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ORIGINAL PAPER

Adapting project management method and ANFIS strategy for variables selection and analyzing wind turbine wake effect

Dalibor Petković · Siti Hafizah Ab Hamid · Žarko Ćojbašić · Nenad T. Pavlović

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Abstract We present a project management methodology designed for the selection of wind turbines wake effect most influential parameters, who need to run wind farm project for large energy conversion. Very frequently, the managers of these projects are not project management professionals, so they need guidance to have autonomy, using minimal time and documentation resources. Therefore, agile method is adapted to assist the project management. Wind energy poses challenges such as the reduction in the wind speed due to the wake effect by other turbines. If a turbine is within the area of turbulence caused by another turbine, or the area behind another turbine, the wind speed suffers a reduction and, therefore, there is a decrease in the production of electricity. In order to increase the efficiency of a wind farm, analyzing the parameters, which have influence on the wake effect, is one of the focal research areas. To maximize the power produced in a wind farm, it is important to determine and analyze the most influential factors on the wake effects or wake wind speeds since the effect has most influence on the produced power. This procedure is typically called variable selection, and it corresponds to finding a subset of the full set of recorded variables that exhibits good predictive abilities. In this study, architecture for modeling complex systems in function approximation and regression was used, based on using adaptive neuro-fuzzy inference system (ANFIS). Variable searching using the ANFIS network was performed to determine how the five parameters affect the wake wind speed. Our article answers the call for renewing the theoretical bases of wind farm project management in order to overcome the problems that stem from the application of methods based on decision-rationality norms, which bracket the complexity of action and interactions in projects.

D. Petković (✉) · Ž. Ćojbašić · N. T. Pavlović
Department for Mechatronics and Control, Faculty of Mechanical Engineering, University of Niš, Aleksandra Medvedeva 14, 18000 Nis, Serbia
e-mail: dalibortc@gmail.com

S. H. Ab Hamid
Faculty of Computer Science and Information Technology, University of Malaya, 50603 Kuala Lumpur, Malaysia

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1 Introduction

The project management field experiences a revolution with two main drivers. The first driver is a practical reconsideration of prescriptions rooted in the rationality of decision theory, which seem to generate technical and commercial failures, internal and external conflicts, and inadequate responses to unexpected events. Project practitioners respond to these shortcomings by proposing new approaches, such as agile methods or partnering approaches, anchored in different rationalities. Researchers aim to better account for project phenomena and outcomes by redirecting efforts away from developing principles for optimizing plans, contracts and charts, and toward understanding the specific nature of social relations, structures, and processes that occur in projects. In particular, they seek to draw upon fundamental sociological theories in order to deepen the understanding of project organizations. We present a project management methodology with agile method for the selection of wind turbines wake effect most influential parameters, who need to run wind farm project for large energy conversion.

Renewable energy sources have attracted lots of attention due to the technology development, their no dependence on fossil fuels, and their friendliness to the environment. The relative low values of the wind turbine-rated capacities available nowadays, compared to conventional power station units, mean that a high number of turbines must be installed in a single site, a wind station or wind farm, in order to reach an installed capacity similar to a conventional power station. This wind turbine cluster disposition, more or less packed, offers some economic advantages related to the investment and to the plant operation and maintenance costs (Grady et al. 2005). But the wind turbine compactness degree is limited by spacing constrains due to wind shadow or wake decay effects (Marmidis et al. 2008), that is, when two wind turbines are placed too close one behind the other in the prevailing wind direction, the total amount of generated power is less than the initially expected individual power sum at the free air stream because the wind power in the air stream available for the downwind turbine is reduced due to the wind power extracted by the upwind rotor turbine (Gonzalez et al. 2010; Changshui et al. 2011). As a consequence, the layout or specific individual wind turbine position determines the overall potential wind energy extraction efficiency of a wind farm (Ekonomou et al. 2012; Saavedra-Moreno et al. 2011; Eroglu and Seçkiner 2012; Yin and Wang 2012). The wind turbine wake effect depends on several different factors such as the terrain morphology, the wind farm area, the wind turbine size, the wind speed, the wind direction, and design of blades (Chen et al. 2013; Ituarte-Villarreal and Espiritu 2011).

The wake effect is the key factor affecting the low efficiency of wind power production. It is very important to predict the relationship between the wake wind speed (wake effect) for various wind turbine and wind farm parameters.

