International Journal on
"Technical and Physical Problems of Engineering"
(IJTPE)
Published by International Organization of IOTPE

ISSN 2077-3528
IJTPE Journal
www.iotpe.com
ijtpe@iotpe.com

June 2024	Issue 59	Volume 16	Number 2	Pages 218-223

IMPROVED ACCURACY OF WIND ENERGY FORECASTS BY MINIMIZING CALCULATION ERRORS

A. Bellat [1] A. Mansouri [2] K. Mansouri [2]

1. PCMT Laboratory, Mohammed V University, Rabat, Morocco, bellatabdelouahad@gmail.com
2. Modeling and Simulation of Intelligent Industrial Systems Laboratory (M2S2I), ENSET Mohammedia, Hassan II University, Casablanca, Morocco, abderrahman.mansourii@gmail.com, khmansouri@hotmail.com

Abstract- This research introduces an advanced approach aimed at improving the precision and efficiency of wind energy forecasting while mitigating the detrimental impacts of wind energy fluctuations on electrical system performance. The methodology involves a two-step modeling process, initially constructing a model based on the wind power curve to predict variations using fundamental physical principles. To address inaccuracies, a data-driven corrective strategy is implemented, employing data mining techniques for analysis and rectification. The amalgamation of outcomes from both phases significantly enhances the accuracy of wind energy predictions. Our proposed strategy outperforms conventional models in terms of both accuracy and cost-effectiveness, representing a significant advancement beyond basic physical and statistical models. This assertion is substantiated by a comprehensive analysis of authentic wind farm data. The comparative study underscores that our approach not only surpasses existing models but also offers a more economically viable solution for wind energy forecasting, marking a notable leap forward in the field. The findings emphasize the practical utility of our approach in optimizing the integration of wind energy into electrical systems, thereby fostering sustainable and reliable energy generation.

Keywords: Performance, Efficiency, Corrective, Wind farm, Wind Energy.

1. INTRODUCTION

Renewable energy, including wind energy, has gained global prominence as a solution to combat fossil fuel dependence and environmental pollution. However, the variable and stochastic nature of wind poses challenges to power system stability, especially given its significant contribution to power generation in regions with ample wind resources. Current approaches to wind energy forecasting include physical models based on numerical weather prediction (NWP) and statistical models such as parametric and non-parametric models [1, 2]. Physical models are good at capturing long-term trends but lack local accuracy and can be time-consuming.

Conversely, models employing statistical approaches, including time series models, support vector machine (SVM) models, neural networks (NN) models, and others, rely on large amounts of data for training but offer better short-term forecasting capabilities. Some studies have proposed improved models by incorporating advanced techniques such as wavelet networks or kernel functions into SVM algorithms [3]. Overall, statistical models show promise in short-term wind energy forecasting. precision. However, as the forecast horizon lengthens, error levels tend to increase.

To address this, innovative approaches such as hybrid models have been suggested to enhance the accuracy of wind power predictions [4]. These hybrid models combine physical models for long-term trend prediction with statistical models for local forecast accuracy improvement, making them more applicable in practical situations. However, the combination of two models may also increase the time required for wind power forecasting. Accurate wind power forecasts are crucial for system operators to mitigate negative impacts. Therefore, the main objective of this study is to devise a wind power forecast system that is highly efficient and effective. To achieve this goal, we have proposed a novel approach that integrates the main wind power prediction with error correction using a model that incorporates accuracy techniques.

The first step in our methodology involves using information on the site to establish an adequate model, which serves as the foundation for the primary wind power forecast. This approach provides advantages in capturing the wind power trend from wind speed variations and requires less computation time compared to conventional numerical weather prediction (NWP) approaches [5, 6]. Secondly, an error correction model is presented to enhance the precision of wind power forecasts. by examining the faults of the primary model and assimilating the advantageous features of data-driven models, this model is capable of enhancing its predictive capabilities. This approach involves analyzing the limitations of the existing model and leveraging the strengths of data-driven models to improve its overall performance.

