Forecasting Short-Term Electrical Loads Using Support Vector Regression with Gaussian Kernel Functions

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Abstract. Power outages that sometimes still occur cause disruption of economic activity around the area, especially the city of Bau-bau, it is necessary to forecast the electrical load in order to determine the characteristics of the electrical load in the area. Short-term electrical load forecasting is used to evaluate the performance of power plants related to loading scheduling and delivery. However, increasing the accuracy of electrical load forecasting has become a fundamental issue in the development of electric power systems. Because the nonlinear condition of the electrical load data affects the accuracy of the electrical load forecasting. Modeling using support vector regression (SVR) to solve nonlinear electrical load forecasting problems is very well used for conditions of lack of information and limited. The proposed SVR modeling uses the Gaussian kernel function and uses historical electrical load data as input data and target data. The criteria for short-term electrical load forecasting accuracy can be determined by calculating the Mean Square Error (MSE). The smaller the MSE value, the better the level of accuracy for forecasting electrical loads. Short-term electrical load forecasting using the Support Vector Regression kernel function Gaussian (SVR-Gaussian) gives very good forecasting results with a small MSE level. Thus, the proposed SVR model has the feasibility of forecasting short-term electrical loads in the city of Bau-bau.

Keywords: Forecasting · Support Vector Regression · Short-Term · Electrical Load

1 Introduction

Forecasting is an activity carried out to take into account something that will happen in the future by using historical data that has happened before, to meet a target or so on. Electrical load forecasting has always been a challenge for researchers to provide the best performance in solving problems related to increasing forecasting accuracy. Electrical load forecasting is a very important issue because it relates to the operation of the electric power system and the evaluation of the performance of electric companies such as scheduling and delivery of loads [1]. The large influence of the nonlinear shape of the load

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data makes it difficult to improve forecasting accuracy [2]. There have been many various methods used by researchers in forecasting electrical loads ranging from nonparametric methods to artificial intelligence methods. And in its development, intelligence methods are popular in forecasting electrical loads [3].

Based on the nonlinear load data pattern, electrical load forecasting is carried out using an artificial intelligence method, namely support vector regression (SVR), which is the development of the support vector machine (SVM). The SVR method has the ability to forecast electrical loads in nonlinear mapping, which has succeeded in solving nonlinear regression and time series problems. Support vector regression has the advantage of learning with less and limited information conditions [4]. In a study conducted by Youlang Yang et al. [5], the performance of SVR in electrical load forecasting has an influence on its parameters, namely ε, σ and C. Wei-Chiang Hong [6], determining the combination of SVR parameters greatly affects the accuracy of forecasting electrical loads. From these two studies, it shows that the determination of the parameters greatly affects the value of the forecasting accuracy of the electrical load.

This study uses daily historical electrical load data obtained from PT. PLN (Persero) Area Bau-bau. This study uses two input data, namely hours and days that have been initialized in advance and target data in the form of average load data from historical load data.

2 Support Vector Regression

SVR is a development in minimizing the calculation risk and loss function in solving nonlinear problems. SVR is a regression form of support vector machine (SVM) to overcome the problem of nonlinear patterns, especially in time series forecasting [7]. The support vector machine uses a linear model with a general form as below:

$$y(x) = wTf(x) + b \tag{1}$$

where x is the input vector, w is the weight parameter (f(x) is the basic function, and b is the bias. For nonlinear regression models f(x) can be expressed in the form of the equation below:

$$f(x) = \sum\nolimits_{k=1}^{mSV} \left(a_k - a_k^*\right) k(x_k, x) + b \tag{2}$$

where k is the Mercer kernel and can be a Gaussian kernel, a polynomial kernel, and a linear kernel. After the training phase, the system only needs to store the support vector, the Lagrange multiplier is not zero $\left(a_k - a_k^*\right)$, , and b are biased. During the testing phase, the function f(x) is used to predict the load.

3 Support Vector Regression Architecture

In the data set {(×1,y1),…,(xi,yi)} x,y ∈ R, where x is the input variable vector and y is the output value based on the target data. The purpose of SVR is to develop a function f(x) to predict the output value accurately by following the target data pattern target [8] (Fig. 1).

