

Decision Technique of Solar Radiation Prediction Applying Recurrent Neural Network for Short-Term Ahead Power Output of Photovoltaic System

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ABSTRACT

In recent years, introduction of a renewable energy source such as solar energy is expected. However, solar radiation is not constant and power output of photovoltaic (PV) system is influenced by weather conditions. It is difficult for getting to know accurate power output of PV system. In order to forecast the power output of PV system as accurate as possible, this paper proposes a decision technique of forecasting model for short-term-ahead power output of PV system based on solar radiation prediction. Application of Recurrent Neural Network (RNN) is shown for solar radiation prediction in this paper. The proposed method in this paper does not require complicated calculation, but mathematical model with only useful weather data. The validity of the proposed RNN is confirmed by comparing simulation results of solar radiation forecasting with that obtained from other method

Keywords: Neural Network; Short-Term-Ahead Forecasting; Power Output for PV System; Solar Radiation Forecasting

1. Introduction

Solar energy is well-known as clean energy because of no carbon dioxide emission. Therefore, photo-voltaic (PV) systems are rapidly gaining acceptance as one of the best solutions for the alternative energy source. However, solar radiation is not constant and the output of PV system is influenced by solar radiation and weather conditions. At 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. In electric companies, solar radiation forecasting 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 forecasting data easily. These decisions are benefits for effective running of hybrid power systems and consequently their profitability depends on the forecast technique. Therefore, a good solar radiation forecasting method is required. Although the technique to forecast the generating power of PV system based on solar radiation forecasting is regarded as an effective method in

practical applications, it requires solving differential equations by using large meteorological and topographic data. In addition, although Meteorological Agency or weather service will provide forecasting data free of charge, the implementation of above-mentioned techniques results in higher cost. Because, these data are forecasting data of a wide area mostly, and are difficult for getting to know the exact value of the place in which the PV system is installed. To overcome these problems, forecasting technique should be inexpensive and easy-to-use. Application of Neural Network (NN) is known as a convenient technique for forecasting. It is possible to forecast solar radiation with only meteorological data. Most of the papers have reported application of feed-forward neural network (FNN) for solar radiation forecasting [1-6]. However, what seems to be lacking is performance comparison for solar radiation forecasting of FNN and other NN. Because the forecast result of using NN is usually case-by-case with stochastic appearance of solar radiation. This paper proposes the power output forecasting of PV system based on solar radiation fore-

casting at several-hour-ahead by using Recurrent Neural Network (RNN). Since RNN is known as a good tool for time-series data forecasting [2-6], the authors propose the application of RNN for solar radiation forecasting. In this paper, the proposed technique for application of RNN is trained by only historical data of solar radiation and tested for the target term. Additionally, these data are observed only one site, and the type of RNN used is Elman network [7-9]. Then, the power output of PV system is calculated by the forecasted solar radiation data. The validity of the proposed RNN is confirmed by comparing the forecasting abilities of FNN and RNN on the computer simulations at several-hour-ahead.

2. Neural Network

Figure 1 shows the flow chart for the learning algorithm of NN, which is adopted in this paper. NN is stratified as shown in the block chart at the left of **Figure 1**. For the purpose to compare the forecasting results of applying FNN and RNN, input data is based on same meteorological data. The information of meteorological data transmits to one direction between each layer in FNN. On the other hand, RNN has feedback structure that information transmits from hidden-layer to input-layer in the learning algorithm. That is the big difference between FNN and RNN. NN is trained by iterating these information transmissions. In solar radiation forecasting, the meteorological data used for training the NN are only the historical data of actual solar radiation (for the period of 16 day). Solar radiation forecasting is obtained by using FNN and RNN with the above-mentioned learning algorithm and forecasting technique. More detail structure and techniques for application of FNN and RNN are mentioned in Sections 2.1 and 2.2.

2.1. Feed-Forward Neural Network

Figure 2 shows the FNN having n and m numbers of input-layer neurons and hidden-layer neurons, and 1 output-layer neuron. These neurons are connected linearly by each other, and $x_1 \sim x_n$ are input data to NN. There are connection weights between each neuron. Output of hidden-layer neurons are transformed nonlinearly by the sigmoid function [1]. The sigmoid function is presented by (1), and the input-and-output characteristic is shown in **Figure 3**.

