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Using artificial neural networks for temporal and spatial wind speed forecasting in Iran

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ABSTRACT

Over the past few years, significant progress has been made in wind power generation worldwide. Because of the turbulent nature of wind velocity, the management of wind intermittence is a substantial field of research in the wind energy sector. This paper presents an investigation of this problem in two parts, the prediction of wind speed in both temporal and spatial dimensions, using artificial neural networks (ANNs). ANNs are novel methods applicable in modeling of complicated systems such as wind speed which generally investigated by a large amount of registered data exemplifying the behavior of.

We first predicted the temporal dimension of wind speed at one-hour time interval, as a short-term wind speed prediction, in three wind observation stations (WOSs) in Iran. In the next part, estimation of wind speed data in a WOS using data from some other nearby WOSs was carried out. Due to the limitation of data collection, two groups of WOSs were selected for this target. The average value of the wind speed histogram error obtained from the best model in both groups is about 2.6% which is certainly promising.

In Iran, the scarcity of meteorological data has resulted in the limited study of wind energy resources. Therefore, this type of spatial prediction is very useful in wind resource assessment in the Iranian wind energy industry. This is a valuable tool that enables the decision maker to precisely detect the high wind speed areas over an entire region in the first step of investigation.

1. Introduction

In recent years, new issues related to the intermittent nature of wind energy have drawn attention of researchers towards the wind speed prediction methods because of the continuous increase of wind power generation worldwide. Wind power is a function of the cube of wind speed [1]. It means that small differences in wind speed estimation results in large differences in wind power estimation. Therefore, more than any other parameters, evaluating the wind speed characteristics is essential to the wind energy industry for site selection and performance prediction of wind farms [2].

In different parts of the world, meteorological data including wind speed distribution is monitored through WOSs. The acquired data is used as input parameter in the exploration of wind energy resources [3–5]. In Iran, a limited number of monitoring stations have been installed by SUNA (renewable energy organization of Iran) and a few of them have adequate and accurate records of wind speed data for interested researchers and investors [6]. The dearth in necessary data has led to limited study of wind energy resources and remains a major challenge in this field [7]. So there is only a few studies at specific locations which have been conducted to assess wind energy potentials in Iran [8–15] and these works needs to be extended. Therefore, developing a new model that could predict wind speed characteristics in any arbitrary place with a few available nearby WOSs data, would be extremely useful in the Iranian wind energy industry. It would help the decision-maker to find the optimal location for the construction of the wind plant regarding the available sites in the area.

ANN is a promising technology in various subjects, like wind energy assessments, including pattern recognition, approximation, and time-series prediction and for this reason, has been widely used in the wind speed prediction field [16–21]. Many different ANN models have been reported in the literature for prediction wind speed for different forms from few seconds to one week ahead. Unfortunately there isn't any standard metric used for comparison and neither any standard databases to test the developed models properly [22]. As Jung and Broadwater concluded [23], different approaches provide better results for different forecast time horizons and they even have significant site dependencies.

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Nomenclature

Terms and definitions

ANFIS	adaptive neuro-fuzzy inference system
ANN	artificial neural network
ASC	absolute sensitivity coefficient
BPNN	back propagation neural network
D	defuzzification
F	fuzzification
I	inference engine
MAE	mean absolute error
MAPE	mean absolute percentage error
MAWEEE	maximum available wind energy estimation error
R	rule
RBFNN	radial basis function neural network
RMSE	root mean square error
RSC	relative sensitivity coefficient
WOS	wind observation site
WS	wind speed
WSHE	wind speed histogram error
WSP	wind speed probability

Therefore it's impracticable to say a single model is making the best for all situations. So it is strongly suggested that different models should be tried in the desired site to obtain the best result as accurate as possible. In the first part of this paper, according to many different types of wind speed prediction, the wind speed for one-hour time interval was predicted in three WOSs in Iran. This type is known as short-term wind speed prediction which BPNN, RBFNN, and ANFIS models has previously showed good results in [24–29].

