Predicting Wattages using Three Time-Series Techniques

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Abstract

In recent years, demand for substitutable energy is increasing. For this reason, people begin to find the best substitutable energy. Among the substitutable energies, solar energy is a typical of its kind. Therefore, research issues relevant to solar energy were actively investigated recently. Predicting output of solar energy is the most widely discussed topic. Therefore, in this study, we attempt to use three techniques to predict output wattages. These models are applied in two experiments based on a collection of data from 09:00 to 15:00 hours. This work compares the performance on predicting wattage values. Experimental results show unsteady changes easily affect the prediction of one-step-ahead forecasting. Moreover, the prediction curves of MLR and BPNN model are intended to depend on the previous day's values. In addition, the results also indicate that the radiation variable is an important index in the forecasting.

Keywords: Time series forecasting, neural networks, solar energy, ARIMA

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I. INTRODUCTION

The wattage value is an important indicator on a solar panel. In the solar energy industry, people want to understand the solar panel operation. For this reason, many people begin to study these issues. Over the past several decades, predicting the output wattage of panels is regarded as one of the significant issues in this industry. The need for predicting wattage becomes important mainly as result of the increasing number of solar energy applications.

Omnipresent time series data, such as stock market index, weighted index and gross domestic product (GDP) rate, are incessantly generated everywhere. Thus, several related applications, including economic forecasting, sales forecasting, and stock market analysis, are developed to tackle those time series data. In the solar power industry, time series data analysis also becomes an emerging issue such as solar energy prediction (Yona et al. 2009), radiation measurement (Nomiyama et al. 2011), etc.

However, it is hard to predict wattages on solar panels, because the outputs of wattage are influenced by many factors, such as temperature, environment and radiation. Therefore, the prediction model selection is significant. Moreover, most papers focus on estimation of reliability of predictions or model applicability domain in traditional way. Therefore, predicting the wattage is a challenge.

The goal of this study is to apply three prediction models, including two linear statistic techniques and one neural network, to predict the output of wattage from the panels. In addition, we conduct two comparison experiments in this study.

The study is organized as follows: the first section describes the motivation and goal of the study; related works are reviewed in section 2; in section 3 introduces three prediction techniques; building model and several experimental results are depicted in Section 4; section 5 is represented our conclusion and future works.

II. LITERATURE REVIEW

Time series prediction related researches, including time series analysis and prediction techniques, are briefly reviewed in this study.

2.1 Time series data prediction

The time series data are recorded in same events by different occurrence time. Each records component is a sequence of data points. The idea of time series is used to predict future variation by the historical data. In real case, the variation is easily affected by a lot of factors, such as trend effect, regularity change and data correlative. The phenomenon of irregular is arranged in four statuses which include the trend changes, cycle changes and the seasonal changes.

2.2 Multiple Linear Regression analysis

Multiple Linear Regression (MLR) analysis is widely used methods of mathematical statistics. In real case, the outputs of wattage variable exists interaction with other influence variables. Therefore, it is difficult to find the causal relationships among influence variables. For this reason, using the Multiple Linear Regression (MLP) model is very significant. In addition, the stepwise procedure is commonly used in MLP model. In our study, the stepwise procedure is used to examine independent variables. In addition, some literatures describe that the MLP model successfully applied in relevant solar issues. For example, (Su et al. 2011) successfully applied a stepwise multiple regression to develop irradiation equations. Their result shows that the model fits to calculate the solar irradiation. In this study, the stepwise regression procedure is used to obtain the fitness model.

2.3 Autoregressive Integrated Moving Average

With the growth of time-series-data, the Autoregressive Integrated Moving Average (ARIMA) model begins to become very important. The model is proposed by Box and Jenkins. And it is a general prediction approach for time series data. The idea of ARIMA, the prediction value is obtained through a linear function based on the random errors of past observations (Wang et al.). In ARIMA (*p, d, q*) where *p* is the number of autoregressive terms, *d* is the number of non-seasonal differences, *q* is the number of lagged forecast errors in the prediction equation. There are three parts in the ARIMA: Auto-regression (AR), Integrative (I), and Moving average (MA). AR (*p*) process is represented as:

$$x(t) = a_0 + a_1\, X(t-1) + a_2\, X(t-2) + \cdots + a_p\, X(t-p) + e(t) \qquad (1)$$

where t is the time period, a_0 is a constant term, $\{a_1, a_2, a_3 \dots a_p\}$ are parameters, and $e(t)$ is white noise, which is supposed to be independently and identically distributed with zero mean and a variance of σ^2. MA (*q*) is represented as:

$$x(t) = u - \theta_1 e(t-1) - \theta_2 e(t-2) - \cdots - \theta_q e(t-q) + e(t) \qquad (2)$$

where u is mean of the series, $\{\theta_1, \theta_2, \theta_3 \dots \theta_q\}$ are parameters, $\{e(t), e(t-1), \dots, e(t-q)\}$ are past random term. Generally, the ARMA (*p, q*) is suitable for predicting output when the change of time-series data is stationary. Unfortunately, in real case, the time-series data is easily affected by many factors. Therefore, we have to use the *difference* parameter to improve non-stationary data. The ARIMA (*p, d, q*) is suited to apply in non-stationary time-series data. The formula is defined as:

$$x(t) = a_0 + a_1 X(t-1) + a_2 X(t-2) + \cdots + a_p X(t-p) + e(t) +$$

$$u - \theta_1 e(t-1) - \theta_2 e(t-2) - \cdots - \theta_q e(t-q) + e(t) \quad (3)$$

