Adaptive neuro-fuzzy estimation of building augmentation of wind turbine power

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Abstract

Wind power is generating interest in many countries as a way to produce inexpensive and sustainable electrical power. Building integrated wind turbines (BIWTs) are an interesting option in this respect. BIWTs are low cost renewable sources of energy. Since the power in wind is proportional to the cubic power of the wind velocity approaching the wind turbine, a small amount of wind speed acceleration leads to a large increase in energy output. To augment free wind speed streams, the open area between two buildings can be used as diffuser by taking advantage of the Venturi effect. A system where two buildings are used to increase the winds kinetic energy is called building augmented wind turbine (BAWT). This article shows that the shape of buildings can be changed to maximize the power generated by wind and power augmentation. To estimate building power augmentation using a simplified turbine model, this paper constructed a process that simulated the augmented power and wind velocity in regard to different building geometries using an adaptive neuro-fuzzy (ANFIS) method. This intelligent estimator was implemented using MATLAB/Simulink. The simulation results presented in this paper demonstrated the effectiveness of the method developed in this study.

1. Introduction

The use of renewable and clean energy has become a very important issue. Wind energy is one of the fastest utilizing energy sources. The power generated by the wind is proportional to the velocity of the free stream, cubed. In order to take higher power outputs from the free wind stream, a suitable system must be constructed to increase its flow velocity [1–3]. Enclosing a wind turbine in a specially designed shroud will increase its output power [4,5] as demonstrated by several researchers [6,7]. In urban environments, shrouding, or using diffuser augmentations on horizontal wind turbines [8] are one way to improve their performance [9,10].

Generating energy from the wind in an urban environment is a worthwhile endeavor, but [11,12] there are significant challenges implementing it on a large scale [13,14]. In urban environments, the wind is usually insubstantial, inconsistent, and erratic in terms of direction and speed [15,16], because of the presence of buildings and other nearby obstructions. To create a reasonable amount of energy from a wind turbine located in urban environments, the turbines must increase the amount of energy they capture [17,18]. In other words, turbines must be designed to work effectively in areas with poor wind resources [19,20].

The ducted wind turbine (DWT) is a recent improvement that may lead to the development of a new paradigm [21–23]. The DWT is a small device that can be incorporated into a building to produce power through wind energy conversion [24–26]. The ducted wind turbine overcomes many of the issues related to the conventional wind turbines in urban environments [27–29] were the generation of wind power is hindered by high levels of air stream turbulence and are constrained by concerns over their visual impact, the noise they make, and public safety [30].

The current trend is to incorporate wind turbines in the structure of a building or above it. Wind turbines that are incorporated within a building are described as being building integrated wind turbines (BIWTs) [31–33]. The size of urban turbines is constrained by the space available, which makes them less viable than their larger standalone counterparts [34]. One way to combat size constraints is to increase power by increasing the kinetic energy...
of the air. One method for increasing the kinetic energy of the air is to accelerate velocity by forcing air through a duct and a turbine by means of a pressure drop between two buildings. The increased wind velocity that occurs between buildings is known as the Venturi effect. Many researchers are using the Venturi effect to increase the kinetic energy of the wind to drive smaller turbines. A system where two buildings are used to increase the kinetic energy of the wind is called a building augmented wind turbine (BAWT) [35–37].

In this study, various building geometries and their effects on power augmentation with a simplified turbine model were analyzed. Since computational fluid dynamics (CFD) for all building geometry parameters would be very challenging and time consuming, soft computing techniques were preferred in this study to estimate power and wind velocity augmentations. This study used soft computing methodologies, such as an adaptive neuro-fuzzy inference system (ANFIS) to estimate the augmented building power and wind velocity. At the same time, the augmented power density of a simplified turbine model was calculated.

Artificial neural networks are flexible modeling tools with the capability of learning the mathematical mapping between input and output variables of nonlinear systems. An adaptive neuro-fuzzy inference system (ANFIS) is a powerful neural network system [38]. It excels learning and predicting and it is an efficient tool for dealing with uncertainties in any system. ANFIS is a hybrid intelligent system that enhances the ability to automatically learn and adapt. It was used by researchers in various engineering systems [39–41]. Currently, there are many studies regarding the application of ANFIS for estimating and real-time identification of many different systems [42–44].

A Fuzzy Inference System (FIS) is at the heart of ANFIS. FIS is based on ‘IF–THEN’ rules and can be used to predict the behavior of uncertain systems. The advantage of FIS is that it does not require any knowledge of the underlying physical processes as a precondition for its application because ANFIS integrates the FIS with a back-propagation learning algorithm provided by the neural network.

