Forecasting in thirty minutes amount of PV power generation using neural network

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Abstract. In recent years, to ameliorate global warming and reduce demand upon fossil energy resources, photovoltaic generation (PV) has been increasingly adopted around the world. However, the amount of PV fluctuates dramatically according to the weather conditions, and may adversely affect the power supply if introduced in large quantities. It is necessary to accurately estimate the amount of potential power generation in local environments and weather conditions to better control the supply of PV. This Local environmental data is wind velocity, atmospheric pressure, amount of solar radiation as well as the quantification of cloud cover by means of a Nephometer. These data were collected over the past year at Sabae city by means of the total weather forecasting system (pyranomete, complex weather sensor, nephometer, cloud bottom height sensor) at Fukui National Institute of Technology. Nephometers are not widely implemented in the collection of local environmental data so this dataset may hold unique insights that could be revealed by means of neural network techniques. In this study a neural network analysis was employed to develop a model of PV potential.

Keywords: photovoltaic generation, Nephometers, neural network

1. INTRODUCTION

Recently, PV is being introduced in large quantities. (Agency for Natural Resources and Energy, 2015) But, PV system experiences increases and decreases in power generation due to meteorological causes. So, the electric power system could experience larger fluctuations due to PV when it is introduced in large quantities. Therefore, there is a need to refine estimates of power consumption and generation by using IT technology such as the Smart grid. (Kazuhiko Hagimmoto, Yuiti Ikeda, 2011) In this investigation, a system that predicts PV power generation based upon present climate is proposed. There are already models forecasting PV that incorporate meteorological data (Susumu Shimada, YuanYuan Liu, etc all, 2012) (Hideaki Ohtake, Takumi Takashima, etc all, 2015) and forecasting power generation by means of NN employing radar data input. (Tomoki Kino, Ninomiya Takayuki, etc all, 2011) (Takanori Matsuyama, Tomohiko Ichikawa, etc all, 2010) In this system input data is acquired from sensors near the PV panels.The paper outlines input parameter selection and forecast creation. Forecasting employs a NN that has previously been used successfully (F. Almonacid*, C. Rus, P.J. Pe´rez, L. Hontoria, 2009) (Subiyanto Subiyanto∗, Azah Mohamed, M.A. Hannan, 2012). Other papers outline forecasting systems that acquire data from meteorological models. This meteorological model data may be vulnerable to errors because of local weather, data, and topography. The forecasting system outlined in this paper doesn't use data from meteorological models. Measured values are acquired and employed in this forecasting system. These measured values include the amount of cloud and short wavelength radiation and they have not been used in other papers.

2. PV generator and measurement system

2.1 PV generator

The PV generators are located at FNCT (35.936N, 136.171E) in the center of the Japan. The city of Sabae is situated at an altitude of 19m above sea level and characterized by a continental climate, relatively cool in winter and extremely hot in summer; this is where this PV generator is located(Figure1) facing towards the south on the roof of building 7[m]. Generation capacity is 5[kW]. The PV installations are fully monitored every 15 minutes to assess the potential of PV technology and the performance of this kind of system

Figure1: Installation status of PV panel.

2.2 Measurement system

The measurement system utilizes two sensors. One of which acquires meteorological data such as amount of solar radiation, rainfall and others. The other machine measures cloud cover. These machines are located nearby the solar panels. This instrumentation takes samples in one minute intervals. Table 1 and 2 show data from this measurement system.

Table1: Meteorology data.

