

Electrical Load Forecasting using SVM Algorithm

Parag Nijhawan, Vinod Kumar Bhalla, Manish Kumar Singla, Jyoti Gupta



Abstract: Electrical load demand is variable in nature. Also, with the increase in technological development and automation, electric load demand tends to rise with time. For this, our generation facilities should be adequate 24x7 to meet the consumer's load demand effectively. Therefore, load demand needs to be predicted or forecasted to avoid the energy crisis. In this paper, support vector machine (SVM) algorithm is explored for electric load forecasting. The live load data for the period of three months i.e., January to March, 2015, from a typical 66kV sub-station of the Punjab State Power Corporation Limited (PSPCL) for a selected site at Bhai Roopa sub-station, Bathinda, situated in the Punjab state of India, is acquired for the presented simulation study. The collected live data is divided into three categories, i.e., validation, training, and testing for the simulation study considering a SVM approach. Then, based on the environmental data input for the next 50 hours, the electric load is predicted. The obtained results from simulation were validated with the live load data of the selected site and found to be within the permissible limits. The mean square error (MSE), root-mean-square error (RMSE), mean absolute error (MAE), absolute percentage error (APE), mean absolute percentage error (MAPE) and sum of squares error (SSE) were calculated to show the effectiveness of the proposed support vector machine (SVM) algorithm based STLF. SVM is one of the effective machine learning algorithms. The errors so obtained clearly suggest that the proposed SVM algorithm gives reasonably accurate results, and is reliable for electric load forecasting.

Keyword - power system planning, machine learning, spinning reserve, Support Vector Machine.

I. INTRODUCTION

Electric load forecasting (STLF) [1]-[2] plays an important role for the secured and effective operation of power system network. Any forecast or prediction method is bound to give certain erratic results or outcomes. In other words, it is just not fair to expect any prediction method to be 100% precise or certain. Forecast precision and accuracy in load predictions lead to better planning of the generation facilities and their effective scheduling which can limit the operating costs. Over-prediction of load result in an unnecessary increase in reserves and thus, higher operating cost. Under-prediction of load could result in a failure in supplying the required reserves, thereby attracting higher operating costs.

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Parag Nijhawan*, EIE Department, Thapar Institute of Engineering and Technology, Patiala (INDIA).

Vinod Kumar Bhalla, CSE Department, Thapar Institute of Engineering and Technology, Patiala (INDIA).

Manish Kumar Singla, EIE Department, Thapar Institute of Engineering and Technology, Patiala (INDIA).

Jyoti Gupta, EIE Department, Thapar Institute of Engineering and Technology, Patiala (INDIA).

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This is due to the use of costly peaking units. Several load forecasting models which include regressive models [3]-[5] and time series models [6]-[8] have been proposed in the literature. Continuous technological advancements in the field of machine learning led to its penetration in the variety of engineering applications.

One such application is the electric load forecasting. In this paper, an attempt has been made to apply one of the machine learning technique i.e., SVM algorithm to solve the electric load forecasting problem. The proposed technique provides an effective solution for an accurate forecasting and practical training of the complete system. Artificial intelligence [9]-[13] is a revolution in the sense that has replaced the need of human experience by the intelligent machines.

In this paper, after introduction in section I, an attempt has been made to carry out the literature survey on electric load forecasting and SVM, in section II and section III, respectively. Section IV presents the methodology adopted to carry out the presented work. Section V highlights the obtained results, which is followed by conclusions in section VI.

II. LOAD FORECASTING

Electrical short-term load forecasting [14-15] is a very important aspect of power system planning and control. It helps in effective management of electrical utilities. To ensure the optimized utilization and erection of generation, transmission and distribution facilities, electric load forecasting plays a vital role [16]. The primary requisite of electric load forecasting problem is that it should be accurate and fast.

Load forecasting is of three types, namely, i.e. Short-term-load forecasting, Medium-term load forecasting and Long-term load forecasting. Electric load forecasting for a particular site and time zone has to be ensured effectively, and then, tested for some other locations(s) and time zone(s) to justify the accuracy of the prediction method. This is of utmost importance for the efficient system operation within a utility company. Sometimes, the electric load prediction is quite accurate but at other times, the prediction method may give quite erratic results. The normalized weather load is a load measured in terms of typical weather, which is an average value of the previously generated peak value of historical data over a precious interval of time [3]. Most of the corporations considered 25 to 30 years of data for electrical load forecasting. The electric load forecasting tends to ensure the decision-making process which prevents overloading for the protection purpose such as system failure, complete blackout, etc., to improve the reliability and efficiency of the power system network [3].

