El Cezeri
Journal of Science and Engineering
ISSN: 2148-3736

Research Article

Wind Power Prediction Based on Polynomial Regression Method

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DOI : 10.31202/ecjse.1722153
Received: 18.06.2025 Accepted: 19.09.2025
How to cite this article:
Hussein H. Saleh, "Wind Power Prediction Based on Polynomial Regression Method.", El-Cezeri Journal of Science and Engineering, Vol: 12, Iss: 3, (2025), pp.(274-282).
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Abstract Accurate prediction of wind energy output from site-specific wind velocity data is essential for evaluating the feasibility and energy yield of wind farm installations. This study presents a predictive framework for wind power assessment based on daily wind velocity datasets from eight Iraqi cities: Duhok, Mosul, Kirkuk, Baghdad, Najaf, Wasit, Qadisiyyah, and Basra. The proposed method employs polynomial regression (POR) as a nonlinear estimation technique to correlate daily wind speed data with turbine power output. POR is selected for its computational simplicity and adequacy in capturing the nonlinearity inherent in wind power curves. The predictive models are calibrated individually for each city using historical wind data and the manufacturer's specified power curve for the turbine. The results indicate that the POR-based predictions closely align with the actual turbine power curve across all sites, demonstrating low prediction error and strong curve-fitting behavior. Notably, Wasit, Qadisiyyah, and Basra exhibited the highest potential for wind energy generation, with annual predicted outputs exceeding 2000 kWh per turbine, indicating promising conditions for small-scale wind energy exploitation. In contrast, northern cities such as Duhok and Mosul yielded significantly lower outputs (<1000 kWh annually), suggesting limited economic viability under the studied configuration.

Keywords: Artificial intelligence, Machine learning, Wind power, Wind velocity.

I. INTRODUCTION

The slowly growing energy field and increasing demand for electric power are still unreliable and unstable in Iraq. Moreover, Iraqi households receive a daily average of less than twenty-four hours of electricity from the national grid [1]. Iraq is heavily dependent on petroleum products and fossil oil, as well as imported natural gas, to generate energy [2]. In addition, since June 2017, Iraq has lost 4 billion dollars annually due to importing natural gas to support forty-six power plants [3]. In most countries, the development and utilization of new power sources as renewable energy are used to reduce dependence on traditional energy sources, diversify energy sources, and reduce CO2 emissions. Among all forms of renewable energy, wind energy is a sustainable and pollution-free source, environmentally friendly, and the fastest growing in many regions around the world [4]. Nowadays, the use of wind farms is increasing in many countries as a low-cost power system, providing energy without operational fuel, and a significant alternative to traditional power plants that require fuel [5]. The accurate assessment of wind power potential is required before planning to implement a wind farm. Many researchers use several methods to predict wind ability, such as data decomposition, empirical models, and machine learning methods.

A novel wind energy forecasting system to enhance forecasting capability by refining the raw time series using horizontal denoising and vertical granulation methods, The predictive performance was evaluated based on wind energy, speed, and direction data in China and Turkey, the proposed system was contribute to the advancement of wind-power prediction theory with substantial potential for practical applications [6]. Three machine learning methods Bayesian optimization (BO) to optimally tune hyperparameters of the Gaussian process regression (GPR), Support Vector Regression (SVR) with different kernels, and ensemble learning (ES) models have been used to employ and investigate their forecasting performance in wind power generation for three wind turbines in France, Turkey, and Kaggle. The results reveal the benefit of considering lagged data and input variables to better forecast wind power [7]. A new hybrid wind speed prediction model is designed based on the SSA (Singular Spectrum Analysis), EMD (Empirical Mode Decomposition), and CNNSVM (Convolutional Support Vector Machine) to reduce the noise and extract the trend information of the original wind speed data, extract the fluctuation features of the wind speed data, decompose the wind speed time series into several sub-layers and predict each of the wind speed sub-layers to investigate the prediction performance of the proposed model. According to the prediction results, the established model had significantly better performance than the seven comparison models from 1-step to 3-step wind speed predictions [8]. A novel wind speed forecasting framework for stationary data based on a hybrid decomposition method and