It is important to determine the parameter *p, d* and *q*. Generally, the parameter 0, 1 and 2 are commonly discussed in ARIMA (*p, d, q*) model. Once the prediction model is established, it is easily to predict the future change by the past values and the current value. Generally, the ARIMA model fit to predict on short-term data. The ARIMA is easily affected by environment factors. For example, (Chowdhury 1987) predicted the Short-term photovoltaic outputs by using solar irradiance data. The result shows that the prediction performance was good in the sunshine by using ARIMA model. The bad prediction result was occurred in the cloud day. Therefore, the author considers that the prediction performance is easily affected by weather change. In this study, we select the historical data of wattage as prediction variable.

2.4 Artificial Neural Networks

In recent years, Artificial Neural Networks (ANN) has been widely used in time series prediction. The main idea of ANN is to simulate the biological neural networks of human brain to extract complex pattern from training data by self-learning [x]. The ANN has inference capability through calculating the large data of amount. An optimal Neural Networks need to train by using sufficiency data. Generally, the prediction results are depended on input data. In addition, the Back-propagation (BP) algorithm is commonly used in ANN model. The concept of BP is based on the gradient steepest descent method that is expected to obtain minimum error. In learning process, the ANN is iterative learning by input vector until all input is entered. Hence, the ANN is no need to adjust at any time. (Elminir et al. 2007) used ANN to predict the diffuse fraction between hourly and daily in Egypt area. The result shows that the ANN mode is more suitable to predict diffuse fraction in hourly and daily scales. In this study, the Back-Propagation Neural Network (BPNN) is used to build and to predict the wattage. The advantage of BPNN is no need to monitor and to adjust each parameter on network connection.

III. THREE FORECASTING MODELS

In this work, we select prediction models from time series analysis to predict daily values of wattage for one-step-ahead forecasting. The section 3.1 and 3.2 described our solar dataset. One artificial neural network technique and two statistical techniques are described in the section 3.3 Moreover, we proposes a construction in Figure 1.

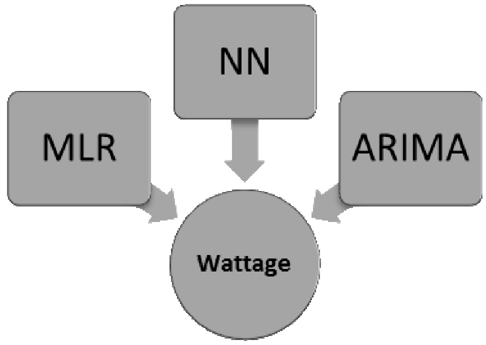

Figure 1 The research framework

3.1 Data preprocessing

In the real solar dataset, it is difficult to directly distinguish normal data from abnormal data because observation values are influenced by environmental change. Since abnormal data need to be removed prior to the training, the average is used to replace the missing values and delete the data points which have zeros.

3.2 Data collection and variable specification

There are five variables in solar datasets which include radiation, ambient, temperature, voltage, and wattage. All data are recorded from 9:00 a.m. to 3:00 p.m. The solar data were collected from December 27th, 2010 to March 19th, 2011. The SPSS software is used to develop formula in MLR and ARIMA model. Then, the Matlab tool is used to build network in neural network model.

3.3 Three prediction models implementation

The variables of solar datasets are selected to build three prediction models. These models are applied in two experiments based on the data of 09:00 to 15:00 hour. In each hour (09:00 – 15:00), the Regression model and Neural Network model used 560 records as training data to build prediction models to predict the wattage (January 21 – January 31). ARIMA model used January's data as training data. Each model is established in section 3.3.1 to 3.3.3

3.3.1 The MLR model building

We use stepwise regression procedure to examine the correlation between influence variables and the wattage variable. The preliminary wattage regression model is represented below.

