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# SEQUENTIAL PROCESS OF FEATURE EXTRACTION METHODS FOR ARTIFICIAL NEURAL NETWORK IN SHORT TERM LOAD FORECASTING

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## ABSTRACT

The first stage of feature extraction involves a transformation of raw data that is from the chronological hourly peak loads to the multiple time lags of hourly peak loads. This is followed by the next feature extraction wherein the principal component analysis (PCA) is used to further improve the input data which will significantly enhance the performance of ANN in forecasting the hourly peak loads with less error. The output of ANN is then converted to a non-stationary form which represents as the forecasted hourly peak load for the next 24 hour. The Malaysian hourly peak loads in the year 2002 is used as case study to verify the effectiveness of ANN in STLF.

**Keywords:** artificial neural network, multiple time lags, principal component analysis, short-term load forecasting.

## INTRODUCTION

In a deregulated electricity industry, there has been a major concern for the power system utilities to provide reliable, cost effective and uninterrupted energy supply to the customer as it is essentially important for economic development of a country (Methaprayoon, 2003). Therefore, the power system utilities is given an essential task to perform load power forecasting in which it will be used as a reference to conduct a right decision making with regards to the above-mentioned issues for the following hours or days. This shows that accurate estimation of load forecasting plays an important role for effective operation of a power system.

The preceding years have shown the diversity of methods used for STLF. This is because of its significant effect on economic and reliable operation of a power system. In the past decade, fuzzy logic and artificial neural network (ANN) are the two AI techniques which have been utilized extensively in STLF due to several advantages over the statistical technique. Recently, the STLF is determined by using the advanced development of AI technique (Kim *et al*., 2000), combination of ANN and fuzzy inference method (Kim *et al*., 2000), (Çevik and Çunkaş, 2015), (Seetha and Saravanan, 2007), (Kazemi *et al*., 2014), (Ying and Pan 2007), (Chaturvedi *et al*., 2015), principal component analysis with ANN (Saleh *et al*., 2008), (Zhao and Liu, 2009), (Platon, 2015), (Wu and Shahidehpour, 2014), evolutionary computation based ANN (Wang *et al*., 2015), (Kouhi *et al*., 2014), (Kavousi-Fard *et al*., 2014), (Liang *et al*., 2014), (Liu *et al*., 2014) and wavelet based ANN (Hooshmand *et al*., 2013), (Ghayekhloo *et al*., 2015), (Dong *et al*., 2014), (Fard and Akbari-Zadeh, 2014), (Zhai, 2015). However, it is important to select an appropriate hybrid model of ANN which gives less error in the STLF results. This includes inappropriate selection of back-propagation algorithm for ANN may cause to inaccurate estimation of STLF results.

In this paper, the ANN is used to perform STLF for the next 24 hours. The performance of ANN is improved due to the significant input data provided by the sequential process of feature extractions. The first stage of feature extraction involves the transformation of raw data that is from the chronological hourly peak loads to the multiple time lags of hourly peak loads. The significant input data for ANN is finally obtained by using the principal component analysis (PCA) and this is considered as the second stage of feature extraction process. The final stage of improvement for the results of STLF is based on the stationary hourly peak loads of ANN output. The ANN can easily forecasts a stationary form of time series and this has been proven in (Mahdi *et al*., 2009), (Zhang, 2003), (Zhang *et al*., 1998), (Lachtermacher and Fuller, 1995), (Khotanzad, 1995), (El-Sharkawi, 1993). The performance of the proposed ANN in STLF is verified by using a case study of Malaysian hourly peak loads in the year 2002.

## METHODOLOGY

This section provides a detail discussion on the concept of feature extractions with artificial neural network (ANN) that used to perform short-term load forecasting (STLF). The Levenberg-Marquardt (LM) technique is used as a back-propagation algorithm for the ANN. There are two cases considered for STLF determination which are the ANN that takes into account

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the multiple time lags and stationary output; and multiple time lags with principal component analysis (PCA) and stationary output. The methodology of stationary time series, feature extraction based multiple time lags, feature extraction based PCA, ANN with LM back-propagation algorithm, and ANN for SLTF is explained elaborately in the following subsections.