If there is a lot of interference or wake generated by the wind turbines, the possibility of mechanical failure would increase as well as the need for more maintenance actions, and an inevitable reduction in power output. In addition to considering the impact of turbines on the others, it is important to take into account the terrain, weather conditions, and wind conditions in the region, such as speed and wind direction (Mokryani and Siano 2013;

Rašuo and Bengin 2010). Several studies have been conducted in recent years in order to maximize energy production and the efficiency of the turbines (Emami and Noghreh 2010; Mustakerov and Borissova 2010).

To build a wind farm with the best features, it is desirable to select and analyze a subset of parameters that are truly relevant or the most influential to the wing turbine wake effect in order to minimalize the effect (Nagai et al. 2009; MacPhee and Beyene 2013).

This procedure is typically called variable selection, and it corresponds to finding a subset of the full set of recorded variables that exhibits good predictive abilities. In this study, architecture for modeling complex systems in function approximation and regression was used, based on neural network. Neural networks can be defined as an architecture comprising massively parallel adaptive processing elements interconnected via structured networks. Thus, the neural network models generated from these data must therefore rely on how effectively the chosen sensor data represent the system. Therefore, in order to build a model that can predict a specific process output, it is desirable to select a subset of variables that are truly relevant to this output. This procedure is typically called variable selection, and it corresponds to finding a subset of the full set of recorded variables that exhibits good predictive abilities (Castellano and Fanelli 2000; Dieterle et al. 2003; Cibas et al. 1996; Anderson et al. 2000). A solution to the variable selection problem could be the utilization of prior knowledge in order to screen out the irrelevant variables. A more advanced approach is to consider the variable selection problem as an optimization procedure via genetic algorithms (Donald 2002), where the objective is to minimize the error between the true values and the model predictions of the explained (output) variables, by selecting the proper explanatory (input) variables. One of the most powerful types of neural network system is adaptive neuro-fuzzy inference system (ANFIS) (Chan et al. 2011; Kwong et al. 2009).

The objective of variable selection is threefold: improving the prediction performance of the predictors, providing faster and more cost-effective predictors, and providing a better understanding of the underlying process that generated the data, i.e., providing the most influential parameters on the predictor (Guyon and Elisseeff 2003; Despagne and Massart 1998; Papadokonstantakis et al. 2005). Variable searching using the ANFIS network was performed to determine how the wind turbine and wind farm parameters affect the output wake wind speed. For the present study, analytical wake model named as Jensen's wake model (Jensen 1983) is chosen, because momentum is considered as conserved inside the wake by this model. The analytical model was used for extracting training and checking data for the ANFIS network. ANFIS (Jang 1993), as a hybrid intelligent system that enhances the ability to automatically learn and adapt, was used by researchers for modeling (Al-Ghandoor and Samhouri 2009; Singh et al. 2012; Petković et al. 2012; Petković and Ćojbašić 2011), predictions (Hosoz et al. 2011; Khajeh et al. 2009; Sivakumar and Balu 2010), and control (Kurnaz et al. 2010; Ravi et al. 2011; [illegible]d et al. 2010; Petković et al. 2012; Tian and Collins 2005) in various engineering systems. The basic idea behind these neuro-adaptive learning techniques is to provide a method for the fuzzy modeling procedure to learn information about the data (Aldair and Wang 2011; Dastranj et al. 2011). The ANFIS is one of the methods to organize the fuzzy inference system with given input/output data pairs (Wahida Banu et al. 2011; Grigorie and Botez 2009). This technique gives fuzzy logic the capability to adapt the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data (Akcayol 2004; Shamshirband et al. 2010, 2014; Khoshnevisan et al. 2014).

2 Materials and methods

2.1 Project management method

Project development organizations are continually challenged by the need to improve the quality of the project products. Technologies are changing rapidly, and any project is becoming scalable and complex. In addition, large-scale, distributed development poses new challenges. To overcome the inability to meet the requirements and to deal with their rapid changing, project development requires the alignment of decisions on the strategic, tactical, and operational levels (Moe et al. 2012). Project development also requires a transition from specialized skills to the redundancy of functions and from rational to naturalistic decision making. Likewise, Wysocki (2009) agreed that by using the agile software development method, there are many factors that will influence the success of a project. Agile method focuses on four manifestos, which are individuals and iterations, working software, customer collaboration, and responding to change. For this project, we adapt the responding to change manifesto.