Registered: 230829 Article Info: 1800 Accepted: 240515
Reserved: 240301 Available: 240630

Essentially, the model incorporates the benefits of data-driven modeling techniques to address the shortcomings of the original model., ensuring accurate mistake correction [7]. Ultimately, the wind power forecast is obtained by combining the findings of the core model with the error correction. Compared to conventional physical models, the suggested method provides higher precision due to error correction, The model is better at representing wind power production trends than statistical models, as it can capture the nuances and complex dynamics of wind power generation more accurately. It outperforms traditional statistical models in accurately depicting real-world production trends [8, 9].

The suggested approach blends the advantages of physical and data-driven models, and its performance is meticulously evaluated using the parameters of the study site. In order to control the reliability of the approach, many simulations were carried out is calculated based on the findings [10], which demonstrate the high efficiency and accuracy of the suggested method in wind power prediction. The paper provides a detailed account of the method, from the central concept to the specific procedures and modeling of the wind power curve. Furthermore, the study thoroughly analyzes the prediction errors of the initial model, leading to the development of an error correction Built upon this dataset.

The wind energy profile is employed to represent the connection between wind speed and power output in the initial model. The inaccuracies in predictions of the initial model are then analyzed to identify any discrepancies between the predicted and actual wind power data [11]. Based on this analysis, a model for correcting errors is built to correct the prediction errors and improve the accuracy of the wind power estimation. The paper begins by presenting the details of the strategy and elaborating on the essential steps. the curve below and its application in estimating wind power are also explicated. Additionally, the initial model's prediction errors are thoroughly examined, and an error correction model is developed derived from these observations. Primary issues are studied in this paper. In particular, we perform nonlinear modeling and analysis, controllers design, and validate the theoretical results [1].

2. APPROACH AND ANALYSIS OF DATA

2.1. Modeling of Energy

The curve in Figure 1 represents the output power as a function of speed. The curve highlights three phases: at *c*, designates the engagement speed; in *r*, denotes the nominal speed; and at *f*, indicating the cut-off speed. The system does not work If the wind speed is below v_c or exceeds v_f. Similarly, when v falls within the range of v_r and v_f, the wind turbines maintain a consistent output power.

Equation (1) is used to calculate the power generated by wind turbines as long as v is between v_c and v_f. To analyze energy generation, considering the impact on adjacent turbines, it is essential to evaluate the performance of individual turbines. A prior investigation [12] examined diverse techniques for estimating the energy output.

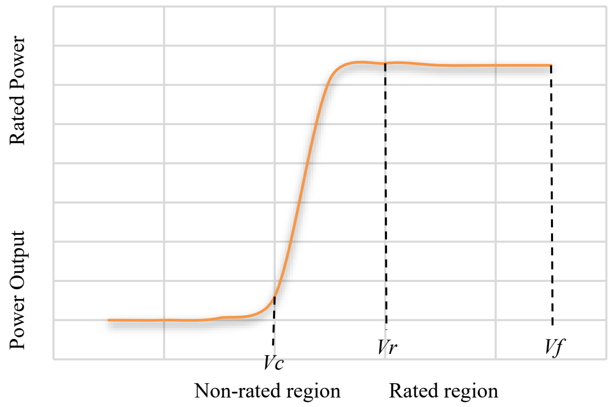

Figure 1. Variation in motor wind energy power

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

where, C_{EF} translates the efficiency factor given in Equation (2):

$$C_{EF} = C_p\eta_m\eta_g \quad (2)$$

Many previous works have assumed a C_{EF} of 40% in their analysis of wind power generation in the presence of wake effects. The total power was calculated based on this assumption is as Equation (3).

$$P_{WF} = \sum_{i=1}^{N_t} P_{WT} \quad (3)$$

The efficiency of the wind farm is described by Equation (4).

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

In order to help optimize the wind farm under study, the Cartesian coordinates (x, y) of the wind turbines, the inter-turbine distances, and the comprehensive, which takes into account superimposed spaces, are provided. The total decrease in velocity is described in [14, 15].