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

where, x is the input data.

In order to learn NN, input data x is standardized and inputted so that each unit output may exist in the activation area shown in **Figure 3**.

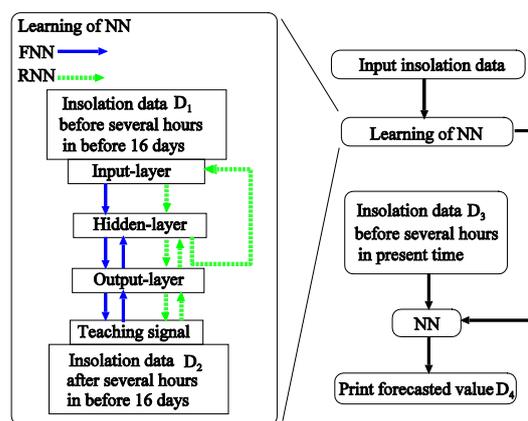


Figure 1. Learning algorithm of NN.

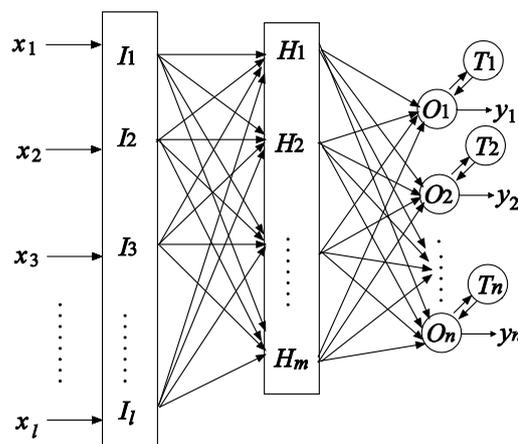


Figure 2. Feed-forward neural network.

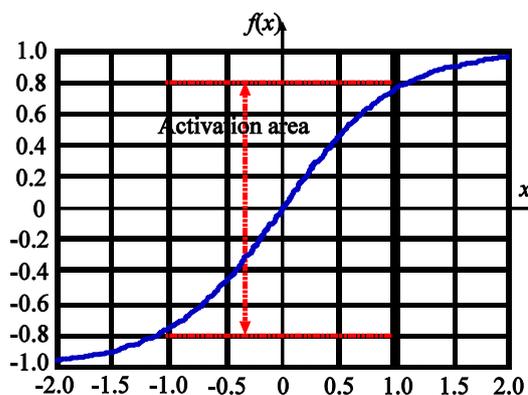


Figure 3. Hyperbolic tangent sigmoid function.

tion area shown in **Figure 3**. In this paper, input data was standardized to between -1.0 and 1.0. Back Propagation(BP) method is adopted for learning the NN. Generally, BP is explained as follows. To begin with, output of hidden units is transmitted to output units. Then, the output of output units is compared with teaching signal T as shown in **Figure 2**. Finally, to minimize the mean square

error margin, each connection weights and the value of each unit are changed in direction of straight line from output layer to input layer. In this paper, Levenberg-Marquardt algorithm was adopted for updating each connection weight of unit [10]. The inertia and learning coefficient are the parameters of NN. The inertia promotes learning speed acts rapidly by changing each connection weights of neurons. The learning coefficient is explained, this parameter is preferred to large. At this time, it is necessary to stable the least square error margin of NN model. The authors decide these parameters by trial-and-error method [5,6]. The effective learning has been improved by multiplying the learning coefficient by the learning increase rate and the learning decrease rate, and then variable of least square error margin is adjusted. Moreover, optimum number of hidden-layer neurons is decided to minimize the output error of NN by simulation result with using the training data [9].

