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# SHORT TERM LOAD FORECASTING USING SUPPORT VECTOR MACHINES FOR DIFFERENT CONSUMER TYPES
# KRATKOROČNA PREDIKCIJA POTROŠNJE ELEKTRIČNE ENERGIJE METODOM VEKTORA PODRŠKE ZA RAZLIČITE TIPOVE POTROŠAČA

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## ABSTRACT

*Deregulated electric energy market pushes utilities to control and maintain production, transmission and distribution system on more economical way. Economical control focuses accurate electric energy forecast. This paper presents short term load forecasting method using support vector machines. Short term load forecasting predicts load in range from one to seven days. Support vector machines is new artificial intelligence methods from family of supervised learning methods and it is successfully used for pattern recognition, classification, regression, forecast and more. Proposed method uses historical data of consumer behavior, historical, actual and forecasted weather data and day type for inputs. Results are shown for three consumer types, residential with distant heating, residential with heating on electric energy and industrial type. Proposed methodology obtained good results in the area of electric power consumption prediction at distribution level. Also, this methodology is useful for prediction of generation and consumption of other types of energy from different sources.*
***Key words**: short term load forecasting, support vector machines.*

## REZIME

*Deregulisano tržište električne energije nameće potrebu pojedinačnim kompanijama da što ekonomičnije upravljaju sistemom proizvodnje, prenosa i distribucije električne energije. Ekonomično upravljanje stavlja u fokus što tačniju prognozu potrosnje energije. U ovom radu prikazana je metoda kratkoročne prognoze potrošnje električne energije pomoću metode vektora podrške. Kratkoročna prognoza se bavi predikcijom u periodu od jednog do sedam dana. Metoda vektora podrške je nova metoda veštačke inteligencije iz familije učenja sa nadzorom koja se uspešno koristi za prepoznavanje oblika i obrazaca, klasifikaciju, regresiju, predikciju i drugo. Predložena metoda kao ulaze koristi istorijske podatke o ponašanju potrošača, istorijske, trenutne i prognozirane vremenske uslove kao i informaciju o tipu dana za koji se radi prognoza. Predloženo rešenje koristi relativno mali skup ulaznih podataka težeći što kraćem vremenu treninga i predikcije tako da je pogodno za izvršavanje u realnom vremenu i pogodno je za sisteme sa velikim brojem tačaka za koje se radi predikcija. U radu su prikazani rezultati za tri vrste potrošača, za gradski tip potrošača sa daljinskim grejanjem, za gradski tip potrošaća sa grejanjem na struju i za industrijskog potrošača. Predloženom metodologijom su postignuti dobri rezultati u oblasti predikcije potrošnje električne energije na distributivnom nivou. Takođe, ova metodologija je upotrebljiva i za predviđanje proizvodnje i potrošnje drugih oblika energije iz različitih energenata.*
***Ključne reči**: kratkoročna prognoza potrošnje električne energije, metoda potpornih vektora.*

## INTRODUCTION

Electric industry experiences big changes and major restructuring in recent years. A competitive pressure and wholesales market opening brings up new challenges upon electricity utility management. Under such condition an intelligent and professional approach to energy management becomes an imperative. Forecasting the electricity demand (or load) on a hourly basis, from one to several days ahead is referred to as Short Term Load Forecasting (STLF). The usual horizon of STLF is usually the next day. STLF is one of the key parameters that help utility operators in making decisions regarding purchasing and selling electric power (*Al-Shaalan*, *2009*), unit commitment, maintenance, load switching and infrastructure planning. The errors in STLF have significant implications for profits, market shares, and share-holder values. Non-linear and random-like behavior of the factors affecting the electricity load demand, as well as the data collection problem **Error! Reference source not found.**, make STLF hard to deal with. It is therefore necessary to develop advanced and more sophisticated STLF methods, for modern power systems (*Grigoras, et al., 2010*).

Many papers has been published on different forecasting problems in a field of electric load and utility operations, like forecasting of load for non-residential buildings (*Penya*, *et al., 2011*), classification of future market prices (*Zareipour*, *et al., 2011*), load forecast for power system with comparatively low load factor (*Pramelakumari*, *et al., 2012*), forecast of building space cooling load (*Zhang*, *et al., 2011*) and much more. Last years brings big penetrations of renewable generating resources in modern electric grid all around the world (*Petrus*, *2011*). While renewable resources don't have significant level of reliability it is even more important for grid operator to have accurate load forecast. This paper introduces new model to tackle the problem of STLF. The model is based on soft-computing method called Support Vector Machines.

