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

Tomohiko Ichikawa, Katsuhiro Ichiyanagi, Kazuto Yukita, Yasuyuki Goto

***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 utilization the pattern matching of the weather map data.

***Keywords*—**forecasting, solar energy, wind power, neural network,

I. 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]-[3]. 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[4][5]. 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[6]. 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.

II. Forecasting of Solar Energy

A. 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[7]. 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.

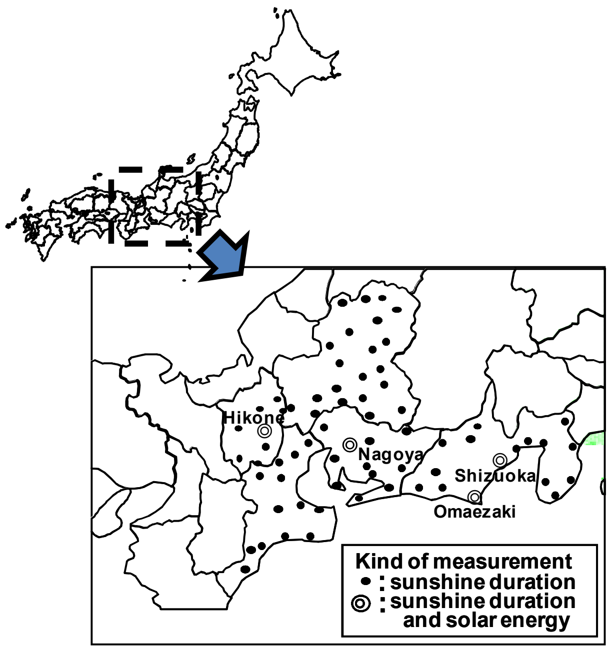


Fig.1 Point of measurement of sunshine duration and solar energy

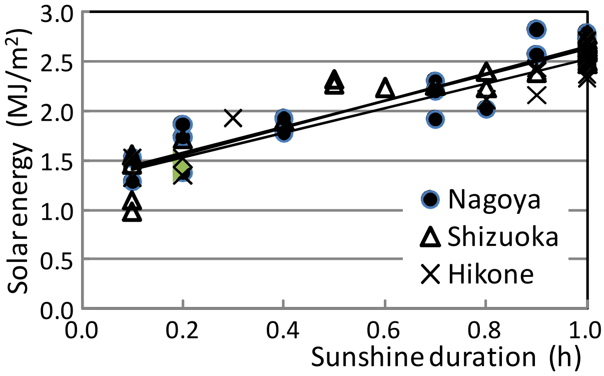


Fig.2 Correlation between of sunshine duration and solar energy during 9:00 – 10:00 in August, 2007

B. *Forecasting of Solar Energy*

In many cases, in which the input-output functional relationships are neither well defined nor easily computable, artificial neural networks are found to be useful[8]-[10]. Moreover, neural networks are able to compute results easily and speedily by training from previous experience.

The neural network used in this paper to forecast the time series of the solar energy is shown in Fig. 3. The input data to the neural network are ten values of the sunshine duration observed at 9 o'clock S_{di}(i=1,…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.

