Application of Neural Network to One-Day-Ahead 24 hours Generating Power Forecasting for Photovoltaic System

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***Abstract*— In recent years, introduction of an alternative energy source such as solar energy is expected. However, insolation is not constant and output of photovoltaic (PV) system is influenced by meteorological conditions. In order to predict the power output for PV system as accurate as possible, it requires method of insolation estimation. In this paper, the authors take the insolation of each month into consideration, and confirm the validity of using neural network to predict one-day-ahead 24 hours insolation by computer simulations. The proposed method in this paper does not require complicated calculation and mathematical model with only meteorological data.**

***Index Terms*— neural network, 24 hours ahead forecasting, power output for PV system, insolation forecasting.**

I. Introduction

IN recent years, introduction of an alternative energy source such as solar energy is expected. Solar energy is well-known as clean energy because of no CO_2 emission. Therefore, photovoltaic (PV) system are rapidly gaining acceptance as one of the best solutions for the alternative energy source. However, insolation is not constant and the output of PV system is influenced by insolation and weather conditions. Using storage battery is one feasible measure to stabilize power output of PV systems. However, it requires additional costs and results in additional waste of used storage batteries. From the point of view to improve the control performance of power systems, there should be an estimation of output of PV system as accurate as possible. Therefore, a good insolation prediction method is required. Although the technique to forecast the generating power of PV system based on insolation prediction is regarded as an effective method in practical applications, it requires to solve differential equations by using large meteorological data. Then, the implementation of these techniques results in higher cost.

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To overcome these problems, it requires that forecasting technique is inexpensive and easy-to-use. Application of NN is known as a convenient technique for forecasting. It is possible to forecast insolation with only meteorological data. Most of the papers have reported application of feed-forward neural network (FFNN) for insolation forecasting [1-3]. However, it is difficult to forecast insolation by using FFNN. This paper proposes the power output forecasting of PV system based on insolation forecasting at 24-hour-ahead by using three different NN model. Selected model are FFNN, radial basis function neural network (RBFNN), and recurrent neural network (RNN). RBFNN is chosen for its structural simplicity and universal approximation property [4,5]. Since RNN is known as a good tool for time-series data forecasting [6,7], RNN is chosen in this paper.

A great deal of effort has been made on solar insolation and generating power forecasting method by using NN. Nevertheless, the author should like to explore a further possibility, which to the best of our knowledge has never been examined. In any ather paper, what seems to be lacking is performance comparison for insolation prediction of several types NN. There is a valid argument. Since the insolation fluctuates depending on weather conditions, so that the the forecast result of using NN is usually case-by-case.

The proposed technique for application of NN is trained by only weather data and tested for the target term. The power output of PV system is calculated by the forecasted insolation data. The validity of the proposed method is confirmed by comparing the prediction abilities of above mentioned NN on the computer simulations at 24-hour-ahead. In electric companies, insolation prediction is an important tool for utilizing the hybrid power systems with the storage battery, solar cells, wind generators, etc. For example, amount of storage battery energy is decided by forecast data easily. These decisions are beneficial for effective operation of hybrid power systems and consequently their profitability, depend on the forecast technique.

II. Neural Network

Fig. 1 shows the flow chart of learning algorithm of NN adopted in this paper. NN is indicated as shown in the left of Fig. 1. For the purpose to compare the forecast results of applying each NN, input data is based on same meteorological

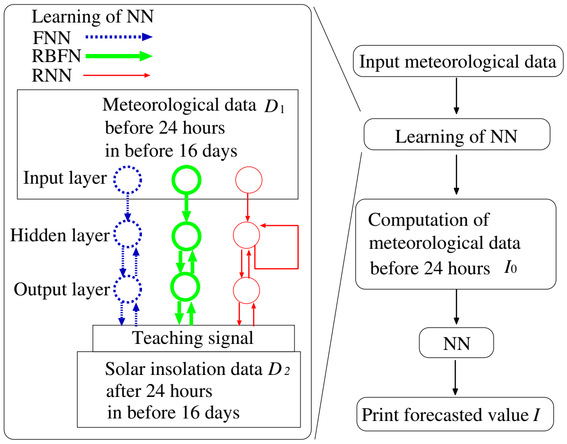

Fig. 1. Learning algorithm of NN.