deep learning models to achieve high estimating accuracy for the Dumat Al-Jandal wind farm in Al-Jouf, Saudi Arabia. According to statistical indicators, the results demonstrated the superiority of the proposed model in single and multiple wind prediction. The average means absolute error, root mean square error, and R-squared error [9]. In Spain, a triple-stage multi-step wind power forecasting approach is proposed by applying attention-based deep residual gated recurrent unit (GRU), network combined with ensemble empirical mode decomposition (EEMD), and crisscross optimization algorithm (CSO), the results demonstrate that the proposed hybrid model has significant advantage over other state-of-the-art models involved in study [10]. Other techniques, such as the Long Short-Term Memory (LSTM) network, were proposed to fit the nonlinearity between data variables and wind power of a wind farm in Hunan, China, during the four seasons of 2020. This method proved the accuracy of wind power prediction and the effectiveness for power dispatching [11]. Several regression methods, namely, Deep neural network (DNN), k-nearest neighbor (KNN) regressor, long short-term memory (LSTM), averaging model, random forest (RF) regressor, bagging regressor, and gradient boosting (GB) regressor are constructed to achieve the prediction of wind power generation, using dataset includes 4 features and 50530 instances. The experimental results illustrated that the proposed optimization of LSTM achieved the best results in forecasting the wind power values [12]. The prior review literature demonstrates the reliability and efficiency of machine learning techniques in modeling wind power. Furthermore, these techniques are complex, less interpretable, require large labeled datasets, and more computational resources, especially for deep networks [13]. As a result, the author suggests simplifying and obtaining higher performance prediction via a polynomial technique for regression. This methodology is easily interpretable, suitable for simpler non-linear data, and requires fewer computational resources. This study provides new insights into using turbine model parameters, presenting a novel wind power prediction model. In contrast to traditional models, the proposed model has reduced implementation complexity and computational burden, as well as ease of real-time implementation.

In Iraq, the number of wind farms for energy generation is almost non-existent. Moreover, the amount of research on wind energy forecasting is limited in circumstances of acute energy deficiency and increasing demand.

To avoid the lack of energy problem, obtain the maximum benefit of renewable energy sources, and understand the ability and reliability of wind power, this study designs and develops a wind power forecasting model based on wind turbine output parameters as the learning stage, followed by the POR method aiming to predict wind energy in eight different locations in Iraq.

II. LOCATION DESCRIPTION AND DATA COLLECTION

Iraq has an area of 437,072 square kilometers, geographically located in the western part of the Asia continent and enjoys considerable climatic diversity [14]. Annually, the highest values of wind velocity are recorded in June and July, while the lowest values are in December. Also, the annual averages of wind velocity were divided into three regions: northern (2.7 m/s), middle (3.6 m/s), and southern (4.1 m/s) [15].

The daily wind velocity recorded at 10 Meters in height for the 2023 season in eight cities, as shown in Figure 1, as well as geographical locations presented in Table 1, are obtained from the Iraqi Meteorological Organization and Seismology (IMOS) [16]. In addition, the performance data of the (GhrepowerFD21-50_61.2kW_21.5) turbine model that determines the output parameters of the turbine at a given wind velocity has been provided from the National Renewable Energy Laboratory (NREL). The parameters of this turbine are presented in Table 2 [17]. The power generated by any wind turbine is dependent on the velocity of the wind hitting it and the characteristics of the turbine model. The parameters associated with the POR method are wind velocity values and their corresponding turbine output power, as shown in Figure 2. The minimum wind velocity required to obtain output power for the suggested turbine is 2.9 meters per second (m/s), which is most appropriate with the natural wind velocity of the study areas. All datasets are available at “https://github.com/Dataset-comp-j”.

Table 1. Geographical Location of the Cities Considered.

City	Latitude (°N)	Longitude (°E)
Duhok	36.8632	42.9885
Mosul	36.3489	43.1577
Kirkuk	35.4666	44.3799
Baghdad	33.3152	44.3661
Najaf	32.0107	44.3265
Wasit	32.5165	45.8160
Qadisiyyah	32.0437	45.1495
Basrah	30.5258	47.7738



Figure 1. Location of the cities on the map of Iraq.

