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An Improvement in Load Forecasting Model using Parametric Tuned Support Vector Machine (SVM) Kernel Based Functions

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***Abstract*—** Short term load forecasting (STLF) has gained huge interest among researchers because of its applications in economics, reliability, unit commitment (UC), economic dispatch (ED) and hydro-thermal coordination (HTC) of power systems. The aim of this study is to find an accurate algorithm as it is very important for the prediction of accurate load forecast. Support Vector Machine Regression Model (SVM-R) using different kernels i-e linear, polynomial and gaussian has been used and each kernel function effectiveness and its performance has been examined on real time series using ISO-New England utility data. LibSVM using R language is utilized in this research to employ SVM-R Model. Artificial Neural Network (ANN) is utilized to compare and check the effectiveness of proposed model and its performance by considering least Mean Absolute Percentage Error.

***Keywords*—** Short term load forecasting (STLF), Support Vector Machine, kernel function, time series, Artificial Neural Network (ANN).

I. INTRODUCTION

Forecasting future load has gained importance because power system operation and management of the future will in turn needs decision-making of a character primarily dissimilar than the methods used currently. It needs to be a bit more quicker, decentralized and should have the ability to treat any kind of uncertaininty. These dissimilarities as a result will eventually need many different methods of forecasting closely integrated with the decision- making process.

As an important factor in prediction of future loads, power system of the future will need several additional capabilities. Accuracy is another important factor and has drawn a lot of research interest among researchers that an accurate short term load forecasting (STLF) is very useful and the main function of it is to make schedules for generation, transmission and daily operational activities of power grids. Failure in above or poor forecasting of load not only cause increase in operational cost but also misleads the planners involved in planning process. As STLF is extremely helpful for decision makers to make accurate forecasts and make plans regarding maintenance, economic unit allocation, unit commitment, economic generation allocation, secure analysis of security systems and daily operational activities. There are certain factors which influence the load as it has been noticed that load gives different patterns mainly due to metrological parameters, special events, working or holidays. Usually it has seen statistical approaches give better results on ordinary days and can forecast very well, but the drawback is their capability to examine the load property. In order to overcome these inabilities different machine learning techniques in combination with other models are used these days. In order to handle these issues proposed model has been introduced and the main objective of this model is to overcome these challenges and also helps in reducing the interaction time. The method advised here is a hybrid technique using support vector machine in combination with statistical models.

II. LITERATURE REVIEWE

With the rapid increase in electic load and consumption every year, researchers and economic strategists show keen interest in load forecasting field for accurate load forecasting. In this section a brief literature survey has been presented mainly focussed on STLF and are reviewed according to techniques that are developed during past few years .

There are many techniques/approaches available in the load forecasting field. A.S.Ahmad et.al [1] classified these techniques into three, which are Engineering Method, Statistical Method and Artificial Intelligence (AI) Method. Statistical methods show good results on ordinary days but their inability to examine load properly and lack of accuracy [1][2]. These methods are not widely used these days. Similarly engineering methods [2] show drawback in terms of lack of input information. So, in order to ovrcome these shortcomings the technique most commonly used these days is Artificial intelligence (AI) which includes Artificial Neural Network (ANN) and Support Vector Machine(SVM) [1][2][3].

Nahi Kandil et. al. introduce ANN model on data set for time series load forecast. The ANN is particularly used as it is simple and robust and because of these attributes it is preferred for forecasting models but the drawback of ANN is its large time consumption in learning stage. The training data has to face several data layers in order to prepare it for forecasting stage. In addition to extra time consumption in learning stage, the neural network model does not provide specific information about its convergence. Therefore specific count of neurons are not well known in advance due to which over fitting and under fitting problems occur [4].

Srinivasan et. al. presented a combined neural and fuzzy approach in which rapid increase in load was analyzed and load growth effect was incorporated. The need for the development and execution of a hybrid fuzzy based one-day ahead load forecaster was discussed which comprised of three steps.In Ist step, the growth trend was analyzed and by making some necessary compensation historical load was updated to the current load demand. In 2nd step Kohonen's self-organizing feature mapping (SOFM) was used to map the load profile. Then by using auto associative memory of ANN the current day load prediction was achieved. Metrological parameters has taken into consideration by a fuzzy parallel processor while making daily predictions. The proposed model indicates better results by showing good forecasting accuracy [5]. Ying Chen et.al. presented a modified technique to improve forecasting accuracy through neural network. The data of previous day with 24 hour samples were used to anticipate load of next day. The noisy nature can be improved with the introduction of high frequency and precipitation components. These two components are added to neural network algorithm as inputs for better forecasting results. This technique was also tested on short term and holidays load forecast and gave better results [6]. M. A. Abu El Magd et. al. proposed a hybrid method by combining ANN and time-series model for anticipating hourly heaps of week days. Two strategies were used in this paper, the 1st depends on relationship/auto-connection coefficient to choose the input factors and plan a measure to choose training sets and the 2nd was creating two calculations for modifying the predictions of occasions, weekends and Mondays. Contrasted with different methodologies, the exactness of the proposed show is incredible [7]. Azzam ul Asar et. al. suggested a hybrid approach by combining the ANN with other intelligent techniques for attaining better accuracy in forecasting problem. ANN and other conventional techniques when used alone didn't give better results due to complexity and non linear nature of load. A multiagent approach by realizing ANN with fuzzy logic was used and results obtained gave better forecasting accuracy and less computational time [8]. Ling et. al. presented a combined model using the addition of improved Genetic algorithm and neural fuzzy logic network. To locate ideal number of fuzzy principles, Genetic algorithm was utilized while fuzzy logic available here was used to manage variable data in stack anticipating and this technique by some ways needs to defeat the regular issues of meeting to nearby minima and affectability to introductory values [9]. Hong-ze li et.al. proposed a new model for estimating future load by using generalized regression neural network (GRNN) in combination with a optimization algorithm called fruit fly (FOA). The spread paramater value for GRNN was automatically selected by FOA. The results attained shows that proposed hybrid technique inspite of small training samples gave smaller MAPE and MSE and better forecasting accuracy as compared to other techniques [10].