Data	unit
infrad body temperatura	[℃]
inclien solar radiation intensity	[W/㎡]
short wave radiation	[W/㎡]
long wave radiation	[W/㎡]
wind direction	[deg]
wind velocity	[m/s]
Temperature	[℃]
Humidity	[%]
atmospheric pressure	[hPa]
amount of rainfall	[mm]

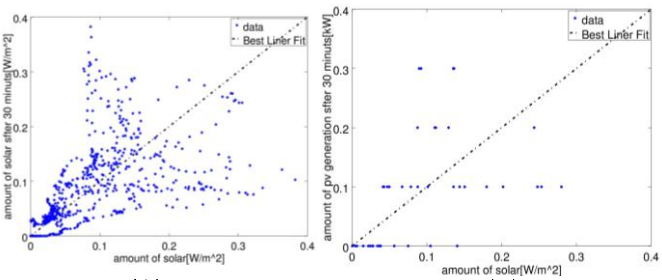
3. Data

Table 1 shows data from the measurement system. At this time, main data are amount of solar radiation, short wavelength radiation, temperature, and PV generation. Forecasts are generated by utilizing these data as input or output parameters. These data were chosen because they were determined to have high degrees of relevance. Graphs of results and correlation concerning each input and output is shown below. Graph (A) is amount of solar radiation after 30minutes and graph (B) is PV output after 30minutes.

The amount of solar radiation was found to be highly correlated with PV as was the amount of solar radiation after 30 minutes. The correlation between Temperature and PV was lower but still high enough to include it as relevant data.

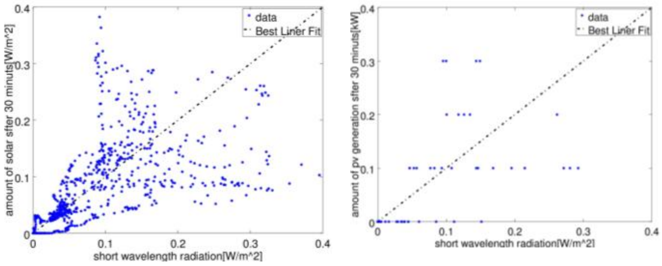
Table2: Amount of cloud data.

data	unit
air temperature	[℃]
amount of cloud	[%]
amount of cloud in low layer	[%]
amount of cloud in middle layer	[%]
amount of cloud in upper	[%]
height of low layer	[m]
height of middle layer	[m]
height of upper	[m]
standard deviation of low layer	[m]
standard deviation of middle layer	[m]
standard deviation of upper	[m]
temperature	[℃]



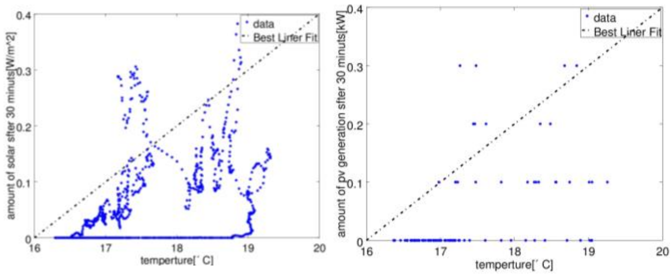
(A) (B)

Figure2: Correlation diagram between solar radiation and PV.



(A) (B)

Figure3: Correlation diagram between short wavelength radiation and PV.



(A) (B)

Figure4: Correlation diagram between temperature and PV.

Table3: Correlation coefficients.

2014/10/5		
Input data	Output data	
	amount of solar	PV generator
amount of solar	0.75	0.67
short wavelength radiation	0.74	0.66
Temperature	0.52	0.45

2014/10/15		
Input data	Output data	
	amoun t of solar	PV generato r
amount of solar	0.81	0.87
short wavelength radiation	0.80	0.84
temperature	0.41	0.42

4. Forecasting method employing meteorological data

Figure5 shows the system contemplated as ideal flowcharts. We explain this flowcharts. “Input parameters” are the amount of the solar radiation, short wavelength radiation, and the temperature. Target parameter is the amount of solar radiation or PV generation in the future. The “cutting data” step of the flow chart involved the exclusion of input parameters measured between sunset and sunrise as these values are unnecessary when deriving a forecast. This extraneous cut data has a volume of 55~60% of the original data. We normalize the input parameter because each parameter has a different unit. So that all input parameters fall in this range [0 1]. The “Part of forecasting” step in the flowchart employs an artificial neural network (ANN or NN). Due to the random nature of cloud cover a need to predict nonlinear values was anticipated so a NN was adopted to generate forecasts.