**Artificial neural network output with stationary time series**

The time series of hourly peak loads is said to be stationary if it is fluctuate with a constant variation around a constant mean. It is reasonable to believe that the hourly peak loads is non-stationary if the time series does not fluctuate with constant variation around its constant mean. In conjunction to the non-stationary form of time series, the first differences of the hourly peak loads given in equation (1) is performed in order to obtain a stationary form of time series, $z_t$.

$$z_t = X_t - X_{t-1} \tag{1}$$

$Xt$ : time series of hourly peak load,
$t$ : time interval which begins with 2, 3,…, $N$,
$N$ : total time intervals.

In the proposed method, the stationary time series is forecasted by the ANN. Then, the stationary time series is applied into equation (2) in order to transform it back to a non-stationary time series which represents as the actual forecasted hourly peak loads, $Y_t$.

$$Y_t = z_t + X_{t-1} \tag{2}$$

Feature Extraction Based Multiple Time Lags of Time Series

The first stage of feature extraction process uses equation (3) to obtain an improved input data of ANN that takes into account the multiple time lags of chronological hourly peak load, $Z_{k,t}$.

$$Z_{k,t} = X_t - X_{t-k} \tag{3}$$

$t$ : time interval,
$k$ : lagging time interval which is 1, 2, 3,…., $K$,
$K$: total number of lagging time interval.

**Feature extraction based principal component analysis**

The principal component analysis (PCA) is a standard data reduction technique which extracts data, removes redundant information, highlights hidden features and visualizes the main relationship that exist between observations (Saleh *et al*., 2008). In this research, the feature extraction type of PCA is used to reduce the input dimension which consists of significant features. This will improves the performance of ANN that yields to a fast and accurate determination of STLF (Saleh *et al*., 2008).

**Short-term load forecasting using artificial neural network**

In this case study, the ANN model is consisting of one input layer, two hidden layers and one output layer. The output layer of ANN is consisting of one neuron which provides the result of stationary hourly peak load at the next 24 hour. The linear activation function is used as a neuron in the output layer of ANN. In particular, the Levenberg-Marquardt (LM) optimization technique is used as the back propagation algorithm of ANN. The logistic tangent function is used as the neurons for each hidden layer and it is used to process the input data that is within the range of 0 to 1 per-unit (p.u.). The per-unit value is referred to as the ratio of actual hourly peak load and the maximum hourly peak load. The cross-validation process is performed in order to avoid over-training of ANN whilst ensuring accuracy of the results. It begins with separating the raw information into three sets of ANN input data that is 80%, 11% and 9% of the input data are used for training, validation and testing of ANN, respectively. The training, validation and testing procedures of ANN are performed at three different multiple time lags of input data that is $K$=24 hour, $K$=48 hour and $K$=72 hour. For every case of $K$, the training, validation and testing ANN procedures are performed based on the stationary output form of hourly peak loads. Once the multiple time lags is performed, the PCA is used to reduce the size of input data wherein it consists of significant features that will further improve the performance of ANN in STLF. The dimension of input data is reduced at 20%, 30%, 40%, 50%, 60% and 70%. The best percentage is chosen by referring to the performance of ANN which provides the result with minimum error. The stationary form of output is then transformed to a non-stationary time series which represents as the result of STLF.

In the training procedure of ANN, the network minimizes the error between the output and desired output by adjusting the weight and biases. The error minimization process is repeated until it converges to a predefined small value of error. Then, the training procedure of ANN is terminated once the minimum error becomes constant. The robustness of the ANN in providing accurate result of STLF is then verified by performing the validation procedure with different set of input data.

The number of neurons in each hidden layer is selected through the ANN training and validation procedures which give the output result with minimum mean absolute percentage error (MAPE) and/or root mean square (rms) error. The architecture of ANN is then used in the testing procedure which provides accurate result of STLF.

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## RESULTS AND DISCUSSIONS

The discussions on STLF results determined by using the ANN model with sequential process of feature extraction methods are presented in this chapter. The Malaysian hourly peak loads in the year 2002 is used as a case study in the assessment of STLF and it is shown in Figure-1.

