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A hybrid neuro-fuzzy power prediction system for wind energy generation

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ABSTRACT

Wind energy generation is expected to increase in future electric grids. The generated wind power has an intermittent nature which may affect power system stability and increase the risk of blackouts. Therefore, a prediction system for wind power generation is essential for optimum operation of a power system with a significant share of wind energy conversion systems. In this paper, a hybrid neuro-fuzzy wind power prediction system is proposed. A wireless sensor network (WSN) is used to measure and transmit the required parameters for the prediction model at the operator centre. Those parameters are the major factors affecting wind farm output power, namely air temperature, wind speed, air density and air pressure. Considering all these factors will increase the prediction accuracy of the proposed model. The proposed prediction model is designed and tested using fuzzy rules with adaptive network. To decide the optimal number of fuzzy rules, the clustering of the data using modified Fuzzy C-Means (FCM) is used to implement hybrid optimization method. The prediction model is tested using four subsets of data divided into four seasons of year. The proposed prediction model is implemented using Matlab. Analysis of results shows that the proposed model has good prediction accuracy and provides a useful qualitative description of the prediction system.

Introduction

Wind is one of the fastest growing energy sources since it is renewable, abundant and pollution-free. The power generated by a wind turbine (WT) generator varies randomly with time due to the variability of wind speed, temperature, and other factors. Uncertainty of wind power and the increase of wind power penetration level in future electric grids will affect power system stability and increase the risk of blackouts. Therefore, forecasting of wind power generation is beneficial for optimum operation of a power system with a significant penetration level of wind energy conversion systems [1–6].

Due to temperature and pressure difference, air density, topography and other factors, wind speed is one of the most difficult meteorological parameters to predict [7]. As a result, the power generated from WT will be difficult to predict. Therefore, the prediction model will inevitably be non-linear and must be more accurate. In recent years, with continuous increase of computer calculation speed, researchers proposed a number of power prediction models based on complex statistics and artificial intelligence techniques as found in [8–19], where the prediction models of wind power generation are categorized into direct and indirect models. Direct prediction models use historical information of wind power output as the prediction model's input and the output of the prediction model is the predicted value of wind power generation. Where, indirect prediction models predict wind power generation by predicting wind speed and then use the power curve to convert wind speed into power output.

Some of the direct prediction models are presented in [8–12]. In [8] a power prediction model with three input variables (wind speed, relative air humidity and power generation time) based on artificial neural network is proposed. One of parameters used to predict the wind power generation in this model is generation time which is not fixed and depend on other parameters such as cut-in and cut-out of wind speed, turbine maintenance, and performance. In [9] an adaptive fuzzy inference system is used to predict wind power generation. This model used wind speed, wind direction, wind vector and other different parameters to predict wind power and pointed out advantages and disadvantages of these parameters. In [10] an Adaptive Neural Fuzzy Inference System (ANFIS) approach for short-term wind power prediction in Portugal

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is proposed using a hybrid particle swarm optimization (PSO). The proposed approach is based on the combination of PSO and ANFIS. In this model, prediction error sometimes arises to more than 21% in different seasons of the year which is considered as high error percentage. In [11] the wind information (wind speed and direction) is expressed by complex numbers on the complex coordinates, and used them as input information of the complex-valued neural network. The prediction model was trained by using complex back propagation algorithm so the prediction error decreases. In [12] a short-term wind farm output power prediction model is presented using fuzzy modeling derived from raw data of wind farm. The developed model did not maintain good prediction accuracy. However, it provided an interpretable model structure which contained several rules, from which it could reveal a useful qualitative description of the prediction system.

Some of the indirect prediction models are presented in [13–19]. In Refs. [13–16] a physical prediction models were based on numerical weather prediction. This method used some meteorological observation data in a certain time as initial values and solved equations of atmospheric dynamics and thermo dynamics to get wind speed forecast value. On one hand, these physical prediction models are traditional and less effective in short-term prediction [13]. On the other hand, the physical systems are complex to implement, take more time for execution, and are site-dependent [16]. In [16] a statistical based wind power forecasting without using numerical weather prediction inputs was carried. The proposed approach consisted of two stages. In the first stage, wavelet decomposition of wind series was carried out and adaptive wavelet neural network (AWNN) was used to regress upon each decomposed signal, to predict wind speed up to 30 h ahead. In the second stage, a feed-forward neural network (FFNN) is used for nonlinear mapping between wind speed and wind power output, which transforms the forecasted wind speed into wind power prediction. This model predict the wind power output with acceptable accuracy but the error of the output power can reach more than 80%. In [17] the space correlation method was used for predicting the wind speed among adjacent locations. This paper pointed out that the proposed model was better than persistent ones. However, this model was not suitable for long-term prediction and the measurement equations were difficult to derive. In Refs. [18,19] a strategy of wind speed prediction was based on fuzzy logic and artificial neural network (ANN). The proposed ANN had less neuron numbers and less learning time process. The proposed fuzzy logic provided significantly less rule base but with less rule and less learning time the accuracy was affected negatively.