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \varepsilon \qquad (4)$$

where y is the average wattage of the hour, X_1 is radiation, X_2 is ambient, X_3 is temperature and X_4 is voltage. y is influenced by the four possible independents. Moreover, in order to examine how the regression model fits the data, the R^2 is used as an index. The formula is defined as below:

$$R^2 = 1 - \frac{\sum(x_t - \widehat{x_t})^2}{\sum(x_t - \overline{x_t})^2} \tag{5}$$

where x_t is original value, $\widehat{x_t}$ is prediction value and $\overline{x_t}$ is mean value. The R^2 range is between 0 and 1. A large R^2 means this model have a goodness of fit. In model building phase, the 560 records are used to filter out significant variables. The criterion of stepwise is used to examine significance between independent variables and the dependent variable. Moreover, the *F–value* is an important index in stepwise procedure. The independent variables are selected if the *F– value* equal or more than 0.1. The independent variable selections are demonstrated in Table 1. For example, the wattage prediction equation on 09:00 is defined as:

$$y = \beta_1 x_1 + \beta_0 \tag{6}$$

The equation (3) describes that the output of wattages is easily affected by radiation variable.

Table 1 The independent selection in stepwise procedure

Date/Hour	09:00	10:00	11:00	12:00	13:00	14:00	15:00
21	x_1	x_1	x_1	x_1	x_1	x_1, x_4	x_1
22	x_1	x_1	x_1	x_1	x_1	x_1, x_4	x_1
23	x_1	x_1	x_1	x_1	x_1	x_1, x_2	x_1
24	x_1	x_1	x_1	x_1	x_1	x_1, x_2	x_1
25	x_1	x_1	x_1	x_1	x_1	x_1, x_2	x_1
26	x_1	x_1	x_1	x_1	x_1	x_1	x_1, x_3
27	x_1	x_1	x_1	x_1	x_1	x_1	x_1
28	x_1	x_1	x_1	x_1	x_1	x_1	x_1
29	x_1	x_1	x_1	x_1	x_1	x_1	x_1
30	x_1	x_1	x_1	x_1	x_1	x_1	x_1
31	x_1	x_1	x_1	x_1	x_1	x_1	x_1

3.3.2 The ARIMA model building

An optimal ARIMA model continuously needs to examine the parameters *p, d,* and *q*. Generally, the auto–correlation function (ACF) plot and partial auto–correlation function (PACF) plot are commonly used to determine the parameter *p* and *q*. we can clearly check the time series data whether it is stationary by ACF plot. For example, if the sequence curve is nonlinear decreasing on ACF plot, that is to say, the time series data appears undirected series. According to the ACF results, we have to transform undirected series to stationary series by using the *difference* term. After the data change to a stationary series, we can determine the parameter AR (p) and MA (q) by using ACF and PACF plot. In addition, the other parameters judgment table in Table2. In this experiment, the SPSS tool is used to determine the parameters and to build the prediction model. All ARIMA prediction models are show in Table 3. Generally, it is necessary to readjust the parameter in each ARIMA models.

Table 2 The parameter judgment table (A table shall not cross pages.)

Parameter	ACF	PACF
AR(*q*)	Spikes decay towards zero	Spikes cutoff to zero
MA(*p*)	Spikes cutoff to zero	Spikes decay to zero
ARMA(*p, q*)	Spikes decay to zero	Spikes decay to zero

In model selection, the Ljung–Box statistics are selected to identify the model fitness. The January 1 – January 20 are selected as training data to predict wattage. The process of prediction is repeated to predict the one-step-ahead forecasting by the previous day.

Table 3 The ARIMA model construction in seven hour

Hour	ARIMA(*p, d, q*)
09:00	ARIMA(*1, 0, 1*)
10:00	ARIMA(2*, 0, 1*)
11:00	ARIMA(2, 0, 2)
12:00	ARIMA(2, 0, 2)
13:00	ARIMA(2*, 0, 1*)
14:00	ARIMA(2*, 1,* 2)
15:00	ARIMA(2*, 0, 1*)

3.3.3 The BPNN model building

We use the Back–Propagation Neural Network (BPNN) to create the prediction wattage architecture. The 4 *x* 5 *x* 1 network architecture is used in this experiment. The 560 records are used as training data.

In training stage, The BPN method determines the weights for connections among the nodes based on data training. The least-mean-square error is measured the actual or expectancy and the estimated values from the output of the neural network (Wang et al.) . The '*trainlm*' is selected as training function. The '*learngdm*' is selected as adaption learning function. The *sigmod* function is used as transfer function of hidden layer.

In addition, there are main three processes. First, we have to set the initial values for connection weights. Second, the output of bias will back to hidden layer, then updating the weights. Finally, the final output by minimize the error between the actual and prediction. Generally, the sufficiency train data that can simulate any kind of data pattern (Wang et al.).

