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SHORT-TERM ELECTRIC LOAD FORECASTING USING LEAST SQUARE SUPPORT VECTOR MACHINES

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Abstract. *This paper presents a model for short-term load forecasting using least square support vector machines. Available data are analyzed and appropriate features are selected for the model. Last 24 hours load demands are used for features in combination with day in week and hour in day. It is shown that temperature is not always a very good feature for the model. Appropriate data set is used for the model training, and then forecasting of day ahead hourly load demands is performed. Experimental results, obtained from real life benchmark, show that the proposed model is effective and accurate.*

Key words: *short-term load forecasting, least square support vector machines, time-series, regression*

1. INTRODUCTION

Efficient planning, operation and maintenance of a power system depend on load forecasting which is an integral part of this process. Electric load forecasting can be categorized into one of the following categories: short-term, mid-term and long-term depending on the time span consideration. Short-term load forecasting (STLF) deals with load forecasting from one hour up to a week ahead. Mid-term load forecasting is related to the time period from a few days to a few weeks and long-term load forecasting is made for the period of one to several years. Each class of load forecasting uses different models to meet the specific objectives of application. STLF is necessary for the control and scheduling operations of a power system and also acts as input to the power analysis functions such as load flow and contingency analysis. Owing to this importance, various methods have been used: linear regression, exponential smoothing, ARMA models [1]

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and data mining models. Data mining techniques like artificial neural networks [2], fuzzy logic [3] and support vector machines [4] have been widely employed for load forecasting. In this paper, we propose the model for short term load forecasting problem using least square support vector machines.

The paper is structured as follows: Section II describes the used technique, in Section III data analysis and our proposed model are given, Section IV provides an evaluation of our model and summarizes the results and Section V presents the conclusions.

2. METHODOLOGY

Support Vector Machines (SVMs) are a set of Machine Learning methods, developed for solving problems of nonlinear classification and regression. They were originally introduced by Vapnik in his statistical learning theory [5]. The main characteristic of these methods is the use of Quadratic Programming (QP) in order to solve convex optimization problems. Least Square Support Vector Machines (LS-SVMs), introduced by Suykens, are a reformulation of standard SVMs [6]. In this version, a set of linear equations is solved instead of a QP for classical SVMs. Therefore, LS-SVMs are more time - efficient then standard SVMs.

SVMs implement the Structural Risk Minimization principle by minimizing an upper bound of the generalization error, instead of minimizing the training error. The goal of regression with LS-SVM is to generate a model which will predict unknown output values based on the known input parameters. In the learning phase, the model is formed based on the known training data (x_1, y_1), (x_2, y_2), ...,(x_n, y_n), where x_i are input vectors, and y_i outputs associated with them. Each input vector consists of numeric features. In the phase of application, the trained model on the basis of new inputs $x_1, x_2, ...,x_n$ makes prediction of output values $y_1, y_2, ...,y_n$.

In case of regression LS-SVM is the optimization problem [7], formulated with:

$$\min_{w,b,e} \frac{1}{2} w^T w + \gamma \frac{1}{2} \sum_{i=1}^{N} e_i^2 \tag{1}$$

subject to:

$$y_i = w^T \varphi(x_i) + b + e_i, i = 1,...,N, \tag{2}$$

where x_i is mapped into a high dimensional feature space with mapping φ.

The problem can be solved using Lagrange multipliers and the solution is presented in form:

$$y(x) = \sum_{i=1}^{N} \alpha_i K(x, x_i) + b\ , \tag{3}$$

where $K(x,x_i)$ represents kernel, defined as the dot product between the $\varphi(x)^T$ and $\varphi(x)$ [8]. In experiments described in this work we used Radial Basis function (RBF) as kernel, defined with:

$$K(x, x_i) = e^{\frac{-\|x-x_i\|^2}{\sigma^2}}\ . \tag{4}$$

More about LS-SVM and kernel functions can be found in [6, 8].

The learning phase of LS-SVM involves an optimal selection of kernel parameters, in this case σ and the regularization parameter γ.

A good choice of these parameters is essential for the estimator performance. In our experiments, we used 10 - fold Cross – Validation in combination with Grid - Search for selecting these parameters. More about parameter selection techniques can be found in [9, 10].

