Prediction of employment figures in the three main industries based on extreme learning machine

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Abstract

Extreme learning machine, with a fast speed of training, achieves globally optimal solutions and excellent generalization ability. This work is based on the production value and employment figure of the three main industries in China during 1996-2012 as research objects. An ELM employment figure prediction model was constructed with production value and the employment figure of the three main industries respectively as the input and output of extreme learning machine. Simulation test results proved a good effect and high accuracy of ELM employment figure prediction model. Besides, the comparison of ELM, BP and RBF algorithms further proved the effectiveness and precision of ELM, which has certain practical application value.

Keywords: three main industries, extreme learning machine, production value, neural network, training samples, test samples

1 Introduction

With the rapid development of economy and continuous upgrading of industrial structure in China, the total employment and structure of labor force have experienced dramatic changes. Under the combined effects of incoming labor force and transfer of laid-off labor and rural labor, employment in China becomes an increasingly severe problem.

Since there are some interconnection influences between industrial structure and employment, additional investment to some industries can directly create large amount of employment opportunities. Additional investments to some industries may not create more employment opportunities, but it can directly or indirectly influence consumption of products in other industries, thus providing employment opportunities. Therefore, the employment opportunities of the whole economic system will be increased accordingly [1].

Adjusting industrial structure is an important way to realize optimization of internal structure of economic system, solving employment problems and increasing employment opportunities in each industry. Therefore, researches on the potential of employment in the three major industries are of great significances to employment.

In recent decades, China has achieved high-speed growth in economy, but employment growth is relatively slow. At present, rural surplus labor and college graduates become main employment forces. They are faced with various employment pressures; some of them are even faced with unemployment. As a result, Chinese people are facing big pressure from employment at present. Besides, the total labor force exceeds the demands of employment, but some places are in a shortage of labors. Therefore, employment structural contradictions become increasingly fierce [2-3].

With huge employment pressure, it is of important theory value and practical significance to broaden visions and fully consider national situations while absorbing employment theory from western economics researches. Only on such basis can prediction of employment figure be achieved effectively.

2 Extreme learning machine neural network

It is clear that the learning speed of feed forward neural networks is in general far slower than required and it has been a major bottleneck in their applications for past decades. Two key reasons behind may be: (1) the slow gradient based learning algorithms are extensively used to train neural networks, and (2) all the parameters of the networks are tuned iteratively by using such learning algorithms. Unlike the traditional implementations, we applied a new learning algorithm called extreme learning machine (ELM) for SLFNs which randomly chooses the input weights and analytically determines the output weights of SLFNs. This algorithm tends to provide the best generalization performance at extremely fast learning speed.
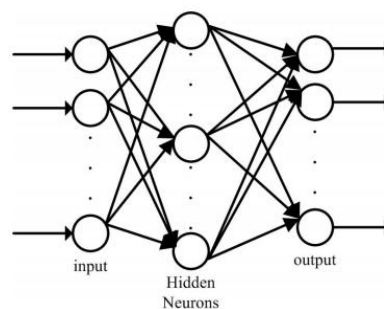

FIGURE 1 Extreme Learning Machine Schematic Diagram

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As pointed out by [4-9], for feed forward networks with many small weights but small squared error on the training examples, the Vapnik-Chervonenkis (VC) dimension (and hence number of parameters) is irrelevant to the generalization performance. Instead, the magnitude of the weights in the network is more important. The smaller the weights are, the better generalization performance the network tends to have. As analyzed above, our method not only reaches the smallest squared error on the training examples but also obtains the smallest weights. Thus, it is reasonable to think that our method tends to have better generalization performance. It should be worth pointing out that it may be difficult for gradient-based learning algorithms like back-propagation to reach the best genera-

lization performance since they only try to obtain the smallest training errors without considering the magnitude of the weights.

3 Data sources and variable selection

In order to predict employment figure in the three main industries in China, this work selected the production value and employment data during 1996~2012 from each industry as samples (Table 1). Employment figure of each industry was considered as explanatory variable L_i, GDP of each industry as the explained variable Y_i. All data comes from *1996~2012 China Statistical Yearbook* [10,11].

