Postgraduate Entrant and Employment Forecasting Using Modified BP Neural Network with PSO

Xianjun Shen
Department of Computer Science
Central China Normal University
Wuhan, China
xjshen@mail.ccnu.edu.cn

Caixia Chen, Tingting He, Jincai Yang
Department of Computer Science
Central China Normal University
Wuhan, China

***Abstract*—It is hard to train the influence variables and to forecast the complex problems due to the time series. Recently the neural network method has been successfully employed to solve the forecasting problem. In this paper, an approach that integrate modified BP neural network optimized with particle swarm optimization algorithm (MBPPSO) is proposed which applied to forecast postgraduate entrant and employment problem. It introduces particle swarm optimization algorithm to optimize the initial weights of the BP neural network, which effectively improve velocity of convergence BP neural network. Moreover, the adaptive adjust learn strategy is introduced to avoid acutely shake of train and decrease the bias error. The experiment results show MBPPSO can achieve reasonable forecast result.**

***key words*—particle swam optimization, BP neural network, postgraduate entrant and employment forecasting**

I. INTRODUCTION

Today, with increasingly progress of the finance crisis all over the world and expands the scale of postgraduate entrant, postgraduate entrant and employment is becoming noticeable focus in every walk of life. Since china's opening up to the outside world, the control of postgraduate allocation has been shifted from administration to the market [1]. As important human resources of the developing of the overall strength of china and especially since the year 1997, which start to large-scale enlarge postgraduate entrant, postgraduate entrant and employment has been remarkably change, thus it is very important problem that study and forecast postgraduate entrant and employment [2].

Focus on the postgraduate entrant and employment problem in china, it is found that there are many kinds of factors influencing the postgraduate entrant and employment, which have many inner factors and environment factors. For example, the number of undergraduates of annual, the employment ratio of undergraduate, the number of students pursuing further education (master degree or doctorate), the value tropism of excellent students, etc, which belong to the inner factors, they often determine whether graduates want to be postgraduate and indirectly effect postgraduate entrant and employment. Meanwhile, the origin of graduate whether it is the well-thought-of university is also important inner factor. The annual educational outlay of nation, the entrant rate of postgraduate, the total outlay of science and technology study which come from nation finance, the long-term development aim and plan of china, the annual velocity of economy development of china and the economic climate of world, etc, which get belong to the environment factors. The factors from the outside environment would influence the decision-making of postgraduate entrant and employment, which also determine whether the different industry and area, the various enterprises and the national department, which want to go would accept postgraduate. For example, well economic climate world and rapidly domestic economic development providing more chance of job and better salary, which must effect postgraduate entrant and attract more postgraduate employment.

The labor market in china is now under the process of transform. Market cannot play its full part in the allocation of postgraduate [3]. Moreover, all kinds of policy also affect postgraduate entrant and employment, which lead to the noisy and non-stationary of the statistical data, so it is hard for us to accurately statistic and forecast the rate of postgraduate entrant and employment. However, the precise forecasting study is the premise of the scientific decision-making. The forecasting results can be affected by lots of complex variables, factors and interactions. Those can't easily be transferred to a real mathematics model. Because of the nonlinear features and complicities, the conventional forecasting ways such as linear regression, expert experience system, ARMA and gray system theory could be disappointing in the accuracy and the velocity of the convergence [1]. In recent few decades, the development of artificial neural networks has bought forward a useful method to solve forecasting problem.

The artificial neural network has the powerful capability to generalize the nonlinear relationships between the inputs and the desired outputs, without considering real problem domain expressions [4]. For the moment, BP neural network is one of the widest application networks on many fields, for example pattern classification, fault diagnosis, character recognition, forecasting, etc [5]. The advantage of BP neural network are massive parallelism, adaptive learning and complete distribution among similar simple units, while the main shortcomings lie in the facts of easily traps to a local optimum, slow velocity of convergence and networks stagnation. Large number improvements have been tried out, but they can't obtain a perfect result because of the unsuitable initial parameter.