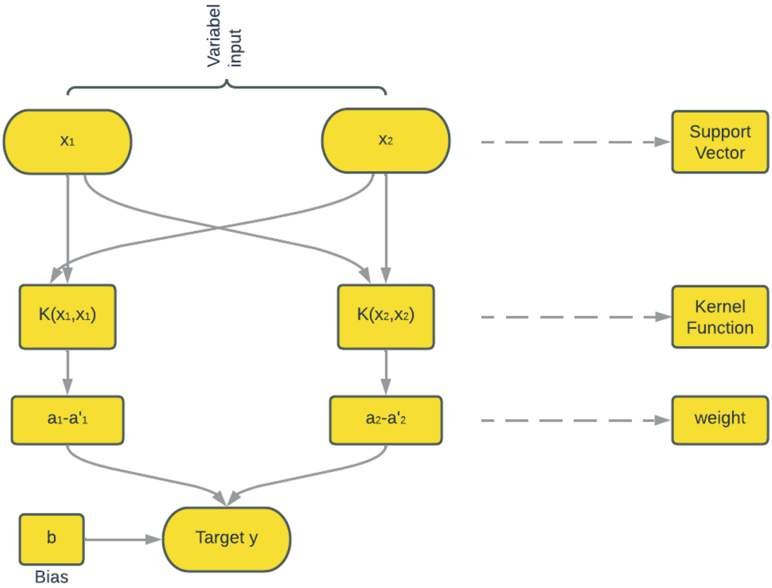


Fig. 1. SVR Architecture

Table 1. Kernel Function

Type	Formula
Gaussian	$G(x_1, x_2) = exp(-\frac{\|x_1, x_2\|^2}{2\sigma^2})$
Linear	$G(x_1, x_2) = x_1{}'x_2$
Polynomial	$G(x_1, x_2) = (1 + x_1{}'x_2)^p$

4 Kernel Function

An important part of SVR is the use of kernel functions. The kernel function aims to convert nonlinear data into a higher dimensional space where the two are linearly separated [9]. There are three types of kernel functions, namely gaussian kernels, linear kernels, and polynomial kernels (Table 1).

5 Accuracy Criteria

In the design of electrical load forecasting, of course, we want an exact result or provide the most approximate picture so that the design made is something realistic. This accuracy is the criteria for the performance of a forecasting method. Small errors mean high forecasting accuracy, in other words, the accuracy of the forecasting results is high. The magnitude of the output error from the forecast can be calculated using the Mean

Square Error (MSE) as below:

$$MSE = \sum_{r=1}^{N} (Xt - Ft)^2 \tag{3}$$

where N is the number of periods, Xt is the actual data for period t and Ft is the forecast value for period t.

6 Methodology

In this study, short-term electrical load forecasting is carried out every 30 min using historical electrical load data on Friday, December 1, 2017, in the city of Bau-Bau. From a total of 5 feeders for which short-term electrical load forecasting will be carried out, there are 240 electrical load sample data divided into two, namely 20% for training data and 80% data for testing. Electrical load data obtained from PT. PLN (Persero) Area Bau-bau.

1. Perform target data input data mapping first:

x_1 = hour input data.

x_2 = day input data.

y = average target load.

Initialize day input data in Table 2:

2. Setting the SVR parameter value epsilon ($\varepsilon = 0.01$) and sigma ($\sigma = 1.75$).

3. Normalize the input data and target data so that they have the same weight and range.

4. Determine the parameter values of the SVR.

5. Create a model of the SVR and use the Gaussian function.

6. Forecasting with the SVR model that has been created.

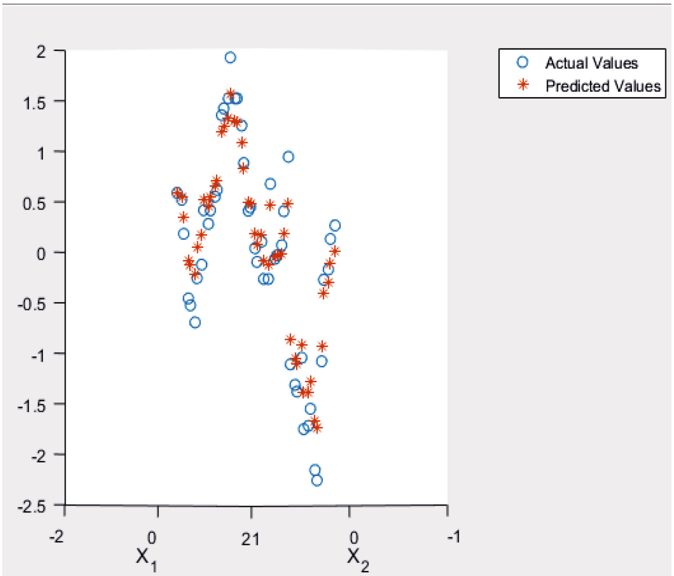
Calculating the error criteria using MSE (Table 3), the smaller the error value the better the forecasting results.