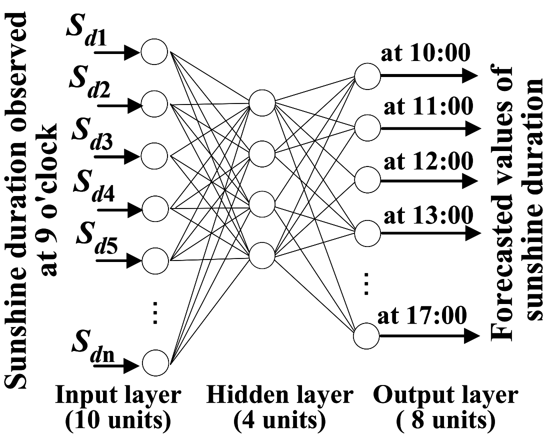


Fig.3 Forecasting system of solar energy

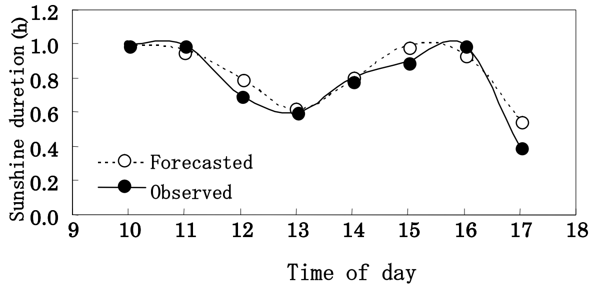


Fig.4 Forecasted result of duration of sunshine on August 23,2001

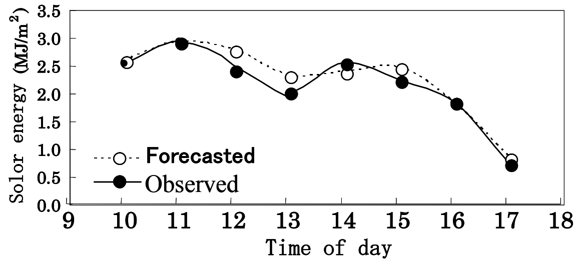


Fig.5 Forecasted result of solar energy on Aug.23,2001

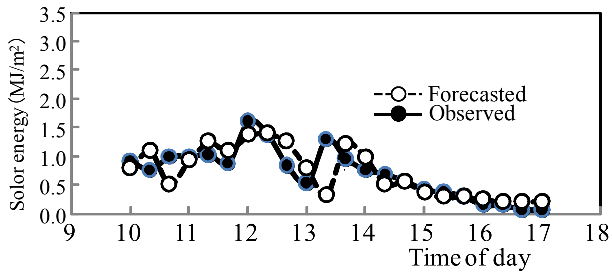


Fig.6 Forecasted result of solar energy on Oct. 14,2007

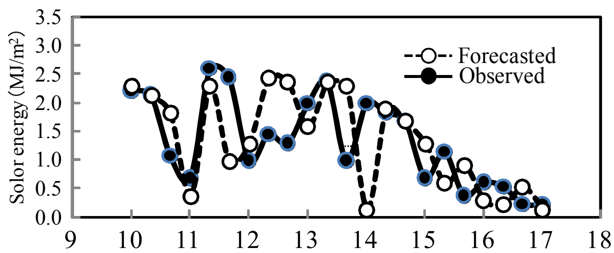


Fig.7 Forecasted result of solar energy on Sep. 28, 2007

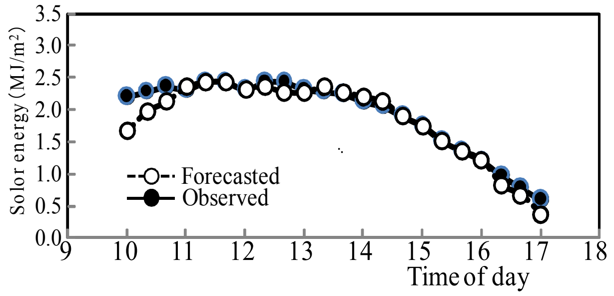


Fig.8 Forecasted result of solar energy on Oct. 28, 2007

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)[6]. The forecasting is carried out at 9 o'clock by using trained neural network.

The sunshine duration on August 25, 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 occasionally cloudy, Fig.8 is in fine, respectively. 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:

$$Error(\mathrm{SDE})) = \sqrt{\frac{\sum_{i=1}^{N}(v_{fi} - v_{oi})^2}{N-1}} \qquad (1)$$

Where N is a number of data, and 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.

III. Forecasting of Wind Velocity

A. 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 ( ), (l=1, 2,…5, =10min.)

The output layer is single node. The output from the neural network is the forecasted wind velocity. The forecasted wind

Table 1 SDE Error of forecasted results

DATE	Observed average solor energy	Forecasted average solor energy	SDE
	MJ/m^2	MJ/m^2	MJ/m^2
Aug. 23,2001	2.16	2.24	0.07
Oct.14,2007	0.72	0.74	0.06
Sep.28,2007	1.35	1.37	0.15
Oct.28,2079	1.94	1.97	0.03
		Averege	0.08

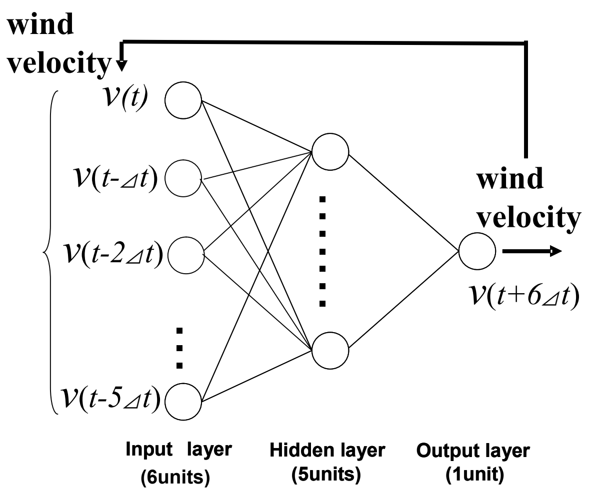


Fig. 9 Forecasting system of time variation of wind velocity

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. 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.

