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 2021 | Issue 47 | Volume 13 | Number 2 | Pages 35-39

IMPLEMENTATION OF ARTIFICIAL NEURAL NETWORK FOR OPTIMIZATION OF A WIND FARM

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Abstract- Permanent evolution of the establishment of wind farms in recent years pushes the designers of wind farms to provide more effort in the optimization in order to reduce the effects of wake and maximize power. Our objective in this present work is to test the optimization of wind farms using ANN (artificial neural network), in the first study phase we will try to choose the wake model (ANN-wake-) which allows to standardize the losses of wake and to maximize the power, in the second study a genetic algorithm is applied based on the information collected from ANN-wake-power model and they are exploited in the second optimization, this allows to find the yaw angles optimal according to the wind directions in the studied wind farm, the results of this study clearly show that the optimization using ANN allowed a standardization of the wake loss and an optimal orientation of the yaw angles, which makes our approach very precise and it has a minimal cost.

Keywords: Wind Farms, Wake, Artificial Neural Network, Yaw Angles, Optimization, Standardization Modeling.

1. INTRODUCTION

The strong demand for electric power has pushed the designers of wind farms to invest more and more in clean energies [1]. The advantage being to reduce greenhouse gas emissions, the major problem facing investors in wind farms is the wake phenomenon [2], in fact the wind turbine transforms part of the kinetic energy wind into mechanical energy. This results in a slowing of the flow and the appearance of a wake behind the wind turbine [2], a long wind trail which is more turbulent and less rapid than the wind upstream of the machine. In wind farms, it is necessary to space the wind turbines in order to prevent the turbulence and the speed deficit existing behind each machine from affecting too much the energy production and the mechanical integrity of the wind turbines located further downstream [3].

As a rule of thumb, in parks, the wind turbines are all the same and the distance between machines is three to nine times the diameter in the direction of the prevailing winds and three to five times the diameter in the direction perpendicular to that of the prevailing winds. Numerical simulation could be a valuable tool for analyzing wind wake and optimizing the location of wind turbines [4] on a farm depending on the characteristics of the machines and the topography of the wind parc.

The methods used which are based on physical models using equations and data for the prediction of wind energy remain more reliable and less expensive [5]. Unlike traditional methods [6], a lot of work has been developed in machine learning to predict energy [7] has tried recurrent neural networks (RNN) and a back-propagation algorithm based on Kalman filter to study the estimation of energy in a wind parc. Other studies developed by [8], applied the (RNN) for the prediction of the wind speed, exploiting the meteorological information [9-10], by the geometric model and the artificial neural network have shown that the use of real local wind data is more reliable compared to the use of average data [11], also confirmed that the geometric model (GM-ANN) is more powerful than the traditional methods.

Maximum power point tracking (MPPT) [12] become the most used method by acting on the pitch angle and the speed of each wind turbine and following the directions of the wind of a wind farm. [13] criticized the forecasting approach (MPPT) and they proposed a wake control method by mastering Yaw angles whose objective is to orient the turbine blades in the windiest direction [7], the work of [14] also attempted to study wake losses in interference zones using Yaw angle optimization.

So far, the studies remain approximate and not precise for the prediction of energy, because all the prediction models used in the literature are based on simplifying assumptions. In this article, we will try using data from wind turbines installed in a wind farm to exploit a model by ANN. The model developed takes into account the wake effect and optimizes the Yaw angles to maximize energy production.

2. DEVELOPMENT OF ANN-WAKE-POWER MODEL

2.1. Methodology

The objective of our model is to predict the energy produced from a wind farm, taking into account the conditions of the wind farm such as, the direction and the speed of the wind, the Yaw angels.

As shown in Figure 1, the process begins with collecting data on wind turbines, wind speeds and directions, and yaw angles. After verifying the standardization of wake losses, the ANN wake model is established. Unlike traditional models, the design of our model targets the overall wind farm, rather than the individual wind power treatment.