Support Vector Machines (SVMs) are the most recent dominant methods used for both non linear and linear data classification/ regression problems [5]. Support vector machine has become more popular among researchers because it uses non linear mapping by converting a data into high dimension (feature) space and then making decision boundaries also called hyper planes using linear functions in new space.

Amit Jain and B.Satish presented a modified technique to improve forecasting accuracy through SVM by clustering the data at pre-processing stage. The data was clustered by setting a threshold value for testing and training patterns of daily average load. The SVM technique implented on both clustered and non clusterd data inputs gave better forecasting results for clustered data [11]. Jae H.Min and Young-Chan Lee used Support vector machine for Bankruptcy prediction problem. Tuning of parameters were done to get the results with less prediction errors. The results obtained show that RBF kernel gave best results on both training and holdout (testing) data as compared to conventional statistical models [12]. Hwang showed the improvement of STLF master framework called LoFy which comprised of three models i.e. day by day, week after week and uncommon days estimating models. As it is currently a well-established truth that there is no single estimating strategy, which ensures exact outcomes throughout the day. Also, the determining consequences of a specialist are better than that of any hypothetical strategies [13]. Ming-Guang Zhang tested support vector machine on sampled data and found better results in comparison with ANN. The SVM works on the training samples and provide separation of data by introducing higher dimensions. The data is trained with load and temperature inputs.The results of SVM regression techniques gave better accuracy and less computational time [14]. The drawback of ANN for selecton of appropirate architecture is replaced in support vector machine by the dilemma of selecting a suitable kernel function [15].

There are certain factors that affect/influence the load and must not be neglected while predicting future load. M.U. Fahad and N.arbab categorized these factors as time factor, economic effect, weather, special events and emphasizes the consideration of these factors while predicting future load. It was observed that "Time of Day" is actually a crucial factor and load curve basically depends on it. Similarly it also depends on day of week , month and season [16]. Another important effect while considering future load is economic effect . Developed and undeveloped countries load curve was compared and observed that highest peak comes from 1100 to 1600 in developed countries while in undeveloped countries it is noticed after 1800 and by adopting "Time of use pricing" load curve peaks can be reduced [17].

Another important factor for load prediction is weather. It has been observed in order to minimize the forecasting error weather must be considered as it is an independent factor in prediction process [18] [19]. In this paper factors affecting the laod forecasting has been analysed and SVM-R kernel based model is proposed for short term load forecasting considering these factors which includes metrological parameters, holiday period, real time data, past data etc.

III. METHODOLOGY

In this paper the technique/method used for predicting future load is Support Vector Machine. Support Vector Machine –SVM (Vapnik, 1979) is used for both nonlinear and linear data classification/regression [5]. The main feature of SVM algorithm is that it uses "nonlinear mapping" which means it converts data used originally in training process into new higher dimension feature space. The data of two different classes is speparated from one another in this new dimension using optimal linear hyper-plane (LHP). The SVM decide this LHP using margins and support vectors, this hyper-plane is also called decision boundary. Hyper-plane separates data into two different classes. The goal is to find out best separating hyper plane (SHP) which gives maximum possible margin between two classes and by using Langrangian algortithm we can get optimized separating hyperplane. SVM-R is obtained by

$$R_m = v^T x + a \tag{1}$$

Where R_m is a forecast variable, v stands for a vector which represents weight at training sample x & a shows bias value. The separating hyper-plane maximum value is given by

$$SHP_{Max} = \frac{2}{\|v\|} \tag{2}$$

Hence, the maximum margin separating hyper plane can be constructed by solving the following Primal optimization problem. After minimizing v SVM-R sets it's v and a which follows with limits as given in equation

$$SHP_{Min}(v, e_d) = \frac{1}{2}\|v\|^2 + \frac{1}{2}\beta\|e_d\|^2 \tag{3}$$

Subject to

$$R_{mi} = v^T x_i + a + e_d, \ \forall i \tag{4}$$

The two main reasons due to which Langrangian function is applied are

- This allows to easily handle constraints
- The dot product is shown by training data between vectors. This arrangement introduces αi (Lagrange multiplier) to form a minimization problem for every constraint. Lagrange function as it deems both the minimizing term and constraint equation is used to find out the solution of the problem in equation (3).