III. METHODOLOGY

The present study aims to extract the total annual values of wind energy using output parameters of specific turbine models and assess the performance of the POR method in predicting the annual amounts of wind power in eight cities in Iraq. To achieve these goals, and to establish the model for every location, two parameters and 16 instances of the (GhrepowerFD21-50_61.2kW_21.5) turbine model have been used as input data to produce the learning stage of the prediction model, and 2904 instances of the daily wind velocity dataset are used to estimate the approximate daily power generated at each location. The parameters of the suggested turbine consist of the output of power levels in the range [1 - 60] kWh at a given wind velocity, as shown in Figure 2. These two parameters have been used as the first inputs to the POR technique to perform the learning process (building a learning model). The second input parameter is the daily wind velocity of one season for a specific location. Both first and second input parameters are basic materials to generate models and obtain the desired output value, as shown in Figure 3.

One of the limitations of the POR method is the risk of overfitting, when the dataset contains noise in the input that leads to poor performance and low accuracy. Therefore, in this study, a few instances of the turbine parameters have negative values. The wind velocity dataset contains values that are out-of-range of the turbine wind parameter. In current research, both the negative values and out of range instances have been removed to minimize prediction errors and produce efficient models.

All values of the wind velocity that are lower than the minimum operating values of the proposed turbine have been removed. The percentage of removed values was (24%, 55%, 35%, 39%, 31%, 24%, 26%, and 20%) in Duhok, Mosul, Kirkuk, Baghdad, Najaf, Wasit, Qadisiyyah, and Basra, respectively.

A. POLYNOMIAL REGRESSION

Polynomial regression is a supervised parametric machine learning algorithm that deal with regression problems [18]. It is a form of linear regression method used when there is a nonlinear relationship between the dependent and independent variables, and it can analyze the relationships between variables by fitting higher degree polynomial functions. It is also considered to be a special case of multiple linear regression [19]. The formulation structure consisted of a single equation with the simplest interpretation of learning parameters that is applicable using fewer computational resources. In predictive methods, the model consists of a random output variable y^and a set of random input variables $x=\{x_1 \ldots, x_k\}$. The following formula represents the polynomial regression fitting between dependent and independent variables:

$$\hat{y} = T_0 + T_1 x + T_2 x^2 + \ldots + T_k x^k \tag{1}$$

The $\hat{y}$ is the output variable, x is the input variable, T_0 is the intercept, $T_1, T_2, \ldots, T_k$ are polynomial regression coefficients, and k is the degree of the polynomial [20]. The characteristic of the polynomial regression method is that it uses one input variable. Also, the formula has the power of the input variable x, which is different from the linear regression methods, where the simpler first-order model (a "straight line") is adequate in describing the trend in the data. The model has tested the null hypothesis:

$$H_0: T_2 = T_3 = 0 \tag{2}$$

If a polynomial term of a given order is retained, then *all related lower-order terms are also retained*. That is, if a quadratic term (x^2) is deemed significant, then it is standard practice to use this regression function:

$$\mu y = T_0 + T_1 x + T_2 x^2 \quad (3)$$

Whether or not the linear term x is significant, the polynomial model is represented hierarchically [21]. One of the procedures for building a polynomial model is selecting the degree of the polynomial, and the highest power of the variable in the polynomial expression is crucial for various applications. In this work, the degree of the polynomial used is 25, which has been selected based on the visual match between the blue curve of turbine parameters and the red scatter points.

Table 2. The Parameters of the (GhrepowerFD21-50_61.2kW_21.5) Turbine Model.

Item	Value	Units
Rated Power	50	kW
Rated Wind velocity	11.3	m/s
Cut-in Wind velocity	4	m/s
Cut-out Wind velocity	25	m/s
Rotor Diameter	14.9	m
Hub Height	31.1	m

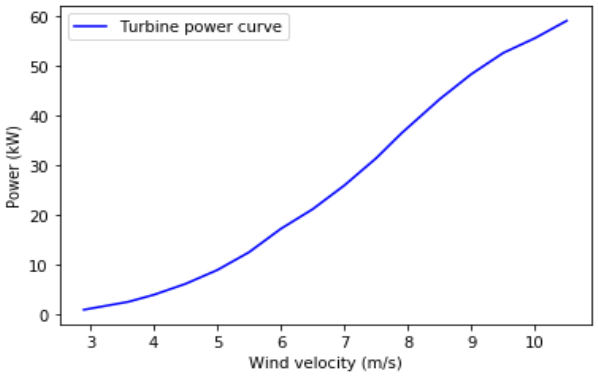


Figure 2. The power curve output of the (GhrepowerFD21-50_61.2kW_21.5) turbine model at a given wind velocity.