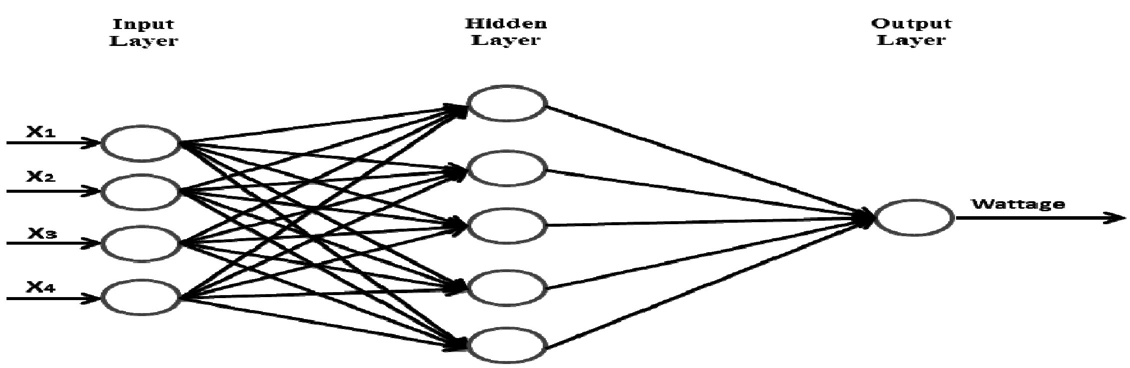

Figure 2 The feed-forward neural network for predicting daily wattage

In this study, our prediction wattage model will be explained in Figure 2. In Figure 2, the network component which include four input nodes, five nodes in single hidden and one output node. The radiation, ambient, temperature and voltage are represented the input nodes respectively. The daily average wattage is represented output node. There are two training procedure in hidden layer phase and output phase. In hidden layer phase, the weight sum of the inputs and transfer function will be calculated below.

$$net_i = \sum_{j=0}^{n} w_{ij} x_j, \quad i = 1, \dots, n \tag{7}$$

$$z_i = f_H(net_i) \qquad i = 1, \dots, n \tag{8}$$

where net_i is represented activation value of the i-th node. The z_i is represented the hidden layer output, then the f_H is represented the activation function of a node (Wang et al.). Genially, the activation function is used sigmoid function. The formula of sigmoid represented as follow:

$$f_H(x) = \frac{1}{1 + \exp(-x)} \tag{9}$$

In the Output phase, the outputs from each five the hidden-layer nodes, then the bias will be back to adjust connection weights. The calculation formula as follow:

$$y_t = f_t\left(\sum_{t=0}^{m} w_{it} z_i\right) \quad t = 1, \dots, n \tag{10}$$

where $f_t(1, 2, \dots, l)$ are represented the activation function, we use the line function in activation function. In this study, the four input nodes, five hidden nodes and one output node are select in the connected feed-forward network.

IV. EXPERIMENTAL RESULTS

We build and compare three models in predicting the wattages. These models are included Regression, ARIMA and Neural Network. There are two experiments. The first experiment uses the specific period (January 20 – January 30) as testing sets. The second experiment uses the original period (January 21 – January 31) as testing sets. The model evaluation criteria are provided in section 4.1. The results of prediction are shown in section 4.2

4.1 The model evaluation criteria

In order to evaluate the prediction performance, we use some evaluation criteria for the three prediction models. These equations are defined as follows. Including the mean absolute percentage error (MAPE), the mean absolute error (MAE) and the root mean–square error (RMSE). These criteria measure the deviation between actual and prediction values.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - \hat{Y}_i\right| \quad (11)$$

$$\text{MAPE} = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{Y_i - \hat{Y}_i}{Y_i}\right| \quad (12)$$

$$\text{RMSE} = \frac{\left(\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2\right)^{\frac{1}{2}}}{(n-1)^{\frac{1}{2}}} \quad (13)$$

where Y_i and $\hat{Y}_i$ are represented the actual values and the prediction values. Generally, good prediction performance is indicated by a small error rate. Moreover, the performance level of MAPE is described in Table 4. The levels are proposed by Lewis in 1982.

Table 4 the MAPE model judgment

MAPE	Prediction
<10%	High Accuracy
10%–20%	Good
20%–50%	Reasonable
>50%	Inaccuracy

4.2 Experimental results on predicting wattages

Prediction performances of the three models are demonstrated respectively in seven–hour prediction interval. First, we select the specific period (January 20 – 30) as testing data to predict the wattage (January 21–31). Second, the present days (January 21– 31) are selected as testing data for predicting wattage (January 21–31). The results of experiment are shown in Figure 3 – Figure 9.

In Figures 3a, 4a, 6a, 8a and 9a, one or more good predictions are obtained by using MLR and BPNN model. For example, an accurate prediction is occurred on January 29 in Figure 1a. However, The Figures 5a and 7a don't have an accurate prediction output on January 21 – January 31.

In Figure 3a – Figure 9a, the prediction curve of MLR a l are intended to depend on the previous day. The testing data is selected specific period (January 20 – January 30). Most of the outputs by the ARIMA model are smooth except for Figures 2, 3 and 4. In addition, In Figures 3b –Figures 9b, predicated values of MLR and BPNN have high similarity with the actual values. The ARIMA model uses the same testing data as the first experiment and therefore, the outputs are the same.