A modified BP neural network with particle swarm optimization (MBPPSO) is proposed in this paper. In this paper, it firstly analyzes the all kind of factor that affects current postgraduate entrant and employment. In the following sections, it briefly describe BP neural network, then present some essentials of PSO. In the section 4, we proposed a sufficient algorithm that modified BP neural network optimized with PSO, and then in the section 5, the algorithm is applied for the postgraduate entrant and employment forecasting. The experiment results show the method has achieved reasonable forecast results. At last, we give a summary of the postgraduate entrant and employment forecasting and future works.

II. BP NEURAL NETWORK AND FORECASTING APPLICATION

Artificial neural networks are powerful tools for prediction of nonlinearities. The neutral network is inspired by simulating the function of human brain and used to represent a nonlinear mapping between input and output vector. The basic idea of back propagation algorithm (BP algorithm) is using sensitivity of the error with respect to the weights, to conveniently modify it during iteration steps [6]. The models comprise individual processing units called neurons that resemble neural activity. Each processing unit sums weighted input, and then applies a linear mapping ability and a flexible structure. It trains the node weights by error-back-propagation algorithm [7]. This algorithm is developed on the basis of the least squares method. The neuron activation function is the logistic sigmoid, which can be calculated by

$$f(x) = 1/(1+e^{-x}) \ . \tag{1}$$

A general BP neural network consists of 3-tier architecture, i.e. an input tier, one or more hidden tiers and an output tier. All of the layers are composed of neurons, which are interconnected with each other by weights.

It supposed that the structure of BP is $N-M-L$. Where N the number of input variable dimension, M is the number of neural cell in hidden tier, L is the output variable dimension. W is the input weight matrix, V is the hidden tier weight matrixr, B_1 is hidden tier threshold vector, B_2 is the output tier threshold vector. Where the input vector is $X=(x_1,x_2,...,x_i,...,x_n)^T$, the output vector of the hidden tier is $Y=(y_1,y_2,...,y_j,...,y_m)^T$, the output vector of output tier is $O=(o_1,o_2,...,o_k,...,o_l)^T$. The conjunction weight matrix is $V=(V_1,V_2,...,V_j,...,V_m)$ that is between the input tier and hidden tier. V_j is the weight vector of j-th neural cell in hidden tier. The conjunction weight matrix is $W=(W_1,W_2,...,W_k,...,W_l)$ that is between the input tier and hidden tier. W_k is the weight vector of k-th neural cell in output tier. $d=(d_1,d_2,...,d_k,...,d_l)^T$ is expectation output vector. η is the learn coefficient of BP neural network. t is current iteration step.

Where the output of output tier is denote net_j.

$$net_j = \sum_{j=0}^{m} w_{jk} y_j \qquad k = 1,2,...,l \ . \tag{2}$$

Where the output of hidden tier is denote net_j.

$$net_j = \sum_{i=0}^{n} v_{ij} x_i \qquad j = 1,2,...,m \ . \tag{3}$$

Where the adjust of output weight is denote ΔW_{jk}.

$$\Delta W_{jk} = \eta * (d_k - 0_k) o_k (1 - o_k) y_j \ . \tag{4}$$

$$w_{jk}(t+1) = w_{jk}(t) + \Delta w_{jk} \ . \tag{5}$$

III. PARTICLE SWARM OPTIMIZATION

The particle swarm optimization algorithm is a swarm intelligence optimization algorithm, whose roots come mainly from artificial life and evolutionary computation [8]. PSO algorithm was inspired by the social behavior of biological organisms, specifically the ability of groups of some species of animals to work as a whole in locating desirable positions in a given area, e.g. birds flocking to a food source. This seeking behavior was associated with that of an optimization search for solutions to non-linear equations in a real-valued search space. In the most common implementations of PSO, particles move through the search space using a combination of an attraction to the best solution that they individually have found, and an attraction to the best solution that any particle in their neighborhood has found [9].