III. SUPPORT VECTOR MACHINE

Support vector machine (SVM) is a semi supervised machine learning tools introduced by Vapnik et al. [17]-[19]. It is extensively used for categorization and classification of data.

Cortes, and Vapnik [17] defined function $f(x) = WT x+B$; W: weight vector and B: bias. Numbers of kernel functions are supported-linear, Polynomial, and Radial. SVM is also extensively applied for regression and prediction of result. Data is feed to this tool to train the model and test the performance with another data set as shown in figure 1.

Various packages support SVM tools. In this research work LIBSVM [18] is used as a tool. SVM has various kernel – Linear, polynomial, radial and it also has strong capability in the form of epsilon-svr regression and nu-svr regression. Based on nature of problem, these kernels can be trained. Tuning of various SVM parameters can improve the width of separating hyper plane resulting in improved efficiency. LIBSVM has data format in the following form. {label feareure1:value feareure-1:value feareure-2:value. . . feareure-n: value}.

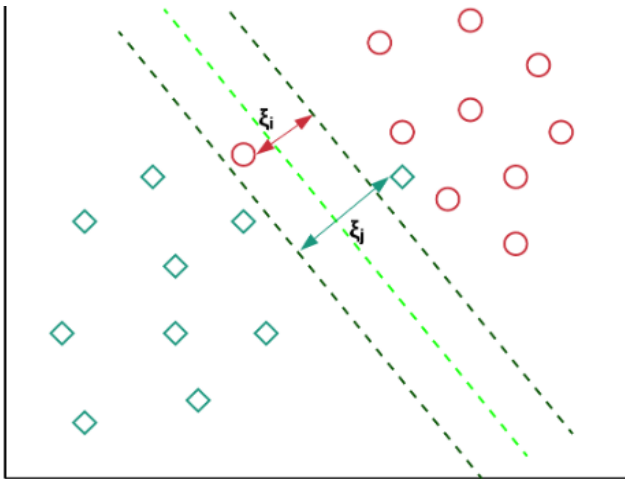


Figure 1. SVM Hyperplane

Features are extracting from the relevant data and then that data is converted to above format for processing. Generally dataset is fragmented into train data set and testing data in 80:20 ratios. SVM uses non-linear class boundaries by mapping the input support vectors non-linearly into a high dimensional feature space. Other training set examples are not too significant for setting up the boundaries. Support vectors are the training examples that are ceiling periphery of hyper plane. Non-parametric kernel regression technique is applied in SVM to estimate the conditional expected value of a random variable. The aim is to trace a non-linear relation between random variables X and Y.

IV. METHODOLOGY

Methodology used for the proposed work is as follows.

- Data is collected from the station
- Data is filtered for execution
- Data is converted to SVM format
- Data is scaled in the range of [-1, 1] [20]

- Training dataset and test data set is separated
- Model is trained using SVM regression technique
- Fivefold cross validation is applied on it to improve the efficiency
- Different kernels models are trained with number of cost, gamma and mean square error (mse) values to improve the accuracy of model till the highest accuracy and lowest mean error is achieved
- Finally trained model is test on the test data set.
- Random data is tested on the trained model to see the performance

V. EXPERIMENTAL RESULTS

In this paper, the authors have made an attempt to present and discuss the results of electrical load forecasting using machine learning optimized technique i.e., SVM. In this work, according to the environmental conditions, acquired from Indian Metrological Department (IMD), Pune, in terms of Dry bulb, Wet bulb temperature, and humidity are taken as input data while load data is taken as the output. The SVM algorithm [17], [19] is used in this work to effectively predict or forecast the electric load at a particular site which is 66kV Bhai Roopa sub-station, Bathinda, situated in the Punjab state of India. The load data and the environmental conditions for the selected site were acquired for the three months – January to March, 2015 from IMD and PSPCL, respectively. The acquired data was used to train the proposed algorithm. Then, the environmental conditions for the next 50 hours were taken as input to predict the hourly electric load for the selected site. The predicted load values were then compared with the actual values of load. The mean square error (MSE), root-mean-square error (RMSE), mean absolute error (MAE), absolute percentage error (APE), mean absolute percentage error (MAPE) and sum of squares error (SSE) were calculated, as shown in Table 1. Data set is divided into training data set and test data set. Then, scaling of data set is done using SVM algorithm. After scaling of training and test data, set model is trained using various kernels by varying the cost, gamma and mean square error (MSE) to finally optimize the model. It was done manually and using LIBSVM [18] is used to find the optimum value for the epsilon and nu regression kernels. Out of all options radial kernel and epsilon-svr regression yielded the desired results. Fivefold cross validation is applied on the training set to improve the accuracy level and confidence in the model. Trained model is then used over test dataset for prediction of values using SVM algorithm. Cross validation resulted as mean squared error comes out to be 0.00572438 for regression as shown in figure 2.