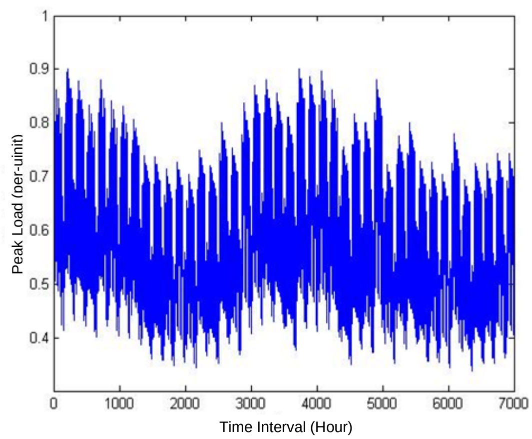


**Figure-1.** The non-stationary form of Malaysian hourly peak loads in the year 2002.

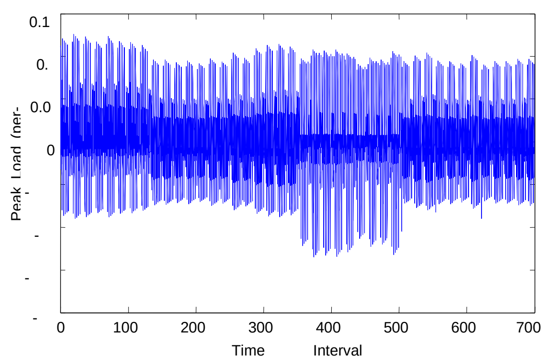


**Figure-2.** The stationary form of hourly peak loads.

It is obvious that the Malaysian hourly peak loads can be categorized as a non-stationary time series whereby it does not fluctuate with constant mean. Therefore, the first difference of time series is performed by using equation (1) in order to obtain a stationary form of hourly peak loads and it is shown in Figure-2. By referring to Figure-2, it is believed that the time series is stationary since it is fluctuating with constant variation around a constant mean.

The non-stationary form of hourly peak loads are divided into three sets of multiple time lags input data that used in the training, validation and testing procedures of ANN. The performance of several proposed methods applied into the ANN model is compared by referring to mean average percentage error (MAPE) of STLF.

### Architecture of artificial neural network

The stationary output of ANN has been obtained for every type of input data which is the multiple time lags of $K$=24 hour, $K$=48 hour and $K$=72 hour. The architecture of ANN used in every case is tabulated in Table-1. It is worth mentioning that the $K$ and types of ANN output either non-stationary or stationary have significant effect on the performance of ANN in forecasting. The results shown in Table-1 prove that $K$=72 hour and stationary output of ANN improves the training and validation procedures of ANN in providing the STLF with minimum rms error.

Prior to its significant effect on the results of STLF, performance enhancement of ANN is performed by considering first stage of feature extraction with $K$=72 hour, second stage of feature extraction using principal component analysis (PCA) and stationary based ANN output. Hence, there are six cases of STLF using ANN in relation to the PCA that used to reduce the input dimension at 20%, 30%, 40%, 50% and 60%. The architecture of ANN and its performance in STLF is shown in Table-2.

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**Table-1.** Performance and architecture of ANN considering *K*=24 Hour, *K*=48 hour and *K*= 72 hour without PCA.

| **ANN output** | **Stationary** | | |
|---|---|---|---|
| Multiple time lags (Hour) | *K* = 24 | *K* = 48 | *K* =72 |
| Training sets | 7000 | | |
| Testing sets | 720 | | |
| Validation sets | 1014 | | |
| Number of input neurons | 23 | 47 | 71 |
| Number of neurons in 1st hidden layer | 13 | 16 | 10 |
| Number of neurons in 2nd hidden layer | 9 | 11 | 5 |
| Number of output | 1 | | |
| Learning rate | 0.95 | 0.00001 | 0.00001 |
| Momentum | 0.0095 | 0.95 | 0.0095 |
| Training function | Levenberg-Marquardt | | |
| Training rms error of STLF | 9.80e-05 | 5.41e-05 | 1.88e-05 |
| Validation rms error of STLF | 0.0001583 | 9.94e-05 | 4.28e-05 |

Performance Comparison of Artificial Neural Network in Short-Term Load Forecasting

The robustness of every ANN architecture is measured through the ANN testing procedure that used for STLF. The performance of ANN testing procedure is investigated by referring to the mean absolute percentage error (MAPE) of hourly peak loads in each day and this is