3. Model Formation

For making a good model it is necessary to chose variables which will be used for model features. This process is the most important but there is no general rule that can be followed in this process. However, some statistical analysis can be very helpful in determining which variables have significant influence on the electric load demand.

3.1. Features selection

3.1.1. Week day feature

Load demand is different from one day to another during the week. Fig. 1 shows load demand for one week in January. It is clear that load demand at the weekends is less than in the week days, and not only for the winter season but also for all seasons. From Fig. 2 it can be noticed that load curve is slightly different from one week day to another, but on the other hand load curves for the same week days are very similar. All this suggests that day in week may be assistance in load forecasting [1, 11].

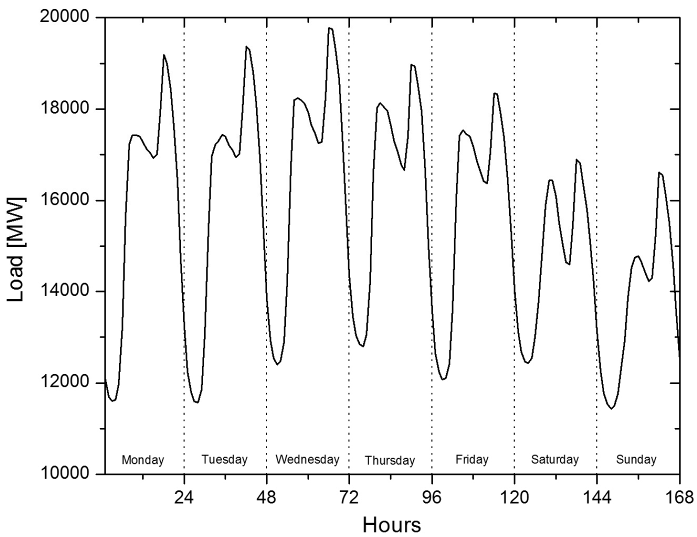

Fig. 1. Load demand by hour during the week

3.1.2. Hour feature

Load changes during the day from one hour to another. Fig. 2 shows daily load demand for each day of the week in January. It can be noticed that load peak occurs twice a day, one is from about 8:00 AM to 10:00 AM and another is from about 6:00 PM to 8:00 PM, and there is a significant difference in load magnitude. Because of this load demand behavior, hour feature may be very useful in short term load forecasting [1, 12].