IV. RESULT AND DISCUSSION

The POR method was applied as the proposed approach to predict wind energy at eight locations in Iraq using the parameters of the (GhrepowerFD21-50_61.2kW_21.5) turbine model and wind velocity dataset of the 2023 season. To evaluate and prove the performance of the POR models, the parameters of turbine models were plotted against the prediction wind power, Figure 4 illustrate the turbine parameters curve and scatter points of the prediction wind power at all locations, the perfect convergence observed between turbine model curve and scatter points indicate to the successful and high accuracy prediction, as seen from Figure 4 the POR models perform well in predicting wind energy and efficient in analysis the parameters of proposed turbine model. Figure 5 shows the monthly means of wind velocity of the study locations, in the north of the country the wind recorded lowest means specifically in Duhok and Musol, whereas the middle cities Baghdad and Najaf have slightly higher means compared with the northern locations, while the best monthly means were in Wasit, Qadisiyyah, and Basra, especially in June and July with velocity exceeded 5 m/s. Table 3 explains the power annual amounts that can be obtained from a single turbine. The total power was less than 1000 kWh in Duhok and Mosul, while exceeding 1000 kWh in Kirkuk, Baghdad, and Najaf. In other locations, total annual energy was recorded in Wasit and Qadisiyyah, which were limited to 2000 kWh for each turbine. The greatest amounts of wind power are registered in Basra city, which exceeded 3000 kWh annually. The wind energy quantities at the study locations present an incentive to encourage investment in the wind energy field and exploit the wind element to support the energy sector. Figure 6 presents the box plots of the wind power density of all proposed locations. It illustrates the annual distribution of predicted wind power for each model achieved based on the POR technique. The Basra location generally recorded high amounts of wind power density distribution exceeding 20 kWh and maximum of 45.8 kWh, as explained at the beginning and end of the upper line extending from the box, whereas the wind power density distribution values in Najaf, Wasit and Qadisiyyah were less than 10 kWh as well as the fluctuation of the higher values. The remaining locations were worst in term of wind power density distribution due to poor wind velocity in these cities at 10 meters. The single points that fall outside the whiskers on the diagram show the outliers of each location. According to the above outcomes, the study locations contain a wealth of wind energy, which could be one of the basic pillars of support for the energy field in Iraq. In addition, these results proved the effectiveness of the (GhrepowerFD21-50_61.2kW_21.5) turbine model in extracting the best amounts from energy, which makes it recommended by the author.

V. CONCLUSION

To understand the ability of wind power, support the national electricity grid, and add a new power source, this study has designed and developed wind power prediction models based on the polynomial regression method for forecasting wind power amounts in eight cities using (GhrepowerFD21-50_61.2kW_21.5) turbine model parameters as training examples for the models.

Table 3. Total Annual Amounts of the Wind Power for a Single Turbine.

Location	Total wind power (kWh)
Duhok	974.7
Mosul	625.7
kirkuk	1224.3
Baghdad	1036.3
Najaf	1548
Wasit	2926.6
Qadisiyyah	2104.7
Basra	3595.2