The primary goal of this study was to establish an ANFIS for estimating a building’s augmented power, wind velocity and power density in regards to the geometry characteristics of the building (building shape and position) and input angle of the wind. The fundamental idea behind soft computing methodology is to collect input/output data pairs and to learn the network from this data. This technique provides fuzzy logic with the ability to change the parameters of the membership function so that the associated FIS can track the input/output data [45–47].

2. Building augmented wind turbines

Wind turbines produce power, represented as $P$: $P$

$$P = \frac{1}{2} \rho \pi r^2 u^3 \eta$$  \hspace{1cm} (1)$$

where the density of the air is represented by $\rho$, rotor radius is indicated using $r$, $u$ is the wind velocity, and $\eta$ represents the efficiency of the wind turbine. Eq. (1) illustrates that the power generated by the wind is proportional the velocity of the free stream, cubed. A building augmented wind turbine (BAWT) system utilizes the Venturi effect where building is used to create a drop of air pressure through the system to increase the kinetic energy of the wind at the turbine rotor. Augmentation of the wind using buildings can be accomplished either by integrating existing buildings with wind turbines or designing buildings aerodynamically. This study focused on BAWT systems where two buildings are using as a wind augmenter with turbines inserted between the buildings as shown in

Fig. 1. In this study, developed and tested a BAWT system using building designs that considered the aerodynamic performance of the augmenters. The key characteristics of these building geometries are smooth and rounded surfaces that avoid creating any obstacles for wind stream flow as shown in Fig. 2. This study analyzed various building geometries with respect to three different parameters to determine their effects on power augmentation for various wind input angles. The three building parameter were taper ($R_t$), forward lean ($R_x$) and spread ($R_y$). All BAWT configurations were analyzed with the wind input angle as a factor in the overall performance. The parameters governing the vertical taper ($R_t$), forward lean ($R_x$) and spread ($R_y$) were:

$$R_t = 1 - D_t/D_0$$

$$R_x = x/R_0 D_0$$

$$R_y = y/R_0 D_0$$

where $D_i$ is the building diameter at half height, $D_0$ is the base diameter of the buildings, $x_i$ is the distance from the symmetry plane to the edge of the top of the building, and $y_i$ is forward shift of the top of the building with respect to the base of the building (Fig. 3).

The goals of this study were as follows:

- To determine the power and wind velocity augmentation factors for each BAWT configurations using ANFIS methodology.
- To determine the augmented power density for each BAWT configurations using ANFIS methodology.
3. Numerical method and computational conditions

The Reynolds-averaged Navier–Stokes equations can be used to demonstrate the flow field as expressed below:

$$\frac{\partial U_i}{\partial x_j} = 0,$$

$$p_U \frac{\partial U_i}{\partial x_j} - \frac{\partial p}{\partial x_i} + \frac{\partial}{\partial x_j} \left\{ \rho \left( \frac{\partial U_i}{\partial x_j} + \frac{\partial U_j}{\partial x_i} \right) - \rho \overline{u_i u_j} \right\} + F_i,$$  \hspace{1cm} (2)

where $\overline{()}$ signifies the Reynolds-averaged value. In Eq. (2), $\rho$ signifies density, $P$ represents mean static pressure, $U_i$ indicates the mean velocity, and $u_i$ and $v$ denote the turbulent fluctuation and kinematic viscosity, respectively. Furthermore, $F_i$ is the body-force term imposed for the representation of a load is represented by $F_i$. In this study, the load inside the diffuser or between two buildings was determined once it is trained.

In this study, the first-order Sugeno model with two inputs and one output was used to train and evaluate the fuzzy inference system. Fig. 3 shows an ANFIS structure with four inputs.

ANFIS model was established in this study to estimate the power and wind building augmentation factor in relation to the three building parameters and wind input angle. Since there were three outputs to determine, three ANFIS networks were modeled. Training and checking data for the ANFIS networks was extracted from the above presented numerical analysis of the proposed building augmentation model. With a proper training scheme and fine filtered data-sets, ANFIS is capable of accurately estimating the augmentation factors and power density since it learns from training data. This measurement-free architecture also makes it immediately available for operation once it is trained.

Fuzzy Inference Systems (FIS) creates the foundation for ANFIS. The FIS structure consists of three components. The first component is a rule base. This component contains a selection of fuzzy rules. The second component is a database, which outlines the membership functions (MFs) used by the fuzzy rules. The third and final component is a reasoning mechanism to perform the inference procedure. These systems are intelligent and can fuse techniques and methodologies with knowledge from a variety of sources. In addition, these systems have human-like proficiency in specific areas, and they can adapt and learn from fluctuating circumstances. In ANFIS a back propagation algorithm is used to tune the neural networks giving it the ability to recognize patterns and adapt to new situations.