Table 2. Initializes day input

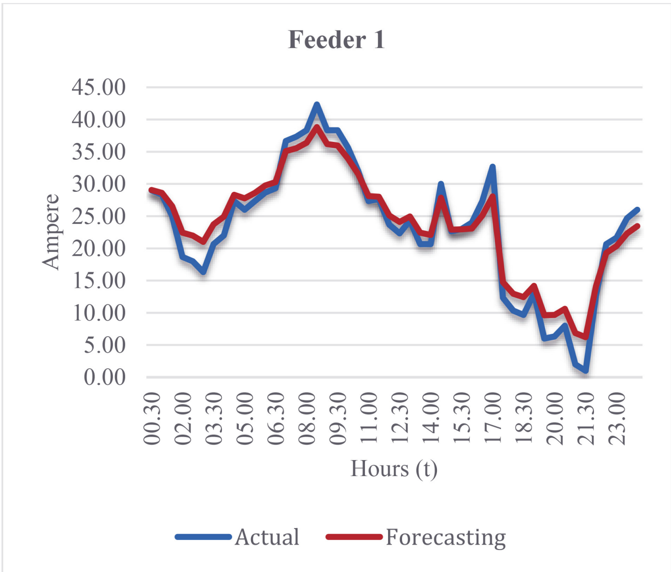
Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	2	3	4	5	6	7

Table 3. Data validation scheme by calculating MSE

Feeder 1	Feeder 2	Feeder 3	Feeder 4	Feeder 5
Actual load 2017	Actual load 2017	Actual load 2017	Actual load 2017	Actual load 2017
Forecasting 2017	Forecasting 2017	Forecasting 2017	Forecasting 2017	Forecasting 2017



(a)



(b)

Fig. 2. Forecasting the electrical load on feeder 1 as training data: (a) data in zscore form; (b) data in the form of denormalization

Table 4. Forecasting the electrical load on feeder 1 as training data

Jam	Actual (Amp)	Forecasting (Amp)
00.30	29.00	29.05
01.00	28.33	28.62
01.30	25.00	26.55
02.00	18.67	22.42
02.30	18.00	21.97
03.00	16.33	21.00
03.30	20.67	23.72
04.00	22.00	24.92
04.30	27.33	28.33
05.00	26.00	27.77

7 Result and Discussion

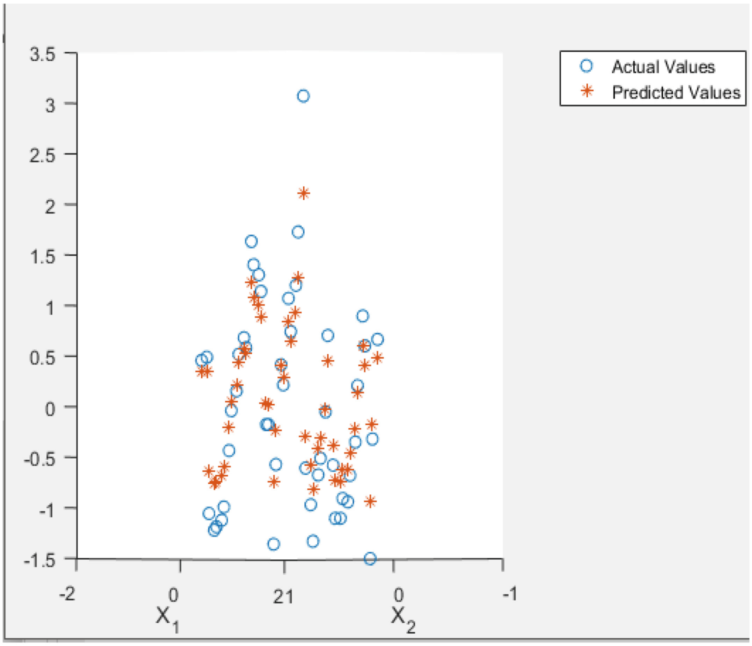
The modeling is done using support vector regression, using the parameters obtained through try and error. In this SVR model, 2 parameters are used in forecasting, namely $\varepsilon = 0.01$ and $\sigma = 1.75$ with a maximum of 100 iterations.