2.2. Recurrent Neural Network

Figure 4 shows the RNN model of Elman type [8]. Neuron characteristic of RNN is the same as that of FNN, and it trained by BP. But, as shown in **Figure 4**, RNN has context-layer. These layers are copy of one-step delayed hidden-layer, and added as feedback structure. The context-layer reflects both input-layer and output-layer information to the structure of RNN, by intervening the feedback structure between output of input-layer and hidden-layer. In consequence, the historical information is maintained to RNN with the progress of learning. In **Figure 4**, Y_t is the output of the hidden-layer, and Y_m is the output of the context-layer. Y_t is represented by the following equation:

$$Y_m = Y_{t-1} + rY_{t-2} + r^2Y_{t-3} + \dots + r^{n-1}Y_{t-n} \quad (2)$$

where, r is called a residual ratio. The value of r is between 0 and 1. Resulting from training RNN, historical information is reflected to RNN. In time-series data forecasting, it is difficult to maintain the historical information by using simply FNN. But, the composition of RNN that as the feedback structure is said to be effective [8].

2.3. Input Data

The meteorological data of last 16 days were used for training the NN. NN was learned by every pattern data of several-hour-ago and several-hour-ahead. Solar radiation changes greatly with seasonal change. Thus, it is difficult to forecast solar radiation on the same study conditions. Therefore, correlation with NN and solar radiation data for forecasting was strengthened by using the data of the amount of global horizontal solar radiation. The maxi-

um solar radiation n value is determined by “Top-of-Atmosphere”, which is incoming to unit area on atmosphere outside, namely global horizontal solar radiation [11]. As shown in **Figure 5**, global horizontal solar radiation changes under a constant regularity in every year. In solar radiation forecasting, it becomes effective to make time progresses learn to NN together with global horizontal solar radiation. Moreover, solar radiation is strongly influenced by the monthly distribution of atmospheric pressure. Because the distribution of atmospheric pressure changes with “migratory anti-cyclone in 4-day cycle” in Japan. Hence, learning data of NN are needed sufficiently. Therefore, the meteorological data of last 16 days were used for training the NN. Moreover, predicted temperature was used as learning data of NN. Since temperature is strongly influenced by the solar radiation change, solar radiation forecasting is improved by correlation of NN with using predicted temperature. Forecast area is Okinawa Prefecture, Naha City of Japan. In this paper, learning data of NN is used for the ground observation data that the “Japan Meteorological Business Support Center” had issued [12]. In solar radiation fore-

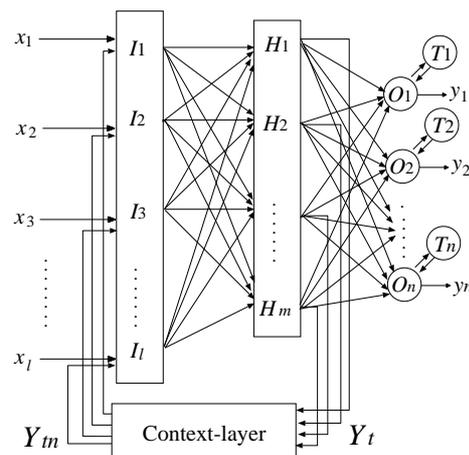


Figure 4. Recurrent neural network (Elman type).

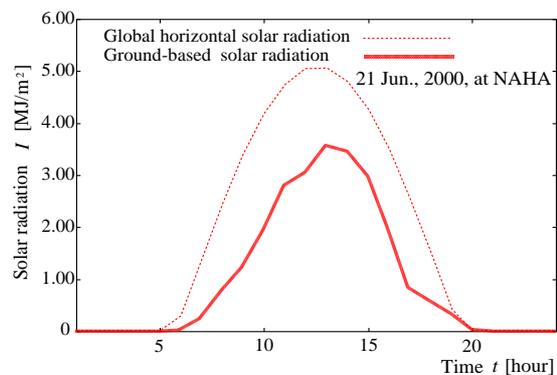


Figure 5. Global horizontal solar radiation for Top-of-Atmosphere.