$$LAG = SHP_{Min}(v, e_d) - \sum_{i=1}^{n} \varphi_i (v^T x_i + a + e_d) \tag{5}$$

Making Lagrange gradient w.r.t v, a, e_d and φ_i to zero, following equations can be obtained respectively

$$\frac{\partial LAG}{\partial v} \rightarrow v = \sum_{i=1}^{n} \varphi_i (x_i) \tag{6}$$

$$\frac{\partial LAG}{\partial a} \rightarrow v \sum_{i=1}^{n} \varphi_i = 0 \tag{7}$$

$$\frac{\partial LAG}{\partial e_d} \rightarrow v\varphi_i = \beta \tag{8}$$

$$\frac{\partial LAG}{\partial \varphi} \rightarrow v v^T x + a + e_d - R_{mi} = 0 \tag{9}$$

Hence, by solving equations 6-9 we can get appropriate values φ and a so SVM-R problem can finally be written as,

$$R_m = \sum_{i=1}^{n} \varphi_i K(L, L_i) + a \tag{10}$$

IV. PROPOSED SVM-R KERNEL BASED MODEL

Fig.1 shows the steps of proposed model which are discussed one by one. First step; in this step the SVM-R model needs input training vectors which contain system load data as a class variable and the meteorological parameters such as dry bulb, dew point, demand, price sensitive demand and hours of a day are its attributes.

Second step; in this step the data is analysed at pre-processing stage and to make the model effective and for accurate load forecasting the input data used must be in same units. There are number of thechniques and methods available for data normalization. In this research the techniques used for normalizing the input data is Min-Max-Scaling [3].

Third step; fine tune the SVM-R model by selecting the best parameters i.e (1) Cost Parameter (C) for linear kernel, (2) Cost parameter (C) and gamma parameter for radial kernel and (3) for polynomial, kernel function parameters c and d has investigated.

In fourth and fifth step; the model is trained according to the training input set and its accuracy is tested on testing data set which contains data of 30 days.

Sixth step; using mean absoluter percentage error (MAPE) the accuracy is being tested between actual real time data and predicted electric load and in the last seventh step; the comparative accuracy between SVM-R moadel and ANN has been discussed interms of MAPE.

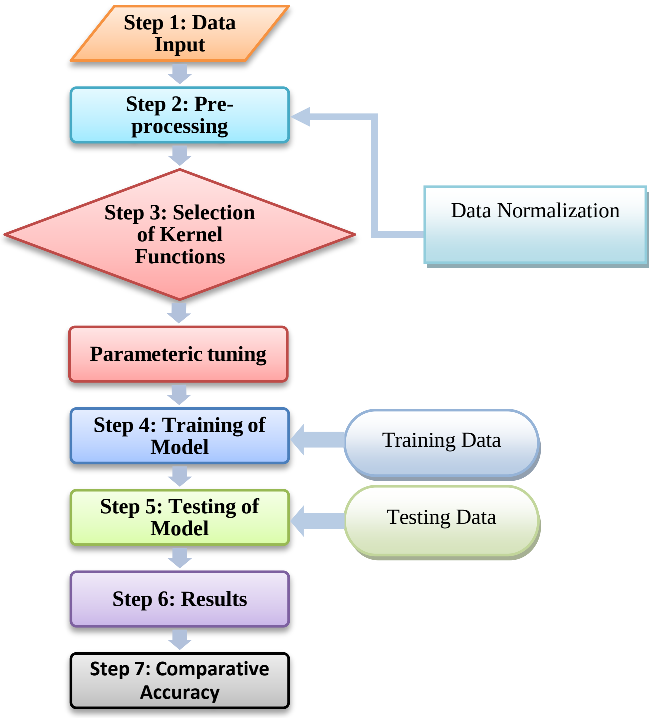


Figure 1. Proposed model

V. DATA SET

The data of ISO New England for our case study in the time span of (2004-2008) is used in this research and thhe data set is available online for researchers which can be accessed easily [6].

The data has been analysed at pre-processing stage and divided into two sets. One is Training set and the other is testing set. Training set includes data from (Jan 2004-Nov 2008) and is used for taining the proposed model while testing set includes data from (Dec 2008) and is used for monthly ahead forecasting comparison.

The sample size of train set used for trainimg the model is (43105) hrs of data while testing set comprises of (744) hrs of data which is used to evaluate/check the potential of the proposed model by comparing the forecasting load vs system actual load. It has been investigated for the best SVM-R parameter so that the least error interms of MAPE could be achieved.

As discussed earlier the most important factor in the load forecasting is season variations. To make accurate load forecasting we have split and arranged the data in five scenarios according to seasonal variation and furthemore in working or weekend period that includes

Scenario A: Spring (Mar-May) Data sample for train set is (10296) and test set is (744).

Scenario B: Summer (Jun-Aug) Data sample for train set is (10296) and test set is (744).

Scenario C: Autum (Sep-Nov) Data sample for train set is (10200) and test set is (720).

Scenario D: Winter (Dec-Feb) Data sample for train set is (10152) and test set is (696).