Based on Fig. 2, the training data carried out on feeder 1 in forecasting electrical loads shows a good SVR ability to follow non-liar actual data patterns. In Fig. 2, part (b) is a form of forecasting data that has been denormalized. The results of forecasting electrical loads can be seen in Table 4 for 10 data forecasting results from 48 data that are trained.

The following are the results of short-term electrical load forecasting using test data using the SVR model and the Gaussian kernel function. It can be seen in the graphic image that the electrical load forecasting capability follows a nonlinear actual data pattern, such as an epidemic picture (Figs. 3, 4, 5 and 6).

Table 5 shows 10 actual data and the results of short-term electrical load forecasting on each feeder with the SVR model and the Gaussian kernel function.

From the forecasting model performed using the SVR on each feeder, it can be seen in Table 6 that the level of accuracy for forecasting the electrical load obtained is based on the MSE value. As said by Hong [10], SVR parameter selection epsilon and sigma very affect the results of forecasting accuracy. The smaller the epsilon value and the higher the variable value slack the accuracy will be higher [11]. The MSE value is used to show the ability of the SVR model to predict electrical loads. Where this value is obtained from a comparison between the actual data and the results of short-term electrical load forecasting on each feeder.



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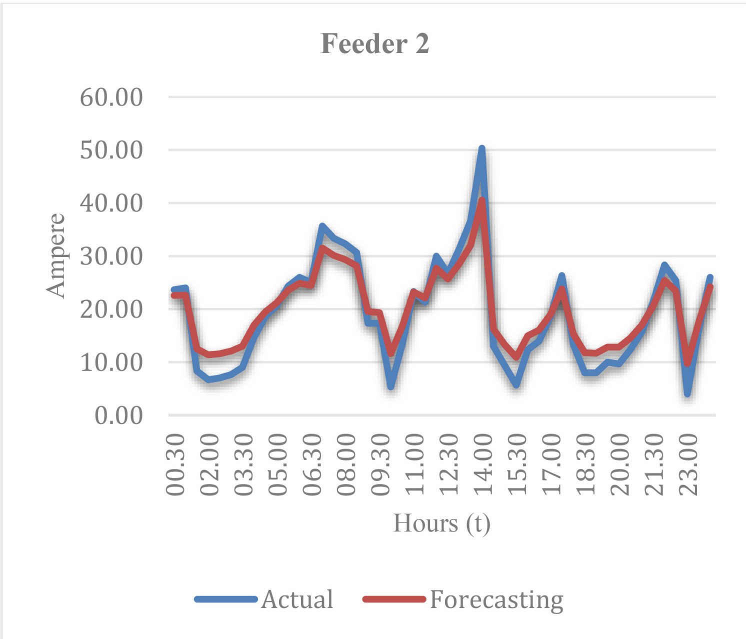


(b)

Fig. 3. Forecasting electrical load on feeder 2 as a test: (a) data in zscore form; (b) data in the form of denormalization