**Table-2.** Performance and architecture of ANN considering *K*=72 hour with PCA and stationary output.

| Multiple time lags (Hour) | *K* = 72 | | | | |
|---|---|---|---|---|---|
| Input data reduction by PCA | 60% | 50% | 40% | 30% | 20% |
| Training sets | 7000 | | | | |
| Testing sets | 720 | | | | |
| Validation sets | 1014 | | | | |
| Number of input neurons | 71 | | | | |
| Number of neurons in 1st hidden layer | 14 | 13 | 14 | 15 | 13 |
| Number of neurons in 2nd hidden layer | 8 | 6 | 6 | 11 | 11 |
| Number of output | 1 | | | | |
| Learning rate | 4.00e-14 | 3.00e-20 | 1.00e-09 | 1.00e-20 | 7.00e-07 |
| Momentum | 4.00e-20 | 6.00e-01 | 8.00e-03 | 4.00e-18 | 2.00e-09 |
| Training function | Levenberg-Marquardt | | | | |
| Type of ANN output | Stationary | | | | |
| Training rms error of STLF | 2.32e-05 | 1.85e-05 | 1.90e-05 | 1.75e-05 | 1.71e-05 |
| Validation rms error of STLF | 5.11e-05 | 4.88e-05 | 4.59e-05 | 4.45e-05 | 5.15e-05 |

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improves the training and validation procedures of ANN in providing the STLF with minimum rms error.

Prior to its significant effect on the results of STLF, performance enhancement of ANN is performed by considering first stage of feature extraction with *K*=72 hour, second stage of feature extraction using principal component analysis (PCA) and stationary based ANN output. Hence, there are six cases of STLF using ANN in relation to the PCA that used to reduce the input dimension at 20%, 30%, 40%, 50% and 60%. The architecture of ANN and its performance in STLF is shown in Table-2.

**Table-3.** Performance and Architecture of ANN considering *K*=24 Hour, *K*=48 Hour and *K*= 72 Hour without PCA.

| ANN output | Stationary | | |
|---|---|---|---|
| Multiple time lags (Hour) | *K* = 24 | *K* = 48 | *K* =72 |
| Training sets | 7000 | | |
| Testing sets | 720 | | |
| Validation sets | 1014 | | |
| Number of input neurons | 23 | 47 | 71 |
| Number of neurons in 1st hidden layer | 13 | 16 | 10 |
| Number of neurons in 2nd hidden layer | 9 | 11 | 5 |
| Number of output | 1 | | |
| Learning rate | 0.95 | 0.00001 | 0.00001 |
| Momentum | 0.0095 | 0.95 | 0.0095 |
| Training function | Levenberg-Marquardt | | |
| Training rms error of STLF | 9.80e-05 | 5.41e-05 | 1.88e-05 |
| Validation rms error of STLF | 0.0001583 | 9.94e-05 | 4.28e-05 |

**Performance comparison of artificial neural network in short-term load forecasting**

The robustness of every ANN architecture is measured through the ANN testing procedure that used for STLF. The performance of ANN testing procedure is investigated by referring to the mean absolute percentage error (MAPE) of hourly peak loads in each day and this is shown in Table-3. The MAPE of forecasted hourly peak loads in each day is determined based on stationary output of ANN for every case of multiple time lags that is *K*=24 hour, *K*=48 hour and *K*=72 hour.

In this case, the best result of STLF with lowest MAPE is obtained based on the ANN testing procedure with multiple time lags of input data *K*=72 and stationary based ANN output. In the case of STLF based stationary output of ANN, it is observed that the input data of *K*=24 hour, *K*=48 hour and *K*=72 hour causes the ANN to execute STLF with minimum MAPE values of 0.79% at day seven, 0.40% at day five, and 0.39% at day six, respectively. Whereby, the input data of *K*=24 hour, *K*=48 hour and *K*=72 is causing the ANN to provide STLF with maximum MAPE values of 20.29% at day twenty nine, 22.16% at day nine, and 7.25% at day three, respectively. On the other hand, the average MAPE values of 6.63%, 5.87% and 1.88% are obtained based on the STLF with stationary output of ANN that considers the input data of *K*=24 hour, *K*=48 hour and *K*=72 hour, respectively. The results signify that the input data of *K*=72 with stationary output of ANN outperformed the other techniques in providing the best results of STLF. By using this technique, the PCA is added as the second stage of feature extraction method to further improve the performance of ANN testing procedure in STLF and this is discussed elaborately in the following paragraph.