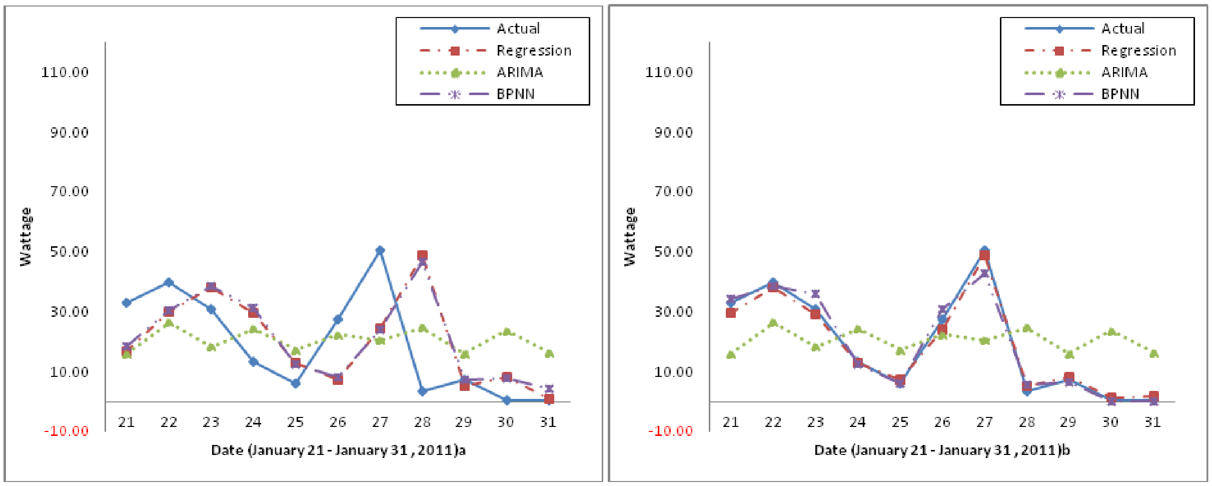

Figure 3 The wattage prediction performance at 09:00

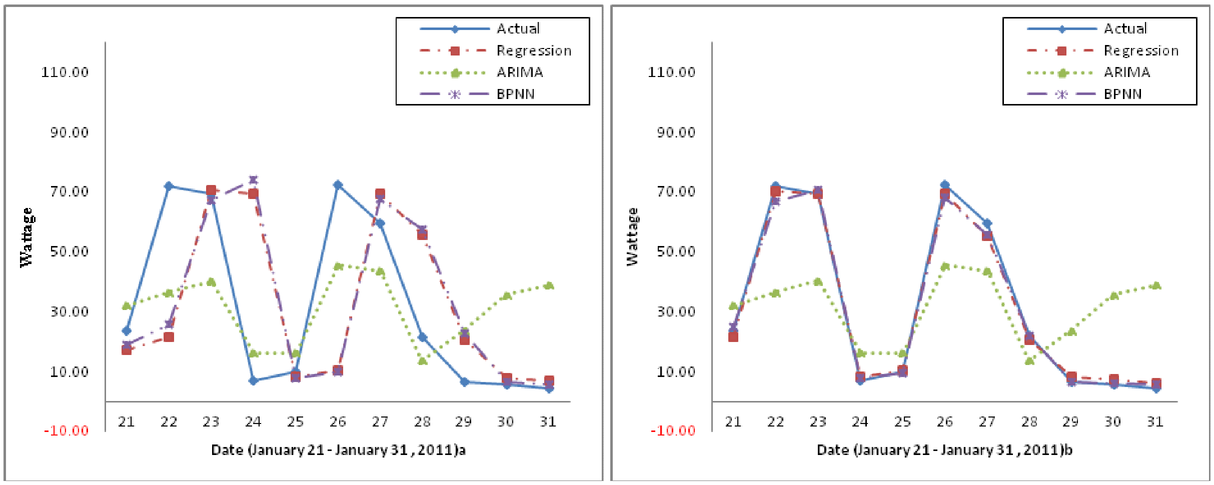

Figure 4 The wattage prediction performance at 10:00

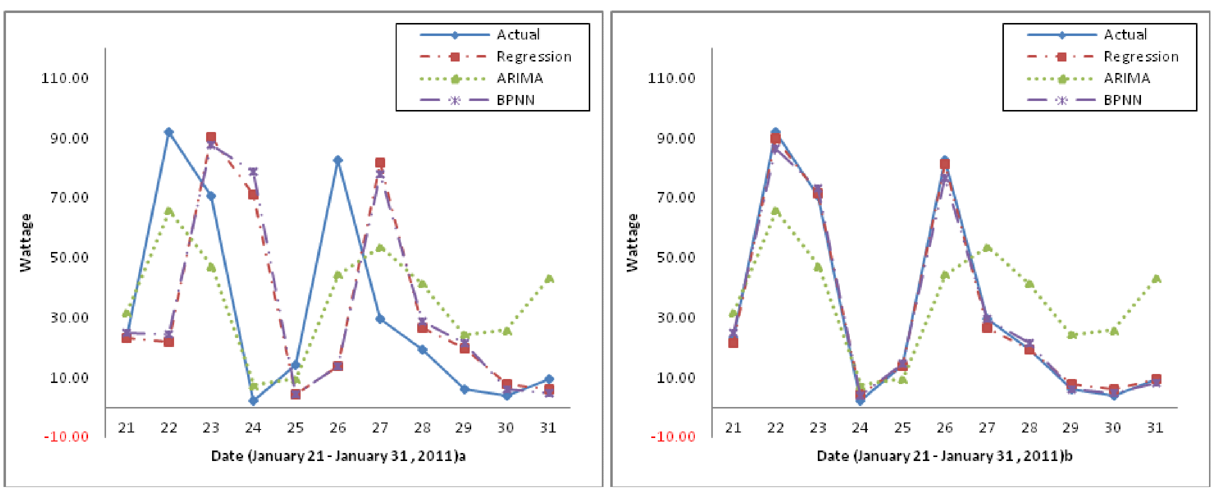

Figure 5 The wattage prediction performance at 09:00

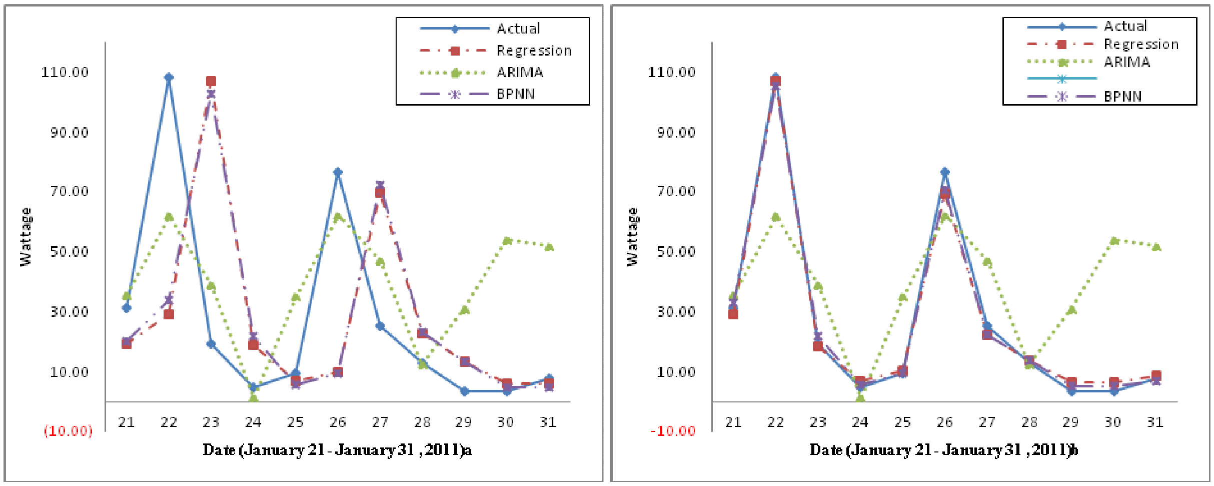

Figure 6 The wattage prediction performance at 12:00

