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INDUSTRIAL STRUCTURE FORECASTING BASED ON GREY NEURAL NETWORK OPTIMIZED BY INTEGRATION ALGORITHM

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Abstract. *The grey neural network (GNN) model is usually established as the forecasting model to deal with nonlinear complex problems. GNN model may lead to low prediction accuracy because it is easy to fall into local optimums and unable to further correct related parameters. In order to overcome this problem, an integration algorithm is proposed to optimize GNN model in this paper. The integration algorithm is called genetic algorithm-particle swarm optimization (GA-PSO) which makes full use of excellent genes inheriting traits of GA and the learning ability of PSO. It is validated of the effectiveness of GNN model respectively optimized by GA, PSO, and GA-PSO through forecasting industrial structure in Jiangsu province. The results show that GA-PSO has higher prediction accuracy compared with GA or PSO. The integration algorithm can be effectively used in regional economy forecasting and also can be used as basic forecasting model of other types.*

Keywords: Genetic algorithm, Particle swarm optimization, Genetic algorithm-particle swarm optimization, Grey neural network, Industrial structure

1. **Introduction.** Grey system theory provides a way to solve the uncertainty of poor information. The theory carries out the correct description and effective monitoring in the form of mathematical model by generating and developing limited known information. In grey system research method, the most representative is GM and its evolution model, which can predict the development tread of poor information, small samples and uncertain system [1]. However, GM and its evolution model are based on time as basic variable and have a certain limitation of interpreting grey system. So prediction results are not very effective with small and nonlinear samples. Neural network technology has been used to deal with these problems, because it has many advantages, such as parallel processing, storing distributed information, fault tolerance and adaptive learning [2]. Tim et al. [3] firstly applied neural network technology in time series forecasting and verified the superiority of forecasting application. Since then, more and more scholars began to study neural network technology and its application in social and economic fields [4,5]. Aiming at the slow training speed and difficulty to determine the number of hidden layer nodes, some scholars combined the advantages of GM and neural network technology to build GNN model to deal with nonlinear problems [6,7].

Because of the randomness of its parameters in initialization process, GNN model is easy to fall into local optimums and unable to further correct related parameters, and thus may lead to low prediction accuracy. In order to overcome this problem, some intelligent optimization algorithms are adopted with the reference of fusing methods of grey system and neural network technology. At present, the mature algorithms are genetic algorithm, tabu search algorithm, ant colony algorithm and particle swarm optimization [8-10]. However, every single algorithm has its own limitations in practical application. In this paper, a further step is carried out, since the single algorithm is substituted by integration algorithm of GA and PSO. Thus the purpose is to seek an integration optimization algorithm of GNN model in order to improve the prediction accuracy. The new proposed methodology makes full use of excellent genes inheriting traits of GA and the learning ability of PSO. It is verified of the scientificity of the methodology through the case study.

This paper is arranged as follows. In Section 2, the research methods including GNN model and GA-PSO integration algorithm are introduced, following the optimization process about how to operate. In Section 3, this new methodology will be verified by means of an application to industrial structure forecasting in Jiangsu province, and the results will be presented and discussed. Finally, some concluding remarks complete this paper in Section 4.

2. Research Method.

2.1. **GNN model.** Suppose that $x_i^{(0)} = \left\{x_i^{(0)}(1), x_i^{(0)}(2), \ldots, x_i^{(0)}(n)\right\}$ $(i = 1, 2, \ldots, N)$ is an original data sequence, where $x_1^{(0)}$ denotes output sequence, and $x_j^{(0)}$ $(j = 2, \ldots, N)$ denotes input sequence of related factors. The initialization is dealt with to eliminate the influence of dimension. So the accumulated generating data sequence can be defined as $x_i^{(1)}(k) = \left\{x_i^{(1)}(2), x_i^{(1)}(3), \ldots, x_i^{(1)}(n)\right\}$. The discrete function of data sequence $x_i^{(1)}$ is continued to the function of time, namely $x_i^{(1)} = x_i^{(1)}(t)$. Considering the effect of data sequence $\left\{x_2^{(1)}, x_3^{(1)}, \ldots, x_N^{(1)}\right\}$ on the change rate of $x_i^{(1)}$, the differential equation of grey model is established as

$$\frac{\mathrm{d}x_1^{(1)}}{\mathrm{d}t} + ax_1^{(1)} = \sum_{i=2}^{N} b_{i-1}x_i^{(1)}(k) \tag{1}$$

where $x_2, x_3, \ldots, x_N$ are input data, x_1 is output data, $a, b_1, b_2, \ldots, b_{n-1}$ are the equation parameters, and the time response function is expressed as:

$$\begin{aligned} x_1^{(1)}(t+1) = {} & \left(x_1(0) - \frac{b_1}{a}x_2(t) - \frac{b_2}{a}x_3(t) - \cdots - \frac{b_{n-1}}{a}x_n(t)\right)e^{-at} \\ & + \left(\frac{b_1}{a}x_2(t) + \frac{b_2}{a}x_3(t) + \cdots + \frac{b_{n-1}}{a}x_n(t)\right) \end{aligned} \tag{2}$$