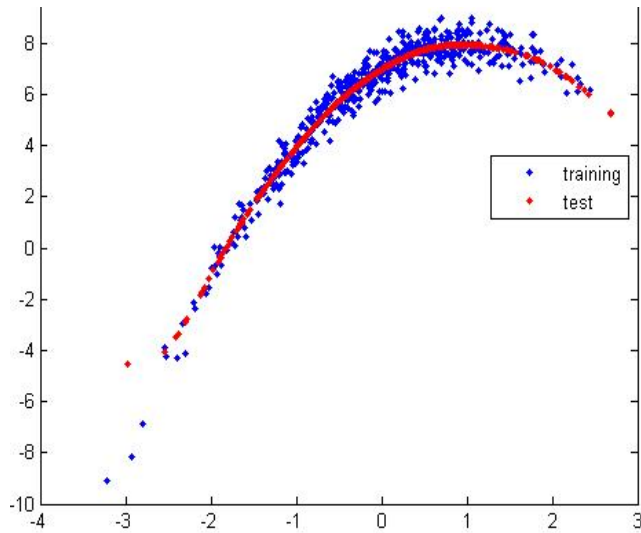


Figure 2. Regression plot- training data vs test data

the accuracy of prediction of electric load using the proposed method, the MSE, RMSE, MAE, APE, MAPE and SSE errors were calculated. The weather data is taken from the IMD, Pune, and load data is taken from one of the 66kV substation of PSPCL situated in Bhai Roopa. From the errors so observed, it can be safely concluded that the proposed methodology gives fairly accurate results, and is reliable in predicting the electric load forecast. The machine learning based SVM approach has proved to be an effective technique of electric load forecasting with minimum deviation from the actual live data. Electrical load forecasting is the need of the day that surely aid in reduction of the generation cost and spinning reserve capacity. It also enhances the reliability of the power system network. Proposed research clearly lays down the foundation for the better performance of power system networks. In the end, it can be safely concluded that the proposed SVM algorithm, if properly trained, has all the potential to predict the electric load at a particular time zone and place quite accurately.

VI. CONCLUSIONS

In this work, electrical load forecasting using machine learning is done with the help of SVM algorithm. To justify

Table I. Comparison between actual and predicted load

S.NO	DRY BULB (°C)	WET BULB (°C)	HUMIDITY (%)	ACTUAL LOAD (MW)	PREDICTED LOAD (MW)	ERRORS					
						MSE	RMSE	MAE	APE	MAPE	SSE
1	9.2	9.2	90	86	83	4.5	2.1	1.5	3.4	1.7	9
2	8.2	6.5	89	84	84	0	0	0	0	0	0
3	7.2	7.2	100	86	85	0.5	0.7	0.5	1.1	0.5	1
4	8.0	7.1	94	84	87	4.5	2.1	1.5	3.5	1.7	9
5	7.8	7.8	100	82	84	2	1.4	1	2.4	1.2	4
6	10.4	9.2	92	84	87	4.5	2.1	1.5	3.5	1.7	9
7	7.8	6.5	91	86	84	2	1.4	1	2.3	1.1	4
8	9.8	7.8	87	84	84	0	0	0	0	0	0
9	8.2	8.2	100	84	86	2	1.4	1	2.3	1.1	4
10	10	9.6	97	84	85	0.5	0.7	0.5	1.1	0.5	1
11	5.2	5.2	100	85	84	0.5	0.7	0.5	1.1	0.5	1
12	10	10	100	90	88	2	1.4	1	2.2	1.1	4
13	8.4	7.1	91	88	86	2	1.4	1	2.2	1.1	4
14	11	10.6	97	84	84	0	0	0	0	0	0
15	9.2	4.2	71	80	83	4.5	2.1	1.5	3.7	1.8	9
16	19.4	11	58	84	83	0.5	0.7	0.5	1.1	0.5	1
17	14.8	11.9	82	86	89	4.5	2.1	1.5	3.4	1.7	9
18	15	13.2	89	86	87	0.5	0.7	0.5	1.1	0.5	1

