CHAPTER-1

LOAD DYNAMICS

1.1 Introduction

This chapter begins with load study which includes identifying the required qualities of the load models & their characteristics. Thereafter the data checks and corrections are also done to befit for the *Short term load forecasting* (STLF). Subsequently, conventional forecasting methods are discussed and casual and time series models are developed. The chapter makes a comparison of forecasting accuracy of the conventional methods and Feed forward neural networks. The study of STLF techniques emphasizes the fact that with forecasting techniques used in this study for load prediction, various load models can be developed. For these models to be considered competitive their formulation should fulfill few basic requirements and their performance should also be within certain permissible range. Some of the preferred qualities of models in the literature include fault tolerance, economy, recursiveness, adaptiveness and accuracy.

1.1.1 Fault Tolerance

The algorithm must be vigorous to the incorrect specification & imprecise data containing anomalies. The load forecasts are such that they should account for the unexpected variations, resulting from the system faults and failures, in the load data.

1.1.2 Computational Economy

Excessive emphasis on accuracy, at times, leads to complex model that would require excessive computational needs, whereas, a load forecasting method should be reasonably simpler with regard to the execution time.

1.1.3 Recursiveness

As new data containing the recent demand data and weather data, is made available, then the forecasting method should be able forecast and predict for the next step.

1.1.4 Adaptiveness

The parameters of STLF model are generally estimated from fixed data sets and precise for a particular time period ahead. New measurement data become available as the forecast time period elapses, the method should be able to move to new data sets and recompute its estimates.

1.1.5 Accuracy

The performance of STLF method depends mainly on forecasting lead time and factors such as type of model & behavior of load. It forms the basis for economic dispatch, system reliability and electricity market. It is considered to be the most important factor in the evaluation of the STLF process.

1.1.6 Automation

As per the need of the modern times, automation is being sought after in various facets of STLF process. It begins with the detection of bad load data which is transferred to the control centre by communication lines. Secondly, automation in the direct access of data to STLF system is also useful. This helps to decrease the burden of dispatcher. It could also be useful in forecasting by deciding a weight for every model to get the overall value, if several models are used to reduce the risk of individual imprecise forecasting. The interface of different load forecasting models should be easy and convenient.

1.1.7 Portability

Load profiles of different regions are usually different. Therefore, different models are used for different areas. If a general model is developed it can be used for different areas leading to the easy portability.

1.2 Load Characteristics

To develop an accurate load forecasting model, deep understanding of load characteristics to be modeled is prerequisite. Such conclusion about load behavior is obtained through statistical analysis of past load data. If different utilities experience similar weather & economic environment then they usually observe similar load behavior and minor modification require in developed load models of particular utility to suit another. Power system load supply is dynamic in nature and directly reflects its behavior in the surrounding environment due to which it can be categorized into base or standard load, a residual load and weather dependent load.

1.2.1 Base Load

This type of load is the largest section of total system load and mainly attributed to economic & business standard conditions of the service area. It usually accounts for more than two-third of the total system load. It can be classified into four different components such as;

- A major component that signifies the economic development of the service area.
- A daily load cycle which results from the daily similarity of consumer activities.
- A weekly load cycle which results from the consumption pattern of a weekday being characteristically different from other weekdays.
- A seasonal component which results from the electricity demand changes as per season changes.

1.2.2 Residual Load

This type of load generally accounts for small fraction of total system load and occurs in load modeling. It results from the behavior irregularities of consuming public as considered in Soliman et al. (1997). Abnormal behavior demands are quite difficult to predict & model; for which they are not considered in most load models. The common factors of the unpredictable load behavior range from public response to strikes, storm, public unrest, major television events, or local public holidays.

1.2.3 Weather Dependent Load

Weather effect on load is generally modeled by demonstrating load as linear regression of illustrative meteorological factors such as atmospheric pressure, humidity, temperature, precipitation, storms and wind speed, etc. While it is accepted that an exceptionally wide variety of illustrative weather variables are required to represent the weather effect because studies have shown that a few basic meteorological factors generally accounts for most of the weather dependent load.

- Temperature: Temperature effects on load pattern are not homogenous and different from one utility to another and one season to another. A decrease in temperature below room temperature during the winter season means an increase in the heating load, but an increase in the temperature above room temperature during summer means increasing the cooling load. Temperature effects are usually modeled by considering the load to be a function of the effective temperature or temperature deviation, rather than the actual temperature. This result from the realization that the general effects of the base temperature are already included in the seasonal load cycle and the only deviations from the norm will result in the load changes. In other words, each utility designs the base load according to the normal temperature of the environment, and any temperature variation will lead to changes in the load.

- Wind Speed: The cooling effect of the wind depends on the wind speed ant its temperature. Some researchers prefer to use wind chill factor as a means of representation of the wind in their models, since the wind-chill factor is strongly correlated with winter load. In summer, it takes the form of heat wave in central India, which affects the load cycle significantly.
- Humidity: A climatic variable affecting air conditioning & related load during summer is the atmospheric humidity level, whose effects are usually eye-catching when temperature is too high. The humidity effect as function of relative humidity is a considerable factor in load model by representing it as the humidity index. The temperature humidity index is a measure of discomfort level or equivalent heat stress in summer and depends on the temperature and relative humidity, and normally shows a strong correlation with summer load and only influences the load above a predetermined threshold temperature.
- Cloud Cover: It has a relatively lesser effect on the load model with respect to the previous mentioned weather factors. The literature indicates that in most cases this factor is often omitted from the load models. Low daylight can result in small rise in daytime light load and can advance the effect of night fall by some time.

1.3 Load Study

The accuracy of any forecasting technique highly depends upon load data consistency, thus load analysis is an important part of system identification. To reduce human errors in load forecasting, historical load data comprehensive study is considered with requisite permission from Northern region load dispatch centre, Delhi, India, for the electrical load data procurement with weather data from Indian Meteorological Department, Delhi centre comprised the wind speed, temperature, and relative humidity.

1.4 Load Profile

Fig. 1.1 shows the hourly load variation of a day where peak demand is frequently occurring around 9pm, where as minimum demand is usually around 4am. Most of the electricity demand/usage is from 6pm to 9pm, which is often repetitive for all days of the month.

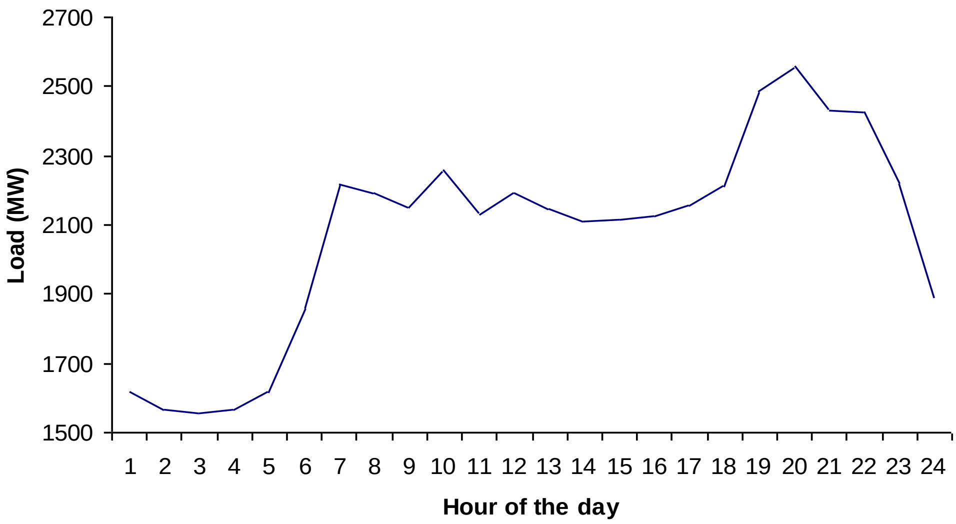


Fig. 1.1. Typical load variation of a day

Fig. 1.2 shows the nature of load variation w.r.t. the load recorded a week earlier and a day earlier with both variations having a considerable degree of similarity. The trends are repetitive over a period of 24 hours. Fig. 1.3 shows the monthly variation of the load.

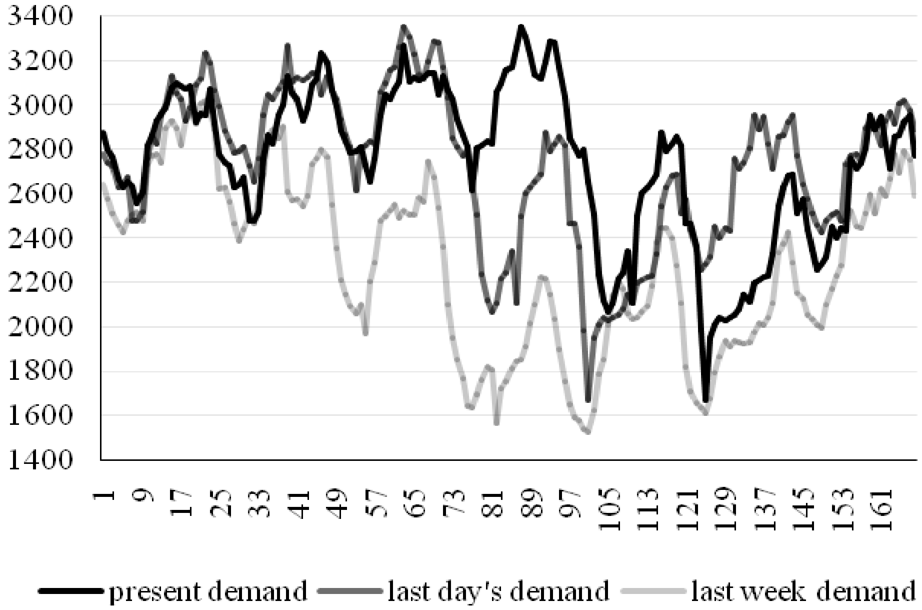


Fig. 1.2. The variation of load patterns (May 2016)

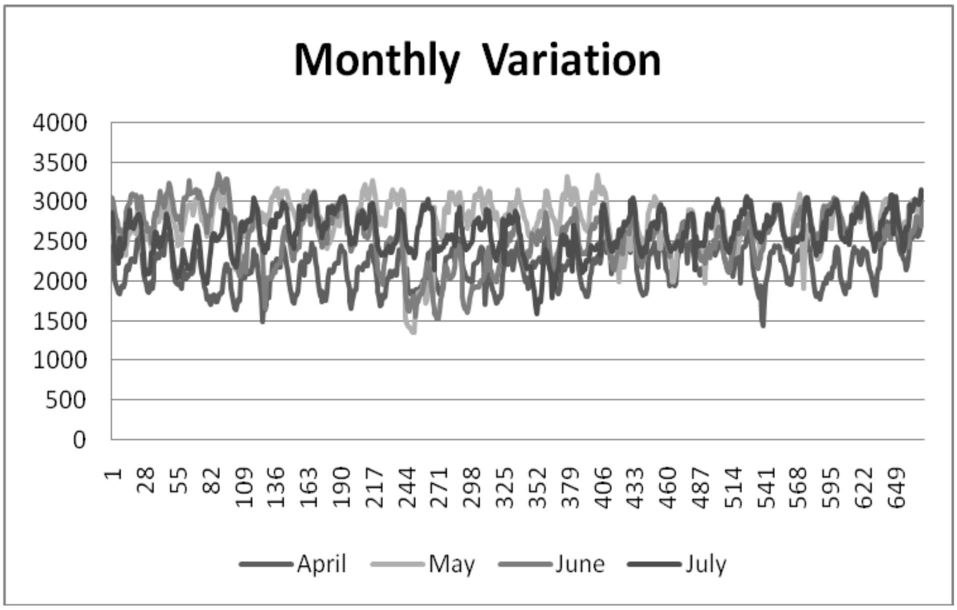


Fig. 1.3. Monthly variation of the load

1.5 Dependence on Weather Parameters

The load variation w.r.t. temperature is shown in Fig. 1.4 & 1.5. During summer, load increases with temperature rise due to continuous working of air conditioning units, where as in winter; it decreases with temperature fall nearly about seven degrees. Thus, electricity consumption increases due to air conditioning in summer and electric heaters in winter. So, a warm day in winter results in load reduction. Variation of other weather parameters humidity and wind speed is shown in Fig. 1.6 & 1.7.

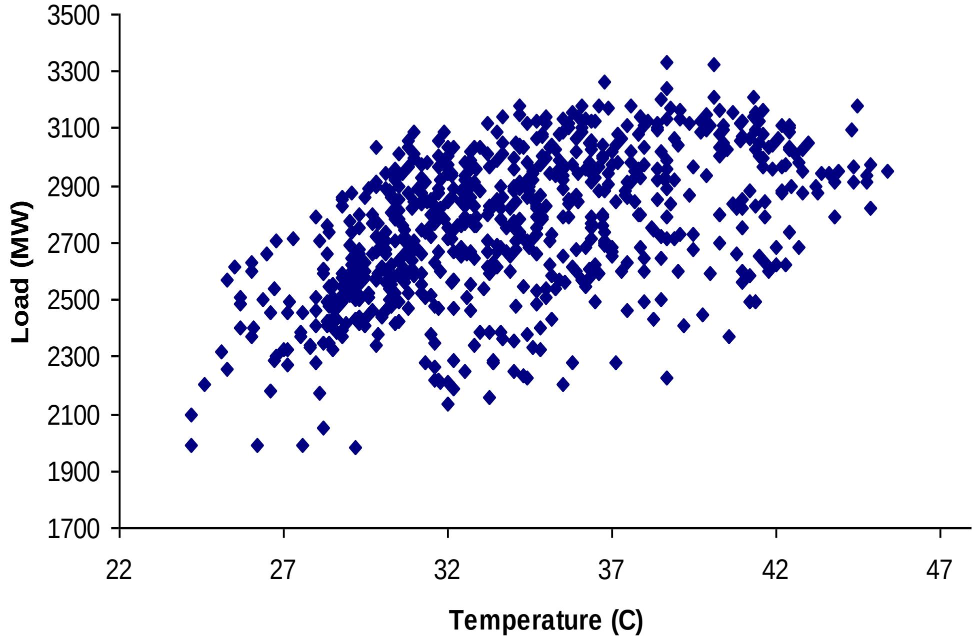


Fig. 1.4. Typical load variation versus temperature (June, 2016)

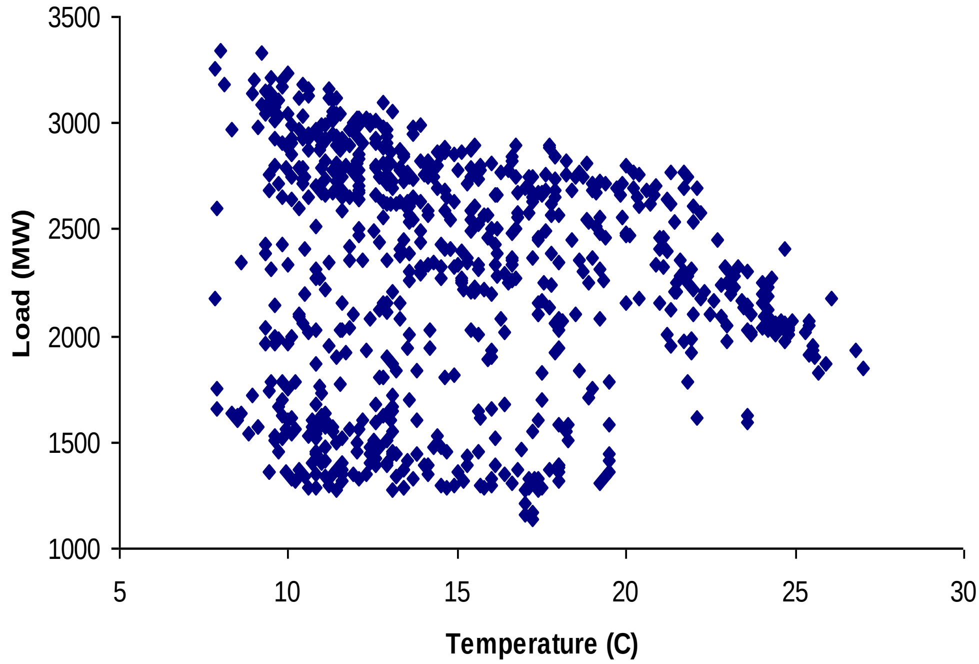


Fig. 1.5. Typical load variation versus temperature (Dec, 2016)

Data examine & correction:

- Before processing, examine all the data (2016).
- Significant growth in load is not visible.
- The present load data have a degree of randomness and wide temperature changes.

With interpolation technique filtering of load data inconsistencies is obtained. Load variations due to public holidays & festivals and, except for Saturdays & Sundays, are not considered now, but that can be taken care of by designing a different forecasting module for special days.