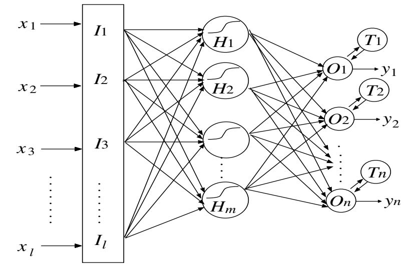

Fig. 2. Feed-forward neural network.

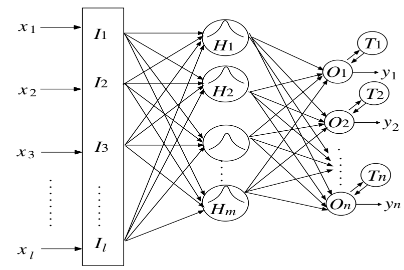

Fig. 3. Radial basis function neural network.

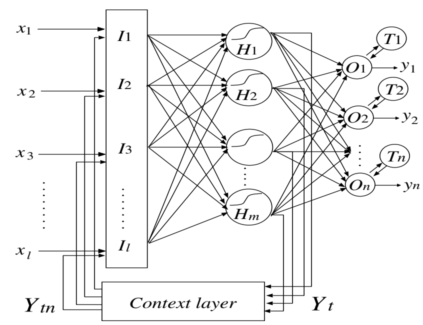

Fig. 4. Recurrent neural network (Elman type model).

data. In learning of FFNN, information transmits to one direction between each layer. The difference between FFNN and RBFNN is that RBFNN has radial basis function in hidden layer. On the other hand, RNN has feedback structure that information transmits from hidden layer to input layer in the learning algorithm. That is the main difference between FFNN and RNN. NN is learned by repeating these information transmission.

In solar insolation forecasting, the meteorological data used for learning the each NN are same data (for the period of 16 days). Forecast results are obtained by using each NN with the above-mentioned learning algorithm and forecasting technique. More detail structure and techniques for application of each NN are mentioned in Sections Ⅱ A, B, and C.

A. Feed-forward Neural Network

Fig. 2 shows the FFNN having l and m neurons in input layer and hidden layer, and n neuron in output layer. These neurons are connected with linear coupling, and $x_1 \sim x_l$ are input data to NN. There are connection weights between each neuron. Output of hidden neurons are converted to nonlinear values by the Hyperbolic tangent sigmoid-function. That function is as follows:

$$f(x) = \frac{2}{1 + \exp(-2x)} - 1 \quad (1)$$

where, x is the input data.

Back Propagation (BP) method is adopted for learning the NN. Generally, BP is explained as follows. To begin with, output of hidden neuron H_m is transmitted to output neuron O_n. Then, the output of output neuron is compared with target signal T_n as shown in Fig. 2. Finally, to minimize the mean square error margin, each connection weights and the output value of each neuron are changed in direction of straight line from output layer to input layer. In this paper, Levenberg-Marquardt algorithm is adopted for updating each connection weights of neurons [8].

The term momentum and learning coefficient are the parameters of NN. The term momentum promote learning speed acts rapidly by changing each connection weights of neurons. The learning coefficient is explained, this parameter is preferred to large. However, if it is too large, network becomes unstable. We assume that the mean square error margin of NN model should not be unstable. The authors decide these parameters by trial-and-error method.

B. Radial Basis Function Neural Network

Fig. 3 shows the RBFNN having l and m neurons in input layer and hidden layer, and n neurons in output layer. Output of hidden neurons H_m are converted by radial basis function. The exact interpolation problem requires every input vector to be mapped exactly on to the corresponding target vector. Consider a mapping from a d-dimensional input space x to a one-dimensional target space t. The data set consists of N input vectors x^p, together with corresponding target t^p. The goal is to find a function $h(x)$ such that

$$h(x^p) = t^p, \; p = 1, ...N. \quad (2)$$

The RBFNN approach introduces a set of N basis functions, one for each point, which take the form $\phi(\|x - x^p\|)$. Thus, the p-th such function depends on the euclidean distance between

x and x^p. The output mapping is then taken to be a linear combination of the basis functions

$$h(x) = \sum_p w_p \phi(\|x - x^p\|). \tag{3}$$

The interpolation condition given by Eq. (3) can then be written in matrix form as

$$W = \Phi^{-1} t. \tag{4}$$

When the weight w^p in Eq. (3) are set to the value given by Eq. (4), the function $h(x)$ represents a continuous differentiable surface that passes exactly through each data point. Several forms of basis function have been considered as for Eq. (5).

$$\phi_j(x^p) = \exp\left(\frac{-x^2}{2\sigma_j^2}\right) \tag{5}$$

where, σ is a parameter whose value controls the smoothness properties of the interpolating function $\phi(x)$.