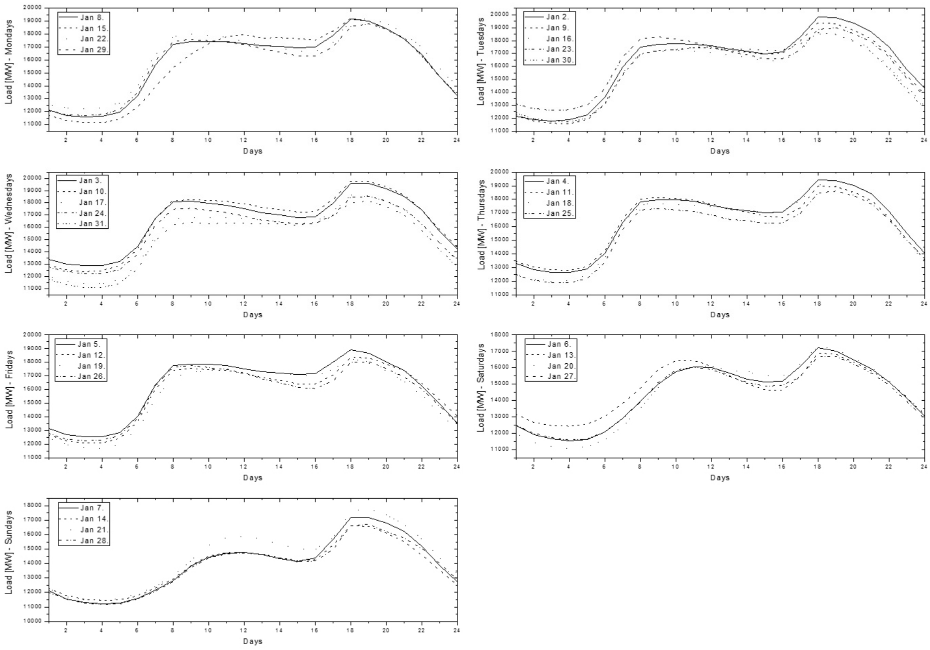

Fig. 2. Daily load demand by hour for each day of the week in January

3.1.3. Temperature feature

Weather variables have significant influence on load demand. Many weather variables can be considered in load forecasting (temperature, wind speed, cloud cover, humidity), but their influence on load demand is different. According to many authors, temperature is a generally accepted variable in electrical load forecasting [11, 12]. However, here one should be careful because temperature forecasting is a more complex problem than electrical load forecasting, and estimated temperature is used for input instead of real.

Fig. 3 shows temperature and load demand by hour during one week in January. Correlation coefficient between temperature and load demand is in range from 0.4 to 0.7 and it is not always positive as can be seen in Fig. 3. Because of that it can not be said that the load demand is in strong correlation with temperature. All this indicates that temperature is not always a very good choice for feature, and can sometimes reduce the accuracy of forecasting.

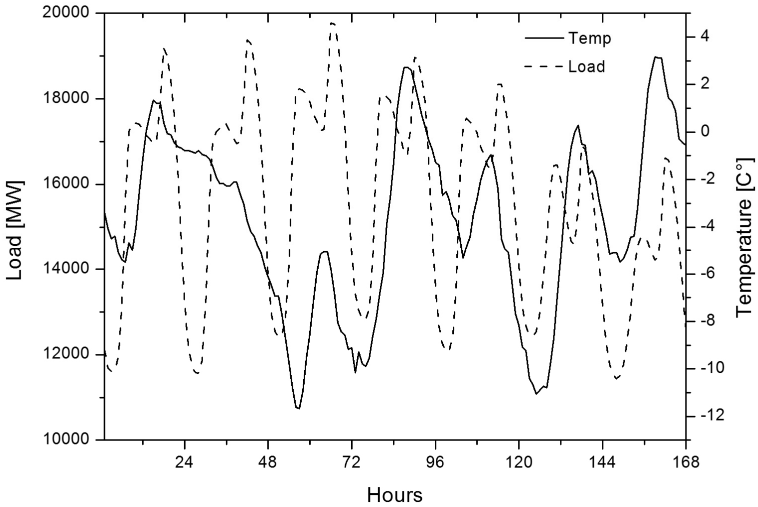

Fig. 3. Temperature and load demand by hour during the week

3.1.4. History load feature

History load demand is another useful variable which can give additional information to the model about expected load. However, for forecasting with a lead time of up to a few hours ahead, load history (for the last few hours) is not available, and therefore, estimated values of this load are used instead. This can lead to a problem in load forecasting since these estimated values are fed back as an input to the forecasting procedure. But Fig. 2 shows that load curves for each day of the week are very similar, which indicates that the usage of history load demand by hour can give information about the expected load to the model [11].

3.2. Model

The various factors that affect the short-term load forecast are analyzed and appropriate features are chosen. Then, training set is formed for LS-SVM. Our proposed model is shown in Fig. 4. Input vectors for LS-SVM model are composed of the following features:

- Load for last 24 hours (P_{i-k}), k = 1, 2, …, 24,
- Day of the week (D),
- Hour of the day (H).

Day of the week is coded with numeric values from 1 to 7, where 1 represents Monday, 2 Tuesday, etc. All features were scaled to range [0, 1] before training LS-SVM.

On the basis of training set LS-SVM creates model which forecasts the next 24 hours load. RBF is chosen for the kernel. In order to form the precise model, it is essential to do an optimal selection of parameters σ and γ. After performing 10 - fold Cross – Validation in combination with Grid – Search, the parameters are chosen as following σ^2= 52.99 and γ= 9079.14. For computation Matlab toolbox LS-SVMlab is used.

