Forecasting Method of Time Series of Solar Energy and Wind Power by Using Wide Meteorological Data

TOMOHIKO ICHIKAWA, KATSUHIRO ICHIYANAGI, KAZUTO YUKITA, YASUYUKI GOTO
Department of Electrical and Electronics Engineering
Aichi Institute of Technology
1247 Yachigusa, Yakusa-cho, Toyota, Aichi 470-0392
JAPAN
w08801ww@aitech.ac.jp, itiya@aitech.ac.jp, yukita@aitech.ac.jp, ygoto@aitech.ac.jp

Abstract: As an alternative energy of fossil fuel, the solar energy and wind power is made effective. This paper describes an application of a neural network for forecasting to time variations of solar energy and wind velocity. The neural network is used to forecast the natural energy and the pattern matching is used to choose the training data of the neural network. It is found from our investigations that forecasting accuracy of the time variation of solar energy and wind velocity is improved by utilizing the pattern matching of the weather map data.

Key-Words: forecasting, solar energy, wind power, neural network, pattern matching, meteorological data

1. Introduction

From the viewpoint of the preservation of the global environment, as an alternative energy of fossil fuel, the natural energy utilization is made effective. Therefore, the photovoltaic power generation and introduction of wind power generation and popularization are advanced. As an alternative energy of fossil fuel, the natural energy utilization is effective, and the photovoltaic power generation and the wind power generation is introduced. The government in Japan examines petroleum and reduction of fossil-fuel consumption such as natural gas and emission reduction of carbon dioxide with it. The government has set the aim of introducing the wind power generation of 11,310 MW by 2020. About introduction of the photovoltaic power generation, it is aimed for "10 times present by 2020, 20 times present by 2030".

It is difficult to utilize natural energy power, such as the solar or wind generation by system interconnection as a power directly [1]. In particular, it is difficult that fluctuation of wind power generation is larger than another natural energy power generation. Various researches have been carried out until now, because practical application is easy for the wind power generation[2]. Then, by estimating the wind power generation quantity with good accuracy, the high-efficient utilization of the wind energy can be expected. In this study, the wind velocity is forecasted by using neural network, and the pattern matching of weather map data[3]. By using the weather map and AMeDAS (Automated Meteorological Data Acquisition System) 10 minute value data, time variation of the wind velocity is forecasted and the results are described as follows.

2. Forecasting of Solar Energy

2.1 Duration of Sunshine and Flux of Solar Radiation

The future system in which the introduction of photovoltaic power generation spread is assumed. It is considered that meteorological data (SDP; offered by Meteorological Agency) according to the observation data on the ground is used. But the observation point of solar energy is very little as shown in Fig. 1.

Then, the relationship between sunshine duration and solar energy at Shizuoka, Nagoya and Omaezaki is examined in order to be able to widely grasp the time series of solar energy by the sunshine duration. An
example of the result is shown in Fig. 2. It is confirmed that there is the correlation between sunshine duration and solar energy. Therefore, the solar energy may be estimated from the sunshine duration.

2.2 Forecasting of Solar Energy
The neural network shown in Fig. 3 is used for the time series of the solar energy. The input data to the neural network are ten values of the sunshine duration observed at 9 o’clock $S_d(i=1, \ldots, n; n$: number of measure point$.)$. The output layer has 8 nodes. The output from the neural network is the forecasted values of sunshine duration from 10:00 to 17:00.

The training of the neural network was repeated using sunshine duration data of the similar weather day extracted by pattern matching method (refer to Appendix). The forecasting is carried out at 9 o’clock by using trained neural network.

Fig. 1 Point of measurement of sunshine duration and solar energy

Fig. 2 Correlation between of sunshine duration and solar energy during 9:00 – 10:00 in August, 2007

Fig. 3 Forecasting system of solar energy

Fig. 4 Forecasted result of duration of sunshine on August 25, 2001
The sunshine duration on August 25th, 2001 was forecasted by using the forecasting system after the training of the neural network. The results are shown in Fig. 4. From this figures, it is confirmed that the forecasted value is close to the observed one. The forecasted value of solar energy was calculated using Fig. 4. The result is shown in Fig. 5. It is also confirmed that the forecasted solar energy is close to the observed one. Other forecasted results of solar energy are shown from Fig.6 to Fig.8. The Fig.6 is in case of cloudy, the Fig.7 is in fine and occasionary cloudy, Fig.8 is in fine, exceptively. From these figures, it is also confirmed that forecasted value is close to the observed ones.

In order to quantitatively compare the forecasted results, the standard deviation of errors of the forecasted values Error(SDE) is estimated by using the following equation:

$$sde = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (v_f - v_o)^2} \quad (1)$$

Where $N$ is a number of data, $v_f$ and $v_o$ are the forecasted and observed values of the solar energy, respectively.

The SDEs of Fig.5 to Fig 8 is shown in Table 1. In the table, observed average solar energy and forecasted one are also shown together. The error shown in SDE is 0.08 MJ/m².

