Electrical Load Prediction for Short Term using Support Vector Machine Techniques

Kartheek Vankadara, I. Jacob Raglend

***Abstract:** The electrical load prediction during an interval of a week or a day plays an important role for scheduling and controlling operations of any power system. The techniques which are presently being used and are used for Short Term Load Forecasting (STLF) by utilizing various prediction models try for the performance improvement. The prediction models and their performance mainly depend upon the training data and its quality. The different forecasting approaches using Support Vector Machine (SVM) depending on several performance indices has been discussed. The accuracy of the forecasting approaches is measured by Mean Absolute Error (MAE), Root Mean Square Error (RMSE), prediction speed and training time. The approach with least RMSE reveals as the best among the SVM methods for short term load forecasting.*

***Keywords:** Load forecasting, machine learning, RMSE, support vector machine.*

I. INTRODUCTION

The increase in demand of most useful energy on earth i.e., electrical energy and due to insufficient availability of conventional resources for generation of electricity, choice for finding different ways to handle out the unavailability is to be seen for. The various approaches led to integration of Non-Conventional Energy Sources (NCES) for optimizing energy that has been consumed by several techniques have been implemented so as to decrease the fuel consumption used for generating power. One type of approach is by optimizing the fuel used for generation at a plant to recognize the exact amount of power which is required to generate for fulfilling the energy demand without any wasting of the fuel on the consumer side. This approach is called load forecasting and behavior of the consumer in terms of load consumed known to provider by comparing with the historical data of the load consumed.

The historical load and current data help significantly in forecasting of upcoming electric load consumption which has become a common practice. The planners create decisions strategically with respect to interchange evaluation, security assessments, coordination of different power generating plants and unit commitment for load forecasting. The electrical load forecasting has become a key research area in the stream of electrical engineering due to growing needs of electricity and unavailability of conventional sources for producing electrical power. The electrical power generating industry needs forecasts with a lead time which ranges between short-term to long-term. But many countries have been privatizing and deregulating the power systems so that electricity can be turned into a product for selling and could be brought at market prices. As the load predictions play an important role in the building of the prices, they have developed a significant for the power generating industry [1]. The improvement of accuracy for load forecasting directly depends upon the system cost.

During forecasting load, several virtual factors are to be well-thought-out for which the local area load depends upon. So, the problem becomes slightly difficult as the present hour load may depend upon previous hour load, load of same hour on the earlier load in weekdays formerly, and so on. But the pattern of the load might show some arbitrariness. For attaining additional probability, considering other features such as humidity, temperature etc. Maximum of the modified and available representations or models for predicting drives have been verified for electric load forecasting [2]. The electric load forecasting is of four different major categories as illustrated in Fig. 1 which are discussed in detail.

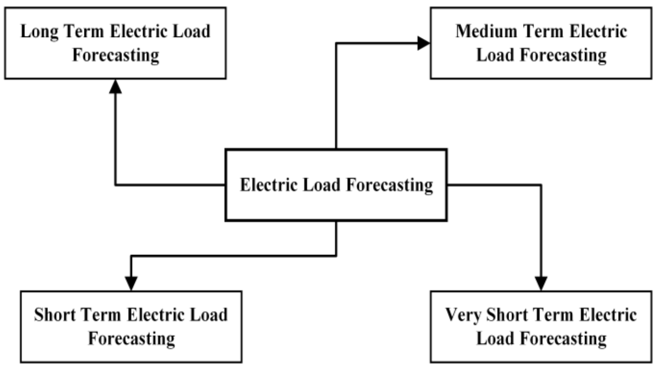

Fig. 1.Types of Electric Load Forecasting

A. Load Forecasting for Long Interval of Time

Forecasting with prospects of nearly one to ten years and every now and then up to some decades is called Long-Term Forecasting. This provides predictions for weekly/monthly for various valley and peak loads which are significant for increasing generation and distribution systems. The electric utility company in other words also comes to know the requirements for future like equipment purchases, expansion and maintenance, staff hiring [3].

