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Clustering based Short Term Load Forecasting using Support Vector Machines

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***Abstract*-- A novel clustering based Short Term Load Forecasting (STLF) using Support Vector Machines (SVM) is presented in this paper. The forecasting is performed for the 48 half hourly loads of the next day. The daily average load of each day for all the training patterns and testing patterns is calculated and the patterns are clustered using a threshold value between the daily average load of the testing pattern and the daily average load of the training patterns. The data considered for forecasting contains 2 years of half hourly daily load and daily average temperature. The proposed architecture is implemented in Matlab. The results obtained from clustering the input patterns and without clustering are presented and the results show that the clustering based approach is more accurate.**

***Index Terms*-- Clustering, Short Term Load Forecasting, Support Vector Machines.**

I. INTRODUCTION

WITH the increase in complexity and an estimated growth of 3-7% electric load per year, the various factors that have become influential to the electric power generation and consumption are load management, energy exchange, spot pricing, independent power producers, non-conventional energy, generation units, etc. In view of this, load forecasting has always been important for planning and operation decision. Timely implementations of such decisions lead to the improvement of network reliability and to the reduced occurrences of equipment failures and blackouts [1]. The taxonomy of load forecasting can be considered as Spatial forecasting & Temporal forecasting. Forecasting future load distribution in a particular region, such as a county, a state, or the whole country is called Spatial forecasting. Temporal forecasting is dealing with forecasting load for a specific supplier or collection of consumers in future hours, days, months, or even years. The temporal forecasting can be broadly divided into 4 types – long term, medium term, short term and very short term. Long term prediction (5 to 20 years) is normally used for planning the growth of the generation capacity. This long term forecasting is used to decide whether to build new lines and sub-stations or to upgrade the existing systems. Medium-term load forecast is used to meet the load requirements at the height of the winter or the summer season and may require a load forecast to be made a few days to few weeks (or) few months in advance [2].

Typically the short term load forecast covers a period of one week. The forecast calculates the estimated load for each hour of the day, the daily peak load and the daily/weekly energy generation. Many operations like real time generation control, security analysis, spinning reserve allocation, energy interchanges with other utilities, and energy transactions planning are done based on STLF [3]. Economic and reliable operation of an electric utility depends to a significant extent on the accuracy of the load forecast. The load dispatcher at main dispatch center must anticipate the load pattern well in advance so as to have sufficient generation to meet the customer requirements. Over estimation may cause the startup of too many generating units and lead to an unnecessary increase in the reserve and the operating costs. Underestimation of the load forecasts results in failure to provide the required spinning and standby reserve and stability to the system, which may lead into collapse of the power system network [4, 5]. Load forecast errors can yield suboptimal unit commitment decisions. Hence, correct forecasting of the load is an essential element in power system.

Most forecasting models and methods have already been tried out on load forecasting, with a varying degree of success. They may be classified as time series (univariate) models, in which the load is modeled as a function of its past observed values, and causal models, in which the load is modeled as a function of some exogenous factors, specially weather and social variables. Some models of the first class suggested in papers are multiplicative autoregressive models [6], dynamic linear [7] or nonlinear [8] models, threshold autoregressive models [9], and methods based on Kalman filtering [10-12]. Some of the models of the second class are Box and Jenkins transfer functions [13, 14] ARMAX models [15, 16], optimization techniques [17], nonparametric regression [18], structural models [19], and curve-fitting procedures [20]. Despite this large number of alternatives, however, the most popular casual models are still the linear regression ones [21-25] and the models that decompose the load, usually into basic and weather dependent components [26-29]. These models are attractive because some physical interpretation may be attached to their components, allowing engineers and system operators to understand their behavior. However, they are basically linear devices, and the load series they try to explain are known to be distinctly nonlinear functions of the exogenous variables.

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In recent times, much research has been carried out on the application of artificial intelligence techniques to the load forecasting problem. Expert systems have been tried out [30, 31], and compared to traditional methods [32]. Fuzzy inference [33] and fuzzy-neural models [34, 35] have also been tried out. However, the models that have received the largest share of attention are undoubtedly the artificial neural networks (NNs). The first reports on their application to the load forecasting problem were published in the late 1980's and early 1990's [36]. Since then, the number of publications has been growing steadily. Judging from the number of papers, NN-based forecasting systems have not turned into a "passing fad" as it was feared they might [37]. It seems that they have been well accepted in practice, and that they are used by many utilities [38].

