VOL. 10, NO. 21, NOVEMBER 2015 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

MEDIUM TERM LOAD FORECASTING USING EVOLUTIONARY PROGRAMMING-LEAST SQUARE SUPPORT VECTOR MACHINE

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ABSTRACT

This paper presents new intelligent-based technique namely Evolutionary Programming- Least-Square Support Vector Machine (EP-LSSVM) to forecast a medium term load demand. Medium-term electricity load forecasting is a difficult work since the accuracy of forecasting is influenced by many unpredicted factors whose relationships are commonly complex, implicit and nonlinear. Available historical load data are analyzed and appropriate features are selected for the model. Load demand in the year 2008 until 2010 are used for features in combination with day in months and hour in days. There are 3 inputs vectors for this proposed model consists of day, month and year. As for the output, there are 24 outputs vectors for this model which represents the number of hour in a day. In EP-LSSVM, the Radial Basis Function (RBF) Kernel parameters are optimally selected using Evolutionary Programming (EP) optimization technique for accurate prediction. The performance of EP-LSSVM is compared with those obtained from LS-SVM using cross-validation technique in terms of accuracy. The experimental results show that the proposed approach gives better performance in terms of Mean Absolute Percentage Error (MAPE) and coefficients of determination (R^2) for the entire period of prediction.

Keywords: medium-term load forecasting; least-square support vector machine, mean absolute percentage error, evolutionary programming.

INTRODUCTION

The first step towards making the right decisions in power industry is an accurate load forecasting. The electricity demand should be experienced in parliamentary procedure to make profitable investments, establish efficient systems, increased capability of living organizations, schedule energy distribution and others. During prediction, an underestimation in energy requirement may result in limited supply of electricity at the consumer end, which led to the reduction of system reliability. On the other hand, an overestimation may cause unnecessary investments or establishments which operate under–capacity and consequently result in uneconomic operating conditions. Electricity load forecasting can be split into three categories: short-term, medium-term and long-term depending on the length of the prediction period. Long-term load forecasting is related to the period from 5 to 20 years and is particularly significant in terms of deciding when to conduct the extension of the electricity network [1]. Medium-term load forecasting is applied to estimate the load in the winter or summer period and usually refers to a period from several days to several weeks, or several months [2]. Short-term load forecasting mainly covers the period of one week and refers to the assessment of load per hour during the day [3].

There are many load forecasting techniques presented by previous researcher. A long time ago, most of load forecasting approaches are based on time series analysis method and statistical method, such as linear regression methods [4] and general exponential smoothing methods [5]. These methods only can predict the linear load series and lack the ability to analyze the non-linear character of load series. With the rapid development of an artificial intelligence algorithm, the techniques with strong self-learning ability were proposed. There are several techniques which are popular in recent years such as artificial neural network (ANN) [6], fuzzy logic [7] and expert systems model [8] that have been used widely in the studies of load forecasting.

In load forecasting techniques, the usage of Artificial Neural Networks (ANN) has been widely implemented. More recent powerful machine learning techniques for electric load forecasting is Support Vector Machine (SVM). Unlike ANN, which try to define complex functions of the input feature space, SVM performs a non-linear mapping (by using the so-called kernel function) of the data into a high dimensional space. SVM was firstly introduced by Vapnik in his statistical learning theory [9]. The main characteristic of these methods is the use of Quadratic Programming (QP) in order to solve convex optimization problems. SVM implement the Structural Risk Minimization principle by minimizing an upper bound of the generalization error, instead of minimizing the training error.

Least-Square Support Vector Machines (LS-SVM) introduced by Suykens, are a reformulation of standard SVM [9]. In this version, instead of solving the Quadratic Programming (QP) problem, which is complex to compute, obtain a solution from a set of linear equations. LS-SVM have a significantly shorter computing time and they are easier to optimize [10]. However, the accuracy of the prediction is depends on the selection of the Radial Basis Function (RBF) parameters. Therefore, in this paper, Evolutionary Programming (EP) is hybrid with LS-SVM for more accurate and optimal result namely

Evolutionary Programming- Least-Square Support Vector Machine (EP-LSSVM).

