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Extreme learning approach with wavelet transform function for forecasting wind turbine wake effect to improve wind farm efficiency

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ABSTRACT

A wind turbine operating in the wake of another turbine and has a reduced power production because of a lower wind speed after rotor. The flow field in the wake behind the first row turbines is characterized by a significant deficit in wind velocity and increased levels of turbulence intensity. To maximize the wind farm net profit, the number of turbines installed in the wind farm should be different in depend on wind farm project investment parameters. Therefore modeling wake effect is necessary because it has a great influence on the actual energy output of a wind farm. In this paper, the extreme learning machine (ELM) coupled with wavelet transform (ELM-WAVELET) is used for the prediction of wind turbine wake effect in wind far. Estimation and prediction results of ELM-WAVELET model are compared with the ELM, genetic programming (GP), support vector machine (SVM) and artificial neural network (ANN) models. The following error and correlation functions are applied to evaluate the proposed models: Root Mean Square Error (RMSE), Coefficient of Determination (R^2) and Pearson coefficient (r). The experimental results show that an improvement in predictive accuracy and capability of generalization can be achieved by ELM-WAVELET approach (RMSE = 0.269) in comparison with the ELM (RMSE = 0.27), SVM (RMSE = 0.432), ANN (RMSE = 0.432) and GP model (RMSE = 0.433).

1. Introduction

A wind farm contains a number of horizontal wind turbines [1,2]. These wind turbines are positioned and aligned in clusters facing the wind direction. Each wind rotor generates a turbulent region called wake [3,4]. Optimal wind turbine placement on a selected wind farm site is of major importance, since it can lead to a remarkable increase in the produced power [5–7]. While dense configurations appear as a good solution, the so called wake effect is a known side-effect of tight spacing of the turbines [8,9]. It is caused by the fact that when extracting energy from the wind, each turbine creates a cone of more turbulent and slower air behind it, and hence the wind speed encountered by downstream wind turbines decreases, leading to reduced energy yield [10–12]. This wake causes a sudden decrease in velocity, consequence it causes a decrease in the quantity of air and wind speed entering the downstream turbine, so that less energy will be produced by the downstream turbine [13,14]. As air comes out of the wind turbine rotor, its initial diameter is almost equals to the diameter of the turbine rotor [15,16] and then it tends to spread out conically [17]. Turbine wake properties and development depends on many factors which include the wind conditions, turbines topology and rotor radius [18]. For planning of large wind farms, modeling of wake effects is an important part of the energy production estimation [19,20]. In order to reduce power losses and to improve the lifetime of the blades it is necessary to obtain a good understanding of the behavior of wind turbine wakes in wind farms [21,22]. Such an understanding can be obtained by numerical simulation of the wake effects in wind farm [23–25].

All wind turbines in the wind farm have different wake effects. However if the some wind turbines have same working conditions than the wake effect will be the same for these wind turbines. Therefore it is suitable to create a model which will forecast wake effect in the whole wind farm in depend on wind turbine location, distance between turbines and rotor radius. Soft computing methods can be used as alternative techniques because they offer benefits such as no required knowledge of internal system variables, simpler solutions for multi-variable problems and factual calculation [26–28].

Nowadays, application of modern computational approaches in solving the real problems and determining the optimal values and functions are receiving enormous attention by researchers in

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different scientific disciplines. Artificial Neural Network (ANN), a major computational approach, have been recently introduced and applied in different engineering fields [29,30]. The ANN method is capable of solving complex non-linear problems which are difficult to solve by classic parametric methods. There are many algorithms for training neural network such as back propagation, support vector machine (SVM), hidden Markov model (HMM), genetic programming (GP). The shortcoming of ANN is its learning time requirement.

In this study, we motivate and introduce the prediction model of wake effect influence on wind speed at any location in the wind farm using the soft computing approach, namely Extreme Learning Machine (ELM) coupled with wavelet transform algorithm (ELM-WAVELET). Wavelet transform (WT) captures both frequency and location information (location in time) [31] and has some desirable properties compared to the Fourier transform [32]. The transform is based on a wavelet matrix, which can be computed more quickly than the analogous Fourier matrix [32]. ELM was introduced by Huang et al. [33] as an algorithm for single layer feed forward neural network. This algorithm is capable to solve problems caused by gradient descent based algorithms like back propagation which applies in ANNs. The ELM is able to decrease the required time for training a neural network. In fact, it has been proved that by utilizing the ELM, the learning process becomes very fast and it generates robust performance.

In this study, a predictive model of wake effect influence on wind speed at any location in the wind farm is developed using the ELM-WAVELET method. The obtained experimental results are compared with the ANN, SVM, ELM the GP models.