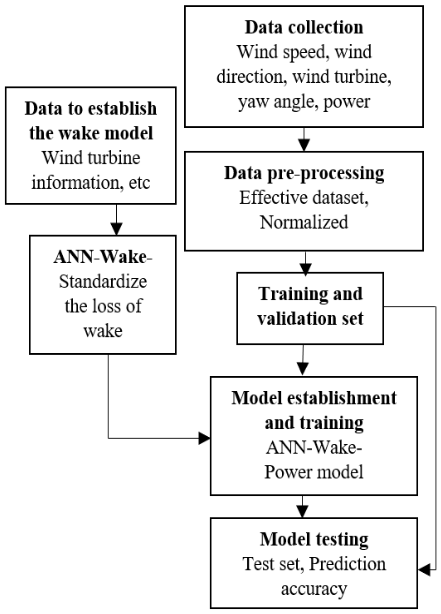

Figure 1. Diagram of the development stages of ANN-wake model

The collected data is processed to retrieve an efficient data set. The model contains an input layer including wind speed and direction data followed by yaw angles, an output layer including powers, and finally, the masked slaps containing neurons. The actual data set will be split into a learning set, validation set, and test set. The ANN model will be trained using the data from the training set. The data from the validation set is used to assess the effectiveness of the model at each training period. Finally, testing is done for the data set.

2.2. Wake Modeling

Behind a wind turbine, a swirling wake develops. In this wake, the average wind speed is reduced since the wind turbine has captured part of the kinetic energy of the natural wind and the intensity of turbulence is increased. The wind leaving the propeller has a lower energy capacity than the wind coming into the propeller.

The wake of a wind turbine therefore has a double effect on the immediate environment:

A decrease in the wind speed behind the wind turbine leading in particular to a drop in production from surrounding wind turbines. An increase in fatigue loads (and therefore a reduction in service life) linked to the increase in the intensity of turbulence.

Reducing wind turbulence and removing heat from the surrounding area can cause temperature changes. According to several studies carried out on the basis of simulation models, the local effects of wind farms could be significant.

As shown in Figure 2, the most widely used wake models in the literature are Jensen's model [22], Frandsen's model [15], Larsen's model [11], Ishihara's model [16], and the 2D Gaussian wake model proposed in Reference [7].

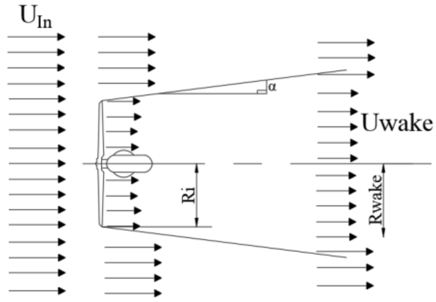

Figure 2. Jensen model principal (Jensen, 1983) [22]

For our study we will use the Jensen model managed by the Equation (1):

$$U_{wake} = U_{In}\left[(1-\sqrt{1-C_T})\left(\frac{R_i}{R_{wake}}\right)^2\right] \tag{1}$$

$$R_{wake,ij} = R_i + \alpha \Delta x_{ij}$$

where, U_{wake} is wind velocity in wake area, U_{In} is incoming wind speed, C_T is thrust coefficient, R_i is rotor radius, R_{wake} is wake radius, Δx_{ij} is distance separate wind turbines and α is wake decay constant.

2.3. Case Study Shiren Wind Farm

The ANN-Wake model will be used in a Sherin wind farm to assess its power. The wind farm location data is summarized in the Table 1.

Wind dominance is defined in the north winds to northwest winds. The ANN-wake model is applied on 1956 time points of the wind speed varying within the limit of 150-198° at a speed between 3 to 11 m/s.

The wind turbine used in the Shiren wind farm is of the UP77-1500 type. The Table 2 summarizes these characteristics.