Although the learning in output neurons O_n of RBFNN are adopted by BP like FFNN in this paper, hidden neurons H_m of RBFNN are adopted by approach shown below. The explanation shown below is summarized [4].

Training the RBFNN aims to minimize the sum-of-squares of error function defined by Eq. (6), its minimum can be found in terms of the solution of a linear equations Eq. (7).

$$E = \frac{1}{2P}\sum_p \sum_k (d_{pk} - o_{pk})^2 \tag{6}$$

$$\Phi^T \Phi W^T = \Phi^T T \tag{7}$$

The formal solution of the weights are given by

$$W^t = \Phi^{\dagger} T \tag{8}$$

where, P is pattern index, $T(= d_{pk})$ is target signal, o_{pk} is output, W is weight matrix, and $\Phi^{\dagger}$ is the pseudo inverse of Φ. Thus, the weight can be found by fast, linear matrix inversion techniques [4].

C. Recurrent Neural Network

Fig. 4 shows the RNN model of Elman type NN. Neuron characteristic of RNN is the same as that of FFNN, and it learned by BP. However, RNN has a *Context layer*. These layer contains copy of hidden layer with time-delay lines, and added as feedback structure. The context layer reflects both input and output layers information to the structure of RNN, by intervening the feedback structure by hidden layer. In consequence, the past information is maintained to RNN with the progress of learning. In Fig. 4, Y_t is the output of the hidden layer, and Y_{tn} is the output of the context layer. Y_{tn} is the following equation:

$$Y_{tn} = Y_{t-1} + rY_{t-2} + r^2 Y_{t-3} + ... + r^{n-1} Y_{t-n} \tag{9}$$

where, r is called a residual ratio. The value of r varies between 0 and 1.

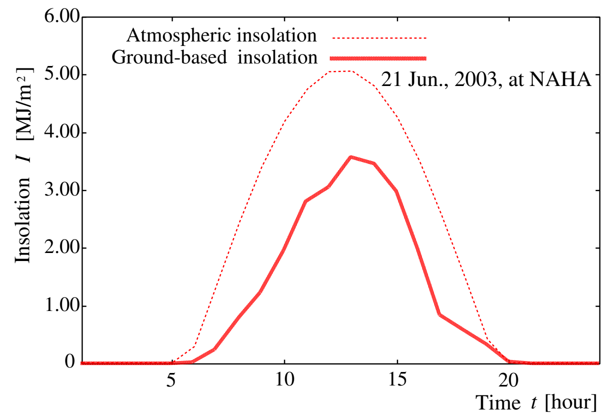

Fig. 5. Atmospheric insolation.

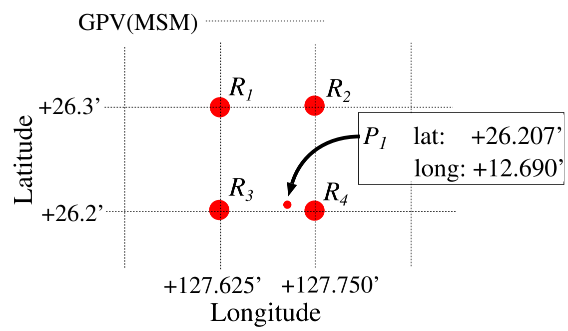

Fig. 6. GPV and prediction region.

As a result of learning RNN, past informations are reflected to RNN. In time-series data forecasting, it is difficult to maintain the past information by using simply FFNN. But, the composition of RNN that has the feedback structure is said to be effective [6].

