Application of Artificial Neural Network to Predict Wind Speed: Case Study in Duhok City, Iraq

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Abstract. Wind speed prediction is very critical for clean energy electricity generation, commitment decision-making, and wind farms planning strategy studies. It is also important for the wind energy industry to determine the characteristics of wind speed for site selection and to know the output of the wind turbine. A prediction of Daily Average Wind Speed (DAWS) for Duhok city, Iraq using Feed Forward (FF) Artificial Neural Network (ANN) is investigated using weather records for Duhok city, Iraq. To build and train the suggested network, MATLAB software is used. The variables that used as inputs are Daily Average of Humidity (H), Pressure (P), Minimum Temperature (Tmin), Solar Radiation (SR), Maximum Temperature (Tmax), day (D) and month (M) to estimate DAWS. The suggested networks are analyzed using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) as statistical values. The proposed network forecasts accurate daily wind speed values based on the outcomes. This suggested method helps to predict the weather and to estimate the output strength of wind turbines.

Keywords: Wind speed, Feed Forward, Artificial Neural Network, RMSE, MAE

1. Introduction

The increasing of environmental pollution, together with increasing global population, and fast depleting reserves of fossil fuel, have encouraged researchers to search for clean and pollution-free resources of energy [1].

Wind energy (WNE), is one type of Renewable Energy (RE) resources for electricity generation (EG). It is one of the world’s fastest and growing source of EG [2], because wind speed is considered one of the most important source of energy that is clean and environmentally-friendly.

Wind Speed (WS) or wind velocity is a key factor in producing wind power and dispersing pollutants in air. WNE, as an RE, alternative to fossil fuels, is plentiful, widely distributed, clean and produces no greenhouse gases emissions during operation [3].

Wind Power (P) produced by a wind turbine is expressed as follow [4]:

\[ P = (0.5) \cdot A \cdot \rho \cdot v^3 \]  (1)
where $A$ is swept area of turbine, $v$ velocity or the speed of wind and $\rho$ is the density of air.

Increasing the WS, will increase the power output effectively since $P$ is proportional to the cube of the wind speed. Based on the station observations in Europe, Australia, and North America, several studies have recorded systematic variations in WS \cite{5}. For wind speed predicting, a number of methods have been developed. These approaches can generally be divided into three models or three groups, namely traditional statistical models and non-conventional models of time series as well as physical models. Physical simulations are also referred to WS meteorological forecasts, which provide the numerical approximation of models describing the case of the atmosphere \cite{6}.

Recently, due to the continuous rise in $P$ generation worldwide, new problems related to the intermittent existence of wind energy have drawn researchers' attention to the methods of WS prediction \cite{7}. Therefore, the evaluation of the WS characteristics is more critical to the wind energy industry than any other parameter for the selection of sites and estimation of wind farms' performance \cite{8}.

Meteorological data including WS and their distribution, are monitored through Wind Observation Stations [WOS] in several parts of the world. The data obtained is used as input variable or factor in the Recognition, of WNE as a RE resources \cite{9-11}. Hence, it would be extremely useful to create a modern model Which is able to forecast WS properties in any random position with a little obtainable close WOSs data. It desiderates help the decision maker to decide, and the engineers, local designers, planners to determine the best location for the construction of wind turbines or wind plants in relation to the sites available. It was proved that Artificial Neural Network (ANN) could be a good promising technology, and a good tool to predict some parameters in different topics such as WNE estimation or assessments, approximation, including pattern recognition, and prediction of time series. It has been widely used in the field of WS prediction \cite{12-17} for this purpose.

Unfortunately, in Iraq including Duhok city, the measuring devices of data collection are not yet installed in many rural and remote locations. Parameters related to wind data, e.g. Wind Atlas maps are not available. Only by extrapolating towns, the wind data can be applied for rural sites with similar meteorological conditions. No special attention has been paid to the development of wind potential estimation models in Duhok city. In this paper, ANN method is proposed for prediction of WS in Duhok city, Iraq, which is required for preliminary design assessment of wind devices for wind sites where reliable data is not readily available. Results from this study will, no doubt, be useful to local designers, planners and manufacturers of wind farm for the studied locations in north area of Iraq.

The main aim of this research is to present ANN models using Feed-Forward (FF) technique for predicting DAWS for Duhok city, Iraq. This study was done on the basis of the meteorological data such as humidity ($H$ (%)), pressure ($P$ (mbar)), minimum temperature ($T_{\text{min}}$ ($^\circ$C)), solar radiation(SR) (W/m$^2$), maximum temperature ($T_{\text{max}}$ ($^\circ$C)), day ($D$) and month ($M$) as inputs and wind speed (WS (m/s)) as output for the period (2013-2018). Meteorological data that collected between 2013 to 2017 were used to train the ANN while data for 2018 were used for both testing and validating the predicted values.