Table 1. Position of wind turbines in the Sherin wind farm [18]

	WT10-1	WT10-2	WT10-3	WT10-4	WT10-5
Longitude	114.355° E	114.358° E	114.362° E	114.365° E	114.372° E
Latitude	40.999° N	40.998° N	40.999° N	40.999° N	40.997° N
Altitude	1857.4 m	1884.5 m	1880.7 m	1877.3 m	1894.1 m

Table 2. Characteristics of UP77-1500 wind turbines [10]

Parameter	Value
Rated power (kW)	1550
Number of blades	3
Hub height (m)	65
Diameter (m)	77.36
Swept area (m2)	4700.3
Cut-in wind speed (m/s)	3.0
Rated wind speed (m/s)	11.0
Cut-out wind speed (m/s)	25.0
Rotate speed (rpm)	9.7-19.5
Rated frequency (Hz)	50

It should be noted that the measured real wind data present errors compared to the power curves of the wind turbines [17-18], this makes the estimate based on the speed data not reliable. However, our model allows us to use different data to reduce the uncertainties of traditional models the table 3, gives an overview of the data used in our model ANN-Wake.

Table 3. Summary of the datasets [18]

	Mean	Min	Median	Max
Wake1	0.051833	0	0.004482	0.261788
Wake2	0.050797	0	0.004693	0.261779
Wake3	0.050801	0	0.005085	0.261751
Wake4	0.052227	0	0.004856	0.259905
Wake5	0.052145	0	0.005704	0.259900
Wind Speed1 (m/s)	9.41	3.24	9.75	14.88
Wind Speed2 (m/s)	10.20	3.06	10.77	15.00
Wind Speed3 (m/s)	9.97	3.00	10.70	14.99
Wind Speed4 (m/s)	8.89	3.07	9.26	14.77
Wind Speed5 (m/s)	10.20	3.04	10.74	15.00
Yaw Angle1 (◦)	0.23	-29.89	0.61	17.82
Yaw Angle2 (◦)	-0.56	-28.93	-1.12	25.60
Yaw Angle3 (◦)	0.59	-28.06	1.34	23.15
Yaw Angle4 (◦)	-0.12	-28.91	-0.07	36.36
Yaw Angle5 (◦)	-0.74	-27.17	-1.02	33.00
Power (kW)	4622.21	125.00	5307.00	7639.00

The power sought by ANN-Wake is included in the output layer, the speed, wind directions and Yaw angles are all included in the input layer, we will have 15 neurons in this layer. There are also two hidden layers containing 32 neurons and 64 neurons respectively. Figure 3, clearly shows in the form of diagrams the structure of ANN-wake.

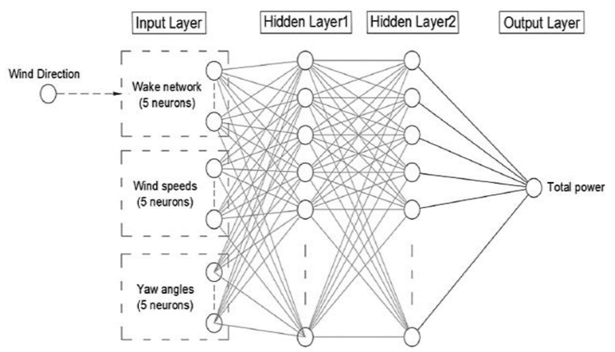

Figure 3. ANN-Wake model process

The equations used in the layers of our model are noted below Equations (2) and (3).

$$S(z) = \frac{1}{1+e^{-z}} \tag{2}$$

$$R(z) = \max(0, z) \tag{3}$$

where, $S(z)$ is sigmoid function and $R(z)$ is Rectified Linear Unit activation function.