Scenario E: Working Hours Data sample for train set is (30768) and test set is (552).

Scenario F: Weekends Data sample train set is (12288) and test set is (192) .

Each scenario has been investigated to get best SVM-R parameter so least error MAPE could be achieved.

VI. SIMULATION RESULTS DISCUSSION AND EVALUATION

The results of the experimentation are explained in this section.

A. *Forecasted Results*

After data normalization the performance of SVM-R has been investigated by using different kernels i-e linear kernel, polynomial kernel and radial kernel and the effectiveness/accuracy of predicted load is calculated using (MAPE). The predicted load curves are compared with system actual load curve to know the effectiveness of proposed model.

Table 1. MAPE Comparison of Kernel functions

	Linear	Radial	Polynomial
(MAPE)	0.216197	0.5900855	3.987059

Table 1 shows the forecasted load accuracy in terms of mean absolute percentage error of three kernels. It is clear from the above table that Linear SVM-R Kernel outclass the performance of polynomial SVM-R and radial SVM-R kernels and gives better results.

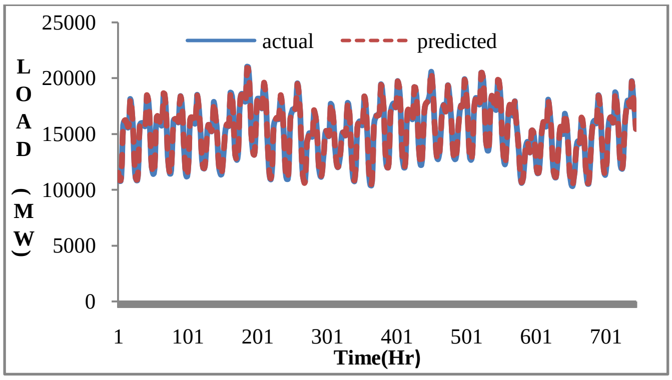


Figure 2. Comparison of Actual vs Predicted Load For Linear Kernel

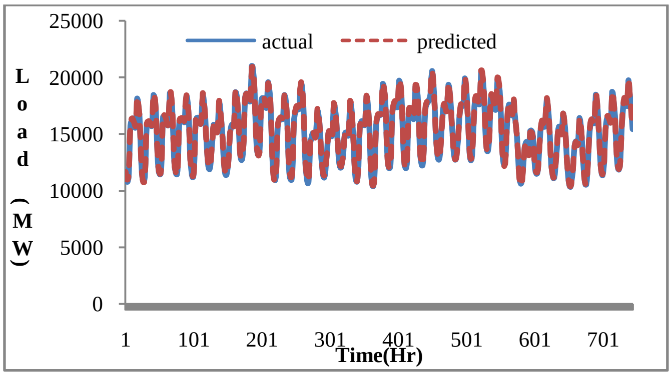


Figure 3. Comparison of Actual vs. Predicted Load For Radial Kernel

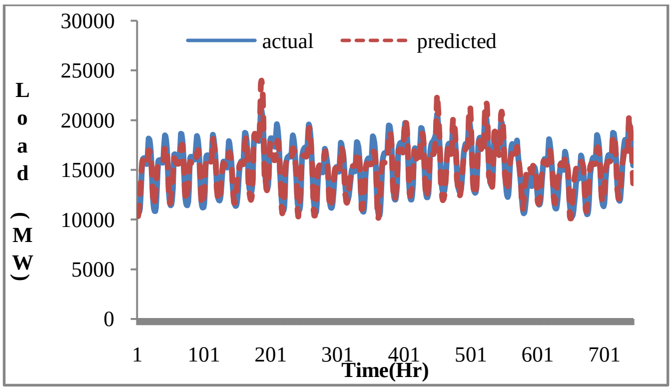


Figure 4. Comparison of Actual vs Predicted Load For Polynomial Kernel

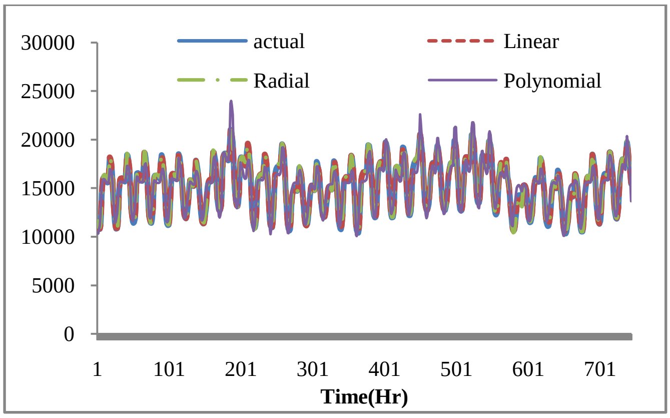


Figure 5. Comparison of Actual vs Linear,Radial,Polynomial Forecasted Loads

Fig .5 shows the actual system laod curve and the predicted load curves using the three kernels. It can be clearly seen from the above figure that linear kernel gives better results then radial and polynomial kernels

B. Parametric tuning using Cost parameter (C) for linear kernel.

The parameter used for the linear kernel is cost (C). The best performance can be obtained by fine tuning the linear kernel using several combinations of kernel parameter Cost (C). The best value of C can be obtained by using grid search technique (GS).