To determine the wind turbine wake effect, the project must start by understanding the wind farm efficiency model. The purpose is to indicate all important variables or parameters of the wind turbine. Every single of variable carries an equation with factors to ensure the model efficiency. Table 1 shows the parameters required. However, the existing parameters and equations are not enough to maximize the power produced in a wind farm. New technique or system is required to having new variables selection that enables to not only maximize the wind turbine wake effect but also capable to predict the efficiency. Then, ANFIS is chosen. The system works as a regression test as in a cyclic process, which changes of variables are made to ensure the best variables are selected.

2.2 Wind farm efficiency model

The wake expands linearly with downstream distance. 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. The wake expands linearly with downstream distance, as stated in Jensen's model as shown in Fig. 1.

Following equation is used to determine the wake wind speed (wake effect) after wind turbine rotor as it shown in Fig. 1:

Table 1 Wake effect parameters

Inputs/output	Parameters description
Input 1	X: wake downstream distance
Input 2	R_r: wake or rotor radius
Input 3	a: axial induction factor
Input 4	z: hub height
Input 5	z_0: roughness of the surface
Output	u: wake wind speed

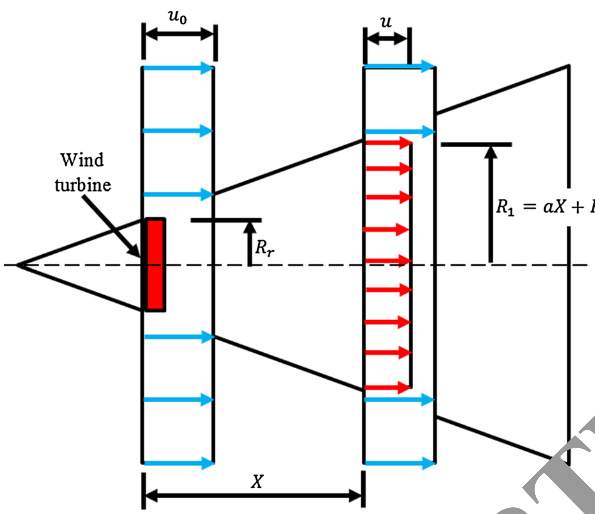

Fig. 1 Schematic of wake model

$$u = u_0 * \left(1 - \frac{2a}{1 + \alpha \left(\frac{X}{\left(R_r \sqrt{\frac{1-a}{1-2a}} \right)} \right)^2} \right). \tag{1}$$

In the above equation, we have

- u_0 is the mean wind speed or which can be explained as the free stream wind speed and in this study was used $u_0 = 12$ m/s
- axial induction factor is denoted by a,which can be calculated from the C_T, thrust coefficient. This can be determined from the expression

$$C_T = 4a(1 - a).$$

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

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

- α the entertainment constant and by using the following equation, it can be obtained as

$$\alpha = \frac{0.5}{\ln \frac{z}{z_0}}.$$

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 $z_0 = 0.3$.

In this study, the used five variables are defined as in Table 1.

Table 2 Roughness classes and lengths

Roughness class	Roughness length z_0 (m)	Energy index (%)	Land scape
0	0.0002	100	Water surface
1	0.03	52	Agricultural area, no fences or hedges, scattered buildings
2	0.1	39	Agricultural area, couple of houses
3	0.4	24	Villages, small town forests or very rough and uneven terrain
4	1.6	13	Very large cities with tall buildings

In the above Table 1, wake downstream distance X is in range 100–500 m, wake or rotor radius is in range 10–40 m, axial induction factor is in range 0.2–0.4, and hub height is in range 30–90 m. For parameter z_0, five roughness classes of the surface were analyzed as listed in Table 2.

2.3 Variable selection using adaptive neuro-fuzzy inference system

Adaptive neuro-fuzzy inference system (ANFIS) can serve as a basis for constructing a set of fuzzy "IF–THEN" rules with appropriate membership function to generate the stipulated input–output pairs. The membership functions are tuned to the input–output data. ANFIS is about taking an initial fuzzy inference (FIS) system and tuning it with a back-propagation algorithm based on the collection of input–output data. The basic structure of a fuzzy inference system consists of three conceptual components: a rule base, which contains a selection of fuzzy rules; a database, which defines the membership functions used in the fuzzy rules; and a reasoning mechanism, which performs the inference procedure upon the rules and the given facts to derive a reasonable output or conclusion. These intelligent systems combine knowledge, technique, and methodologies from various sources. They possess human-like expertise within a specific domain—adapt themselves and learn to do better in changing environments. In ANFIS, neural networks recognize patterns and help adaptation to environments. Fuzzy inference systems incorporate human knowledge and perform interfacing and decision making.

