Wind Speed Modeling based on Artificial Neural Networks for Jeju Area

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Abstract

This paper develops and evaluates a wind speed prediction model for Jeju area based on artificial neural networks, aiming at providing an accurate estimation of wind power generation to the smart grid system. For the history data accumulated for 10 years, the monthly speed change is modeled mainly to find the seasonal effect on tracing and resultant error patterns. A 3-layer model experimentally selects the number of hidden nodes to 10 and learns from 115 patterns, each of which consists of 5 consecutive speed values as input and one estimation output. The evaluation result shows that the error size is less than 5 % for 50 % of tracing and that slow charging over the median value opens a chance of further improvement. Finally, the monthly model makes it possible to build a refined day-by-day and hour-by-hour wind speed model based on the classification of months into winter, rainy, and other intervals.

Keywords: *smart grid, renewable energy, wind speed model, artificial neural network, seasonal*

1. Introduction

[1]The smart grid is a future power network made smart mainly by integrating ever-growing information and communication technologies [1]. Built upon two-way real-time communication between power providers and consumers, it pursues smart power consumption, efficiently regulating the generation and consumer sides [2]. Renewable energy integration is one of its major goals, and there are a variety of renewable energies including wind, sunlight, tides, geothermal heat, and the like. However, as the load and generation balance is the most critical requirement in the power network, the integration of inconsistent and uncontrollable renewable energy makes the power regulation more complex. Accordingly, an automatic generation controller must keep track of the real-time fluctuations not just in system load but also in the availability of renewable energy.

Wind power is apparently one of the most promising renewable energy sources and keeps extending its coverage in power generation. It can significantly reduce greenhouse gases and air pollution created when obtaining electric energy by burning fossil fuels like natural gases and coal [3]. Hence, many countries are making their efforts to promote the wind power penetration. However, the wind power generation faces the problem of intermittency and uncertainty, as the power can be generated just in sufficiently windy weather, while wind variation depends on so many factors such as season, terrain, temperature, air pressure, and so

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on. More innovative and intelligent technologies are needed to alleviate this problem and wind power forecasting is one of the most fundamental methods to coordinate the operation of wind generators combined with other energy generator plans [4].

Precise forecasting not only reduces the frequency regulation cost but also prompts renewable energy integration to the smart grid. The operation includes regulation, spinning reserve, supplemental reserve, replacement reserve, and voltage control [5]. As electricity cannot be saved to be consumed later on necessary basis, power management must maintain interconnection frequency and match generation to load within the control area. Strategies for power system operation are based on forecasts of diverse conditions on generation and demand. Here, the past data of wind speed can give us useful information for forecasting the amount of wind power generation. Exploiting the history data is generally based on pattern recognition [6]. Namely, if we input a specific pattern of wind speed, the forecast model gives the most similar ones in the past.

According to [7], forecasting methods can be classified into physical and statistical approaches. While physical models try to find the best estimate based on physical, meteorological, and technical factors, statistical models identify explanatory input variables in measurement value streams, usually employing recursive least squares and ANNs (Artificial Neural Networks). The ANN can efficiently model non-linear time series, for which a mathematical model can hardly be built, by means of self-learning, self-organization, and auto-adaptation. Moreover, it can benefit from parallel processing and distributed storage. In addition, there are some ANN libraries available in the public domain, making it possible to build and test an ANN model for any time series just after defining input variables and generating learning patterns. It can be combined with other technologies such as fuzzy logic and ARMA (AutoRegression Moving Average) [7].

In this regard, this paper designs a wind speed forecast model based on ANN in Jeju province, Republic of Korea. Jeju area has much wind all year round and its local government is building many wind generation facilities. We can exploit the hour-by-hour wind speed data measured at a wind farm located in the west coast area for past 10 years. At the current stage, to catch the seasonal trend of wind speed, this paper concentrates on modeling monthly speed patterns. After that, more refined forecast model can be built based on the speed trend classification and its error dependency. The training phase first extracts the learning patterns after converting the history data to monthly averages and then submits to the ANN. Finally, the ANN model can generate the monthly forecast for the given number of previous sequences based on a 3-layer architecture.

2. Background and Related Work

The Republic of Korea was designated as one of the smart grid initiative countries together with Italy during the expanded G8 Summit in 2009 [8]. The Korean national government launched the Jeju smart grid test-bed, aiming at testing leading-edge technologies and developing business models in 5 major areas consisting of smart power grid, smart place, smart transportation, smart renewables, and smart electricity services. The smart renewable area builds a renewable energy generation complex including wind farms and stably integrates it to the power distribution network. Every control scheme can be designed and implemented in TOC (Total Operation Center) as shown in Figure 1. Moreover, homes or buildings are encouraged to install their own generation facilities and battery devices for renewable energy sources [4]. Several consortiums are developing business models concerning renewable energy trading and scalable system integration solutions.

