Neural Networks: An Attempt to Predict Daily Solar Generated Power

ニューラルネットワーク：日々の太陽光発電出力量の予測

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Abstract

It is a known fact that Japan relies heavily on foreign sources to meet its energy needs. Japan's energy supply has been stabilized by increasing the use of nuclear power, natural gas, and new energy sources, and by introducing conservation measures. Japan is one of the world leaders in solar power generation. This study attempts to build a neural network to predict the solar electric power generated from the college's 10 kW solar power generation system.

Keywords: Solar power generation, Neural network, Neuron, Mean squared error, Multilayer perceptron

Introduction

According to the Agency for Natural Resources and Energy of the Ministry of Economy, Trade and Industry, Japan had generated 1130 MW of solar electric power at the end of 2004[1]. This makes Japan the leader in world solar power generation. Solar energy like other new energy sources such as wind power, biomass energy has been touted for their ability to produce little or no CO_2.

Solar cells are basically classified into two types: silicon solar cells and compound solar cells. Silicon solar cells are further classified into crystalline (single and poly-crystalline cells) and amorphous solar cells. Cell and module efficiencies vary according to each type. Active researches on solar cells have led to a constant increase in solar cell efficiencies[2].

Kiryu Junior College's solar power generating system by Sanyo Electric Co. Ltd is a 10kW HIT (Heterojunction with Intrinsic Thin Layer) solar cell consisting of 56 modules. The HIT solar cell is a single thin crystalline silicon wafer surrounded by ultra-thin amorphous silicon layers. Its lifespan is estimated to be more than 20 years[3]. The Solar module specifications are shown in Table 1. The module conversion efficiency is about 16.1%.

Photovoltaic evaluation systems like the "I-V curve tracer" enables on-site performance measurements of solar power generation systems. However, these systems are costly, and require skills to operate.

A neural network mimics the brains ability to learn from a given input or inputs. The human brain consists of billions of cells called neurons which send information signals to each other through a complex network of connections. Neural networks learn the same way a child learns. For example, a mother shows his child a red, round fruit and tells him it is an apple. The color, shape and even the taste are the input parameters while the "apple" is the output. Thus in order to teach the neural network, it must be fed with sufficient input data and a corresponding output. With the advancement of computer technology, research on neural networks has steadily increased. Neural networks have found applications in pattern recognition[4], classification and identification[5], prediction[6,7], and control[8]. Other applications of neural networks are those involving environmental modeling[9], and weather forecasting[10]. In a previous paper[11], the authors built a neural network to predict the solar generated power using temperature, humidity, and irradiance data. A satisfactory agreement between the actual power output and the predicted neural network output was reported. In this paper, the authors propose a simple prediction model utilizing neural networks that can forecast solar power output given the day and month. A significant decrease in the actual solar power output compared to the predicted output could be attributed to a decrease in the solar power generating system's efficiency. This network model could be used as a simple, preliminary method for evaluating a solar power generating system.

Table 1. Solar Module Specifications

Model	HIP 190B2 Sanyo Electric Co. Ltd.
Rated Power (Pmax)	190W
Maximum Power Voltage (Vpm)	54.8 V
Maximum Power Current (Ipm)	3.47 A

Data Preparation

For a neural network model to work it should be fed with a sufficient amount of data. Input data consists of daily solar generated power for 12 months. The total monthly solar generated power is shown in Fig. 1. The maximum amount of 1472.9 kWh was generated on March, while the least was that of July at 814.9 kWh. The variations in the monthly solar generated power were caused by daily weather fluctuations and seasonal variations.

The dates and months were tagged as the inputs. These are symbolic data i.e. December (the 12th month) should not be interpreted as having a greater weight than January (the 1st month).

Analyzing the data range (1-31: dates, 1-12:months, 2-70:solar generated power output) suggests that the values for the solar power generated output should be normalized. Preliminary tests showed a large mean squared error for non-normalized solar power generated output data.

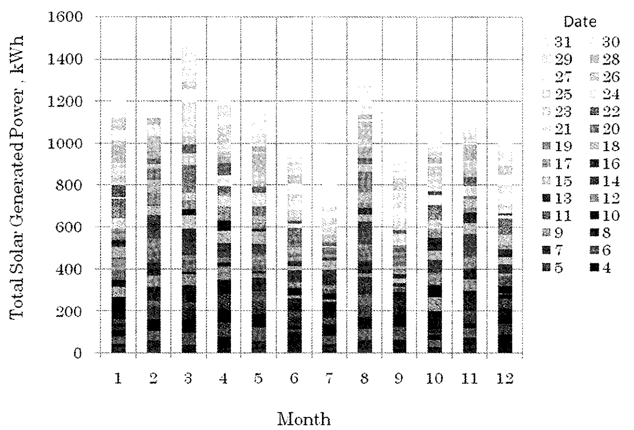

Fig. 1. The total monthly generated solar power.

Building the Neural Network

The network was built using a multilayer perceptron model which consisted of 43 input processing elements or neurons, 1 output processing element, 54 exemplars, and one hidden layer.

Multilayer perceptrons (MLP) are backpropagation-trained layered feedforward networks. MLP's are one of the most common neural network models. Figure 2 shows a schematic of a MLP model with one hidden layer. Input information is processed as they pass through the hidden layers. The strength of the interconnections between the neurons or weights affects the output. In a backpropagation model, the output corrections are fed back to the network during training, minimizing error as the training proceeds.