2. Materials and methods

2.1. Wind turbine wake model

The conversion of wind power into electrical power is performed by wind turbines which are grouped into a wind farm in order to minimize the installation, operation and maintenance cost. As the number of wind turbines in the farm increases, the average power output per wind turbine decreases because of the presence of wake effects within the wind farm. The wake effect reduces wind speed of air stream available for the downwind turbine, leading to a lower power extracted by the turbines.

For the present study analytical wake model named as Jensen's wake model [34] is chosen, because momentum is considered as conserved inside the wake by this model. The wake expands linearly with downstream distance. Therefore, this model is suitable for the far wake region. The wake has a radius, at the turbine which is equal to the turbine radius R_r while, R_1 is the radius of the wake in the model. R_1 is considered as radius of the downstream wake; the relationship between R_1 and X is that downstream distance when the wake spreads downstream the radius R_1; that increases linearly proportional, X. Mean wind speed is u_0 or which can be explained as the free stream wind speed and in this study was used $u_0 = 12\,\mathrm{m/s}$. The calculation of the overall wind speed at the downstream turbine is done using Eq. (1).

$$u_{i+1} = u_i * \left(1 - \sqrt{\left(\frac{2a}{1+\alpha\left(\frac{X}{\left(R_r\sqrt{\frac{1-a}{1-2a}}\right)}\right)^2}\right)^2 + \left(\frac{2a}{1+\alpha\left(\frac{X}{\left(R_r\sqrt{\frac{1-a}{1-2a}}\right)}\right)^2}\right)^2}\right)$$
$$i = 0, 1 \ldots . N \tag{1}$$

In the above equation we have:

- axial induction factor is denoted by a which can be calculated from the C_T, thrust coefficient. This can be determined from the expression [34]:

$$C_T = 4a(1-a) \tag{2}$$

- X is considered as the distance downstream of the turbine, while R_1 is related with R_r as represented using following equation [34]:

$$R_1 = R_r\sqrt{\frac{1-a}{1-2a}} \tag{3}$$

- α is the entertainment constant and by using the following equation; it can be obtained [34]:

$$\alpha = \frac{0.5}{\ln\frac{z}{z_0}} \tag{4}$$

In the above equation, z is used to denote the hub height and roughness of the surface is denoted by z_0. The value for surface roughness varies from field to field. For plain terrains the value for $z_0 = 0.3$. The values for different variables are as under:

- $X = \{100,\ 200,\ 300,\ 400,\ 500\}$ m
- $R_r = \{10,\ 20,\ 30,\ 40\}$ m
- $u_0 = 12$ m/s
- $a = 0.326795$
- $\alpha = 0.09437$
- $i = 0, 1 \ldots .\ 20$

2.2. NPV for wind farm project investment

Capital budgeting is finance terminology for the process of deciding whether or not to undertake an investment project. There are two standard concepts used in capital budgeting: net present value (NPV) and interest rate of return (IRR). Net present value, NPV, of the profit to be derived from the wind farm is

$$\begin{aligned} NPV &= -CF_0 + \sum_{t=1}^{n} \frac{T * P_T(CPPU, C, E, N_t) * CU - M}{(1+r)^t} \\ &= -CF_0 + \sum_{t=1}^{n} \frac{CF_t}{(1+r)^t} \\ n &= 20 \text{ years} \end{aligned} \tag{5}$$

where CF_0 represents total investment in the wind farm (cost of turbines, installations and land cost), CF_t is the net revenue from selling electricity from the wind farm, r is the appropriate financial interest rate, T is total operating time per period, n is the number of years for project investment, P_T is the total extracted power from all wind turbines in the wind farm and it depends on total cost C, cost per power unit $CPPU$, efficiency E and the number of turbines N_t. CU is the unit sale price of electricity and M is the cost of operation and maintenance of the wind farm per period.Interest rate of return, IRR, can be derive when the $NPV = 0$ or

$$\begin{aligned} 0 &= -CF_0 + \sum_{t=1}^{n} \frac{T * P_T(CPPU, C, E, N_t) * CU - M}{(1+IRR)^t} \\ &= -CF_0 + \sum_{t=1}^{n} \frac{CF_t}{(1+IRR)^t} \end{aligned} \tag{6}$$

In this study the used values for different variables and parameters are as under:

- $X = 200$ m
- $R_r = 40$ m
- $u_0 = 12$ m/s
- $a = 0.326795$
- $\alpha = 0.09437$
- $N_t = 1 - 100$ turbines

- $r = 1 - 10\%$ per year
- $T = 7884$ h/year
- $CU = 0.6 - 1.5$ \$/kW h
- $CF_0 = N_t * (CT + CI + CL * (N_t))$
- $CT = 450,000\$$ – cost per turbine
- $CI = 100,000\$$ – cost per turbine installation
- $CL = 100\$$ – cost of land per turbine
- $M = 0.015 * CT * N_t$

2.3. Extreme learning machine

Extreme learning machine (ELM) as a tool of learning algorithm has been firstly introduced for a single layer feed-forward neural network (SLFN) architecture [33,35, 36]. ELM algorithm chooses the input weights randomly and determines the output weights of SLFN analytically. It has more suitable general capability with faster learning speed and also is capable to determine all the network parameters analytically that prevents human intervention. Other advantages include ease of use, quick learning speed, higher performance, and suitability for different nonlinear activation and kernel functions [37–39].