To have visibility on the performance of the ANN-Wake model we calculate the coefficient of determination denoted by $R^2(w,\overline{w})$. The expression of the coefficient of determination is shown in Equation (4).

$$R^2(w,\overline{w}) = 1 - \frac{\sum_{i=1}^{n}(w_i - \hat{w}_i)^2}{\sum_{i=1}^{n}(w_i - \overline{w})^2} \tag{4}$$

where, n is number of variables, w_i is ith observation of the response variable, $\hat{w}_i$ is value estimated by the regression function and $\overline{w}$ is mean value of the observations of the response variable.

According to the values in the Table 4, the ANN-wake-model is very efficient since it takes into account the wake effect and also all the values of $R^2(w,\overline{w})$ is tends towards the value 1.

Table 4. ANN-Wake model performance

	Training	Validation	Test	All
$R^2(w,\overline{w})$	0.9954	0.9941	0.9955	0.9951

After the first power estimate made by the ANN-wake-model, the second step aims to optimize based on the Yaw angles. Indeed, to overcome the reduction in Energy caused by the wake [19-20], an adjustment of the yaw angles according to the directions of the wind is necessary to increase the efficiency of wind farm [23-24].

3. YAW ANGLE OPTIMIZATION STEPS

3.1. Optimization Steps

In literature, the algorithm most used in the optimization of wind farms is the genetic algorithm. This choice is explained by its precision and its reduced computation time, in this part of the study we will use GA (the genetic algorithm) to evaluate the power ratio noted in the Equation (5).

$$Ratio_{power} = \frac{P_{actual}}{P_{theoretical}} \tag{5}$$

where, $Ratio_{power}$ is power ratio, P_{actual} is actual power generation and $P_{theoretical}$ is theoretical power generation.

Figure 4 shows the optimization process using the genetic algorithm, the objective function is to be optimized is the total power ratio. The steps of the optimization process are explained in [21].

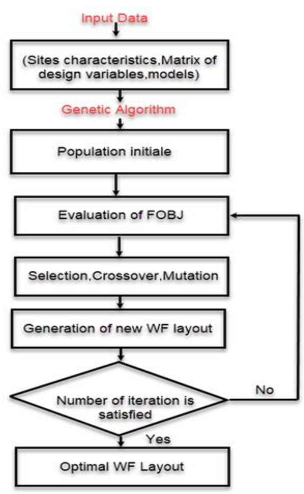

Figure 4. Steps of the genetic algorithm

3.2. Results and Discussion

Figure 5 shows a comparison between real data and optimized power ratio data, the speed used in this study is assumed to be 9 m/s, the optimization results show that the energy maximization is obtained in the directions comprised between 164°-180°, it is recalled that this optimization is carried out between a direction range 150° -200° and yaw rotation angles comprised between +20° and -20°, the increase in the power ratio which tends towards the value 1 is explained by the fact that the angles of the turbines are optimized so as to have minimal and uniform wake losses.

