# ore Accurate Wind Power Prediction Based on Intelligent Error Correction Model

Bellat Abdelouahad, Mansouri Abderrahman, Tyass Ilham, Mansouri Khalifa and Raihani Abdelhadi



February 8, 2023

# More accurate wind power prediction based on intelligent error correction model

Bellat Abdelouahad, Abderrahman Mansouri, Tyass Ilham,Khalifa Mansouri, Raihani Abdelhadi
*Modeling and Simulation of Intelligent Industrial Systems Laboratory (M2S2I), ENSET Mohammedia, Hassan II University, Casablanca, Morocco*

*bellatabdelouahad@gmail.com , abderrahman.mansourii@gmail.com, tyass1@yahoo.fr,khmansouri@hotmail.com ,abraihani@yahoo.fr*

***Abstract*—In order to limit the negative impacts of wind energy fluctuations on power system performance, this research suggests an improved hybrid method to improve the accuracy and efficiency of wind energy forecasts. This strategy mainly consists of a two-phase modeling technique. First, a main model based on the wind power curve is developed, whose function is to anticipate the evolution of wind power using physical mechanisms. The errors of the initial model are then extracted and become the study objectives of the second phase. Using the modeling capabilities of data mining techniques, data-driven models for error correction are developed. The ultimate results of wind energy projection are a combination of these two steps. The analysis of a real wind farm demonstrates that the proposed method outperforms conventional models in terms of accuracy and cost analysis. Using a specific degree of improvement, the quantitative results reveal significant improvement over the baseline physical model and conventional statistical models.**

***Keywords— hybrid, efficiency, errors, data mining, wind farm***

## I. INTRODUCTION

To combat the challenges of fossil fuel energy and environmental pollution, renewable energy is being created on a global scale. Wind energy is one of the most promising renewable energies and has progressed quickly over the past decade [1]. Today, wind energy accounts for a significant fraction of the power system [2], particularly in regions with abundant wind resources, such as China, the United States, Europe, etc. Nonetheless, the fluctuating and stochastic character of wind poses significant obstacles to the steady functioning of power systems [3] in light of the substantial volume of wind power output. Indeed The usual physical model is founded on numerical weather prediction (NWP) [6], which forecasts wind speed before transforming it into wind power. This technique is often based on the wind power curve, which may be modeled using parametric or non-parametric approaches [7]. Physical models are superior at forecasting the long-term trend of wind variation because they incorporate the physical process of both wind growth and wind power generation. However, local area precision is low and time consumption is significant. Statistical models use a significant quantity of data to train a fitting model between inputs and outputs, such as parametric models (e.g., time series model, support vector machine (SVM) model, etc.) and non-parametric models (e.g., neural networks (NN) model and other data-driven models) [8–10]. For instance, the auto-regression and moving average (ARMA) model was fundamentally and routinely employed in the forecasting of wind speed or wind power time series [11]. Traditional NN models are commonly used non-parametric data-driven models; [12] utilized two advanced models by introducing the wavelet network and the feed-forward network. In [13], an improved wind power prediction model was developed by including the wavelet kernel function into the SVM algorithm. In general, statistical models exhibit great short-term forecast precision. However, error levels will grow as the forecast horizon lengthens. Hybrid models are innovative prediction approaches proposed to enhance wind power forecast ability [14]. They employ physical models to anticipate long-term trends and statistical models to increase the accuracy of local forecasts. Consequently, hybrid models have more applicability. However, the combination of two models will undoubtedly enhance wind power's time consumption.

System operators are always expected to have accurate wind power forecast systems in order to prevent negative effects.

According to the above description, the purpose of this study is to develop a highly effective and efficient wind power forecast system. Therefore, we suggest a future forecast technique in this work by integrating prediction of main wind power with error correction. The suggested technique is a hybrid model that takes physical mechanism and data mining into account. First, we use historical wind power and wind speed data to construct an appropriate wind power curve model. Using the created wind power curve, the primary wind power forecast could be made. This method provides benefits for getting the wind power trend from wind speed variation. Compared to conventional NWP approaches, the basic model is highly straightforward and requires less computation time. Second, we present an error correction model to increase wind power forecast accuracy. This model investigates the faults of the core models and incorporates the modeling benefits of data-driven models. Consequently, the accuracy of mistake correction can be ensured.