4. Adaptive neuro-fuzzy inference system

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In this study, three ANFIS networks with four inputs were used and three membership functions were associated with each input. Bell-shaped membership functions were chosen with a maximum equal to 1 and a minimum equal to 0. MATLAB contains a fuzzy logic toolbox, which was used to train and evaluate the fuzzy inference system. Fig. 4 shows an ANFIS structure with four inputs.

In this study, the first-order Sugeno model with two inputs and Takagi and Sugeno type fuzzy IF–THEN rules were used as shown below:

$$C_{eq} = \frac{T}{2} \rho U^2 AD = \frac{1}{2} \rho U^2 AD \int_{r_h}^{r_0} dT = \frac{1}{AD} \int_{r_h}^{r_0} C_q K^2 2\pi r^2 dr, \hspace{1cm} (7)$$

where $A = \pi (D/2)^2$ and $K = U_0/U_0$ indicates the acceleration factor. Eq. (8) was used to calculate the power coefficient:

$$C_w = \frac{T}{2} \rho U^2 A = \frac{\omega}{2} \rho U^2 A \int_{r_h}^{r_0} dT = \frac{1}{A} \int_{r_h}^{r_0} \left( \frac{roh}{Ur} \right) C_q K^2 2\pi r^2 dr. \hspace{1cm} (8)$$

Finally, the total torque coefficient generated by the blades can be determined as:

$$C_t = \frac{nw(C_l \cos \beta + C_D \sin \beta \{1 + (roh/U_h)^2\})}{2\pi r}, \hspace{1cm} (4)$$

where $n$ is the number of blades, $\omega$ is the angular velocity of the wind turbine, $c$ is the chord length, and $b = \tan^{-1}(U_i/roh)$. In Eq. (4), $C_l$ and $C_D$ are the drag and lift coefficients, respectively, for the relative angle of attack $\alpha = \beta - \gamma$, where $\gamma$ is the angle of blade setting.

The following equation was used to estimate the torque generated by the blades of the wind turbine:

$$T = \int_{r_h}^{r_0} dT = \int_{r_h}^{r_0} \frac{1}{2} \rho \left\{ U_i^2 + (roh)^2 \right\} (C_l \sin \beta - C_D \cos \beta) ncr dr$$

$$= \int_{r_h}^{r_0} \frac{1}{2} \rho U^2_i (C_l \sin \beta - C_D \cos \beta) \{1 + (roh/U_h)^2\} ncr dr$$

$$= \frac{1}{2} \rho \int_{r_h}^{r_0} U^2_i C_l ncr \frac{2\pi r^2 dr}{2\pi}$$

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$$C_t = \frac{nw(C_l \sin \beta - C_D \cos \beta \{1 + (roh/U_h)^2\})}{2\pi} \hspace{1cm} (6)$$

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$$= \frac{1}{2} \rho \int_{r_h}^{r_0} U^2_i C_l ncr \frac{2\pi r^2 dr}{2\pi} \hspace{1cm} (5)$$

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The first layer consisted of input variable membership functions (MFs). The purpose of this layer was to supply the input values to the next layer. In the first layer, every node was an adaptive node with a node function:

\[ O = \mu(i), \]

where \( \mu(i) \) are MFs.

Bell-shaped MFs with a maximum equal to 1 and a minimum equal to 0 were chosen:

\[ f(x; a, b, c) = \frac{1}{1 + \left( \frac{x-c}{a} \right)^{2b}} \]

(10)

where the bell-shaped function depended on three parameters named \( a, b \) and \( c \). Parameter \( b \) is usually positive. Parameter \( c \) is located in the center of the curve as shown in Fig. 5.

The second layer was a membership layer and it determined the weights for each MF. It received the input values from the first layer and then it behaved like an MFs to represent the fuzzy sets of the respective input variables. Every node in the second layer was non-adaptive. The second layer multiplied incoming signals and sent out the product as shown below:

\[ w_i = \mu(i) * \mu(i)_{i+1} \]

(11)

Each node output represented the firing strength of a rule or weight.

