Research on the Influence Factors of Pension Mode Selection for Different Population

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Abstract

Correctively analyzing the influence factors of pension mode selection is one of key issues for public administration and is becoming a hot research field for the unit and researcher related. The paper advances a novel BP neural network algorithm for analyzing the influence factors of pension mode selection. First, the paper analyzes the influence factors of pension mode selection; Second aiming at the shortages of the existing BP neural network algorithm for analyzing influence factors, the paper adopts he immune genetic algorithm and simultaneous analysis and design---SAND algorithm to improve traditional BPNN algorithm to speed up model convergence and to simplify model structure. Finally the simulation results shows that not only the problem of convergence speed has been solved, but also the simplicity of the model structure and the accuracy of the classification are ensured when the new algorithm are used in analyzing the influence factors of pension mode selection practically.

Keywords

Pension mode selection, BP neural network, immune genetic algorithm , simultaneous analysis.

1. Introduction

The aging Population has become one of major questions of world concern. In 1998, China has been an old-age country. Form 2010 to 2040, the aging of Population will enter the rapid development Period. So pension mode selection and its influence factors has become a research hotspot for the researchers in the field of public administration.

At present, the methods wildly used of mining key influencing factors of pension mode selection and calculating their action intensity in the research field are linear curve fitting method including Chebyshev algorithm and square method [1], linear regression algorithm[1], and BP neural network method[2]. The method of mining key influencing factors and calculating their action intensity of pension mode selection is a multi-factor and multi-indicator calculation process, and many uncertainties are involved in; thus it is not east to say which method is good or bad. So the methods of linear regression algorithm and linear curve fitting method have lots of advantages such as simple calculation structure, easiness to operate, high algorithm efficiency and easiness to understand, but the two methods will lead to lower calculation accuracy[3]. The BP neural network method takes the strong non-linear information processing capability of neural network, and has its unique advantages in processing multi-indicator and multi-factor system; and it has high calculation accuracy, so BP algorithm is wildly used in the industry. But BP neural network algorithm also has such defects as low in rate of convergence and complicated in model structure.

The paper overcomes the defects (slow convergence speed) of original BP neural network algorithm by improving BP neural network algorithm with the immune genetic algorithm and simultaneous analysis and design---SAND algorithm. By these improvements, it not only solves the defects of convergence speed of BP algorithm, but also the simplifies the model structure, then can ensures the calculation accuracy of the presented algorithm, so the paper presents a new BPNN model for analyzing the action intensity of influencing factors of pension mode selection.

2. Mining Influencing Factors of Pension Mode Selection

The research perspective of analyzing the influencing factors of pension mode selection for the researchers at present differs greatly[2,3,4]. The influencing factors of pension mode selection designed by foreign researchers always means pension mode selection itself. But, the researchers in China mine the influencing factors of pension mode selection in a more abstract and deep way, and the constructed influencing factor system is more complicated. With reference to the literatures at abroad and home, this paper considering the specific and concrete characteristics of pension mode selection, designs an extensive and scientific influencing factor system of pension mode selection based on the factor properties. The system includes 20 influencing factors which belong to 3 first-class properties respectively, showing in Table 1 for details.

Table 1. Influencing Factor System of Pension Mode Selection

Target	First-class properties	Influencing factors
Influencing factor system pension mode selection	Personal Factors	Sex
		Age
		Marital status
		Educational level
		Health status
		Professional experience
		Professional status
	Family Factors	Family size
		Number of children
		Number of boys
		Willingness to live with children
		Distance from children
	Economic Factors	Monthly income
		Income source
		Income stability
		Savings situation
		Medical insurance status
		Endowment insurance status
		Personal economic status
		Pension mode of friends

3. Analysis Model Design

3.1 Simultaneous Analysis and Design.

De Castro indicated that there were similarities among the quality of weight value initialization of back-propagation neutral network and the relationship of network output and the quality of antibody instruction system initialization in the immune system and the quality of immune response. A simultaneous analysis and design---SAND algorithm was advanced to solve the problem regarding the weight value initialization in the back-propagation network[6]. In SAND algorithm, each antibody corresponds to a weight value vector of neuron given in one of several layers of neural networks, the length is l, and the affinity $aff(x_i, x_j)$ between antibody x_i and antibody x_j is shown by their derivative of Euclidean distance function $D(x_i, x_j)$ in Formula 1. In which, ε is a positive of value adoption 0.001. The definition of Euclidean distance function $D(x_i, x_j)$ is shown in Formula 2[5].

$$aff(x_i, x_j) = \frac{1}{D(x_i, x_j) + \varepsilon} \tag{1}$$

$$D(x_i, x_j) = \sqrt{\sum_{k=1}^{l} (x_{ik} - x_{jk})^2} \tag{2}$$

SAND algorithm aims to reduce the similarities between the antibodies and produce the antibody repertoire to cover the entire form space with the best, so energy function is maximized. The energy function is shown in Formula 3[6].

$$E = \sum_{i=1}^{N} \sum_{j=i+1}^{N} D(x_i, x_j) \tag{3}$$

In the method of Eculidean form space, the energy function is not percentage. With a view to the diversity of the vector, SAND algorithm has to define the stop condition. Given vector $x_i, i = 1,2,...N$, its standardization is unit vector $I_i, i = 1,2,...N$, $\bar{I}$ shows to calculate the average vector. Therefore, Formula 4 shows the diversity of unit vector, in which, $\left\|\bar{I}\right\|$ means the average vector distance from the origin of coordinate. Formula 5 shows the stop condition U of SAND algorithm.

$$\left\|\bar{I}\right\| = (I^T I)^{1/2} \tag{4}$$

$$U = 100 \times (1 - \left\|\bar{I}\right\|) \tag{5}$$

3.2 BP Neural Network Design Based on Immune Genetic Algorithm.

According to the actual application, providing that both the input and output number of node and the input and output values in BPNN have been confirmed, activation function adopts S type function. The following steps show BP neural network design based on immune genetic algorithm.