Ultimately, the forecast is comprised of core model findings and error correction. Due to error correction, the suggested model provides more precision than conventional physical models. In contrast, it has a greater ability to represent the trend of actual wind power production when compared to statistical models.

The above explanation leads us to the conclusion that the suggested method combines the benefits of two types of models. Experiments are conducted using industrial wind farm data in order to evaluate the performance of the suggested method. Then, many analyses are conducted, including discussion and comparison with other models, improvement degree calculation, data validation, cost analysis, and uncertainty analysis. All of the trials demonstrate that the suggested method can predict wind power with high effectiveness and efficiency.

in this paper we will first describe the central concept of the method and the specific procedures. then we present the modeling of the wind power curve and how to use it to estimate the wind power. The prediction errors of model 1 are analyzed in the next part and then the error correction model will be built based on these data.

## II. METHODOLOGY AND DATA ANALYSIS

### *II.1 Energy modeling*

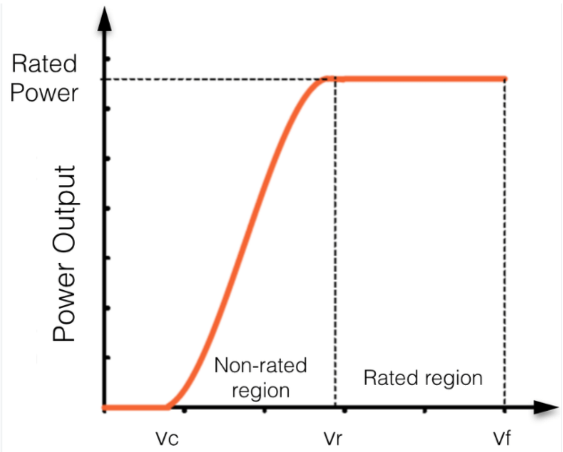


Fig. 1. caption wind power curve.

Figure 1 shows a diagram of an ideal wind power curve, which shows how wind turbines make power from the wind. There are three important points on the curve. Point c is the cut-in speed, point r is the rated speed, and point f is the cut-out speed.

When the wind speed is less than vc or more than vf, wind turbines produce nothing. When the wind speed is between vr and vf, the output of wind turbines stays the same. When wind speed drops between vc and vf, the power produced by wind turbines is found by (3).

In order to determine energy production under the wake effect, it is necessary to calculate the power of each wind turbine. Some wind turbine power estimation methods were evaluated in [12]. An approximate estimate of wind turbine energy output is shown below.

$$P_{WT} = \frac{1}{2}\rho\pi\frac{D^2}{4}C_{EF}(V_f - V_{df})^3 \tag{1}$$

Where,

$C_{EF}$ represents the efficiency factor expressed in equation (4):

$$C_{EF} = C_p\eta_m\eta_g \tag{2}$$

In this research, the C EF is considered to be 40 percent. The total power generated by wind turbines operating under the wake effect is :

$$P_{WF} = \sum_{i=1}^{N_t} P_{WT} \tag{3}$$

The following equation describes the efficiency of the wind farm:

$$\eta_{WF} = \frac{P_{WF}}{(\frac{1}{2}\rho\pi\frac{D^2}{4}C_{EF}{V_f}^3)} \tag{4}$$

In order to assist in the optimization of the studied wind farm, the locations of the wind turbines are provided in Cartesian coordinates (x,y), the distances between the turbines, and the overall wind speed deficit, which includes overlapping zones, is used. [14,15] describes the total velocity decrease as follows:

$$V_{dft} = \sqrt{\sum_{i=1}^{N_{up}}\left(\frac{A_{OV}}{A}\right)(V_{df})^2} \tag{5}$$

where P is the wind power generation, A is the swept area of the wind turbine blades,ρ is the air density, Cp is the wind power output coefficient, and v is the wind speed. When air density and wind speed are supplied for a particular circumstance, equation (3) defines the physical process by which a certain wind turbine generates wind power. Therefore, wind power curve models are constructed in [13,6] to predict wind power.