casting, input data $x_1 - x_{12}$ as shown in **Figures 2 and 3**, $x_1 - x_3$ is (solar radiation data of 3 hour before)-(1 hour before), $x_4 - x_6$ is (atmospheric global solarradiation of 3 hour before)-(1 hour before), $x_7 - x_9$ is (atmospheric pressure of 3 hour before) - (1hour before), $x_{10} - x_{12}$ is (temperature of 3 hour before)-(1 hour before), and teaching signal $T_1 - T_3$ is (solar radiation data of 3 hour after)-(1 hour after). These data of NN are shown in **Table 1**. At forecasting time, since the forecast results are obtained by only $x_1 - x_{12}$ to NN as input data, teaching signal $T_1 - T_3$ are not needed. But, predicted temperatures $x_{10} - x_{12}$ are needed for input of NN. Although predicted temperature could predict by changing teaching signal T into temperature, in this paper, predicted temperature inputted actual data. Because of that is to compare the forecasting results by using the historical data which made $x_{10} - x_{12}$ (temperature of 3 hour before) - (1 hour before). Calculation results of the forecasted error from solar radiation forecasting in each month are shown in Section 4.

3. Solar Radiation Forecasting Result by Using FNN and RNN

Table 2 shows the parameters in learning of NN, each parameter is fixed. The calculation time was 20 - 30 seconds. The learning of NN was simulated with CPU-Intel(R)-Celeron(R)-2.7GHz computer. This Section shows the simulation results of solar radiation forecasting and calculated Mean Absolute Percentage Error(MAPE) for the forecasted error by using FNN and

RNN in each month. MAPE is represented by:

$$MAPE [\%] = \frac{100}{N} \sum_{i=1}^N \frac{|P_f^i - P_a^i|}{P_a^i} \quad (3)$$

where, N is the number of data, P_f is the forecast value, P_a is the actual value, and i is the number of forecasting days. **Figure 6(a)** is the result of using only the historical data in solar radiation forecasting. **Figure 6(b)** is there sult of using predicted temperature. As shown in **Figure 6**, that a forecast error was decreased by using predicted temperature. In this paper, to compare the forecast performance of FNN and RNN by simulation, each parameters of NN, e.g., number of neurons, learning coefficient, and input data are limited.

However, the number of hidden-layer neurons is 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-layer neurons; however, there is no general solution for this problem. In this paper, a trial-and-error method has been used to de-

Table 1. Input data.

$x_1 - x_3$	Solar radiation at 2 hour ago-present time
$x_4 - x_6$	Atmospheric global solar radiation at 2 hour ago-present time
$x_7 - x_9$	Atmospheric pressure at 2 hour ago-present time
$x_{10} - x_{12}$	Temperature at 1 hour ahead-3 hour ahead
	Teaching signal
$T_1 - T_3$	Solar radiation at 1 hour ahead-3 hour ahead

Table 2. Learning parameters of NN.

Number of input layer neuron	12
Number of hidden layer neuron	20
Number of output layer neuron	3
Learning coefficient	0.01
Inertia coefficient	0.25
Learning time	800

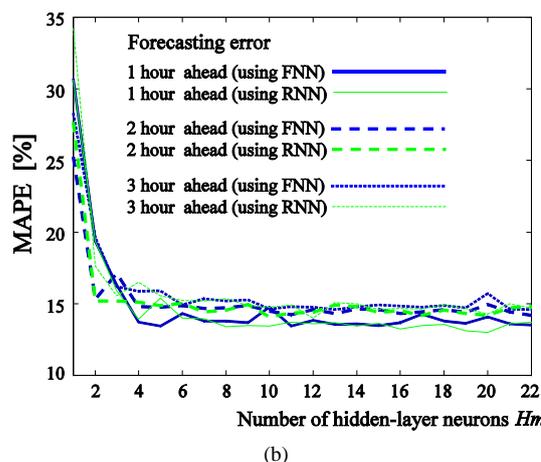
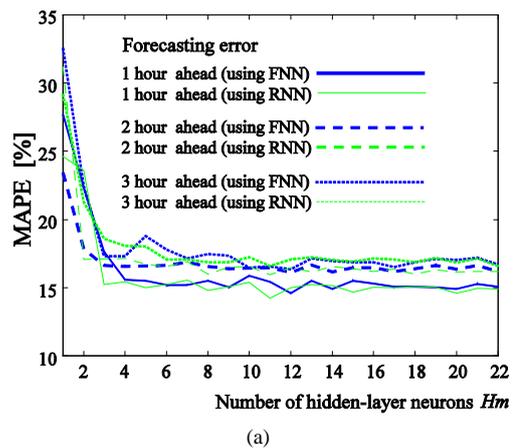
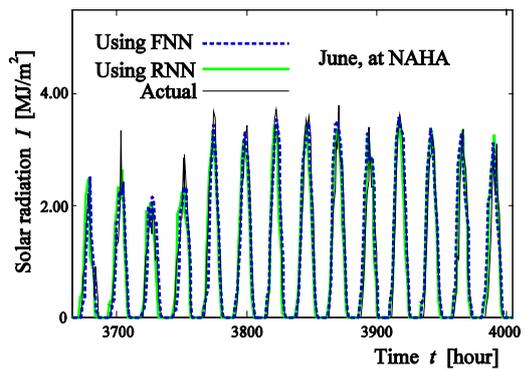