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

Equation (5) expresses the power generation of a wind turbine. A and P give respectively the power and the air generated by the blades whereas Cp and V is respectively expressing the power factor and the speed. to predict the power output of wind turbines [13, 6].

2.2. Methodology

The logistic function curve, expressed as $g(x) = 1/(1+e^{(-x)})$, is displayed in Figure 3. Given its resemblance in trend to Figure 2, the previously specified function was employed to align with the curve in Figure 2 [15, 16]. The resulting wind power curve model, as shown in Table I may serve as the primary forecasting model.

The proposed wind power prediction approach, as depicted in Figure 2, whose objective is to improve the precision of error correction wind forecasts. The approach comprises two primary components: data modeling and data rectification. Initially, previous wind data, such as wind energy and velocity, is used to model the wind power curve, which facilitates wind power forecasting. Model 1 utilizes the supplied wind speed to predict wind power, and errors of prediction are calculated by estimate the wind prediction with prior wind measures. Subsequently, rectification error prediction model is developed by choosing appropriate factors and AI algorithms based on the error analysis. Combining the results of both models in a more precise wind energy forecast. The proposed methodology is subjected to review and discussion.

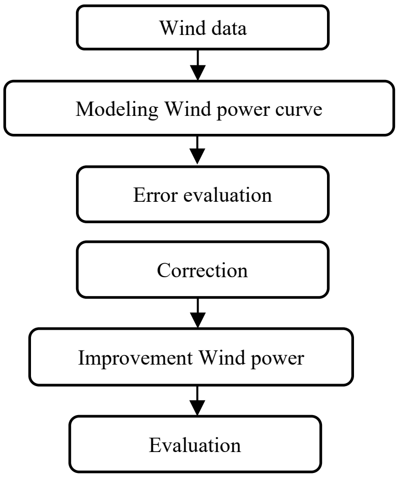

Figure 2. Sample caption for a graphical representation

The plot of the logistic function, represented previously in Figure 3 [16]. It is observed that a specific segment of the plot of the curve described above presents a function similar to the function studied. To adapt the wind power curve to this model, they chose to use the logistic function as a mathematical [17, 18] model. As in (6), wind power curve model derived from this approach could be considered as accurate estimation model.

$$P=\begin{cases}\dfrac{k}{1+e^{(-av+b)}}+\varepsilon & v \prec v_{out}\\ 0 & v_{out}\le v\end{cases} \tag{6}$$

where, v is wind speed, v_{out} is cut out speed, ε is model's stochastic variability and coefficients a, b, and k are mutually independent.

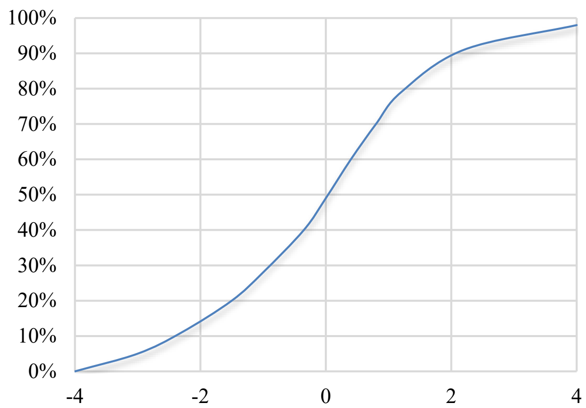

Figure 3. Representation of logistic function

3. ADJUSTMENT OF WIND ENERGY VALUES ACCORDING TO THE DEVIATIONS OBSERVED IN MODEL 2

3.1. Assessment of Inaccuracies

The forecast results from the curve in Figure 5 demonstrate a disparity among the predicted and actual values. there are marked inaccuracies within a specific time frame. While Model 1 relies on the wind power curve, its projections be able successfully capture the model of power. However, examining only the wind power curve does not identify the unpredictable and variable aspects of wind energy [19, 20]. Therefore, a rectification of defects technique is established to develop the reliability of the projections. The inaccuracies of a prediction model are calculated according to Equation (7) in the suggested method.

