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Abstract

Electricity load forecast, as the core of electricity scheduling, plays a vital role in meeting the basic needs of modern human life. It has been widely studied in the past few decades. However, literature studies have shown that, as a problem of time series forecast, electricity forecast is prone to be influenced by many environmental factors, which result in lacking accuracy and stability in practice. In this paper, the General Vector Machine (GVM), a new type learning machine which was derived from Neural Network (NN) and Support Vector Machine (SVM), is applied into electricity load forecast. Meanwhile, copy-dynamics idea is introduced to electricity load forecast. Results reveal that, based on copy-dynamics, the maximum precision promotion of GVM reaches 71.7%, compared with BP. Hence, GVM and copy-dynamics models have great potential in electricity load forecast.

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GVM based copy-dynamics model for electricity load forecast

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Abstract. Electricity load forecast, as the core of electricity scheduling, plays a vital role in meeting the basic needs of modern human life. It has been widely studied in the past few decades. However, literature studies have shown that, as a problem of time series forecast, electricity forecast is prone to be influenced by many environmental factors, which result in lacking accuracy and stability in practice. In this paper, the General Vector Machine (GVM), a new type learning machine which was derived from Neural Network (NN) and Support Vector Machine (SVM), is applied into electricity load forecast. Meanwhile, copy-dynamics idea is introduced to electricity load forecast. Results reveal that, based on copy-dynamics, the maximum precision promotion of GVM reaches 71.7%, compared with BP. Hence, GVM and copy-dynamics models have great potential in electricity load forecast.

Keywords: electricity load forecast, GVM, copy-dynamics

1 Introduction

In the past century, the electricity has gradually permeated almost everywhere. From daily life to the expansion of multinational corporations, electricity has accompanied individuals and has served on the national regeneration, which brings forth extensive research interests for electricity forecast. Meanwhile, numerous forecast models are proposed, in which back propagation neural network (BP) is proved effective for electricity load [1,2,3].

In fact, the using of BP depends on the so-called Empirical Risk Minimization (ERM) strategy [4]. ERM indicates that, provided sufficient training samples, the training model is able to forecast test samples with a high accuracy. Unfortunately, limited to the finite training samples and surplus hidden nodes, BP

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often suffers from the over-fitting problem [5,6]. In this case, the overall cost, which represents the error between actual values and forecasting values, usually has distinct trends 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, BP model could possibly perform well on training samples, while it results in a poor performance in new situations.

In 2016, Zhao proposed General Vector Machine (GVM) [7], which has a basic structure of a three-layer neural network. Meanwhile, based on Struct Risk Minimization (SRM) strategy, GVM is designed as a mixer of neural network and SVM, and it has been successfully applied in samll samples forecasts [8,9,10], including time series forecast problem [11]. In this paper, we apply GVM into electricity forecast based on copy-dynamics modeling.

The remainder of this paper is organized as follows: The details of GVM is displayed in Section 2. Sect. 3 introduces copy-dynamics idea, 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

The whole structure of GVM is in fact equivalent to a three-layer neural network [12]. Hence, GVM is able to fit any functions with enough hidden nodes [13]. We assume that a GVM model consists of M input nodes, N hidden nodes and L output nodes. The outputs of hidden nodes h_n and output layer y_l are given as Eq. (1).

$$\begin{cases} h_n = f(\beta_n(\sum_{i=1}^M W_{1n}x_i + b_n)) \\ y_l = \sum_{i=1}^M W_{2l}h_n \end{cases} \quad (1)$$

In Eq. (1), x denotes the input vector, and W_{1n} is the weight vector connected between input nodes and the n th hidden node. Hence, $\sum W_{1n}x_i$ is the weighted sum of the input nodes. b_n denotes the bias of n th hidden node from bias vector W_b . β_n denotes the parameter of n th hidden node from parameter vector W_β , which will be discussed in detail in the next subsection. f is the transfer function of hidden nodes. Similar to neural network, common transfer functions of GVM include *sigmoid* and *tanh* functions.

Hence, h_i is the output of the i th hidden node. W_{2l} is the weight vector connected between the l th output node and the hidden nodes, and the outputs of hidden nodes are linearly connected to the output nodes by matrix W_2 . In fact, the weight matrix W_2 is fixed after randomly initialized as -1 or 1. Hence, adjustable weight matrices of GVM contain W_β , W_1 , W_b .