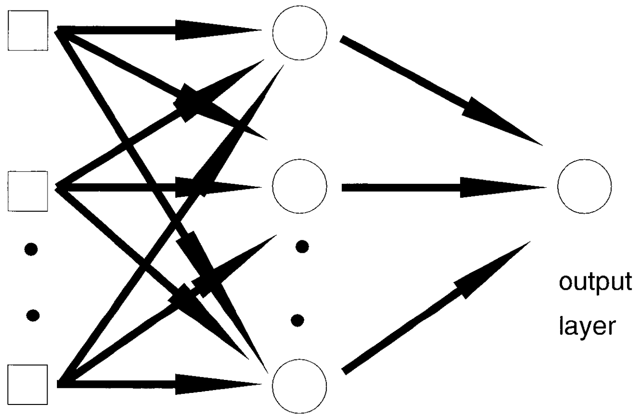

Fig. 2. A multiple layer perceptron.

Training the Network

In order for the network to learn it must be trained. Training involves presenting data or information to the network repeatedly until it gets the desired output. The hidden layer consisted of 4 processing elements with a hyperbolic tangent (tanh) transfer function which defines how the neuron's activation value is to be output. Training was accomplished with 60% of the available data. Fifteen percent was allotted for cross-validation, while 25% was for testing. A cross-validation criterion which prevents network overtraining was applied. This enables the training to terminate if there was no improvement in the cross validation error within the specified number of epochs, thus preventing the network to memorize. Network memorization of the data training set hinders its ability to generalize new data.

To speed up training and stabilize convergence, a momentum learning rule was applied. Momentum learning allows the network to find a reasonable result with less iteration by adjusting the weights to change in response to the gradient step.

Figure 3 shows the progress of the training process for 1000 epochs. The average mean square errors (MSE) are plotted against the epochs or the number of iterations over the training set. The mean square error is defined as the difference between the actual output data and the response predicted by the model. The training curves show large MSE average values during the initial phase of the iteration set, but decreases sharply after a few iterations. The cross validation curve is shown above the training curve. The average of the minimum training error over 50 runs was 0.00506, while the minimum MSE was 5.26E-05.

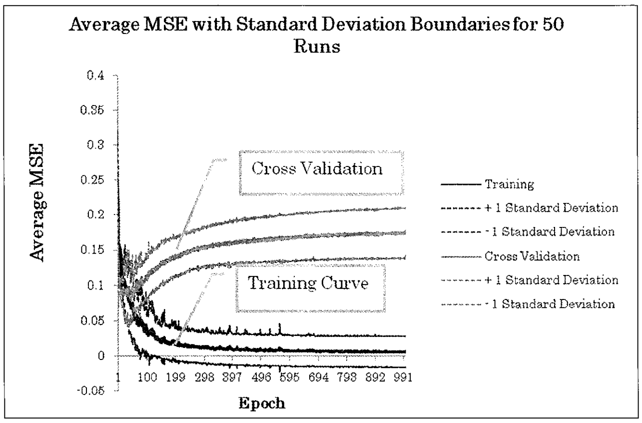

Fig. 3. The training and cross validation curves.

Testing the Network

The network model was tested with 25% of the data as mentioned earlier. Figure 4 shows the plot of the desired output vs. the actual network output using the trained network model described earlier, while Table 2 shows the trained network's performance during testing. The network's performance was evaluated using the mean square error, mean absolute error, and the minimum and maximum absolute errors. Although the network model did fairly well during training, its performance during testing needs much improvement.

Table 2. Performance of the trained network model.

Mean square error (MSE)	3.50303
Mean absolute error (MAE)	1.51997
Minimum absolute error	0.01593
Maximum absolute error	3.66100

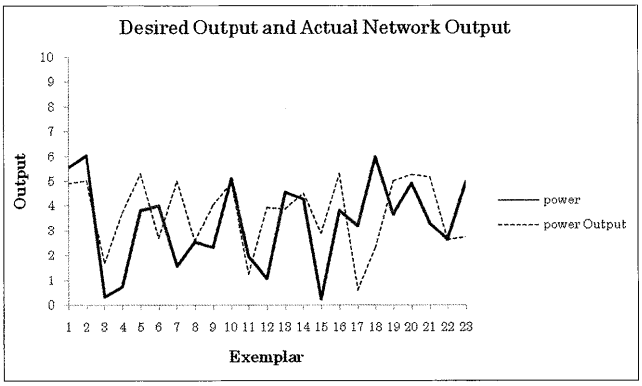

Fig. 4. Plot of the desired output vs. the actual network output

Calculation of the linear correlation coefficient gave a value of 0.33, which means that the fit of the model to the data is rather poor. From these results, it is clear that input data based on the date and month of a given year alone does not give satisfactory predictions of the solar generated power. It is suggested that parameters which can account for dynamic weather conditions be added to as inputs to the network.

Conclusions

Although the best network architecture was chosen after several training attempts, the testing performance was still rather poor. It is therefore concluded that good prediction of daily solar generated power using only the dates and months as inputs is difficult to attain even with neural networks. Since the input data plays a pivotal role in the neural network performance, it is suggested in future works that input data should include temperature, humidity, irradiation and other parameters that could take into account the seasonal and temporal atmospheric variabilities.

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ニューラルネットワーク：日々の太陽光発電出力量の予測

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要　約

本研究は，ニューラルネットワークを用いて日々の太陽光発電出力の予測をしようとする試みである．十二ヶ月の日々の太陽光発電出力量のデータを用いてニューラルネットワークのモデルを構築した．最適なモデルを得るため，十分な学習を行った．しかしながら，今回のニューラルネットワークモデルによる予測では満足のいく成績を得ることが出来なかった。今後，これらの改善と実験データやパラメーターを増やすことを検討する必要があると考えられた．

キーワード：太陽光発電，ニューラルネットワーク，ニューロン，平均二乗和誤差，階層型パーセプトロン