$$e_n = p_n - \hat{p}_n \tag{7}$$

Equation (6) establishes that the projected error (e_n) is derived from the observed p_n and projected $\hat{p}_n$ wind power generation values. The errors in forecasting are also time-dependent due to the nature of wind power data. The significance of prior data in time series prediction is widely acknowledged in existing literature [21, 22]. Consequently, we have leveraged this idea to compute the historical parameter values in our time series forecasting model [23], as presented in Equation (8).

$$\hat{y}(t)=f\left(y(t-T),y(t-2T),...,y(t-nT)\right) \tag{8}$$

The error correction model includes the predicted quantity $\hat{y}(t)$ and the nth quantity noticed $y(t-nT)$, where T is the estimate margin of the elaborated data. The output of the results of error model is represented by The value $e(t)$ is associated with the correction curve f, representing the updated prediction in Model 2 which is the corrective model, takes into consideration the number of data collected, wind turbine speed and power as reflected in Equation (9).

$$e(t)=f\begin{pmatrix}e(t-1),e(t-2),...,e(t-m),v(t-1),v(t-2),\\ ...,v(t-n),p(t-1),p(t-2),...,p(t-l)\end{pmatrix} \tag{9}$$

The variables l, m, and n denote the quantity of past values employed for prediction, errors are denoted $e(t)$, while speed-related information is indicated by $v(t)$, $p(t)$ it's the wind power information. The outcome of the error correction model is reflected by the error $e(t)$.

3.2. Examining Gasiri Wind Farm: A Case Study

Prediction and modeling techniques developed in this study can be exploited to analyze site of wind farm, which is situated Jeju Island, South Korea.

The logistic function's adjustment parameters, obtained by minimizing the sum of squares error, are presented in Table 1. The first model studied forecasting is constructed by taking the average of the functions analyzed in the previous sections.

Table 1. The four stages in estimating parameters for a logistic function

	k	*a*	*b*
phase1 1	190	0.3985	3.9531
phase1 2	190	0.5385	3.6255
phase1 3	190	0.3985	3.7129
phase1 4	190	0.3165	3.7131

3.3. Results and Discussion

Figure 4 presents the results of analysis of errors, showcasing the accurate forecasts of model 1 for the projected periods p1, p2, and p3 using data mining techniques. The wind power forecast based on wind power curve models demonstrates that the predicted values follow the overall trend of the measured values. Notably, a significant disparity between the measured and predicted parameters is observed.

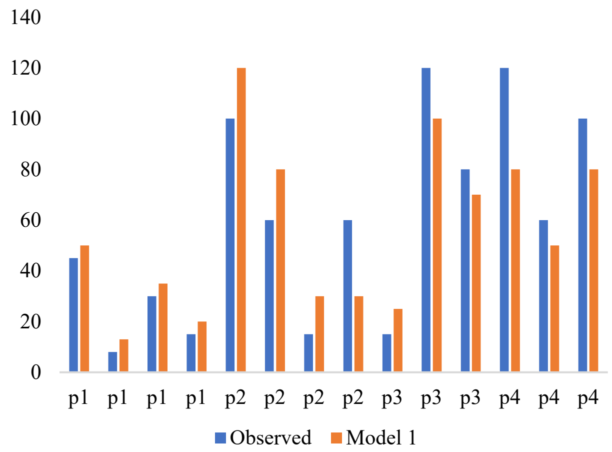

Figure 4. Power generation by implementing Model 1

This emphasizes the efficacy of the second phase of our approach, which aims to decrease the errors in forecasting. After examining, a minor variation can be observed among the projected values and the observed values. It is apparent that the disparity in projections increases from period p2 to p4, Figure 5 indicating that our model has effectively corrected the inaccuracies.