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**Table-4.** MAPE of STLF determined by ANN testing procedure considering *K*=24 hour, *K*=48 hour and *K* = 72 hour.

| | | **MAPE (%) for STLF based stationary output** | |
|---|---|---|---|
| Day | *K*=24 hour | *K*=48 hour | *K*=72 hour |
| 1 | 13.56 | 9.88 | 0.87 |
| 2 | 3.55 | 2.23 | 3.68 |
| 3 | 10.06 | 5.17 | 7.25 |
| 4 | 2.4 | 1.64 | 0.7 |
| 5 | 1.24 | 0.4 | 0.79 |
| 6 | 2.66 | 2.06 | 0.39 |
| 7 | 0.79 | 3.56 | 1.95 |
| 8 | 19.64 | 18.34 | 1.83 |
| 9 | 20.92 | 22.16 | 1.39 |
| 10 | 4.18 | 4.56 | 3.87 |
| 11 | 9 | 3.26 | 1.42 |
| 12 | 1.8 | 0.84 | 0.53 |
| 13 | 3.18 | 1.47 | 0.95 |
| 14 | 1.25 | 3.35 | 1.77 |
| 15 | 12.15 | 10.11 | 1.13 |
| 16 | 14.16 | 18.28 | 1.17 |
| 17 | 2.6 | 2.24 | 3.25 |
| 18 | 4.76 | 2.42 | 2.04 |
| 19 | 2.59 | 1.39 | 1.28 |
| 20 | 1.64 | 1.46 | 1.25 |
| 21 | 2.16 | 6.42 | 1.79 |
| 22 | 19.02 | 12.91 | 3.29 |
| 23 | 2.69 | 5.69 | 2.21 |
| 24 | 7.38 | 5.35 | 2.17 |
| 25 | 1.37 | 0.64 | 2.23 |
| 26 | 1.33 | 1.33 | 1.23 |
| 27 | 4.2 | 1.53 | 0.64 |
| 28 | 0.9 | 4.26 | 1.95 |
| 29 | 20.29 | 17.27 | 1.54 |
| Minimum MAPE | 0.79 | 0.40 | 0.39 |
| Maximum MAPE | 20.92 | 22.16 | 7.25 |
| Average MAPE | 6.63 | 5.87 | 1.88 |

In Table-5, the ANN testing procedure that takes into account the input data of *K*=72 with 20%, 30%, 40%, 50% and 60% of input reduction using PCA provide the STLF based stationary output of ANN with minimum MAPE values of 0.57% at day two, 0.23% at day two, 0.35% at day five, 0.19% at day one and 0.34% at day seven, respectively. Besides that, the STLF based stationary output of ANN with maximum MAPE values of 6.63% at day three, and 5.69 % at day three, 6.77% at day three, 5.77 at day three and 6.23% at day three are obtained due to the 20%, 30%, 40%, 50% and 60% of input reduction performed by the PCA for *K*=72 hour, respectively. Furthermore, the STLF based stationary output of ANN with average MAPE values of 1.85%, 1.97%, 1.74%, 1.97% and 2.15% are obtained due to the

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20%, 30%, 40%, 50%, 60% and 70% of input reduction made by the PCA for *K*=72 hour, respectively.

The results elucidate that the multiple time lags of *K*=72 hour with 40% of input reduction using PCA is the finest approach which improves the performance of ANN testing procedure in STLF based stationary output. This is due to the fact that the proposed method gives the minimum, maximum and average MAPE results which are lower than the benchmarked results provided by the ANN with *K*=72 hour and stationary output. Figure-3 present the

**Table-45** MAPE of STLF based stationary output of ANN considering multiple time lags of *K*=72 hour with and without using PCA.