The population of PSO is called a swarm and each individual in the population of PSO is conceptualized as a volume-less particle. Each particle in PSO flies in the search space with a velocity that is dynamically adjusted according to its own flying experience and its companions' flying experience. Each point of which is a potential global optimum of the function $f(x)$ over a given domain.

All particles in PSO, which consists of a swarm of n particles moving about in a D-dimensional search space, are kept as members of the swarm through the course of the algorithm run. Suppose that the search space is D-dimensional, and then the particle i of the swarm can be represented as $X_i=(x_1,x_2,...,x_{id})$. The best previous position (the position giving the best fitness value) of the particle i is recorded and represented as $Pbest_i=(p_{i1},p_{i2},...,p_{id})$. The position of the best particle of the whole swarm is represented as $p_{gd}=(p_{g1},p_{g2},...,p_{gd})$. The rate of the position change for particle i is represented as $V_i=(v_{i1},v_{i2},...,v_{id})$ .Particles were originally initialized in a uniform random manner throughout the search space; velocity is also randomly initialized. These particles then move throughout the search space by a fairly simple set of update equations. The algorithm updates the entire swarm at each time step by updating the velocity and

978-1-4244-3521-0/09/$25.00 ©2009 IEEE

position of each particle in every dimension by the following rules:

$$v_{id}^{t+1}=\omega v_{id}^{t}+c_1 rand_1()\times(p_{id}-x_{id}^{t})+c_2 rand_2()\times(p_{gd}-x_{id}^{t})\ . \quad (6)$$

$$x_{id}^{t+1}=x_{id}^{t}+v_{id}^{t} \quad 1\le i\le n \quad 1\le d\le D\ . \quad (7)$$

Where n is the size of swarm; ω called inertia weight that is considered crucial for particle swarm optimization convergence behavior and employed to control the impact of the history of velocities on the current velocity. On the understanding that ω is set to 0.729. c_1 and c_2 are two positive constants, called the cognitive and social parameter respectively; $rand_1()$ and $rand_2()$ are two random functions uniformly distributed within the range [0, 1]. For equation (1), the first part represents the inertia of pervious velocity; the second part is the “cognition” part, which represents the private thinking by itself; the third part is the “social” part, which represents the cooperation among the particles [10].

IV. MODIFIED BP NEURAL NETWORK OPTIMIZED WITH PSO ALGORITHM

Classic BP neural network is a multi-layer feed forward networks with input-layer, hidden-layer and output-layer. From theory, it had proved that a three-layered neural network (one hidden layer) can realize arbitrary mapping of continuous function. Because of adapting gradient descent method, the neural network is easily trapped to local optimum, which leads to descent of global performance [11].

To improve the performance of BP neural network, we will discuss a new algorithm to integrate modified BP with PSO algorithm. η is important coefficient of BP neural network that adjust velocity of convergence, which termed step length of learn. In this paper, it adopt adaptive adjust learn coefficient strategy. Where E is bias function, t is current iteration step, $\eta(t)$ is learn coefficient that has not modified, $\eta(t+1)$ is the modified learn coefficient, $\lambda*(\partial E/E)$ is the increment of learn coefficient. λ is a constant which adjust to based on status of algorithm.

$$\Delta E=E(t+1)-E(t)\ . \quad (8)$$

$$\frac{\partial E}{E}=\frac{E(t+1)-E(t)}{E(t+1)}\ . \quad (9)$$

$$\eta(t+1)=\eta(t)-\lambda\frac{\partial E}{E} \qquad 0<\lambda<1\ . \quad (10)$$

In course of algorithm running, it shows the bias error E is increasing if ΔE is bigger than zero ($\Delta E=E(t+1)-E(t)>0$), which indicate the current output is parting from the expectation output, it need decrease ΔW , thus η need to decrease. If ΔE is less than zero, it the bias error E is decreasing, which indicate the current output is closing to the expectation output. When the bias error E is very small, ΔW is accordingly very small, so it adopt $\partial E/E$ that magnify the change extent of ΔE , which can effectively guide to adjust the learn coefficient [12], thus the adaptive adjust strategy will be accelerate the velocity of convergence and avoid acutely shake of train. WP is the input vector which is mapped to the position of particle, D is the dimension of particle.