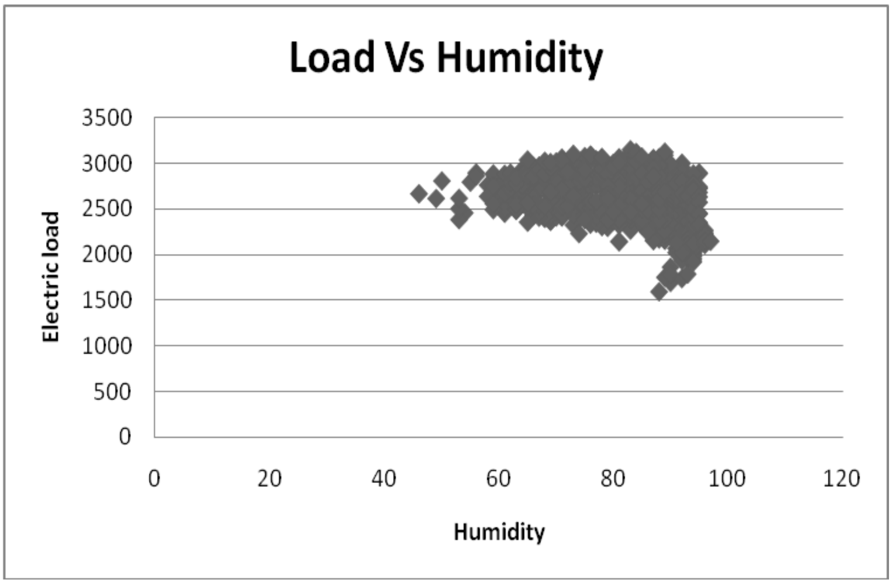


Fig. 1.6. Load variation Vs humidity

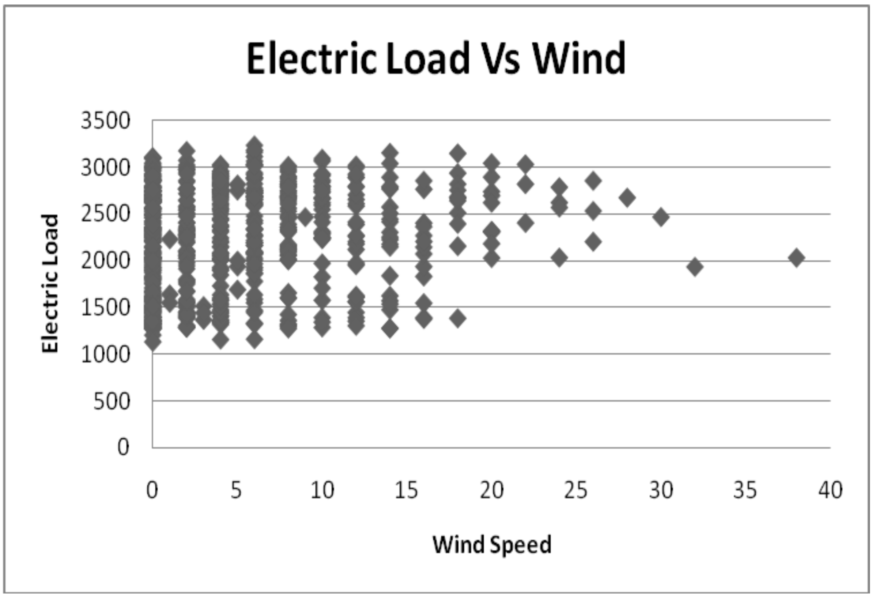


Fig. 1.7. Load variation with wind speed

CHAPTER-2

CONVENTIONAL APPROACHES

An exhaustive study is done to implement popular traditional techniques. First of all, the most common method that is often taken for conventional method, the polynomial curve fitting using the *multiple linear regression* (MR) is considered. For this, the casual and time series models are developed.

2.1 Multiple Linear Regressions

The load is modeled in terms of non climatic & climatic variables, which affects load in multiple linear regression method. The explanatory variables of these models are identified through analysis on each of the independent variables with the load. The load model MR using this method may be expressed as;

$$y(k) = a_0 + a_1x_1(k) + \dots\dots\dots + a_n\, x_n(k) + a(t) \qquad (1)$$

where:

$y(k)$ = electrical load at k^{th} hour

$x_1(k), \dots\dots x_n(k)$ = explanatory variables at the k^{th} hour

$a(t)$ = random variable with zero mean & constant variance

$a_0, a_1, \dots\dots\dots\dots a_n$ = regression coefficients.

Another MR_2 model is developed using the same approach involving quadratic temperatures. The temperature sensitive part of the load in this model is expressed as;

$$Y(k) = a_0 + a_1T(k) + a_2T^2 \qquad (2)$$

In the above model higher order terms are included to investigate the prediction capability of quadratic curve. The coefficients a_0, a_1, a_2 are determined using least square techniques and use the same data as in the linear model MR.

2.2 Time Series Formulation (TS)

Time series formulation includes the time delay variables along with the causal variables. The formulation of identifying the coefficients is the same as in the case of multiple regressions. The time series formulation also includes the trend of the forecasted variables and therefore is more accurate. The load at k^{th} hour can be mathematically expressed as;

$$L(k) = a_0 + a_1\, L(k\text{-}1) + a_2\, L(k\text{-}2) + a_3\, L(k\text{-}3) \qquad (3)$$

Where:

$L(k)$ = Load at k^{th} hour,

$L(k\text{-}1)$ = Load at $K\text{-}1^{th}$ hour ……etc.

There are various other types of time series models as well, but for the purpose of comparison with the proposed methods, only simpler and basic version has been considered.

2.3 Feed Forward Neural Network (FFNN)

Neural Networks possess the properties required for load forecasting such as ability to learn complex non-linear mappings, non linear & smooth interpolation, and adaptation on to different statistical distributions. They can improve their performance by learning from the past experiences and making generalizations of the knowledge of different scenarios. A flow chart of *Artificial Neural Networks* (ANN) is presented in Fig. 2.1. However FFNN with learning algorithm such as back-propagation requires rather a longer time and results in not too accurate prediction due to non stationary nature of the data, and its dependence on temporal, seasonal and annual variations. FFNN is a widely used neural network paradigm in the neural network based STLF literature. Supervised BPNN Model proposed by Singh & Malik (1995) has been implemented for the purpose of comparison.

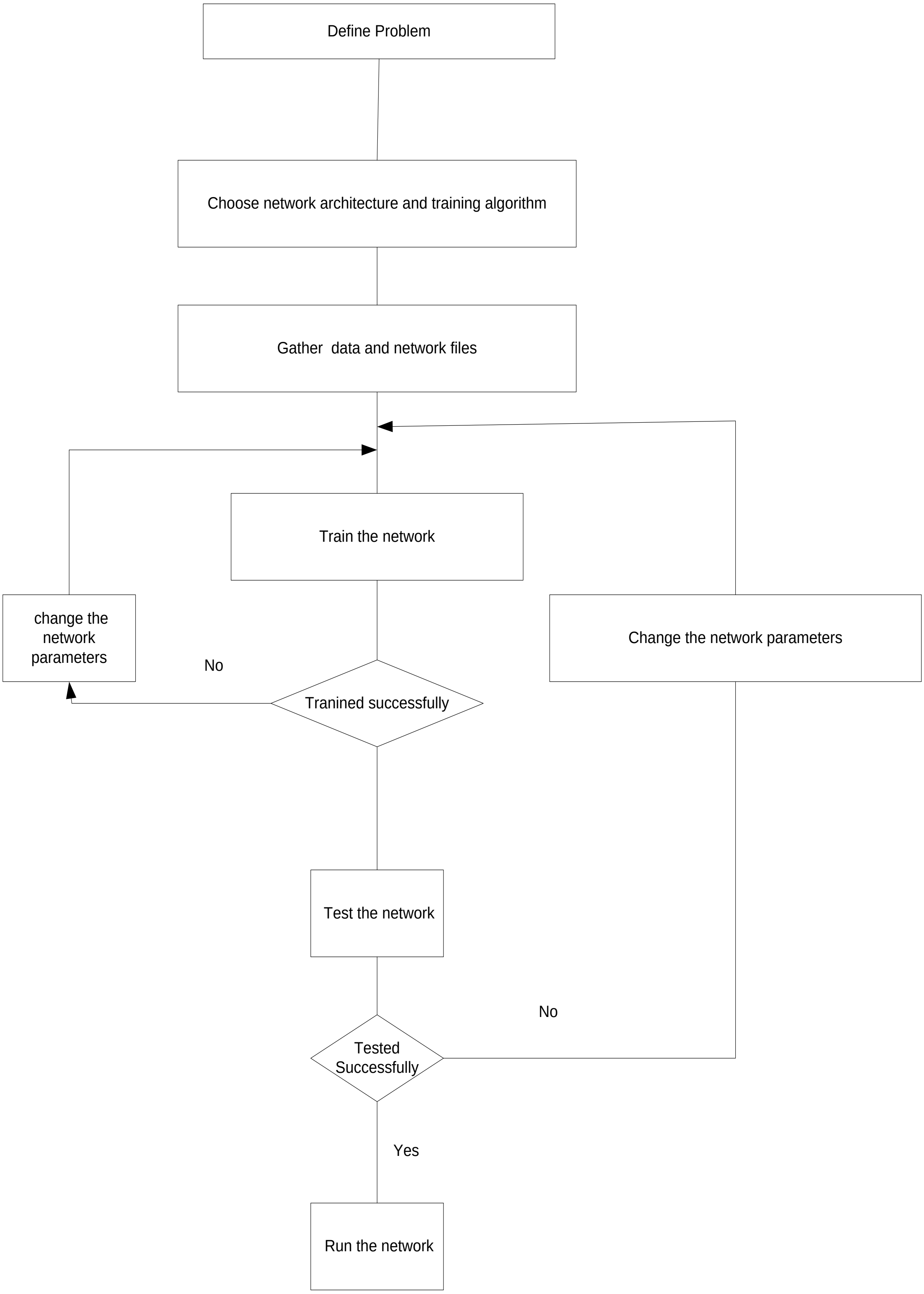


Fig. 2.1. Flow chart for model formulation of ANN

CHAPTER-3

PARTICLE SWARM OPTIMIZATION BASED SUPPORT VECTOR REGRESSION

Development of new learning techniques in machine learning has been a major focus in the last decade. This Chapter deals with *Support Vector Regression* (SVR) based STLF. The method is devised as optimization problem using MAPE as an objective function. The optimization of SVR parameters is achieved with the help of *Particle Swarm Optimization* (PSO). The accuracy of the method is demonstrated on a practical system load data which is taken from Northern region load dispatch centre in Delhi. The method takes the lowest number of inputs which only consist of the past load values. *Support vector machine* (SVM) is a novel machine learning tool based on *Statistical Learning Theory* (SLT), proposed by Vapnik and coworkers. It replaces *Empirical Risk Minimization* (ERM) principle, that is usually employed in ANN, with the *Structural Risk Minimization* (SRM) principle which minimize an upper bound to the generalization error instead of minimizing the training error. On the basis of above principle, SVM will be equivalent to solving a linear constrained quadratic programming problem, so that the solution of SVM is always unique & optimal. Originally, SVM has been developed for solving the classification problems with remarkable performance. With the introduction of Vapnik's ε-insensitive loss function, SVM has been extended to solve regression problem called SVR.

The essential difference between classification and regression problems is in the desired outputs. For classification problems the outputs are restricted to {-1, 1}. In the regression, the outputs can take real values, and thus training data is in the form of input-output pairs. In the regression, one requires a measure of the approximation error, which is used in place of margin for the hyper plane of SVM classifier. Recently, SVR has been applied to various applications with excellent performances as cited in **Sopankevych (2009)**. The noisy, non stationary and chaotic nature of time series data exhibited in electric load appears to lend itself to the use of the non-traditional time series prediction method such as SVR. There is also a great deal of research concentrating on SVM. The basic architecture of SVM has been shown in Fig. 3.1.

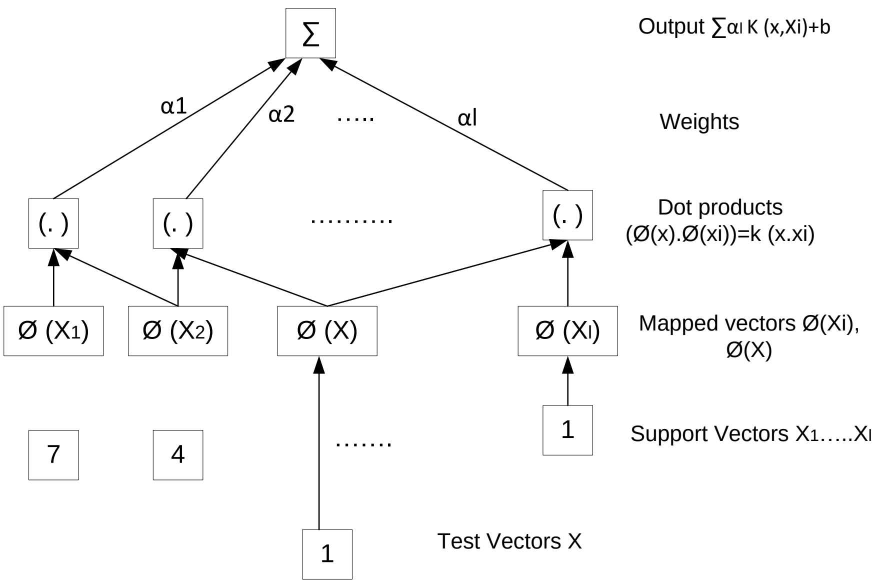


Fig. 3.1 SVM Architecture

The SVM forecasts the load curve by using the load information of the days with the weather conditions similar to the objective days, and have an advantage of dealing not only with the non-linear relationship of the loads, but also with the loads of the weekends & special days. In general, the data of several similar days need to be considered to improve the accuracy of load forecasting. The mapping and the weights of the methods cannot reflect the actual influence degree of the factors due to lack of adequate cognition of these factors. In the past, Chen et al. proposed SVR approach for EUNITE network competition which is the prediction of daily maximal load. It was concluded that use of temperature data doesn't work always because of the inherent difficulty in predicting temperature in case it is not available. It also concluded that this SVR approach is most suitable for determining the accurate prediction model for the data provided in the competition. They described the winning approach for the competition [**Chen et al. (2004)**]. **Mohandes (2002)** compared the results of a SVR using a sigmoid kernel function and the ε-insensitive loss function to an autoregressive model of order one for short-term electric load forecasting. **Dong et al. (2005)** discussed the use of SVM model to predict the electrical load necessary for commercial building. The comparison of SVR with other major artificial intelligence techniques is given in Table 3.1.

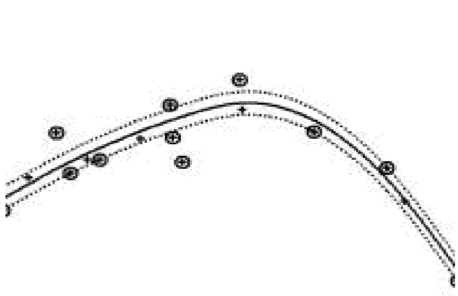
Table 3.1 Comparison of SVR with other major AI techniques

Important Features	Artificial Intelligence Techniques				
	Neural Network	Expert System	Fuzzy Logic	Genetic Algorithm	Support Vector Regression
Adaptability	Good	Bad	Rather bad	Good	Good
Maintainability	Good	Bad	Rather good	Rather good	Good
Learning ability	Good	Bad	Bad	Good	Very good
Imprecision tolerance	Good	Bad	Good	Good	Very Good
Knowledge representation	Bad	Rather good	Good	Rather bad	Bad
Explanation ability	Bad	Good	Good	Rather bad	Bad
Uncertainty tolerance	Good	Rather good	Good	Good	Very good
Generalization performance	Good	Bad	Bad	Bad	Excellent

CHAPTER 4

LOAD DATA PREDICTION USING SVR OVERVIEW

With SVR, user generally confronted with two problems, first is to choose the subset of optimal input features for SVR, and second is to set the best kernel parameters. Input space dimension is large & contain noise. It increases model complexity and result in SVR's forecasting ability reduction. By obtaining maximum information from given data set with less features utilization, we can save noteworthy computation time and build models that generalize better the unseen data points as described in Vapnik et al. (1997). Figs. 4.1(a)-(c) depict the support vector regression. For feature selection, fuzzy curve method is retained as it keeps the number of input feature to minimum [Lin and Cunningham (1995)]. Parameters setting precisely can improve the SVR regression accuracy in addition to feature selection. Inappropriate settings of parameter may create significant performance differences. Thus, selection of optimal hyper-parameter is an essential step in SVR design as discussed in Fan and Chen 2006.



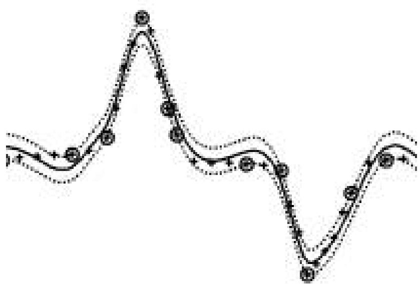


Fig. 4.1(a) Support Vector Regression; Fig. 4.1(b) Support Vector Regression

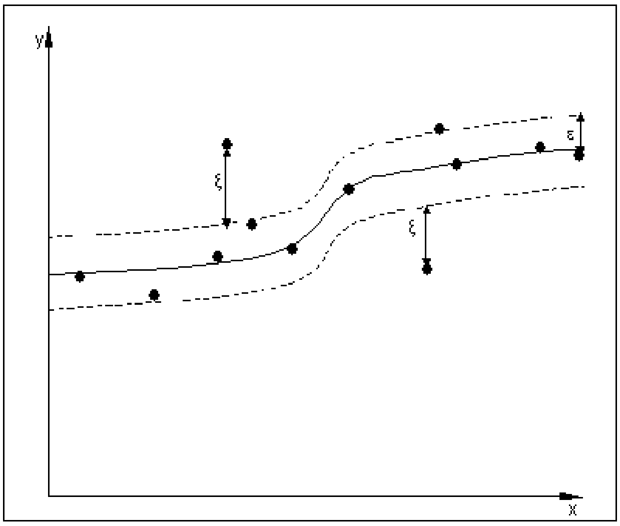


Fig. 4.1(c) Support Vector Regression

4.1 SVR Parameters

Excessively large parameters value in SVR leads to over fitting, while disproportionately small values lead to under fitting. Different parameter settings may create significant performance difference. Thus, selection of optimal hyper-parameter is an essential step in SVR design. The parameters are as follows;

- Regularization parameter 'C' which determines the tradeoff between minimizing the training error and minimizing the complexity of the model.

- Bandwidth of the kernel function ($\sigma^{2)}$ which represents the variance of the Gaussian kernel function.
- The tube size of e- insensitive loss function (ε); which is the approximation accuracy placed on the training points. Parameter ε controls the width of the ε- insensitive zone, used to fit the training data. The value of ε can affect the number of SVs used to construct the regression function. Larger ε value results in fewer SVs selected, and also results in more 'flat' (fewer complexes) regression estimates.

The kernel parameters implicitly define the nonlinear mapping from the input space to the high dimensional feature space. However, we must notice that each of them reaching optimal point sometimes does not lead to a good performance of SVR, but when the combination of them arrives at the optimal value, we may get a good performance. SVR generalization performance (estimation accuracy) and efficiency depend on the hyper-parameters [C, and ε, kernel parameter (σ^2)]. Therefore, the main issue is to locate the optimal hyper-parameters for a given data set.

Computational intelligence-based techniques, such as *Genetic Algorithm* (GA) and PSO can be used to solve the above problem. GA is the search technique to find the approximate solutions to the optimization problems [**Goldberg (1989)**]. GA represents a particular class of evolutionary biology such as inheritance, mutation, natural selection, and recombination (or crossover). While it can rapidly locate good solutions, even in complex search spaces, it has some disadvantages associated with it:

- Unless the fitness function is defined properly, GA may have a tendency to converge towards local optima rather than the global optimum of the problem;
- Operating on dynamic data sets is difficult;
- For specific optimization problems, and given the same amount of computation time, simpler optimization algorithms may find better solutions than GAs.

