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Extreme learning machine approach for sensorless wind speed estimation

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A B S T R A C T

Precise predictions of wind speed play important role in determining the feasibility of harnessing wind energy. In fact, reliable wind predictions offer secure and minimal economic risk situation to operators and investors. This paper presents a new model based upon extreme learning machine (ELM) for sensor-less estimation of wind speed based on wind turbine parameters. The inputs for estimating the wind speed are wind turbine power coefficient, blade pitch angle, and rotational speed. In order to validate authors compared prediction of ELM model with the predictions with genetic programming (GP), artificial neural network (ANN) and support vector machine with radial basis kernel function (SVM-RBF). This investigation analyzed the reliability of these computational models using the simulation results and three statistical tests. The three statistical tests includes the Pearson correlation coefficient, coefficient of determination and root-mean-square error. Finally, this study compared predicted wind speeds from each method against actual measurement data. Simulation results, clearly demonstrate that ELM can be utilized effectively in applications of sensor-less wind speed predictions. Concisely, the survey results show that the proposed ELM model is suitable and precise for sensor-less wind speed predictions and has much higher performance than the other approaches examined in this study.

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1. Introduction

Wind speed plays important role in operation and management of wind energy [1]. Investigators directly measure or estimate speed of the wind. Measurement of wind speed is considered most difficult among various climatological variables [2,3]. Nevertheless, it is important for wind energy systems to accurately measure and estimate wind speed [4,5]. Report from the Intergovernmental Panel on Climate Change [51] raises concern on global warming. Therefore, various nations are looking to increase their share of energy consumption from renewable sources such as wind energy.

Many wind energy systems use generation systems with variable speed [6] as it extracts more wind power than a system that works at constant speed [7,8]. Rotation speed of turbine shaft adapts to varying wind speed to extract maximum power [9]. In other words, the main feature of variable generation system is rotation speed of turbine shaft adapts according to wind speed [9–11]. Normally, engineers deploy wind speed anemometers for measuring wind speed. However, high coast of wind anemometers discourage their usage in broad applications. For example in one wind farm one anemometer cannot be used since wind speed varies from one turbine to another [12–15]. Therefore, engineers replace anemometers with digital estimators for broad application like wind farm [16,17]. Digital wind estimator's working principal is based on the characteristics of wind turbines. For this reasons, it is desirable to replace the mechanical anemometers by the digital wind-speed estimator based on the turbine attribute [16,17]. Published literature report many wind speed estimation methods [18–23].

In addition to traditional methods, soft computing methods can be used for estimating speed of wind. Soft computing methods do not require knowledge on internal system variables. In addition, it offers advantages such as simpler solutions for multi-variable problems and factual calculation [24]. Soft computing is a novel approach for making computationally intelligent systems.

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According to Zadeh [25], soft computing is an excellent technique that implements nature and human intelligence to understand an environment of imprecision and uncertainty.

Recent research works have applied the Neural network (NN) as a major computational approach in different fields [26–28]. NN uses the classic parametric approach for solving complex nonlinear problems. There are many algorithms for training neural network such as back propagation, support vector machine (SVM), and hidden Markov model (HMM). However, researchers consider longer learning time of NN as drawback. Huang et al. [29,30] introduced an algorithm for single layer feed forward NN which is known as Extreme Learning Machine (ELM). Use of ELM decreases time required for training the neural networks. In fact, it has been proved that by utilizing the ELM, learning becomes very fast and it produces good generalization performance [31]. Researchers have applied ELM for solving problems in many scientific areas [32–37]. ELM is a powerful algorithm with faster learning speed comparing with traditional algorithms like back-propagation (BP). It also has a better performance too. ELM tries to get the smallest training error and norm of weights.

Fewer studies were found on application of ELM in wind energy area. Wu et al. [38] performed an investigation to develop an ELM based model for estimating wind speed and sensorless control of wind turbine systems. Salcedo-Sanz et al. [39] combined the coral reefs optimization (CRO) with extreme learning machine (ELM) to predict short term wind speed in a wind farm in USA. Wan et al. [40] using extreme learning machine (ELM) proposed a model for short-term probabilistic wind power forecasting fora wind farm in Australia.

Literature review of this work found that no research work till date applied ELM for sensorless estimation of wind speed based main parameters of wind turbine. Therefore, this research work developed an ELM-based model for sensorless estimation of wind speed. Further this investigation derives a correlation between wind speed and main parameters of wind turbines such as, power coefficient, blade pitch angle and rotor speed. The merit of extreme learning machine was verified by comparing its predictions accuracy with support vector machine with radial basis kernel function (SVM-RBF), Artificial Neural Network (ANN) and Genetic Programming (GP) successfully employed in sensorless wind speed area estimations. The developed model would estimate the wind speed without using active sensors.