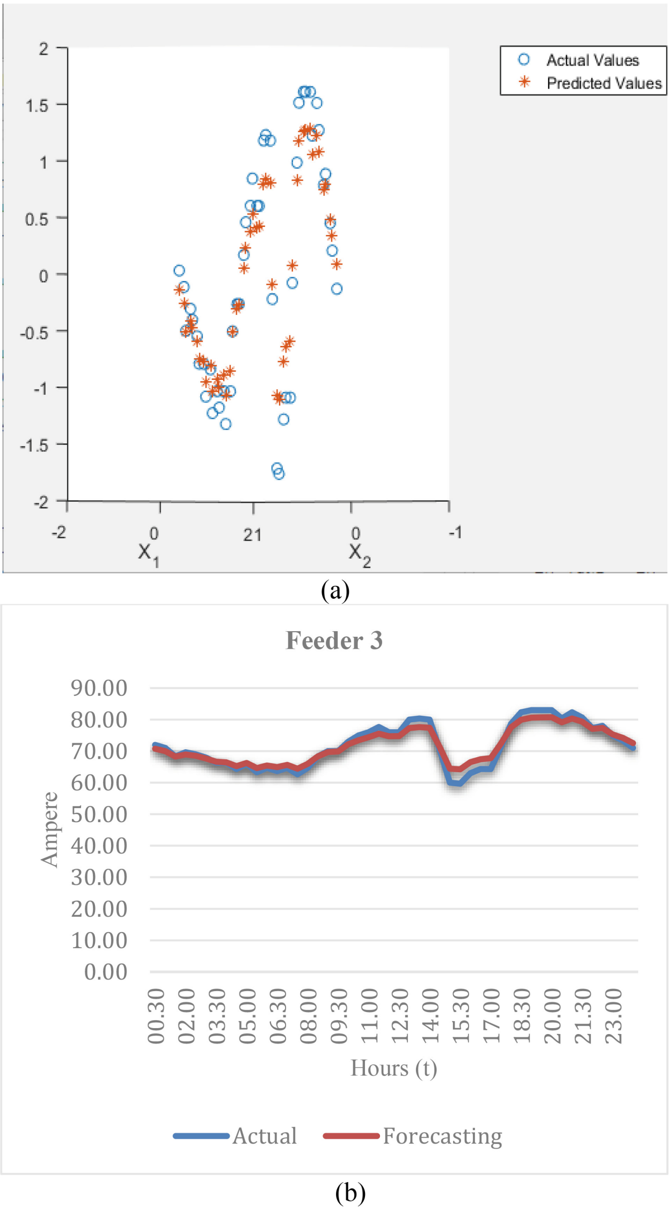
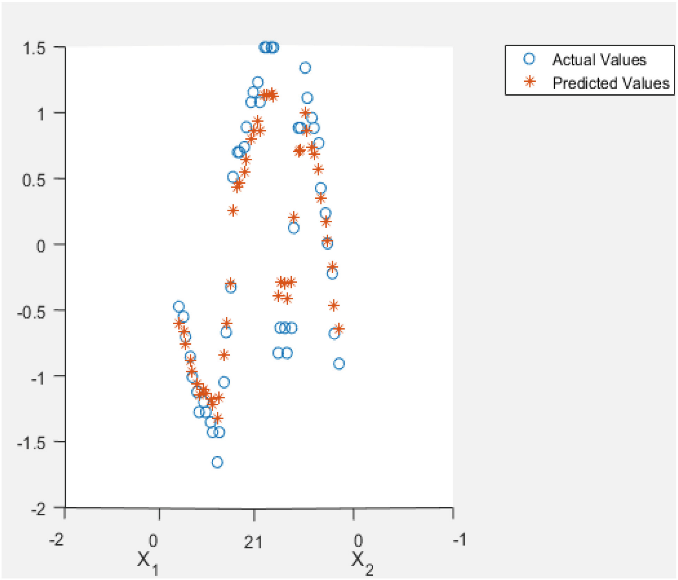
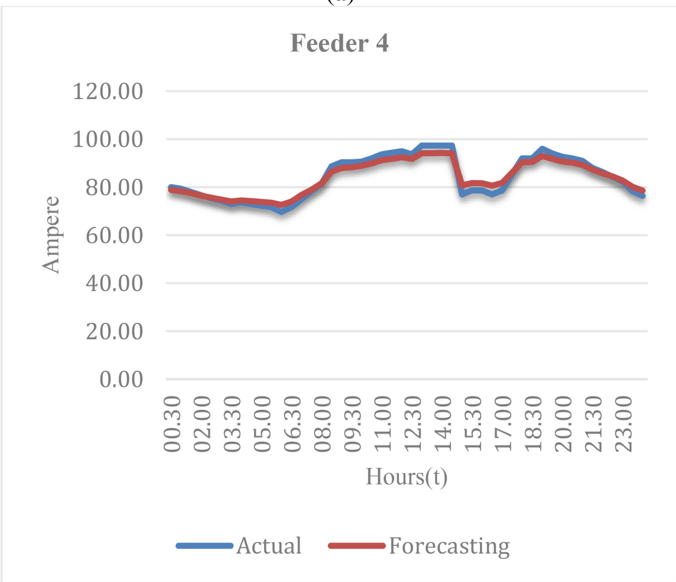


Fig. 4. Forecasting electrical load on feeder 3 as a test: (a) data in zscore form; (b) data in the form of denormalization

