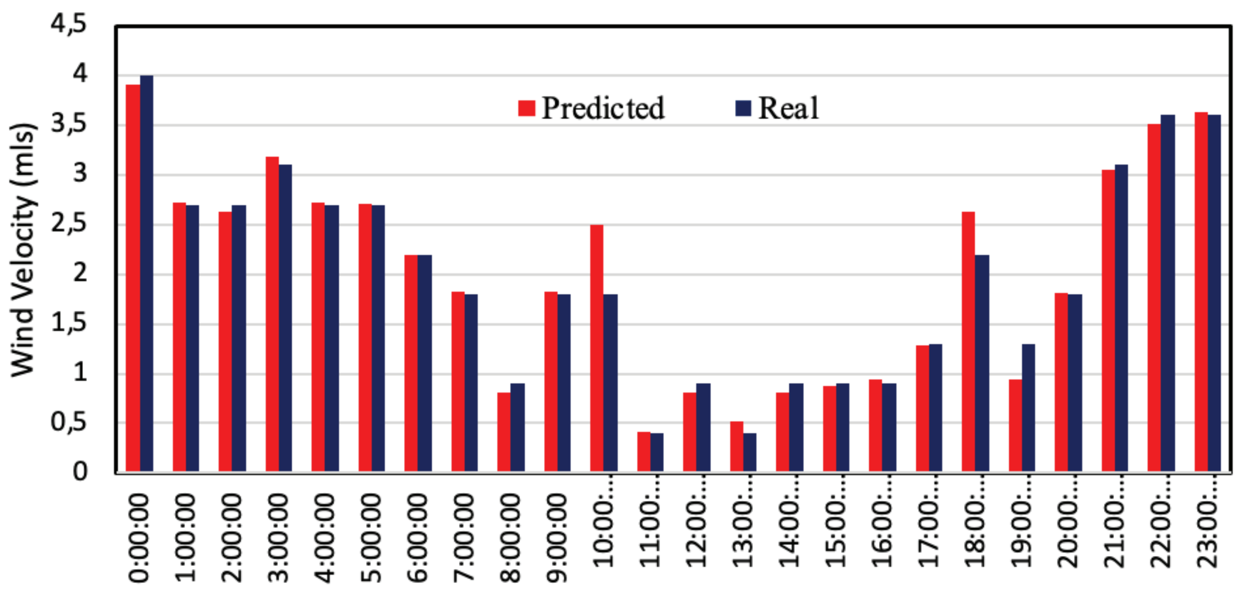


Figure 7. Wind speed distribution during the day (15 May 2022).

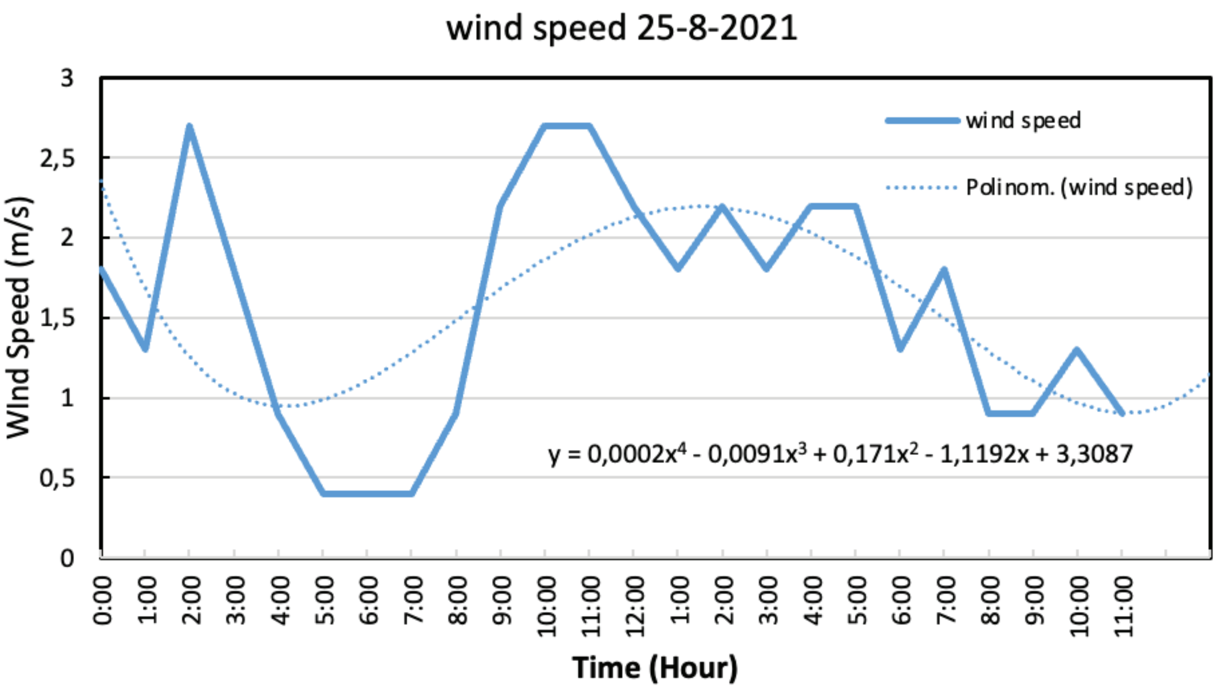


Figure 8. Wind speed record with the fitting equation 25-8-2021.

below, the error percentage is the difference between plus and minus with respect to real records. These errors are traditional cases for each mathematical algorithm because the related process which related to the percentage tolerance.

Overall, the data on wind speed has made it possible to trust the values recorded by neural networks in these kinds of specialized investigations. This study employs a novel approach to solving problems by using prior cases or the so-called objective function, which yields results as near to reality as feasible without requiring repeated season-by-season waiting.

CONCLUSION

In order to capture intricate, non-linear correlations in data, neural networks shine. They can simulate complex patterns that linear models can find difficult to represent. They are able to successfully manage high-dimensional and diversified data because of these capabilities. They eliminate the need for human feature engineering by automatically extracting pertinent characteristics from raw data. This capacity to extract valuable characteristics comes in handy for tasks where the underlying patterns are hard to explain or not clearly understood.

The ANN can be used to solve difficult problems and control non-linear equations. In this work, it has been used to predict the wind speed for specific days, months and years. This can be an easier manner for the researcher in this field for wind-turbine arrays which are used. The predicted values of wind speed are compared with those real records obtained by the weather station (Vantage Pro), and some errors were recorded because the ANN give its output through mathematical equations and a soft comparator. The recommended work in this study has led to the development of some important challenges that should be taken into account in further research and studies:

1. Industrial values and states that depend on a small number of variables and fall within a specified range can be predicted by artificial intelligence.
2. The wind speed forecast came very close to the numbers observed and measured by meteorological systems.
3. The ability to anticipate speed values, starting with speed per hour and per day, average speed per month, greatest speed per day, average speed per year, etc., is one of this sort of network's benefits.
4. The artificial intelligence technology revolution will use this data, among others, to pinpoint future directions for scientific inquiry and new developments.

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

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