TABLE 1 Production value and employment figure of each industry

Year	Y_1 / 100 Million RMB	L_1 / 10 Thousand People	Y_2 / 100 Million RMB	L_2 / 10 Thousand People	Y_3 / 100 Million RMB	L_3 / 10 Thousand People
1996	5866.6	38349	11699.5	14226	9357.3765	12979
1997	6963.7629	37434	16454.431	14868	11915.731	14071
1998	9572.6948	36489	22445.399	15254	16179.763	15456
1999	12135.811	35468	28679.458	15628	19978.46	16851
2000	14015.39	34769	33834.959	16180	23326.243	17901
2001	14441.886	34730	37543.002	16495	26988.147	18375
2002	14817.626	34838	39004.189	16440	30580.466	18679
2003	14770.028	35364	41033.582	16235	33873.445	18987
2004	14944.723	36043	45555.878	16217	38713.954	19823
2005	15781.269	36513	49512.291	16284	44361.611	20228
2006	16537.02	36870	53896.768	15780	49898.902	21090
2007	17381.718	36546	62436.312	16077	56004.726	21809
2008	21412.734	35269	73904.312	16920	64561.292	23011
2009	22420	33970	87364.579	18084	73432.866	23771
2010	24040	32561	103162	19226	84721.4	24614
2011	28627	31444	124799	20629	103879.59	24917
2012	34000	30654	146183.4	21109	120486.61	25717

Y_1 refers to the production value of the first industry; Y_2 the production value of the second industry; Y_3 the production value of the third industry. L_1 is the employ-

ment figure of the first industry; L_2 the employment figure of the second industry; L_3 the employment figure of the third industry.
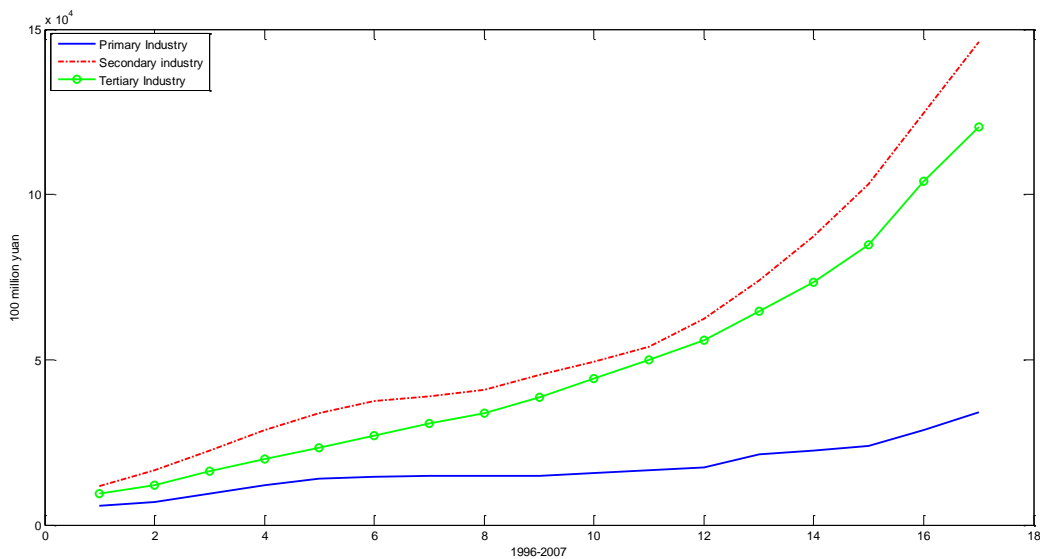

FIGURE 2 Change curve of production value in each industry over the year
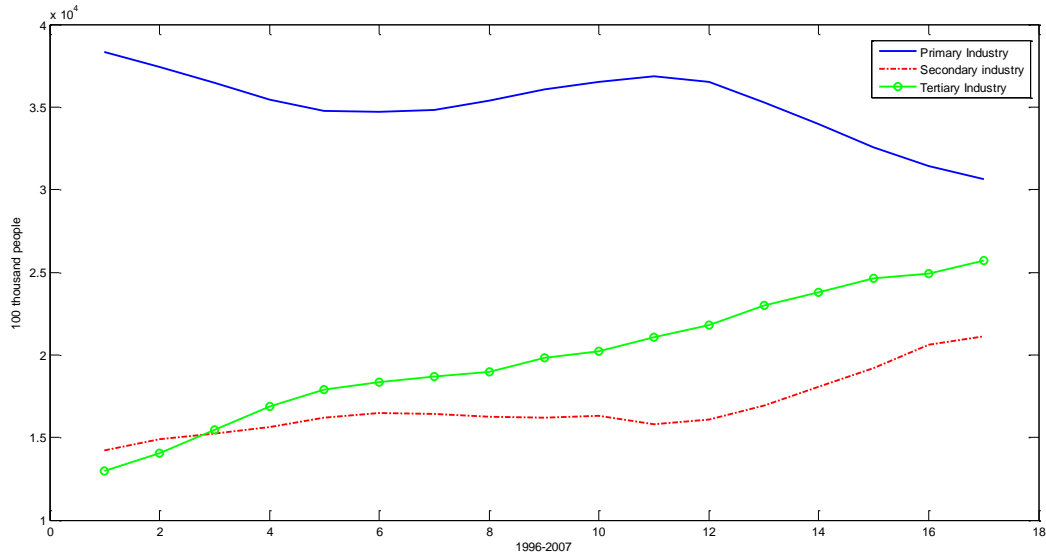
FIGURE 3 Change curve of employment figure in each industry over the year

Figures 2 and 3 show that production values of the 2nd and 3rd industries increased year by year since 1996. And, the growth rate of the 2nd industry was greater than that of the 3rd industry. On the contrary, employment figure of the 1st industry declined year by year, implying that the 1st industry's allocation of labor ability was getting weaker. However, employment figures of the 2nd and 3rd industries also increased year by year. It means employment absorption capacity of the 2nd and 3rd industries is far greater than that of the 1st industry.