B. 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 Tables 2. The wind velocity observed at forecast site is in every 10 minutes, above-mentioned method are shown in Fig. 10 to Fig. 12. In

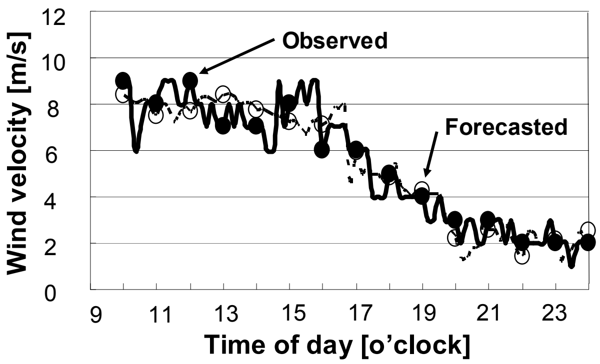


Fig. 10. Time series of forecasted wind velocity (January 1, 2001)

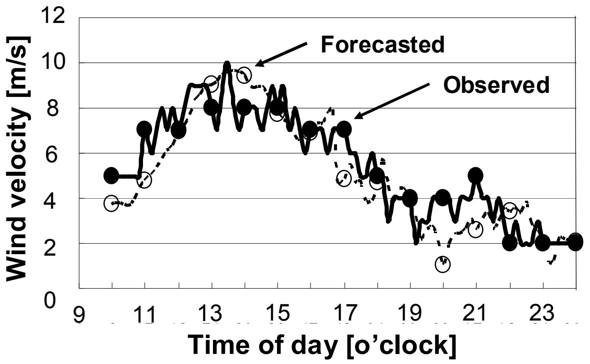


Fig. 11. Time series of forecasted wind velocity (January 6, 2001)

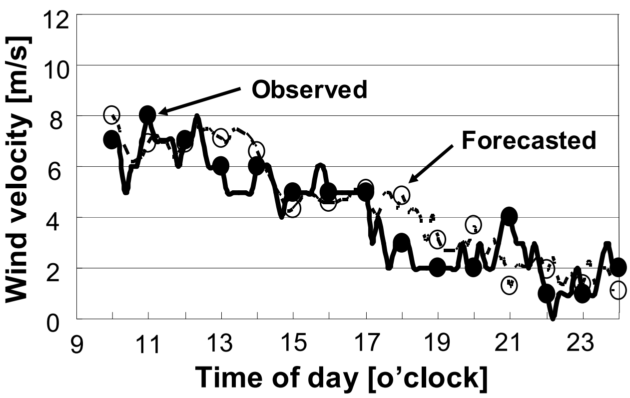


Fig. 12 . Time series of forecasted wind velocity(January 14, 2001)

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.

Table 3 Error of forecasted wind velocity

Date	Observed average wind velocity per day	Forecasted error			
		with pattern matching method		without pattern matching method	
		SDE	maximum	SDE	maximum
	m/s	m/s	m/s	m/s	m/s
Jan. 1,2001	6.2	0.8	2.1	1.7	3.8
Jan. 3,2001	4.9	2.1	6.8	2.6	7.1
Jan. 4,2001	4.8	1.5	5.1	1.9	6.2
Jan. 6,2001	4.3	1.2	3.0	3.2	6.0
Jan.12,2001	5.0	1.8	6.1	2.7	7.1
Jan.14,2001	4.3	1.2	3.0	3.4	7.5
Average	4.9	1.5	4.3	2.6	6.3

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.

IV. ATC Estimation of Power System Transient Stability by Applying Forecasted Solar Energy

To conduct the electric power transactions effectively and to operate the power system efficiently while maintaining reliability under the deregulated environment, it is required that ATC(Available Transfer Capability) should be calculated at high speed with reasonable precision. It is necessary to know the ATC in order to deal with futures transaction of such electric power. We already presented the estimation method of the ATC by using neural network[11]. By using the ATC estimation method and the forecasted solar energy, the effect on ATC for the fluctuation of the transaction electric power is examined in this section. As an example, the simulation for the ATC estimation was carried out on the assumption of fluctuation power by the solar energy utilization.Those results are described in the following.