In this study, wavelet analysis is employed to decay time series of wake wind speed data to individual components, where the decomposed components can be considered for data inputs into the ELM model. More details about ELM model can be found in Refs. [40–47].

2.4. Support vector machine

The main purpose of SVMs is to determine data correlation through the method of non-linear mapping. Kernel methods enable function in a high-dimensional, *implicit* feature space without calculating the data coordinates in the respective space, instead, through a simple computation of the inner products between the images of all data pairs in the feature space. The results obtained from higher-dimensional feature space correlates with the data derived from the original, lower-dimensional input space. More details about SVM approach can be found in Refs. [48–62].

2.5. Model performance evaluation

The following statistical indicators were selected in the performance evaluation of ELM-WAVELET, ELM, ANN, GP, SVM-WAVELET, and SVM models:

(1) root-mean-square error (RMSE)

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}}, \tag{7}$$

(2) Pearson correlation coefficient (r)

$$r = \frac{n\left(\sum_{i=1}^{n} O_i \cdot P_i\right) - \left(\sum_{i=1}^{n} O_i\right)\cdot\left(\sum_{i=1}^{n} P_i\right)}{\sqrt{\left(n\sum_{i=1}^{n} O_i^2 - \left(\sum_{i=1}^{n} O_i\right)^2\right)\cdot\left(n\sum_{i=1}^{n} P_i^2 - \left(\sum_{i=1}^{n} P_i\right)^2\right)}} \tag{8}$$

(3) coefficient of determination (R^2)

$$R^2 = \frac{\left[\sum_{i=1}^{n}\left(O_i - \overline{O_i}\right)\cdot\left(P_i - \overline{P_i}\right)\right]^2}{\sum_{i=1}^{n}\left(O_i - \overline{O_i}\right)\cdot\sum_{i=1}^{n}\left(P_i - \overline{P_i}\right)} \tag{9}$$

where n is the total number of test data; and O_i and P_i are the predicted wake wind speed values by soft computing methods and measured values, respectively.

Table 1
Comparative performance statistics of the ELM-WAVELET, ELM, SVM, ANN and GP predictive models.

Soft computing model	Statistical indicator		
	RMSE	R^2	r
ELM-WAVELET	0.269	0.9956	0.997
ELM	0.270	0.9956	0.997
SVM	0.432	0.9887	0.994
ANN	0.432	0.9887	0.994
GP	0.433	0.988	0.994

3. Results and discussion

3.1. Performance analysis

In this section performance results of wake wind speed prediction using the soft computing models are reported. Fig. 1(a) presents the accuracy of developed ELM-WAVELET predictive model. Consequently, Fig. 1(b), (c), (d) and (e) presents the accuracy of developed ELM, SVM, ANN and GP predictive models, respectively. It can be seen that the most of the points fall along the diagonal line for ELM-WAVELET prediction model. The prediction results are in a very good agreement with the measured values for ELM method. This observation can be confirmed with very high value for coefficient of determination. The number of either overestimated or underestimated values produced is limited. It is obvious that the predicted values enjoy high level precision.

In order to demonstrate the merits of the proposed ELM-WAVELET approach on a more definite and tangible basis, ELM-WAVELET prediction accuracy was compared with prediction accuracy of ELM, SVM, ANN and GP methods, which were used as a benchmark. Conventional error statistical indicators, RMSE, r and R^2, were used for comparison. Table 1 summarizes the prediction accuracy results for test data sets since training error is not credible indicator for prediction potential of particular model.

ELM-WAVELET model outperform other soft computing models according to the results in Table 1. The ELM-WAVELET model provides significantly better results than benchmark models. On the basis of RMSE analysis with comparison with ELM, SVM, ANN and GP, it may be concluded that the proposed ELM-WAVELET outperformed the results obtained with benchmark models.

4. Conclusion

The study carried out a systematic approach to create the ELM-WAVELET for the prediction of wake wind speed production in wind farm. A comparison of ELM-WAVELET method with ELM, SVM, ANN and GP was performed in order to assess the prediction accuracy. Accuracy results, measured in terms of RMSE, r and R^2, indicate that the ELM-WAVELET predictions are superior then the ELM, SVM, ANN and GP. Additionally, results reveal robustness of method.