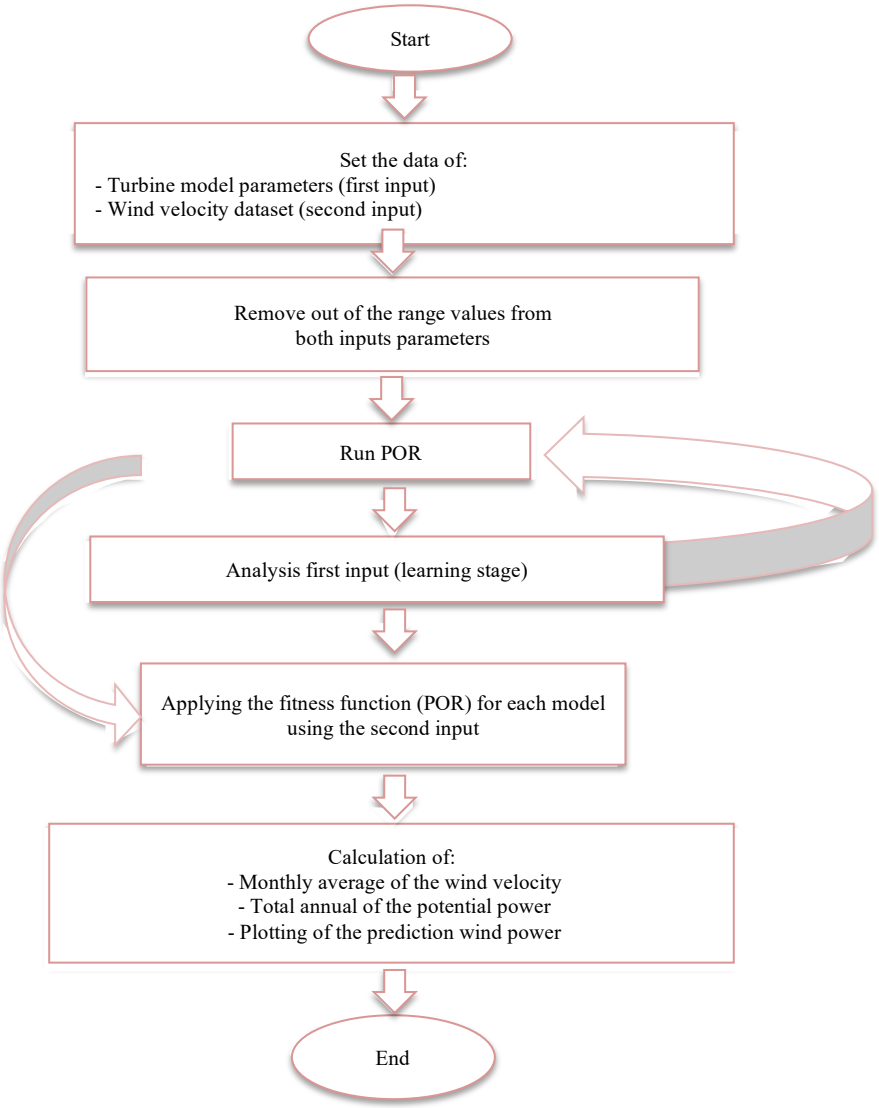


Figure 3. Flowchart of the core structure of the study [22].