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19	12.6	9.5	81	85	84	0.5	0.7	0.5	1.1	0.5	1
20	12.4	9.2	81	83	85	2	1.4	1	2.4	1.2	4
21	10.2	9.4	95	83	83	0	0	0	0	0	0
22	10.2	9.4	95	84	87	4.5	2.1	1.5	3.5	1.7	9
23	10.4	7.9	85	84	86	2	1.4	1	2.3	1.1	4
24	12	9.2	83	80	83	4.5	2.1	1.5	3.7	1.8	9
25	11.2	8.4	83	80	82	2	1.4	1	2.5	1.2	4
26	18.2	9.5	57	80	82	2	1.4	1	2.5	1.2	4
27	18.7	12.4	66	84	85	0.5	0.7	0.5	1.1	0.5	1
28	16.7	13.2	80	84	83	0.5	0.7	0.5	1.1	0.5	1
29	20.4	10	51	85	83	2	1.4	1	2.3	1.1	4
30	20.4	7.1	42	85	84	0.5	0.7	0.5	1.1	0.5	1
31	19.4	6.2	42	87	86	0.5	0.7	0.5	1.1	0.5	1
32	21.2	7.8	42	89	88	0.5	0.7	0.5	1.1	0.5	1
33	21.7	11.9	53	85	88	4.5	2.1	1.5	3.5	1.7	9
34	23.2	11.9	49	85	88	4.5	2.1	1.5	3.5	1.7	9
35	22.7	15.9	65	87	87	0	0	0	0	0	0
36	21.4	15.7	70	89	87	2	1.4	1	2.2	1.1	4
37	24.2	14	52	90	88	2	1.4	1	2.2	1.1	4
38	18.4	13.1	71	87	86	0.5	0.7	0.5	1.1	0.5	1
39	22.2	14	60	84	85	0.5	0.7	0.5	1.1	0.5	1
40	23	15.7	64	80	82	2	1.4	1	2.5	1.2	4
41	24.7	18.5	68	85	84	0.5	0.7	0.5	1.1	0.5	1
42	23	19.2	79	84	82	2	1.4	1	2.2	1.1	4
43	20.7	13.1	62	84	84	0	0	0	0	0	0
44	19.7	13.3	34	85	84	0.5	0.7	0.5	1.1	0.5	1
45	20	7.1	43	85	82	4.5	2.1	1.5	3.5	1.7	9
46	19.2	11.6	61	80	82	2	1.4	1	2.5	1.2	4
47	12.8	11.3	91	84	83	0.5	0.7	0.5	1.1	0.5	1
48	20	10	52	75	78	4.5	2.1	1.5	4	2	9
49	21.6	11.2	51	78	80	2	1.4	1	2.5	1.2	4
50	16.6	14.5	87	80	82	2	1.4	1	2.5	1.2	4

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Manish Kumar Singla is PhD Scholar in the Electrical and Instrumentation Engineering Department at Thapar Institute of Engineering and Technology, India. He received his B.E. and M.E. degrees in Electrical Engineering from the Punjab Technical University and Thapar Institute of Engineering and Technology, in India, respectively. His current fields of interest include Power Systems, Artificial intelligence, High Voltage Engineering, Fuel Cell.
E-mail: msingla0509@gmail.com



Jyoti Gupta is PhD Scholar in the Electrical and Instrumentation Engineering Department at Thapar Institute of Engineering and Technology, India. She received her B.E. and M.E. degrees in Electrical Engineering from the Punjab Technical University and Thapar Institute of Engineering and Technology, in India, respectively. Her current fields of interest include power systems, Artificial intelligence, Renewable Energy.
E-mail: jg118207@gmail.com

AUTHOR PROFILE



Dr. Parag Nijhawan is presently Associate Professor in the Electrical and Instrumentation Engineering Department at Thapar Institute of Engineering and Technology, India. He received his B.E. and M.E. degrees in Electrical Engineering from the Punjab Technical University and Punjab Engineering College in India, respectively. He did his PhD. in Electrical Engineering from National Institute of Technology, Kurukshetra. He has more than 19 years of work experience that includes teaching and research. His research focus includes renewable energy sources, power quality improvement, grounding and FACTS devices.
E-mail: parag.nijhawan@rediffmail.com



Dr. Vinod Kumar Bhalla is currently working as an Assistant Professor in the Computer Science and Engineering Department at Thapar Institute of Engineering and Technology, India. He has experience of more than 15 years in both Industry and Academia. He has taught many courses to UG/PG in his area of expertise in web technologies. He has guided many thesis leading to M.Tech, and M.E. of different streams.
E-mail: vkballa@thapar.edu