The experimental results show that an improvement in predictive accuracy and capability of generalization can be achieved by ELM-WAVELET approach (RMSE = 0.269) in comparison with the ELM (RMSE = 0.27), SVM (RMSE = 0.432), ANN (RMSE = 0.432) and GP model (RMSE = 0.433).

Selected soft computing approaches are data-driven methods, which represents their main limitation. In other words, these methods have high dependence on training data selection. However, if there are errors in the training data, the soft computing methods can overcome the errors since they are highly robust methods on data fluctuations. The most important task during preparation of the training data is to cover all possible situations

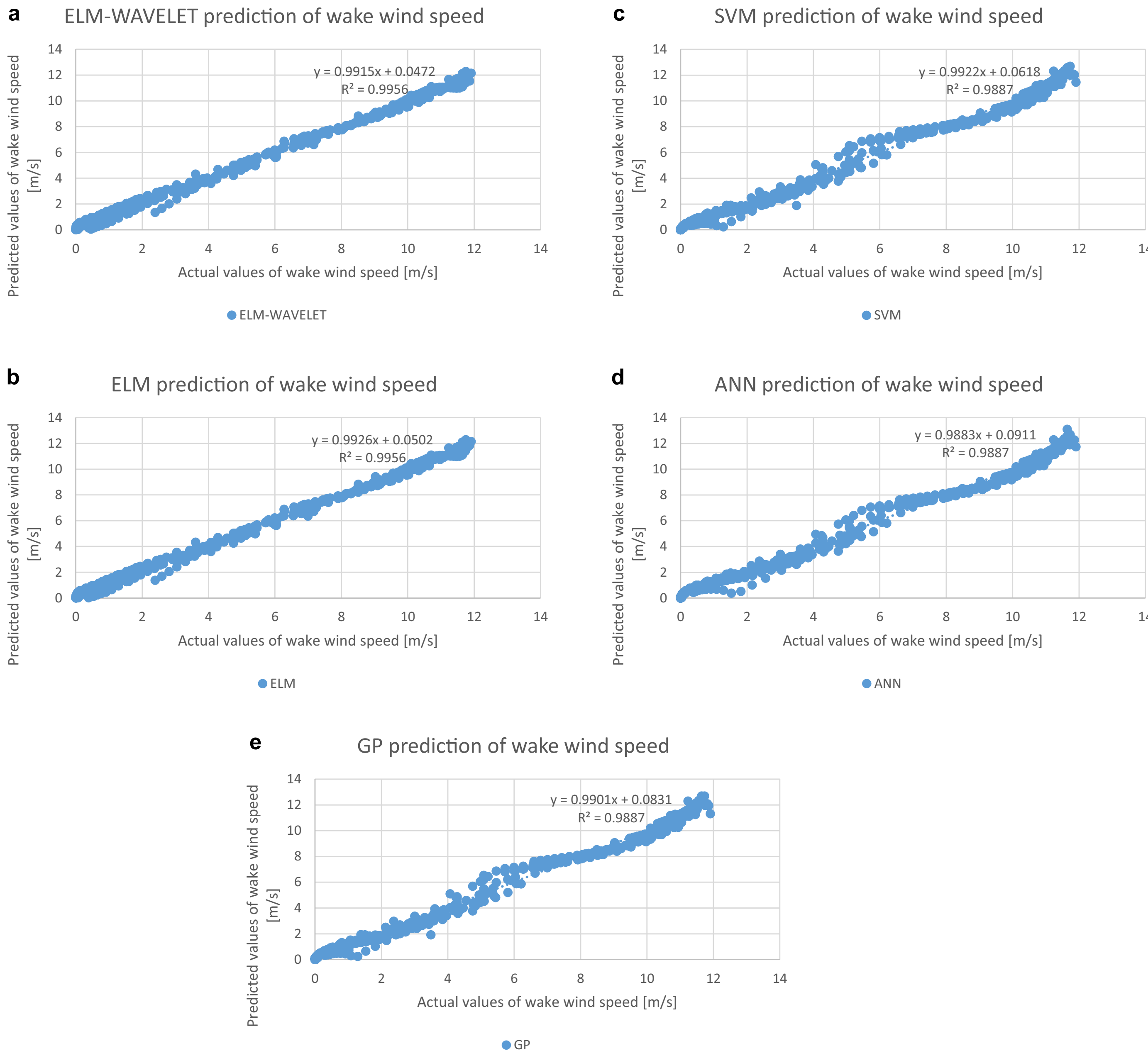

Fig. 1. Scatter plots of actual and predicted values of wake wind speed using (a) ELM-WAVELET, (b) ELM, (c) SVM, (d) ANN and (c) GP method.

in the data, which allows the soft computing methods to work in all conditions.

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