LEAST-SQUARE SUPPORT VECTOR MACHINE

Let $D=\{ (x_1,y_1), (x_2,y_2),\ldots\ldots, (x_i,y_i) \}$ be a training set with input data $x_k \in R^d$ and corresponding output data $y_k \in R$. Learning from the training data can be viewed as a multivariate function f approximation that represents the relation between the input and output data [HYPERLINK \l "ZLu081" 10]. In a general case, the input data are mapped into a feature space by nonlinear function $\Phi(x)$, the SVM function $f(x)$ can be expressed as:

$$f(x) = \omega^T \Phi(x) + b \tag{1}$$

where ω^T is a m -dimensional vector and b is a scalar.

With the application of Mercer theorem, the LS-SVM model for function estimation becomes:

$$f(x) = \sum_{k=1}^{i} \alpha_k K(x, x_k) + b \tag{2}$$

The following are popular kernel function $K(x, x_k)$ used for SVM regression or classification problems:

a. Linear kernel

$$K(x, x_k) = x^T x_k \tag{3}$$

b. Polynomial kernel with degree d and tuning parameter c

$$K(x, x_k) = (x^T x_k / c + 1)^d \tag{4}$$

c. Radial Basis Function (RBF)

$$K(x, x_k) = exp(-\|x - x_k\|^2 \quad /2\sigma^2) \tag{5}$$

According to [11,12], a nonlinear LS-SVM model with Radial Basis Function (RBF) kernel are able to provide better prediction performance as compared to other technique, therefore it is applied in this study.

INPUT DATA

The historical load data are collected from Georgia, United State of America (USA) and consists of calendar information, hourly electrical load in MW. The data can be downloaded from [13]. The training data consists of 731 data were selected from January 2008 to December 2009. Meanwhile, the testing data consists of 361 were selected from January 2010 to December 2010. There are 3 inputs to the LS-SVM consists of day, month and year while there are 24 outputs which represent the number of hour in a day. Figure-1 and Figure-2 illustrate the actual load demand for training and testing respectively. The figure shows the variations of load behaviour due to varying industrial activities, weather conditions, etc.

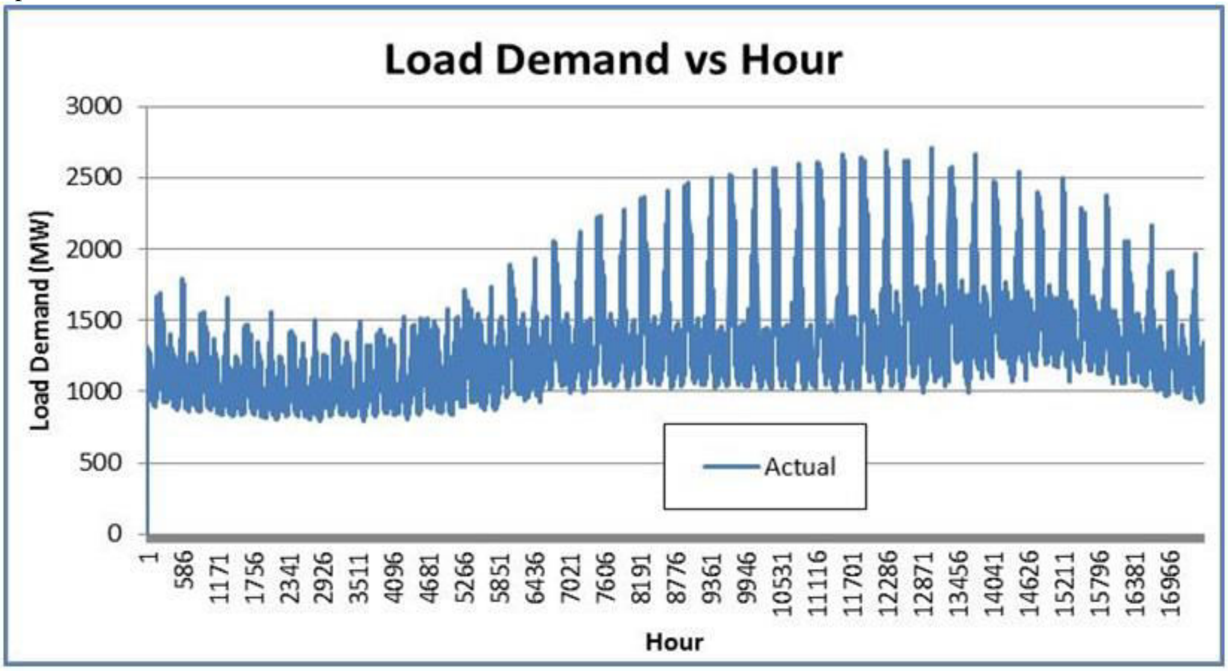

Figure-1. Actual load demand for training data.

ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

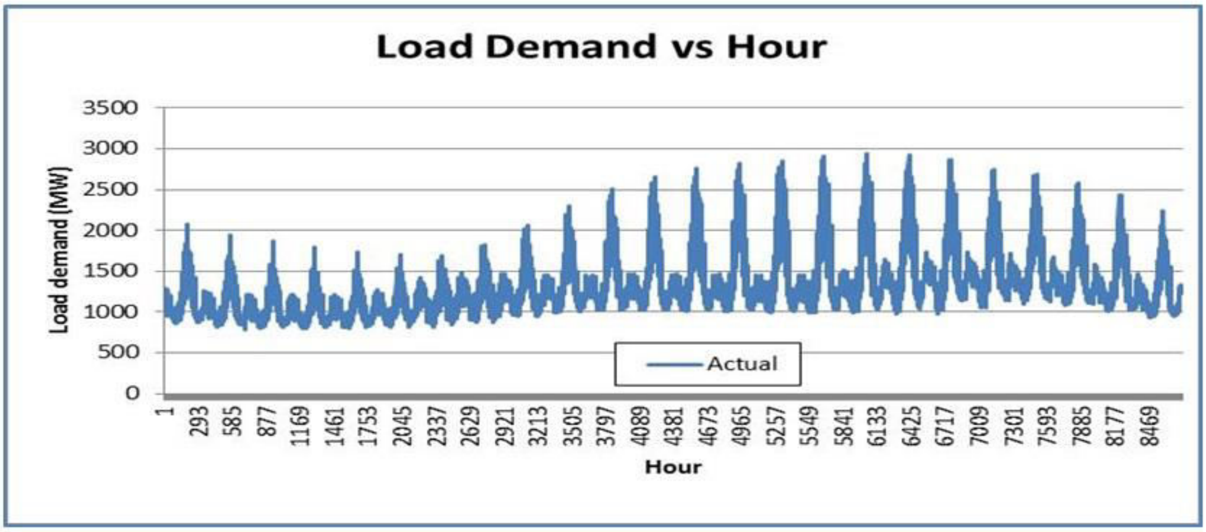

Figure-2. Actual load demand for testing data.

DEVELOPMENT OF LSSVM

In order to obtain an LS-SVM model (RBF kernel), two parameters need to be tune i.e. gamma (γ) and sigma (σ^2). Gamma is a regularization parameter for determining the traded-away between the smoothness of the calculated function and training error minimization. Meanwhile, σ^2 is the kernel function parameter (squared bandwidth). In this study, 10-fold cross validations were used to determine the tuning parameters. Cross-validation may lead to higher average performance than the application of any single classification strategy. It will also reduce the risk of poor performance [14].

In this paper, suitable features were selected and various factors that affecting loads forecasting were analyzed. The training data were selected from the historical load data in year 2008 to 2009 with the 3 input vectors consist of day, month and year while for the output vectors are hour of the day which are 24 outputs. As for the testing data, the data were chosen from the historical load data in year 2010 where it consists of 3 inputs which are day, month and year and also have 24 outputs vectors which represent the number of hour in a day. The accuracy of the prediction is assessed using Mean Absolute Percentage Error (MAPE) using equation (6).

$$M = \frac{1}{n}\frac{\sum(|Predicted - Actual|)}{\sum Predicted}\ X\ 100\% \qquad (6)$$

Further evaluation can be done by calculating the correlation of determination, R^2 using equation (7).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Predicted - Actual)^2}{\sum_{i=1}^{n}(Actual - Average_{actual})^2} \qquad (7)$$

R^2 is frequently used in determining the correlation between parameters in the mathematical model. The value of R^2 closed to unity indicates that the network performances good and consistent. The overall performance of LS-SVM is carried out using the following steps:

Step 1: Load training and testing data.
Step 2: Tune the parameters of γ (L_1) and σ^2 (L_2) using cross-validation technique.
Step 3: Train the data with the previously determined tuning parameters.
Step 4: Simulate the model on the test data
Step 5: Visualize the result.
Step 6: Calculate MAPE and R^2 using equation (5) and (6)
respectively.

