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Combined General Vector Machine for Single Point Electricity Load Forecast

Binbin Yong
University of Wollongong, yongbb14@lzu.edu.cn

Yongqiang Wei

Jun Shen
University of Wollongong, jshen@uow.edu.au

Fucun Li
University of Wollongong, fl626@uowmail.edu.au

Xuetao Jiang

See next page for additional authors

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Keywords
point, vector, combined, single, machine, general, forecast, load, electricity

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Authors
Binbin Yong, Yongqiang Wei, Jun Shen, Fucun Li, Xuetao Jiang, and Qingguo Zhou

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Binbin Yong[1,2], Yongqiang Wei[1], Jun Shen[3,4], Fucun Li[3], Xuetao Jiang[1], and Qingguo Zhou[1] ⋆

[1] School of Information Science and Engineering, Lanzhou University, Lanzhou, Gansu, China
{yongbb,weiyq18,jiangxt18,zhouqg}@lzu.edu.cn
[2] School of Physical Science and Technology, Lanzhou University, Lanzhou, Gansu, China
[3] School of Information Systems and Technology, University of Wollongong, NSW, Australia
jshen@uow.edu.au,fl626@uowmail.edu.au
[4] Department of EE and CS, Research Lab of Electronics, Massachusetts Institute of Technology, Cambridge, 02139, MA, USA

Abstract. General Vector Machine (GVM) is a newly proposed machine learning model, which is applicable to small samples forecast scenarios. In this paper, the GVM is applied into electricity load forecast based on single point modeling method. Meanwhile, traditional time series forecast models, including back propagation neural network (BPNN), Support Vector Machine (SVM) and Autoregressive Integrated Moving Average Model (ARIMA), are also experimented for single point electricity load forecast. Further, the combined model based on GVM, BPNN, SVM and ARIMA are proposed and verified. Results show that GVM performs better than these traditional models, and the combined model outperforms any other single models for single point electricity load forecast.

Keywords: General Vector Machine, Electricity load forecast, Time series forecast, Combined model

1 Introduction

Electricity load forecast is the base of electrical power system planning, which plays an important role in insurance of national life and stability of social economy. Hence, it has been a widely studied issue and many forecast methods are proposed. As a classical statistical learning model, Back propagation neural network (BPNN) is proved effective for electricity load [1]. However, limited to the finite training samples and surplus hidden nodes, BPNN often suffers from the over-fitting problem [2]. As shown in Fig. 1, the overall cost, which represents the error between actual values and forecasting values, usually has different trends

⋆ Corresponding author: zhouqg@lzu.edu.cn

in training samples and test samples. Generally, test cost will firstly reduce together with the training cost, and then it might increase after a minimum value. It means, BPNN model could possibly perform well on training samples, while it results in a poor performance for new situations.

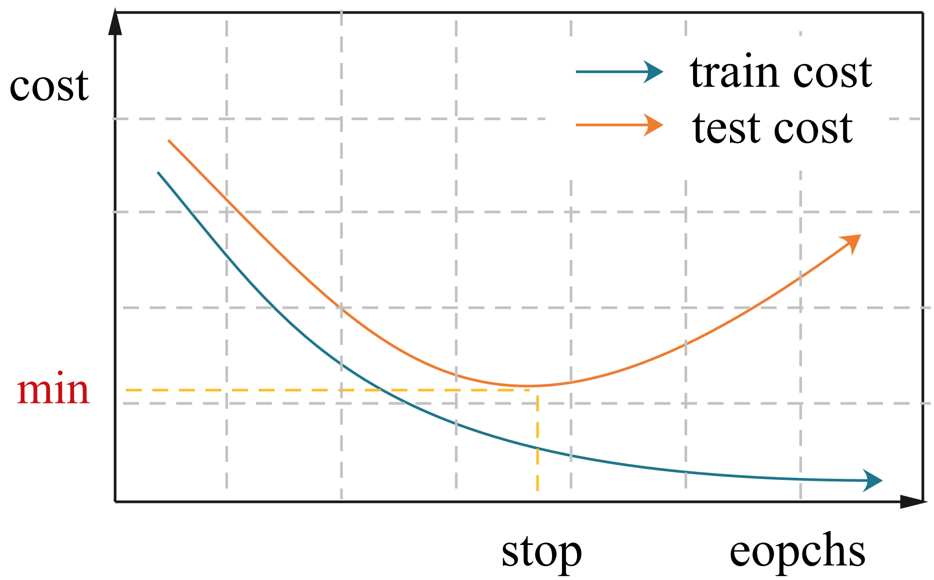

Fig. 1. The display of over fitting.

Due to the over-fitting problem, BPNN has issues in many different time series forecast scenarios. Meanwhile, over-fitting issue remains a controversial issue in the academic field. In order to deal with the problem, many approaches were proposed to eliminate the over-fitting phenomena [3].