A. Assumed Solar Power and Electric Power Demand

The solar energy on July 5, 2001, is forecasted by above-mentioned method. Based on the forecasted result, the electric power generation is assumed as shown in Fig. 13. In the figure, the maximum solar power is supposed to 0.3 p.u., and the forecasted value at 9 and 12 o'clock are shown by" ○ " and " ● " , respectively. The forecasted result at 12 o'clock is closer to the observed one shown by " ● "than the result at 9 o'clock, by retrying to forecast.

On total demand of the electric power system, the time variation of daily electricity demand load was assumed as shown in Fig. 14. In the figure, the maximum value of the total demand of the load is shown as 1.0 p.u..

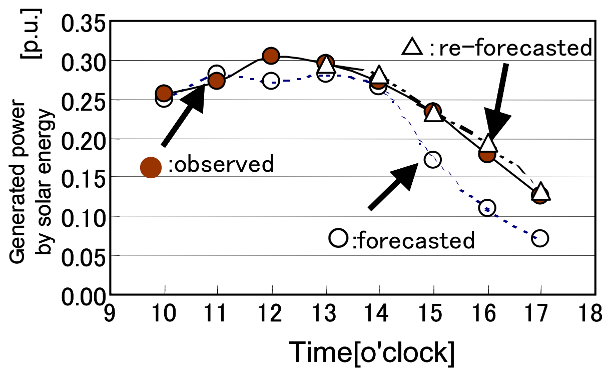


Fig.13 Generated power by forecasted solar energy on July 5, 2001

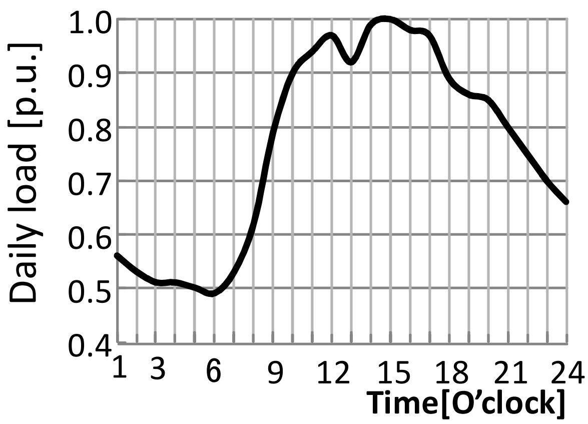


Fig.14 Daily load variation pattern

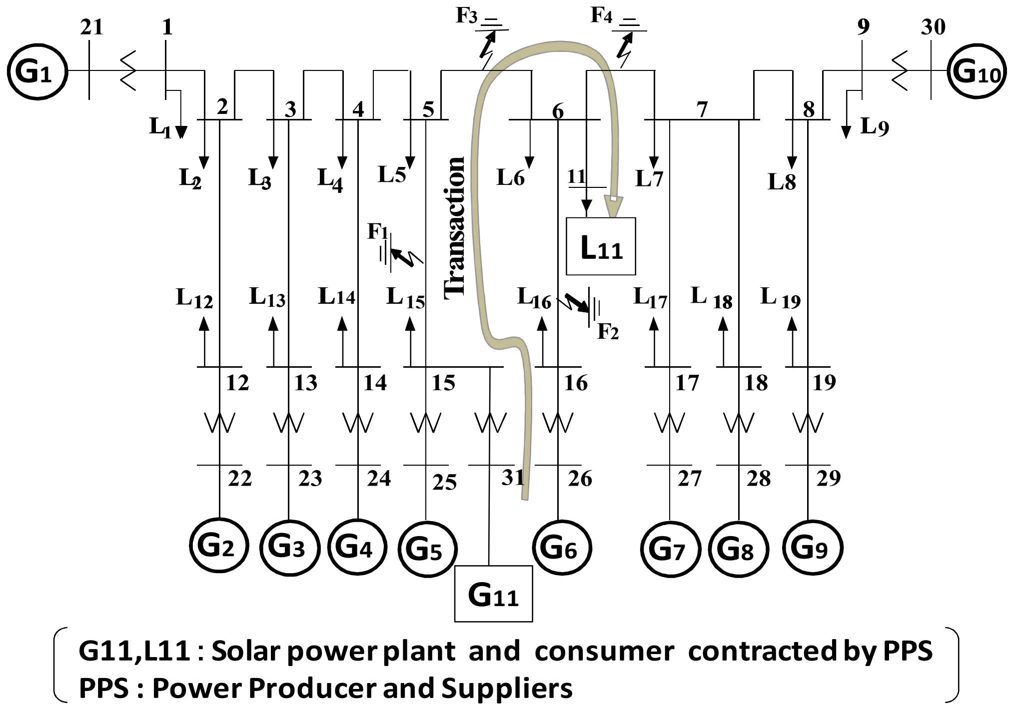


Fig.15 10-machine power system with solar power plant and transaction power route

B.Model Power System

The simulations of estimation of ATC were carried out for the 10-machine system shown in Fig. 15[12-13]. The distributed generators that PPS(Power Producer and Supplier) owns are contained in G11 and the consumer that contracted a transaction with PPS is contained in L11. It is assumed that power transaction is performed from G11 to L11. Each branch in this figure consists of two transmission lines.

It was assumed carrying out the solar power transaction between G11 and L11 as shown in Fig.15. In the each load flow condition, three-phase earth faulting on one of two lines, is assumed. By using the neural network and the relationship of the load demand and the fault line, the maximum transaction capability MTC is estimated[11]. The estimated ATC is obtained by subtracting the transaction power of the solar power. The estimated ATC are shown in tables 4 and Fig. 16.

According to Fig. 16, it is proven that the value of ATC greatly changes and the minimum value gives ATC of the whole system. In the cases of the Line 5-15 fault in which the minimum value is given, the result by using the observed solar energy is shown in Fig. 17. The ATC with forecasted data does not leave the one with observed so much.

The Fig. 18 shows the estimated result of ATC by using the forecasted solar energy for five hours obtained at 12 o'clock. In the figure, the result by using the observed value of solar energy is also shown. It is proven that both results using measured value and predictive value are shown at the almost equal value.