(1) Every layer of BPNN carries on the weight value initialization separately by SAND algorithm.

(2) Antibody code. The initial weight value derived by SAND algorithm constructs the structures of BPNN. Each antibody corresponds to a structure of BP neural network. The number of hidden node and network weight value carry on the mixture of real code[7].

(3)Fitness function design. Fitness function $f(x_i)$ is defined as the mean value function of squared error of neural network in Formula 6, in which, $E(x_i)$ is shown by Formula 7. In Formula 7, p is the total training sample, o is the number of node of output layer, T_j^n and Y_j^n are the n training sample's expected output and actual output in the j output node separately, and ξ is the constant larger than zero.

$$f(x_i) = \frac{1}{E(x_i) + \xi} \tag{6}$$

$$E(x_i) = \frac{1}{2p} \sum_{N=1}^{p} \sum_{j=1}^{o} (T_j^n - Y_j^n)^2 \tag{7}$$

(4) Genetic operation. The model here adopts the Gaussian compiling method to go on the genetic operation so as that each antibody decoding is the corresponding network structure and change the network weight value as shown in Formula 8, in which, x_i and x_i^m are the antibodies before and after the variation, μ (0,1) shows that the mean value is zero and squared error is normal distribution

random variable of l, and $\partial \in (-1,1)$ is the individual variation rate. It is seen in Formula 8 that the variation degree varies inversely as the fitness, i.e. the lower the fitness is (the less the fitness value of objective function is), the higher the individual variation rate is, or vice versa. After the variation, all the hidden node and weight value components constitute a new antibody again.

$$x_i^m = x_i + \partial \exp(-f(x_i)) \times \mu(0,1) \tag{8}$$

(5)Group renewal based on density. In order to guarantee the antibody diversity, improve the entire searching ability of the algorithm, the model adopts the Euclidean distance and the fitness based on the antibodies to calculate the similarity and density of the antibody. Providing that there are x_i and x_j antibodies, and $\eta \succ 0$ and $t \succ 0$, given constants, the fact that Formula 9 is satisfied indicates that x_i and x_j antibodies are similar, the number of antibody similar to the antibody x_i is the density of x_i marked by C_i. The probability of selecting antibody x_i is $p(x_i)$ as shown in Formula 10, in which, α and β is the adjustable parameters between (0, 1), and $M(x)$ is the maximum fitness value of all the antibodies. It is seen in Formula 10 that while the antibody density is high, the probability of selecting the antibody with high fitness is low, and conversely high. Therefore, excellent individual is not only retained, but the selection of similar antibodies is reduced, and the individual diversity is guaranteed[8].

$$\begin{cases} D(x_i, x_j \leq \eta \\ \left| f(x_i) - f(x_j) \right| \leq t \end{cases} \tag{9}$$

$$p(x_i) = \alpha C_i [1 - \frac{f(x_i)}{M(x)}] + \beta \frac{f(x_i)}{M(x)} \tag{10}$$

4. Experiment Confirmation

Experimental data come from 1500 samples in Nanchang city of Jiangxi Province. In order to make the selected samples' data representatives, 500 samples are elder than 60, 500 samples are younger than 40, and the age of the rest 500 samples are within the interval of [40,60]. Specific calculation results see Table 2 .

5. Conclusion

The research of pension mode selection is still developing, including Influencing factors and analyzing algorithm. As to the insufficient convergence rate of factor analysis algorithm of neural network, this paper puts forward a new algorithm based on improved neural network. Simulation result shows that the improved BP neural network algorithm can increases the accuracy of factor analysis, accelerates the convergence rate of algorithm. Managers of public administration can provide more individual service for specific people accordingly, and make full use of limited resources to produce maximum utility.

Table 2 The Calculation Results of the 20 Influencing Factors

First-class properties	Influencing factors	Relative influencing intensity
Personal Factors	Sex	0.6312
	Age	1.2071
	Marital status	1.9821
	Educational level	1.4481
	Health status	1.2311
	Professional experience	1.7812
	Professional status	1.9931

Family Factors	Family size	1.4762
	Number of children	0.9521
	Number of boys	0.8214
	Willingness to live with children	1.8843
	Distance from children	1.9813
Economic Factors	Monthly income	2.2012
	Income source	1.2135
	Income stability	2.1091
	Savings situation	1.2210
	Medical insurance status	1.6570
	Endowment insurance status	1.4451
	Personal economic status	2.2122
	Pension mode of friends	0.9921

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