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B. Medium Term Electric Load Forecasting

Medium term electric load prediction is for a time period of nearly one to twelve months. This type of prediction depends upon largely on factors like elements which influence demand due to new loads and their addition into the network, demand patterns for various seasonal variations, large consumers and their maintenance requirements [4]. Moreover, this type of prediction utilizes loads on hourly basis for peak load of days. With this information, it is understandable that whether to consider certain amenities/plants for maintaining or not for a given period of time. This will help in forecasting commissioning events and major tests. This can also help for deciding outage times for major parts and plants. The estimation techniques used for this type of prediction are same as that of short term electric forecast. But, it would be seen that, the medium term electric load prediction sensitivity on power system operations will be less than the short term electric load prediction.

C. Short Term Electric Load Prediction

Short Term Load Forecast (STLF) is for span of nearly a day to a week. Short term electric load predicting helps in estimating the load flows and for making decisions which prevent over-loading. The implementation of such timely decisions leads for the improvement of the network reliability and the reduced equipment failures as well as blackouts. Furthermore, short term electric load forecasting plans several utility processes such as fuel purchases, generation, security analysis and maintenance. The main predicting errors lead to extreme conventional scheduling or excessive risky scheduling which make heavy penalties economically.

The short term electric load predicting is essential for forecasting economically of the generation capacity. A good example about the worthiness of load forecasting and its accuracy is a rise of 1% in predicting the error caused an estimated rise of ten million pounds for operation for an electrical utility in United Kingdom [5].

D. Very Short Term Electric Load Prediction

The time span of this type of forecasting lies between single digit to several minutes in dozens. As the predictions have very short time, it will be easy to monitor the varying load frequency which are weak and functions of the economic dispatch for the energy management systems. Very short term electric load prediction can achieve the purpose of the real time control and for security evaluation [6].

E. Short Term Electric Load Prediction Importance

STLF plays a vital role in the preparation of economic and reliable for a smart power system. Major objective of STLF is for providing load forecasting of generation scheduling, evaluation of the security at any time of the power system and dispatcher information timely. The main function of the STLF is to arise the functions of scheduling which determine the extreme economic commitment of the generation sources considering the operational constraints, reliability requirements as well as equipment limitations. For a hydro system generating electric power, the load forecasting is important for the hydro scheduling function for determining the discharges optimally from the reservoirs. For a thermal system, the load forecasting is required for unit commitment to determine minimum cost for the start-up and shutdown of units. For mixed thermal and hydro system, the load forecasting is required for the coordination of hydro-thermal for planning the hourly operation of several resources to reduce the production costs [7], [8].

In section II, various Support Vector Machine (SVM) forecasting techniques considered for forecasting are discussed. In section III, various performance metrics and in section IV, the results of various SVM techniques presented in section II are evaluated based on performance metrics. The best SVM technique based on the performance metrics is proposed for electric load forecasting.

II. SVM TECHNIQUES FOR FORECASTING – A CASE STUDY

In machine learning techniques, there are supervised and unsupervised learning techniques where Support Vector Machine (SVM) techniques used in this paper for electric load forecasting come under supervised learning technique. The supervised learning techniques are connected with algorithms which are learned to analyze the data being utilized for classification and regression analysis.

SVM is a method which is discriminative to bring the computational learning theory with the help of previously known methods for linear discriminant functions as well as optimization.

SVM has been introduced by Vapnik [9] for solving the tasks like density estimation and pattern recognition. The approach was developed depending upon the theory of statistical learning. But, most traditional models like neural networks implementing empirical risk for minimization principle, SVM tries to implement the minimization principle for structural risk so as to seek in order to minimize interval term and training error. However, it resulted in good performance for generalization. Because of the good properties like selecting models automatically, training with quadratic programming where global best solution is existed and also having good ability for small samples to learn [10].