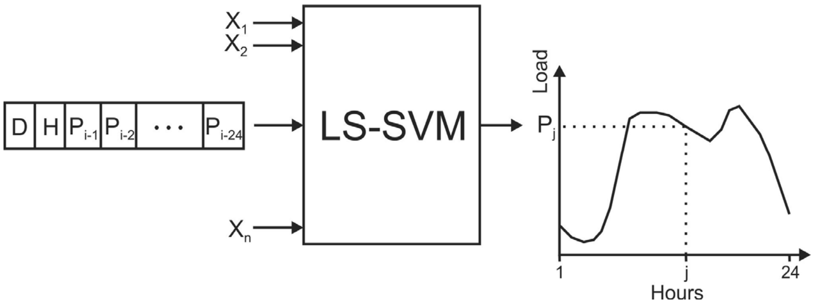

Fig. 4. Architecture of the proposed model

After training LS-SVM, we have used it for recursive prediction of load demand for the next day, from hour to hour. First, one hour ahead prediction is performed:

$P(t+1) = \text{LS-SVM}(P(t), P(t-1), ..., P(t-23), \text{D}, \text{H}(t+1))$,

then to predict the load value for the next hour, the same model is used:

$P(t+2) = \text{LS-SVM}(P(t+1), P(t), \ldots, P(t-22), \text{D}, \text{H}(t+2))$,

and for the last hour:

$P(t+24) = \text{LS-SVM}(P(t+23), P(t+22), \ldots, P(t), \text{D}, \text{H}(t+24))$.

It is important to emphasize that the predicted values are used for next predictions, instead of true, which are unknown. Usage of the predicted values as inputs affects the accuracy of the next prediction, so it is very important that we have a well-trained model in order to avoid propagation of errors.

4. RESULTS

The data used for experiments is from New England region, and consist of: calendar information, hourly electric load in MW and hourly temperatures, for the period from 1999 to 2003. The data can be downloaded from [13].

To evaluate the accuracy of the model, for each day in one week in January, load forecasting by hour is done. Training model was committed with training segment that contains data from December, January and February 2000.

The prediction accuracy is evaluated using Mean Absolute Percentage Error (MAPE) and Absolute Percentage Error (APE). The equations which describe these errors are:

$$MAPE = 100\frac{1}{n}\sum_{i=1}^{n}\left|\frac{P_i - \hat{P}_i}{P_i}\right|, \tag{5}$$

$$APE = \frac{P_i - \hat{P}_i}{P_i}100 , \tag{6}$$

where P_i and $\hat{P}_i$ are the real and the predicted value of load demand on the i[th] hour and n is the number of hours.

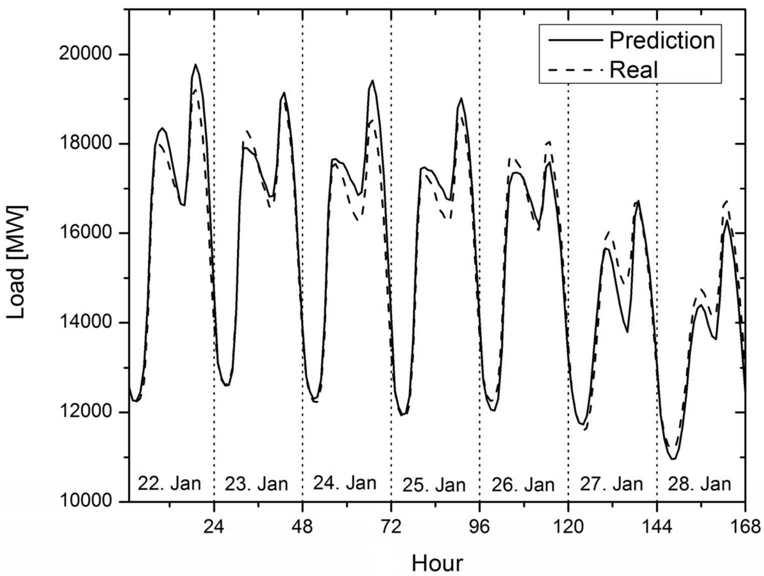

Fig. 5. Estimated and real load demand for one week in January

Fig. 5 shows estimated and real load demand by hour, for the period from January 22 to January 28, 2001, where January 22 is Monday and so on. In Table 1 MAPE for each day in the week are shown. The average MAPE for the entire week is 2.16%.