Then, based on SLT, Vanpik proposed the famous Support Vector Machine (SVM) [4], which has solid theoretical foundation and trys to find a hyperplane that separates samples with a largest margin, is proved to be very effective for small samples. SVM evolves in a quicker pace than BPNN due to its solid theoretical foundation and excellent generalization ability for small samples [5,6]. However, in the case when the training samples is vary small, SVM may select noise samples as support vectors, and hence misses the optimal model. Since Hiton proposed deep learning [7] in 2006, the neural network recovers once again. Arguments about the merits and demerits of neural network and SVM continues [8,9]. Meanwhile, some researchers try to find models that ensemble both the advantages of BPNN and SVM.

General Vector Machine (GVM) [10,11], which has a basic structure of three-layer neural network, is designed as a mixer model of neural network and SVM. In fact, GVM is applicable to cases of lacking samples [12,13], and it has been

successfully applied in time series forecast problem, such as electricity demand forecast [14]. Meanwhile, development of modern technology generates the demand for more accurate electricity forecast. Therefore, many traditional models, e.g. BPNN [15], SVM [16,17] are widely researched in electricity load forecast. In addition to the traditional models, some alternative approaches are also explored [18,19]. Unfortunately, due to the instability of electricity demand, electricity load forecast is still a great challenge. In this paper, we firstly applied GVM, BPNN, SVM and ARIMA into electricity load forecast. Then, the combined model of these four types models are researched.

The remainder of this paper is organized as follows. The introduction of GVM model is displayed in Section 2. Section 3 shows the single point forecast models, and applies it into electricity load forecast. The experiments and analysis are given in Section 4. At last, Section 5 concludes our work.

2 GVM model and the Monte Carlo training algorithm

The GVM model and its training algorithm are shown in Fig. 2. Instead of support vectors, general vectors make the model not sensitive to individual sample, so as to gain the generalization ability of GVM model. In contrast to neural network, in the design of GVM, the parameter β is imported into the hidden nodes to reduce the design risk. By adjusting β, GVM will keep robust for small fluctuations of the input feature vector.

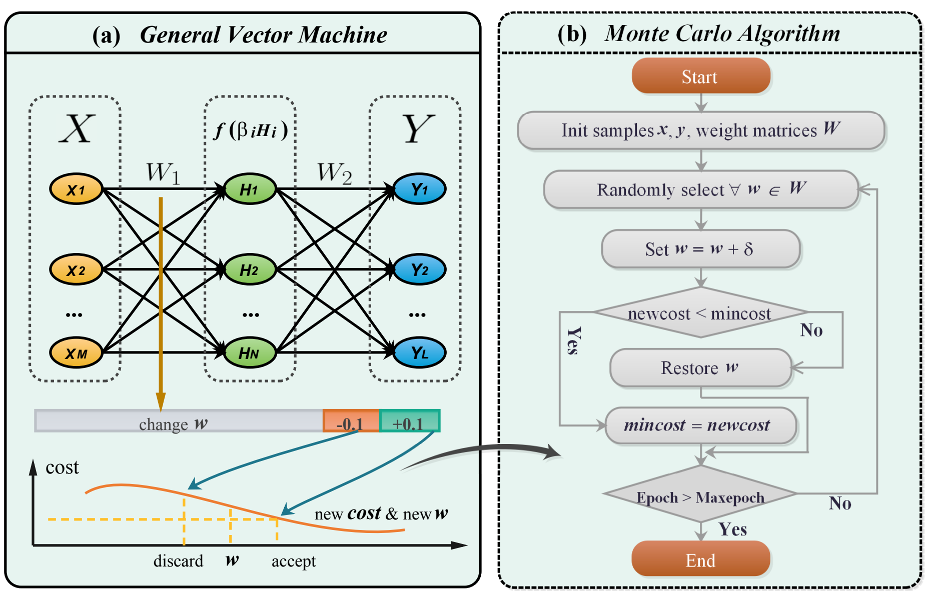

Fig. 2. (a) The structure of GVM. (b) The MC algorithm used to train GVM model.

GVM introduces the Monte Carlo (MC) algorithm to train the model. The basic idea of training GVM is that the change of a weight would be accepted while the overall cost decreases. Specifically, it randomly changes one weight of the weight matrices in a small deviation, and GVM will accept the weight change while the overall cost is reduced. By this way, the training GVM model will gradually converge to a stable state. The pseudo-code of generating a new weight is given in Function (1), which repeatedly and randomly finds a new weight near the old one until the new weight is within the weight range.