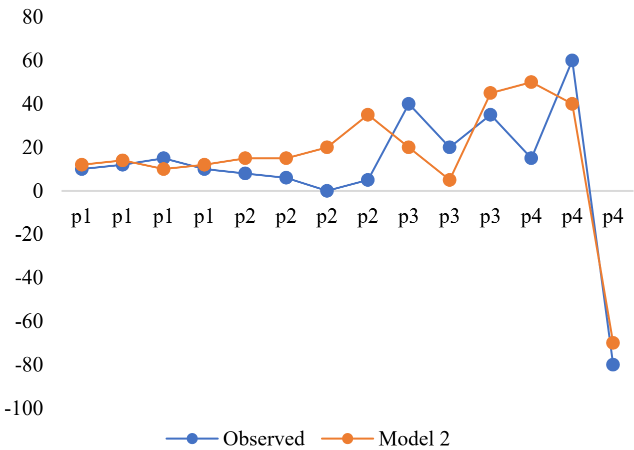

Figure 5. Forecasting errors using neural network algorithms

Moreover, our model requires some response time to gather sufficient data and produce precise outcomes.

Table 2. Power prediction results

	MAE	RMSE	BIAS
Model2	11.526	16.547	0.003
NN	15.2547	36.445	0.075
Model1	16.577	35.154	-19.55

The data for wind energy error metrics is presented in Table 2. The table provides information on the various measurements of discrepancies in wind power. prediction achieved by our suggested models, comprising of Model 1 and data mining methods for direct wind energy forecasting. Among the standard data-based models, it is evident that the neural network (NN) model delivers the best performance, exhibiting the lowest error rates in wind generation prediction. This underscores the effectiveness of NN algorithms in reducing the inaccuracies in forecasting.

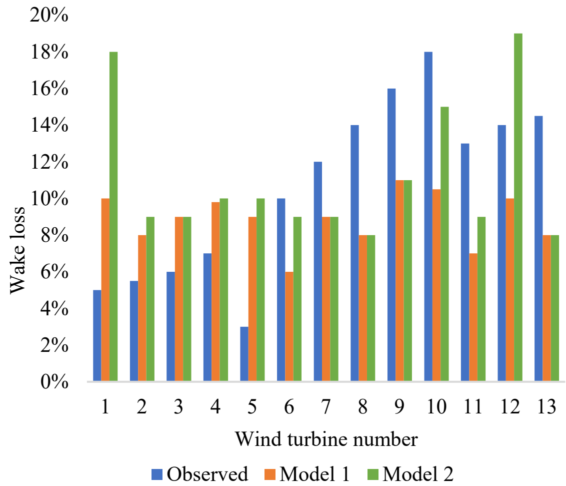

Figure 6. Power generation by implementing Model 2

The results displayed in Figure 6 provide a comparison of the wake losses in two models that were examined, clearly indicating that Model 2 effectively minimizes the wake losses. This improvement validates the necessity of a correction algorithm to rectify the forecasting errors. The decision that was taken will make it possible to identify the most efficient layout of the wind farm studied. With this determination, it will be possible to optimize the performance and output of the wind farm., while ensuring a balance between maximum energy output and minimal wake losses. Additionally, conventional techniques can be employed to further improve the forecasting accuracy and achieve the best possible results.

4. CONCLUSIONS

This research has successfully introduced a novel and advanced technique for improving the precision and effectiveness of wind power generation forecasting. The two-tiered approach, consisting of Model 1 and Model 2, demonstrates a significant leap forward in the field. Model 1, employing a logistic function-based analysis of the wind power curve, serves as the foundational element of the proposed technique. Its ability to discern the shape of the curve provides valuable insights, but recognizing its limitations, the study introduces Model 2 to address and correct these shortcomings. Model 2 employs data-driven approaches, incorporating correlational examination and meticulous factor selection to optimize its performance. The synergy of these two models results in a hybrid approach that not only overcomes the limitations of individual models but also significantly enhances the overall accuracy of wind energy predictions.

The improvements, as indicated by error metrics, range from a notable 35% to an impressive 73% when compared to existing models. This substantiates the effectiveness of the proposed hybrid model in providing more reliable and precise wind power forecasts. Looking ahead, the proposed hybrid model will undergo further validation in subsequent research, ensuring its robustness and applicability across diverse wind power scenarios. The aim is to establish its superiority over existing models documented in the relevant literature, thereby solidifying its position as a pioneering solution in the realm of wind power forecasting. In summary, this research not only contributes a state-of-the-art forecasting technique but also sets the stage for continued advancements in the field of renewable energy. The proposed hybrid model showcases a promising trajectory for enhancing the efficiency of wind power generation forecasting, thereby playing a pivotal role in the sustainable development of clean energy sources.