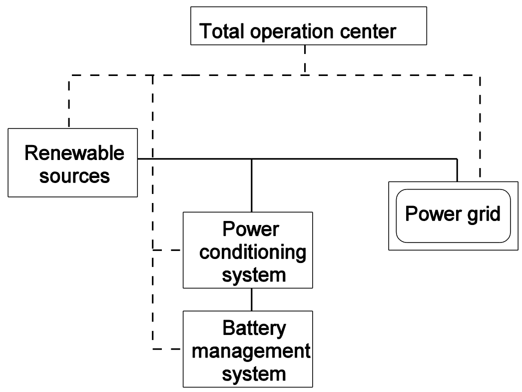

Figure 1. Power Grid and Renewable Energy

There are so many researches indeed on wind speed modeling, so this section reviews some work based on pattern recognition. First, based on the observation that wind speed dynamics can be classified by a set of trend patterns, and that the duration of each pattern is different, [9] proposes the methods of wind pattern identification and subsequent wind pattern modeling exploiting wind speed data history. It first groups wind speed variation into rising and decreasing patterns to build a mathematical estimation for each pattern using linear, exponential, logarithmic, and S-function models. Here, the authors do not take the fluctuation interval as a wind pattern. For each model, the correlation coefficients are calculated and a regression model is added for better forecasting. This work finds out that wind pattern models can show better results for short term wind speed forecast for the wind speed data obtained in a wind farm in Inner Mongolia.

Next, the forecasting system designed in [7] consists of the wind power prediction and a fuzzy index models. The prediction model provides an initial prediction based on a self-organized map and three radial basis neural networks. It separates the time series of wind speeds according to the speed level of small, medium, and large. Each set trains respective ANNs differently. Then, the fuzzy model identifies poor networks after estimating the quality of numerical predictions based on 27 inference rules. This model was applied to an actual offshore wind farm and it can be used effectively for operation planning within 48 hours ahead. Anyway, each region has its own wind forecast model, which can be developed by the diverse combination of existing methods and parameter tuning.

As an interesting study on the wind speed distribution for the offshore environment having greater wind energy potential, [10] compares several models in terms of three metrics, namely, probability R2, estimate of average turbine power output, and estimates of extreme wind speed. This evaluation is built using 10-minute wind speed time series at 187 ocean buoy stations managed by NDBC (National Data Buoy Center). The authors consider not just Weibull distribution but also other relevant Reileigh, Kappa, and Wakeby distributions. This work concludes that Reileigh distribution is best for 10-minute average wind speeds, Kappa distribution shows the lowest mean square error for power output estimation, and 2-parameter lognormal distribution yields the best estimate for extreme wind speeds.

3. Wind Speed Modeling

3.1 Artificial Neural Network Model

As for the stream data analysis, the ANN (Artificial Neural Network) can model the complex nonlinear behavior of target objects, without a mathematical or statistical formulation [11]. Here, neuron nodes compete to become active under certain constraint, and the connection between winning nodes will be strengthened in each training epoch. Training data sets are generally acquired by experimental measurement or environmental observation. Such an ANN model can be easily constructed for future trend prediction based on the past data. Time-series problems are one of the most representative applications for the ANN. They can be approximated by taking a specific time period as input patterns and the next value as the subsequent output. Namely, each set of history data, mainly a series of values, is fed to the training procedure to decide the weight of links in the ANN. The approximation is quite similar to pattern recognition in the large volume of history data [12].

There are some ANN libraries available in the public domain. For example, FANN (Fast ANN) is a free open source neural network library, which provides rich set of convenient API functions, particularly making it easy to handle training data set [13]. Moreover, to make an ANN learn a problem, we have to do nothing but define a function having a set of input and output variables. Regarding to the principle of function approximation by example, this library defines the text file format through which we can specify the learning patterns. It implements a multilayer ANN in C programming language, supporting diverse training schemes, mainly based on the back propagation algorithm, which changes the weights in the neural network model by propagating the error backwards from the output layer to the input layer. After the training phase, we can save the network and reload it for evaluation.

3.2 Training Pattern Generation

ANN modeling begins with the training phase, and training data sets must be designed and created. We have 10-year history data stream, which is equivalent to 120 month. To focus on the monthly behavior, hourly speed values are grouped by month, and then averaged, resulting in 120 sequence values. For annual tracing, the number of values is only 10, so the monthly pattern enables us to capture the large-scale wind change and investigate the seasonal effect. For the sequence of wind speed values, we build 115 sets of training patterns for a 3-layer network consisting of input, hidden, and output layers. Each set consists of 6 consecutive speed values. First 5 are taken as inputs and the 6-th one for the output. As no other input variable is employed in the tracing model, our ANN includes 5 nodes in the input layer and 1 node in the output layer.

In addition to the input and output layers, the number of nodes in the hidden layer must be decided. As there is no explicit optimal method to select the number of hidden nodes, it is experimentally decided. In this regard, Figure 2 shows the modeling error when the number of hidden nodes is 10, 20, 30, and 40, respectively, according to the training epoch. An epoch corresponds to a single iteration through the process of updating the weight of each link in the network. The FANN training phase displays the modeling error as training process goes by. This figure shows that the modeling error gets smaller according to the progress of training epoch. It finds out that modeling errors for all cases are almost same, even if some error spikes take place within 1,000 iterations for 30 and 40 node cases. Hence, we set the number of hidden nodes to 10 from now on.