## MATERIAL AND METHOD

### Support Vector Machines

Support Vector Machines (SVM) appeared in the early nineties as optimal margin classifiers in the context of Vapnik's statistical learning theory and became a promising technique for data classification and regression. SVM is a part of the supervised learning field of methodologies. The formulation embodies the Structural Risk Minimization (SRM) principle, which has been shown to be superior to traditional Empirical Risk Minimization (ERM) principle, employed by conventional neural networks. SRM minimizes an upper bound on the expected risk, as opposed to ERM that minimizes the error on the training data. It is this difference which equips SVM with a greater ability to generalize, which is the goal in statistical learning. SVMs were developed to solve the classification problem, but recently they have been extended to the domain of regression problems. The term SVR is typically used to describe regression with support vector methods. Support vector regression (SVR) which can be used for time series prediction is briefly introduced in this paper. For given training data (x1, y1), (x2, y2) ...(xl, yl), where $x_i$ are input vectors (vectors are composed of attributes) and yi are the appropriate output values of $x_i$, the Support Vector Regression solves quadratic problem, by adding possibility of errors

$$\min \frac{1}{2} w^T w + C \sum_{i=1}^{l} (\xi_i + \xi_i^*) \qquad (1)$$

with constraints:

$$y_i - (w^T \Phi(x_i) + b) \le \varepsilon + \xi_i; \quad (w^T \Phi(x_i) + b) - y_i \le \varepsilon + \xi_i^*$$

Where: w is a weight which determines the distance between two categories (the margin), $x_i$ is mapped to a higher dimensional space using mapping kernel function Φ, $\xi_i$ is the upper training error ($\xi^*_i$ is the lower) subject to the ε-insensitive tube. The width of tube ε and the cost of error C are parameters which determine the limit of maximal tolerance and therefore control regression quality.

For ease of graphical representation (Fig. 1), we adopt $y \in \{-1, +1\}$ as a set of output values and input values are two-dimensional $\mathbf{x}_i \in R^2$.

The data are linearly separable, and can be separated by an infinite number of hyperplane. Fig. 1 clearly shows that margin is a bandwidth that separates the two classes. Obviously, the best generalization ability is just the hyperplane with the largest margin. And it is this basic idea of SVM method: from all hyperplanes that minimizes the training error, find the one that has the highest margin.

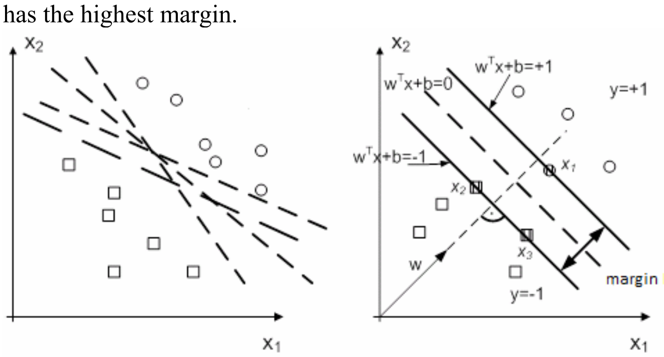


*Fig. 1. SVM margin*

If the constraints of equation (1) are observed, it implies that most of data $x_i$ should be putted in the margin (within the tube). An error $\xi_i$ or $\xi^*_i$ which should be minimized in the objective function, appears when sample $x_i$ is not in the tube. Thus SVR avoids under fitting and over fitting the training data.

SVM is a more general and flexible method for regression problems than traditional least square regression. In SVM method data are mapped into higher dimensional spaces, while traditional regression ε is always zero. SVMs have been successfully applied to real-world data analysis problems, often providing more accurate results when compared with other regression techniques (*Kecman, 2001*).