$$\begin{aligned}WP=(&w_{11},w_{21},\ldots,w_{j1},\ldots,w_{m1},\ldots,w_{1l},w_{2l},\ldots,w_{jl},\ldots,w_{ml},\\ &b2_1,b2_2,\ldots,b2_l,v_{11},v_{21},\ldots,v_{i1},\ldots,v_{n1},\ldots,\\ &v_{1m},v_{2m},\ldots,v_{im},\ldots,v_{nm},b1_1,b1_2\ldots,b1_m)^T\end{aligned} \quad .(11)$$

$$D=K*M+K+N*K+N=K*(M+N+1)+N\ . \quad (12)$$

It is supposed that $X=\{x_1,x_2,\ldots,x_p\}$ is input train sample, $T=\{t_1,t_2,\ldots,t_p\}$ is the output target vector. Where p is the size of train sample set. x_p is N dimensions vector, t_p is L dimensions vector. According to the principle BP neural network, α_{jp} is the output of the p-th train sample that is j-th neural cell in hidden tier. β_{kp} is the output of the p-th train sample that is k-th neural cell in output tier.

$$\alpha_{jp}=\sum_{i=1}^{n}v_{ij}x_i-b1_j\ . \quad (13)$$

$$\beta_{kp}=\sum_{j=1}^{m}w_{jk}y_k-b2_k\ . \quad (14)$$

The bias error $E(X)$ is given by

$$E(X)=\frac{1}{P}\sum_{i=1}^{P}\sum_{k=1}^{l}(d_k-o_k)^2\ . \quad (15)$$

The fitness of particle is given by

$$f(W)=E(X)\ . \quad (16)$$

Where t is the current iteration generation, T_{max} is set to the maximum number iteration generation. δ is threshold value that denote desired biases. $fitness(t)$ is so far the best fitness of whole swarm. The stop criterion of algorithm is given that algorithm will be stop if $fitness(t)<\delta$, or current iteration generation exceed T_{max} . The algorithm firstly initialize weights of the BP neural network, and then use PSO to optimize the weights of the BP algorithm until the fitness of the problem is not increase effectively, which denote net the desired biases, thus the new algorithm will effectively improve in both accuracy and velocity of convergence.

The main step of algorithm can be summarized as follows:

Step 1: Initialize the particle swarm randomly, Set T_{max}, c_1, c_2 and $V_{\max}$.

Step 2: Calculate fitness of all particles;

Step 3: Compare the evaluated fitness value of each particle with its previous best values $pbest_i$, If the current value is better than the previous best values, then set the current value as the best value of the particle.

Step 4: Compare the evaluated fitness value of each particle with the previous global best value $gbest$ if the current value is better than the previous global best values, and then reset the current value as the global best value of the swarm.

Step 5: Updating the position and velocity of particles by using equations (6) and (7).

Step 6: If $fitness(t) < \delta$, or $t > T_{max}$ is met, then break; otherwise, go to Step 2.

Step 7: Decode $gbest$ to the parameter of the BP neural network.

Step 8: Take the weights and threshold value which optimize by PSO as the initial parameters, the BP network make autonomous learning and forecasting.

Step 9: Out the forecast results.

V. Application to Postgraduate Entrant and Employment

From the viewpoint of the model of postgraduate entrant and employment, it is widely dealing with many factors including both subjective and objective factors, factors with and without form, material and spiritual factors, human and nonhuman factors. Under the circumstances of higher education in China shifting from "elite education" to "popular education" and large-scale enlarge postgraduate entrant, several variables have been shown to influence the postgraduate entrant and employment, such as the number of master postgraduate entrant, the number of doctor postgraduate entrant , the total number of postgraduate entrant, the number of master supervising teacher, the number of doctor supervising teacher, the total number of supervising teacher, etc.