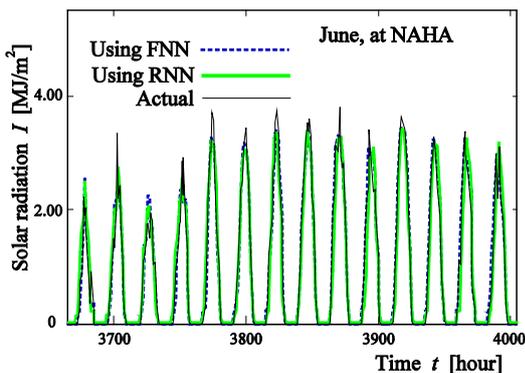
Figure 6. Forecast error to number of hidden-neurons. (a) Using past data of temperature; (b) Using forecasted data of temperature.

termine the appropriate number of hidden-layer neurons [9]. It starts with 1 neuron and then gradually increases the number and calculates the learning error. Learning of NN is carried out until it reaches the lowest training error. In **Figure 6(b)** for this study, the optimized number of hidden-layer neurons is 20. Thus, trial-and-error method has been used to determine the number of input neurons, too. Hence, appropriate parameters of NN are determined in this paper.

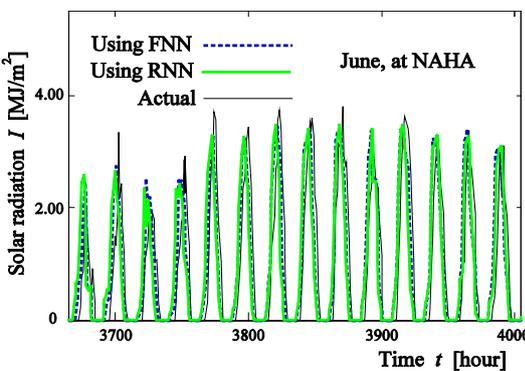
Figure 7 shows the results of solar radiation forecasting in June. These results show the forecast errors are



(a)



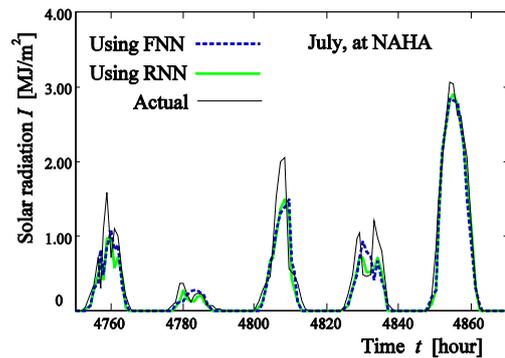
(b)



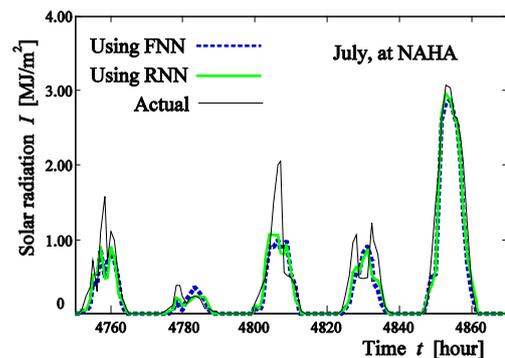
(c)

Figure 7. Several hours ahead solar radiation forecasting (Jun., 2000). (a) 1 hour ahead; (b) 2 hour ahead; (c) 3 hour ahead.