DEVELOPMENT OF EP-LSSVM

Although the LS-SVM had been useful in forecasting the electrical load, the heuristic selection of training parameters could be a little bit tedious and causes the learning machine to get a local optimal solution instead of a global optimal solution. In order to obtain more accurate and optimal result, an optimization is needed. Thus, Evolutionary Programming (EP) is hybrid with LS-SVM in the load forecasting of electrical load demand.

Evolutionary Programming (EP) is one of Evolutionary Programming paradigms. The objective of the EP is to optimize any fitness which can be represented using mathematical equations. Although EP was initially proposed as an approach to artificial intelligence [15], it has been recently applied with success to many numerical and combinatorial optimization problems. Optimization by EP can be summarized into two major steps which are the solution in the current population will be mutates and select the next generation from the mutated and the current solution. These two steps can be considered as a population-based version of the classical generate-and-test method, where the application of mutation is apply to generate new solutions (offspring) and the selection is used to identify which of the newly generated solutions should survive to the next generation [16].

VOL. 10, NO. 21, NOVEMBER 2015 ISSN 1819-6608
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In EP-LSSVM, regularisation parameter (gam) and kernel function parameter (sigma) are the variables to be optimised in the EP optimisation technique. Figure-3 shows the flowchart of EP.

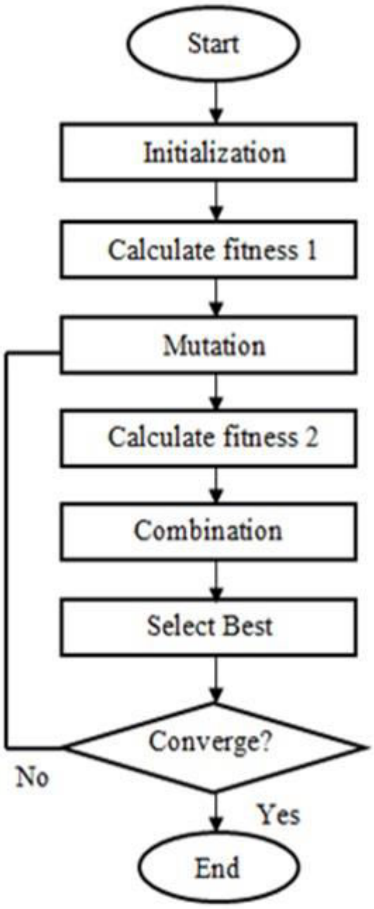

Figure-3. Flowchart of EP

The initial value of each population is generated randomly. Then the initial population is updated through mutation process as shown in equation (8):

$$x_{i+m,j} = x_{i,j} + N(0,\beta(x_{j\,min})\left(\frac{f_i}{f_{max}}\right)) \tag{8}$$

Where, $x_{i,j}$ is a parents and $x_{i+m,j}$Li is an offspring that will produce when the parent is mutated. β is search step and f_i is the fitness of ith components of the respective vectors. N (0,1) is a normally distributed one-dimensional random number with mean 0 and 1.

The generated offspring population from the mutation process are combined (combination process) with the parent and then were sorted according to their fitness. The best population in mutated population will be selected and stored in every generation. Mean absolute percentage error (MAPE) had been used as a fitness value to quantify the performance of the prediction. The termination criterion is specified by the difference between the maximum and minimum fitness to be less than 0.0001. The proposed EP-LSSVM model is summarized in the following procedure:

Step 1: Load training data and testing data from LS-SVM file.
Step 2: Generate random numbers to represent parameter gamma γ (L_1) and sigma σ^2 (L_2). L_1 and L_2 are set to be random numbers between 0 and 1000.
Step 3: Calculate fitness value by calling LS-SVM program with the parameter generated in Step 2.
Step 4: Load the set of random numbers into initial population. The maximum numbers of population pool is 20.
Step 5: Mutate the population using equation (7).
Step 6: To calculate the fitness value of mutated population by calling LS-SVM program.
Step 7: Combine parents and offspring. The total population now is 40.
Step 8: Rank and select the best 20 population with the highest fitness value.
Step 9: Convergence test by setting the difference between the maximum and minimum fitness to be less than 0.0001.
Step 10: If it is converge, stop. Otherwise, repeat Step 5 to Step 10.