Fuzzy logic toolbox in MATLAB was used for the entire process of training and evaluation of fuzzy inference system. Figure 2 shows an ANFIS structure for two inputs,

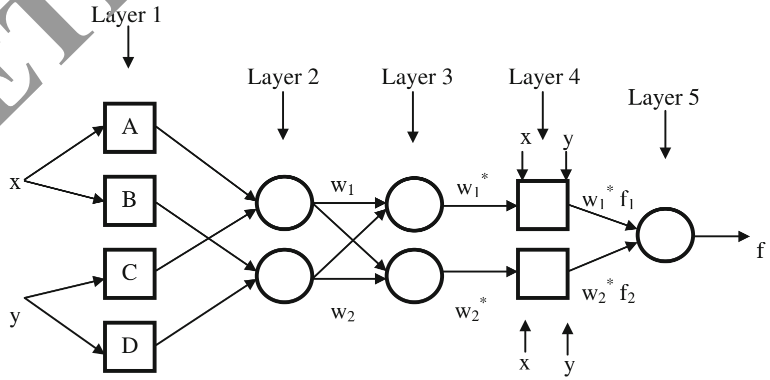

Fig. 2 ANFIS structure

the most influential parameters on the wake wind speed and one output, estimated wake wind speed. Here, the analysis was constrained on the selection of two of the most influential parameters on the wake effect.

In this work, the first-order Sugeno model with two inputs and fuzzy IF–THEN rules of Takagi and Sugeno's type is used:

$$\text{if } x \text{ is } A \text{ and } y \text{ is } C \text{ then } f_1 = p_1 x + q_1 y + r_1.$$

The first layer consists of input variables membership functions (MFs), inputs 1 and 2. This layer just supplies the input values to the next layer. In the first layer, every node is an adaptive node with a node function $O = \mu_{AB}(x)$ and $O = \mu_{CD}(x)$ where $\mu_{AB}(x)$ and $\mu_{CD}(x)$ are MFs. In this study, bell-shaped MFs with maximum equal to 1 and minimum equal to 0 is chosen, such as

$$\mu(x) = \mathrm{bell}(x; a_i, b_i, c_i, d_i) = \frac{1}{1 + \left[\left(\frac{x - c_i}{a_i}\right)^2\right]^{b_i}}.$$

where $\{a_i, b_i, c_i, d_i\}$ is the set of parameters set that in this layer are referred to as premise parameters. In this layer, x and y are the inputs to nodes and they represented the combinations of the two most influential parameters of the wind turbine on the power coefficient.

The second layer (membership layer) checks for the weights of each MFs. It receives the input values from the first layer and acts as MFs to represent the fuzzy sets of the respective input variables. Every node in the second layer is non-adaptive, and this layer multiplies the incoming signals and sends the product out like $w_i = \mu_{AB}(x) * \mu_{CD}(y)$. Each node output represents the firing strength of a rule.

The third layer is called the rule layer. Each node (each neuron) in this layer performs the precondition matching of the fuzzy rules, i.e., they compute the activation level of each rule, the number of layers being equal to the number of fuzzy rules. Each node of these layers calculates the weights, which are normalized. The third layer is also non-adaptive, and every node calculates the ratio of the rule's firing strength to the sum of all rules' firing strengths like $w_i^* = \frac{w_i}{w_1 + w_2}$, $i = 1, 2$. The outputs of this layer are called normalized firing strengths.

The fourth layer is called the defuzzification layer, and it provides the output values resulting from the inference of rules. Every node in the fourth layer is an adaptive node with node function $O_i = w_i^* x f = w_i^*(p_i x + q_i y + r_i)$ where $\{p_i, q_i, r\}$ is the parameter set and in this layer is referred to as consequent parameters.