D. Neural Networks Design

In this paper, to compare the forecasting performance of each NN by simulation, each learning parameters of NN, e.g., number of neurons, learning coefficient, and input data are fixed. Where, the number of hidden neurons H_m are decided to minimize the output error of NN by simulation result with using the training data. There are some methods for obtaining the number of hidden neurons H_m, however there is no general solution for this problem [7]. In this paper, a trial-and-error method has been used to determine the appropriate number of hidden neurons H_m. Hence, number of hidden neurons H_m are determined by using training data in advance of the forecasting. The details of learning data are explained in Section II E.

E. Input Data

The meteorological data of last 16 days are used for training the NN. NN is learned by every pattern data of 24-hour-ago and 24-hour-ahead. Solar radiation changes greatly with seasonal change. Thus, it is difficult to forecast insolation on the same study conditions. Therefore, correlation with NN and

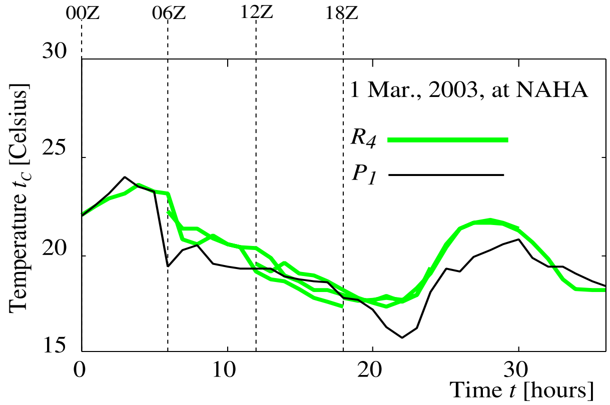

Fig. 7. Sample data of GPV (temperature data).

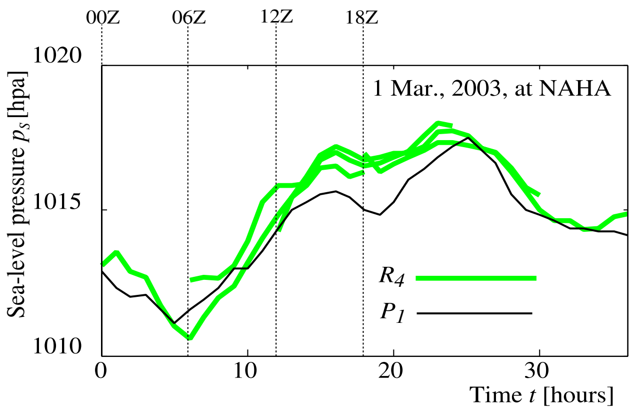

Fig. 8. Sample data of GPV (Pressure data).

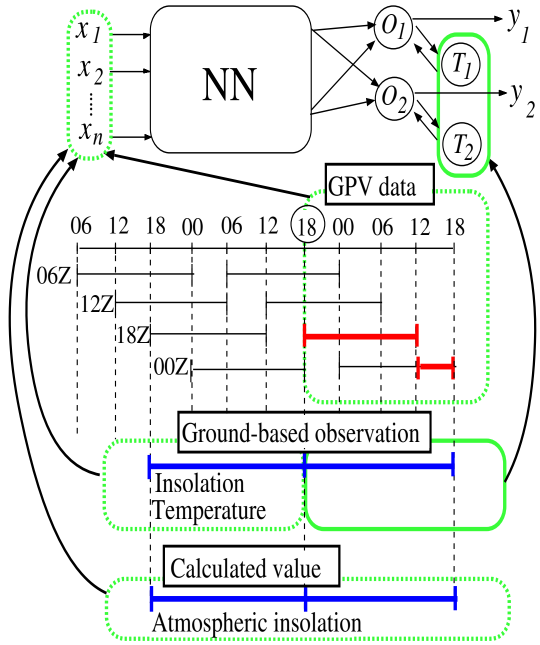

Fig. 9. Observing interval of GPV.

insolation data for forecasting is strengthened by using the data of the amount of atmospheric insolation. "Atmospheric insolation" is incoming to unit area on atmosphere outside, namely "Atmospheric global solar radiation" [9]. As shown in Fig. 5, atmospheric insolation changes under a constant regularity in every year. In insolation forecasting, it becomes effective to make time progresses learn to NN together with atmospheric insolation. Insolation is strongly influenced by the monthly distribution of atmospheric pressure. Because distribution of atmospheric pressure changes by "migratory anti-cyclone in 4-day cycle". "migratory anti-cyclone in 4-day cycle" is the high pressure seen in the Japanese Islands especially in spring and autumn. If a weather chart is seen, the low pressure and the high pressure will be located in a line by turns, and the weather will also change periodically. Hence, training data of NN are needed sufficiently. Therefore, the meteorological data of last 16 days are used for training the NN. Moreover, prediction temperature is used as training data of NN. Since temperature is strongly influenced by the insolation change, insolation forecasting is improved by correlation of NN with using prediction temperature.