PSO is another evolutionary computation technique developed by **Kennedy & Eberhart (1995),** which was inspired by the social behavior of bird flocking and fish schooling. PSO has its roots in artificial life and social psychology. It utilizes the population of the particles that move through the problem hyperspace with the given velocities. At each iteration, the velocities of individual particles are stochastically adjusted according to the historical best position of the particle itself and the neighborhood best position. Both the particle best and the neighborhood best are obtained according to the user defined fitness function as given in **Eberhart et al. (2001)**. The movement of each particle naturally evolves to an optimal or near optimal solution. The word swarm comes from the irregular movements of the particles in the problem space, and is more similar to a swarm of mosquitoes rather than a flock of birds or a school of fish. PSO is computational intelligence -based technique that is not largely affected by the size and nonlinearity of the problem, and can converge to the optimal solution in many problems where most analytical methods fail to converge [**Valle et al (2008)**]. It can, therefore, be effectively applied to different optimization problems in power systems. A number of papers have been published in the past few years and these papers focus on the issue of optimization. Moreover, PSO has some advantages over other optimization techniques such as GA, namely the following;

- PSO is easier to implement and there are a few parameters to adjust.
- In PSO, every particle remembers its own previous best value as well as the neighborhood best; therefore, it has a more effective memory capability than GA.
- PSO is more efficient in maintaining the diversity of the swarm [Engelbrecht (2006)] (more similar to the ideal social interaction in a community), since all the particle uses the information related to the most successful particle in order to improve themselves, whereas in GA, the worse solutions are discarded and only the good ones are saved; therefore, in GA the population evolve around a sunset of the best individuals.

Given the training data $(x_1, y_1),\ldots,(x_l, y_l)$, where x_i are the input vectors and y_i are the associated output value of x_i, the support vector regression solves an optimization problem stated as;

$$\min_{w,b,\xi,\xi^*} \quad \frac{1}{2} w^T w + C \sum_{i=1}^{l} (\xi_i + \xi_i^*) \tag{4}$$

Subject to
$$\begin{aligned} & y_i - (w^T \phi(x_i) + b) \le \varepsilon + \xi_i^*, \\ & (w^T \phi(x_i) + b) - y_i \le \varepsilon + \xi_i, \\ & \xi_i, \xi_i^* \ge 0, \quad i = 1, \ldots, l \end{aligned}$$

Where x_i is mapped to a higher dimensional space by the functions ϕ, ξ_i^*, is the upper training error (ξ_i is the lower) subject to the ε-insensitive tube $\left| y - (w^T \phi(x) + b) \right| \le \varepsilon$. The parameters which control the regression quality are the cost of error C, the width of the tube ε, and the mapping function ϕ. Details on use of SVM for time series prediction are given in **Sopankevych (2009)**.

The constraints of equation-(4) imply that we should put most data x_i in the tube $\left| y - (w^T \phi(x) + b) \right| \le \varepsilon$. This situation can be clearly seen in Fig. 4.1(c). If x_i is not in the tube, there is an error ξ_i or ξ_i^* which we would like to minimize through the objective function. SVR avoids underfitting & overfitting of the training data by minimizing the training error $C \sum_{i=1}^{l} (\xi_i + \xi_i^*)$ as well as the regularization term $(1/2)w^T w$. For the traditional least-square regression, ε is always zero and data is not mapped into higher dimensional space. Hence, SVR is a more general and flexible tool for the treatment on regression problem. Since ϕ might map x_i to high or infinite dimensional space, we deal with its dual problem stated as;

$$\begin{aligned} \min_{\alpha,\alpha^*} \quad & \frac{1}{2} (\alpha - \alpha^*)^T Q (\alpha - \alpha^*) \\ & + \varepsilon \sum (\alpha_i + \alpha_i^*) + \sum_{i=1}^{l} y_i (\alpha_i - \alpha_i^*) \end{aligned} \tag{5}$$

Subject to
$$\begin{aligned} & \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) = 0, \\ & 0 \le \alpha_i, \quad \alpha_i^* \le C, \quad i = 1, \ldots, l \end{aligned}$$

Where $Q_{ij} = \phi(x_i)^T \phi(x_j)$. However, this inner product may be expensive computationally because $\phi(x)$ has too many elements. Hence, we apply kernel trick to do the mapping implicitly. That is to employ some special forms which are inner products in the higher dimensional space yet they can be calculated in the original spaces. Some examples are polynomial kernels and RBF kernel.

4.2 SVR BASED ON PSO

A PSO has two binary operators: velocity update & position update. At each iteration; particle is accelerated towards the particle's previous best position and the global best position. The new velocity for each particle is calculated based on its current velocity, the difference from its previous best position, and the difference from the global best position.

The new velocity is then used to calculate the next position of the particle in the search space. This process is iterated a number of times or until a minimum error is achieved. The velocity and position vector of PSO are shown in Fig. 4.2.

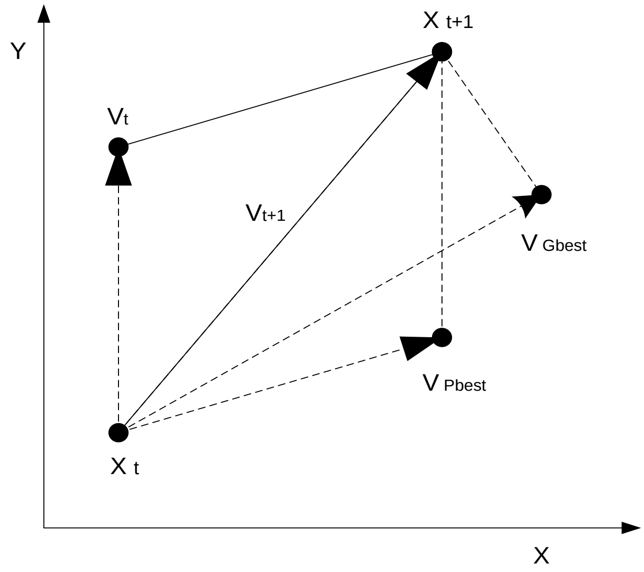


Fig. 4.2 The velocity and position vectors of PSO

The PSO algorithm can be described as follows: Let $X_i = (x_{i1},x_{i2},\ldots,x_{iD})$ represent the 'particle' current position and $V_i = (v_{i1},v_{i2},\ldots,v_{iD})$ its velocity. The local best location is denoted as $P_{best,i} = (p_{i1},p_{i2},\ldots,p_{iD})$. Let $P_{gbest} = (p_{g1},p_{g2},\ldots,p_{gd})$ represent the global best position of the all particles. The D- dimensional velocity is formulated as:

$$v_{id}^{(k+1)} = h^{(k)} v_{id}^{(k)} + c_1 r_1 (p_{id}^{(k)} - x_{id}^{(k)}) + c_2 r_2 (p_{gd}^{(k)} - x_{id}^{(k)}) \qquad (6)$$

$$x_{id}^{(k+1)} = x_{id}^{(k)} + v_{id}^{(k)} \qquad (7)$$

where i=1, 2,…n and d=1, 2,….D; and D is the number of dimensions of each particle. k is the iteration index. c_1,c_2 are the constants of acceleration. These are positive constants and are known as personal and social learning factors. These constants influence the speed of each particle. A low value of c_i minimizes the speed of optimization process and requires a large number of iterations. Large values of c_i numerically unstablize the optimization process. Hence, the acceleration constants given satisfy constraint $c_1 + c_2 \leq 5$. Moreover, r_1,r_2 are two random numbers uniformly distributed within the range of [0,1]. h is the inertia weighting factor. Proper selection of weight h provides a balance between the global and the local explorations, thus requiring less iteration on an average to find an optimal solution. Typically h is reduced linearly, from h_{max} to h_{min}, each iteration; these are set at h_{max}= 0.9 and reduce it to h_{min}= 0.1. A particular value of h is computed from:

$$h = [h_{\max} - \{iter \times (h_{\max} - h_{\min}) / iter_{\max}\}] \qquad (8)$$

Where iter is the number of current iterations and $iter_{max}$ is the maximum number of iterations.

This algorithm reflects better properties with its characteristics such as scalability, adaptation, speed, autonomy, fault tolerance and parallelism in different applications. PSO algorithm has the disadvantages such as sensitivity to initial values, easily trapping into local optimum, premature convergence, parameters selection problems, slow convergence in the later stage of evolution. PSO is sensitive to the choice of inertia weight and learning factor parameters. The use of PSO to find the optimal hyper parameters of SVR to achieve better prediction in terms of lower MAPE value is given in Flow chart in Fig. 4.3.

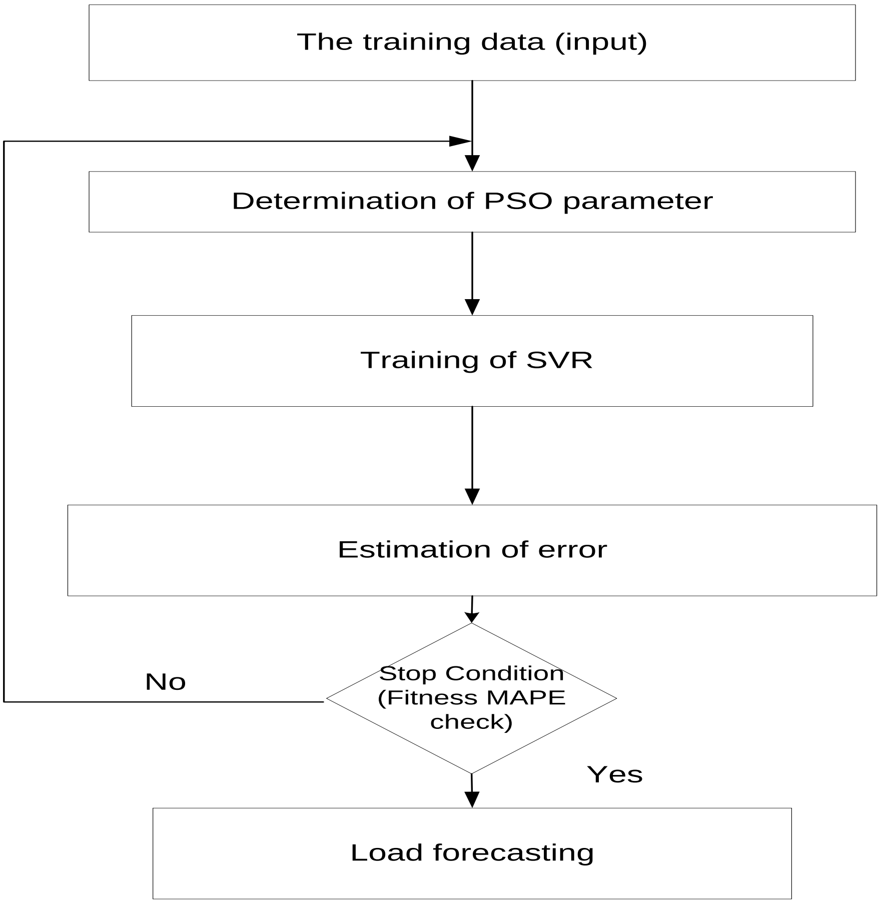


Fig. 4.3 Flowchart for hybrid PSO-SVR for short term load forecasting

4.3 Algorithm for PSO-SVR

- Initialize the parameters of SVR network. PSO is used to optimize the parameters of SVR. Initialize the parameters of PSO algorithm as well with T=1, Tmax=1000.
- Forecast Load L with the given SVR and PSO parameters using load database.
- Estimate MAPE using forecasted load and actual load data.
- Check MAPE ≤ specified value then selecting the minimum of P_{lbest} and compare it with the previous P_{gbest} value, if found less than given value, then replace P_{gbest} with P_{lbest} value and go to step 6, else T= T+1.
- Judge the condition for step 6, if the maximum iterative times Tmax are met and E< ε (ε is a given parameter), then P_{gbest} is the optimal solution which represents the SVR parameters. Otherwise, calculate the velocity and new position of each particle according to equation (3) and equation (4) and then go to step 2.
- According to the optimized SVR parameters, SVR network structure is established to forecast the load
- End,

CHAPTER 5

RESULTS

It is observed that preprocessing is needed to 'clean' data by removing the outlier, missing values, or any irregularities, as the forecasting models are sensitive to such defective data. Moreover, load series is complex and exhibits several levels of seasonality. Some of the factors influencing the load profile are the position of day in a week as well as in a month, holiday or non holiday. The other important factor is the weather. It is observed that the past load data plays a key role in the prediction of load, therefore the understanding of the basic load characteristics is an essential step for model formulation. It is considered to be comprising of base, variable and random factors. Based upon the individual significance of these factors, different models can be used for the purpose of load forecasting for better results. In the load study, load dynamics and its property are discussed through load profiles and its dependency on variable weather factors. Data checks and correction are used to get rid of inconsistencies in the data. Popular conventional techniques such as Time series model, MLR model and feed-forward neural network are compared as the conventional methods. Results are shown in Tables 5.1-5.4.

A final comparison is made on MR, TS, and FFNN in Table 5.5, where $MR_{(t)}$ stands for multiple regression with temperature variable only, while $MR_{(thw)}$ stands Multiple regression with temperature, humidity and wind as weather variables. TS_1 stands for the time series, while TS_2 stands for the time series with a consideration of weather effect besides the trend of forecasted variable, which in this study, is the temperature variable.

Table 5.1. Comparison of Conventional approaches and ANN

S.No.	Important features	Time series method	Regression Analysis	Artificial neural networks
1	Load information	Considered	Considered	Considered
2	Weather information	Ignored	Considered	Considered
3	Functional relationship between load and weather	Ignored	Required	Not required
4	Complex mathematical calculation	Required	Required	Not required
5	Time required for prediction	More	More	Less
6	Adaptability	Less	Less	More

Table 5.2. Forecasting results of Multiple Regression methods

Duration	Season	Model /Month 2016	Conventional Regression (MR) (MAPE)		MR_2 Method (MAPE)
			MR(t)	MR(t,h,w)	
Saturday	Summer	April	9.89	7.13	9.16
		May	10.74	9.69	9.05
		June	8.82	5.57	3.55
	Rainy	July	5.83	5.06	4.11
		August	7.33	7.64	6.20
		September	8.64	7.71	9.85
Sunday	Summer	April	10.28	7.05	4.90
		May	10.64	13.70	8.70
		June	9.72	10.01	7.70
	Rainy	July	9.48	7.32	8.25
		August	7.82	5.63	5.13
		September	11.64	6.40	8.86
Whole week	Summer	April	14.16	8.54	9.14
		May	9.58	11.21	8.38
		June	11.18	6.40	5.95

	Rainy	July	5.57	5.50	5.34
		August	6.15	5.83	5.80
		September	8.24	7.03	7.04

Table 5.3. Forecasting results of Time series methods

Duration	Season	Model / Month 2016	Time Series (MAPE)	
			TS 1	TS 2
Saturday	Summer	April	4.53	4.41
		May	5.14	5.06
		June	4.74	4.92
	Rainy	July	4.98	4.27
		August	4.78	3.84
		September	4.99	4.04
Sunday	Summer	April	5.21	4.99
		May	4.90	4.06
		June	4.12	3.44
	Rainy	July	4.30	3.48
		August	4.15	4.06
		September	5.40	5.19
Whole week	Summer	April	5.70	5.65
		May	5.63	4.88
		June	4.81	3.82
	Rainy	July	4.43	3.45
		August	4.90	4.86
		September	5.16	5.10

Table 5.4. Forecasting results of Feed forward neural network

Duration	Season	Model / Month 2016	FFNN (MAPE)
Saturday	Summer	April	5.20
		May	5.86
		June	2.94
	Rainy	July	3.64
		August	6.25
		September	3.68
Sunday	Summer	April	6.90
		May	3.82
		June	2.18
	Rainy	July	6.26
		August	2.42
		September	3.12
Whole week	Summer	April	4.41
		May	4.86
		June	5.24
	Rainy	July	3.23
		August	3.96
		September	4.21

Table 5.5. Comparison forecasting results of Conventional methods for summer and rainy season of year 2016

Duration	Season	Model / Month 2016	Conventional Regression (MR)		MR_2	TS		FFNN
			$MR_{(t)}$	$MR_{(t,h,w)}$		TS_1	TS_2	
Saturday	Summer	April	9.89	7.13	9.16	4.53	4.41	5.20
		May	10.74	9.69	9.05	5.14	5.06	5.86
		June	8.82	5.57	3.55	4.74	4.92	2.94
	Rainy	July	5.83	5.06	4.11	4.98	4.27	3.64

		August	7.33	7.64	6.20	4.78	3.84	6.25
		September	8.64	7.71	9.85	4.99	4.04	3.68
Sunday	Summer	April	10.28	7.05	4.90	5.21	4.99	6.90
		May	10.64	13.7	8.7	4.90	4.06	3.82
		June	9.72	10.01	7.70	4.12	3.44	2.18
	Rainy	July	9.48	7.32	8.25	4.30	3.48	6.26
		August	7.82	5.63	5.13	4.15	4.06	2.42
		September	11.64	6.40	8.86	5.40	5.19	3.12
Whole week	Summer	April	14.16	8.54	9.14	5.70	5.65	4.41
		May	9.58	11.21	8.38	5.63	4.88	4.86
		June	11.18	6.40	5.95	4.81	3.82	5.24
	Rainy	July	5.57	5.50	5.34	4.43	3.45	3.23
		August	6.15	5.83	5.80	4.90	4.86	3.96
		September	8.24	7.03	7.04	5.16	5.10	4.21

In this study, four week load data of a month has been used to predict the electric load data of first week of next month for the year 2016. We have taken only the load data, as the input considering it strictly as the time series problem. If the weather variables are also considered, then the prediction of weather variables would be a prerequisite to the prediction of load data. It is reported in the literature that the inclusion of weather prediction leads to more error; hence weather variables are not considered in this study.

Relatively large values for parameters of SVR lead to over-fitting, while a disproportionately small values lead to under-fitting. Different parameter settings can cause significant difference in performance [**Keerthi (1998)**]. Therefore, selecting parameters is an important step in SVR design. The regularization parameter C determines the tradeoff between the training error and the model complexity. The kernel function (σ^2), in this study has been taken as Gaussian. The tube size of ε-insensitive loss function indicates the accuracy of the training data points. SVR performance or estimation accuracy depends on the above hyper parameters (C, σ^2, ε). Therefore principal issue is to find the optimal hyper-parameters for a given data set. The parameters of SVR are learned using PSO considering MAPE as a fitness function. The selected parameters of PSO are given in Table 5.6.