Function (1) Generate a new weight

Input:

index index of weights (including W_β, W_1, W_b) to change
W represents W_β, W_1, W_b
WR range of weight matrices
step range of weights change

Output: new weight

function NEWW($index, W, WR, step$)
    $newW \leftarrow W[index]$
    repeat
        $\delta \leftarrow rand() * step$
        $newW \leftarrow newW + \delta$
    until $abs(newW \leq WR)$
    return $newW$
end function

3 Single point forecast modeling and the combined model

In this paper, we focus on the forecast models for electricity load forecast. The electricity load data is collected from Queensland in Australia every half-hour, which means that there are 48 electricity load data per day. We select the data ranging from May 2, 2011 to July 3, 2011, which includes 3,024 data of 9 weeks. As shown in Fig. 3, a single point forecast model is constructed with 7 input nodes and 1 output node. The first 8 weeks data is used as the training data, in which the first 7 weeks data is used as the input vector and the eighth week data are seen as the output vector. When testing, the data from the second week to the ninth week is used as the test data, in which the data from the second week to the eighth week is used as input vector and the data of the ninth week is used as the output vector. The models to forecast the above input-output include GVM, BPNN, SVM and ARIMA. As talked above, BPNN represents a three-layer neural network, which is trained by back propagation algorithm. GVM is trained by MC algorithm. For SVM, time series forecast is in fact a regression problem (also called SVR). According to our experiments, the usage of radial basis function (RBF) as kernel function achieves better forecast results.

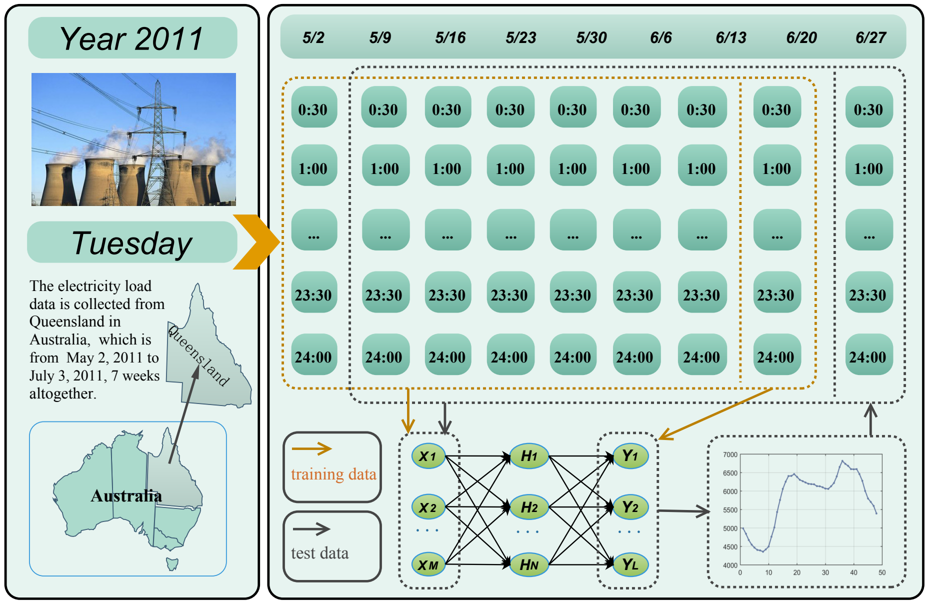

Fig. 3. Single point forecast modeling.

When selecting the parameters of regularization (penalty coefficient) c and kernel width (radius of kernel function) g, the grid method is used to search the best regularization parameter c and kernel parameter g.

In order to further improve the forecast performance, we try to combine the GVM, BPNN, SVM and ARIMA models. Similar to the training algorithm of GVM, the combined model is trained by Monte Carlo (MC) algorithm. That is, the weights of these four component models are initialized equally. Then, the weights are randomly changed in a small range, and the change of reducing the overall cost will be accepted.

4 Experiments and analysis

In this section, we will show the experiments results of single point forecast models and the combined model. Four metrics including Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are used to evaluate the performances of these models.

4.1 Comparisons on the single point forecast models

For SVM model, we search the parameters c and g from 2^{-10} to 2^{10} divided by 0.1 to find the best pairs of c and g, and the best parameters are listed in Table. 1.

Table 1
The best regularization parameter $c(2^x)$ and the kernel parameter $g(2^x)$ of SVM model.

	Mon.	Tue.	Wed.	Thu.	Fri.	Sat.	Sun.	All
$c(2^x)$	6.20	10.0	0.49	8.15	10.0	9.90	-0.50	-5.29
$g(2^x)$	-8.48	-8.12	-8.48	-2.65	-4.00	-4.10	-3.10	-3.89

The single point forecast results of four types models including GVM, GVM, BPNN, SVM and ARIMA are shown in Table 2. The best forecast results of single models are highlighted in boldfaces, which mainly occurs in GVM model. By comparing all the original models, we find that GVM performs the best in the models, which proves that GVM is suitable for electricity load forecast.

Table 2
Experimental results: the electricity load forecast results of single point models.