In the given dataset for training $(x_1,y_1), (x_2,y_2),\ldots,(x_n,y_n)$ where x_n are the input vectors and y_n are the corresponding or desired outputs, the output is given for solving the optimization problem as

$$\min_{\omega,b,\varepsilon,\varepsilon^*} \frac{1}{2}\omega^T\omega + C\sum_{n=1}^{t}\left(\varepsilon_n + \varepsilon_n^*\right) \tag{1}$$

$$\text{subject to } y_n - \left(\omega^T\phi(x_n)+b\right) \le \in + \varepsilon_n^*,$$
$$\left(\omega^T\phi(x_n)+b\right) - y_n \le \in + \varepsilon_n,$$
$$\varepsilon_n, \varepsilon_n^* \ge 0$$

where x_n is to dimensional space for the function ϕ, ε_i^* is for the higher or upper training error and for the lower it is ε_i subjected to insensitivity tube-$\left|y-\omega^T\phi(x)+b\right| \le \in$. The parameters controlling the quality of the regression are width of the tube $\in$, error cost C and ϕ, mapping function.

A. Primal formula for linear SVM regression

For finding linear function

$$f(x) = x^{|}\beta + b \qquad (2)$$

Function is to be ensured flat, and find the f(x) for nominal value ($\beta^{|}\beta$) which can be formulated to minimize for convex optimization problem.

$$J(\beta) = \frac{1}{2}\beta^{|}\beta \qquad (3)$$

All the residuals subjecting to have less than ε and can be written in equation form as

$$\left| y_n - \left(x_n^{|}\beta + b \right) \right| \leq \varepsilon \qquad (4)$$

It is not so possible that function f(x) will exist for satisfying all points for these constraints. The consideration of infeasibility constraints leads for the introduction of slack variables ε_n and ε_n^* for every point. This is same as concept of soft margin in the SVM classification. As the slack variables will allow the errors in the regression for existing values of ε_n and ε_n^* but still satisfying the necessary conditions.

With the inclusion of slack variables, the objective function leads to which is called primal formula given by [11]

$$J(\beta) = \frac{1}{2}\beta^{|}\beta + C\sum_{n=1}^{N}\left(\varepsilon_n + \varepsilon_n^* \right) \qquad (5)$$

Subjected to constraints as stated for (1).

B. Dual formula for linear SVM regression

The problems which are described previously for optimization are simpler in computation for solving its Lagrangian dual formulation. The dual problem solution will provide lower bound of the minimization problem to the solution. The best values of the dual and primal problems are not necessarily to be equal and the difference between them is duality gap. But, as the problem becomes convex and tries to satisfy the constraint conditions, value of the best solution is given to the original problem with the help of dual problem solution.

The dual formula can be obtained by constructing Lagrangian function with the introduction of non-negative multipliers α_n and α_n^* for every observation from primal function which leads to dual formula where minimization is

$$L(\alpha) = \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\left(\alpha_i - \alpha_i^*\right)\left(\alpha_j - \alpha_j^*\right)x_i^{|}x_j + \varepsilon\sum_{i=1}^{N}\left(\alpha_i - \alpha_i^*\right) + \sum_{i=1}^{N} y_i\left(\alpha_i^* - \alpha_i\right) \qquad (6)$$

$$\text{subject to } \sum_{n=1}^{N}\left(\alpha_n - \alpha_n^*\right) = 0$$

$$0 \leq \alpha_n \leq C; 0 \leq \alpha_n^* \leq C$$

The parameter β can be described completely as a linear combination for the observations during training with the equation

$$\beta = \sum_{n=1}^{N}\left(\alpha_n - \alpha_n^*\right)x_n \qquad (7)$$

The function f(x) then can be stated as

$$f(x) = \sum_{n=1}^{N}\left(\alpha_n - \alpha_n^*\right)\left(x_n^{|}x\right) + b \qquad (8)$$

C. Primal formula for non-liner SVM regression

The linear model cannot be adequately described in some of the regression problems. The Lagrange dual formulation in such cases will allow the described technique previously for extending to the non-linear functions.

D. SVM alternative names

Sparse kernel machines is the other name for SVM. These methods forecast based upon the linear combinations of kernel function which is to be evaluated at training points. So thin that all pairs which are training points cannot be used. The other name for SVM is maximum margin classifiers.