Table 5.6. Summary of PSO parameter settings

PSO parameter	Parameter settings
Iteration times	100-1000
Population size	30 - 80
The minimum inertia weight	0.1
The maximum inertia weight	0.9
The minimum velocity	0.1
The maximum velocity	0.9
Personal and Social learning factors (C1, C2) or Learning rate	2.0

The results in terms of MAPE obtained for the Year 2016 using the PSO based SVR model are given in Table 5.7. Moreover, Table 5.8 presents the weekly predictions numbering 168 observations classified for different ranges for PSO- SVR forecast model. It shows that large errors are more frequent in the month of November and December. The actual and predicted load data for the first week of different months are given in Figs. 5-12.

The sample data of this study is relegated to (Appendix A.V). The results of PSO-SVR underperform in comparison to other proposed models. It is mainly due to its lack of provision to deal with uncertainty, associated with randomness in data.

Table 5.7. PSO-SVR method of forecasting for year 2016

Month (Year 2016)	PSO based Support Vector Regression	
	Mean	Max
January	3.41	3.95
February	3.28	3.78
March	2.97	3.54
April	3.74	4.32
May	3.39	3.94
June	3.18	3.82
July	2.64	3.09
August	3.01	3.57
September	2.61	3.06
October	3.54	4.03
November	4.31	4.82
December	5.53	6.93

Table 5.8. Number of observations out 168 for different ranges for PSO-SVR forecast model

Error MW Month (1^{st} week) 2016		0 -50	51-100	101-200	>200
Rainy Season	July	80	52	27	09
	August	74	45	39	10
	September	90	41	24	13
Winter Season	October	68	53	35	12
	November	69	53	23	23
	December	52	45	37	34

5.1 SVR Results

Month of June to December, Year 2016 prediction & error data is given in Table 5.9 to 5.15, listing actual value, predicted value, error from actual value, SVR parameters value, MAPE obtained for the given month. All the months data is not tabulated deliberately as the data is not for public use and has a restricted access. It requires prior written permission from the source for the use (source NRLDC Delhi). SVT prediction results for summer season from June to December are expressed in Fig. 5.1-5.7.

Table 5.9. SVR June-2016 prediction & Error results

Actual	Predicted	error_pred	jere	je	jC	jMape	j_sort
2779	2415.181	-363.819	-362.696	7.9873	7.4235	3.1774	0.237815
2714	2775.112	61.11181	61.44788	Same set of values			0.353473
2645	2612.738	-32.2624	-19.447				0.512041
2605	2545.578	-59.4216	-37.7443				0.758211
2445	2519.701	74.70063	-2.2906				2.62745
2570	2350.765	-219.235	68.32831				3.207898
2493	2531.614	38.61369	29.22189				3.23978
2424	2431.362	7.361563	-32.7062				4.078784
2388	2381.168	-6.83183	39.23275				5.212937
2330	2370.585	40.58457	96.70327				5.274739
2415	2326.325	-88.6747	-21.3475				6.831828
2499	2446.105	-52.8949	19.74385				7.242297
2591	2525.788	-65.2122	-73.5181				7.361563
2598	2612.828	14.82779	28.70441				7.750163
2632	2601.489	-30.5105	27.49441				7.999797
2626	2640.572	14.57209	-26.8308				8.252609
2683	2620.86	-62.1398	-36.9454				8.502309
2682	2681.488	-0.51204	-35.9287				8.756861
2588	2650.227	62.22691	133.6041				9.263716
2890	2524.291	-365.709	139.1812				11.34818
2932	2874.023	-57.9775	-52.3881				12.53415
2966	2837.479	-128.521	188.8386				13.70236
3001	2862.088	-138.912	-127.888				14.01166
2380	2889.827	509.8268	-85.3074				14.38762

2587	2175.246	-411.754	-87.4669	Same set of values	14.57209
2613	2559.418	-53.582	-25.8812		14.82779
2632	2531.808	-100.192	-17.0566		16.51842
2552	2495.93	-56.0705	-88.1413		17.49368
2546	2450.565	-95.435	-2.6066		18.00672
2497	2465.737	-31.2626	38.2313		18.19593
2434	2420.298	-13.7024	90.70095		19.55803
2382	2379.373	-2.62745	-92.2194		19.61052
2460	2359.419	-100.581	133.3812		20.37924
2579	2476.793	-102.207	132.4825		22.75373
2714	2600.19	-113.81	-0.18113		24.44193
2796	2731.344	-64.6559	42.01085		25.23446
2794	2794.353	0.353473	-83.9086		25.83942
2740	2777.92	37.91973	-7.4037		28.71549
2945	2718.866	-226.134	49.68137		29.33425
2945	2964.558	19.55803	-5.3232		30.13383
2910	2913.24	3.23978	-33.3203		30.51051
2792	2870.644	78.64386	-64.5988		30.94239
2875	2730.629	-144.371	197.2369		30.97391
2822	2833.348	11.34818	44.99642		31.26264
2983	2738.277	-244.723	-52.0797		31.65544
2934	2921.466	-12.5341	114.5269		32.2624
3085	2817.086	-267.914	-4.84356		32.51809
2933	2991.817	58.81747	-56.8194		33.94759
2821	2781.54	-39.4596	-181.107		34.09249
2747	2688.361	-58.6389	-6.41158		35.09107
2679	2630.509	-48.4911	-115.437		36.86173

2628	2571.171	-56.8286	0.024594	Same set of values	36.92858
2440	2537.096	97.09571	-37.6949		37.88324
2554	2341.279	-212.721	8.024179		37.91973
2525	2516.747	-8.25261	-40.8071		38.29606
2469	2477.757	8.756861	-44.3696		38.61369
2544	2444.787	-99.2133	-18.1319		39.45955
2683	2553.437	-129.563	172.5085		40.58457
2732	2703.285	-28.7155	-31.9954		41.35383
2832	2730.661	-101.339	-150.599		44.5216
2901	2839.916	-61.0839	14.36992		46.35442
2953	2895.775	-57.2249	-9.76157		46.71449
2963	2940.246	-22.7537	-18.5283		48.49113
2971	2941.666	-29.3342	-6.5456		48.65962
2953	2945	-7.9998	-40.7776		49.06311
2825	2911.934	86.93428	-101.677		52.89491
2894	2760.842	-133.158	145.7058		53.58201
3027	2849.027	-177.973	92.49997		54.94672
3031	2968.233	-62.767	-15.8756		56.07046
3019	2933.098	-85.9021	52.59725		56.82858
3081	2915.407	-165.593	-27.0451		57.22489
2863	3000.938	137.9383	-42.7717		57.97747
2769	2749.389	-19.6105	-40.7668		58.24974
2802	2688.564	-113.436	-17.8349		58.63888
2712	2746.092	34.09249	-61.3769		58.81747
2680	2633.286	-46.7145	4.670088		59.42161
2567	2611.522	44.5216	-259.823		60.26371
2677	2490.984	-186.016	60.05901		61.08395

2656	2650.787	-5.21294	33.37152	Same set of values	61.11181
2625	2608.482	-16.5184	-62.2299		61.45435
2624	2587.071	-36.9286	-21.7236		62.13982
2797	2600.686	-196.314	42.52193		62.22691
2920	2804.683	-115.317	-1.27855		62.46918
3003	2909.437	-93.5626	-40.0638		62.76696
3038	2979.75	-58.2497	-112.992		64.16464
3053	3006.646	-46.3544	-23.9132		64.65593
3095	3016.049	-78.9513	-3.19241		65.21224
3181	3061.505	-119.495	-24.1364		68.16062
2936	3147.858	211.8583	-49.6493		68.16829
2916	2847.832	-68.1683	-7.78275		68.17102
2909	2876.482	-32.5181	136.9214		69.86943
3026	2857.738	-168.262	99.01169		70.76505
3083	2979.852	-103.148	78.1565		71.20111
3019	3000.804	-18.1959	40.20916		71.29595
3051	2904.928	-146.072	-35.0589		73.89317
2975	2956.993	-18.0067	99.91907		74.55182
2398	2863.379	465.3789	-165.832		74.70063
2324	2229.318	-94.6817	7.526806		76.01396
2235	2284.063	49.06311	-39.7184		77.76114
2159	2194.091	35.09107	-24.5609		78.64386
2138	2129.498	-8.50231	19.94024		78.95133
2209	2121.696	-87.3038	105.479		81.43633
2277	2208.829	-68.171	57.73746		82.7305
2266	2275.264	9.263716	-26.8977		85.90206
2339	2262.986	-76.014	0.117262		86.93428

2652	2363.83	-288.17	321.5925	Same set of values	87.30382
2643	2704.454	61.45435	-149.842		88.06053
2597	2628.655	31.65544	35.47934		88.67468
2561	2585.442	24.44193	-49.0272		93.31895
2624	2553.235	-70.7651	41.81478		93.56265
2654	2628.766	-25.2345	-24.1866		94.68166
2658	2643.612	-14.3876	-59.0897		95.43497
2698	2635.531	-62.4692	15.22859		97.09571
2673	2673.238	0.237815	-42.7019		98.76745
2644	2629.988	-14.0117	89.15546		99.21331
2843	2597.87	-245.13	144.3185		100.1925
2704	2811.507	107.5071	-112.644		100.5808
2777	2601.953	-175.047	155.572		101.339
2688	2718.974	30.97391	-77.0891		102.2067
2668	2594.107	-73.8932	-46.5685		103.148
2846	2579.897	-266.103	1.366879		105.4234
2858	2789.839	-68.1606	-86.9852		105.6607
2842	2777.835	-64.1646	-70.8863		107.5071
2754	2758.079	4.078784	64.17047		110.6496
2782	2666.137	-115.863	-44.4756		113.4357
2826	2720.339	-105.661	92.53275		113.8104
2782	2761.621	-20.3792	117.0222		115.3174
2714	2706.758	-7.2423	-34.717		115.8629
2793	2641.18	-151.82	-13.8586		119.4951
2893	2752.897	-140.103	211.4787		122.7367
3025	2851.469	-173.531	-80.1532		123.2934
3068	2985.27	-82.7305	147.9524		128.5208

3066	3005.736	-60.2637	-153.471	Same set of values	129.5632
3129	2999.066	-129.934	46.54025		129.9345
3154	3076.239	-77.7611	62.78788		133.1578
3165	3093.704	-71.296	-36.0882		137.9383
3028	3099.201	71.20111	-87.2562		138.9115
2971	2940.866	-30.1338	22.49838		140.1033
3068	2903.978	-164.022	159.7358		141.252
3128	3017.35	-110.65	130.7215		142.873
3121	3051.131	-69.8694	-24.1827		144.3713
3142	3018.707	-123.293	-3.37347		146.0717
3129	3040.939	-88.0605	-17.631		151.8205
3064	3026.117	-37.8832	-8.51456		152.0038
3000	2963.138	-36.8617	-61.4571		164.022
2961	2906.053	-54.9467	-36.3916		165.5929
2912	2873.704	-38.2961	-16.4366		168.2617
2906	2831.448	-74.5518	-41.4502		173.5315
2869	2835.052	-33.9476	27.18734		175.047
2841	2792.34	-48.6596	24.01964		177.9734
2794	2768.161	-25.8394	121.7085		186.0163
2750	2719.058	-30.9424	-23.8377		196.3137
2603	2684.436	81.43633	45.51786		211.8583
2791	2531.145	-259.855	141.5476		212.7208
2880	2786.681	-93.3189	105.3439		219.2352
2951	2845.577	-105.423	-10.4755		226.1341
2918	2910.25	-7.75016	-126.478		226.4437
3090	2863.556	-226.444	-50.4704		244.7233
3074	3068.725	-5.27474	258.9021		245.1296

3049	3007.646	-41.3538	-112.99	Same set of values			259.8554
3127	2984.127	-142.873	-40.4079				266.1027
3079	3078.242	-0.75821	66.7181				267.9144
2997	3000.208	3.207898	86.30222				288.1699
3056	2903.996	-152.004	165.3923				363.8192
3117	2975.748	-141.252	-56.2332				365.7092
3141	3018.263	-122.737	152.5539				411.7539
3038	3020.506	-17.4937	-85.1443				465.3789
2989	2890.233	-98.7674	30.45287				509.8268

Table 5.10. SVR July-2016 prediction & Error results

Actual	Predicted	error_pd	jlere	jle	jiC	jlMape	jl_sort
2879	2930.438	51.43774	302.7724	4.7455	8.5686	2.6457	0.395264
2802	2832.423	30.42321	-106.154	Same set of values			0.955089
2764	2762.051	-1.94912	-42.7679				1.014439
2671	2731.326	60.32567	-13.5663				1.238527
2626	2633.964	7.964347	-142.939				1.265538
2653	2596.194	-56.8056	149.212				1.949121
2633	2634.266	1.265538	-91.1688				2.041024
2558	2613.583	55.58255	-69.5932				2.068276
2608	2547.891	-60.1092	-49.7826				2.094021
2817	2620.775	-196.225	-90.3245				2.44087
2864	2849.124	-14.8761	42.21558				4.022184
2931	2871.232	-59.7679	15.85068				4.45363
2964	2940.741	-23.2593	25.08178				4.904918
2987	2968.708	-18.2916	-58.0458				6.363776
3077	2990.915	-86.0849	-19.415				6.487391
3098	3085.436	-12.5637	-63.4753				7.014788

3083	3091.785	8.784518	9.391005	Same set of values	7.964347
3072	3072.395	0.395264	-50.7724		8.465711
3085	3052.014	-32.9855	-121.21		8.749007
2926	3043.225	117.2247	299.9212		8.784518
2960	2862.093	-97.9071	7.505954		11.43322
2956	2928.433	-27.5671	52.83532		12.40165
3072	2919.41	-152.59	60.28567		12.56371
2917	3047.381	130.3813	-590.695		13.26279
2782	2859.087	77.08739	306.0709		13.94623
2738	2735.906	-2.09402	5.589402		13.99217
2727	2707.806	-19.1945	34.931		14.04429
2626	2702.624	76.62405	-20.0903		14.55582
2643	2594.073	-48.9268	24.16334		14.87609
2673	2626.441	-46.5594	-33.2106		15.91655
2481	2654.834	173.8343	-50.3853		17.99793
2481	2439.448	-41.5517	-56.2116		18.29163
2517	2486.048	-30.9522	49.45818		18.36381
2759	2533.674	-225.326	61.05548		19.14217
2866	2799.398	-66.6019	71.79191		19.19445
2827	2880.531	53.5308	18.89768		19.37073
2953	2824.149	-128.851	-53.7707		19.47071
3004	2973.561	-30.4386	-97.0455		22.51891
3130	3009.783	-120.217	165.6058		23.25931
3051	3140.003	89.00338	-68.5202		23.42678
3030	3032.068	2.068276	-69.2354		23.47099
2931	3019.741	88.74067	-146.394		25.0248
2987	2908.321	-78.6788	72.66015		25.22322

3094	2981.945	-112.055	-74.2327	Same set of values	25.43264
3118	3085.388	-32.6117	170.4777		26.71127
3236	3089.585	-146.415	-54.0408		27.56705
3189	3214.025	25.0248	184.6855		28.03802
3069	3140.85	71.85046	-134.339		28.35778
2994	3016.519	22.51891	-53.9183		29.75366
2883	2951.51	68.51014	-26.7863		30.20724
2835	2837.041	2.041024	-30.5675		30.42321
2784	2803.142	19.14217	-18.5862		30.43857
2792	2755.428	-36.5719	-167.392		30.55126
2815	2770.631	-44.3686	140.9711		30.95217
2726	2794.432	68.4319	-44.0698		31.67457
2654	2697.968	43.96767	-67.4189		32.61174
2759	2644.507	-114.493	45.30905		32.67932
2956	2778.038	-177.962	84.69092		32.98551
3045	2982.003	-62.9967	-15.5212		33.56302
3027	3050.471	23.47099	48.4777		33.57351
3073	3019.018	-53.9824	9.130619		34.08853
3105	3076.962	-28.038	-0.14771		34.33422
3106	3104.761	-1.23853	-38.03		34.58545
3107	3099.985	-7.01479	-34.8504		36.57193
3124	3097.289	-26.7113	-57.3345		37.15306
3112	3111.045	-0.95509	-155.526		38.72316
3124	3089.911	-34.0885	59.67864		41.55171
3144	3100.377	-43.6231	113.4499		42.26661
3146	3117.642	-28.3578	-5.50935		42.64971
3050	3114.413	64.41347	5.53666		43.62307

3133	3007.601	-125.399	83.90864	Same set of values	43.96767
3065	3111.268	46.26847	-214.212		44.36858
3028	3021.513	-6.48739	-67.3362		44.42792
2934	2989.858	55.85773	39.70645		45.65037
2862	2891.754	29.75366	-99.4953		45.93176
2815	2828.263	13.26279	-25.0212		46.26847
2616	2788.417	172.417	-111.371		46.55945
2805	2575.671	-229.329	117.8186		46.92513
2819	2816.559	-2.44087	-48.5167		47.046
2839	2805.426	-33.5735	-45.412		48.92679
2826	2827.014	1.014439	-22.7688		51.43774
3057	2817.223	-239.777	140.4475		51.62348
3098	3079.636	-18.3638	66.95113		53.22685
3158	3090.99	-67.0103	36.68625		53.5308
3171	3156.956	-14.0443	-4.66937		53.98241
3260	3162.682	-97.3178	-20.7693		55.58255
3353	3260.37	-92.6298	9.654611		55.85773
3305	3347.65	42.64971	50.70592		56.1634
3230	3277.046	47.046	-281.266		56.20395
3140	3198.961	58.96082	-17.0341		56.68268
3122	3107.444	-14.5558	-34.8697		56.69982
3200	3099.718	-100.282	99.37279		56.80564
3291	3183.84	-107.16	36.63829		58.80448
3283	3263.529	-19.4707	-58.7097		58.96082
3173	3231.804	58.80448	60.53543		59.76794
3037	3110.328	73.32782	-61.1433		60.03878
2854	2976.458	122.4577	-549.725		60.10922