### *II.2 Methodology*

The curve of the logistic function g(x)=1/(1+e-x) is seen in Figure 3 [15]. Since it has the same trend as the portion of the wind power curve from point c to point f in Figure 2, the logistic function [5] was employed to fit the wind power curve. As shown in the table below, the created wind power curve model might serve as the principal forecast model.

Figure 2 illustrates the central concept of the proposed wind power prediction, which aims to enhance the accuracy of wind power forecasts by using error correction. The procedure consists mostly of two components: data and data rectification. First, the wind power curve is modeled using historical wind data (including wind power and wind speed) so it may be utilized for wind power forecasting. Model 1 predicts wind power based on wind-supplied speed; prediction errors are established by comparing wind forecasts to previous wind predictions. After assessing the error's composition, the rectification prediction model is constructed by selecting parameters and prediction algorithms. By merging the outputs of models 1 and 2, a more accurate forecast of wind energy is generated. The suggested methodology is reviewed and debated.

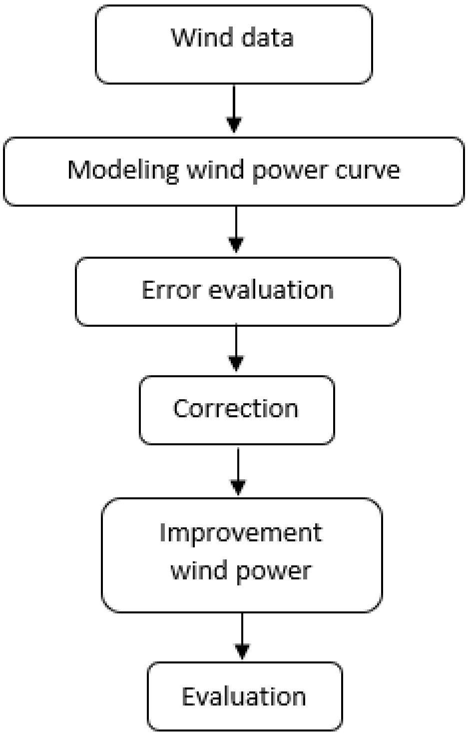

Fig. 2. Example of a figure caption.

The curve of a logistic function, g(x)=1/(1+ex), is shown in Figure 3[17]. It follows the same pattern as part of the wind power curve, so the logistic function was used to fit the wind power curve [16,18]. We could use the model-made wind power curve as our main prediction model.

$$p = \begin{cases} \frac{k}{1+e^{(-av+b)}} + \varepsilon & v < v_{out} \\ 0 & v \geq v_{out} \end{cases} \quad (6)$$

where :

$v$ : Wind speed

$v_{out}$ : Cut out speed

$a, b, k$ : Independent coefficients

$\varepsilon$ : Random error of the model

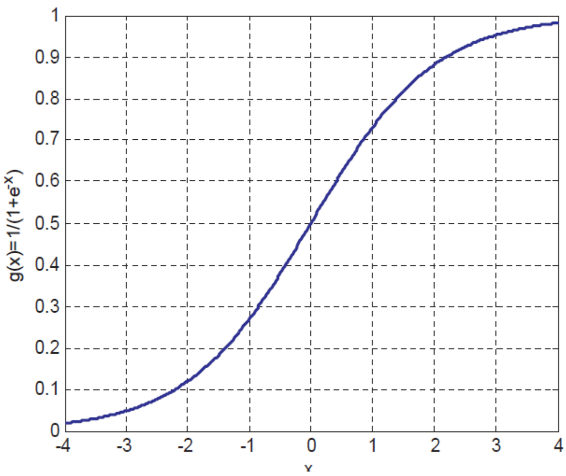

Fig. 3. Trend of logistic function.