E. Techniques utilized mathematically

The techniques used mathematically for SVM are linearly separable and non-linear separability case. For a linear separability case, an suitable non-linear mapping for a higher dimension can be separable always in two categories by hyperplane. Whereas in non-linear separability case the data which is preprocessed for representing in higher-dimensional space than the original space is to be handled. The computation overhead can be reduced by Kernel trick.

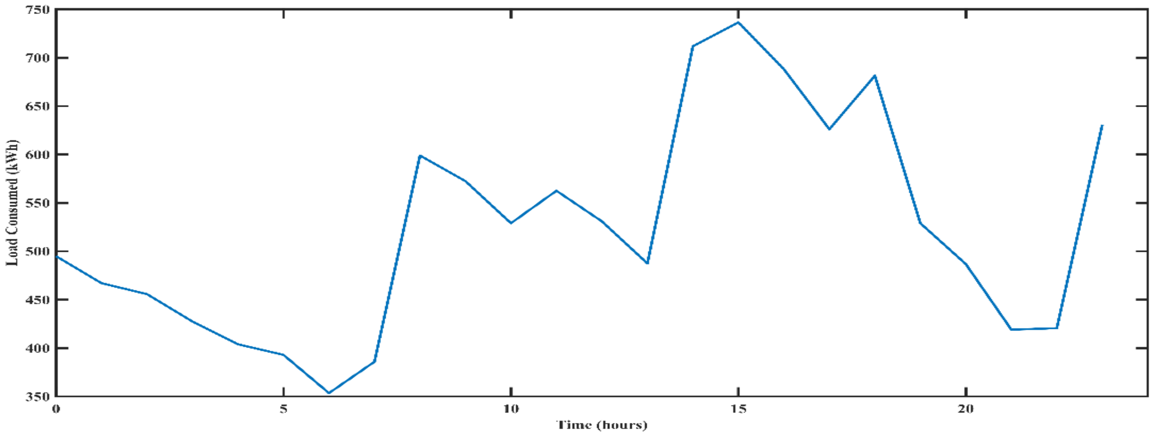

Fig. 2. Load considered for Forecasting

The model used for SVM is illustration of examples as points in space which are mapped within the same space to predict. These belong to section depending upon which side they fall.

A real time electric load data has been considered as the dataset for forecasting considering a working day data for electrical load forecasting as shown in Fig. 2.

III. PERFORMANCE METRICS

The forecasting result does not state which method is accurate for selecting the forecasting method for which different performance metrics can be used, but no one has identified a common method in standard. So, we have to utilize performance metrics for understanding the method and its characteristics. In this paper, two performance metrics for forecasting are used where each of them highlights in different scenarios. They are Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) which are expressed as

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2} \quad (9)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|y_i - \hat{y}_i\right| \quad (10)$$

where $\hat{y}_i$ is the forecasted and y_i is the actual values. The performance metrics are smaller then they indicate the method is more accurate. The prediction speed and training time are also taken into consideration for evaluation purposes.

IV. RESULTS

Different SVM techniques like linear, quadratic, cubic, gaussian, medium gaussian and coarse gaussian SVM are used for forecasting electric load which has been consumed in a day has been considered. The comparison of different SVM forecasting methods is illustrated in Table - I.

The figures from 3 to 8 report the forecasted load when applied with different SVM techniques. In each and every figure the actual load data with respect to forecasted load data is shown for a better comparison.