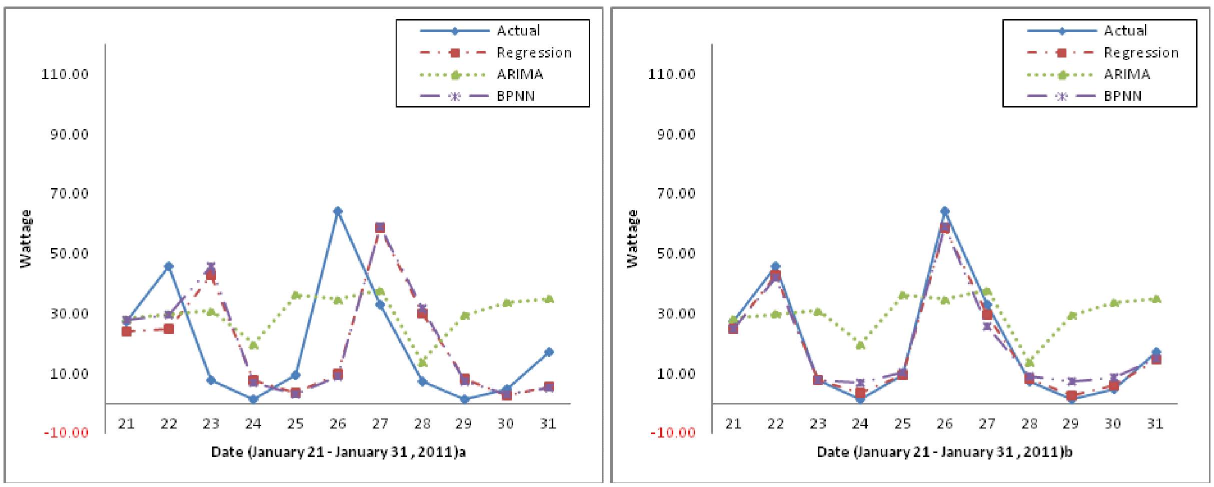

Figure 7 The wattage prediction performance at 13:00

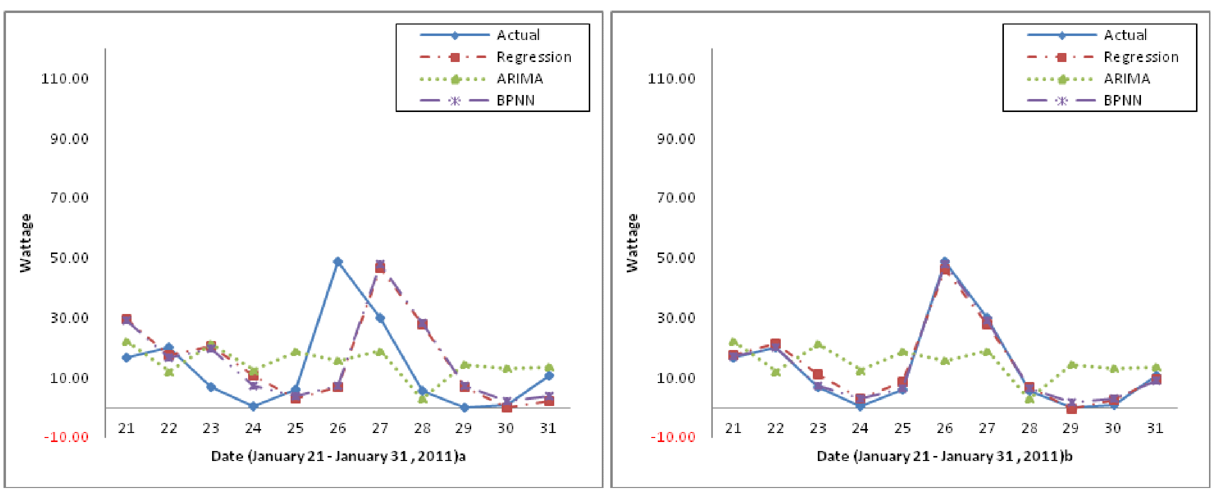

Figure 8 The wattage prediction performance at 14:00

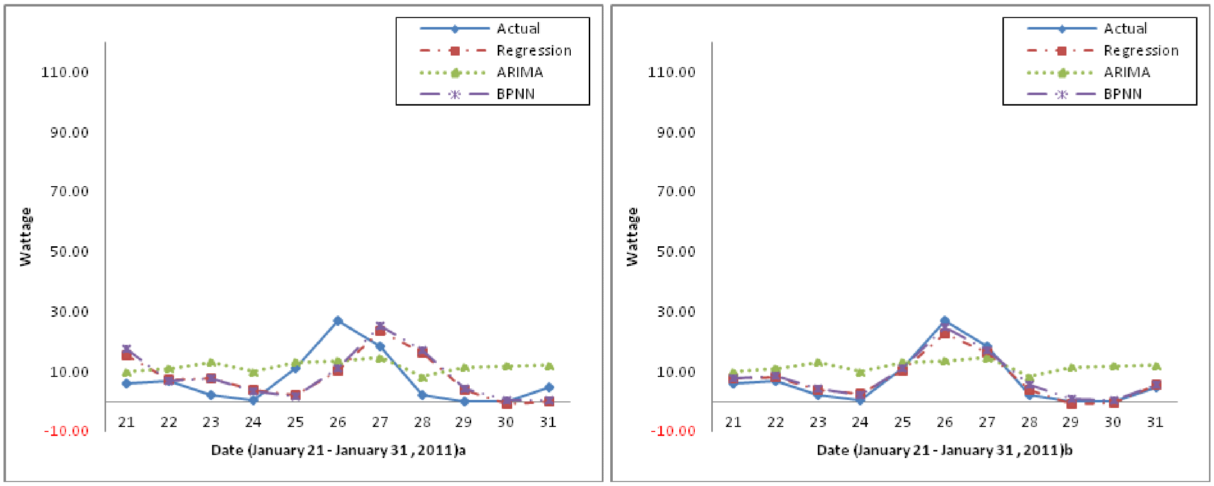

Figure 9 The wattage prediction performance at 15:00

In Table 5, we use the model criterion to evaluate the performance of wattage forecasting in seven–hour by using MLP models. The symbol '+' and '–' represent move testing data (January 20 – January 30) and fixation testing data (January 21 – January 31). Table 5 shows that the R^2 range between 99% – 97% which means the four independent variable explanatory is high with respect to the wattage variable. The results of wattage demonstrated that the moving test data obtained worse outcome than fixation test data.