Generally, statistical models have the advantage that they require no mathematical modeling and use available historical measurements for stochastic approximation between wind predictions and wind power output measurements. However, those models are not suitable for long-term prediction and it is very difficult for prediction model based on statistics to further improve prediction accuracy [7].

The indirect prediction models used the power curve to convert wind speed into power output. This may cause a delay and some error in calculations. The power curve depends on the wind speed not on the efficiency and other mechanical parameters of the wind turbine which could be changed with time. So the power curve should be correct every specified time interval.

Both direct and indirect methods are not complete prediction systems due to their limitations such as collecting, transmitting, and saving data and the display method of the prediction values to operator. The complete prediction system should consist of an efficient way to collect values of real time parameters from the wind turbine (specifically offshore wind turbines) using any communication media then save the collected data to a database. Thereafter, predicting the power generation and display this predicted value to the wind farm operator.

Real-time data collection technology is a challenging task, which requires not only to maximize efficiency, but also to take into account cost, reliability and other factors, to promote the security and stability of the grid. Wind power generation systems are installed in relatively abundant area of wind resources such as in the sea or the valley, with bad environment, complicated topography, transportation inconvenient factor. In order to get a real-time data from the WT, The wireless sensor networks (WSNs) has a feasibility to collect a real-time data from WT. A wireless sensor network is a technology for the collection and communication of the correlative Real-time data in wind power prediction [20]. Researchers have done many effective jobs in WSN for monitoring the WT parameters [21,23].

In this paper, a wireless sensor network (WSN) for collecting the real-time data from wind turbine is proposed. Applying WSN in wind power prediction will be feasible [21]. The wireless sensors used in [21] are modified to measure output power, temperature, density, pressure, and wind speed sensors. The values of these parameters are the inputs to the prediction model of wind power generation. The historical data are used as inputs to increase accuracy of the predicted wind power value. In order to achieve the highest creditable prediction accuracy, the modeling techniques is designed using the combination of a Fuzzy Classifier with a Temporal Neural Network techniques based on historical data and the real-time data which are vital for the wind power prediction.

This paper is organized as follows. A background for both a WT modeling and WSN technology are firstly presented. The data used in the prediction model (historical and real-time) is discussed at second. Thirdly, the architecture of applying WSN in wind power prediction and data flow in the system is described. Fourthly, the structure of the prediction model is designed to predict the output power of WT. Finally, the data from Alaska Center for Energy and Power (ACEP) is used to train and evaluate the prediction model as a case study and the result is shown. Case study demonstrates that the prediction model has a good agreement with the data selected and can describe input–output relations using a set of rules in the IF-THEN form.

Background

Wind turbine modeling

In this section describes the details of wind turbine modeling. First, wind energy conversion system is discussed briefly. Then, the modeling and major factors affecting wind farm output power are presented in order to be used in the proposed wind power prediction model. Wind farm output power comes from wind power captured by WTs. The output power from ideal and practical wind turbines is discussed in the following section [22].

Essentially, wind energy is kinetic energy, and it can be calculated using Eq. (1).

$$E = \frac{1}{2} m v^2 \text{ (joules)} = \frac{1}{2} (\rho A x) v^2 \tag{1}$$

where m is the air mass (kg) and v is the air speed in the upstream wind direction at the entrance of rotor blades (m/s), A is the cross-sectional area in m^2, ρ is the air density in kg/m^3, and x is the thickness of the parcel in m.

Wind power P_w (in W) is the time derivative of the kinetic energy and can be derived from kinetic energy of wind using:

$$P_w = \frac{dE}{dt} = \frac{1}{2}\left(\rho A \frac{dx}{dt}\right) \cdot v^2 = \frac{1}{2}(\rho \cdot A v) \cdot v^2 = \frac{1}{2} \cdot \rho A v^3 \tag{2}$$