In this paper, an attempt is being made to predict the next day load by using SVM by clustering the training patterns with respect to the testing pattern. The paper is organized as follows: Section – II discusses the basics of SVM and literature on SVM for STLF. Section – III explains the proposed architecture and its description. The solution methodology and the results are presented in Section – IV and Section – V respectively. Section – VI contain the conclusions & the future work.

II. Support vector machines

Support Vector Machines has been firstly introduced by Vapnik [39] on the basis of statistical learning theory to solve machine learning tasks such as regression, pattern recognition and density estimation. The SVM implements the structural risk minimization principle which seeks to minimize the training error and a confidence interval term, as against to the empirical risk minimization principle used in neural network models. This leads to the good performance of generalization and due to its good properties such as automatic selection on models (parameters and locations of basis functions), being trained with quadratic programming (globally optimal solution existed) and good learning ability for small samples, the SVM begun to receive more and more attention in recent years.

In this section, we briefly introduce Support Vector Regression (SVR), which can be used for time series prediction. Given training data (x_1, y_1), (x_2, y_2) … … (x_n, y_n) where x_i are input vectors and y_i are the associated output value of x_i, the Support Vector Regression is an optimization problem.

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

subject to $y_i - (w^T \phi(x_i) + b) \leq \varepsilon + \zeta_i$,

$(w^T \phi(x_i) + b) - y_i \leq \varepsilon + \xi_i^*$,

$\zeta_i, \xi_i^* \geq 0, \; i = 1, 2, \ldots \ldots \ldots l$,

where x_i is mapped to a higher dimensional space, ζ_i is the upper training error (ξ_i^* is the lower) subject to the ε-insensitive tube $|y - (w^T \phi(x) + b)| \leq \varepsilon$. The parameters which control the regression quality are the cost of error C, the width of tube ε and the mapping function, ϕ [40].

The constraints of (1) imply that we would like to put most data x_i in the tube $|y - (w^T \phi(x) + b)| \leq \varepsilon$. If x_i is not in the tube, there is an error ζ_i or ξ_i^* which we would like to minimize in the objective function. For traditional least-square regression, ε is always zero and data are not mapped into higher dimensional spaces. Hence SVR is a more general and flexible treatment on regression problems [40, 41].

Mohandes [42] forecasted the load using SVM and compares its performance with the autoregressive method. Chang. et. al. [43] used SVM to predict the daily maximum load for one month and this proposed model won the competition organized by EUNITE network. Li and Fang [44] also proposed SVM for short term load forecasting.

III. Proposed Architecture

The proposed model forecasts the next day load by clustering the available past data. The various factors that affect the load forecast are weather information, time factors & customer classes. Among these, forecasted weather parameters are the most important factors in short-term load forecasts. The weather parameters usually considered are temperature and humidity as they have direct influence on many kind of electrical consumption and others like wind speed, rain, fog etc., are less important. The time factors include the time of the year, the day of the week and the hour of the day. The load on weekdays behaves differently compared to the load on weekends. In addition to that, the load behaves differently on different weekdays (Monday and Friday load data is different from Tuesday to Thursday data). The different customer classes categorized by electric utility companies are residential, commercial and industrial. The electric usage pattern is different for customers that belong to different classes but is somewhat alike for customers within each class.

The proposed architecture is shown is Fig. 1. The objective of the proposed architecture is to recognize the above factors from the training data and predict the load accordingly. Thus a suitable architecture along with appropriate inputs is needed. There are no general rules to follow in the selection of input variables. It depends largely on experience, professional judgment and preliminary experimentation. The demand for electricity is known to vary by the time of the day, week, month, temperature and usage habits of the consumers. Though usage habit is not directly observable, it may be implied in the patterns of usage that have occurred in the past. For solving an STLF problem all of these inputs are not needed at the same time. Depending on the forecast to be made, whether daily or hourly; the choice of input variables will change.