Table 4. Estimated results of ATC

Base load[p.u.]							Fault Line				Estimated MTC	Forecasted		Observed	
L2	L3	L4	L5	L6	L7	L8	5-15	6-16	5-6	6-7	[p.u.]	Solar Power	ATC [p.u.]	Solar Power	ATC [p.u.]
3.15	3.15	3.15	3.15	3.15	4.73	3.15	1	0	0	0	0.86	0.25	0.61	0.26	0.60
3.29	3.29	3.29	3.29	3.29	4.94	3.29	1	0	0	0	0.66	0.28	0.38	0.27	0.39
3.40	3.40	3.40	3.40	3.40	5.09	3.40	1	0	0	0	0.50	0.27	0.23	0.30	0.20
3.22	3.22	3.22	3.22	3.22	4.83	3.22	1	0	0	0	0.76	0.28	0.48	0.30	0.46
3.47	3.47	3.47	3.47	3.47	5.20	3.47	1	0	0	0	0.40	0.26	0.14	0.27	0.13
3.50	3.50	3.50	3.50	3.50	5.25	3.50	1	0	0	0	0.34	0.17	0.17	0.23	0.11
3.43	3.43	3.43	3.43	3.43	5.15	3.43	1	0	0	0	0.45	0.11	0.34	0.18	0.27
3.40	3.40	3.40	3.40	3.40	5.09	3.40	1	0	0	0	0.50	0.07	0.43	0.12	0.38
3.12	3.12	3.12	3.12	3.12	4.67	3.12	1	0	0	0	0.91	0.00	0.91	0.00	0.91
3.15	3.15	3.15	3.15	3.15	4.73	3.15	0	1	0	0	1.25	0.25	1.00	0.26	0.99
3.29	3.29	3.29	3.29	3.29	4.94	3.29	0	1	0	0	1.05	0.28	0.77	0.27	0.78
3.40	3.40	3.40	3.40	3.40	5.09	3.40	0	1	0	0	0.90	0.27	0.63	0.30	0.60
3.22	3.22	3.22	3.22	3.22	4.83	3.22	0	1	0	0	1.15	0.28	0.87	0.30	0.85
3.47	3.47	3.47	3.47	3.47	5.20	3.47	0	1	0	0	0.80	0.26	0.54	0.27	0.53
3.50	3.50	3.50	3.50	3.50	5.25	3.50	0	1	0	0	0.68	0.17	0.51	0.23	0.45
3.43	3.43	3.43	3.43	3.43	5.15	3.43	0	1	0	0	0.85	0.11	0.74	0.18	0.67
3.40	3.40	3.40	3.40	3.40	5.09	3.40	0	1	0	0	0.90	0.07	0.83	0.12	0.78
3.12	3.12	3.12	3.12	3.12	4.67	3.12	0	1	0	0	1.30	0.00	1.30	0.00	1.30