4 Employment figure prediction based on extreme learning machine

With production value and employment figure of the three main industries, respectively, as the input and output of extreme learning machine, a training model was established to predict employment figure. There were two sets of samples: 17 training samples and 5 test samples, all verifying the prediction ability of extreme learning machine network.
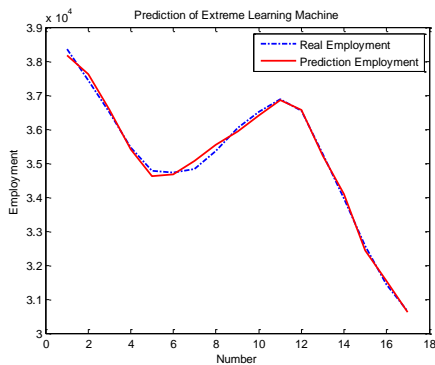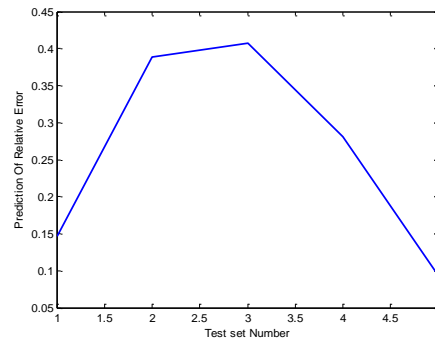

a) Prediction results of training samples
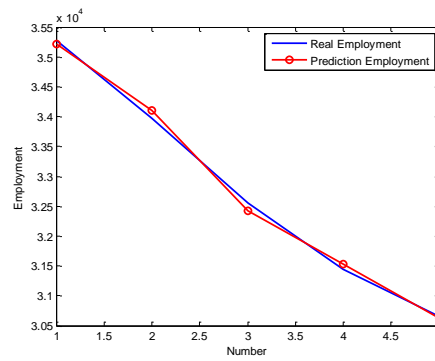
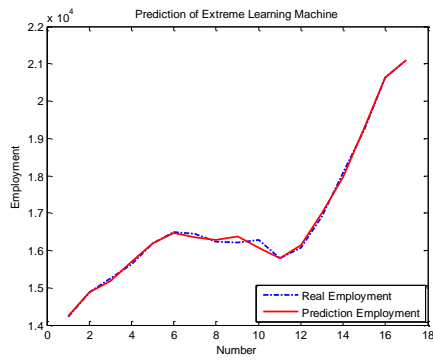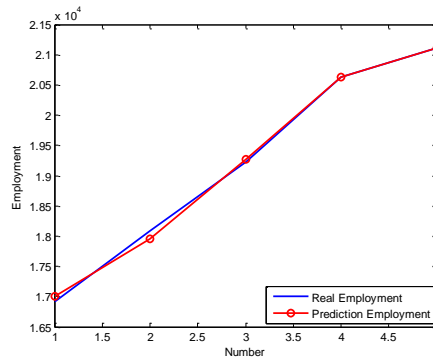b) Prediction results of test samples
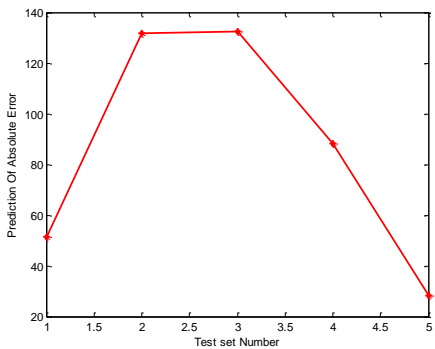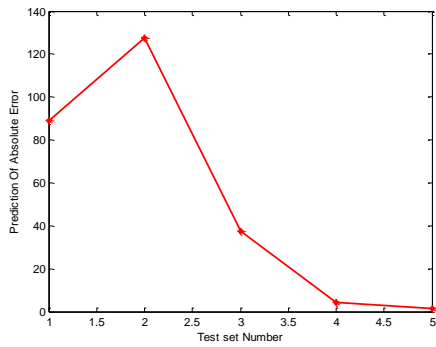

c) Absolute Error

d) Relative Error

FIGURE 4 Prediction results and errors of employment figure of the 1st industry
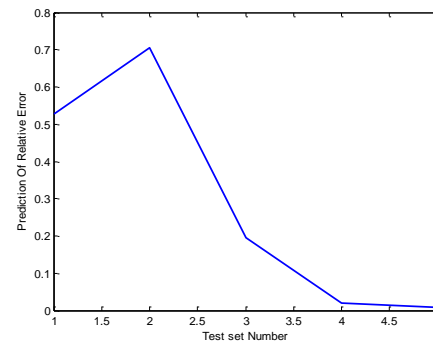
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a) Prediction results of training samples