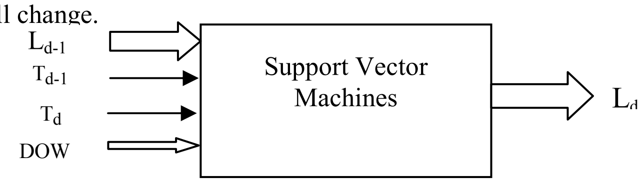


Fig. 1 Proposed architecture for STLF

A. Description of Proposed Architecture

INPUTS: 53

Load (L_{d-1}): 48 half-an-hour loads

Temperature (T_{d-1}): 1 (average temperature)

Forecasted day's average Temperatures (T_d):1

Day Of the Week (DOW) to be forecasted: 3 (Sunday-001, Monday-010, Tuesday-011, Wednesday100, Thursday-101, Friday-110, Saturday-111)

OUTPUTS: 48

Forecasted Load (L_d): 48 half-an-hour loads

IV. Solution Methodology

A. Data Analysis

The data considered for forecasting the load for the next day of the proposed architecture contains electricity load and temperature. The data set contains daily load data of every half an hour for two consecutive years and average daily temperature for the same two consecutive years. The 2 years data contains 104 daily load curves for each day of a week. The data is divided into 2 sets with 91 training patterns and 13 testing patterns for each day of the week.

Fig. 2 represents the daily load curves of the input and output training set (91 each) for weekday, Wednesday. The load curves clearly show that the load is periodic in nature. The upper part of Fig. 2 shows the 91 load curves of Tuesday and the lower part of Fig. 2 shows the 91 load curves of Wednesday. The dotted lines represent the yearly average load curves of Tuesday and Wednesday. The average load is calculated for each day of input training pattern (here, Tuesday) and the patterns are clustered based on the average load of the input testing pattern (here, Tuesday).

B. Creating the Sample Set

The SVM is trained with the historic data before testing them. The first step for training them is to obtain an accurate historical data . The data should be chosen that is relevant to the model. How well the data is chosen is the defining factor in how well the SVM output will match the event being modeled. There should be some correlation between the training data and the testing data. In the load data, in general all the Sunday's load data look alike, all the Monday's data