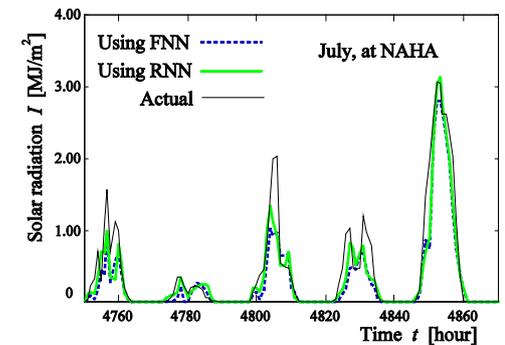
minimized by using RNN. The result of using RNN, forecast error (MAPE) is 10.85% in 1-hour ahead, 12.61% in 2-hour ahead, and 12.97% in 3-hour ahead. The result of using FNN, forecast error is 12.36% in 1-hour ahead, 12.81% in 2-hour ahead, and 13.90% in 3-hour ahead. As shown in **Figure 7**, it is possible to obtain good forecasting results by the progress of effective learning in the solar radiation changing with regularity. **Figure 8** shows the results of solar radiation forecasting in July. The result of using RNN, forecast error (MAPE) is 15.86% in 1-hour ahead, 16.06% in 2-hour ahead, and 15.40% in 3-hour ahead.



(a)



(b)



(c)

Figure 8. Several hours ahead solar radiation forecasting (Jul., 2000). (a) 1 hour ahead; (b) 2 hour ahead; (c) 3 hour ahead.

The result of using FNN, forecast error is 18.58% in 1-hour ahead, 20.10% in 2-hour ahead, and 20.33% in 3-hour ahead. As shown in **Figure 8**, as forecast time lengthens, forecast error increases. That appeared prominently in result of **Figure 8(c)**. In that case, mean squared error of NN model becomes unstable. Although the time-series information is destroyed by the fluctuation of solar radiation in July, forecast errors are minimized by using RNN. **Figure 8** demonstrated the result that time-series information is maintained to RNN structure by the progress of effective learning. **Figure 9** shows the calculated MAPE of solar radiation forecast in

each month. Result of maximum forecast error is appeared in July, and result of minimum error is appeared in June, and there are 5% - 0% difference. That reason is above-mentioned in **Figure 8**, and forecast errors are minimized by using RNN from 1-hour ahead to 3-hour ahead forecasting. The validity of using RNN is confirmed from results of **Figure 9**.

4. 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 solar radiation forecasting value obtained by NN are shown. And, the authors confirm the validity of the proposed method. In the PV system [13], per unit area of power output P_s is given as:

$$P_s = \eta SI (1 - 0.005(t_o + 25)) \quad [\text{kW/m}^2] \quad (4)$$

where, η is the conversion efficiency of solar cell array (%), S is the array area (m^2), I is the solar radiation (kW/m^2), t_o is the outside air temperature ($^{\circ}\text{C}$). 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 solar radiation will be falling on the solar cell array, and it does not consider the incidence angle of solar radiation and solar cell array. Moreover, assume that the conversion efficiency of solar cell array η is 15.7%, array area S is 1 m^2 . As shown in (4), since conversion efficiency of solar cell η and array area S are constant. Therefore, we can see the power output P_s is the function of outside air temperature t_o and solar radiation I . In this paper, power output of PV system is computed as temperature data $x_{10} - x_{12}$ which used in the solar radiation forecasting is temperature t_o . The forecast power output result of the PV system in July that the solar radiation forecast error has been improved is shown in **Figure 10**. Thus, the power output of PV system can be forecasted from the solar radiation forecasting.