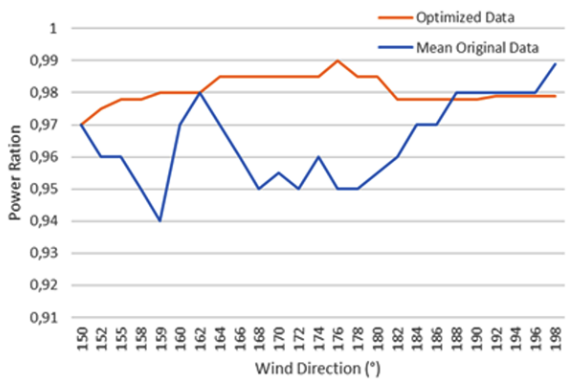

Figure 5. Comparison of original data and optimized results

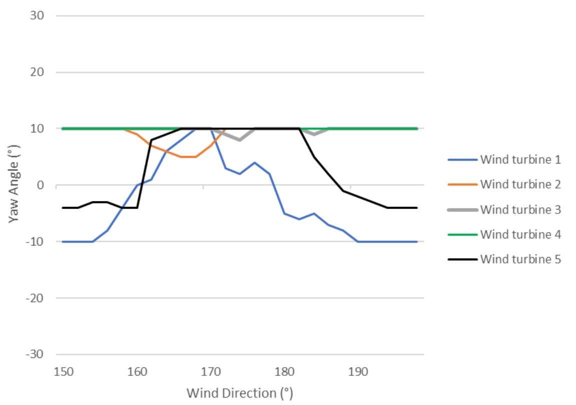

Figure 6. Angle optimization results in the range of -10° to 10°

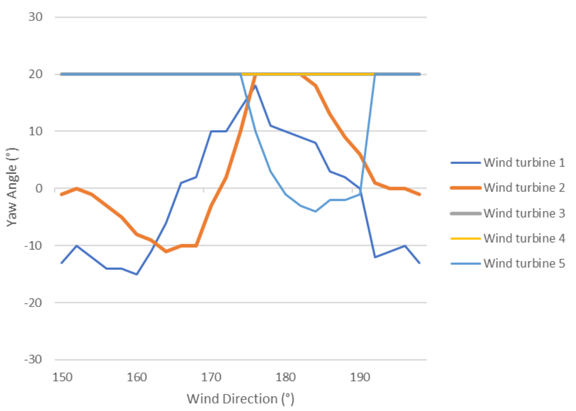

Figure 7. Angle optimization results in the range of -20° to 20°

We also notice in Figures 6 and 7, that the wind turbines (Wind turbine 1, wind turbine 2 and Wind turbine 5) are regrouped in the direction range between 170°-180°. These results seem logical and agree with the first study. We also justify the optimization of the angles in these directions by the minimization of the wake effect, on the other hand the wind turbines (wind turbines 3 and 4) have several directions and different yaw angle values. This can be explained by the position of these wind turbines vis a vis the wind turbines upstream and downstream in order to minimize the wake.

4. CONCLUSIONS

In this present work we tried to develop a new model based on neural networks to predict the energy of a wind farm, the optimization results applied to a wind farm containing five wind turbines, showed the efficiency of this model which was able to improve the studied power ratio up to 0.97 in all directions, subsequently another optimization process based on the Yaw angles of the turbines. This process uses a genetic algorithm to improve the power produced by a wind farm and standardize the wake losses.

This study shows the importance of installing the Neurons networks in wind farm optimization studies. Note also that this type of study requires a large amount of data to have very precise results. In the next studies we will try to test this model on hilly terrain with a large number of wind turbines.

REFERENCES

[1] H. Sun, X. Gao, and H. Yang, "A Review of Full-Scale Wind-Field Measurements of the Wind-Turbine Wake Effect and a Measurement of the Wake-Interaction Effect", Renew. Sustain. Energy Rev., Vol. 132, No. June, p. 110042, 2020.

[2] 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, 2017.

[3] J. Serrano Gonzalez, M. Burgos Payan, J.M. Riquelme Santos, "Optimal Design of Neighboring Offshore Wind Farms: A Co-Evolutionary Approach", Appl. Energy, Vol. 209, No. July, pp. 140-152, 2018.

[4] L. Wang, M.E. Cholette, Y. Fu, J. Yuan, Y. Zhou, A. C.C. Tan, "Combined Optimization of Continuous Wind Turbine Placement and Variable Hub Height", J. Wind Eng. Ind. Aerodyn., Vol. 180, No. March, pp. 136-147, 2018.

[5] DEWEK, "Wind Energy Wind Energy", Vol. 10, No. October 2017.

[6] S. Tao, Q. Xu, A. Feijoo, G. Zheng, J. Zhou, "Nonuniform Wind Farm Layout Optimization: A State-of-the-Art Review", Energy, Vol. 209, 2020.

[7] N. Kermani, "Analysis of Turbulent Wake Behind a Wind Turbine", Aerodyn, No. June, pp. 53-68, 2013.

[8] S.A. MirHassani, A. Yarahmadi, "Wind Farm Layout Optimization under Uncertainty", Renew. Energy, Vol. 107, pp. 288-297, 2017.