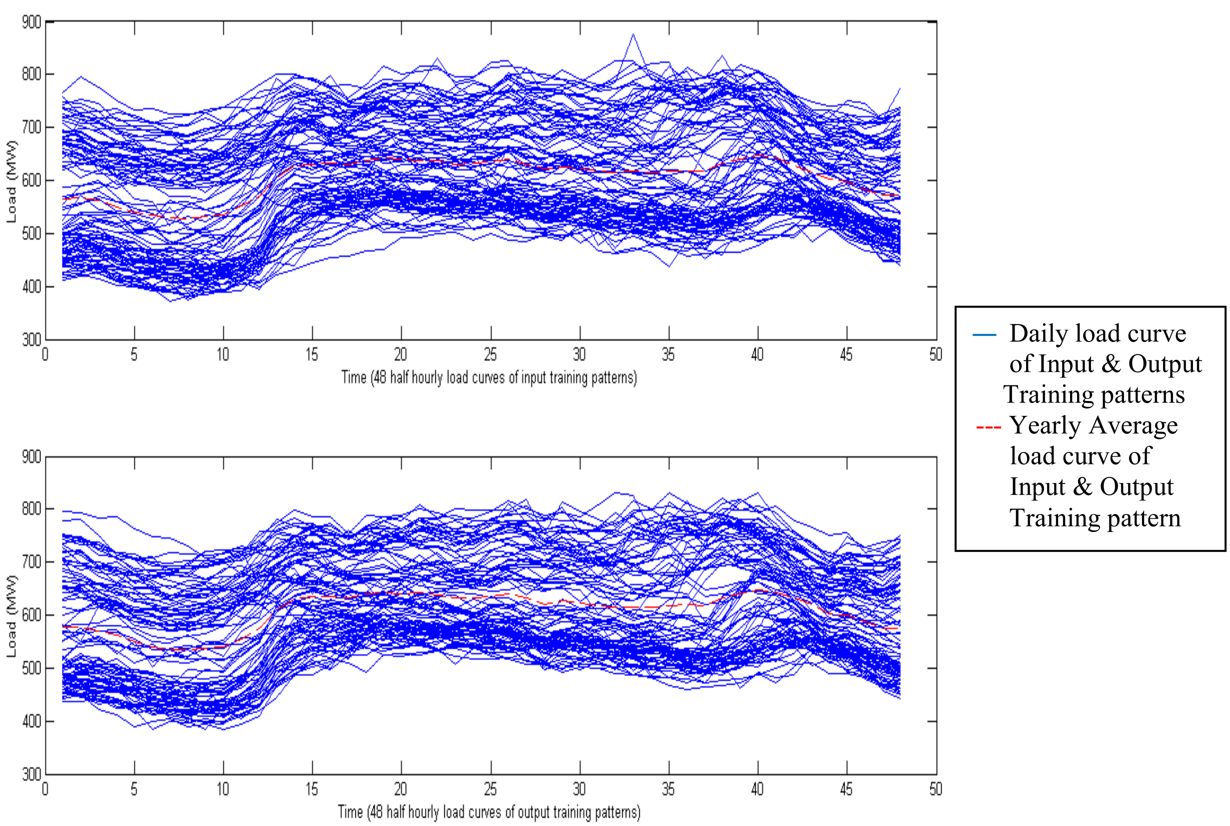


Fig. 2 Input and Output training patterns for Wednesday (Without Clustering)

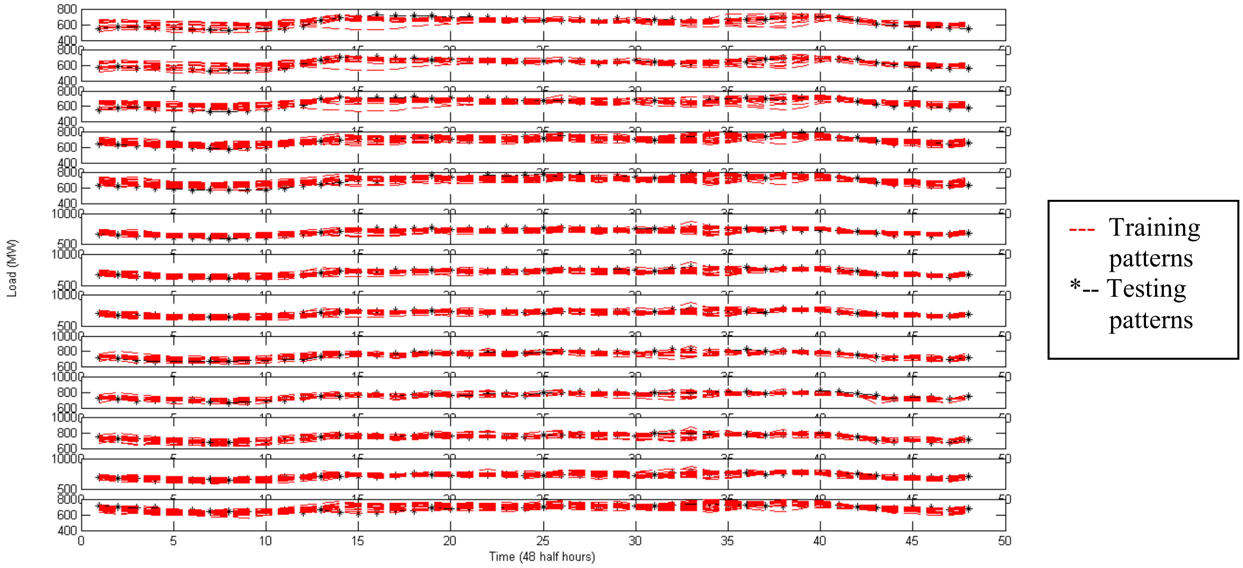


Fig. 3 Clustering of training patterns for different testing patterns for Wednesday

look alike and this holds fairly well for all the days of the week. Hence for testing a day, the training data considered is the past data, same as that of the testing day.

C. Data Preparation

In this stage, the typical (raw) input data has to be arranged as input and output pattern pairs for training the SVM. The 53 inputs for the SVM to be arranged as one column vector and the 48 outputs are to be arranged as another column vector. This is to be done for all the days of the past data.

D. Normalization

Normalization is an important stage for training the SVM [45, 46]. The data is normalized in such a way that the higher values should not suppress the lower values in order to retain the activation function [47]. Both the load and the temperature data should be normalized to the same range of values.