Just write about input data assume, Naha City, Okinawa Prefecture in Japan is chosen as forecast area. The training data of NN is used ground-observation data and Grid Point Value (GPV) data that are "Japan meteorological business support center" has issued [10]. Strictly speaking, GPV is the daily operational weather forecasting data provided by the Numerical Prediction Division of Japan Meteorological Agency (NPD/JMA). NPD/JMA produces many kinds of aviation weather forecast products which are derived from numerical weather prediction (NWP) output data. In this paper, meso-scale NWP model (MSM) data is used for 24 hours ahead forecasting simulation. Fig. 6 shows the GPV $R_1 \sim R_4$ and prediction region P_1 which data are used for this paper. Figs. 7 and 8 show the observing 18-hours interval of GPV. The strong similarity between P_1 and R_4 are confirmed by Figs. 7 and 8. Also, similarity between P_1 and $R_1 \sim R_4$ is confirmed. MSM data are represented by follows, and there are not insolation data.

GPV(MSM) data: Insolation, Temperature, Atmospheric pressure, Humidity, Cloud amount, Wind speed, and Rainfall.

The observing interval of input data is shown in Fig. 9, and input data is shown in Table I. In Fig. 7 and Fig. 9, 18Z is represented by Coordinated Universal Time (UTC). If it is changed to Japan Standard Time (JST), it will be in 3:00 a.m. In this paper, forecast time is started at after 3:00 a.m to 24-hours ahead. Although lack data is excepted, even when lack data arises at forecast time, it is using the data distributed at past time, and it is possible to acquire the forecast value of insolation. The determination method of input data shown in Table I is shown in the simulation result of Section III.

III. Simulation Results

Table II shows the parameters in learning of NN, each parameter is fixed. The learning of NN is simulated with CPU-Intel(R)-Celeron(R)-2.7GHz computer. The calculation time of one-day-ahead forecasting is 20∼30 seconds. In this paper, to compare the forecast performance of each NN by simulation,

TABLE I

INPUT OF METEOROLOGICAL DATA.

Input (Grand-based observation)	
x_1	Insolation at 1∼24 hours ago
x_2	Temperature at 1∼24 hour ago
Input (Calculated value)	
x_3	Atmospheric insolation at 1∼24 hours ago
x_4	Atmospheric insolation at 1∼24 hours ahead
Input (GPV data)	
$x_5 \sim x_8$	Relative humidity at 1∼24 hours ahead ($R_1 \sim R_4$)
Target signal (Grand-based observation)	
T_1	Insolation at 1∼24 hours ahead
T_2	Temperature at 1∼24 hours ahead

TABLE II

LEARNING PARAMETERS OF NN.

Number of input neurons I_l	8
Number of hidden neurons H_m	16
Number of output neurons O_n	2
Learning coefficient	0.001
Term momentum	0.25
Learning time	1000

TABLE III

MEAN ABSOLUTE PERCENTAGE ERROR.

Pattern	FFNN	RBFNN	RNN
P_{d1}	15.93%	15.16%	15.20%
P_{d2}	15.54%	15.90%	16.27%
P_{d3}	17.07%	17.09%	16.86%
P_{d4}	14.99%	17.21%	14.67%
P_{d5}	16.54%	16.33%	15.93%
P_{d6}	17.33%	18.90%	16.30%

each parameters of NN, e.g., number of neurons, learning coefficient, and input data are limited. The learning time is decided that the learning of NN should not be over-training.

The input data shown in Table I shows the input pattern P_{d4} shown below $P_{d1} \sim P_{d6}$. However, since they are difficult to standardize inputting the wind speed and the rainfall data of $R_1 \sim R_4$ into NN, therefore, they are not inquiring.