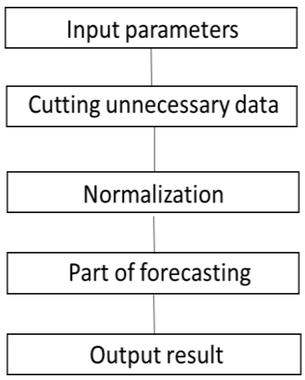


Figure5: Flow chart of prediction system.

4.1 Neural network (NN)

This paper employs simple hierarchical with three layers to forecast PV generation or the amount of solar radiation by meteorological data. We used input data that is 31 days on 2014/10. Test data is one of used data, and test data is other 30 days. Weather in japan change by cycle of the seasons. Training data is selected to think that seasonal changes of weather. So, it is day that be close to test data. Input layers are composed of the amount of solar radiation, short wavelength radiation, and the temperature. Output layer is composed of PV generation or the amount of solar radiation after 30 minutes have passed. If the output layer is PV generation, every 15 minutes a forecast is made of PV generation expected 30 minutes later. But, if it’s the amount of solar radiation, the forecasts are generated in 1 minute intervals predicting solar radiation levels either 3, 15 or 30 minutes later. Sampling intervals are different from each other in meteorological data and PV generation. So, if forecasting PV generation, meteorological data takes an average of 15 minutes. Predicting the time is for twenty-four hours from the midnight on the prediction day. Learning condition of NN is 8 middle layers and the learning coefficient is 0.01. A description of the NN is shown below and is based that employed by previous researchers. (Subrahmanyam Pulipaka, Rajneesh Kumar, 2015).

4.2 NN’s theory

Artificial Neural Network (ANN) model Artificial neural networks are a powerful mathematical tool used to identify the nature of a curve, recognize a pattern or map the behavior of a nonlinear data with respect to a target parameter. A typical neural network consists of an input layer, few hidden layers and an output layer connected with nodes. The core architecture of a neural network is illustrated in Figure. 11. Weights and biases are also integral part of the architecture that determine the efficiency of the neural network. The illustration shown is a multilayer perceptron model of a neural network. This network is initialized and conFigureureured in the following way.

・The inputs to be given to the neural network are determined, along with the number of hidden layers and the neurons in each hidden layer
・The weights and biases are initialized for each layer
・From the input layer, the input vectors (Ii) are multiplied with the initialized weight (wi,1) and summed with the respective node bias (bi,1) given by

$$a_{1,1} = \left[\sum_{i=1}^{n}\left(I_i w_{i,1}\right) + b_{i,1}\right] \quad (1)$$

・This sum is given to an activation function which is often a sigmoid (log or tan). The most commonly used activation function is log sigmoid (r) given by

$$\sigma\left(a_{1,1}\right) = \frac{1}{(1+e^{-a_{1,1}})} \quad (2)$$

・The output of the activation function acts as the input to the next layer and step 3–4 are repeated until the output layer is reached.
・After reaching the output layer, the value of the output parameter obtained is examined and compared with the target parameter.
・Performance parameters like MSE or SSE along with gradient are calculated as per the training algorithm specifications. where ti,k – is the target value and oi,k is the output obtained

$$\text{MSE} = \left(\frac{1}{n}\sum_{i=1}^{n}\sum_{j=!}^{k}\left(t_{i,k} - o_{i,k}\right)^2\right) \quad (3)$$

・The training algorithm based on its specifications of updating the weights of biases, uses the obtained performance parameters to update the weights in the network.

- The previous steps are repeated until the desired performance parameter value or validation checks are obtained and then the neural network training is completed.
- The resultant neural network can be used in forecasting the output parameter based on the sets of input parameters given to the network.