3.15	3.15	3.15	3.15	3.15	4.73	3.15	0	0	1	0	1.06	0.25	0.81	0.26	0.80
3.29	3.29	3.29	3.29	3.29	4.94	3.29	0	0	1	0	0.89	0.28	0.61	0.27	0.62
3.40	3.40	3.40	3.40	3.40	5.09	3.40	0	0	1	0	0.76	0.27	0.49	0.30	0.46
3.22	3.22	3.22	3.22	3.22	4.83	3.22	0	0	1	0	0.98	0.28	0.70	0.30	0.68
3.47	3.47	3.47	3.47	3.47	5.20	3.47	0	0	1	0	0.68	0.26	0.42	0.27	0.41
3.50	3.50	3.50	3.50	3.50	5.25	3.50	0	0	1	0	0.65	0.17	0.48	0.23	0.42
3.43	3.43	3.43	3.43	3.43	5.15	3.43	0	0	1	0	0.72	0.11	0.61	0.18	0.54
3.40	3.40	3.40	3.40	3.40	5.09	3.40	0	0	1	0	0.76	0.07	0.69	0.12	0.64
3.12	3.12	3.12	3.12	3.12	4.67	3.12	0	0	1	0	1.10	0.00	1.10	0.00	1.10
3.15	3.15	3.15	3.15	3.15	4.73	3.15	0	0	0	1	0.86	0.25	0.61	0.26	0.60
3.29	3.29	3.29	3.29	3.29	4.94	3.29	0	0	0	1	0.74	0.28	0.46	0.27	0.47
3.40	3.40	3.40	3.40	3.40	5.09	3.40	0	0	0	1	0.66	0.27	0.39	0.30	0.36
3.22	3.22	3.22	3.22	3.22	4.83	3.22	0	0	0	1	0.80	0.28	0.52	0.30	0.50
3.47	3.47	3.47	3.47	3.47	5.20	3.47	0	0	0	1	0.60	0.26	0.34	0.27	0.33
3.50	3.50	3.50	3.50	3.50	5.25	3.50	0	0	0	1	0.58	0.17	0.41	0.23	0.35
3.43	3.43	3.43	3.43	3.43	5.15	3.43	0	0	0	1	0.63	0.11	0.52	0.18	0.45
3.40	3.40	3.40	3.40	3.40	5.09	3.40	0	0	0	1	0.66	0.07	0.59	0.12	0.54
3.12	3.12	3.12	3.12	3.12	4.67	3.12	0	0	0	1	0.89	0.00	0.89	0.00	0.89

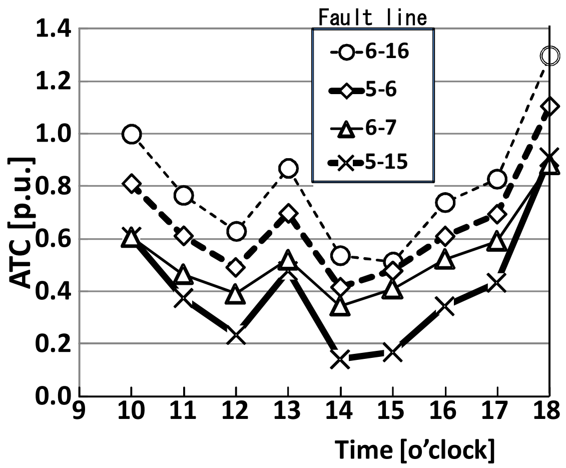


Fig.16 Estimated results of ATC by forecasted solar power data at 9:00 on July 5, 2001