Fig 6. shows the best cost value which is **30** on which MAPE is **0.2149602**

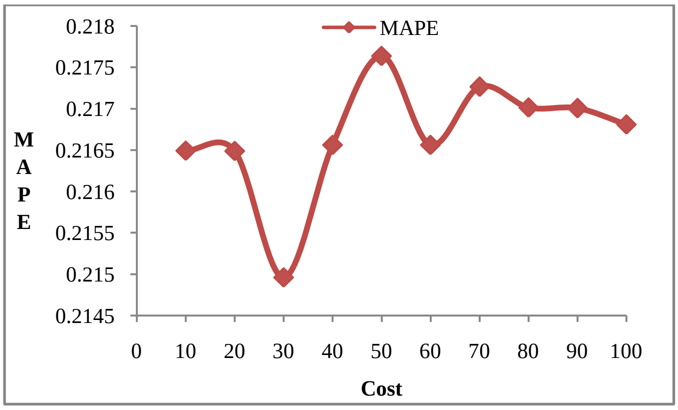


Figure 6. Parametric tuning using cost parameter(c) for Linear kernel

C. Parametric tuning using Cost parameter(C) and regularization paramer (gamma) for Radial kernel.

The parameters used for fine tuning the radial kernel are Cost (C) and gamma. The best value can be obtained by using various combinations of cost parameter (C) and regularization parameter gamma. Fig .7 shows the best values of cost (C) and gamma which are **2** and **0.5** using GS technique on which MAPE is **0.5344289.**

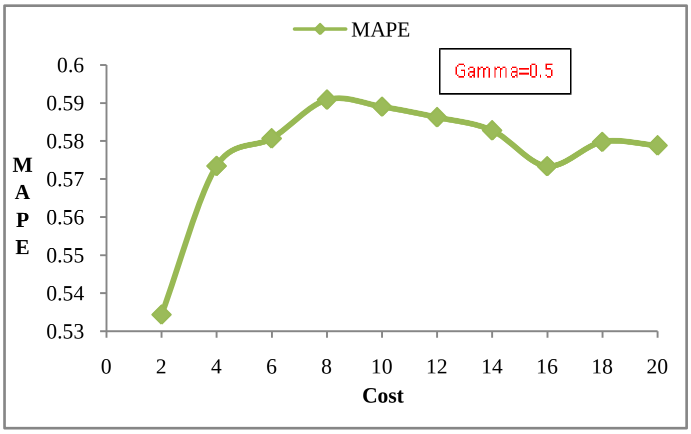


Figure 7. Parametric tuning using cost parameter(c) and regularization parameter (gamma) for Radial kernel

D. Parametric tuning using Cost parameter(C), regularization parameter (gamma) and d for Polynomial kernel.

The effect of using parameters for fine tuning the polynomial kernel can be seen in fig.8. It is clear from the fig below that using best optimal values of Cost ,gamma and d which are **15**,**0.5** and **3** the minimum value of MAPE is **3.965224.**

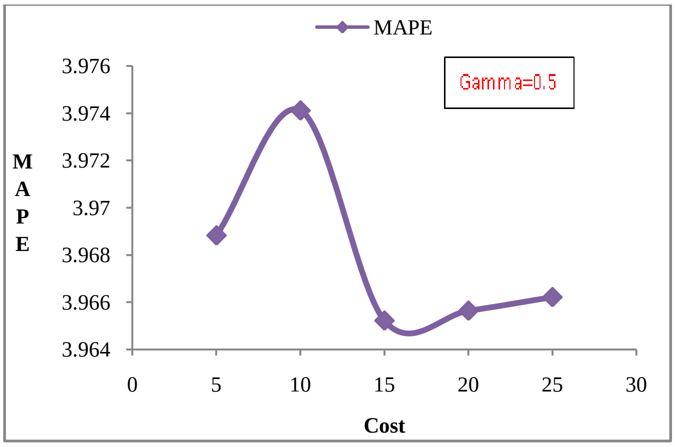


Figure 8. Parametric tuning using cost parameter(c) ,regularization parameter (gamma) and d for polynomial kernel

Table.2 below shows the optimal combination of parameters used for linear,radial and polynomial kernel.

Table.2.Optimal combination of parameters

	Linear		Radial			Polynomial			
	C	MAPE	C	γ	MAPE	C	γ	d	MAPE
Data	30	0.21496	2	0.5	0.5344289	15	0.5	3	3.965224

E. Forecasted result using ANN

Artificial neural network is widely used in machine languages and has a very good forecasting accuracy. It gives excellent forecasting accuracy in time-series load forecast..In this paper for comparison purpose we use back propagation artificial neural network (BPNN).