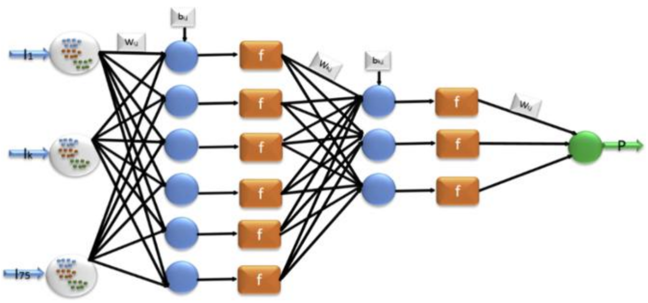
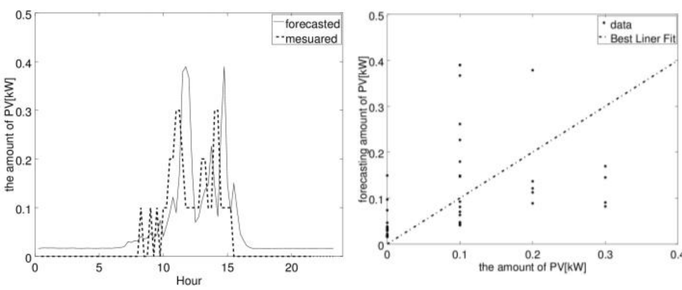


Figure6: Neural network model. (Subrahmanyam Pulipaka, Rajneesh Kumar, 2015).

5. Results

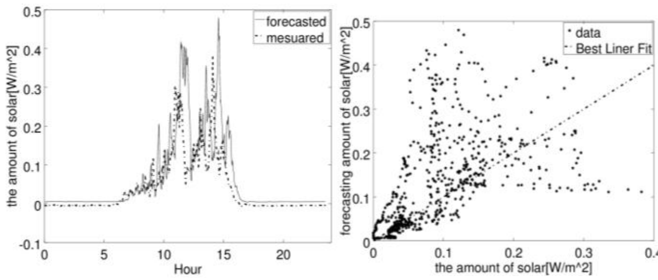
Forecasted amounts of solar radiation and PV generation after 30 minutes are shown in Figures 7 thru 12. Test data has two pattern. They are days that is obscured by cloud all day long and other wise. For the purpose of comparison predictions of the amount of solar radiation 3 minutes and 15 minutes in the future were generated on 2014/10/5. In Figures 7 thru 12 part (A) is predicted and measured values of PV generation and part (B) is correlation diagram between predicted and measured values.



(A) (B)

Figure7: Forecasted PV generation after 30 minutes on 2014/10/5.

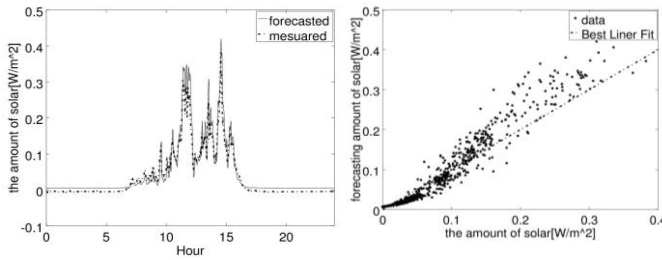
Results in Figure & (B) are not available due to resultant PV being less than the resolving power of 0.1[kW].



(A) (B)

Figure8: Forecasted amount of solar radiation after 30 minutes on 2014/10/5.

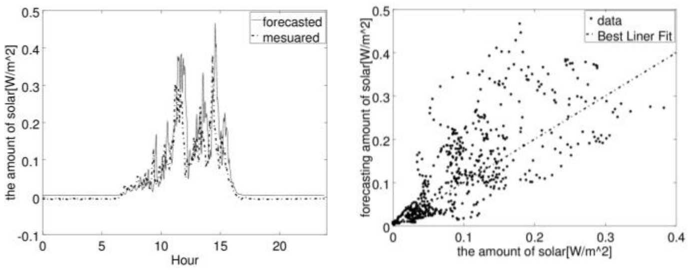
Forecasted values are higher than measured values as indicated by a majority of data points localized above the best linear fit line and is due to the time interval employed for forecasting and the amount of data surmised.