2812	2796.083	-15.9166	-3.20182	Same set of values	60.32567
2771	2779.749	8.749007	-102.646		62.70033
2802	2741.961	-60.0388	-87.0203		62.99666
2654	2782.7	128.7004	-38.8039		64.41347
2507	2602.819	95.819	45.02543		65.18787
2237	2454.485	217.4845	30.3597		65.38323
2120	2176.204	56.20395	-49.2979		66.60194
2065	2095.551	30.55126	33.12588		67.0103
2104	2057.075	-46.9251	251.5625		68.4319
2221	2114.591	-106.409	-92.5047		68.51014
2247	2238.534	-8.46571	-86.6701		68.90736
2340	2251.006	-88.9935	-79.073		68.98871
2110	2352.445	242.4445	18.1682		69.81571
2501	2092.234	-408.766	-23.0878		70.51134
2603	2569.437	-33.563	-38.7534		71.85046
2630	2617.598	-12.4017	6.031659		73.32782
2656	2630.567	-25.4326	-56.8438		73.42829
2688	2650.847	-37.1531	-47.69		76.62405
2877	2677.334	-199.666	183.4824		77.08739
2794	2878.037	84.03725	-163.381		77.58444
2825	2751.572	-73.4283	97.41137		78.67877
2855	2798.3	-56.6998	-94.6226		84.03725
2821	2825.905	4.904918	0.035555		86.0849
2463	2783.209	320.209	196.3946		86.50325
2466	2397.093	-68.9074	6.877897		88.74067
2363	2454.035	91.03497	-7.9924		88.99354
1984	2332.16	348.16	-77.5328		89.00338

1970	1935.666	-34.3342	41.38582	Same set of values	91.03497
1949	1981.679	32.67932	39.54768		92.59252
2007	1961.068	-45.9318	-46.8255		92.62985
2043	2029.008	-13.9922	-64.0331		92.74634
2030	2060.207	30.20724	81.93057		95.819
2044	2039.978	-4.02218	79.55586		97.31779
2053	2057.454	4.45363	110.8134		97.90714
2082	2068.054	-13.9462	17.98553		100.2823
2147	2101.35	-45.6504	-13.076		106.4087
2115	2171.683	56.68268	54.12674		106.4122
2200	2131.011	-68.9887	5.277663		107.1595
2213	2232.371	19.37073	-4.65011		107.9556
2226	2232.364	6.363776	-148.974		112.0548
2234	2245.433	11.43322	-53.3621		114.4927
2327	2249.416	-77.5844	88.71729		117.2247
2545	2348.172	-196.828	41.44523		120.217
2631	2568.3	-62.7003	-7.14882		122.4577
2682	2625.837	-56.1634	39.2985		125.3782
2687	2663.573	-23.4268	4.762627		125.399
2514	2660.509	146.5087	-46.6563		128.7004
2577	2470.588	-106.412	-47.4791		128.8505
2443	2568.378	125.3782	-26.3646		130.3813
2346	2411.383	65.38323	-39.8198		132.4496
2260	2325.188	65.18787	-1.37383		133.5823
2282	2247.415	-34.5855	-38.4585		146.415
2317	2285.325	-31.6746	-24.952		146.5087
2454	2320.418	-133.582	-45.9843		148.3926

2400	2470.511	70.51134	-40.71	Same set of values	152.5903
2448	2409.277	-38.7232	-150.067		172.417
2431	2475.428	44.42792	190.207		173.8343
2759	2455.029	-303.971	43.45086		177.9618
2711	2818.956	107.9556	43.96056		180.6261
2741	2715.777	-25.2232	-57.4481		196.2252
2803	2760.733	-42.2666	155.7673		196.8281
2958	2825.55	-132.45	-56.3308		199.6658
2892	2984.593	92.59252	-35.0774		217.4845
2946	2876.184	-69.8157	67.05363		225.3257
2823	2909.503	86.50325	-70.3795		229.3295
2717	2768.623	51.62348	-83.2495		239.7772
2855	2674.374	-180.626	70.28332		242.4445
2863	2845.002	-17.9979	65.50293		303.9708
2926	2833.254	-92.7463	42.01305		320.209
2954	2900.773	-53.2268	-69.2546		348.16
2774	2922.393	148.3926	5.062664		408.7664

Table 5.11. SVR August-2016 prediction & Error results

Actual	**Predicted**	**Eror_prd**	**auere**	aue	auC	AuMape	Au_sort
2409	2616.375329	207.375329	-53.8019	5.3951	6.7577	3.0123	0.515104
2318	2325.778569	7.77856946	-26.1744	Same set of values			2.021524
2274	2295.220505	21.2205051	2.114184				2.39298
2238	2267.459167	29.4591671	-66.4577				2.78675
2553	2235.681067	-317.31893	-5.77002				3.667563
2326	2643.609575	317.609575	49.69799				4.014177
2449	2261.056689	-187.94331	-18.1697				4.560566
2421	2485.648662	64.6486621	-60.0191				5.133069

2471	2412.69259	-58.30741	77.6422	Same set of values	6.025153
2706	2484.252573	-221.74743	200.3356		6.436391
2741	2765.050234	24.0502343	-1.22424		7.291125
2673	2737.046193	64.0461929	70.22305		7.778569
2782	2640.657249	-141.34275	32.94144		7.947453
2901	2798.971357	-102.02864	34.69348		8.463805
2681	2915.889405	234.889405	105.6656		9.13295
2696	2602.211622	-93.788378	20.2829		10.03734
2667	2688.254011	21.254011	6.466935		10.50444
2720	2647.141322	-72.858678	20.77299		11.59548
2811	2722.876723	-88.123277	43.66063		12.06202
2825	2821.332437	-3.6675632	-133.679		12.86516
2846	2811.078985	-34.921015	104.9829		12.89995
2797	2833.198854	36.1988542	9.293131		13.62015
2716	2764.807404	48.8074036	140.6877		13.81837
2505	2677.72964	172.72964	-161.761		16.71039
2350	2436.613661	86.6136607	-65.9205		17.64396
2083	2305.885637	222.885637	12.83953		18.85161
2159	2016.855275	-142.14472	16.09675		19.7867
2125	2194.404369	69.4043687	-84.4853		20.31717
2098	2128.279963	30.2799627	56.43554		20.68721
2139	2104.664336	-34.335664	34.25663		21.22051
2375	2164.457717	-210.54228	-190.258		21.25401
2361	2449.360154	88.3601543	60.93512		21.73719
2398	2359.50158	-38.49842	37.31236		22.2749
2484	2410.39036	-73.60964	233.4709		24.05023
2626	2507.532798	-118.4672	46.09289		24.67476

2622	2660.451722	38.4517224	-53.9125	Same set of values	27.05371
2503	2611.806319	108.806319	153.7715		27.23852
2435	2463.027079	28.0270788	33.73685		27.8116
2558	2413.917289	-144.08271	133.9603		28.02708
2455	2589.934351	134.934351	-88.277		28.09458
2541	2422.397497	-118.6025	28.90212		29.45917
2610	2562.207929	-47.792071	-67.6778		30.27996
2697	2622.742899	-74.257101	107.0427		30.65067
2861	2711.286991	-149.71301	113.3837		31.18945
2807	2891.243476	84.2434761	19.9175		31.67072
2710	2772.963846	62.963846	140.6739		32.13244
2631	2667.252617	36.2526175	-47.6613		32.69426
2472	2597.395104	125.395104	-72.1731		33.62347
2346	2421.172401	75.1724013	-10.2726		33.64441
2215	2311.097648	96.0976481	-63.3233		33.94361
2134	2184.585985	50.5859846	5.924703		34.33566
2109	2122.620146	13.6201465	-18.5742		34.92101
2055	2115.918525	60.9185247	39.00099		35.45156
2076	2055.312793	-20.687207	36.41799		35.47459
2165	2098.28662	-66.71338	-79.1188		35.59874
2214	2203.962661	-10.037339	-32.1741		36.19885
2185	2238.16703	53.1670298	135.7227		36.25262
2401	2186.671512	-214.32849	177.9599		37.0408
2330	2467.805114	137.805114	50.48464		37.93315
2259	2312.23474	53.2347402	-19.587		38.45172
2211	2244.644409	33.6444088	76.17734		38.49842
2169	2206.040796	37.0407959	44.42663		39.35483

2177	2167.86705	-9.1329495	19.15502		39.63871
2163	2190.811595	27.8115954	28.72394		39.79409
2225	2170.746992	-54.253008	44.97592		40.00191
2376	2253.231378	-122.76862	12.12208		41.672
2460	2424.548442	-35.451558	44.74605		41.77322
2598	2484.170294	-113.82971	46.21251		42.56627
2710	2632.336776	-77.663224	26.82875		47.33654
2629	2731.227975	102.227975	-65.4492		47.60785
2515	2594.727358	79.727358	139.2396		47.79207
2344	2475.859725	131.859725	-62.5874		48.8074
2152	2295.232022	143.232022	11.61894		50.21202
2072	2105.623465	33.6234651	-56.4276		50.58598
2028	2063.598745	35.5987445	-21.2028		51.18089
2008	2032.674757	24.6747574	-6.2192		53.16703
1987	2020.943606	33.9436058	-168.006		53.18678
2093	2000.308005	-92.691995	257.5758		53.23474
2256	2140.330086	-115.66991	-27.6207		53.97741
2274	2313.354828	39.3548275	32.32085		54.25301
2383	2286.416799	-96.583201	-1.71532		55.55066
2565	2418.423444	-146.57656	251.3519		58.30741
2604	2614.504439	10.5044389	-3.1983		60.91852
2610	2607.978476	-2.0215237	75.57753		62.96385
2523	2603.685047	80.6850472	25.10391		64.04619
2523	2492.349328	-30.650672	116.0064		64.64866
2531	2519.404523	-11.595477	100.6744		64.66466
2577	2529.663456	-47.336544	-37.3066		64.95552
2583	2585.39298	2.39297989	-23.1848		66.71338

2611	2578.867557	-32.132443	-33.1271		67.85275
2730	2612.318278	-117.68172	39.65473		69.40437
2897	2753.453361	-143.54664	112.9547		70.35089
2854	2927.155493	73.1554928	100.375		70.80568
2849	2821.761479	-27.238521	1.957986		72.85868
2704	2828.5696	124.5696	-69.6501		73.15549
2553	2647.358442	94.3584425	-69.3207		73.60964
2349	2501.371251	152.371251	-114.402		74.2571
2291	2290.484896	-0.5151041	32.75936		74.86189
2238	2279.773222	41.7732221	-11.292		75.1724
2214	2230.710394	16.710394	58.5178		77.66322
2184	2216.694262	32.6942617	-141.107		79.72736
2281	2186.235326	-94.764674	-91.3546		79.99752
2446	2317.670964	-128.32904	-220.709		80.68505
2456	2496.001909	40.0019093	-42.0066		83.66257
2490	2458.810545	-31.189455	-32.3557		84.24348
2737	2498.656917	-238.34308	40.01217		86.61366
2757	2799.56627	42.5662696	90.69366		87.96654
2629	2749.48328	120.48328	-18.9642		88.12328
2647	2582.335336	-64.664664	76.89258		88.303
2728	2644.337432	-83.662568	-262.588		88.36015
2775	2739.525406	-35.474594	446.3775		90.86736
2761	2773.865164	12.8651639	-15.4802		92.692
2784	2742.327998	-41.672002	2.593268		93.78838
2772	2776.014177	4.01417741	25.77273		94.35844
2864	2753.817648	-110.18235	33.47972		94.76467
3048	2873.292286	-174.70771	190.3481		94.83443

3006	3076.805678	70.8056781	-121.018		96.09765
2961	2967.436391	6.43639137	72.70176	Same set of values	96.5832
2916	2923.291125	7.29112476	38.2734		97.20309
2735	2880.38834	145.38834	-24.0418		102.0286
2586	2665.997517	79.9975166	-329.975		102.228
2516	2533.643958	17.6439577	113.8266		108.5678
2464	2491.053706	27.0537063	-102.236		108.8063
2382	2446.955521	64.955521	-350.007		110.1824
2368	2359.536195	-8.4638053	82.07141		113.1481
2455	2367.033462	-87.966538	-37.2329		113.8297
2475	2481.025153	6.02515306	42.94587		115.3669
2412	2479.85275	67.8527497	-0.64105		115.6187
2550	2394.535502	-155.4645	-41.3378		115.6699
2722	2588.072899	-133.9271	0.070774		117.6817
2771	2763.052547	-7.9474534	-12.5545		118.4672
2767	2772.133069	5.1330688	9.213698		118.6025
2682	2752.350887	70.3508871	40.24481		120.4833
2694	2646.392152	-47.607848	-65.0286		122.7686
2858	2686.545614	-171.45439	79.91223		124.5696
2850	2889.794086	39.794086	-24.189		125.3951
2817	2829.899947	12.8999469	-1.54212		128.329
2842	2790.819114	-51.180886	-6.00363		131.8597
2907	2832.138113	-74.861887	81.04236		131.93
3001	2906.165574	-94.834426	184.3734		133.9271
2949	3004.550658	55.5506579	24.25747		134.9344
2964	2910.022589	-53.977411	33.63331		137.8051
2926	2944.851608	18.8516081	0.901339		141.3428

2777	2892.366859	115.366859	-162.782	Same set of values	142.1447
2625	2715.86736	90.8673605	119.78		143.232
2532	2569.933146	37.9331462	-146.598		143.5466
2477	2499.274905	22.2749047	-55.4259		144.0827
2463	2458.439434	-4.5605655	-60.067		145.3883
2418	2457.638709	39.6387093	40.61257		146.5766
2557	2405.242391	-151.75761	21.57867		149.713
2616	2594.262813	-21.737187	121.1764		151.7576
2606	2626.317169	20.3171689	-95.1184		152.3713
2709	2595.851936	-113.14806	61.71541		155.4645
2956	2729.048222	-226.95178	-32.5806		166.2683
2843	3009.268294	166.268294	331.1908		171.4544
2794	2791.21325	-2.7867505	-135.538		172.7296
2796	2764.329281	-31.670719	55.16794		174.7077
2879	2781.796905	-97.203095	64.42405		187.9433
2935	2884.787976	-50.212024	150.3555		207.3753
2944	2930.181629	-13.818371	-92.0027		210.5423
2905	2924.786703	19.7867032	93.23286		214.3285
2885	2872.937983	-12.062017	-115.945		221.7474
2975	2859.381295	-115.6187	-50.5393		222.8856
3067	2978.696998	-88.303002	183.3249		226.9518
3095	3066.905418	-28.094582	-15.1749		234.8894
3127	3073.813217	-53.186783	79.85709		238.3431
2997	3105.567765	108.567765	30.90863		317.3189
2800	2931.929996	131.929996	-165.175		317.6096

Table 5.12. SVR September-2016 prediction & Error results

Actual	**Predicted**	**Eror_prd**	**Sere**	se	sC	sMape	s_sort

2596	2897.608051	301.608051	-184.592	1.4281	1.4845	2.617	0.067271
2485	2467.86862	-17.13138	-2.53399	Same set of values			0.230643
2459	2437.4818	-21.5182	-14.7539				1.005914
2428	2438.746245	10.7462451	-17.7774				1.235935
2392	2411.008529	19.0085286	321.9932				1.317708
2436	2377.602468	-58.397532	-281.668				1.582949
2515	2438.376964	-76.623036	198.249				1.721372
2437	2517.342139	80.3421387	-41.7391				2.43701
2475	2403.079055	-71.920945	76.39731				2.666178
2775	2481.116307	-293.88369	245.867				3.575979
2858	2837.366743	-20.633257	21.59661				4.393977
2829	2851.358057	22.3580565	-14.0416				4.677175
2749	2807.01239	58.0123904	183.639				5.811898
2748	2734.850389	-13.149611	150.202				6.346058
2810	2768.875307	-41.124693	-191.857				7.406674
2859	2845.675628	-13.324372	114.4469				7.437524
2909	2885.469811	-23.530189	14.60751				7.845831
2777	2922.798148	145.798148	104.7442				9.349286
3001	2744.818215	-256.18178	122.7204				10.54725
3003	3034.724909	31.7249089	45.01025				10.5918
3085	2970.433074	-114.56693	76.86772				10.74625
3044	3066.184808	22.1848082	9.665999				11.28701
2953	2989.615317	36.6153172	0.836619				11.46841
2857	2888.328571	31.3285711	-129.054				11.90713
2661	2800.40601	139.40601	-59.4038				11.99372
2594	2592.764065	-1.2359347	-204.787				12.15407
2546	2564.08438	18.0843797	140.4412				12.92962

2467	2521.987197	54.9871973	-59.3429	Same set of values	12.97471
2453	2441.712994	-11.287006	-24.6259		13.10628
2475	2446.676721	-28.323279	38.34828		13.14961
2488	2476.531592	-11.468408	224.5872		13.32437
2455	2484.271014	29.2710138	-56.1196		13.71943
2553	2439.325857	-113.67414	62.49541		14.10391
2714	2576.17778	-137.82222	102.2477		14.69663
2735	2739.677175	4.67717454	150.1435		14.91439
2749	2720.667237	-28.332763	-8.2961		15.57295
2735	2736.005914	1.0059143	-76.9976		16.16638
2778	2721.686605	-56.313395	-5.12768		16.65796
2875	2783.57565	-91.42435	157.5146		16.90486
2902	2886.427051	-15.572949	-116.823		17.13138
2901	2887.893716	-13.106284	127.8703		18.08438
2874	2881.437524	7.43752398	71.24301		18.40488
3015	2847.552152	-167.44785	105.5148		18.79861
3092	3016.010153	-75.989847	185.8605		18.83386
3048	3046.417051	-1.5829487	-32.1769		19.00853
3054	2972.666619	-81.333381	-18.7502		19.16672
2956	2981.27431	25.2743104	0.721645		19.19031
2730	2987.195493	257.195493	-93.2724		19.74286
2601	2625.808297	24.8082966	-53.9057		20.63326
2560	2539.032006	-20.967994	-83.6826		20.96799
2509	2527.833861	18.8338606	-46.9024		21.00376
2411	2479.672852	68.6728519	-14.2897		21.00994
2360	2379.16672	19.1667203	-62.1325		21.5182
2447	2341.200742	-105.79926	23.73057		21.75164