The fifth layer is called the output layer, which sums up all the inputs coming from the fourth layer and transforms the fuzzy classification results into a crisp (binary). The single node in the fifth layer is not adaptive, and this node computes the overall output as the summation of all incoming signals

$$O_i^4 = \sum_i w_i^* x f = \frac{\sum_i w_i f}{\sum_i w_i}.$$

The hybrid learning algorithms were applied to identify the parameters in the ANFIS architectures. In the forward pass of the hybrid learning algorithm, functional signals go forward until layer 4 and the consequent parameters are identified by the least squares estimate. In the backward pass, the error rates propagate backwards and the premise parameters are updated by the gradient descent.

3 Results

A comprehensive search was performed within the available inputs to select the set of the most optimal combinations inputs (Table 1) that most influence the output parameter (wake effect). Essentially, the functions build an ANFIS model for each combination and train it for one epoch and report the performance achieved. In the beginning, the one most influential input in predicting the output was determined (Fig. 3). It can be seen that the wake downstream distance X has the most influence on the wake effect. The left-most input variable in Fig. 3 has the least error or the most relevance with respect to the output.

The plot and results from the function (Fig. 3) clearly indicate the input variable wake downstream distance X as the most influential for wake wind speed prediction. The training and checking errors are comparable, which indirectly suggests that there is no overfitting. This means it can be increased and explored to select more than one input parameter to build the ANFIS model. To verify this, search for the optimal combination of 2 input parameters can be performed.

The results in Fig. 4 indicate that input 1/input 2 (wake downstream distance X/rotor radius R_r) forms the optimal combination of two input attributes for wake effect prediction. Further, search can be performed for the optimal combination of three input parameters. The results in Fig. 5 indicate that input 1/input 2/input 3 (wake downstream distance X/ rotor radius R_r/axial induction factor a) forms the optimal combination of three inputs

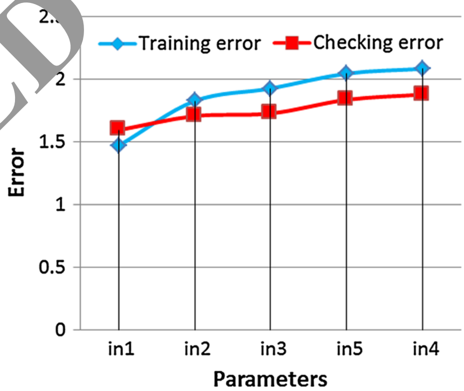

Fig. 3 Every input parameter's influence on the wake effect

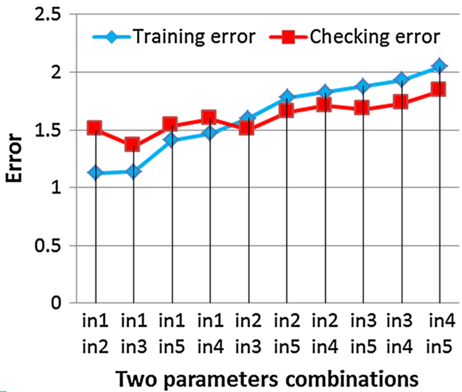

Fig. 4 Influence of two input parameters optimal combinations on the wake effect

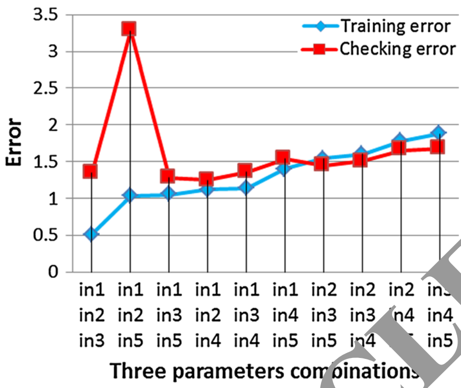

Fig. 5 Influence of three input parameters optimal combinations on the wake effect

Table 3 ANFIS regression errors for wake effect prediction

	Wake effect training error	Wake effect checking error
Input 1	1.471	1.5964
Input 1/input 2	1.1215	1.5011
Input 1/input 2/input 3	0.5184	1.3424