5. Conclusion

This paper proposed the power output forecasting for PV system based on solar radiation forecasting by using RNN. The merit of the proposed method is that it does not require complicated calculations but the mathematical model with only meteorological data. At that time of solar radiation forecasting, it can be possible to shorten the forecast time by using only historical data. Moreover, RNN is a good tool for time-series data forecasting. RNN is able to forecast solar radiation accuracy. In fact, it is possible to forecast preferred results by using only historical data in short time. The validity of the pro-

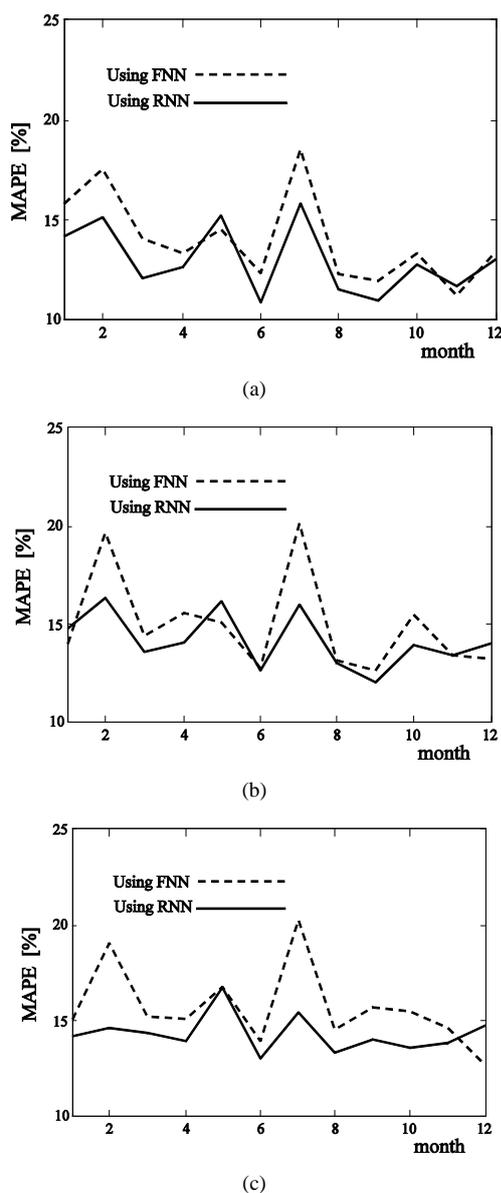


Figure 9. Mean absolute percentage error in each month(1 Jan. 31 Dec., 2000, solar radiation). (a) 1 hour ahead; (b) 2 hour ahead; (c) 3 hour ahead.

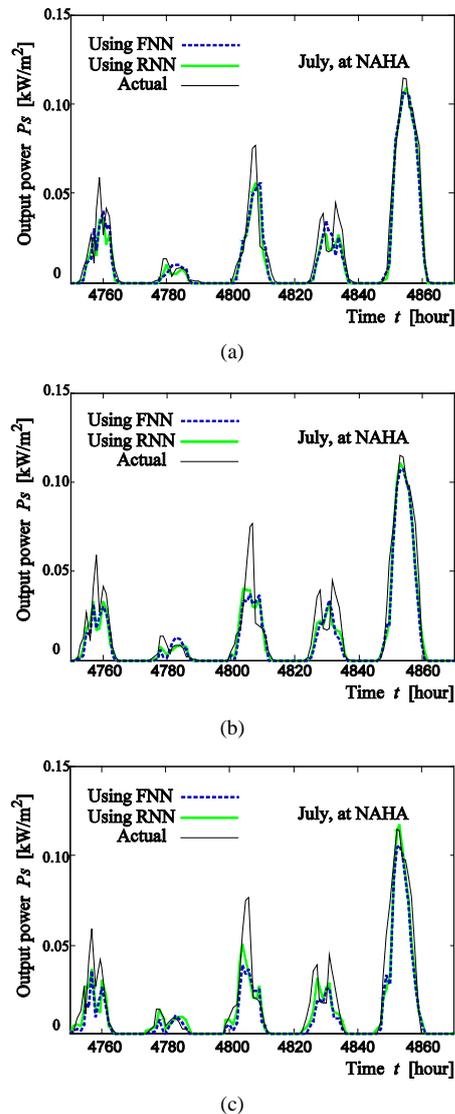


Figure 10. Forecast results of several hour ahead power output for PV system (Jul., 2000). (a) 1 hour ahead; (b) 2 hour ahead; (c) 3 hour ahead.

posed RNN is confirmed by comparing forecasting results with that obtained from FNN. It is found that forecast errors are greatly minimized by RNN. Hence, the proposed RNN shows a good performance to forecast power output of PV system.

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