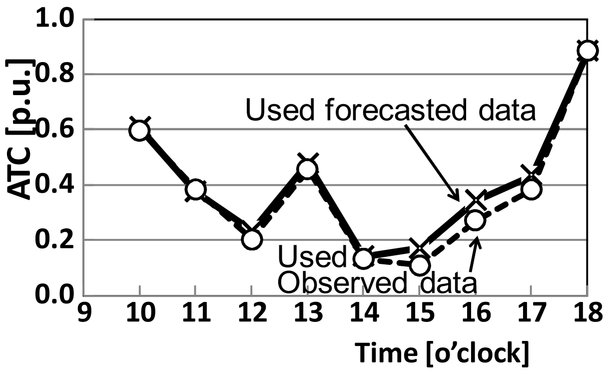


Fig.17 Estimated result of ATC at 9:00 on July 5, 2001

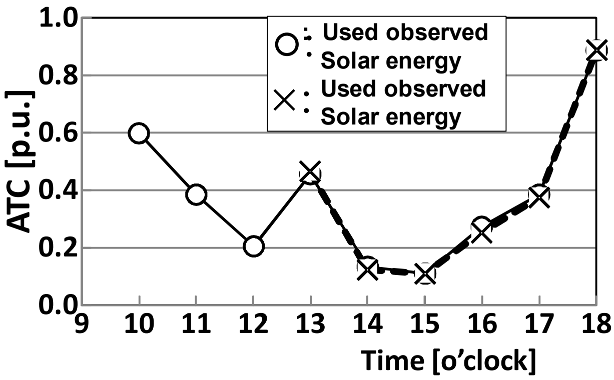


Fig.18 Estimated result of ATC at 12:00 July 5, 2001

V. CONCLUSION

In this paper, the forecasting of the time series of solar energy and wind energy was described for the prediction of the electric power of solar plants and wind farms. The Nagoya district in Central Japan was examined as a case study on the forecasting of the time series of the natural energy. In this study, the ability of the forecasting method of solar and wind energy was tested and following results have been derived.

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.
5) In case of fluctuating solar power generation, the possibility of the ATC estimation is confirmed by using forecasted solar energy.

APPENDIX

Pattern Matching of Weather Map

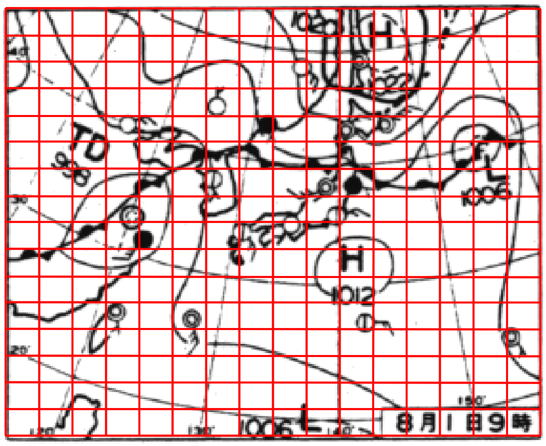
The distribution of atmospheric pressure and the existence of the front have a major effect on the weather. In this study, the weather map database is made by using the weather map at 9:00 reported in "Weather Map Diary" in the "Meteorological Yearbook 1999 -2007". The weather map on the one day is divided 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.

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

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



(a) Weather map

6	8	8	8	9	9	9	9	10	11	11	11	11	10	10	9
6	8	8	8	9	9	9	9	10	11	11	11	11	10	9	9
6	7	8	8	9	8	8	9	10	11	11	11	11	9	9	9
7	7	8	8	8	8	8	9	10	10	11	11	9	7	7	9
7	7	7	8	8	8	8	9	9	9	9	9	8	8	8	9
7	7	7	7	7	7	8	8	9	9	9	9	8	8	8	9
7	7	6	6	6	7	8	8	8	8	8	8	8	8	8	9
7	7	6	6	6	7	8	8	8	8	8	8	8	8	8	9
7	7	6	6	6	7	8	8	8	9	9	9	8	8	8	9
7	7	7	7	7	8	8	8	8	9	9	9	8	8	8	9
7	7	7	7	7	8	8	8	8	9	9	9	8	8	8	9
7	7	7	7	7	8	8	8	8	8	8	8	8	8	8	9
7	7	7	7	7	8	8	8	8	8	8	8	8	8	8	9
7	7	7	7	7	7	7	7	7	8	8	8	8	8	8	9
7	7	7	7	7	7	7	7	7	7	7	8	8	8	8	8
7	7	7	7	7	7	7	7	7	7	7	7	8	8	8	8

(b) Matrix of atmospheric pressure
App-Fig. 1 Data base of weather map

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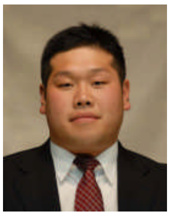

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