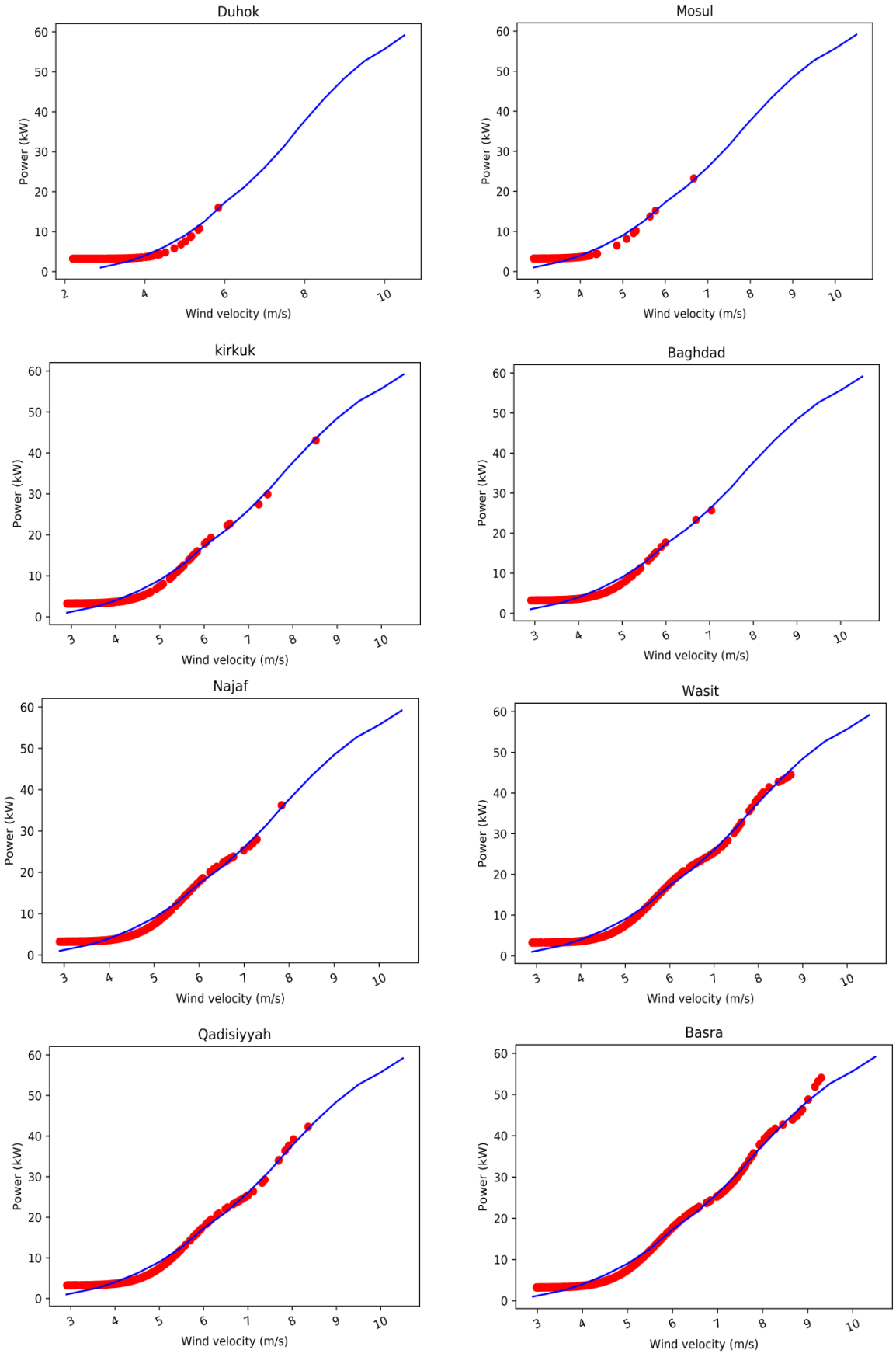


Figure 4. Turbine parameters curve and scatter points of the predicted wind power at all locations.