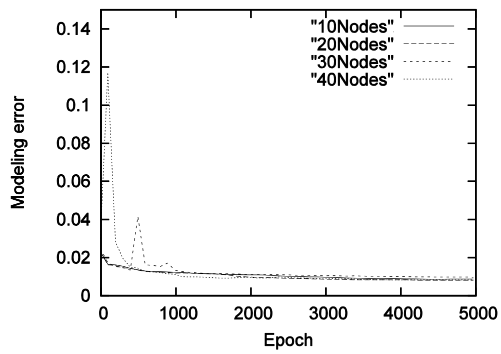

Figure 2. Modeling Error

4. Prediction Analysis

After the training phase, input patterns consisting of 5 consecutive values are submitted to the neural network model built in the previous. Then, each output, namely, the predicted or traced value, is compared with the actual value and Figure 3 plots the result. Actually, for the ANN library, output values are normalized to the interval of [0, 1.0] in the training phase and the output generation. The output values are mapped to the original range of [0, 4.51] mps (meter per second), and then recovered to the original value range. The figure shows that it is impossible to find any annual regularity in wind speed variation. It is definitely due to the unpredictability of heavy storms. The traced speed gets closer to the actual variation after 2004, indicating that with more training patterns, the accuracy gets improved. Moreover, when the speed is higher than the median value, our model tends to go a little bit faster, and vice versa, opening the possibility to further improve the tracing or prediction accuracy.

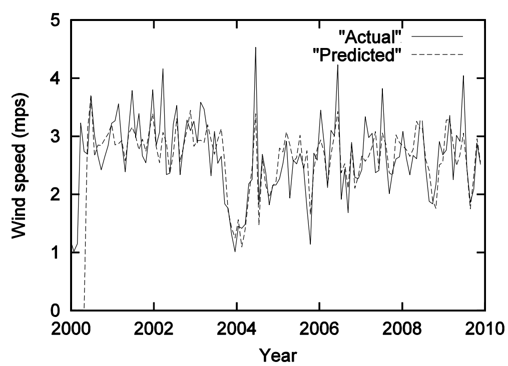

Figure 3. Trace Analysis

Next, Figure 4 plots the error distribution for 114 test inputs. The x-axis denotes the error size which is the difference between predicted and actual values represented in the normalized range. For 50 % of tracing, the error size lies between 0.0 and 0.05, namely, less than 5 %. The maximum error is 0.28. This figure shows that our training scheme and the neural network model works quite well for the monthly speed change. Even if we do neither take into account the time warping effect nor define time-scale variable, our model traces the sequence pattern for the different lengths of up-down patterns.

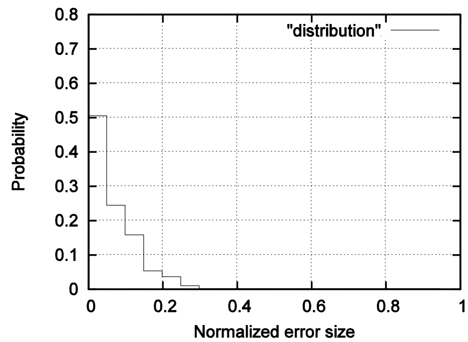

Figure 4. Estimation Error Distribution

Figure 5 shows the error trace result, which provides the pattern of overestimation and underestimation. As in the case of Figure 3, the unpredictability of seasonal storms is the major obstacle in finding annual patterns. Even though the overestimation area is slightly larger than the underestimation area, either one does not dominate. Moreover, no one lasts more than 3 months. At any rate, the pattern of overestimation and underestimation seems to be more affected by annual difference.

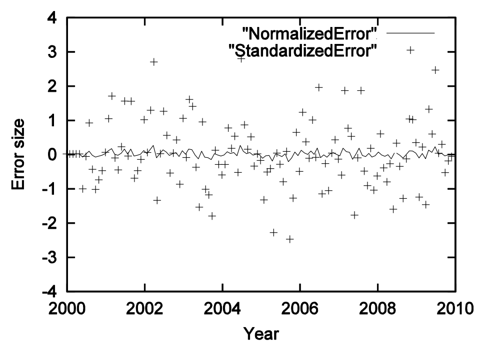

Figure 5. Error Trace Analysis

5. Conclusions

In this paper, we have developed a wind speed prediction model based on artificial neural networks for Jeju province, which has very windy weather and its local government is endeavoring to build an area-wide wind generation facilities. An accurate estimation of wind power generation can help the smart grid to make the operation plan of many generation equipments. For the history data accumulated for 10 years, or 120 months, monthly speed change is modeled mainly to find the seasonal trace characteristics and error patterns. The 3-layer model experimentally sets the number of hidden nodes to 10 and learns from 115 patterns, each of which consists of 5 consecutive speed values as input and one estimation output. The evaluation result shows that for 50 % of tracing the error size is less than 5 % while the maximum error is 28 %. As future work, we are planning to refine our prediction model first, mainly adding critical input variables such as season and wind direction to build a more accurate hour-by-hour estimation model and corresponding wind power generation model.

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