## III. CORRECTION OF WIND ENERGY BASED ON THE ERROR OF THE SECOND MODEL

### *III.1. Error evaluation*

Error is the difference between expected and observed values. According to the results of Model 1's prediction in Figure 5, the inaccuracy is significant at a certain period. Given that model 1 is based on the wind power curve, its predictions can accurately represent the wind power trend. By analyzing the wind power curve, it is impossible to determine the random and fluctuating components of wind power[19,20]. Therefore, a method for error correction is presented to increase the accuracy of predictions. First, a prediction model's mistakes are specified in (6).

$$e_n = p_n - \hat{p}_n \quad (7)$$

where en is the predicted error; P and Pˆare the observed and predicted values of wind power generation, respectively.

Given that the provided wind power data is a time series, the related forecast errors are likewise time series. According to [21,22],historical data play crucial roles in time series forecasting.Therefore, we used this concept to determine the historical values of a parameter in time series prediction modeling, as shown below.

$$\hat{y}(t) = f(y(t-t), y(t-2T), \ldots, y(t-nT) \quad (8)$$

where $\hat{y}(t)$ and $y(t-nT)$ represent the forecast value and the $n^{th}$ historical observed value, respectively, and $T$ is the historical data prediction interval. In the error correction model, the output is the error e(t), and the fitting function f represents the prediction model. Due to the fact that mistakes in the primary model (Model 1) are connected to historical error values, wind power, and wind speed, the corrective model 2 is written as (10)

$$e(t) = f(e(t-1), e(t-2), \ldots, e(t-m), v(t-1), v(t-2), \ldots, v(t-n), p(t-1), p(t-2), \ldots, p(t-l)) \quad (9)$$

m, n, and l are the number of historical values; $e(t)$ represents error data; $v(t)$ represents wind speed data; and $p(t)$ represents wind power data.

### *III.2. Case Study: Gasiri Wind Farm*

the prediction and our models will be applied to the study of the Gasiri wind farm located in South Korea, precisely on Jeju Island.

TABLE I. FOUR SEASONS OF FITTING THE PARAMETERS OF A LOGISTIC FUNCTION.

| | k | a | b |
|---|---|---|---|
| period 1 | 190 | 0,3985 | 3,9531 |
| period 2 | 190 | 0,5385 | 3,6255 |
| period 3 | 190 | 0,3985 | 3,7129 |
| period 4 | 190 | 0,3165 | 3,7131 |

The adjustment parameters of the logistic function are shown in Table 1 by reducing the sum of squares error [13,23]. The forecasting model 1 for wind energy is created by averaging the parameters of the four logistic functions described before.

## IV. RESULTS AND DISCUSSION

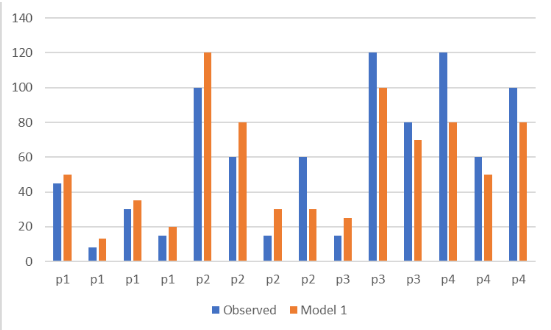


Fig. 4. Prediction of wind power using Model 1.

Figs. 4 illustrates the error prediction results. The projected periods p1, p2 and p3 of model 1 are predicted with high accuracy using data mining methods.

In addition this figure 4 shows that the wind power forecast is performed. The use of wind power curve models for the prediction reveals that the anticipated wind power maintains the general trend of the measured values. It is also observed that there is a remarkable difference between the two parameters in terms of measurement and prediction, this proves the usefulness of the second step of our strategy which will reduce prediction errors.