Consider to increasingly evolutional of the finance crisis all over the world and the current economic climate of china, such as the gross domestic product, the annual total education outlay of country, the finance education outlays of country and the finance science and technology outlays of country and so on.

To study the determinants of postgraduate entrant and employment factors and forecast postgraduate entrant and employment in china, a number of important and crucial parameters, which need to consider, thus the study model extractive extract from the mainly factors which affect the postgraduate entrant and employment forecasting.

x_1 is the gross domestic product;

x_2 is the total education outlay of country;

x_3 is the finance education outlays of country;

x_4 is the finance science and technology outlays of country;

x_5 is the number of master postgraduate entrant;

x_6 is the number of doctor postgraduate entrant;

x_7 is the total number of postgraduate entrant;

x_8 is the number of master postgraduates;

x_9 is the number of doctor postgraduates;

x_{10} is the total number of postgraduates;

x_{11} is the number of master supervising teacher;

x_{12} is the number of doctor supervising teacher;

x_{13} is the number of total supervising teacher;

x_{14} is the rate of postgraduates employment;

VI. Experimental Results

For training modified BP neural network combined particle swarm, the postgraduate entrant and employment forecasting is considered as a minimal optimization. The train samples data are mainly come from the ministry of finance people's republic of china, ministry of education of the people's republic of china and the national bureau of statistics of china. The algorithm is develops by Virtual C++ language and implemented.

Experiment emluator show MBPPSO algorithm has better convergence performance. The forecasting results obtained in MBPPSO algorithm are given in Table 1~Table 4. Table 1 shows the forecasting result of the number of master postgraduate entrant. Table 2 shows the forecasting result of the number of doctor postgraduate entrant. Table 3 shows the forecasting result of the total number of postgraduate entrant. Table 1~ Table 3 shows the expectation data of recent two year that is under the data of postgraduate entrant in fact, which report by different media (It is not authoritative release, such as the ministry of education of the people's republic of china and the national bureau of statistics of china.). The expectation data of postgraduate employment come from the report data by media and literature [13]. Table 4 shows the forecasting result of the rate of postgraduate employment that is decline as a whole, which foreshow the increasingly serious of the postgraduate employment foreground in the near future.

TABLE I. THE NUMBER OF MASTER POSTGRADUATES ENTRANT

Year	Expectation	MBPPSO	
		Forecasting	*Bias Error (%)*
1998	57546	60978	5.96
1999	72310	72900	0.82
2000	103342	98938	-4.26
2001	133104	133322	0.16
2002	164269	168258	2.43
2003	220185	215042	-2.34
2004	273002	273835	0.31
2005	310037	312016	0.64
2006	341970	341611	-0.10
2007	360590	360850	0.07
2008		373744	
2009		376404	

978-1-4244-3521-0/09/$25.00 ©2009 IEEE

TABLE II. THE NUMBER OF DOCTOR POSTGRADUATES ENTRANT

Year	Expectation	MBPPSO	
		Forecasting	*Bias Error (%)*
1998	14962	15413	3.01
1999	19915	19003	-4.58
2000	25142	25289	0.58
2001	32093	32770	2.11
2002	38342	39267	2.41
2003	48740	46638	-4.31
2004	53284	53285	0.00188
2005	54794	55806	1.85
2006	55955	55747	-0.37
2007	58022	56453	-2.70
2008		48048	
2009		45733	

TABLE III. THE TOTAL NUMBER OF POSTGRADUATES ENTRANT

Year	Expectation	MBPPSO	
		Forecasting	*Bias Error (%)*
1998	72508	75372	3.95
1999	92225	90341	-2.04
2000	128484	125603	-2.24
2001	165197	166208	0.61
2002	202611	208312	2.81
2003	268925	262187	-2.50
2004	326286	326697	0.13
2005	364831	366864	0.56
2006	397925	397701	-0.056
2007	418592	418474	-0.36
2008		430778	
2009		433725	