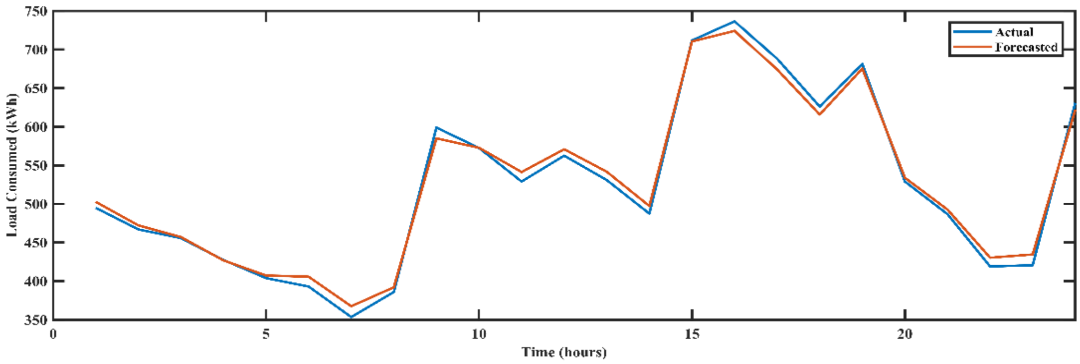

Fig. 3. Load forecasting using linear SVM

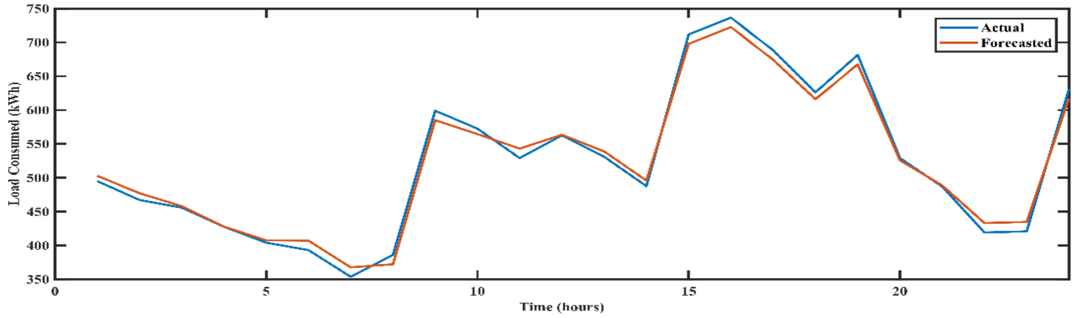

Fig. 4. Load forecasting using quadratic SVM

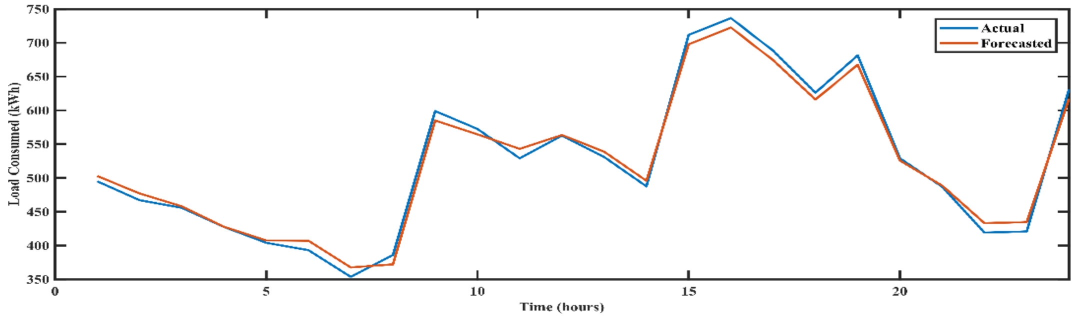

Fig. 5. Load forecasting using cubic SVM

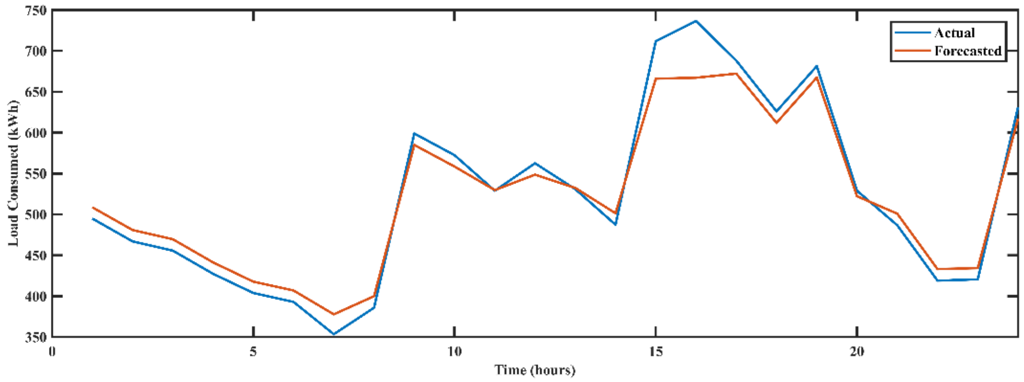

Fig. 6. Load forecasting using fine gaussian SVM

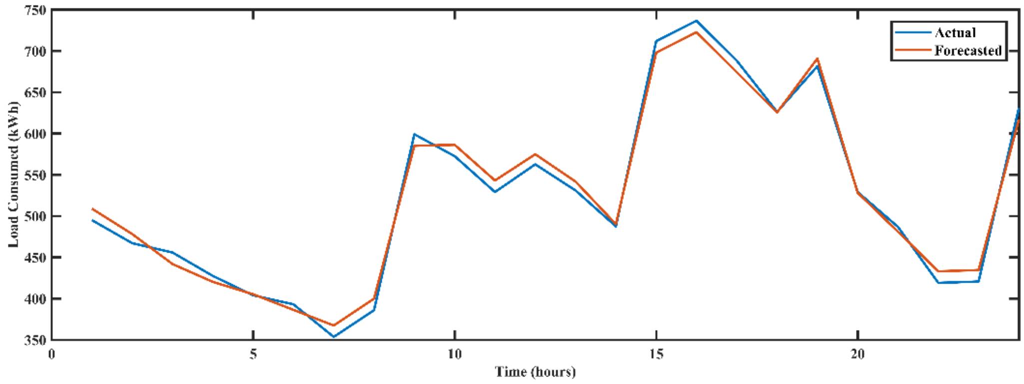

Fig. 7. Load forecasting using medium gaussian SVM

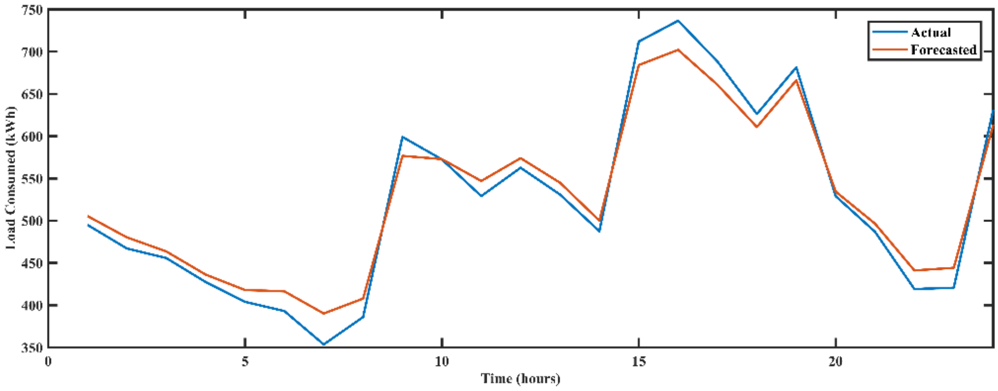

Fig. 8. Load forecasting using coarse gaussian SVM

TABLE - I: Comparison of the different SVM Methods

SVM Model	RMSE	MAE	Electrical Load (kWh)
Linear	10.04	8.36	12654.2
Quadratic	12.62	10.86	12586.1
Cubic	16.51	14.28	12639.8
Fine Gaussian	35.38	28.23	12684.9
Medium Gaussian	38.32	26.21	12632.9
Coarse Gaussian	104.42	86.30	12551.8

The electrical load (kWh) in table I illustrates the forecasted electrical load by using that particular SVM model for the day.

V. CONCLUSION

In this work, various SVM forecasting techniques for hour-ahead electric load were presented. This forecasting system uses the dataset for training so as to precisely estimate the electrical load consumed. From the comparison based on the performance indices, it can be shown that the forecasting system which is proposed can estimate the electrical load. The feasibility and accuracy of the forecasting system which is proposed is then validated. The errors are due to the number of input and training variables used for forecasting. The proposed system when compared with different techniques are evaluated on the basis of performance indices.

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