It is obvious that accurate and detailed knowledge of the wind characteristics of the region is essential for efficient conversion and utilization of the wind energy resources. In the studies mentioned above and also in the first part of this work, it is assumed that there is a long existing wind data which would be enough for studying the wind energy. Subsequently, wind speed forecasting or location optimization of wind plants could be conducted. However in many places, especially in Iran, there is no data on wind speed. In the second part of this research therefore, estimation of the wind speed database of a WOS was carried out using data from the available nearby WOSs.

It should be noted that, the spatial forecasting of wind speed is a new subject in wind engineering studies and up to now, has been mainly investigated by mapping and objective analysis methods [30–36]. For example, González-Longatt et al. [34] combined a simple geo-statistical Kriging method and an orographic correction to propose a method to obtain mean wind speeds and wind power maps at a horizontal resolution of 15 × 15 km in Venezuela. Balog et al. [37] evaluated the wind energy potential over the Mediterranean basin with two regional climate models. A wind energy resource atlas and the probability density function of wind speed are presented. For the same purpose, Charabi et al. [38] and Al-Yahyai and Charabi [39] used numerical weather prediction (NWP) models to local assessment of wind resources in Oman and Jiang et al. [40] used remotely sensed wind field data to analysis wind energy potentials in China's coastal areas. Finally, Conan et al. [41] used the sand erosion technique as an initial qualitative vision to detect the high speed zones for wind turbine micro siting in a complex terrain, the Alaiz mountain (Spain).

While in these studies only the annual or the monthly mean wind speed could be obtained, every 3-h interval wind speed during a whole year can be calculated with reasonable accuracy by the innovative approach described in this paper provided that there are enough WOSs in the vicinity of the desired place which is satisfied in most regions of Iran.

The rest of this article is organized as follows. The proposed method which is based on three ANN models is described in Section 2. The sensitivity analysis is briefly introduced in this section, too. The estimation accuracy evaluation are presented in Section 3. The input data is defined and the simulation is carried out on the applicative cases in Section 4. Finally conclusions are outlined in Section 5.

2. Methodology

2.1. ANN models

Artificial neural network (ANN) is primarily designed to model the internal operational features of the human brain and nervous system. ANN models can be used for various applications including pattern recognition, pattern classification, nonlinear mapping, and generally for computer simulation. There are different types of ANN models for a problem depending on various parameters such as the complexity of the function, the architecture, training algorithm, and the number of training cases [42]. Among the various types of ANNs, we chose BPNN, RBFNN and ANFIS model. These ANN models are described briefly as follows.

2.1.1. BPNN

A back propagation network is a supervised learning network that learns with a teacher. The network is trained with a training data that consists of an input vector set and a target vector set. While training the network, model parameters have to be adjusted to minimize the error between the target and the predicted output. The energy function, e, is used as a stopping criterion for this reason during the entire learning procedure [26]:

$$e = \frac{1}{2}\sum_{all}(O - O^*)^2 \qquad (1)$$

where O and O^* are network output and desired output, respectively.

In the first phase of the training, the input vectors are propagated in the forward direction from the input to the output layer and in the second phase, the error is propagated in the backward direction to update the weights for minimizing the errors. More details about BPNN are described in Refs. [43–45].

2.1.2. RBFNN

The RBFNN model has a form similar to that of BPNN. RBF networks are capable of providing an acceptable solution for any continuous function mapping, owing to their structure, which is characterized by a combination of non-supervised and supervised training. In the hidden layer, a classification of the training set's samples to the universes is accomplished, and the kernels of these universes consist of the weight matrix of the hidden layer. The second layer is linear and is trained, thanks to the real power values (target vector). The output of the hidden neurons H_m is converted by the radial basis function of the neuron and is expressed as [26]:

$$H_m(x) = f(\varphi\|x_i - C_i\|) = exp\left((x_i - C_i)^2/\sigma_i^2\right) \qquad (2)$$

where m, is the hidden neuron and σ, is the parameter, which controls the smoothness of the Gaussian function φ; x_i is the input vector and C_i refers to the center of the input point of vector x. Each