2556	2458.01281	-97.98719	73.8162		22.10031
2489	2566.035369	77.0353689	26.74117		22.18481
2547	2458.552775	-88.447225	-22.0403		22.35806
2763	2555.704291	-207.29571	239.6113		22.62002
2731	2797.728794	66.7287943	-94.6598		23.53019
2744	2703.155378	-40.844622	-22.8181		24.8083
2733	2731.278628	-1.7213717	-13.8976		25.27431
2735	2724.452753	-10.547247	-25.995		25.35121
2825	2739.77496	-85.22504	15.13271		26.29989
2829	2843.696634	14.6966343	-20.2997		26.34939
2771	2816.468365	45.4683648	59.21075		26.91414
2864	2742.27958	-121.72042	130.9129		28.24686
3033	2858.32479	-174.67521	55.30008		28.32328
3039	3022.833623	-16.166377	137.8941		28.33276
2974	2975.317708	1.31770792	113.0839		29.05085
2966	2894.78819	-71.21181	-59.9386		29.27101
2898	2910.154069	12.1540693	-41.785		30.95013
2770	2832.567305	62.5673049	-102.08		31.32857
2594	2701.691644	107.691644	-124.646		31.72491
2459	2531.623403	72.6234032	-28.1043		31.93112
2362	2416.106098	54.1060984	-33.1454		32.10211
2307	2323.657964	16.6579644	-25.6101		34.94482
2263	2289.299893	26.2998933	-35.7242		34.97325
2340	2248.462947	-91.537053	101.4895		36.61532
2469	2347.839462	-121.16054	133.9546		36.6603
2469	2480.993723	11.9937235	-11.6018		38.86062
2536	2440.346647	-95.653353	110.6845		40.0583

2768	2512.913058	-255.08694	163.6627		40.84462
2703	2760.105313	57.1053133	16.41916		41.12469
2676	2611.133882	-64.866118	26.30206		41.2641
2616	2605.408199	-10.591801	-60.2537		42.28824
2596	2553.71176	-42.28824	37.52587		42.66246
2697	2565.824637	-131.17536	3.410031		43.01434
2739	2696.337538	-42.662462	32.64687		44.11485
2829	2730.237269	-98.762731	-21.6899		45.46836
2776	2819.014345	43.0143446	12.44302		50.50249
2953	2722.373368	-230.62663	100.2709		54.1061
3073	2939.342875	-133.65712	146.5541		54.91335
2951	3019.76679	68.7667898	-45.0172		54.9872
2874	2842.068885	-31.931115	50.80281		55.94695
2783	2786.575979	3.57597949	-98.1899		56.3134
2682	2701.742861	19.742861	-80.2922		57.10531
2466	2607.946836	141.946836	-144.78		58.01239
2391	2383.154169	-7.8458315	-5.183		58.39753
2295	2356.945851	61.9458507	-44.8231		60.66552
2263	2265.666178	2.66617791	-21.9564		61.94585
2251	2256.811898	5.81189791	-38.9506		62.5673
2337	2245.746995	-91.253005	86.4131		62.73796
2481	2350.209127	-130.79087	128.8715		62.80617
2480	2498.404881	18.4048811	-30.8408		64.86612
2576	2471.926599	-104.0734	8.002086		66.72879
2804	2593.576893	-210.42311	215.4728		67.55755
2830	2843.719428	13.7194276	-46.1615		68.67285
2815	2815.067271	0.06727131	-141.61		68.76679

2783	2794.907129	11.9071291	20.20551		71.21181
2796	2767.753142	-28.246858	38.4729		71.92094
2820	2794.648789	-25.351211	53.17795		72.6234
2859	2824.026753	-34.973247	10.86031		75.98985
2845	2864.190311	19.1903105	42.90435		76.62304
2869	2808.334483	-60.665517	-17.3117		77.03537
3129	2829.490307	-299.50969	96.60278		79.78691
3040	3126.805802	86.8058023	175.2305		80.34214
2884	2928.114848	44.1148478	-47.9577		81.33338
2862	2756.861583	-105.13842	12.78648		85.22504
2732	2773.264105	41.2641046	20.88883		85.50169
2643	2628.085605	-14.914395	-121.372		86.8058
2445	2560.788742	115.788742	-68.192		88.44723
2342	2354.929616	12.9296159	-15.0273		89.41571
2314	2291.899695	-22.100305	-27.494		89.75
2200	2289.749999	89.7499988	-68.4681		91.25301
2192	2165.085856	-26.914144	-1.04357		91.42435
2638	2188.354408	-449.64559	77.67786		91.53705
2401	2713.332226	312.332226	-10.9873		93.50332
2408	2314.496678	-93.503322	-83.6002		95.65335
2419	2397.996244	-21.003756	125.5432		97.98719
2573	2426.098504	-146.9015	103.8796		98.44089
2680	2612.442455	-67.557545	-29.2661		98.76273
2646	2708.737962	62.737962	-41.5404		101.0463
2648	2640.593326	-7.4066737	-118.849		104.0734
2631	2660.050853	29.0508532	-5.69141		104.2834
2649	2594.08665	-54.91335	161.5945		105.1384

2638	2633.606023	-4.393977	-45.4374		105.7993
2618	2620.43701	2.43700996	-39.233		107.6428
2617	2600.095143	-16.904857	19.78429		107.6916
2908	2594.830514	-313.16949	58.23703		113.6741
2985	2934.497506	-50.502494	92.86643		114.5669
2943	2936.653942	-6.346058	-43.5637		115.7887
2877	2864.025293	-12.974707	68.04878		121.1605
2771	2793.62002	22.6200196	-2.47194		121.7204
2607	2686.786911	79.7869113	-102.535		130.7909
2419	2523.283399	104.283399	-75.6636		131.1754
2324	2345.75164	21.7516401	-32.8055		131.6266
2268	2286.798608	18.7986084	-22.1138		133.6571
2226	2247.009944	21.0099444	1.845639		137.8222
2159	2214.946947	55.9469467	-42.4686		139.406
2181	2142.139377	-38.860623	144.1533		140.0715
2269	2183.498307	-85.501693	24.52129		141.9468
2316	2279.339701	-36.660299	-26.0043		145.7981
2257	2297.058301	40.0583006	97.05553		146.9015
2341	2209.3734	-131.6266	206.6931		167.4478
2426	2324.953747	-101.04625	-186.584		174.6752
2315	2404.415706	89.4157055	-32.0668		207.2957
2265	2250.89609	-14.10391	-15.9348		210.4231
2237	2227.650714	-9.3492857	53.1303		230.6266
2213	2212.769357	-0.2306432	53.9424		255.0869
2230	2195.055184	-34.944816	11.12197		256.1818
2332	2224.357245	-107.64275	-39.5902		257.1955
2380	2347.897893	-32.102107	-13.6535		293.8837

2739	2372.600389	-366.39961	100.9412				299.5097
2802	2775.650605	-26.349395	91.30873				301.6081
2844	2745.559111	-98.440889	44.39162				312.3322
2638	2778.071504	140.071504	78.45555				313.1695
2555	2524.049874	-30.950126	-81.1114				366.3996
2424	2486.80617	62.8061696	-116.232				449.6456

Table 5.13. SVR October-2016 prediction & Error results

Actual	**Predicted**	**Eror_prd**	**oere**	oe	oC	oMape	o_sort
2200	2413.41445	213.41445	-294.329	5.8847	2.2737	3.5556	0.197686
2027	2094.8918	67.8917996	43.16146	Same set of values			0.717354
2006	1981.190587	-24.809413	19.9446				1.449055
1936	2016.409894	80.409894	-21.4326				2.751283
1949	1938.443878	-10.556122	-30.8559				2.884097
2056	1981.720007	-74.279993	45.03505				3.022238
2193	2104.051775	-88.948225	58.34516				3.721422
2282	2235.284991	-46.715009	-97.5504				4.472135
2314	2315.449055	1.44905474	64.6568				4.911685
2426	2352.737639	-73.262361	278.9275				5.181216
2589	2501.479392	-87.520608	-0.66452				6.407188
2590	2674.914998	84.9149977	-19.321				6.613413
2467	2619.255463	152.255463	-45.5355				8.656396
2421	2475.716843	54.7168432	26.75903				9.491369
2446	2466.407939	20.4079387	48.33957				9.589621
2508	2511.721422	3.72142232	18.46958				10.38095
2551	2562.441126	11.4411258	32.52988				10.48289
2719	2573.91701	-145.08299	-134.642				10.52339
2942	2733.552387	-208.44761	276.0271				10.55612

2891	2921.811037	30.8110368	-32.5799	Same set of values	11.44113
2769	2764.527865	-4.4721348	133.7486		11.65305
2613	2625.751726	12.7517259	-5.76078		12.43724
2444	2471.440445	27.4404452	-11.6253		12.75173
2287	2324.531896	37.531896	-7.19202		13.661
2143	2190.170914	47.170914	-120.145		13.89366
2037	2069.315802	32.3158023	18.51038		14.15924
2065	1988.412631	-76.587369	-16.5497		15.10248
1903	2059.979876	156.979876	-58.1189		15.67158
1890	1849.876953	-40.123047	6.561938		16.64393
1938	1887.19297	-50.80703	16.8702		19.385
2080	1953.639985	-126.36002	-2.03995		19.39823
2114	2123.491369	9.49136881	-41.3353		20.40794
2078	2132.897709	54.8977089	103.807		21.38004
1992	2107.460569	115.460569	122.2658		22.05149
1983	2049.036196	66.0361957	-16.9733		23.44805
1820	2085.473765	265.473765	30.01502		24.76009
1767	1899.577745	132.577745	2.398526		24.76838
1734	1904.903548	170.903548	61.8909		24.80941
1691	1884.938993	193.938993	94.67937		25.54447
1861	1845.328418	-15.671582	19.32385		26.22525
1840	2060.450736	220.450736	24.50549		26.51397
2031	1958.319658	-72.680342	6.602574		27.12327
2489	2169.927532	-319.07247	182.2033		27.24864
2523	2637.428913	114.428913	82.92545		27.44045
2482	2494.437243	12.4372433	17.22413		27.47598
2341	2433.133009	92.1330094	105.5192		28.23978

2269	2275.613413	6.61341258	-6.01316	Same set of values	30.15739
2119	2239.323976	120.323976	-225.79		30.81104
1937	2074.57077	137.57077	-2.34222		32.3158
1847	1903.929573	56.9295726	27.6059		32.60051
1794	1860.162378	66.1623779	-22.4001		35.94473
1751	1827.644152	76.6441525	-74.1215		37.12374
1804	1789.840756	-14.159244	-25.7185		37.5319
1946	1864.477831	-81.522169	91.80251		38.62345
2196	2016.390102	-179.6099	76.2576		39.2092
2192	2268.923469	76.923469	-94.4748		39.79752
2259	2196.196615	-62.803385	83.4342		40.12305
2379	2308.62468	-70.37532	194.7884		41.37105
2500	2448.120855	-51.879145	-81.4047		42.89812
2453	2557.377548	104.377548	47.1852		43.27593
2404	2466.328374	62.3283739	4.943028		43.47323
2408	2432.760093	24.7600932	15.98665		44.14243
2470	2459.517114	-10.482886	90.24452		44.86278
2506	2530.768381	24.7683806	-12.8024		46.71501
2502	2541.797523	39.797523	-35.9777		47.17091
2633	2515.355136	-117.64486	133.328		48.70812
2947	2657.095297	-289.9047	177.0544		49.40076
2877	2974.04931	97.0493097	20.41949		50.80703
2705	2760.602492	55.6024924	17.60898		51.59267
2591	2563.876728	-27.123272	92.84903		51.87914
2461	2538.888384	77.8883841	4.292369		53.12745
2251	2357.992531	106.992531	-44.4079		54.71684
2109	2148.209203	39.2092027	-91.0986		54.89771

2030	2052.051486	22.0514864	-61.306	Same set of values	55.60249
1978	2004.225249	26.2252493	-54.3627		55.84328
1929	1967.623446	38.6234461	-26.7873		56.92957
1947	1925.619964	-21.380036	-43.0741		57.33691
2084	1962.44414	-121.55586	71.03907		57.53223
2237	2120.353324	-116.64668	93.67884		58.8981
2243	2259.643926	16.6439262	-36.8878		60.62869
2266	2263.115903	-2.8840967	82.18999		62.32837
2380	2317.363599	-62.636401	238.8181		62.6364
2339	2468.479609	129.479609	-76.0298		62.80339
2303	2390.772993	87.7729933	68.86055		64.90119
2237	2371.826089	134.826089	10.15723		66.0362
2211	2311.237993	100.237993	42.28864		66.16238
2233	2308.088742	75.0887424	127.6764		66.84436
2254	2341.083205	87.083205	34.13867		67.58704
2325	2352.47598	27.4759795	98.76328		67.8918
2479	2409.865047	-69.134953	-42.762		69.13495
2826	2538.555871	-287.44413	240.3563		70.37532
2768	2881.051978	113.051978	131.8432		71.84299
2650	2665.102481	15.102481	-59.5113		72.41177
2519	2532.661004	13.6610036	56.41766		72.68034
2390	2409.398235	19.3982345	12.63002		73.26236
2254	2296.898123	42.8981235	-7.24358		73.73563
2073	2172.876815	99.8768152	-134.144		74.27999
1939	2003.901187	64.9011874	14.25003		75.08874
1917	1905.346947	-11.653053	-72.4001		76.58737
1891	1926.944731	35.9447306	-16.467		76.64415

1913	1902.619051	-10.380949	-27.0722	Same set of values	76.92347
1965	1936.760223	-28.239777	67.12255		77.88838
2059	1991.412962	-67.587038	102.4926		78.01027
2138	2082.156725	-55.843275	-43.8387		79.32878
2123	2183.62869	60.6286899	92.75783		80.40989
2068	2174.673006	106.673006	196.143		81.52217
2103	2140.12374	37.1237397	-26.8359		81.66913
2064	2220.429905	156.429905	6.921006		83.21427
2000	2168.049952	168.049952	-1.70495		84.915
1962	2111.014021	149.014021	38.64291		87.0832
1878	2085.70409	207.70409	32.54745		87.52061
1899	1996.053566	97.0535665	42.80937		87.77299
1863	2050.852309	187.852309	-10.4991		88.94823
2085	1972.981171	-112.01883	71.52702		89.52484
2306	2224.330874	-81.669126	307.5162		89.8518
2366	2393.248638	27.2486379	-86.0259		92.13301
2376	2371.088315	-4.9116845	-17.912		95.92212
2327	2352.544471	25.544471	127.9882		97.04931
2210	2276.844361	66.8443614	-31.9044		97.05357
2034	2153.687181	119.687181	27.02292		99.87682
1951	1983.600513	32.6005134	-112.255		100.238
1886	1944.898098	58.8980983	-10.2727		104.3775
1812	1895.214266	83.214266	10.61191		106.673
1786	1830.142434	44.1424344	-109.475		106.9925
1781	1824.275928	43.2759282	8.821944		112.0188
1965	1822.292675	-142.70732	421.5241		113.052
2133	2043.475159	-89.524841	-357.242		114.4289

2183	2193.523387	10.5233867	97.9317	Same set of values	115.4606
2261	2230.842607	-30.157393	4.220152		116.6467
2487	2338.519962	-148.48004	131.4897		117.6449
2470	2601.038158	131.038158	48.18854		118.3054
2463	2507.862777	44.8627766	-71.0351		119.6872
2454	2511.532232	57.5322318	10.1724		120.324
2431	2509.010267	78.010267	-28.9481		121.5559
2437	2485.708124	48.7081237	52.81317		125.6201
2249	2485.589201	236.589201	1.000226		126.36
2510	2253.454018	-256.54598	-3.48414		129.4796
2707	2627.671224	-79.328776	15.57906		131.0382
2945	2740.218065	-204.78194	309.4225		132.5777
2927	2933.407188	6.40718777	36.07483		134.8261
2810	2819.589621	9.58962095	15.16843		137.5708
2676	2676.717354	0.71735372	30.18917		142.7073
2499	2550.59267	51.5926701	-7.16457		144.8657
2297	2386.851797	89.8517966	-66.5861		145.083
2080	2205.620115	125.620115	-94.8784		148.48
2007	2015.656396	8.65639638	-20.6927		149.014
1962	2003.37105	41.3710502	-31.4285		149.1131
1921	1974.127446	53.1274462	-40.3105		152.2555
1935	1938.022238	3.02223812	-78.729		156.4299
2083	1964.694589	-118.30541	14.27447		156.9799
2280	2135.134322	-144.86568	53.82152		164.0285
2315	2338.448046	23.4480464	3.736429		168.05
2322	2327.181216	5.18121609	-67.5122		170.9035
2514	2364.886902	-149.1131	110.2166		179.6099

2532	2603.84299	71.8429899	71.28699	Same set of values			187.8523
2499	2572.735628	73.735628	-114.377				193.939
2370	2534.028468	164.028468	0.893035				204.7819
2426	2399.48603	-26.51397	-11.8716				207.7041
2469	2512.473226	43.4732264	-24.2687				208.4476
2516	2535.385003	19.3850026	8.933529				213.4144
2553	2566.893658	13.8936578	79.01224				220.4507
2640	2567.588233	-72.411767	1.920879				236.5892
2912	2629.139518	-282.86048	343.5666				256.546
2859	2908.400757	49.4007565	-5.32895				265.4738
2741	2738.248717	-2.7512834	96.9104				282.8605
2611	2610.802314	-0.1976859	-137.325				287.4441
2436	2493.336912	57.3369122	44.87933				289.9047
2230	2325.922116	95.9221157	-64.4629				319.0725

Table 5.14. SVR November-2016 prediction & Error results

Actual	**Predicted**	**Eror_prd**	**nere**	ne	nC	nMape	n_sort
1550	1544.733056	-5.2669441	-161.108	3.73	4.25	4.3144	0.092418
1490	1547.179604	57.1796037	0.292152	Same set of values			0.35125
1449	1516.358468	67.358468	73.6862				1.113041
1613	1493.004375	-119.99563	-65.9515				1.603136
1952	1751.910231	-200.08977	35.42989				2.377142
2271	2140.591107	-130.40889	82.04911				3.254165
2454	2399.219832	-54.780168	74.6321				4.087389
2409	2471.668543	62.6685428	27.80422				5.061893
2220	2312.051241	92.051241	1.608146				5.266944
2106	2087.685972	-18.314028	104.9102				6.405176
2037	2047.83334	10.8333398	114.4062				7.395967