RESULTS AND DISCUSSION

The training and testing data were selected from the historical load data available in [13]. Historical electrical load data from January 2008 until December 2009 were selected as training data. While the electrical load data from January 2010 to December 2010 were selected as testing data for this analysis. In this paper, 731 data and 365 data were selected as a training data and testing data respectively. Figure-4 shows the training data patterns that were plotted using LS-SVM. The graph that shows the comparison between the predicted and targeted outputs during testing are illustrated in Figure-5. It can be seen from the graphs that the predicted outputs are slightly different with the targeted outputs. In order to improve the prediction performance, EP is used to optimize the value of RBF parameters in EP-LSSVM. The results from EP-LS-SVM is presented in Figure-6 while the comparison between the targeted and actual for testing data are shown in Figure-7.

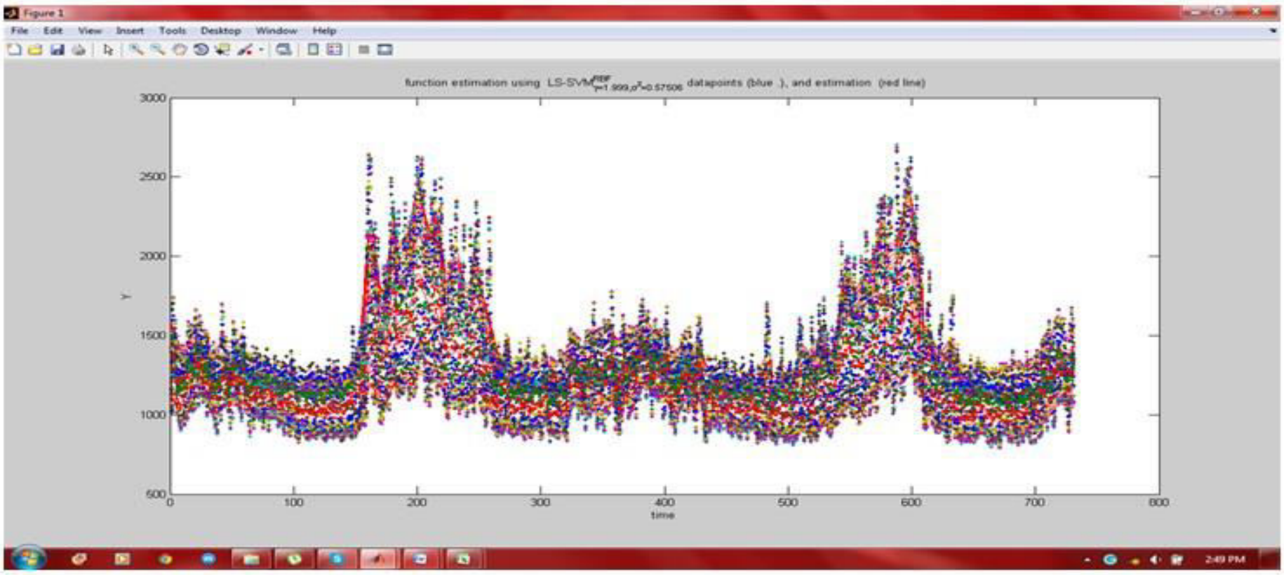

Figure-4. Graph of training data using LSSVM.