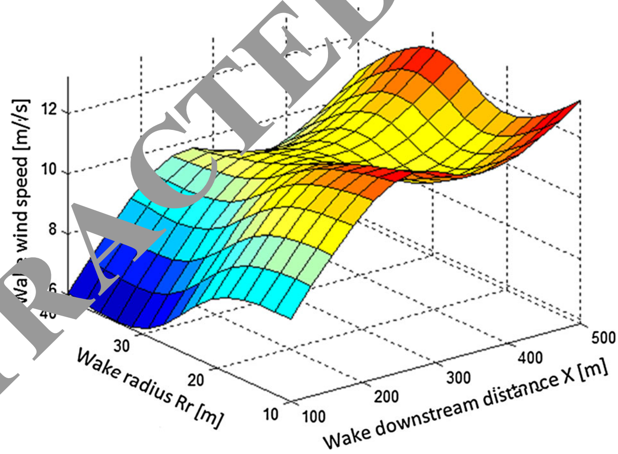

Fig. 6 ANFIS predicted relationship between the most influential wake effect parameters and wake wind speed

attributes for wake effect prediction. Table 2 shows ANFIS regression errors for one input and for optimal combinations of the two and three inputs. It may not be appropriate to use more than two inputs for building the ANFIS model since a model with a simple structure was always preferred. Therefore, emphasis will be focused on the two input ANFIS for further examination. The selected input parameters from the original training and checking datasets were then extracted.

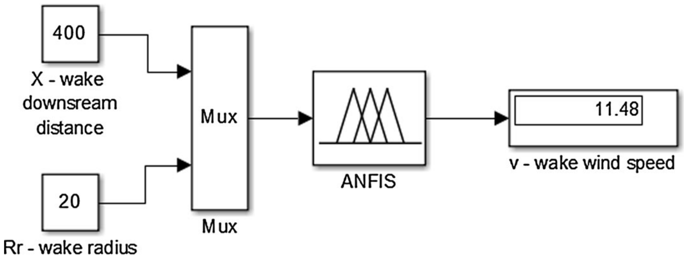

Fig. 7 Matlab SIMULINK block diagram for the estimation of wake wind speed

The used function for all parameters only trains each ANFIS for a single epoch to be able to quickly find the right inputs. Now that the inputs are fixed, and the number can be increased for epoch on ANFIS training (100 epochs) (Table 3).

The ANFIS input–output (decision) surface of the model for wake wind speed (wake effect) is shown in Fig. 6. The input–output surface shown is a nonlinear and monotonic surface, and illustrates how the ANFIS model will respond to varying the wake downstream distance and wake or rotor radius or how the inputs affect the wake wind speed.

Two of the most influential wake effect parameters are implemented in MATLAB SIMULINK block diagram (Fig. 7) for fast estimation of wake wind speed.

4 Conclusion

The main contribution of this research is a project management methodology with agile method, specific to the selection of wind turbine wake effect most influential parameters, which helps with the strategic project formulation, and is validated through the successful implementation of each of the proposed tools and activities.

Wind energy and consequently wind farms constitute one of the greatest renewable energy sources with rapid expansion all over world. One of the main problems in the design and construction of a wind farm, in order to maximize its energy production and its efficiency, is the optimal configurations of wind turbines to be installed. The grouping of turbines in a wind farm introduces two major issues: a wind turbine operating in the wake of another turbine has a reduced power production and shortens the lifetime of the rotors. The additional turbulence in the wake could be a reason for increased material fatigue through flow induced vibrations at the downstream rotor. There are many parameters that have to be included in the wake effect prediction and estimation.

Many parameters (input variables) define wake wind speed (wake effect) such as wake downstream distance, rotor or wake radius, hub height, surface roughness, axial induction factor, and free wind speed as well. The inclusion of many input variables, however, has many drawbacks: explaining the model is difficult, irrelevant variables act as noise, and deteriorating the generalization capability of the model and data collecting can be much more costly. It is therefore useful to invent methods that allow reducing the number of input variables, thus reducing the complexity of the model, and possibly gaining better predictive performances and insights into the relevance of the variables for the problem.

In this study, a variable selection method using ANFIS network with cyclic agile method was performed to determine which wind turbine and farm parameters have the most influence on the wake wind speed. The two selected parameters were used as inputs to

ANFIS network for building a regression procedure to estimate the wake wind speed or wake effect.

Simulations were run in MATLAB, and the results were observed on the corresponding output blocks. The main advantages of the ANFIS scheme are computationally efficient, well adaptable with optimization and adaptive techniques. This can also be combined with expert systems and rough sets for other applications. ANFIS can also be used with systems handling more complex parameters. Another advantage of ANFIS is its speed of operation, which is much faster than in other control strategies; the tedious task of training MFs is done in ANFIS.

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