1996	2027.133403	31.1334027	-60.7081	Same set of values	7.492342
1875	2018.919234	143.919234	-91.3305		9.471516
1864	1870.405176	6.40517629	36.59504		10.83334
1993	1925.373051	-67.626949	55.00382		11.10008
2073	2114.323267	41.3232668	55.21976		11.16794
2212	2146.308456	-65.691544	31.29875		12.21914
2436	2278.488074	-157.51193	182.4592		13.04455
2640	2501.968161	-138.03184	203.4171		13.34428
2570	2654.412905	84.4129054	-59.1123		13.54101
2151	2429.148986	278.148986	28.69021		15.51755
1946	1866.765221	-79.234779	22.21284		17.83294
1804	1817.344276	13.3442759	10.13774		18.21936
1680	1733.167562	53.1675624	3.728234		18.31403
1568	1635.467969	67.4679689	-11.2351		18.76993
1493	1545.985088	52.9850883	-0.83348		19.60479
1460	1502.945762	42.9457618	97.3753		19.70694
1568	1497.690752	-70.309248	-166.039		20.12409
1934	1669.536747	-264.46325	70.98779		21.05348
2158	2127.113989	-30.886011	46.01653		23.54039
2476	2229.479603	-246.5204	110.0104		24.31179
2314	2552.763956	238.763956	-38.6415		25.90791
2251	2168.572333	-82.427667	-50.0693		26.28478
2243	2195.116024	-47.883976	-79.2723		26.34728
2203	2234.979644	31.9796439	-1.6741		26.78054
2093	2189.538964	96.5389642	-209.545		26.83305
1953	2061.101824	108.101824	-38.3439		28.47926
1880	1926.572844	46.5728437	-95.2986		30.81954

1863	2177.847277	314.847277	-122.274		30.88601
1858	1923.730144	65.7301442	89.84441		31.1334
2043	1916.745104	-126.2549	-196.548		31.19967
2495	2165.377695	-329.62231	130.6437		31.97964
2637	2688.686864	51.6868636	315.9864		32.02353
2583	2618.104828	35.1048281	-186.031		35.10483
2403	2453.351272	50.3512721	-0.50402		35.5452
2175	2223.117296	48.1172965	-63.3371		35.97312
1852	1997.831774	145.831774	43.44612		36.81344
1673	1669.745835	-3.2541651	-85.4346		38.81834
1533	1600.458921	67.4589209	-90.1986		40.31012
1486	1503.832937	17.8329369	-4.73227		41.32327
1437	1516.817951	79.8179505	-34.4462		41.89576
1474	1471.622858	-2.3771421	-53.4892		42.94576
1552	1552.35125	0.35125031	32.58358		44.25323
2012	1637.841692	-374.15831	76.12531		44.74932
2463	2250.377449	-212.62255	154.0711		45.08436
2397	2637.631345	240.631345	-125.806		45.37822
2346	2286.840119	-59.159881	81.57961		45.92361
2311	2269.104242	-41.895758	89.10328		46.57284
2176	2267.624361	91.6243613	68.49332		47.60529
2165	2103.73588	-61.26412	-84.8684		47.82991
2101	2174.60177	73.6017701	-0.79549		47.84076
2061	2092.19967	31.1996697	41.83991		47.88398
2080	2075.912611	-4.0873894	67.61654		48.1173
2065	2126.120961	61.1209612	18.31493		49.42563
2184	2087.99294	-96.00706	3.669134		49.89584

2707	2248.585012	-458.41499	165.423		50.16066
2807	2911.850728	104.850728	298.292		50.35127
2688	2738.786592	50.786592	-137.477		50.6208
2579	2502.989906	-76.010094	-19.431		50.78659
2374	2414.310119	40.3101193	78.66158		51.68686
1959	2180.134141	221.134141	-12.4068		52.13859
1713	1703.528484	-9.4715164	-71.7497		52.21311
1588	1593.061893	5.06189326	12.48288		52.98509
1526	1556.819537	30.8195367	14.71494		53.16756
1489	1541.138594	52.1385938	-5.09452		54.78017
1549	1524.688207	-24.311793	-24.5441		54.78652
1707	1632.366333	-74.633667	34.06641		57.1796
2039	1820.468227	-218.53177	118.0824		57.97885
2481	2198.835963	-282.16404	86.11958		59.15988
2401	2636.017055	235.017055	-48.9438		59.28026
2357	2285.245066	-71.754934	29.88167		61.12096
2296	2288.507658	-7.4923422	100.8256		61.26412
2220	2246.780542	26.7805421	-100.202		62.66854
2103	2185.3937	82.3937003	-17.4802		62.88641
2054	2067.044546	13.0445464	-60.4668		63.68988
2055	2068.541011	13.541011	-15.9251		63.82153
2011	2101.563276	90.563276	2.783598		64.7382
2122	2037.990034	-84.009966	-21.3808		65.643
2199	2206.395967	7.39596676	35.24816		65.69154
2646	2237.581176	-408.41882	109.8215		65.73014
2731	2819.524107	88.5241065	292.9498		67.35847
2714	2669.746769	-44.253231	-161.779		67.45892

2527	2589.886407	62.8864068	14.71083		67.46797
2245	2328.388412	83.3884117	23.93175		67.62695
2031	2032.113041	1.11304112	17.33255		70.30925
1730	1889.125459	159.125459	-8.42559		71.75493
1571	1582.100083	11.1000827	-66.8924		73.60177
1519	1531.219139	12.2191385	-21.3457		74.41803
1484	1547.689882	63.6898819	44.06027		74.63367
1476	1528.213113	52.2131127	-28.271		74.8141
1632	1535.734064	-96.265936	18.53719		76.01009
2188	1762.660235	-425.33976	24.82612		78.80266
2485	2463.946517	-21.053483	57.34659		78.95894
2460	2562.191876	102.191876	34.05351		79.23478
2340	2375.545202	35.5452018	-58.3516		79.81795
2328	2235.985607	-92.014393	-63.94		82.3937
2257	2306.425627	49.4256272	28.38371		82.42767
2173	2220.605286	47.6052862	-101.308		83.38841
2082	2147.642998	65.6429977	-92.6952		83.79587
2053	2071.76993	18.7699305	-64.7831		84.00997
2086	2084.396864	-1.6031363	-130.439		84.41291
2097	2147.620803	50.6208027	-10.4825		84.56976
2210	2135.185903	-74.814097	-124.92		88.52411
2656	2272.970295	-383.02971	173.5528		90.56328
2773	2832.280259	59.2802586	70.32617		91.62436
2666	2723.978846	57.9788462	-48.1779		92.01439
2502	2501.907582	-0.0924178	11.55445		92.05124
2412	2327.430237	-84.569763	-12.5978		96.00706
2042	2291.903449	249.903449	-47.5539		96.26594

1693	1812.533195	119.533195	-84.9305	Same set of values	96.53896
1642	1527.030901	-114.9691	15.64856		97.96609
1609	1656.829909	47.8299094	-32.0053		100.2297
1610	1636.347283	26.347283	-60.7483		101.7608
1691	1655.026885	-35.973115	-19.1006		102.1919
1789	1769.293062	-19.706938	-29.3702		104.8507
2147	1861.872926	-285.12707	149.2081		104.875
2422	2314.981063	-107.01894	52.51448		107.0189
2414	2497.795874	83.7958738	-37.2608		108.1018
2372	2343.520744	-28.479256	48.97395		110.712
2342	2309.976467	-32.023533	177.4605		114.9691
2335	2308.166954	-26.833046	-125.86		115.077
2280	2327.840757	47.8407569	18.56059		119.5332
2158	2255.966087	97.9660872	6.835793		119.9956
2144	2118.092088	-25.907912	-10.1368		126.2549
2156	2167.167941	11.1679406	22.93982		130.4089
2167	2187.124091	20.124091	-179.541		138.0318
2324	2183.776886	-140.22311	355.2003		140.2231
2688	2382.35902	-305.64098	73.88292		143.9192
2758	2802.749325	44.7493249	196.7153		145.8318
2790	2679.288012	-110.71199	-36.1137		146.9448
2582	2682.229722	100.229722	13.91132		157.5119
2325	2361.813438	36.8134382	40.61807		159.1255
2032	2110.95894	78.9589396	-9.64446		183.9766
1793	1842.895836	49.895836	-37.1924		192.8386
1618	1672.786519	54.7865187	-67.638		200.0898
1581	1561.39521	-19.60479	52.66515		212.6226

1507	1608.760767	101.760767	-12.9029	Same set of values			218.5318
1570	1524.076394	-45.923606	-31.3857				221.1341
1708	1657.839336	-50.160664	16.44223				235.0171
2056	1816.638489	-239.36151	122.9888				238.764
2475	2232.421431	-242.57857	118.0175				239.3615
2549	2627.802659	78.8026588	-51.6583				240.6313
2439	2502.821532	63.8215316	11.4203				242.5786
2440	2335.125042	-104.87496	193.7869				246.5204
2374	2412.818337	38.8183373	-63.3044				249.9034
2305	2323.219358	18.2193582	-18.2889				264.4633
2256	2271.517548	15.5175476	-93.2764				278.149
2053	2245.838628	192.838628	123.5743				282.164
2097	1981.92295	-115.07705	12.08032				285.1271
2136	2159.540385	23.5403853	34.33408				305.641
2320	2173.055194	-146.94481	33.75253				314.8473
2756	2397.623229	-358.37677	108.0409				329.6223
2859	2904.084363	45.0843627	291.5069				358.3768
2763	2789.284775	26.2847751	-91.4141				374.1583
2521	2585.738196	64.7381962	28.28242				383.0297
2367	2292.581971	-74.418029	38.16814				408.4188
2166	2211.378222	45.3782223	-18.0491				425.3398
1826	2009.976608	183.976608	-47.9177				458.415

Table 5.15. SVR December-2016 prediction & Error results

Actual	**Predicted**	**Eror_prd**	**dere**	de	dC	dMape	d_sort
1399	1382.235601	-16.764399	13.72866	9.0799	1.1225	5.5376	0.528784
1333	1406.117395	73.1173947	-70.742	Same set of values			0.914866
1289	1368.923423	79.9234234	-88.7785				1.403268

1333	1349.045004	16.045004	94.32231	Same set of values	4.26632
1451	1443.40725	-7.5927498	160.1695		4.495857
1788	1587.466804	-200.5332	88.71157		7.419763
2311	2007.151805	-303.84819	32.07365		7.59275
2685	2551.749407	-133.25059	-60.8141		9.423755
2757	2747.576245	-9.4237554	-66.2721		9.97345
2839	2610.777013	-228.22299	51.67216		10.29641
2388	2701.350619	313.350619	9.101547		11.16283
2158	1982.867482	-175.13252	-19.015		11.60707
1955	1962.419763	7.41976276	-136.344		12.21799
1882	1824.941461	-57.058539	3.794717		13.61179
1842	1865.876084	23.876084	64.9762		14.10328
1921	1857.368113	-63.631887	-52.9746		14.38085
2149	1993.998197	-155.0018	63.19195		15.42892
2359	2262.295286	-96.704714	154.28		15.9556
2483	2405.522121	-77.477879	135.9271		16.045
2400	2435.702874	35.7028741	-74.2001		16.7644
2299	2217.560808	-81.439192	-241.463		17.321
2078	2123.611404	45.6114038	132.6028		19.96914
1678	1861.374071	183.374071	5.321292		22.80479
1502	1416.861662	-85.138338	-49.0395		23.65152
1373	1432.572022	59.5720218	-72.09		23.87608
1294	1361.49732	67.4973197	-64.945		23.93526
1268	1332.040403	64.0404033	-63.0543		24.00006
1288	1347.586552	59.5865516	43.64819		24.48338
1529	1395.601583	-133.39842	227.5945		24.78567
1951	1739.799563	-211.20044	-15.7818		27.3761

2476	2200.057182	-275.94282	227.1416	Same set of values	28.18123
2735	2687.106561	-47.893439	-252.005		30.42902
2807	2710.630157	-96.369843	116.6601		32.06828
2925	2656.886864	-268.11314	69.3566		32.78462
2455	2797.569395	342.569395	-16.0155		35.1904
2328	2028.095595	-299.9044	-78.5887		35.70287
2279	2170.417999	-108.582	-87.7096		36.01551
2164	2191.376102	27.3761021	-30.0702		37.24559
1975	2056.303242	81.3032424	-289.848		38.11339
2045	1855.114941	-189.88506	-67.568		38.49934
2203	2083.670908	-119.32909	122.1098		39.87482
2651	2252.411691	-398.58831	312.6117		42.73078
2784	2798.380847	14.380847	-75.8792		43.84754
2700	2676.348479	-23.651521	-17.9537		44.23856
2532	2453.96416	-78.03584	-14.4906		44.62543
2357	2258.821479	-98.178521	-7.94918		45.6114
1930	2112.567114	182.567114	-112.578		47.25025
1662	1597.630976	-64.369024	30.22034		47.4834
1495	1493.596732	-1.4032677	-66.0906		47.89344
1354	1429.284215	75.2842153	-28.2278		49.22714
1334	1334.528784	0.52878354	-103.17		50.33093
1372	1402.42902	30.4290205	-23.5067		50.3481
1542	1472.058139	-69.941861	-33.9504		53.38296
1897	1699.854379	-197.14562	339.7524		55.93291
2531	2106.409725	-424.59028	159.7262		55.99236
2866	2804.359191	-61.640809	-268.082		57.05854
2952	2867.885919	-84.114081	86.45137		58.36251

3052	2781.7965	-270.2035	66.04264	Same set of values	59.57202
2654	2888.8899	234.8899	-69.7403		59.58655
2417	2235.786994	-181.21301	87.86002		59.82159
2179	2166.78201	-12.21799	-60.8607		61.64081
2075	1984.572294	-90.427706	-15.7049		63.63189
2022	1997.214332	-24.785668	15.06197		64.0404
2110	1991.035055	-118.96494	-55.7579		64.36902
2408	2153.22487	-254.77513	103.9745		66.11536
2711	2518.035528	-192.96447	456.3419		67.34873
2893	2749.347154	-143.65285	-125.681		67.49732
2714	2801.368859	87.3688593	-19.9334		67.78786
2563	2401.047815	-161.95218	124.5418		69.57116
2290	2300.296409	10.2964087	1.223285		69.94186
1841	1995.560777	154.560777	-179.975		71.20449
1513	1513.914866	0.91486609	52.09816		72.85368
1382	1337.374568	-44.625432	5.728805		73.10577
1325	1369.238563	44.2385627	-40.171		73.11739
1300	1374.987725	74.9877251	-71.7736		74.98773
1338	1376.113385	38.1133854	-0.03522		75.28422
1577	1449.243387	-127.75661	42.62693		77.21045
2025	1778.364265	-246.63573	183.6707		77.47788
2400	2277.254437	-122.74556	244.9952		78.03584
2771	2522.013824	-248.98618	-261.357		79.92342
2843	2818.51662	-24.48338	101.0497		79.94124
2970	2688.889146	-281.11085	31.86926		81.28166
2480	2847.550478	367.550478	-2.2731		81.30324
2245	2037.400546	-207.59945	-59.3538		81.43919

2197	2036.80711	-160.19289	8.766837	Same set of values	82.4055
2095	2134.874821	39.8748209	-1.65388		84.11408
2044	2019.999937	-24.000063	-83.9887		85.13834
2088	2014.894228	-73.105772	93.29446		86.22465
2240	2106.55087	-133.44913	-10.7476		87.36886
2712	2285.06024	-426.93976	411.8799		88.83055
2866	2870.495857	4.4958575	-103.806		89.12702
2793	2760.931715	-32.068285	73.0856		90.42771
2636	2541.760793	-94.239207	-23.9893		90.86674
2332	2354.804785	22.8047854	-35.6148		94.23921
1939	2008.571161	69.5711613	42.31488		96.36984
1621	1632.607073	11.6070727	-134.628		96.70471
1475	1432.26922	-42.73078	7.210063		98.17852
1368	1435.787865	67.7878649	-18.043		104.284
1338	1376.499342	38.4993416	-84.3284		108.582
1377	1405.181228	28.1812284	-76.5693		109.3767
1554	1482.795513	-71.204487	68.37004		113.6596
2005	1718.296739	-286.70326	387.2615		114.9377
2639	2264.055188	-374.94481	-32.7055		118.9649
2889	2893.26632	4.26632037	-111.599		119.3291
2980	2833.141429	-146.85857	-8.69719		122.7456
3061	2815.033886	-245.96611	124.4331		124.6917
2620	2890.81361	270.81361	-28.4227		126.4347
2446	2186.921624	-259.07838	-23.1117		127.7566
2228	2243.955605	15.9556047	-43.6916		133.2506
2057	2043.388211	-13.611789	-0.43311		133.3984
2031	1940.133261	-90.866739	11.56882		133.4491

2075	2021.617037	-53.382963	-45.9093	Same set of values	134.4898
2279	2098.304875	-180.69513	81.91478		143.6528
2767	2356.349871	-410.65013	383.4157		146.8586
2843	2929.224646	86.2246464	-73.5733		154.5608
2775	2693.718343	-81.281657	-30.5145		155.0018
2549	2533.571078	-15.428922	46.89196		160.1929
2319	2241.789549	-77.210451	128.9542		161.8643
1940	2053.659612	113.659612	-218.685		161.9522
1694	1646.749751	-47.250249	-76.6723		175.1325
1465	1544.94124	79.94124	137.0043		176.4856
1325	1375.348095	50.3480952	-61.8051		179.555
1291	1327.01551	36.0155102	-44.2842		180.6951
1316	1374.362511	58.3625105	14.14796		181.213
1628	1432.388829	-195.61117	-6.86988		182.5671
2064	1879.420098	-184.5799	261.7733		182.857
2581	2310.832474	-270.16753	73.30517		183.3741
2866	2777.16945	-88.83055	-93.9251		184.5799
2961	2846.062273	-114.93773	50.79841		189.8851
3052	2801.803791	-250.19621	57.51401		192.3043
2468	2887.659536	419.659536	50.60856		192.9645
2205	1964.635407	-240.36459	-26.1198		195.6112
2034	1990.152462	-43.847538	-73.5779		197.1456
1937	1927.02655	-9.97345	51.69902		200.5332
1868	1903.1904	35.1903997	1.680381		207.5995
1905	1867.754414	-37.245586	-9.93713		211.2004
2074	1964.623321	-109.37668	150.226		227.9566
2613	2178.951148	-434.04885	306.1724		228.223