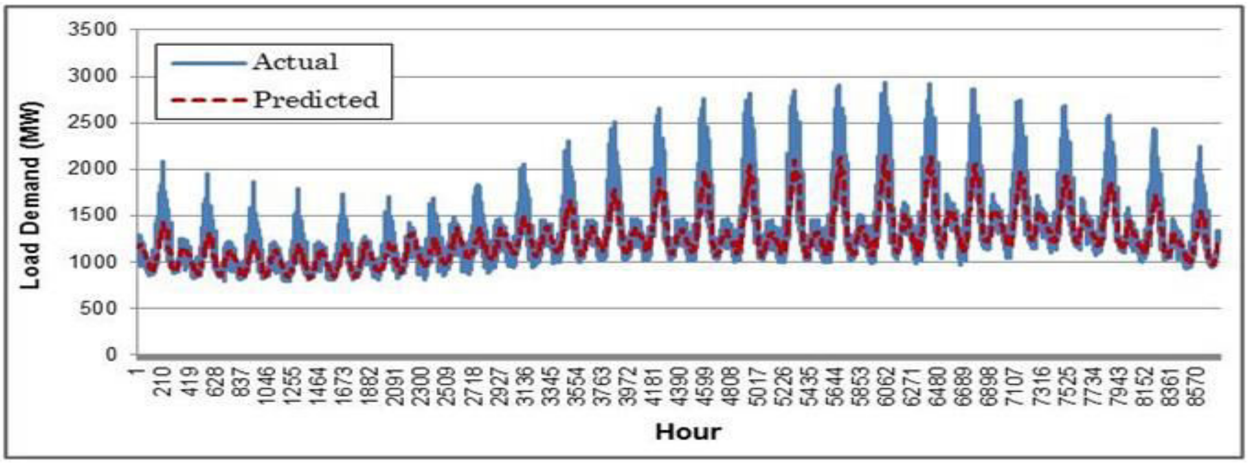

Figure-5. Predicted and actual value of testing data produced by LS-SVM.

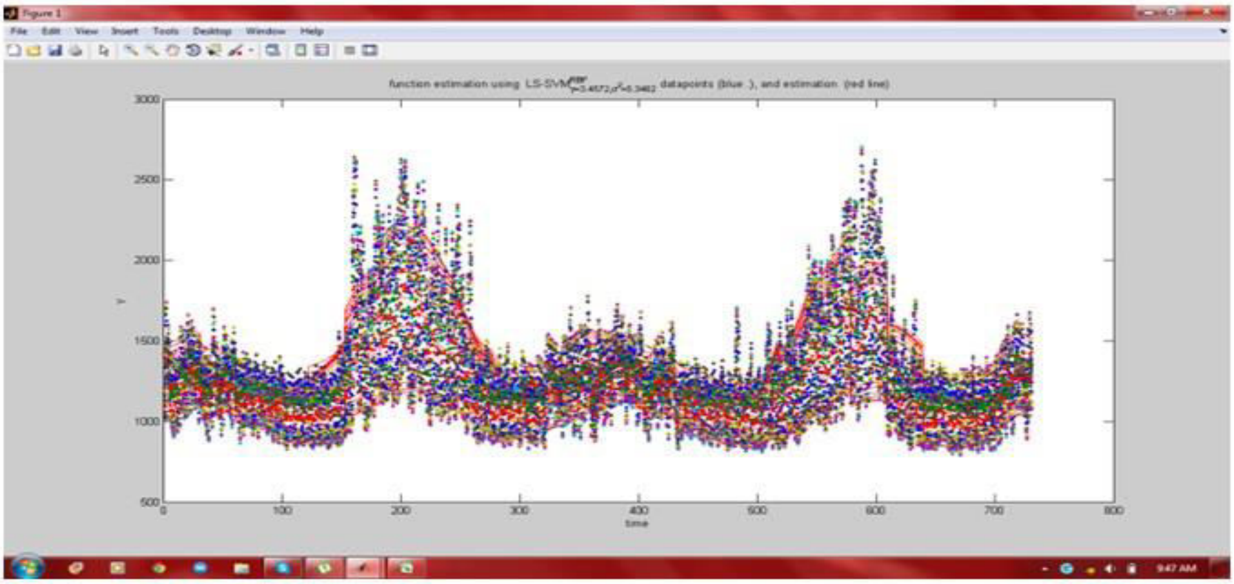

Figure-6. Graph of training data using EP-LSSVM.