E. Clustering

The daily average load is calculated for all the 104 patterns for all the days of the week. The patterns are clustered based on the threshold value of the difference between the daily average load of the input training patterns and the daily average load of the input testing pattern.

Fig. 3 shows the clustered input training patterns for all the 13 testing patterns by considering a threshold value of 30MW for Wednesday. TABLE I and TABLE II contains the patterns matched for each Testing pattern for Thursday and Saturday respectively. From these two tables, one can observe that out of the 91 training patterns available for each day, when the patterns are clustered on the daily average load of the input, the maximum number of patterns available are 22 (for 8th testing pattern for Saturday) and minimum number of patterns available are 5 (for 11th testing pattern for Saturday).

TABLE I

PATTERNS CLUSTER FOR ALL THE 13 TESTING PATTERNS FOR THURSDAY

Serial No.	Testing pattern Number	No. of Training patterns matched
1	1	20
2	2	12
3	3	10
4	4	15
5	5	19
6	6	16
7	7	20
8	8	18
9	9	17
10	10	12
11	11	6
12	12	12
13	13	19

TABLE II

PATTERNS CLUSTER FOR ALL THE 13 TESTING PATTERNS FOR SATURDAY

Serial No.	Testing pattern Number	No. of Training patterns matched
1	1	10
2	2	10
3	3	10
4	4	14
5	5	18
6	6	13
7	7	20
8	8	22
9	9	17
10	10	10
11	11	5
12	12	17
13	13	14

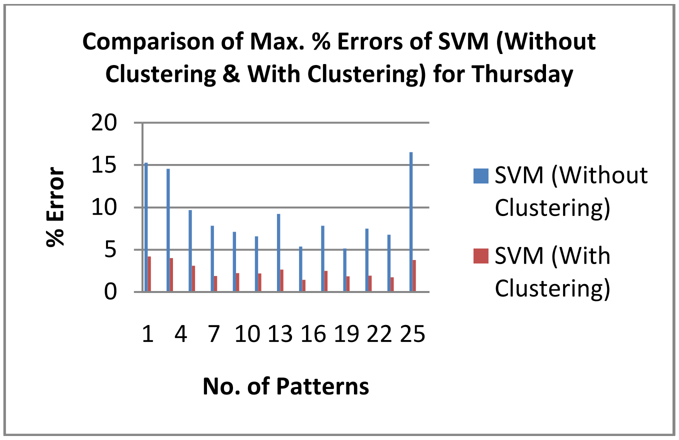


Fig. 4. Comparison of Maximum % Errors of SVM (Without Clustering & With Clustering) for different testing patterns for Thursday

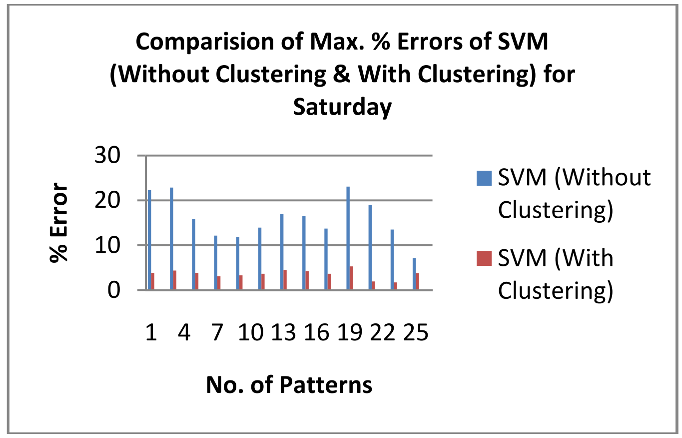


Fig. 6. Comparison of Maximum % Errors of SVM (Without Clustering & With Clustering) for different testing patterns for Saturday