Table 1 SDE Error of forecasted results

<table>
<thead>
<tr>
<th>DATE</th>
<th>Observed average solar energy</th>
<th>Forecasted average solar energy</th>
<th>SDE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MJ/m²</td>
<td>MJ/m²</td>
<td>MJ/m²</td>
</tr>
<tr>
<td>Aug.23,2001</td>
<td>2.16</td>
<td>2.24</td>
<td>0.07</td>
</tr>
<tr>
<td>Oct.14,2007</td>
<td>0.72</td>
<td>0.74</td>
<td>0.06</td>
</tr>
<tr>
<td>Sep.28,2007</td>
<td>1.35</td>
<td>1.37</td>
<td>0.15</td>
</tr>
<tr>
<td>Oct.28,2007</td>
<td>1.94</td>
<td>1.97</td>
<td>0.03</td>
</tr>
<tr>
<td>Average</td>
<td></td>
<td></td>
<td>0.08</td>
</tr>
</tbody>
</table>
3. Forecasting of Wind Velocity

3.1 Configuration forecasting system

The neural network shown in Fig. 9 was used for the wind velocity forecasting. The system consist of three layers; an input layer, a hidden layer and an output layer. The input data to the neural network are six values of the wind velocity \( w_i \), \( (i=1, 2, \ldots, 5, \Delta t=10\) min.) The output layer is single node. The output from the neural network is the forecasted wind velocity. The forecasted wind velocity derived as an output from the neural network at time \( t \) is recurrently reused as an input datum at each new forecasting step for time \( t + \Delta t \). The hidden layer has five nodes by trial and error from viewpoints of prediction error and calculation time. The back propagation method is used in the training of the network.

![Fig. 9 Forecasting system of time variation of wind velocity](image)

3.2 Selection of similar weather map

The data for the training of the neural network is in January, 2001, and the day which gives wind velocity greater than 4m/s are used for the forecasting. The training of the neural network is repeated using wind velocity data of the similar weather day selected by the pattern matching method in the 10 minute interval.

The forecasting at 9 o'clock of the day is started using the forecasting system after the training of the neural network, and the wind velocity in the one hour ahead is forecasted in the 10 minute interval. The data for the training and the forecasting the wind velocity on January 1 is shown in Table 2. The wind velocity observed at forecast site is in every 10 minutes.

### Table 2. Used data for training and forecasting wind velocity on January 1, 2001

<table>
<thead>
<tr>
<th>Order of similarity</th>
<th>Date</th>
<th>Note</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Jan. 1,2001</td>
<td>used to forecast</td>
</tr>
<tr>
<td>2</td>
<td>Jan. 4,2000</td>
<td>used to train</td>
</tr>
<tr>
<td>3</td>
<td>Dec. 24,2000</td>
<td>used to train</td>
</tr>
</tbody>
</table>

3.3 Forecasted Results of Wind velocity

By using the data of similar weather day in Table 2, the training of the neural network was carried out. The observed data are obtained in the ten minutes interval. The forecasted results obtained by the above-mentioned method are shown in Fig. 10 to Fig. 12. In these figures, forecasted value and observed value are respectively shown ○ in and •.

From these figures, it is confirmed that the forecasted value is close to the observed one. In Fig. 10 and Fig. 12, the time variation of the wind velocity is generally uniform in the decrease term, and the forecasted results are close to observed ones, respectively. As shown in Fig. 11, though the time variation of the wind velocity is comparatively large, it is confirmed that the forecasted value is close to the observed one and the change pattern is also similar.

![Fig. 10. Time series of forecasted wind velocity (January 1, 2001)](image)
The error of the forecasted values obtained by the (1) is shown in Table 3. In the table, the forecasted and observed values of the average wind velocity are also shown together. In case of the results without the pattern matching method for the training of the neural forecasting system, the data before three days was used.

According to the Table 3, it is confirmed that the forecasted error SDE with pattern matching method is 1.5 m/s in average and 4.3 m/s in average maximum error. On the other hand, it is confirmed that the forecasted error SDE without pattern matching method is 2.6 m/s in average and 6.3 m/s in average maximum error. These errors without pattern matching method are greater than errors with ones. Therefore, it is confirmed that forecasted result of the wind velocity is comparatively good, though the forecasting of the natural phenomenon is difficult.

5. Conclusion

In this paper, the forecasting of the time series of solar energy and wind energy are described for the prediction. The Nagoya district in Central Japan is examined as a case study on the forecasting of the time series of solar energy wind energy.

(1) By using pattern matching method, the accuracy of the forecasting of solar energy and wind energy is improved.

(2) By forecasting the sunshine duration, forecasting the solar radiation is possible.

(3) On the forecasting of solar energy, the forecasted error SDE (standard deviation of errors) with pattern matching method is 0.08MJ/m² in average and 0.15MJ/m² in average maximum error.

(4) On the forecasting of wind velocity, the forecasted error SDE with pattern matching method is 1.5 m/s in average and 4.3 m/s in average maximum error.

References:

Appendix

Pattern Matching of Weather Map

The distribution of atmospheric pressure and the existence of the front have a major effect on the weather. In this study, the weather map database is made by using the weather map at 9:00 reported in “Weather Map Diary” in the “Meteorological Yearbook 1999-2007”[4]. The weather map on the one day is divided in the 256(16×16) block, and next, 2 items (atmospheric pressure, front) are made into the data. The value of the atmospheric pressure is divided every 4hPa from 980hPa to 1036hPa. Therefore, the matrix (16×16) in every day is obtained. By similar method, the four types of the warm front, the stationary front, the occluded front and the case without the front are converted into the matrix of the front.

App-Fig. 1 shows an example of data base of weather map. The figure (a) is an example of the weather map used to forecast the solar energy. The figure (b) shows the matrix obtained by using Table 1 and figure (a).

The index $J_t$ expressing similarity of a weather map is calculated by atmospheric pressure $P_{0i}$ of a prediction object day, atmospheric pressure $P_i$ on the weather day that should compare a past with front $Z_{0i}$, front $Z_i$.

$$J_t = \sum_{i=1}^{256} |P_{0i} - P_i| + |Z_{0i} - Z_i|$$ (1)

The weather map with which the value of the $J_t$ is approximate for zero is similar to weather map of the object day.