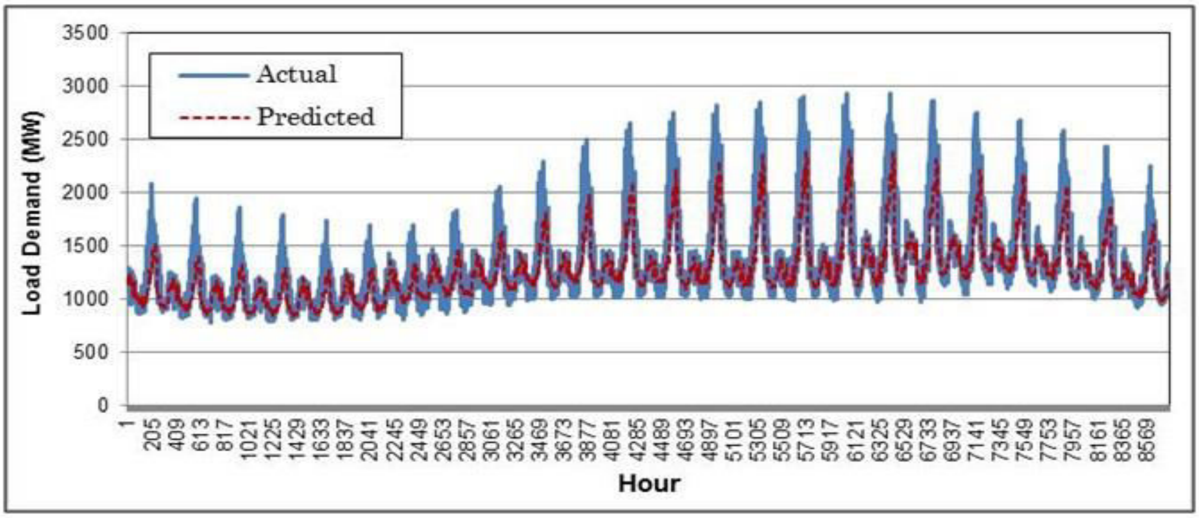

Figure-7. Predicted and actual value of testing data produced by EP-LSSVM.

From Figure-6, it can be observed that the predicted outputs are quite similar with the targeted outputs. The prediction performance result for the hybrid technique EP-LSSVM is compared to the prediction performance of LS-SVM. In LS-SVM, cross validation is employed to tune the parameters of RBF Kernel with 10-fold cross validation. On the other hands, the parameters of RBF Kernel in EP-LSSVM are optimally selected. The tuned parameters and the result of prediction performance for both techniques are tabulated in Table-1.

Table-1. Tuned parameters and results.

Parameter	Gamma, γ	Sigma, σ^2	MAPE (%)	R^2
LSSVM	1.9999	0.57506	10.4094	0.6506
EP-LSSVM	3.4572	5.3462	9.2531	0.7182

Based on the results in Table 1, the MAPE value for EP-LSSVM is slightly lower than the LS-SVM with cross validation technique. The value was reduced from 10.4094% to 9.25318%. Furthermore, the performance of EP-LSSVM in terms of coefficient of determination (R^2) is larger which indicates that the prediction is more accurate compared to the LSSVM.

These results meet the conditions of accuracy in load forecasting which the value of MAPE must below the 10% and the value of regression must approach to 1 as near as possible. Thus, the proposed technique EP-LSSVM is more optimal and accurate to forecast the electrical load demand rather than LS-SVM technique.

CONCLUSIONS

In order to offer a high quality and dependable service to the consumers, it will be essential for electric power distribution companies to forecast regarding electric load demand in the future. Various methods of electrical load forecasting are discussed in this paper. All of these methods can forecast the load of the power system, but the amount of previous data and such variables which they need to forecast, make them different in accuracy.

In this paper, the Evolutionary Programming-Least Square Support Vector Machine (EP-LSSVM) was proposed to forecast medium term load demand due to its good performance in generalization, optimization, ability to avoid local minimum and get the global optimal solution. In EP-LSSVM, EP is used to optimize the kernel parameters such as gamma and sigma. The objective of the optimization is to minimize the MAPE between the predicted and targeted output. The forecasted results obtained from EP-LSSVM were compared to the results obtained using conventional LS-SVM. The results revealed that EP-LSSVM provides better prediction performance as compared to LS-SVM with cross-validation technique. Operators can rely on this accurate mid-term load forecasting in making decisions for unit commitment, system security analysis, dispatching schedule and load flow analysis.

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