Specially, for electricity load forecast in this paper, it only needs one linear output node to represent the forecasting value of next time. Hence, we will not discuss the complex structure of GVM for classification and pattern recognition.

More concretely, as shown later, the GVM model for electricity load forecast consists of 7 input nodes, 150 hidden nodes and 1 output nodes.

In contrast to neural network, in the design of GVM, the parameter β is imported into the hidden nodes to reduce the design risk, as shown in Eq. (2).

$$y'' = \frac{d^2y}{dx^2} = \beta^2 w_2 w_1 f''(w_1 x + b) \quad (2)$$

In fact, the second derivative of output y with respect to feature x (y'') for GVM is derived as Eq. (2), which is controlled by w_1, w_2, f'' and β . By adjusting β , GVM will keep robust for small fluctuations of the input feature vector.

In general for regression problems, such as time series forecast, GVM selects Eq. (3) as the cost function, in which y'_i represents the i th forecasting output value and y_i is the i th actual value from the training samples. In this paper, we also import another three metrics to verify the effectiveness of GVM model, which is Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), as defined in Eq. (4).

$$COST = \frac{1}{2} \sum_{i=1}^N (y'_i - y_i)^2 \quad (3)$$

$$\begin{cases} MAPE = \sum_{i=1}^N \frac{|y'_i - y_i|}{y_i} \times 100\% \\ MAE = \frac{\sum_{i=1}^N |y'_i - y_i|}{N} \\ RMSE = \sqrt{\frac{\sum_{i=1}^N (y'_i - y_i)^2}{N}} \end{cases} \quad (4)$$

In fact, the cost function (Eq. (3)) has the same trend with RMSE, which represents the discreteness of forecasting values and actual values. MAPE denotes the relative errors and MAE shows the mean error of the forecast models. Hence, the using of these three metrics could evaluate the forecast models more comprehensive.

GVM introduces 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.

3 GVM copy-dynamics forecast

In fact, traditional methods of electricity load forecast are most based on point forecast. In this section, we will present a new copy-dynamics method for electricity load forecast, as shown in Fig. 1.

The idea of copy-dynamics is based on the fact that a three-layer neural network with enough hidden nodes is able to describe any functions. Hence, for a dynamics system, we can collect the input-output values as dataset, by which we can train a neural network to represent the relationship between input and output of the dynamic system. Furthermore, the neural network could be used to forecast the behavior of the dynamics system. In fact, GVM is very suitable for performing copy-dynamics, due to its robust stability.

Fig. 1. Copy-dynamics modeling.

In this paper, we still focus on electricity load forecast. The electricity load data is collected from Queensland in Australia, which includes 3,024 data in 9 weeks and ranges from May 2, 2013 to July 3, 2013.

The copy-dynamics model for electricity load forecast is shown in Fig. 2. More concretely, the first 336 data (first week) are used as the input vector, and the 337th data is used as the output, which form the 1st sample. Then, the next 336 data (from 2nd to 337th) and the 338th data are used as the input vector and the output of the second sample. In this way, we can construct 336 training samples by using 2 week electricity load data.

Based on these 336 training samples, we can train a neural network to copy the law of electricity load, which could be used to predict the electricity load in future. In this paper, we mainly combine copy-dynamics idea with GVM to forecast electricity load. Meanwhile, as a comparison, traditional BP is also used to execute copy-dynamics for electricity load forecast.

Fig. 2. Copy-dynamics forecast model for electricity load forecast.

4 Experiments and analysis

In our experiments, we test the influence of different hidden nodes for copy-dynamics electricity load forecast based on BP and GVM, respectively. And we will compare the forecast results of these two type of models based on their best network structures.

The detailed results of electricity load by BP and GVM are shown in Table 1 and Table 2. From Table 1 we can see that BP achieves best forecast results with 5 hidden nodes, and more hidden nodes tend to worse forecast results, which means complex network structure and over-fitting. On the contrary, in Table 2, GVM achieves its best structure with 400 hidden nodes, and more hidden nodes tend to lower forecast error. In fact, different to BP, GVM model controls over-fitting by control parameter β . Meanwhile, more hidden nodes are used to improve the forecasting accuracy. However, we can also see from Table 2 that the forecast accuracy will keep stable, when the number of hidden nodes is in excess of 400.