REFERENCES

[1] K. Nilsson, S.P. Breton, J.N. Sorensen, S. Ivanell, "Airfoil Data Sensitivity Analysis for Actuator Disc Simulations Used in Wind Turbine Applications", Journal of Physics: Conference Series, Institute of Physics Publishing, Vol. 15, pp. 362-370, September 2014.
[2] T. Ishihara, 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, June 2018.
[3] A. Bellat, I. Tyass, Kh. Mansouri, A. Raihani, "Optimization of Wind Farms by the Particle Swarm Algorithm Considering Gaussian Wake Model", International Journal on Technical and Physical Problems of Engineering (IJTPE), Issue 48, Vol. 13, No. 3, pp. 48-54, September 2021.
[4] I. Katic, J. Hojstrup, N.O. Jensen, "A Simple Model for Cluster Efficiency", APA, Vol. 1, pp. 407-410, 1987.
[5] M. Gaumond, et al., "Benchmarking of Wind Turbine Wake Models in Large Offshore Windfarms", Torque 2012, The Science of Making Torque from Wind, Vol. 5, pp. 182-185, 2012.
[6] T. Ishihara, A. Yamaguchi, 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", Wind Energy, Vol. 9, No. 1-2, pp. 39-53, 2006.
[8] M. Bastankhah, F. Porte Agel, "A new Analytical Model for Wind Turbine Wakes", Renew. Energy, Vol. 70, pp. 116-123, October 2014.
[9] X. Gao, H. Yang, 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, July 2016.
[10] A. Mittal, L.K. Taylor, K. Sreenivas, A. Arabshahi, "Investigation of two Analytical Wake Models Using Data from Wind Farms", ASME 2011 International Mechanical Engineering Congress and Exposition (IMECE 2011), Vol. 6, No. Parts A and B, pp. 1215-1222, 2011.
[11] L. Parada, C. Herrera, P. Flores, V. Parada, "Wind farm Layout Optimization Using a Gaussian-Based Wake Model", Renew. Energy, Vol. 107, pp. 531-541, July 2017.
[12] M.A. Hassoine, F. Lahlou, A. Addaim, A.A. Madi, "Improved Evaluation of the Wind Power Potential of a Large Offshore Wind Farm Using Four Analytical Wake Models", International Journal of Renewable Energy Development, Vol. 11, No. 1, pp. 35-48, February 2022.
[13] H. Kim, K. Kim, C. Bottasso, F. Campagnolo, I. Paek, "Wind Turbine Wake Characterization for Improvement of the Ainslie Eddy Viscosity Wake Model", Energies, Vol. 11, No. 10, p. 2823, October 2018.
[14] H. Shayeghi, A.M. Moghaddam, "Impact of Wind Turbine for Management of Residential Energy Hubs Using IGDT Considering Uncertainty", International Journal on Technical and Physical Problems of Engineering (IJTPE), Issue 46, Vol. 13, No. 1, pp. 91-102, March 2021.
[15] N. Charhouni, M. Sallaou, 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, Vol. 93, pp. 2157-2165, 2015.
[17] A. Emami, P. Noghreh, "New Approach on Optimization in Placement of Wind Turbines within Wind Farm by Genetic Algorithms", Renewable Energy, Vol. 35, No. 7, pp. 1559-1564, 2010.
[18] A. Mittal, L.K. Taylor, "Optimization of Large Wind Farms Using a Genetic Algorithm", ASME International Mechanical Engineering Congress and Exposition, Proceedings (IMECE), pp. 3159-3172, 2012.
[19] S.A. Grady, M.Y. Hussaini, M.M. Abdullah, "Placement of Wind Turbines Using Genetic Algorithms", Renewable Energy, Vol. 30, No. 2, pp. 259-270, 2005.
[20] J. Serrano Gonzalez, M. Burgos Payan, J.M. Riquelme Santos, "Optimal Design of Neighboring Offshore Wind Farms: A Co-Evolutionary Approach", Applied Energy, Vol. 209, pp. 140-152, 2018.
[21] P. Hou, W. Hu, M. Soltani, C. Chen, Z. Chen, "Combined Optimization for Offshore Wind Turbine Micro Siting", Applied Energy, Vol. 189, pp. 271-282, 2017.
[22] A.P.J. Stanley, A. Ning, "Massive Simplification of the Wind Farm Layout Optimization Problem", Wind Energy Science, Vol. 4, No. 4, pp. 663-676, 2019.
[23] J. Bilabo, E. Bravo, O. Garcia, C. Varela, C. Rebollar, "Particular Case of Big Data for Wind Power Forecasting: Random Forest", Internation Journal on Technical and Physical Problem on Engineering (IJTPE), Issue 42, Vol. 12, No. 1, pp. 25-30, March 2020.