2. Materials and Method

2.1. Data Collection
The data collected for $T_{\text{min}}, T_{\text{max}}, D, M, H, P, SR$ and WS were acquired from the Directorate of Meteorology and Seismology based in Duhok city \cite{18}, Iraq, that covers six years (2013-2018). Minimum, maximum, mean and standard deviation of meteorological variable for (2013-2018) are shown in Table 1.
Table 1. Description data.

| Meteorological variable | Min. | Max. | Mean | S.D |
|-------------------------|------|------|------|-----|
| Tmax(°C)                | 2.1  | 48.1 | 27.38| 11.55|
| Tmin(°C)                | -7.7 | 31.1 | 12.09| 7.96 |
| R(%)                    | 10.6 | 99   | 49.34| 23.86|
| P(mbar)                 | 990  | 1033 | 1010.16| 8.84 |
| SR(W/m²)                | 4    | 395  | 177.98| 82.58|
| WS(m/s)                 | 0    | 12.1 | 2.05 | 1.61 |

2.2. The Proposed Artificial Neural Network (ANN)

Artificial Neural Networks (ANNs) are non-algorithmic, yet intensely parallel, information processing systems. By observing previously documented data, the connection between the input and output variables is learned. An ANN is similar to a biological neural system consisting of layers called neurons of parallel elemental units. The ANN contains neurons that are joint with number of links through which the information passes. Neural networks are used to resolve a problem through training [19-22].

A fully connected, three-layer, feed-forward, perceptron neural network is used for the wind speed forecast as shown in Figure 1. Completely linked implies that in the following layer, the output from each input and hidden neuron is transmitted to all of the neurons.

The ANN-FF learning procedure is utilized to know the prediction and validation of the difference in wind speed by year. In these networks, Tmax, Tmin, D, M, R, P and SR are the input variables for the models. In comparison, wind speed during the six-year data study is the output component. After many trials of various numbers of hidden layers and neuron numbers, the model with twenty neurons and single hidden layer showed the best performance in predicting DAWS. The Levenberg-Marquardt algorithms for training with tangent transfer functions were investigated. This is to evaluate the optimum architecture of the ANN-FF, representing the highest determination coefficient, the lowest RMSE and the lowest MAE [23,24].

Two separate cases are used to forecast wind speed values using ANN in order to examine several local meteorological data results. DAWS values expected by seven input data values, as shown in Figure 1, in the first cases. The complete structure is also applied to the wind speed values in the second cases.

![Figure 1. Structure of artificial neural network.](image-url)
The model output was determined on the basis of the MAE and RMSE [19,25] in ANN-FF approaches, in order to measure how similar the expected values and the actual values are. The MAE and RMSE are calculated as:

\[
\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |W_{S_{p, i}} - W_{S_{m, i}}| \tag{2}
\]

\[
\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (W_{S_{p, i}} - W_{S_{m, i}})^2} \tag{3}
\]

where \(W_{S_{m, i}}\) and \(W_{S_{p, i}}\) are the measured and the predicted wind speed, respectively, and \(n\) is the number of samples.

3. Results and Discussion

The weather data that used for the duration (2013-2018) include 2191 daily records for Duhok city, Iraq. The records of the time (2013-2017) were used to train the network, while the network was checked or tested using 365 records (year 2018). The DAWS values are predicted using two different cases:

3.1. First case for prediction DAWS

In this case, DAWS predicted by seven input meteorological data as mentioned. The test results of this case are shown in Figure 2. The predicted DAWS values are compared with the Measured Values (MV). The results showed that the prediction was good. The values of MAE and RMSE for the expected DAWS for Duhok city are 0.98 and 1.34, respectively, based on the suggest evaluation standard. The results showed that the proposed model provides reliable outcomes. In addition, the MAE and RMSE value indicates that the built model is capable of predicting future values with reasonable accuracy.

![Figure 2. Comparison of results for first case of prediction DAWS.](image)

3.2. Second case for prediction DAWS

In this case, DAWS was predicted by seven input meteorological data and added WS. The result of this case is shown in Figure 3. The predicted DAWS values are compared with the MV. The prediction is very precise for the test data (see Figure 3). The values of MAE and RMSE for the expected DAWS for Duhok city are 0.038 and 0.076, respectively, based on the suggest evaluation standard. It is clear to be observed that the proposed model provides very precise results. In addition, the MAE and RMSE values indicate that the built model is capable of predicting future values with high accuracy as compared to the first one.
Figure 3. Comparison of results for second case of prediction DAWS.

The regression plots for ANN predict DAWS for the best case are shown in Figure 4. The correlation among the target and the output variables point out R over each Figure. The regression is equal to 0.99948 for test situation. The results showed that DAWS forecast is close to the MV. The regression values for validation and training are 0.99927 and 0.99945, respectively, and for all data is equal to 0.99942.

Figure 4. Regression plot for training, validation, test and all data.
4. Conclusion

In Duhok city, Iraq, the Daily Average Wind Speed (DAWS) predictions were made using Feed Forward Artificial Neural Networks (FF-ANN) with very good accuracy. Models of ANN using MATLAB were created for the period of six years (2013-2018). The MAE and RMSE values for forecasting DAWS were 0.98 and 1.34, respectively, for the first case and 0.038 and 0.076, respectively, for the second case. The correlation among the target and the output variables was found to be 0.99948 for the best case forecast DAWS for test results. These predictions can be used to assess the power production from the wind turbines.

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