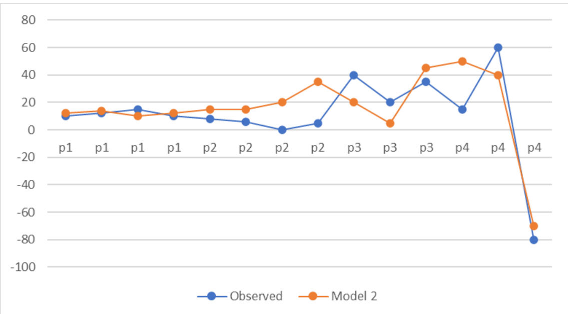


Fig. 5. Prediction of errors based on NN algorithms.

in the figure.5 , we notice a slight difference in prediction between the elements observed and from the period p2 to p4 we observe that the difference in prediction increases, this means that our model has corrected the errors, we also note that our model requires a response time to collect the maximum amount of data and produces the results.

TABLE II. WIND POWER PREDICTION PERFORMANCE.

| | BIAS | MAE | RMSE |
|---|---|---|---|
| Model1 | -19,55 | 16,577 | 35,154 |
| Model2 | 0,003 | 11,526 | 16,547 |
| NN | 0,075 | 15,2547 | 36,445 |

Table 5 illustrates the wind energy prediction error measures using our model, including Model 1 and model and data mining techniques to directly predict wind energy. Considering only traditional data-driven models, NN provides the best performance and lowest error measures for predicting wind generation. This also proves the power of NN algorithms to contribute to the minimization of prediction errors.

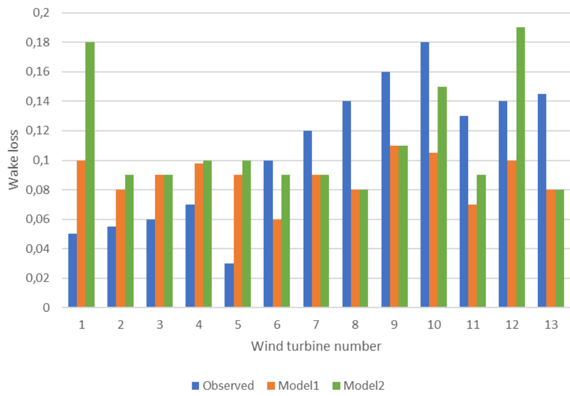


Fig. 6. Prediction of wind power using Model 1.

In Figure 6, which compares wake losses for the two models discussed above, it is evident that model 2 significantly reduces wake loss. This notable development validates the desire of The forecast can be fixed using standard techniques by using a correction algorithm. By making this decision, it becomes possible to determine the best configuration for all of the wind turbines in the Gasiri wind farm, one that optimizes energy output while balancing wake losses.

## V. CONLUSION

In this study, a novel hybrid model is developed to increase the precision and effectiveness of wind energy forecasting. First, the logistic function is used to develop a physical model (Model 1) based on the morphology of the wind power curve. Then, wind energy predictions are made using this primary model. This model approximates the wind energy development trend. Consequently, a corrective model (Model 2) based on data-driven methodologies is developed to target Model 1's flaws. This procedure involves correlational analysis and parameter selection to maximize Model 2. The final wind energy projection is achieved by the outcomes. In comparison to existing models using error metrics, the suggested method improves accuracy by 35 to 73%, according to the study's findings. In the next study, we will attempt to validate our model against other models in the literature.

## REFERENCES


[1] K. Nilsson, S.-P. Breton, J. N. Sørensen, and al -, “Determination of Wind Turbine Near-Wake Length Based on Stability Analysis Related content Airfoil data sensitivity analysis for actuator disc simulations used in wind turbine applications,” J. Phys. Conf. Ser. OPEN ACCESS.

[2] T. Ishihara and G. W. Qian, “A new Gaussian-based analytical wake model for wind turbines considering ambient turbulence intensities and thrust coefficient effects,” J. Wind Eng. Ind. Aerodyn., vol. 177, pp. 275–292, Jun. 2018.

[3] N. O. Jensen, “General rights A note on wind generator interaction,” 1983.

[4] I._; Katic, J._; Højstrup, and N. O. Jensen, “A Simple Model for Cluster Efficiency,” APA, 1987.