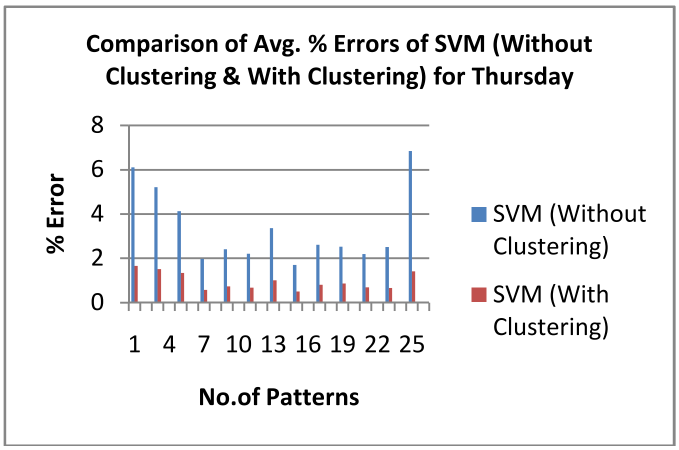


Fig. 5. Comparison of Average % Errors of SVM (Without Clustering & With Clustering) for different testing patterns for Thursday

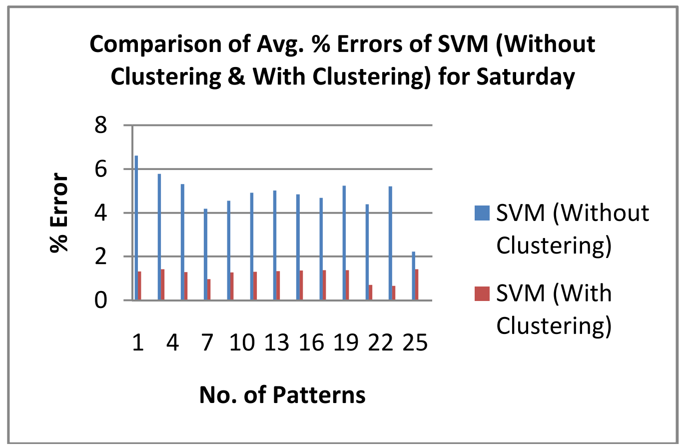


Fig. 7. Comparison of Average % Errors of SVM (Without Clustering & With Clustering) for different testing patterns for Saturday

TABLE III
PATTERNS CLUSTER FOR 6TH TESTING PATTERN FOR DIFFERENT THRESHOLDS

Day	Patterns Matched (30 MW Threshold)	Patterns Matched (60 MW Threshold)
Sunday	18	38
Monday	22	35
Tuesday	25	33
Wednesday	20	33
Thursday	16	34
Friday	19	31
Saturday	13	31

TABLE IV
COMPARISON OF MAXIMUM & AVERAGE % ERRORS OF SVM (WITH CLUSTERING FOR 30MW & 60MW) FOR 6TH TESTING PATTERN

Day	% Error	SVM (30MW Threshold) (With Clustering)	SVM (60MW Threshold) (With Clustering)
Sunday	Max. % Error	2.4107	3.4858
	Avg. % Error	0.6918	0.9135
Monday	Max. % Error	4.4398	5.3416
	Avg. % Error	2.0543	2.5649
Tuesday	Max. % Error	2.5825	3.4628
	Avg. % Error	0.9873	1.1730
Wednesday	Max. % Error	1.8074	2.7459
	Avg. % Error	0.6985	0.9718
Thursday	Max.% Error	2.1755	3.6971
	Avg. % Error	0.6810	1.3210
Friday	Max. % Error	2.1195	2.8252
	Avg. % Error	0.5778	0.9514
Saturday	Max. % Error	3.6555	5.6409
	Avg. % Error	1.3023	2.6320

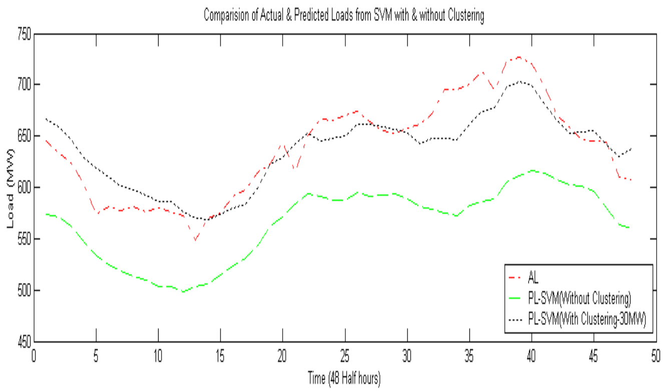
V. Results

A. Without clustering

The SVM is trained initially with the corresponding day patterns without doing clustering i.e., for predicting Wednesday's load curve, it is trained with all the Tuesday's load patterns. Hence for each day, the SVM is trained with 91 patterns.