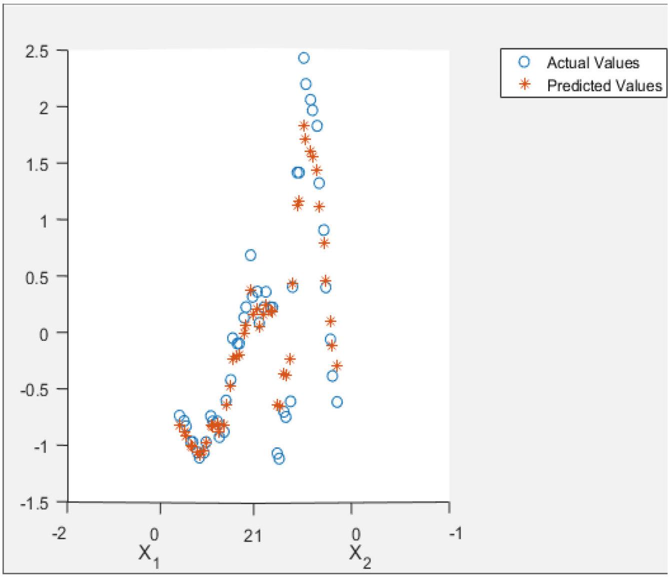


(a)

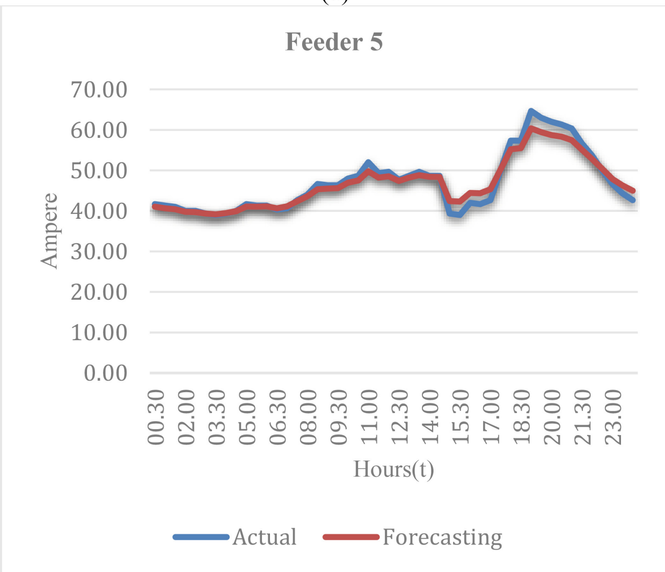


(b)

Fig. 5. Forecasting electrical load on feeder 4 as a test: (a) data in zscore form; (b) data in the form of denormalization



(a)



(b)

Fig. 6. Forecasting electrical load on feeder 5 as a test: (a) data in zscore form; (b) data in the form of denormalization

Table 5. The results of forecasting the electrical load on the feeder with test data

Jam	Feeder 2		Feeder 3		Feeder 4		Feeder 5	
	Actual	Forecasting	Actual	Forecasting	Actual	Forecasting	Actual	Forecasting
00.30	23.67	22.56	72.00	70.79	80.00	78.85	41.67	41.04
01.00	24.00	22.64	71.00	70.00	79.33	78.30	41.33	40.65
01.30	8.33	12.51	68.33	68.30	78.00	77.51	41.00	40.42
02.00	6.67	11.36	69.67	68.96	76.67	76.43	40.00	39.80
02.30	7.00	11.58	69.00	68.56	75.33	75.65	40.00	39.70
03.00	7.67	12.09	68.00	67.67	74.33	74.83	39.33	39.33
03.30	9.00	13.01	66.33	66.65	73.00	74.09	39.00	39.16
04.00	14.67	16.95	66.33	66.44	73.67	74.48	39.33	39.46
04.30	18.67	19.51	64.33	65.26	73.00	74.22	40.00	39.95
05.00	20.67	21.20	66.00	66.24	72.33	73.85	41.67	41.08

Table 6. MSE value on each feeder

MSE				
Feeder 1	**Feeder 2**	**Feeder 3**	**Feeder 4**	**Feeder 5**
0.0594	0.1054	0.0690	0.0567	0.0553

8 Conclusion

Short-term electrical load forecasting using support vector regression with the Gaussian kernel function shows that the short-term electrical load forecasting results have good performance by providing a small accuracy value based on the MSE results for each feeder. From the results of forecasting the smallest MSE value on feeder 5 is 0.0053 and the highest on feeder 2 is 0.1054. Based on the MSE value, the support vector regression model with the Gaussian kernel function is able to model short-term electrical load forecasting using non-liar data properly.

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