BIOGRAPHIES

Name: **Abdelouahad**
Surname: **Bellat**
Birthday: 08.05.1981
Birthplace: Safi, Morocco
Bachelor: Mechanical Engineering, ENSET, Rabat, Mohamed V University, Rabat, Morocco, 2006
Master: Mechanical Engineering, Mechanical Engineering Department, ENSAM, Mohammed V University, Rabat, Morocco, 2017
Doctorate: Mechanical Engineering and Artificial Intelligence, Higher Normal School of Technical Education (ENSET), Hassan II University, Casablanca, Morocco, 2021
The Last Scientific Position: Assoc. Prof., Laboratory of Mechanical and Thermal Processes and Controls, National School of Arts and Crafts, Mohammed V University, Rabat, Morocco, Since 2021
Research Interests: Design and Optimization of Wind Farms Using Artificial Intelligence Algorithms, Application of AI in Mechanical and Industrial Engineering
Scientific Publications: 14 Papers

Name: **Abderrahman**
Surname: **Mansouri**
Birthday: 02.12.1999
Birthplace: Mohammedia, Morocco
Bachelor: Industrial Engineering, ENSET, Mohamed V University, Rabat, Morocco, 2019
Master: Industrial Engineering, ENSET, Hassan II University, Mohammedia, Morocco, 2022
Doctorate: Student, Industrial Engineering and Artificial Intelligence Department, Higher Normal School of Technical Education (ENSET), Hassan II University, Mohammedia, Morocco, Since 2023
The Last Scientific Position: Engineer Specializing in Synergy of Industrial Engineering and Artificial Intelligence
Research Interests: Industrial Engineering and Artificial Intelligence
Scientific Publications: 1 Paper

Name: **Khalifa**
Surname: **Mansouri**
Birthday: 20.05.1968
Birthplace: Azilal, Morocco
Bachelor: Mechanical Engineering, ENSET, Mohammedia, Hassan II University, Casablanca, Morocco, 1991
Master: Certificate of Advanced Studies, Physics Option Computer Calculation of Structures, Faculty of Sciences, Mohammed V University, Rabat, Morocco,1992
Doctorate: Calculation of Structures on Computer and CAD, Mechanical Department, Faculty of Sciences, Mohamed V University, Rabat, Morocco,1994
Doctorate: Computer Science, Computer Science Department, Faculty of Sciences and Technology, Hassan II University, FST, Mohammedia, Morocco, 2016
The Last Scientific Position: Scientific Manager, Distributed Computing Systems Research Team, SSDIA Research Laboratory and Deputy Director Responsible for Educational Affairs, ENSET, Mohammedia, Morocco
Research Interests: Real Time Systems, Information Systems, e-Learning Systems, Modeling, Optimization, and Numerical Computing of Industrial Systems, Application of AI in Mechanical and Industrial Engineering
Scientific Publications: 422 Papers, 10 Books
Scientific Memberships: Director of Modeling and Simulation of Intelligent Industrial Systems Laboratory (M2S2I), ENSET, Mohammedia