[5] M. Gaumond et al., “Benchmarking of Wind Turbine Wake Models in Large Offshore Windfarms,” in Proceedings of Torque 2012, The science of making torque from wind, 2012.

[6] T. Ishihara, A. Yamaguchi, and Y. Fujino, “Development of a new wake model based on a wind tunnel experiment,” Glob. Wind Power, p. 6, 2004.

[7] S. Frandsen et al., “Analytical modelling of wind speed deficit in large offshore wind farms,” in Wind Energy, 2006, vol. 9, no. 1–2, pp. 39–53.
[8] M. Bastankhah and F. Porté-Agel, “A new analytical model for windturbine
wakes,” Renew. Energy, vol. 70, pp. 116–123, Oct. 2014.
[9] X. Gao, H. Yang, and L. Lu, “Optimization of wind turbine layout position in a wind farm using a newly-developed two-dimensional wake model,” Appl. Energy, vol. 174, pp. 192–200, Jul. 2016.
[10] A. Mittal, L. K. Taylor, K. Sreenivas, and A. Arabshahi, “Investigation of two analytical wake models using data from wind farms,” in ASME 2011 International Mechanical Engineering Congress and Exposition, IMECE 2011, 2011, vol. 6, no. PARTS A AND B, pp. 1215–1222.
[11] L. Parada, C. Herrera, P. Flores, and V. Parada, “Wind farm layout optimization using a Gaussian-based wake model,” Renew. Energy, vol. 107, pp. 531–541, Jul. 2017.
[12] W. Tong, S. Chowdhury, J. Zhang, and A. Messac, “Impact of Different
Wake Models On the Estimation of Wind Farm Power Generation,” 2012.
[13] H. Kim, K. Kim, C. Bottasso, F. Campagnolo, and I. Paek, “Wind Turbine Wake Characterization for Improvement of the Ainslie Eddy Viscosity Wake Model,” Energies, vol. 11, no. 10, p. 2823, Oct. 2018.
[14] L. G. Salgado, “Experimental analysis of analytical wake models for wind turbines.”
[15] N. Charhouni, M. Sallaou, and K. Mansouri, “Design analysis of critical concepts influence wind farm production and efficiency,” Int. J. Eng. Res. Africa, vol. 40, pp. 136–150, 2018.
[16] J.Y.J. Kuo, D.A. Romero, C.H. Amon, “A mechanistic semi-empirical wake interaction model for wind farm layout optimization,” Energy, **93**, 2157–2165, 2015, doi:10.1016/j.energy.2015.10.009.
[17] A. Emami, P. Noghreh, “New approach on optimization in placement of wind turbines within wind farm by genetic algorithms,” Renewable Energy, **35**(7), 1559–1564, 2010, doi:10.1016/j.renene.2009.11.026.
[18] A. Mittal, L.K. Taylor, “Optimization of large wind farms using a genetic algorithm,” in ASME International Mechanical Engineering Congress and Exposition, Proceedings (IMECE), 3159–3172, 2012, doi:10.1115/IMECE2012-87816.
[19] S.A. Grady, M.Y. Hussaini, M.M. Abdullah, “Placement of wind turbines using genetic algorithms,” Renewable Energy, **30**(2), 259–270, 2005, doi:10.1016/j.renene.2004.05.007.
[20] J. Serrano González, M. Burgos Payán, J.M. Riquelme Santos, “Optimal design of neighbouring offshore wind farms: A co-evolutionary approach,” Applied Energy, **209**, 140–152, 2018, doi:10.1016/j.apenergy.2017.10.120.
[21] P. Hou, W. Hu, M. Soltani, C. Chen, Z. Chen, “Combined optimization for offshore wind turbine micro siting,” Applied Energy, **189**, 271–282, 2017, doi:10.1016/j.apenergy.2016.11.083.
[22] A.P.J. Stanley, A. Ning, “Massive simplification of the wind farm layout optimization problem,” Wind Energy Science, **4**(4), 663–676, 2019, doi:10.5194/wes-4-663-2019.
[23] B. Abdelouahad, M. Khalifa, R. Abdelhadi, “Development of a multiple