Table 1

Experimental results: copy-dynamics forecasting errors (represented by MAPE, MAE and RMSE) of BP for electricity load forecast, based on different hidden nodes. With the increase of the number of hidden nodes, BP achieves its best structure with 5 hidden nodes, and more hidden nodes lead to big forecasting errors for long interval forecast. On the other side, with the increase of forecast interval, the forecasting errors tend to be larger.

MAPE(%)							
nHid	1-week	2-week	3-week	4-week	5-week	6-week	7-week
4	5.3963	10.718	13.541	15.229	16.244	16.903	17.434
5	3.4632	4.2318	6.3647	8.4591	10.066	11.262	12.153
6	3.6579	4.6440	7.1348	9.1927	10.829	12.241	13.538
10	3.3946	3.6706	5.6413	9.3381	12.407	14.643	16.343
20	3.5328	3.9573	5.3035	8.4813	13.566	18.248	21.927
30	3.6524	4.3770	6.9871	12.885	18.795	23.321	26.839
40	3.6003	4.0359	6.2366	12.573	20.068	25.588	29.836
50	3.6369	4.9474	13.613	24.082	31.159	35.877	39.399
MAE							
nHid	1-week	2-week	3-week	4-week	5-week	6-week	7-week
4	316.15	607.93	762.71	851.54	907.85	948.28	976.69
5	204.05	244.24	364.05	476.55	566.44	636.57	684.23
6	213.21	262.82	401.53	512.14	603.25	686.54	932.50
10	199.45	211.30	321.19	522.73	693.30	821.74	914.34
20	206.56	226.77	301.44	475.34	760.98	1029.0	1230.6
30	213.88	250.26	395.87	718.91	1049.3	1309.6	1503.2
40	209.88	229.41	350.74	695.58	1112.7	1428.8	1664.5
50	213.31	284.34	770.61	1342.7	1736.4	2009.2	2201.6
RMSE							
nHid	1-week	2-week	3-week	4-week	5-week	6-week	7-week
4	438.38	823.90	987.04	1071.4	1127.1	1170.6	1194.5
5	258.19	320.17	506.09	661.19	772.91	857.21	907.31
6	273.73	353.42	564.17	709.68	828.31	932.50	1009.6
10	252.84	264.35	443.12	755.34	979.06	1135.1	1233.4
20	259.25	280.15	398.71	707.63	1179.6	1545.9	1769.6
30	267.82	313.02	575.66	1133.5	1606.9	1920.8	2122.4
40	264.48	287.34	482.01	1124.8	1733.8	2109.6	2342.4
50	269.04	369.28	1242.1	2020.1	2451.1	2722.2	2897.1

Table 2

Experimental results: copy-dynamics forecast results of GVM of different hidden nodes.

MAPE(%)							
nHid	1-week	2-week	3-week	4-week	5-week	6-week	7-week
50	3.6837	4.4391	5.5474	6.6005	7.3420	8.1471	8.8491
100	3.4474	3.6082	4.0925	4.6682	5.3938	6.0795	6.5948
150	3.2797	3.1293	3.3160	3.8103	4.2171	4.9844	6.0013
200	3.5899	3.3456	3.3991	3.6366	3.9432	4.2984	4.5192
250	3.5465	3.1949	3.1439	3.2189	3.4784	3.7848	3.9675
300	3.5727	3.2515	3.2120	3.3445	3.5352	3.7965	3.9007
350	3.3850	2.9249	2.8336	2.8275	2.9700	3.1734	3.6654
400	3.4686	3.0894	2.9961	2.9801	3.1834	3.4531	3.6032
MAE							
nHid	1-week	2-week	3-week	4-week	5-week	6-week	7-week
50	215.23	251.05	309.54	361.58	401.77	449.35	485.10
100	204.29	209.34	235.92	265.17	306.98	349.14	376.50
150	195.16	183.24	193.93	220.60	243.20	288.27	345.40
200	211.46	193.65	196.89	207.37	225.56	249.24	260.65
250	208.23	184.49	181.97	183.63	199.33	220.07	229.46
300	209.74	187.29	185.10	189.79	201.35	219.44	224.51
350	198.60	168.64	163.60	161.31	170.50	184.96	211.73
400	203.19	177.70	172.56	169.23	182.02	200.51	208.61
RMSE							
nHid	1-week	2-week	3-week	4-week	5-week	6-week	7-week
50	265.93	305.84	387.80	469.88	522.79	582.45	626.64
100	264.99	271.96	307.14	345.40	403.79	461.66	494.84
150	251.37	237.47	259.15	298.61	336.28	408.60	499.14
200	264.74	245.41	249.23	259.91	284.63	323.13	336.62
250	258.80	232.86	230.92	232.08	253.61	282.48	299.16
300	258.09	235.29	232.87	239.40	253.49	286.76	293.45
350	245.00	212.20	207.43	206.64	218.77	243.72	274.82
400	250.38	220.75	215.57	211.73	229.56	261.60	271.27