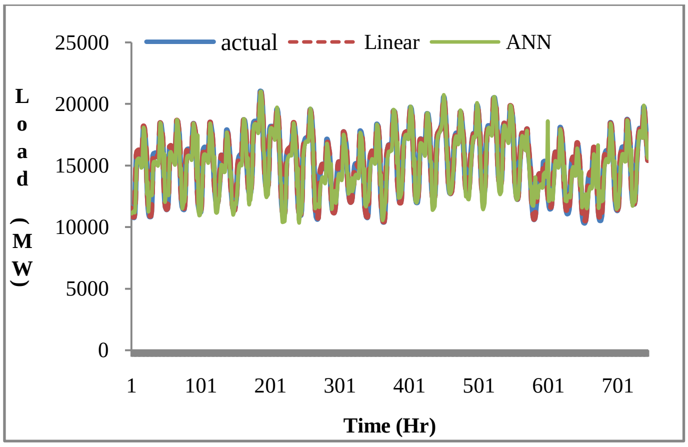


Figure 9. Comparison of Actual vs Proposed SVM-R Linear Vs ANN Forecasted Loads

The comparison of MAPE for load forecast between SVM-R and ANN in table.3 shows extraordinary performance of SVM-R model. Artificial neural network gives some of disadvantages such as over learning, architecture selection ,loacal minimal point and type over depending.

Table 3. MAPE Comparison of SVM-R vs ANN

	Linear	Radial	Polynomial	ANN
MAPE	0.2149602	0.5344289	3.965224	4.1858331

F. Comparison of results.

Fig. 10 shows the SVM-R linear kernel gives the better results in terms of mean absolute percentage error (MAPE) i-e 0.2149602 as compared to radial and polynomial having MAPE of 0.5344289 , 3.965224. As it is seen in the figure the results are also compared to BPNN model to compare the effectiveness of proposed SVM-R model and it can be observed that SVM-R model gives better results then BPNN model.

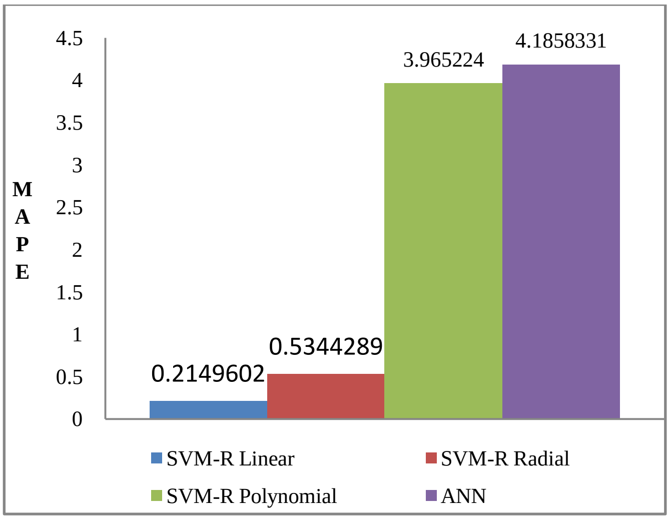
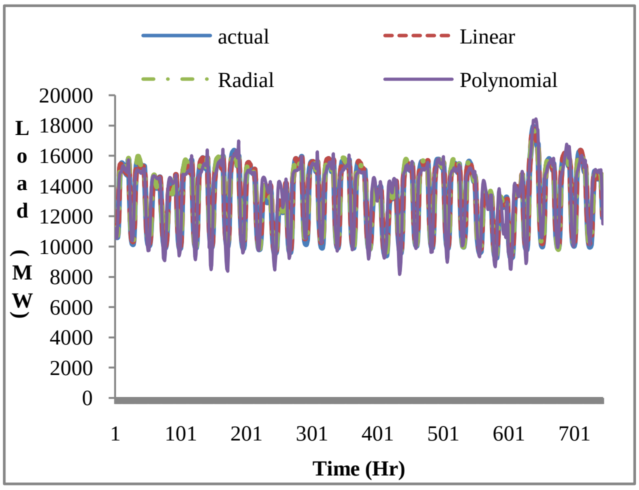


Figure 10. MAPE Comparison (Linear,Radial,Polynomial) and ANN

G. Scenario result analysis using SVM-R.

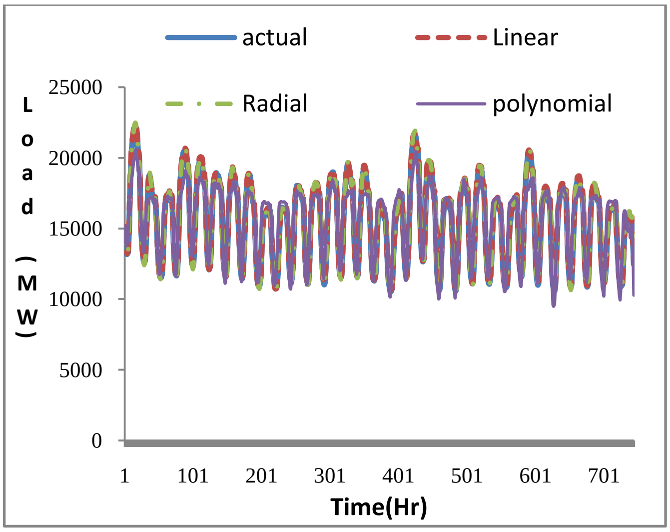
The electric load demand varies according to seasons for exmple in summer season electric load demand is higher as compared to other seasons. To make load forecasting more accurate and precise we have divided the data into six scenarios as discussed earlier. Fig.11(a-f) below shows the comaprison of actual vs predicted/forecasted load for scenarios