P_{d1}: Insolation, Temperature, Atmospheric insolation at 24-hour ago, and Atmospheric insolation at 24-hour ahead.
P_{d2}: P_{d1} + Temperature for the $R_1 \sim R_4$.
P_{d3}: P_{d1} + Atmospheric pressure for the $R_1 \sim R_4$.
P_{d4}: P_{d1} + Humidity for the $R_1 \sim R_4$.
P_{d5}: P_{d1} + Cloud amount for the $R_1 \sim R_4$.
P_{d6}: P_{d1} + Temperature, Atmospheric pressure, Humidity, and Cloud amount for the $R_1 \sim R_4$.

Table III shows the simulation results of insolation forecasting based on the conditions of the input pattern $P_{d1} \sim P_{d6}$, and calculates forecast error (MAPE: mean absolute percentage error). MAPE is represented by:

$$MAPE\ [\%] = \frac{100}{N} \sum_{i=1}^{N} \frac{|P_f^i - P_a^i|}{P_a^i} \qquad (10)$$

where, N is number of data, P_f is forecast value, P_a^i is actual value, and i is number of forecasting time.

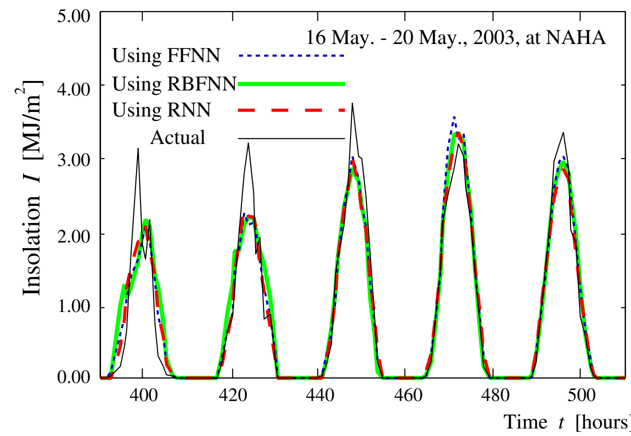

Fig. 10. 24 hours ahead insolation forecasting (2003/May).

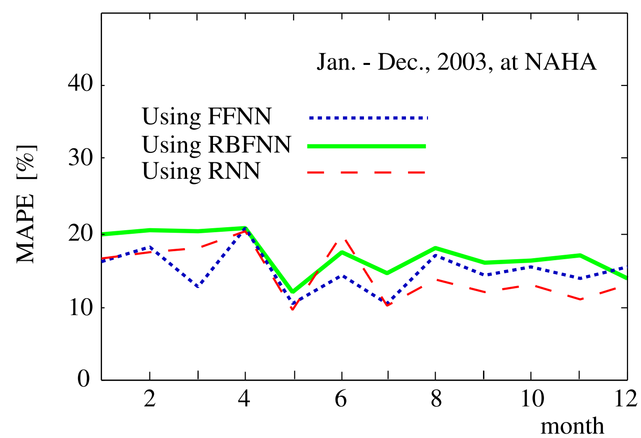

Fig. 11. Mean absolute prediction percentage error in each month (Insolation).

We can confirmed the validity of using GPV data, when we compared the result of P_{d1} and P_{d4} in Table III. That the forecast error is decreased by using GPV data. On the other hand, if we compare the result of P_{d4} and P_{d6} in Table III, that the forecast error is increased by using more input data. In order that RBFNN may interpolate training data correctly, RBFNN is greatly influenced by training data at the time of prediction. Therefore, in order to raise prediction accuracy, selection of more suitable data is needed.

Fig. 10 shows the results of 24-hours ahead insolation forecasting by using input pattern P_{d4} in May. As shown in Fig. 10, it is possible to obtain good forecasting results by the progress of effective learning in the insolation changing with regularity.

Fig. 11 shows the calculated MAPE of insolation forecast in each month. Since the result of maximum forecast error and minimum error are no difference, the validity of using NN is confirmed from results of Fig. 11. Also, forecast error of RBFNN are larger than the result of FFNN and RNN. In order that RBFNN may interpolate training data correctly, RBFNN is greatly influenced by training data at the time of prediction. Therefore, it is consider that the forecast error are minimized by using more suitable training data.