[9] C. Carrillo, A.F. Obando Montano, J. Cidras, E. Diaz Dorado, "Review of Power Curve Modelling for Wind

Turbines", Renew. Sustain. Energy Rev., Vol. 21, pp. 572-581, 2013.
[10] H. Sun, X. Gao, H. Yang, "A Review of Full-Scale Wind-Field Measurements of the Wind-Turbine Wake Effect and a Measurement of the Wake-Interaction Effect", Renew. Sustain. Energy Rev., Vol. 132, No. June, p. 110042, 2020.
[11] T. Gocmen, P. Van Der Laan, P.E. Rethore, A.P. Diaz, G.C. Larsen, S. Ott, "Wind Turbine Wake Models Developed at the Technical University of Denmark: A Review," Renew. Sustain. Energy Rev., Vol. 60, pp. 752-769, 2016.
[12] J.F. Herbert Acero, O. Probst, P.E. Rethore, G.C. Larsen, K.K. Castillo Villar, "A Review of Methodological Approaches for the Design and Optimization of Wind Farms", Energies, Vol. 7, No. 11, pp. 6930-7016, 2014.
[13] S. Li, "Wind Power Prediction Using Recurrent Multilayer Perceptron Neural Networks", IEEE Power Eng. Soc. Gen. Meet. Conf. Proc., Vol. 4, pp. 2325-2330, 2003.
[14] WindEurope, "Wind Energy in Europe in 2018 - Trends and Statistics", Trends Stat., p. 32, 2019.
[15] 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.
[16] T. Ishihara, A. Yamaguchi, Y. Fujino, "Development of a New Wake Model Based on a Wind Tunnel Experiment", Glob. Wind Power, p. 6, 2004.
[17] M. Bastankhah, F. Porte Agel, "A New Analytical Model for Wind-Turbine Wakes", Renew. Energy, Vol. 70, pp. 116-123, 2014.
[18] H. Sun, C. Qiu, L. Lu, X. Gao, J. Chen, H. Yang, "Wind Turbine Power Modelling and Optimization Using Artificial Neural Network with Wind Field Experimental Data", Appl. Energy, Vol. 280, No. September, p. 115880, 2020.
[19] S. Tao, Q. Xu, A. Feijoo, P. Hou, G. Zheng, "Bi-Hierarchy Optimization of a Wind Farm Considering Environmental Impact", IEEE Trans. Sustain. Energy, Vol. 11, No. 4, pp. 2515-2524, 2020.
[20] J. Serrano Gonzalez, M. Burgos Payan, J.M. Riquelme Santos, "Optimal Design of Neighboring Offshore Wind Farms: A Co-Evolutionary Approach", Appl. Energy, Vol. 209, No. July, pp. 140-152, 2018.
[21] A. Bellat, K. Mansouri, A. Raihani, K. Tajeddine, "Optimizing the Wind Farm Layout for Minimizing the Wake Losses", Adv. Sci. Technol. Eng. Syst. J., Vol. 6, No. 1, pp. 309-315, 2021.
[22] N. O. Jensen, "A Note on Wind Generator Interaction", Riso-M-2411, Riso Natl. Lab. Roskilde, pp. 1-16, 1983.
[23] H. Shayeghi, M. Alilou, B. Tousi, R.D. Doltabad, "Multi-Objective Allocating the Protective Devices Beside Wind Turbine and Photovoltaic Panel in the Distribution System", Int. J. Tech. Phys. Probl. Eng., Vol. 12, No. 2, pp. 51-57, 2020.
[24] N. Maftouni, S. Akbari, "Building Energy Optimization of a Residential Building and Designing a Wind Farm to Support the Energy, Considering Economic Issues", Int. J. Tech. Phys. Probl. Eng., Vol. 12, No. 3, pp. 23-29, 2020.

BIOGRAPHIES

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