Scenario A

Figure 11(a). Comparison of Actual vs SVM-R Forecasted Loads For Scenario A

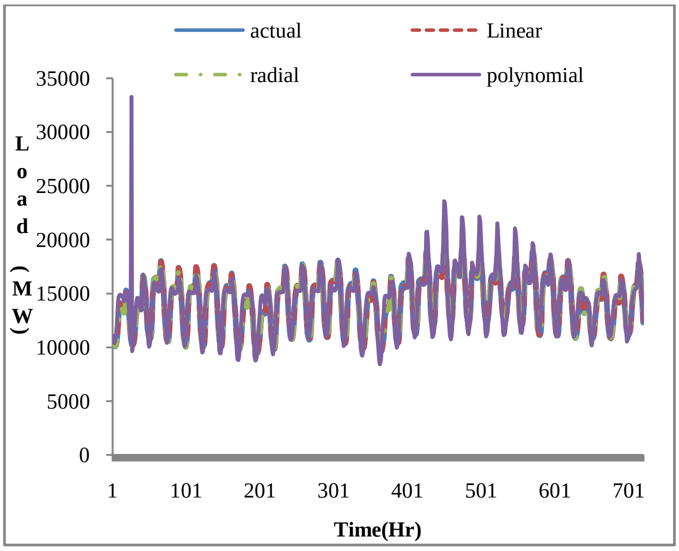
Fig.11 (a) shows actual system load data curve and predicted load curves using different kernels of SVM for data set regarding spring season i.e. Mar-May. The input data set used for training samples is 10296 and testing set is 744.



Scenario B

Figure 11(b). Comparison of Actual vs SVM-R Forecasted Loads For Scenario B

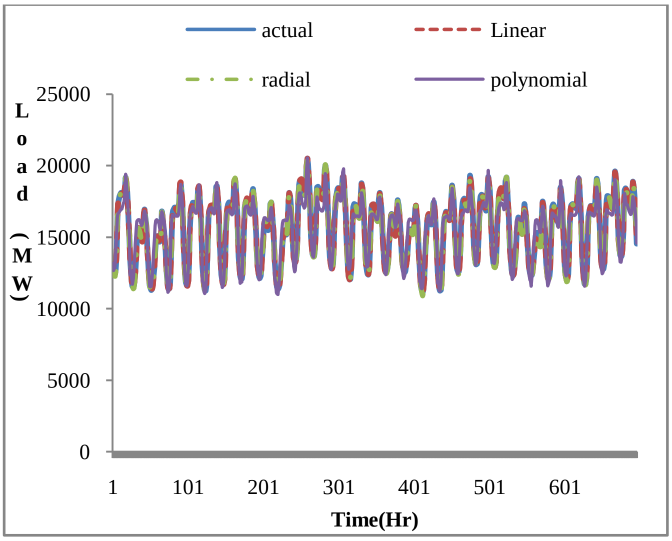
Fig.11 (b) shows actual system load data curve and predicted load curves using different kernels of SVM for data set regarding summer season i.e. Jun-Aug. The input data set used for training samples is 10296 and testing set is 744



Scenario C

Figure 11(c). Comparison of Actual vs SVM-R Forecasted Loads For Scenario C

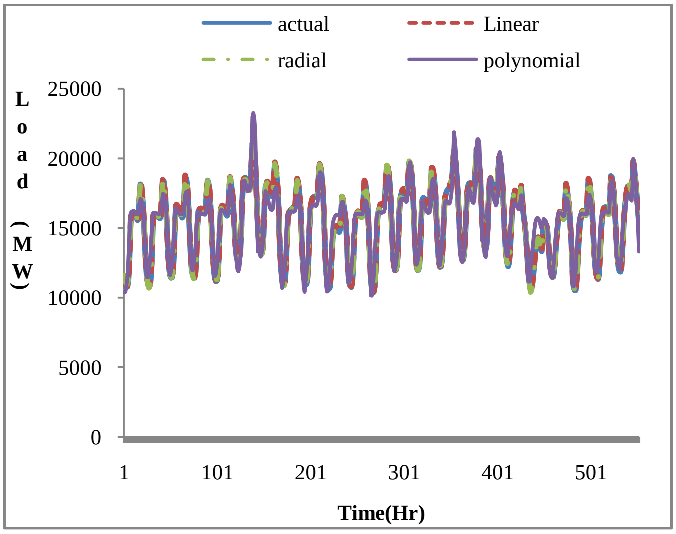
Fig.11 (c) shows actual system load data curve and predicted load curves using different kernels of SVM for data set regarding autumn season i.e. Sep-Nov. The input data set used for training samples is 10200 and testing set is 720