The third layer was the rule layer. Each node in the second layer performed a pre-condition matching process for the fuzzy rules. In other words, they compute the activation level of each rule and the number of layers equal to the number of fuzzy rules. Each node in layer three calculated normalized weights. Like the second layer, this layer was also non-adaptive. In this layer, ever node calculated the ratio of the firing strength of a rule to the sum of the firing strenght of all rules:

\[ w_i^* = \frac{w_i}{w_1 + w_2} \]

(12)

\[ i = 1, 2. \]

Normalized firing strenghts and weights are the output of this layer.

The fourth layer is known as the defuzzification layer. This layer takes the inference of the rules and generates output values. The fourth layer contains only adaptive nodes with the following node function:

\[ O_i^4 = w_i^*f_i = w_i^*p_i + q_i + r_i + s_i + t \]

(13)
where \([p, q, r, s, t]\) is the parameter set. In the fourth layer, the parameter set is known as consequent parameters.

The fifth and final layer is the output layer. This layer sums the inputs from the defuzzification layer and transforms the fuzzy classification into a binary result. The output represents the estimated modulation transfer function of the optical system. The single, non-adaptive node in the output layer calculates the overall output as the aggregate of all incoming signals:

\[
O^4_i = \sum_i w_i x f = \frac{\sum w_i f}{\sum w_i} \quad (14)
\]

Hybrid learning algorithms were used to identify the parameters in the ANFIS architectures. In the forward pass of the hybrid learning algorithm, functional signals travelled forwards until defuzzification layer and the parameters were indentified using the least squares estimate. In the backward pass, the error rates propagated backwards and the premise parameters were updated by the gradient descent.

5. Results

 Initially, the ANFIS networks were trained with the extracted data from the computational fluid dynamics simulations. There were three ANFIS networks: ANFIS-1 estimated the wind velocity augmentation factor, ANFIS-2 estimated the power augmentation factor, and ANFIS-3 estimated the augmented power density. Three bell-shaped membership functions were used for each input during the training procedure. Further increasing the number of membership functions was not appropriate because there were too many parameters to estimate. The root mean square errors for the three ANFIS networks were:

![Fig. 7. ANFIS prediction of power augmentation factor.](image)

![Fig. 8. ANFIS prediction of augmented power (energy) density.](image)
The final predictions for wind, power, and power density augmentation factors surfaced after training of the ANFIS networks as shown in Figs. 6–8.

The augmented wind velocity, power and augmented power density were influenced by vertical building taper ($R_t$), forward lean of the building ($R_f$), spread of the building ($R_y$) and wind input angle and these factors were executed in MATLAB Simulink block diagram as shown in Fig. 9. Fig. 9 demonstrates that the wind input angle ranged from 0$^\circ$ to 60$^\circ$. This approach is very useful for quickly estimating the augmentation factors for BAWT projects since computational fluid dynamics simulations can be very challenging and time consuming.

6. Conclusion

In this study, the acceleration of air velocity through a duct and a turbine was established by means of a pressure drop between two buildings. The effect of different building geometries and wind input angles on power augmentation was analyzed using a simplified turbine model. The total power captured by the various building configurations was compared. The parameters for building geometry were: $R_t$ (vertical building taper), $R_f R_t$ (the forward lean of the building) and $R_y R_f$ (the spread of the building). An ANFIS network was used to develop a Simulink model in MATLAB to predict the building augmented power and estimate the wind. MATLAB was used to run simulations and the results were observed on the corresponding output blocks. An ANFIS scheme was choose because it was computationally efficient and well-adaptable with optimization and adaptive techniques. ANFIS can also be used with systems that handle increasingly complex parameters. Another advantage of ANFIS is its speed of operation as it is much faster than other control strategies because the tedious task of training systems that handle increasingly complex parameters. ANFIS can also be used with optimization and adaptive techniques. ANFIS can also be used with systems that handle increasingly complex parameters. Another advantage of ANFIS is its speed of operation as it is much faster than other control strategies because the tedious task of training systems that handle increasingly complex parameters. ANFIS can also be used with systems that handle increasingly complex parameters.

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The generation of renewable energy in urban environments has received an increasing attention. The amount of electricity produced by a wind turbine depends on the speed of the available wind resource and the area swept by the blades. Relatively small differences in either factor can result in significant differences in the amount of electricity generated. Wind power is directly proportional to the cube of wind speed approaching a wind turbine. This means that even a slight acceleration in wind speed will cause a large increase in the wind power output. Diffuser-augmented wind turbines are capable of concentrating the energy in the wind and permit more power to be extracted. The use of architectural structures to provide an augmentation source for the wind has been pursued by ambitious architects but the effects of building augmentation are still uncertain. Due to technical and architectural barriers, the uptake of wind energy converters into buildings has been limited.

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