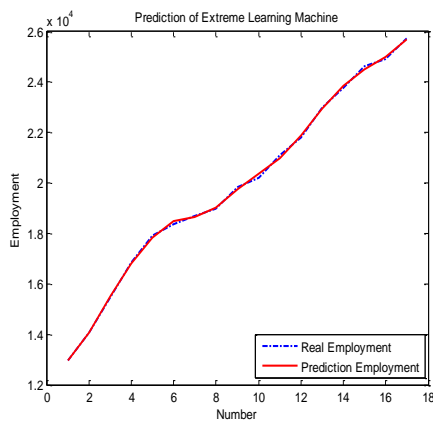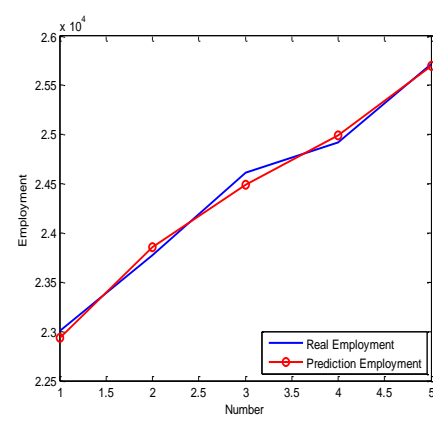b) Prediction results of test samples
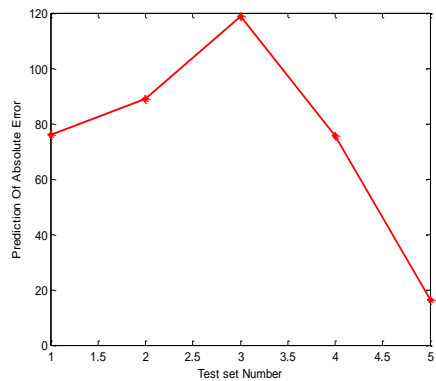
c) Absolute error

d) Relative error

FIGURE 5 Prediction results and errors of employment figure of the 2nd Industry
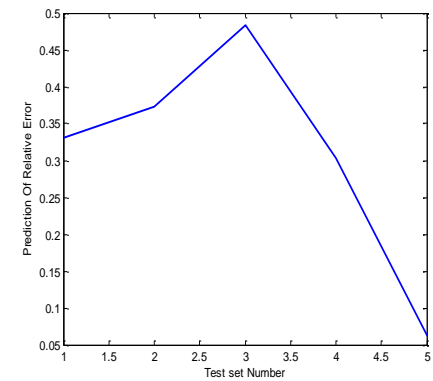

a) Prediction results of training samples

b) Prediction results of test samples

c) Absolute error

d) Relative error

FIGURE 6 Prediction results and errors of employment figure of the 3rd industry

Figure 3-5 respectively showed the prediction results of extreme learning machine. Figure 3a-5a, explained prediction results of training samples, presenting a good prediction and strong generalization ability. Figure 3 (b), Figure 4 (b) and Figure 5 (b) presented prediction results of test samples, mainly verifying the effectiveness and accuracy of extreme learning machine. It can be seen from Figure 3 (c) (d), Figure 4 (c) (d) and Figure 5 (c) (d) that this algorithm achieves good effects.

In order to compare and verify the superiority of this algorithm, the prediction results of ELM, BP neural network and RBF neural network were compared. It can be seen that ELM has the best prediction results; RBF neural has a worse prediction results compared with ELM; BP neural network has the worst. Comparison of those different algorithms verified the effectiveness and accuracy of ELM. Therefore, extreme learning machine, with certain practical application significance, can be used to classify and predict problems.

5 Conclusions

Based on production value and employment figure of the three main industries during 1996-2012 in China as research objects, this work established ELM employment figure prediction model. It was used to predict employment figures when production value and employment figure of the three main industries were respectively used as output and input of extreme learning machine. Comparison of ELM, BP and RBF further proved the effectiveness and high accuracy of ELM. Thus, this algorithm, with certain practical application value, can be used to classify and forecast problems.

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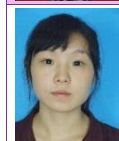
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