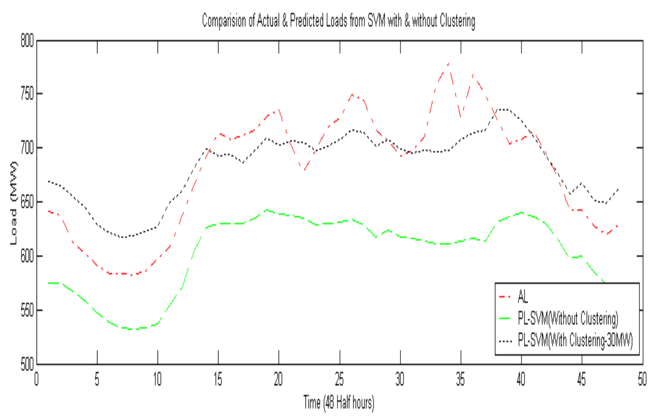
B. With clustering

In this step, the training patterns are clustered by using a threshold value of 30 MW between the daily average load of the testing pattern and the daily average load of the training patterns for all the days.



*AL – Actual Load, PL-SVM – Predicted Load from SVM

Fig. 8 Comparison of Actual & Predicted loads from SVM for Thursday for 6th testing pattern



*AL – Actual Load, PL-SVM – Predicted Load from SVM

Fig. 9 Comparison of Actual & Predicted loads from SVM for Saturday for 6th testing pattern

Fig. 4 and Fig. 5 show the comparison of maximum and average percentage errors of SVM (without clustering & with clustering) for all the testing patterns for Thursday respectively. The results show that the maximum and average % errors are less when the training patterns are clustered. Similarly, the comparisons of maximum and average percentage errors of SVM (without clustering & with clustering) for all the testing patterns for Saturday are presented in Fig. 6 and Fig. 7 respectively.

Fig. 8 and Fig. 9 shows the comparison of actual and predicted loads from SVM (without & with clustering – 30 MW) for Thursday & Saturday for 6th testing pattern, respectively. The predicted loads obtained by using clustering approach are more accurate than the loads obtained without clustering.

The patterns are also clustered by considering 60 MW threshold. TABLE III contains the patterns clustered for 6th testing pattern for each day. As predicted, the patterns matched are more when the threshold value between the daily average load of the testing input pattern and the daily average load of the training input pattern is increased.

With the patterns obtained by considering the threshold value of 60 MW, TABLE IV shows the comparison of maximum and average percentage errors of SVM (with clustering for 30 MW & 60 MW threshold values) for 6th testing pattern for all the days. The results show that the maximum and average % errors are less for all the days for 30 MW threshold when compared to the 60 MW threshold. It also shows that maximum and average % errors are less for 60 MW threshold compared to the errors when patterns are not clustered (refer Fig. 4, Fig. 5, Fig. 6 and Fig. 7, Thursday's and Saturday's 6th testing pattern for errors without clustering).

VI. Conclusions & Future Work

A novel approach for day ahead forecasting using clustering and SVM technique is discussed in this paper. A pre-processing step, by means of clustering, is introduced while considering the patterns for training the SVM. In general, all the Sunday's load data look alike, all the Monday's load data look alike and this holds good for all the days of the week. The SVM is trained by considering 2 approaches: by considering all the previous patterns of the similar day (without clustering) and by using a threshold between the daily average loads of all the input training patterns and the daily average load of the input testing pattern (with clustering). The results are presented for both the cases (without clustering and with clustering) and for different threshold values which result in forming different cluster patterns. The forecasted load obtained by clustering the training patterns is following the actual load closely compared to the forecasted load obtained without clustering. The proposed method does not require any heavy computational burden and can be easily utilized for forecasting the next day load in energy utilities. One of the most important conclusions from the present work is to show the applicability of clustering techniques for choosing training patterns for SVM based methods for getting better short term load forecasting results. By using pattern recognition techniques, the patterns, similar to that of the input of the testing pattern, can be chosen (instead of clustering based on the daily average load corresponding to the day to be forecasted) from the past data and then trained. This may be another good approach and may still reduce the forecasting error. The authors are working on this direction and the results for that study will be presented in a future publication.

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