## Short Time Load Forecasting As Time Series

Field of short-term forecasting is traditionally related to the concept of time series. Mathematically speaking time series is a vector $\vec{x}$ dependent on time t.

$$\vec{x}(t), t = 0,1,2... \qquad (2)$$

Vector elements are values of observable variable and for an instance can be ambient temperature, pressure in tank, merchandise price, number of predefined event… Theoretically, $\vec{x}$ is continuous function of time variable but for practical purposes time is usually viewed in terms of discrete time steps. This means that an instance of vector $\vec{x}$ is measured at end of usually fixed time interval. Vector $\vec{x}$ can contain one or more components and it defines univariante or multivariante time series. Forecasting of future developments of the time series is most wide spread and imminent application of time series analysis in literature. Problem of time series forecasting can be described as problem of finding function $F : \Re^{k \times n + l} \to R^k$ (with k being the dimension of $\vec{x}$) such as to obtain an estimate $\hat{\vec{x}}$ (t + d) of vector $\vec{x}$ at time t + d, given the values of $\vec{x}$ up to time t, plus a number of additional time-independent variables (exogenous values) $\pi_i$:

$$\hat{\vec{x}}(t+d) = F(\vec{x}(t), \vec{x}(t-1), ..., \pi_1, ..., \pi_l) \qquad (3)$$

d is called the lag for prediction. Size of d implies how much future values are going to be predicted i.e. d = 1 means that only subsequent vector is going to be estimated (e.g. forecasting of consumption for next hour). Additional $\pi_i$ values are very often very hard to determine but these values can be very important for accurate forecasting. $\pi_i$ can be, for instance, size of area for which electric load is forecasted (*Dorffner, 1996*).

## Forecasting Model

Forecasting model is based on SVM technique. Inputs are selected through series of tests to obtain best fit of load curve and network architecture was chosen according selected inputs. (Peng, 1990). Proposed model is shown on Figure 2. Parameter with strongest impact on forecasting of load is previous consumer behavior. Weather data has also a very big impact on consumer behavior and load forecast (*Fan*, *et al., 2011*) in combination with day type.

At the begging of the training data preparation function calculated integrated values.

Defined inputs and outputs from model are:

Inputs:

- Integrated temperature for forecasting day *d*
- Integrated load for previous day *d-1*
- Day type code (0 – workday, 1 – weekend)

Outputs

- 24 hourly forecasted load

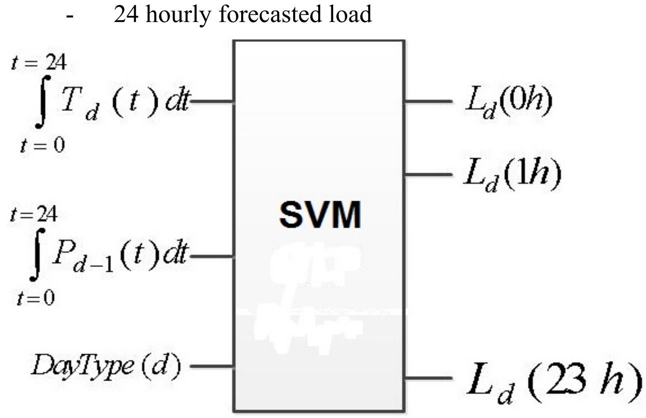


*Fig. 2. Forecaster model*

Model is kept relatively small to reduce training and forecasting time which is suitable for large scale systems with significant number of consumers. (*Ilić et al., 2011)*

Model has been developed in MS Visual Studio v2010 using .NET 4.0 libraries. For data storage (historical load and historical temperature) model uses MS SQL 2005 database.

## RESULTS AND DISCUSSION

The model is evaluated based on its prediction errors. The error measure which is most commonly employed in the field of STLF, and which was used in the evaluation of the results here presented, is the mean absolute percentage error (MAPE), which is defined as

$$MAPE = \left( \frac{|x_i - y_i|}{x_i} \right) \times 100 \qquad (4)$$

where $x_i$ is the actual values and $y_i$ is the predicted values at time instance $i$.

Testing has been done on real life measurement for two types of consumers, industrial consumer and residential consumer and for two year periods, summer and winter.

Test results are shown in Figures 4, 5, 6 and 7. Tests shows that forecasting solution gives better forecasting results for industrial type consumer than for the residential type. These result are expected because industrial consumers are more deterministic, less influenced by temperature or other stochastic factors and has simpler shape. For the residential consumer it is shown that results are more accurate for winter comparing to summer. During winter consumers uses distant heating which is not related to electric load but during the summer air conditioning has big impact on load and brings additional unknown to the problem. Test has been run on multiple consumers and average errors are given in table 1.