2. Wind speed model

Available power from wind energy is function of swept area of turbine blade, density of air, wind speed, and height of rotor. The available power is given as:

$$P_w = \frac{1}{2}\rho A v^3 \tag{1}$$

where P_w is the available power in Watt, ρ is the density of air in kg/m^3, and v is the speed of wind m/s and A is the swept are of rotor blades (m^2). Wind turbines capture only a part of this available power due to mechanical and operational losses. The ratio of captured power to available power is called the power coefficient (C_p), and which is function of the effective wind speed V_e, blade pitch angle β, rotor radius R, and rotor speed Ω_r. The value of C_p can be expressed as [10]:

$$C_p(\beta, V_e, \Omega_r, R) = 0.5176\left(\frac{116}{\frac{1}{\frac{R\Omega_r}{V_e}-0.08\beta}-\frac{0.035}{\beta^3+1}} - 0.4\beta - 5\right)e^{\frac{-21}{\frac{1}{\frac{R\Omega_r}{V_e}-0.08\beta}-\frac{0.035}{\beta^3+1}}} + 0.0068\frac{R\Omega_r}{V_e} \tag{2}$$

Table 1
Brief of the input parameters.

	Mean	Maximum	Minimum
Power coefficient (Cp)	0.2	0.4	0.06
Blade pitch angle (deg)	20.5	45	0
Rotor speed (rpm)	7.9	13.3	1.03

Primary objective of this work is to express wind speed V_e in terms of three turbine parameters: blade pitch angle β, rotor speed Ω_r and power coefficient C_p for rotor radius $R = 75$ m; expressed as $V_e(C_p, \beta, \Omega_r)$. For this purpose, this study used ELM. Later ELM estimated wind speed using three wind turbine parameters.

2.1. Input parameters

Soft computing technique used the measured parameters of wind turbine as their input. Neural network training and testing used 70% and 30% of the measured data respectively. Table 1 shows summary of the input parameters.

3. Extreme learning machine

Extreme Learning Machine (ELM) algorithm was introduced as a learning tool for feed-forward neural network (SLFN) architecture with single layer [29,41,42]. ELM randomly selects the input weights and analytically computes SLFN output weights. ELM algorithm has favorable general capability with faster learning speed. This algorithm does not require too much human intervention, and can run much faster than the conventional algorithms. It analytically determines the network parameters and hence requires no human interventions. ELM is an efficient algorithm with numerous advantages including ease of use, higher performance, quick learning speed, suitability for nonlinear activation and kernel functions.

3.1. Single hidden layer feed-forward neural network

Single hidden layer feed-forward neural network (SLFN) operates using L hidden nodes. Mathematical representation of SLFN unifies additive and RBF hidden nodes as given below [43,44]:

$$f_L(x) = \sum_{i=1}^{L}\beta_i G(a_i, b_i, x), \quad x \in R^n, \quad a_i \in R^n \tag{3}$$

where a_i and b_i are the hidden nodes learning parameters. β_i is the weight which connects the ith hidden node and the output node. $G(a_i, b_i, x)$ shows the output value of the ith hidden node for the input x. The additive hidden node with the activation function of $g(x) : R \to R$ (e.g., sigmoid and threshold), $G(a_i, b_i, x)$ is [41]:

$$G(a_i, b_i, x) = g(a_i \cdot x + b_i), \quad b_i \in R \tag{4}$$

where a_i denotes the weight vector which connects the input layer and ith hidden node. Also, b_i is the bias of the ith hidden node a_i. x is the inner product of vector a_i and x in R^n. Using Eq. (4) can find $G(a_i, b_i, x)$ for RBF hidden node with activation function $g(x) : R \to R$ (e.g., Gaussian) [41]:

$$G(a_i, b_i, x) = g(b_i\|x - a_i\|), \quad b_i \in R^+ \tag{5}$$

a_i and b_i represent the center and impact factor of ith RBF node. R^+ represents set of all positive real values. A particular case of SLFN that has RBF nodes in its hidden layer forms RBF network. For N, arbitrary distinct samples $(x_i, t_i) \in R^n \times R^m$ where, $n \times 1$ input vector is represented by x_i and $m \times 1$ target vector is represented by t_i. If

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