Table 5 The statistical test between the measured and the predicted for seven hours by using MLP

Hour	MAE	MAPE (%)	RMSE	R^2(%)
09:00+	14.42	279	19.81	99.6
09:00–	1.53	32	1.88	99.6
10:00+	22.56	145	34.45	99.4
10:00–	1.80	13	2.23	99.4
11:00+	28.88	349	42.27	99.6
11:00–	1.47	19	1.86	99.6
12:00+	30.08	145	45.79	99.6
12:00–	2.23	23	2.99	99.6
13:00+	17.77	201	24.73	99.6
13:00–	2.15	34	2.78	99.6
14:00+	12.65	866	17.66	99.2
14:00–	1.82	90	2.23	99.2
15:00+	6.69	582	8.68	97.3
15:00–	1.71	181	2.05	97.3

According to Table 6, the prediction value variation is very huge in MAE, RMSE and MAPE by the ARIMA model. In this study, the univariate ARIMA model is not adequate in prediction wattage since the wattage is easily affected by other factors in this case. Therefore, it is not easy to predict wattage by using historical data of wattage alone, despite the ARIMA is commonly used in handling time–series data.

Table 6 The statistical test between the measured and the predicted for seven hours by using ARIMA.

Hour	MAE	MAPE (%)	RMSE
09:00	16.30	818	21.92
10:00	21.79	722	27.49
11:00	24.16	971	31.98
12:00	28.25	487	40.22
13:00	22.95	1460	30.40
14:00	18.52	1906	26.19
15:00	10.31	1932	14.33

According to Table 7, the results of MAE, MAPE and RMSE by the BPNN are similar to those by the MLP model. In MAE and RMSE, the prediction at *15:00+* is better than other prediction time. In MAPE statistical test, the prediction at *12:00+* is better than other prediction.

Table 7 The statistical test between the measured and the predicted for seven hours by using BPNN.

Hour	MAE	MAPE (%)	RMSE
09:00+	14.20	308	19.31
09:00–	2.17	29	3.23
10:00+	22.52	149	35.00
10:00–	1.81	7	2.67
11:00+	29.25	379	42.71
11:00–	2.05	12	2.93
12:00+	29.85	148	44.62
12:00–	2.03	16	2.67
13:00+	17.55	195	25.18
13:00–	3.54	96	4.37
14:00+	12.31	876	17.49
14:00–	1.12	231	1.43
15:00+	6.93	582	9.08
15:00–	1.58	172	1.89

V.CONCLUSION

In this work, the MLP, ARIMA and BPNN techniques are applied to predict wattage. The independent variables included radiation, ambient, temperature and voltage. The output value is the predicted wattage (January 21 – 31) for seven hours. The 560 records are selected as training data to use in MLP and BPNN. In ARIMA training phase, the training data is selected by the historical data of wattage. In addition, in this study, we conducted two experiments. The first experiment used January 20 – 30 as the testing set. Then, the second experiment used January 21 – 31 as the testing set. The MAE, MAPE and RMSE are used as evaluation criteria. The results and summaries are represented as follows.

(1) By using the January 20 – 30 testing set which means to predict the wattage using the independent variables of the previous day, the results show that the prediction of one-step-ahead forecasting wattage is very difficult since the wattage is unsteady in our dataset. Although the BPNN has aligned the error rate, it is still affected by other factors.

(2) By using the January 21 – 31 testing set which means to predict the wattage using

the independent variables of the same day. The results show that the error between the actual value and the predicted value is small.

(3) In the statistics test by MAE, MAPE and RMSE, the results show that the deviation is very huge by using the January 20 – 30 testing set for seven hours. Although the prediction is very good by using the January 21 – 31 testing set for seven hours, it is not practical to predict the wattage by using the same–day independent variables.

We use the existing prediction models to predict the wattage. We believe that the prediction is useful by using the previous–day independent variables, although it is very difficult to predict the wattage. In real case, the wattage is not only affected by four influence variables but also the other variables including wind speed, rain, geography and so on. For future work, it is worth to investigate how to select the most important variables for forecast.

ACKNOWLEDGEMENTS

The work is supported by the National Science Council, Taiwan, under grant NSC 100-2410-H-224-003-MY2.

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應用三種時間序列的技術在太陽能板之預測

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摘要

近年來，氣候的變遷、能源的消耗，替代性的能源漸漸的開始被重視。因此，許多人紛紛的開始尋找出所謂的"第二能源"。在替代能源中，太陽能相關的研究議題是最典型的一種。而預測太陽能板所產生的熱能是最常被討論與研究。因此我們嘗試應用三種最常見的預測模型(迴歸、ARIMA、倒傳遞神經網路)來預測太陽能板上所產生的熱能。在實驗階段，我們將預測的時間期間為二種時段。結果顯示，預測熱能效能容易受到前一天資料的影響，此外迴歸與倒傳遞神經網路二者的預測曲線相似前一天的值。此外我們發現日照變數是預測太陽能最重要的指標。

關鍵字: 時間序列、神經網路、太陽能源、ARIMA