With the best structures of BP (5 hidden nodes) and GVM (400 hidden nodes), we compare the forecast results of BP and GVM based on copy-dynamics, as shown in Fig. 3. Figure (a) shows the forecast results of 1 week (the first week after training samples), in which GVM performs similar but more smooth than BP. Figure (b) presents the forecast results of 2 weeks. It obviously reveals that

GVM is more stable and smooth than BP for long forecast. In fact, from Table 1 and Table 2 we can easily see that GVM keeps stable even for forecasting 7 weeks, while BP suffers big errors when forecasting 7 weeks electricity load, and the maximum precision promotion of GVM reaches 71.7%. Overall, compared with traditional point forecast, copy-dynamics needs less training samples (only 2 weeks). Moreover, point forecast model could only forecast the load of the next point. However, GVM with copy-dynamics idea forecasts long interval with stability.

Fig.3. Experimental results: the forecast results of BP and GVM based on copy-dynamics for the 1st and 2nd weeks.

5 Conclusion

GVM is a latest model for time series forecast, which performs well for small-samples forecasts. Hence, it has been gradually applied in many time series forecast problems, which are usually lack of training samples. In this paper, a new copy-dynamics based electricity load forecast method is introduced. Results prove that the combination of GVM and copy-dynamics is very effective for electricity load forecast.

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References

1. W. Charytoniuk, M. S. Chen, Very short-term load forecasting using artificial neural networks, *IEEE Transactions on Power Systems* 15 (1) (2002) 263–268.
2. W. Chen, Y. Wu, S. Lou, X. Xiong, A short-term load forecasting method based on arima-bpnn, in: *Iet International Conference on Advances in Power System Control, Operation and Management*, 2006, pp. 379–379.
3. A. Laouafi, M. Mordjaoui, D. Dib, One-hour ahead electric load and wind-solar power generation forecasting using artificial neural network, in: *Renewable Energy Congress*, 2015, pp. 1–6.
4. V. Vapnik, *The nature of statistical learning theory*, Springer-Verlag, 1995, pp. 988 – 999.
5. D. E. Rumelhart, G. E. Hinton, R. J. Williams, Learning representations by back-propagating errors, *Nature* 323 (6088) (1986) 533–536.
URL <http://dx.doi.org/10.1038/323533a0>
6. D. M. Hawkins, The problem of overfitting, *Cheminform* 35 (19) (2004) 1.
7. H. Zhao, General vector machine, *arXiv preprint*.
8. Q. Zhou, B. Yong, F. Li, J. Wu, Z. Xu, J. Shen, H. Chen, A novel monte carlo based neural network model for electricity load forecasting, *International Journal of High Performance Computing & Networking* 1 (1) (2018) 1.
9. B. Yong, Z. Xu, J. Shen, H. Chen, Y. Tian, Q. Zhou, Neural network model with monte carlo algorithm for electricity demand forecasting in queensland, in: *Australasian Computer Science Week Multiconference*, 2017, p. 47.
10. B. Yong, J. Shen, Z. Shen, H. Chen, X. Wang, Q. Zhou, Gvm based intuitive simulation web application for collision detection, *Neurocomputing* 279.
11. Q. Zhou, H. Chen, H. Zhao, J. Shen, A local field correlated and monte carlo based shallow neural network model for nonlinear time series prediction, *Scalable Information Systems*.
12. A. Sasaki, H. Ninomiya, A study of 3-layer neural network with feedback connections, in: *IEICE General Conference*, 2001.
13. V. Kreinovich, O. Sirisaengtaksin, 3-layer neural networks are universal approximators for functionals and for control strategies, *Neural Parallel & Scientific Computations* 1 (3).