2815	2847.784619	32.7846189	-48.843	Same set of values	234.8899
2690	2762.853685	72.8536847	142.3059		240.3646
2563	2428.510162	-134.48984	-62.857		245.8766
2340	2322.679	-17.321	16.12701		245.9661
2006	2072.115359	66.1153595	-34.3744		246.6357
1605	1731.434726	126.434726	-16.5969		248.9862
1450	1367.594501	-82.405499	-40.0069		250.1962
1351	1418.348732	67.3487325	18.01357		254.7751
1320	1379.821588	59.8215879	-120.832		259.0784
1347	1402.932907	55.9329072	27.06676		268.1131
1480	1465.896721	-14.103279	19.35081		270.1675
1835	1642.695739	-192.30426	207.2913		270.2035
2404	2076.171868	-327.82813	205.2283		270.8136
2780	2675.716048	-104.28395	-102.146		275.9428
2855	2843.837167	-11.162833	-43.7771		281.1109
2957	2711.123393	-245.87661	142.0589		286.7033
2643	2825.857046	182.857046	-13.1006		299.9044
2321	2297.064742	-23.935258	11.90279		303.8482
2270	2042.043434	-227.95657	11.93029		313.3506
2017	2196.554955	179.554955	-169.896		327.8281
1906	1855.669069	-50.330931	144.3996		342.5694
1957	1867.872982	-89.127018	-19.7552		367.5505
2036	2016.030863	-19.969137	152.1359		374.9448
2462	2081.338025	-380.66198	355.8934		380.662
2773	2648.308294	-124.69171	-53.5205		398.5883
2630	2806.485577	176.485577	7.304003		410.6501
2426	2370.007643	-55.992357	-14.4165		419.6595

2210	2162.516604	-47.483396	128.1156	Same set of values	424.5903
1819	1980.864329	161.864329	-9.74409		426.9398
1596	1546.772856	-49.227144	-153.919		434.0489

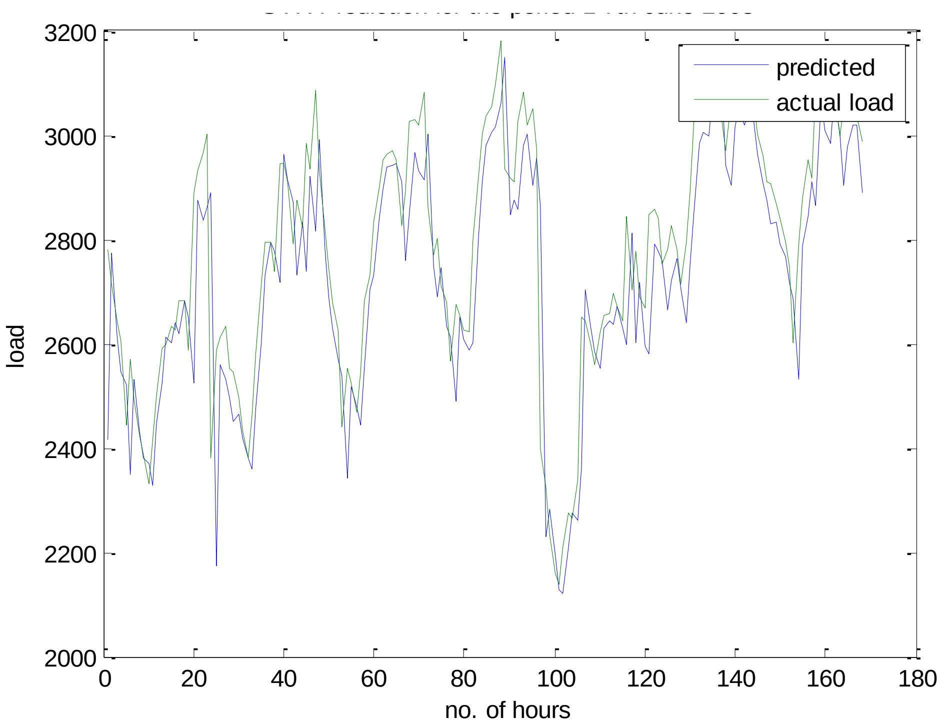


Fig. 5.1. SVR prediction for summer season (June 2016)

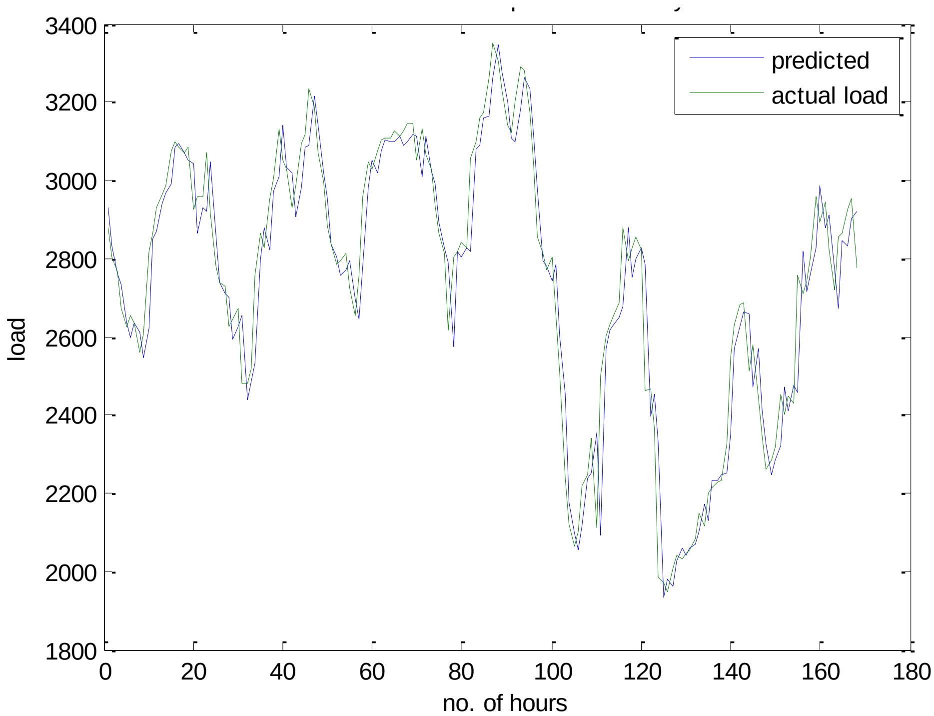


Fig. 5.2. SVR prediction for rainy season of (July 2016)

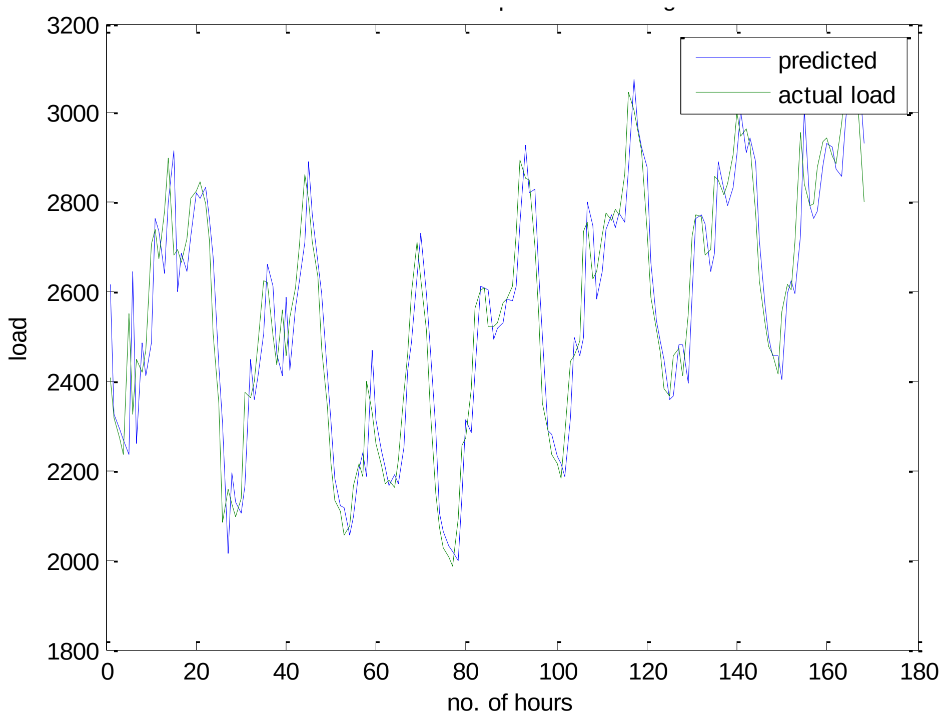


Fig. 5.3. SVR prediction for rainy season (August 2016)

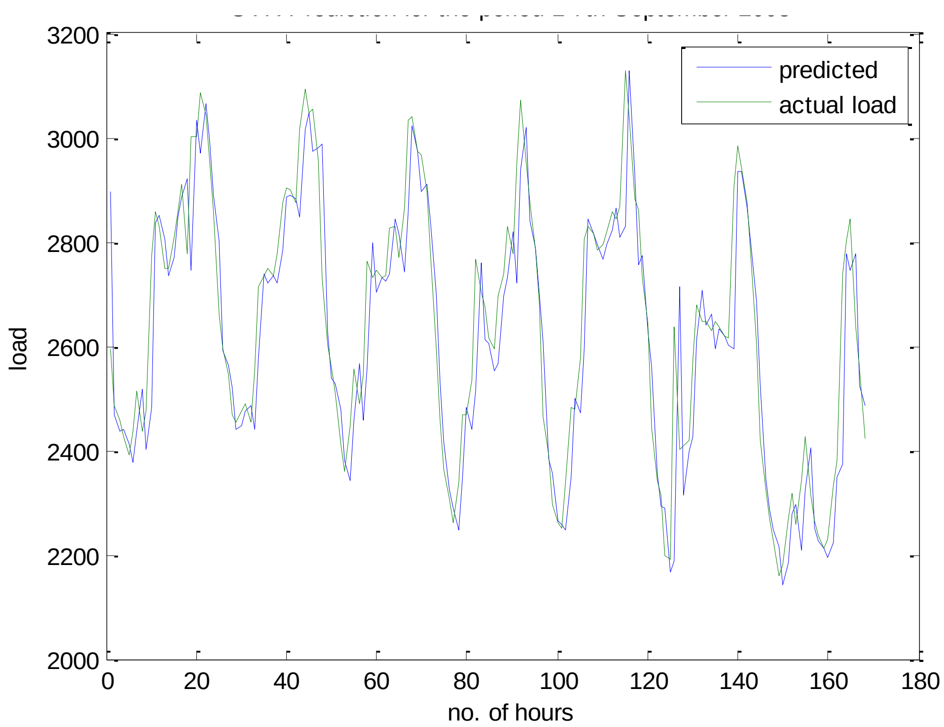


Fig. 5.4. SVR prediction for rainy season (September 2016)

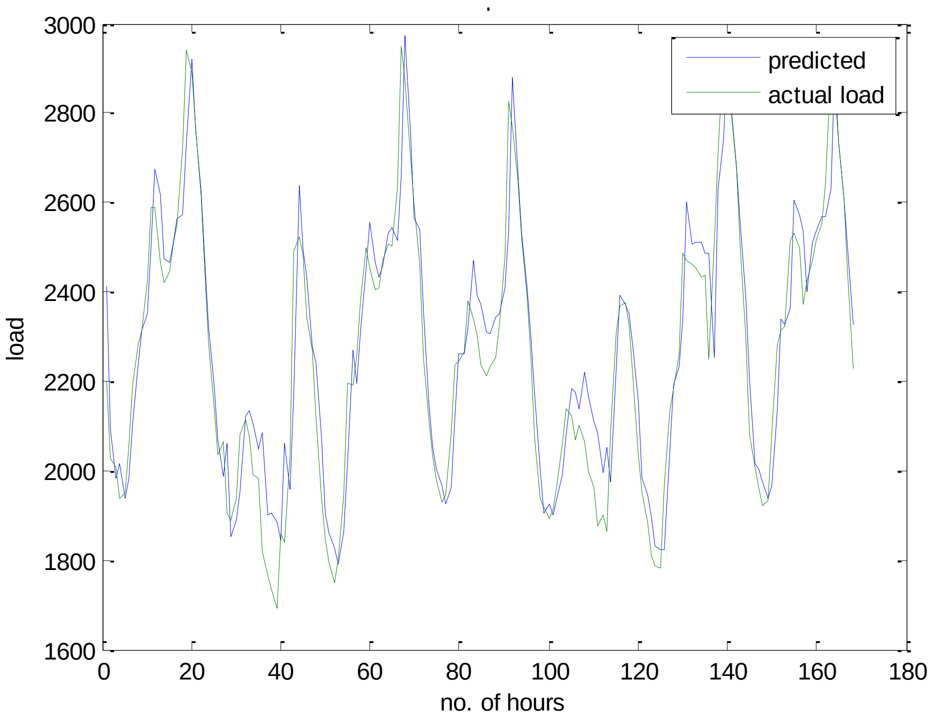


Fig. 5.5. SVR prediction for winter season (October 2016)

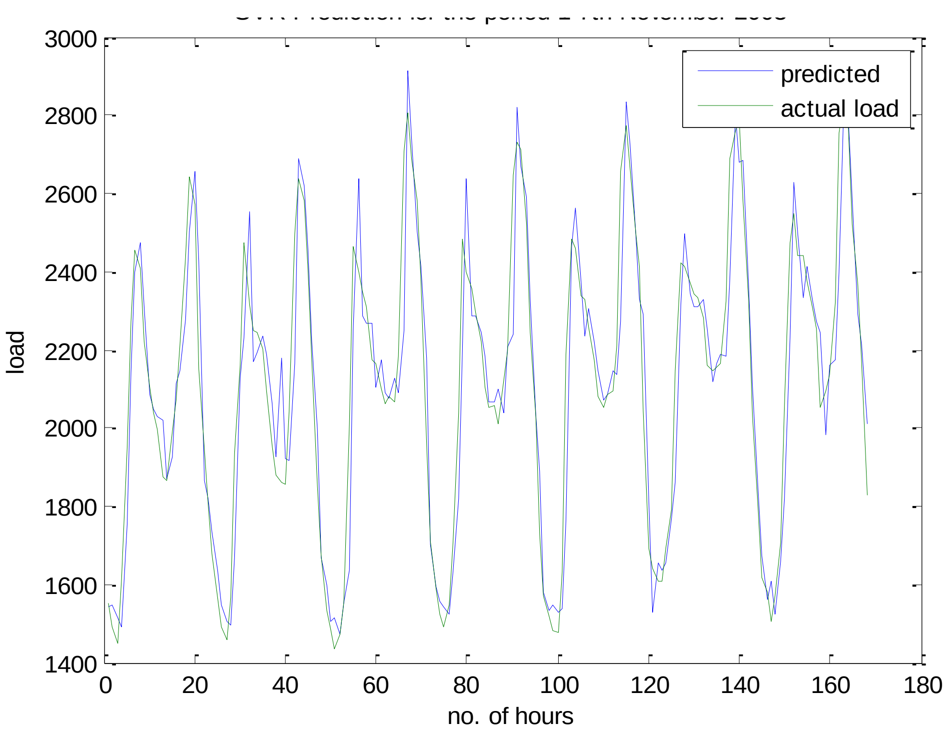


Fig. 5.6. SVR prediction for winter season (November 2016)

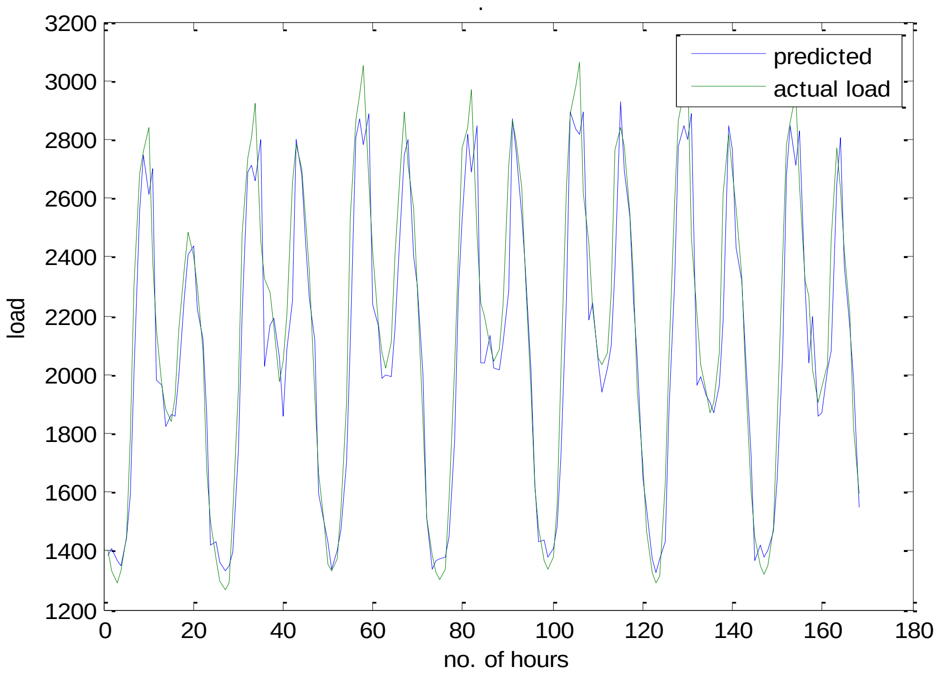


Fig. 5.7. SVR prediction for winter season (December 2016)

5.2 Conclusion

It is observed that data checks and appropriate correction is essential for improving the forecasting accuracy. The conventional models are basically linear devices and the load series they try to explain are known to be distinctly nonlinear function of the exogenous variables. Therefore they find difficulty in capturing the complex non-linear relationship of input and output sets unlike neural network which delivers better results in such conditions. The conventional forecasting methods are not competent enough to follow the sudden load changes contrary to neural network abilities. Once reasonable training with sufficient samplers has been insured as NN are data driven, then the NN model can also forecast for different type of weathers and seasons for new data samples, thus enabling the forecasting model to be more reliable. The conventional models face limitation in numbers of inputs variables as it results in loss of generalization capability. However neural networks make use of existing feature selection techniques for input variables selection. Issues of over fitting and overtraining can be handled with the help of cross-validation and regularization techniques respectively. There is still difficulty in finding definite theoretical knowledge or formal procedure to find parameters such as number of hidden layers and the neuron in hidden layer, even to establish, theoretically, how many parameters are too many, for a given sample size. Beside preliminary load study, conventional and Feed-forward neural network are compared and it is realized that the FFNN has better forecasting ability, in case the randomness in data is significant. Otherwise conventional methods give competitive results with its simple models.

A hybrid PSO-SVR system is developed for the purpose of short-term load forecasting. It is observed that considering the load data as a time series, non traditional methods like SVR turns out to be a promising approach for the improved forecasting. Selection of proper parameters of SVR is critical for its efficiency. For this purpose, a suitable optimization approach should be adopted. It is observed, that for the optimization of SVR parameters, PSO is more suitable than GA, in terms of easy implementation, reduced computation time, and judicious use of memory space.

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