TABLE IV. THE RATE OF POSTGRADUATES EMPLOYMENT

Year	Expectation	MBPPSO	
		Forecasting	*Bias Error (%)*
2000	0.936	0.942874	0.73
2001	0.938	0.937509	-0.0005
2002	0.922	0.930721	0.95
2003	0.93	0.920408	-1.03
2004	0.956	0.907825	-5.04
2005	0.895	0.894899	-0.0001
2006	0.848	0.884210	4.27
2007		0.876153	
2008		0.869681	
2009		0.832255	

VII. CONCLUSION

The postgraduate entrant and employment forecasting problem is a very complex study which relate to many factors including both subjective and objective factors, human and nonhuman factors, the development stratagem of nation and the long-term human resource layout of nation. Under the climate of large-scale enlarge postgraduate entrant and circumstances of increasingly evolutional of the finance crisis, it is need to elaborate consider all king of factors. In this paper, an approach based on neural network optimized with PSO algorithm is proposed which applied to forecast postgraduate entrant and employment. Experiment results show the forecasting result is under the expectation data in recently two year (2008 and 2009), and the ratio of postgraduate employment that is gradually decline, which will help to make scientific and reasonably long-term layout about postgraduate entrant and employment. The postgraduate entrant should properly rectify by the demand of different specialty, the ratio of the postgraduate employment, size of supervising teacher and the requirement of market economy, etc, and then make a scientific and rational development decision-making, which is also the key of the future study work.

REFERENCES

[1] Chengsong Qing, Xiang Sun, Forecasting the Area Flowing of Postgraduate Employment Based on KRNN method, The 4th international conference of Wireless communications, Networking and mobile computing, 2008, pp. 1-4.

[2] Chen Shao-xiong, Wang Jing-yi, Yin Liu-ying, A discussion on the recruitment scale model of Fraduate education in china, Tsinghua Journal of education, vol. 25(4), 2004, pp. 79-85.

[3] Luo Gui-ming, Research on approach to prediction and caculation of postgraduate education, Journal of chaohu college, vol. 9(6), 2007, pp. 125–127.

[4] H. R. Keyhani, T. Kassnei, Woung and M. Rahman, A bybrid fuzzy Neural network bus load modeling and predication, IEEE Trans Power Systems, 1999, pp. 718-724.

[5] Rui-Ping Li, M. Mukaidono, and I.B. Turksen, Study on feature weight and feature selection in pattern classification neural networks, IEEE International Conference on Systems, Man, and Cybernetics, vol. 3, 1996, pp. 1972 – 1976.

[6] S. Hayashi, T. Asakura, and Sheng Zhang, Study of machine fault diagnosis system using neural networks Neural Networks, Proceedings of the International Joint Conference on neural networks vol. 1, 2002, pp. 956 – 961.

[7] R. H. Nilscn, Kolmogorov's mapping neural networks existence theorem, Proceedings of the first IEEE International Conference on neural networks, vol. 3, 1987, pp. 11-14

[8] R. C. Eberhart, Y. Shi, particle swarm optimization: developments, applications and resources, Proceedings of the IEEE Congress on Evolutionary Computation, 2001, pp. 81-86

[9] K. E. Parsopoulos, and M.N. Varhatis, Recent approaches to optimization problems through particle swarm optimization, in Natural Computing 1, Kluwer Academic publisher, vol. 1, no. 2-3, 2002, pp. 235-306.

[10] P. J. Angeline, Evolutionary optimization versus particle swarm optimization: philosophy and performance difference, Proceedings of the 7th International Conference on Evolutionary Programming Conference, Lecture Notes in computer Science, vol. 1447, pp. 601-610.

[11] K. Funahashi, On the approximate realization of continuous mapping by neural networks, Neural Networks, vol. 2, 1989, pp. 183-192.

[12] He Qing-bi, Zhou Jian-li, The convergence and improvements of BP Neural network, Journal of chongqing Jiaotong university, vol. 24(1), 2005, pp. 143-145.

[13] Yin fa-yue, How to forecast the prospect of the employment of graduate students, University Education Science, 2008, (01), pp. 94-100