	MAPE(%)							
	Mon.	Tue.	Wed.	Thu.	Fri.	Sat.	Sun.	All
GVM	**0.9803**	**1.4591**	**1.7692**	3.1568	2.9631	2.2151	1.5976	**2.3614**
BPNN	1.7990	1.8836	2.3726	**3.0676**	3.2271	1.9492	1.5378	2.7536
SVM	3.4149	3.1351	3.1588	4.0683	**1.4160**	**1.5219**	**1.0536**	3.3901
ARIMA	6.5651	4.6551	4.4776	6.4666	5.2850	1.8155	1.1165	4.3696
	MAE							
	Mon.	Tue.	Wed.	Thu.	Fri.	Sat.	Sun.	All
GVM	**58.617**	**86.990**	**105.03**	**177.62**	170.15	115.07	83.592	**131.13**
BPNN	104.62	110.32	141.53	182.69	193.01	106.62	82.538	155.23
SVM	196.06	189.32	172.14	230.15	**83.890**	**78.665**	82.538	179.49
ARIMA	382.26	269.71	267.67	377.4	300.38	94.516	**57.530**	249.66
	RMSE							
	Mon.	Tue.	Wed.	Thu.	Fri.	Sat.	Sun.	All
GVM	**82.809**	**110.86**	**155.52**	**198.66**	185.57	136.68	96.127	**156.61**
BPNN	134.78	132.80	168.90	202.21	219.74	128.90	104.07	193.13
SVM	237.57	214.14	214.23	301.05	**124.48**	**92.701**	104.07	214.28
ARIMA	495.86	339.90	328.75	445.09	341.68	110.81	**72.090**	301.13

The **boldfaces** are best results.

4.2 Comparisons on the combined model

In this subsection, the combined model ensembles GVM, BPNN, SVM and ARIMA are tested. As discussed above, MC algorithm is adopted to find the combined weights of component models. After a period of training, the combined weights almost keep stable, which are shown in Table 3. We can see that the combined models are able to take full use of the advantages of each component model, and achieve higher forecasting precisions than component models. The forecast results of the combined model (red curve) and the actual (blue curve) are shown in Fig. 4. We can see that the electricity load is well forecast.

Table 3
Experimental results: the combined weights of component models, and MAPE, MAE, and RMSE of the combined model.

	GVM(ω1)	BPNN(ω2)	SVM(ω3)	ARIMA(ω4)	MAPE	MAE	RMSE
Mon.	0.5491	0.3953	0.0329	0.0226	0.92712	51.392	61.277
Tue.	0.5692	0.4255	-0.0079	0.0132	1.1288	65.577	78.902
Wed.	0.3635	0.5963	-0.0343	0.0745	1.3029	77.097	113.24
Thu.	0.2900	0.6502	0.0303	0.0295	1.3792	76.851	101.47
Fri.	0.2317	0.25223	0.2883	0.2277	1.3591	74.714	100.07
Sat.	-0.0848	0.2250	0.7316	0.1283	1.4975	78.753	88.717
Sun.	0.0444	0.0209	0.7470	0.1877	1.0346	53.34	61.441
All	1.6407	0.1281	-0.5353	-0.2335	1.7143	98.975	128.81

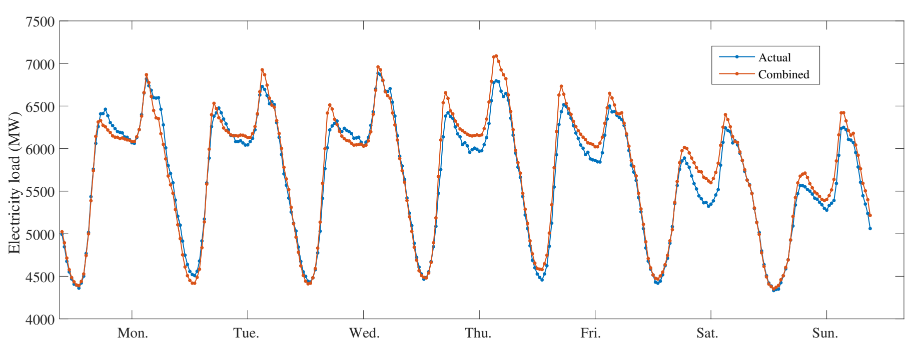

Fig. 4. Experimental results: the electricity load forecast results of combined model.

5 Conclusion

Electricity load forecast, as an important and difficult time series forecast issue, has been researched by single point modeling method in this paper. As a newly proposed model, GVM has also been applied into electricity load forecast and achieved better forecast results than other traditional forecast models. Further, the combined model ensembles GVM and traditional BP, SVM and ARIMA are explored in this paper. Meanwhile, MC algorithm is pioneered to find the combined weights of the component models. Results demonstrate that the combined models outperforms the component models and MC is effective for training combined model.

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