Table 1. MAPE errors for each day in the week

Day	January 22	January 23	January 24	January 25	January 26	January 27	January 28
MAPE	2.25	0.93	3.04	1.97	1.88	2.47	2.62

Fig. 6 shows estimated and real load demand by hour for January 26. Also, for the same day, in Table 2 APE errors for each hour are shown. From Fig. 6 it can be noticed that the maximum deviations occur in hours around load peaks. The maximum deviations are 643 MW which is at 7:00 AM and 519 MW which is at 6:00 PM. The number of hours with APE less than 2% is 11, between 2% and 3% is 10 and there are 3 hours with APE between 3% and 4%.

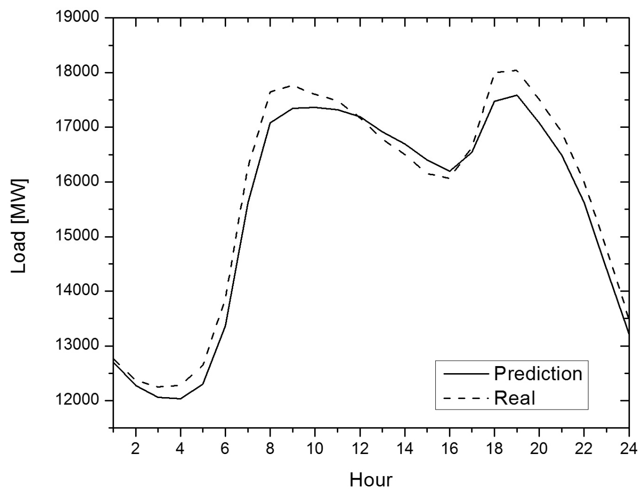

Fig 6. Estimate and real load demand for January 26

Table 2. Hourly APE errors for January 26

Hour	Predicted [MW]	Real [MW]	APE [%]
1	12704.2	12765	0.48
2	12276	12371	0.77
3	12063.6	12254	1.55
4	12036.1	12283	2.01
5	12304.2	12644	2.69
6	13368.4	13867	3.60
7	15623.6	16267	3.96
8	17081.6	17646	3.20
9	17344.3	17766	2.37
10	17361.8	17604	1.38
11	17325.2	17483	0.90
12	17196.2	17176	-0.12
13	16916.8	16786	-0.78
14	16695.9	16502	-1.18
15	16400.4	16153	-1.53
16	16194.5	16069	-0.78
17	16538.8	16642	0.62
18	17477.4	17997	2.89
19	17591.2	18043	2.50
20	17079.4	17512	2.47
21	16491	16910	2.48
22	15626.2	16003	2.35
23	14402.6	14775	2.52
24	13212.5	13490	2.06

5. Conclusion

Because of their good generalization performance, ability to avoid local minima and get the global optimal solution, LS-SVMs are well suited for electrical load forecasting. In this study one model for short term load forecasting is proposed. Different features that affect load demand are analyzed, and appropriate are chosen for the model. It was shown that temperature is not always a very good choice for the feature. The training set was carefully chosen to “match” the season which is predicted. The trained model has been applied successfully to real life data, and experimental results are competitive with other solutions. Further research should be oriented towards formation of individual training sets, one for each day of the week, in order to reduce errors in hours around load peaks.

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KRATKOROČNO PREDVIĐANJE ELEKTRIČNOG OPTEREĆENJA PRIMENOM METODA PODRŽAVAJUĆIH VEKTORA

Miloš Božić, Miloš Stojanović, Zoran Stajić

U radu je prikazan model za kratkoročno predviđanje električne potrošnje, primenom metoda podržavajućih vektora. Analizirani su raspoloživi podaci i u skladu sa tim su izabrani odgovarajući atributi za formiranje modela. Za atribute su izabrani dan u sedmici, čas u okviru *dana, kao i 24 vrednosti električnog opterećenja po časovima za prethodni dan. Pokazano je da temperatuta nije uvek najbolji izbor za atribut. Odgovarajući trening skup je korišćen za obuku modela, a zatim je vršeno predviđanje električne potrošnje za naredni dan po časovima. Rezultati testiranja pokazuju da je predloženi model konkurentan sa drugim rešenjima.*

Ključne reči: *kratkoročno predviđanje električne potrošnje, metoda podržavajućih vektora, vremenske serije, regresija*