(A) (B)

Figure9: Forecast amount of solar radiation after 3 minutes on 2014/10/5

A best linear fit was generated from data gathered and forecasts were made but there was a time evident that became greater with increased solar radiation.



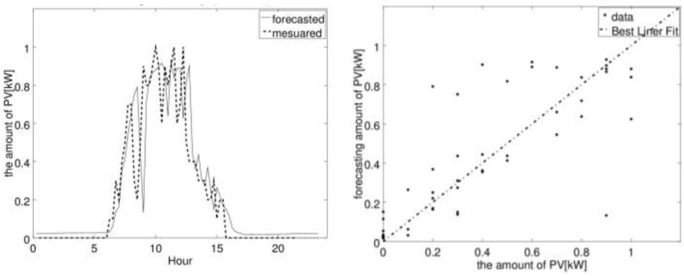
(A) (B)

Figure10: Forecast amount of solar radiation after 15 minutes on 2014/10/5.

Though the forecasted values in Figure 9(A) are higher than measured values they are closer than the forecasted and measured values in Figure 10(A).
The distribution of the majority data points above the line of best fit in Figure 9(B) reflect the higher forecasted values.

Table4: Statistical data.

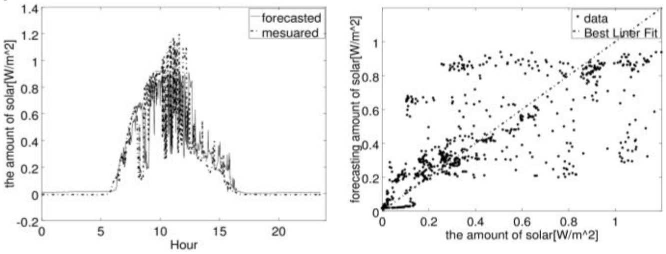
	2014/10/5 (solar after 3)	2014/10/5 (solar after 15)	2014/10/5 (solar after 30)	2014/10/15 (solar after 30)	2014/10/5(PV)	2014/10/15(PV)
standard deviation (original)	0.070	0.070	0.070	0.31	0.078	0.32
average(original)	0.038	0.038	0.039	0.20	0.041	0.21
standard deviation (prediction)	0.072	0.075	0.077	0.28	0.084	0.31
average(prediction)	0.043	0.051	0.055	0.21	0.059	0.23
MSE	0.017	0.0021	0.0038	0.030	0.0064	0.024
RMSE	0.00029	0.046	0.062	0.17	0.080	0.15



(A) (B)

Figure11: Forecast PV generation after 30 minutes on 2014/10/15.

The increased power generation on 2014/10/15 (Figure 11) relative to that of 2014/10/05 (Figure 7) resulted in a better forecast generated from a best linear fit line derived from data gathered.



(A) (B)

Figure12: forecast amount of solar radiation after 30 minutes in 2014/10/15.

There is a much greater difference in some successive measured values than some successive predicted values (Figure 12). The random nature of the scattered cloud cover could be a contributing factor to this phenomenon.

Table4 has statistical data about all results. All results on 2014/10/5 are better than those of 2014/10/15 as indicated by the corresponding RMSE of each day. As expected the error observed on 2014/10/5 is lower than that of 2014/10/15 as indicated by the comparison of derived standard deviations.

6. Conclusions and future actions

In this paper a system of forecasting expected PV generation and solar radiation was outlined. Improvements to this system could involve including other parameters as input data. This expansion of input data would hopefully improve accuracy and could for example possibly include the amount of cloud cover and rainfall. Random aspects of environmental factors impact measured results so nonlinearity in predicted results may be required and the amplitude of this nonlinearity may be refined by employing fuzzy NN and hop field NN. It would also be informative to compare this forecasting system with others to aid in future improvements.

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