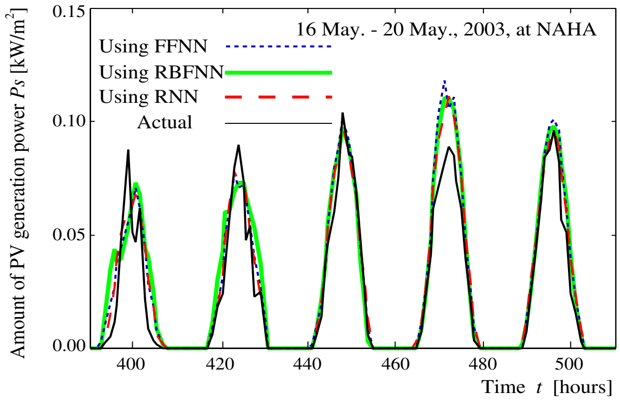

Fig. 12. Prediction of 24 hours ahead power output for PV system (2003/May).

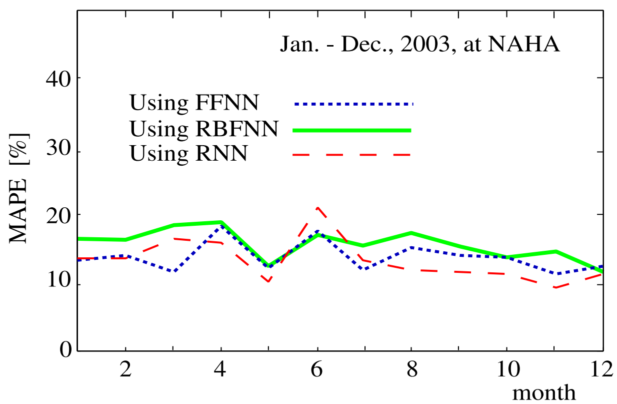

Fig. 13. Mean absolute prediction percentage error (Power output for PV system).

IV. Forecasting Result of Power Output for PV System

In this Section, the method of calculating the power generation electric power of PV system from the insolation forecasting value obtained by NN are shown. And, the author confirm the validity of the proposed method. In the PV system [11], per unit area of power output P_s is represented by:

$$P_s = \eta S I(1 - 0.005(t_O + 25)) \quad [\mathrm{kWm}^{-2}] \qquad (11)$$

where, η is the conversion efficiency of solar cell array (%), S is the array area (m^2), I is the insolation (kWm^{-2}), t_O is the outside air temperature (°C). If the above equation of PV system is used, the power output of PV system can be forecasted by using only weather data. In this paper, assume that sum total insolation will be falling on the solar cell array, and it does not consider the incidence angle of insolation and solar cell array. Moreover, assume that the conversion efficiency of solar cell array η is 15.7%, array area S is $1\mathrm{m}^2$. As shown in (11), since conversion efficiency of solar cell η and array area S are constant. Therefore, we will can see the power output P_s is the function of outside air temperature t_O and insolation I. In this paper, power output of PV system is computed as forecst temperature data y_2 which used in the insolation forecasting is temperature t_O.

The forecast power output result of the PV system in May that the insolation forecast error has been improved is shown in Fig. 12. Thus, the power output of PV system can be forecasted from the insolation forecasting. As shown in Section III, the MAPE of power output for PV system in each month is shown in Fig. 13. As shown in calculated result of Fig. 13, since there is no great difference in the MAPE of power output, the validity of the proposal technique can be confirmed.

V. Conclusions

This paper proposed the power output forecasting for PV system based on insolation prediction by using NN. The merit of the proposed method is that it does not require complicated calculations and the mathematical model with only meteorological data. At that time of insolation forecasting, it can be possible to shorten the forecast time by using only meteorological data. Moreover, selected model are FFNN, RBFNN, and RNN. RBFNN is chosen for its structural simplicity and universal approximation property. Since RNN is known as a good tool for time-series data forecasting, RNN is chosen in this paper. Although the result are mixed in each month, simulation results indicate that RBFNN and RNN outperform the result of FFNN in some month. In fact, it is possible to forecast preferred results by using only meteorological data in short time. The validity of the proposed NN is confirmed by one-day-ahead 24 hors forecasting simulation.

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