Scenario D

Figure 11(d). Comparison of Actual vs SVM-R Forecasted Loads For Scenario D

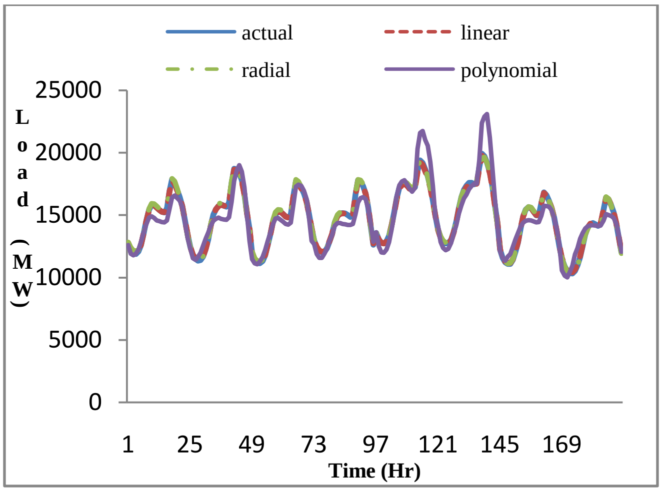
Fig.11 (d) shows actual system load data curve and predicted load curves using different kernels of SVM for data set regarding winter season i.e. Dec-Feb. The input data set used for training samples is 10152 and testing set is 696.



Scenario E

Figure 11(e). Comparison of Actual vs SVM-R Forecasted Loads For Scenario E

Fig.11(e) shows actual system load data curve and predicted load curves using different kernels of SVM for data set regarding working hours. The input data set used for training samples is 30768 and testing set is 552.



Scenario F

Figure 11(f). Comparison of Actual vs SVM-R Forecasted Loads For Scenario F

Fig.11(f) shows actual system load data curve and predicted load curves using different kernels of SVM for data set regarding weekends. The input data set used for training samples is 12288 and testing set is 192.

The performance accuracy using three kernels is shown in table.4 .It is observed from the table the difference between forecasted error is very small between linear and radial kernels. Radial kernel shows extraordinary performance for Scenario A and B while SVM-R Linear kernel gives exemplory performance for Scenario C, D, E and F then radial and polynomial.

Table 4. Scenario Wise MAPE Comparison

	Linear	Radial	Polynomial
Scenario A	0.8855717	0.68289363	4.183518
Scenario B	0.834787	0.8188903	5.080259
Scenario C	0.5324723	0.7122615	4.494134
Scenario D	0.2745534	0.4343161	3.336685
Scenario E	0.4703293	0.4804051	3.933487
Scenario F	0.3126424	0.552294	4.161799

H. Scenario result comparison.

The results shown in Fig. 12 gives the comparison between the proposed SVM-R model and ANN model. Both models proves to be good for load forecasting but the comparison between SVM and ANN shows the excellent performance of SVM model and gives better results.

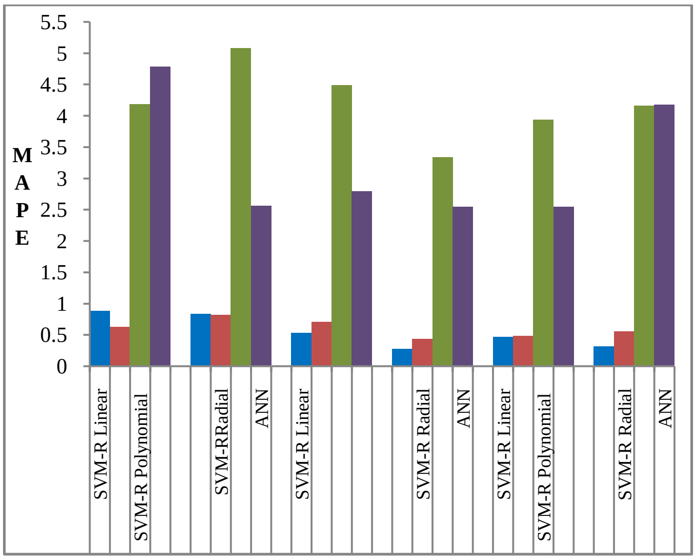


Figure 12. MAPE Comparison (Linear,Radial,Polynomial) and ANN

CONCLUSION

In this study, we have concluded that load data is highly complex and non-linear in nature. So we proposed a parametric tuned SVM-R kernel based model.

Proposed SVM-R model is implemented on ISO-New England data set. It is concluded that parametric tuned SVM-R Linear kernel having MAPE of 0.2149602 gives extraordinary performance and gives better results then polynomial and radial kernel having MAPE of 0.5344289 and 3.965224. The proposed model is then compared to BPNN model to compare the effectiveness of proposed model in terms of MAPE and it is concluded that SVM-R outclass the performance of BPNN model having MAPE 4.1858331.

In this research, we have also incorporated some of the factors that influence the load forecasting by dividing our data set in six scenarios according to seasonal variations , working hrs and weekends. Proposed SVM-R model has been implemented to select the suitable kernel for each scenario and it is concluded that SVM-R Radial kernel gives better results for scenario A and B by giving minimum MAPE values of 0.68289363, 0.8188903. Similarly for scenarios C, D, E and F SVM-R Linear kernel gives better results having minimum MAPE of 0.5324723, 0.27455345, 0.4703293, 0.3126424 as compared to radial and polynomial kernel. There is a huge scope of automatic feature selection, optimization of parameters using PSO and other hybrid techniques to further improve efficiency.

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