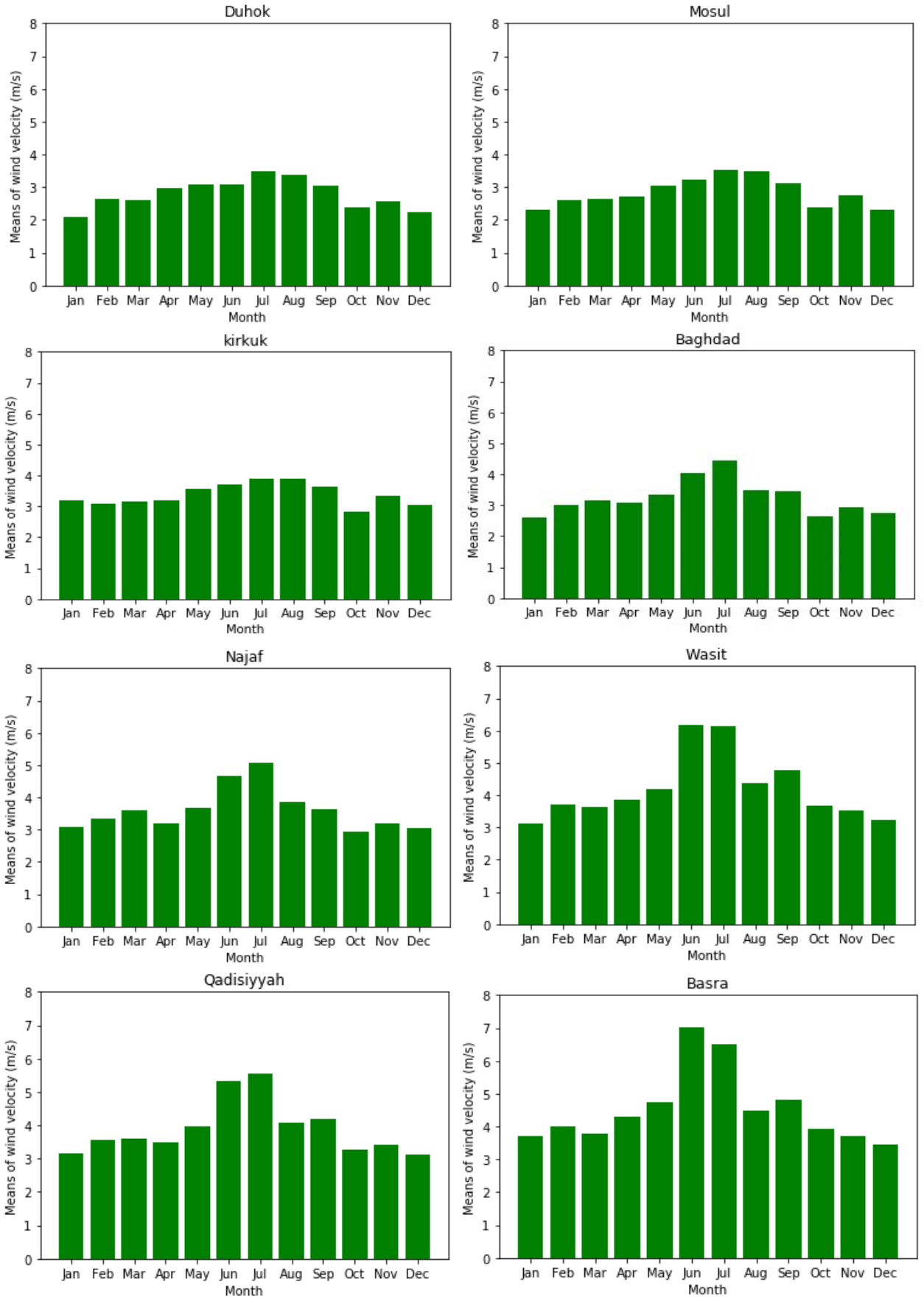


Figure 5. Monthly means of wind velocity of the study locations.

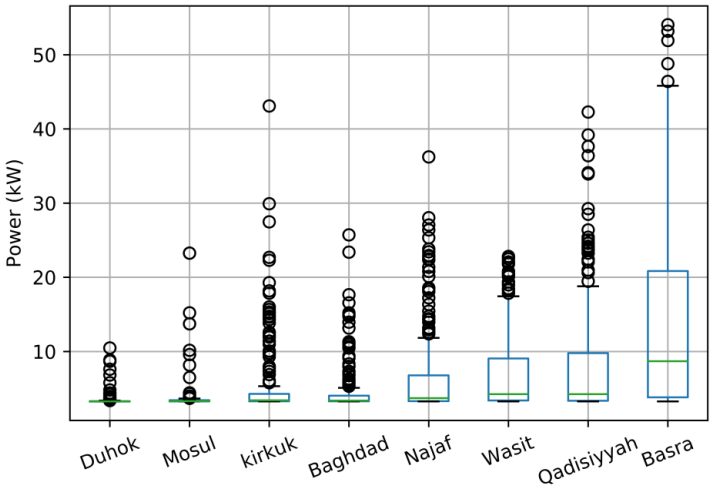


Figure 6. Box plots of wind power density at all proposed locations.

Annually, the monthly means of wind velocity at the southern locations recorded high velocities exceeding 5 m/s, especially in June and July, while the means of wind velocity began to gradually decrease in the middle and northern regions during the season. The results of this study demonstrate variations in the values of wind energy in the north, middle, and south locations. The northern locations have modest quantities of wind power due to the scarcity of wind velocity at 10 meters. However, the best wind velocity averages were in the middle and southern regions, where high quantities of wind power are available. Also, Qadisiyyah and Basra were recognized as powerful producers of wind energy. As a result, Figure 4 proved the accuracy and superior capability of POR as a less complex technique in extracting wind energy potential at different locations and gave better performance. Furthermore, the results of this work encourage the self-sufficient energy, saving billions of dollars spent on importing energy or fuel to operate conventional power plants and investing in clean energy. In addition to developing the energy field. The study confirms the viability of polynomial regression for wind energy estimation when turbine specific performance data is available. However, for future work, the inclusion of additional meteorological variables (e.g., air density variation, turbulence intensity, and diurnal wind patterns) and comparison with more advanced machine learning models (e.g., SVR, ANN) could improve generalizability and robustness. Furthermore, this element could be useful in wind power forecasting and understanding the wind density of each location.

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