| | MAPE (%) for STLF based stationary output | | | | | |
|---|---|---|---|---|---|---|
| Day | *K*=72 hour without PCA | *K*=72 hour with PCA | | | | |
| | | **60%** | **50%** | **40%** | **30%** | **20%** |
| 1 | 0.87 | 1.54 | 0.19 | 0.64 | 0.87 | 0.58 |
| 2 | 3.68 | 1.63 | 0.27 | 1.58 | 0.23 | 0.57 |
| 3 | 7.25 | 6.23 | 5.77 | 6.77 | 5.69 | 6.63 |
| 4 | 0.7 | 0.81 | 2 | 0.74 | 1.45 | 0.81 |
| 5 | 0.79 | 0.86 | 1.41 | 0.35 | 1.21 | 0.78 |
| 6 | 0.39 | 1.08 | 1.33 | 0.54 | 0.71 | 1.68 |
| 7 | 1.95 | 0.34 | 1.63 | 0.63 | 1.39 | 0.60 |
| 8 | 1.83 | 5.06 | 3.16 | 2.44 | 2.81 | 0.91 |
| 9 | 1.39 | 1.27 | 2.39 | 1.88 | 4.93 | 5.44 |
| 10 | 3.87 | 3.31 | 0.93 | 3.66 | 1.27 | 2.64 |
| 11 | 1.42 | 1.04 | 0.49 | 1.19 | 1.75 | 1.77 |
| 12 | 0.53 | 1.25 | 0.59 | 1.11 | 1.08 | 1.15 |
| 13 | 0.95 | 1.68 | 1.11 | 0.75 | 1.37 | 2.5 |
| 14 | 1.77 | 1.51 | 1.9 | 2.01 | 1.74 | 0.83 |
| 15 | 1.13 | 3.56 | 2.69 | 1.74 | 3.58 | 1.43 |
| 16 | 1.17 | 1.75 | 2.72 | 2.58 | 3.63 | 4.77 |
| 17 | 3.25 | 1.98 | 1.24 | 1.98 | 2.42 | 1.53 |
| 18 | 2.04 | 1.33 | 1.17 | 2.44 | 0.72 | 1.70 |
| 19 | 1.28 | 1.06 | 1.28 | 0.78 | 1.84 | 2.25 |
| 20 | 1.25 | 2.73 | 3.25 | 1.07 | 1.13 | 2.15 |
| 21 | 1.79 | 1.47 | 2.17 | 1.28 | 1.26 | 1.27 |
| 22 | 3.29 | 3.15 | 2.49 | 1.35 | 1.82 | 1.51 |
| 23 | 2.21 | 4.07 | 1.58 | 2.42 | 1.05 | 2.35 |
| 24 | 2.17 | 1.56 | 2.39 | 1.76 | 3.86 | 1.92 |
| 25 | 2.23 | 2.53 | 4.62 | 2.82 | 2.00 | 2.62 |
| 26 | 1.23 | 1.24 | 1.65 | 0.91 | 1.33 | 1.32 |
| 27 | 0.64 | 0.95 | 1.62 | 0.82 | 1.5 | 1.49 |
| 28 | 1.95 | 0.75 | 1.27 | 2.26 | 1.85 | 0.65 |
| 29 | 1.54 | 5.9 | 3.89 | 2.00 | 2.72 | 0.94 |
| Minimum MAPE | 0.39 | 0.34 | 0.19 | 0.35 | 0.23 | 0.57 |
| Maximum MAPE | 7.25 | 6.23 | 5.77 | 6.77 | 5.69 | 6.63 |
| Average MAPE | 1.88 | 2.15 | 1.97 | 1.74 | 1.97 | 1.85 |

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actual and forecasted chronological hourly peak loads which bring to the MAPE results of STLF based stationary output of ANN whilst considering *K*=72 hour with 40% of input reduction using PCA.

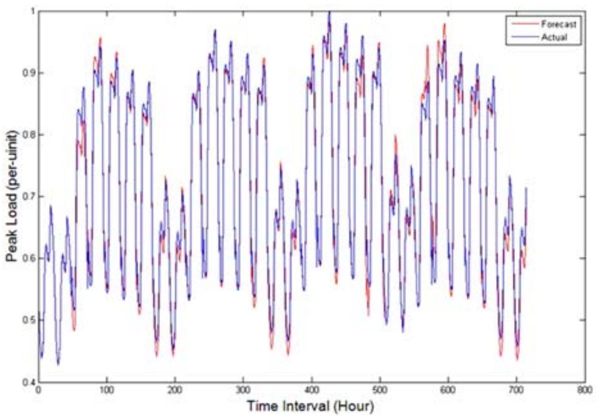


**Figure-3.** Comparison between the actual and forecasted chronological hourly peak loads based on the stationary output of ANN considering *k*=72 hour with 40% of input reduction using PCA.

## CONCLUSIONS

This paper has presented a new approach of artificial neural network (ANN) in performing the short-term load forecasting (STLF). The proposed method comprises of ANN model incorporating with the first stage of feature extraction using multiple time lags of input data, second stage of feature extraction using principal component analysis (PCA) and stationary output. The results have shown that it is important to accurately specify the total number of lagging time interval, *K*, for the input data of ANN in which this may significantly affect the performance of ANN. Then, the PCA technique is used to reduce the size of input data while retaining the significant features which may further improve the performance of ANN in STLF. The results have also shown that the ANN with stationary output provides more accurate results of STLF. In particular, the best minimum MAPE error of STLF is obtained from the stationary output of ANN in which it also considers the significant features of input data extracted by using the multiple time lags of *K*=72 hour with 40% of input reduction using PCA.

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