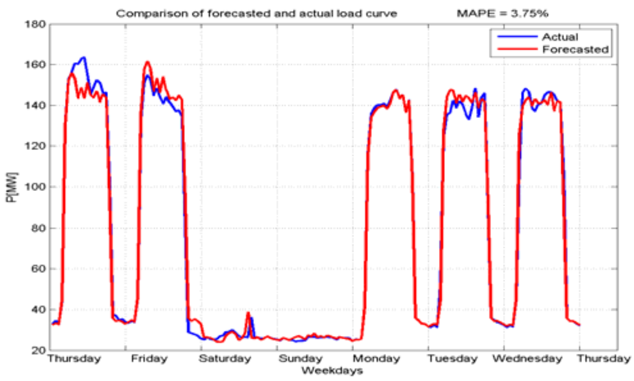


*Fig. 3. 7 day forecast for industrial consumer during summer*

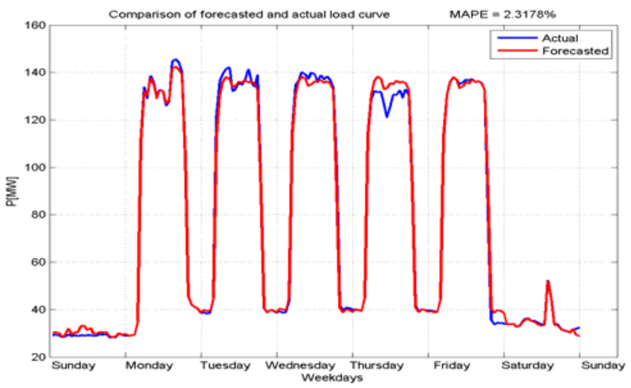


*Fig. 4. 7 day forecast for industrial consumer during winter*

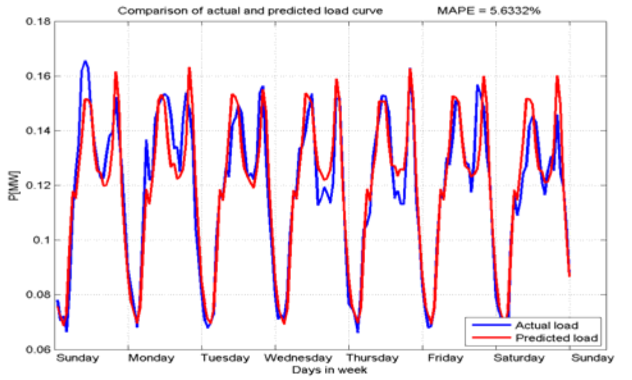


*Fig. 5. 7 day forecast for residential consumer during summer*

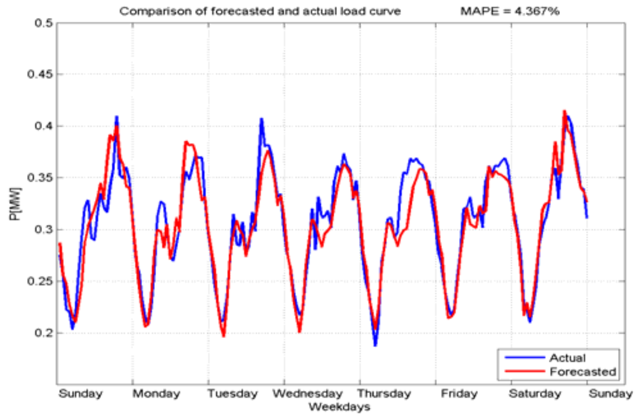


*Fig. 6. 7 day forecast for residential consumer during winter*

*Table 1. Average forecasting error*

| Consumer Type | Average error during summer [%] | Average error during winter [%] |
|---|---|---|
| Industrial | 3.9 | 5.82 |
| Residential | 2.45 | 4.41 |

## CONCLUSION

Rapid social and economic development of modern urban areas imposes a need for scientific planning of utility operations and management, where load forecasting is one of crucial points. To improve the accuracy of forecasting and utility operation forecasting model has been proposed. The proposed model gives acceptable results while maintaining simple structure which is suitable for systems with large number of nodes for which forecasting is needed. Possible improvements for prosed solution could be including more detailed number of weather conditions to calculate apparent temperature (feel temperature) more precise and to calculate peak load during the day which is also very important information for grid operator. Parallel to optimizing utility operation it is very important to reduce load and to optimize power consumption to increase grid reliability and support sustainable development (*Nikolic, 2011*).

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