If defining $d = \frac{b_1}{a}x_2(t) + \frac{b_2}{a}x_3(t) + \cdots + \frac{b_{n-1}}{a}x_n(t)$, Formula (2) can be converted as

$$x_1^{(1)}(t+1) = \left((x_1(0) - d) - x_1(0) \cdot \frac{1}{1+e^{-at}} + 2d \cdot \frac{1}{1+e^{-at}}\right) \cdot (1 + e^{-at}) \tag{3}$$

The GNN model can be obtained when Formula (3) is mapped to neural network. So, prediction can be obtained by inverse accumulated generating of $x_1^{(1)}(t+1)$ and mathematically expressed as:

$$x_1^{(0)}(t+1) = x_1^{(1)}(t+1) - x_1^{(1)}(t) \tag{4}$$

2.2. **GA-PSO integration algorithm.** GA can inherit excellent genes of parent to offspring by selection, crossover and mutation. It has strong global search ability, but the solving efficiency is reduced on account of the growth of the computation time. In PSO algorithm, the particle can compare itself with outstanding particles and improve its fitness by learning from them, imitating the self-knowledge and social learning mechanism. The operation of PSO algorithm is simple, but it has poor global search ability due to the faster convergence speed. This paper proposes an integration algorithm called GA-PSO which makes full use of excellent genes inheriting traits of GA and the learning ability of PSO. GA-PSO adopts the optimized model of "parent genetic and self-learning", which conforms to the theory of biological evolution and the process of self-learning.

Suppose that there are m particles in D dimension search space. The location of the i-th particle is defined as $\boldsymbol{X}_i = (x_{i1}, x_{i2}, \ldots, x_{iD})^T$, $(i = 1, 2, \ldots, m)$, which denotes a potential solution. In PSO algorithm, all particles have fitness values which are evaluated and optimized by the fitness function. The size of fitness values is used to measure the advantages and disadvantages of corresponding particles. The process of particles learning from the outstanding particles is known as "flying". The flying speed of the i-th particle is expressed as $\boldsymbol{V}_i = (v_{i1}, v_{i2}, \ldots, v_{iD})^T$. The velocity and position of particles update according to the following two formulas:

$$v_{id}^{n+1} = w^n \cdot v_{id}^n + c_1 r_1^n \cdot \left(pbest_{id}^n - x_{id}^n\right) + c_2 r_2^n \cdot \left(gbest_d^n - x_{id}^n\right) \tag{5}$$

$$x_{id}^{n+1} = x_{id}^n + v_{id}^{n+1} \tag{6}$$

where i $(i = 1, 2, \ldots, m)$ denotes the number of particles, d $(d = 1, 2, \ldots, D)$ denotes the dimension of solution vector, n denotes the number of iterations, w denotes inertia weight, c_1 and c_2 denote accelerating constants, r_1 and r_2 denote random numbers, uniformly distributed in $[0, 1]$, $pbest$ denotes the optimal position of the particle recorded, and $gbest$ denotes the optimal position of the whole population. The inertia weight can be determined by using liner decreasing weight strategy in order to obtain better optimization results. The inertia weight w^n of the n-th generation is calculated by the following formula:

$$w^n = (w_{\text{start}} - w_{\text{end}}) \cdot (N - n)/N + w_{\text{end}} \tag{7}$$

where w_{start} and w_{end} denote the inertia weight of initial time and termination time, n denotes the current number of iterations, and N denotes the biggest number of iterations.

Then GA is used to improve the accuracy of PSO algorithm by continuous selection, crossover and mutation. Firstly, the fitness value of individual is calculated by generating into objective function. Then the proportion of this fitness value accounting for the total of group fitness value is calculated as the probability of the individual selected. The process of selection uses the method of roulette, that is, for individual $\boldsymbol{X}_i$, set its fitness value as $f(\boldsymbol{X}_i)$, and the probability is selected as follows:

$$p(\boldsymbol{X}_i) = \frac{f(\boldsymbol{X}_i)}{\sum_{i=1}^{m} f(\boldsymbol{X}_i)}, \ (i = 1, 2, \ldots, m) \tag{8}$$

The crossover operation of individual can be realized by the middle way of restructuring of real value and the intersection at a certain probability p_c. The new individual obtained by crossing two individuals $\boldsymbol{X}_i^n$, $\boldsymbol{X}_j^n$ of the n-th generation is as follows:

$$\begin{cases} \boldsymbol{X}_i^{n+1} = r^n \boldsymbol{X}_i^n + (1 - r^n) \boldsymbol{X}_j^n \\ \boldsymbol{X}_j^{n+1} = r^n \boldsymbol{X}_j^n + (1 - r^n) \boldsymbol{X}_i^n \end{cases} \tag{9}$$

where r denotes random number, uniformly distributed in $[0, 1]$. The value of r is different because of crossover operation of different individuals and positions. In mutation stage of GA, each location x_{id} $(d = 1, 2, \ldots, D)$ of individual $\boldsymbol{X}_i$ is mutated at a certain probability p_m. The mutation formula is defined as follows:

$$x'_{id} = x_{id} + r_{id} \cdot \Delta x_{id} \tag{10}$$

where r_{id} denotes random number, uniformly distributed in $[0, 1]$, and Δx_{id} denotes the mutation range corresponding to x_{id}.

The calculation of GNN model optimized by GA-PSO includes three basic stages, namely the structure determination of GNN model, algorithm design of GA-PSO and the forecasting of GNN model. The optimization process is shown as Figure 1.

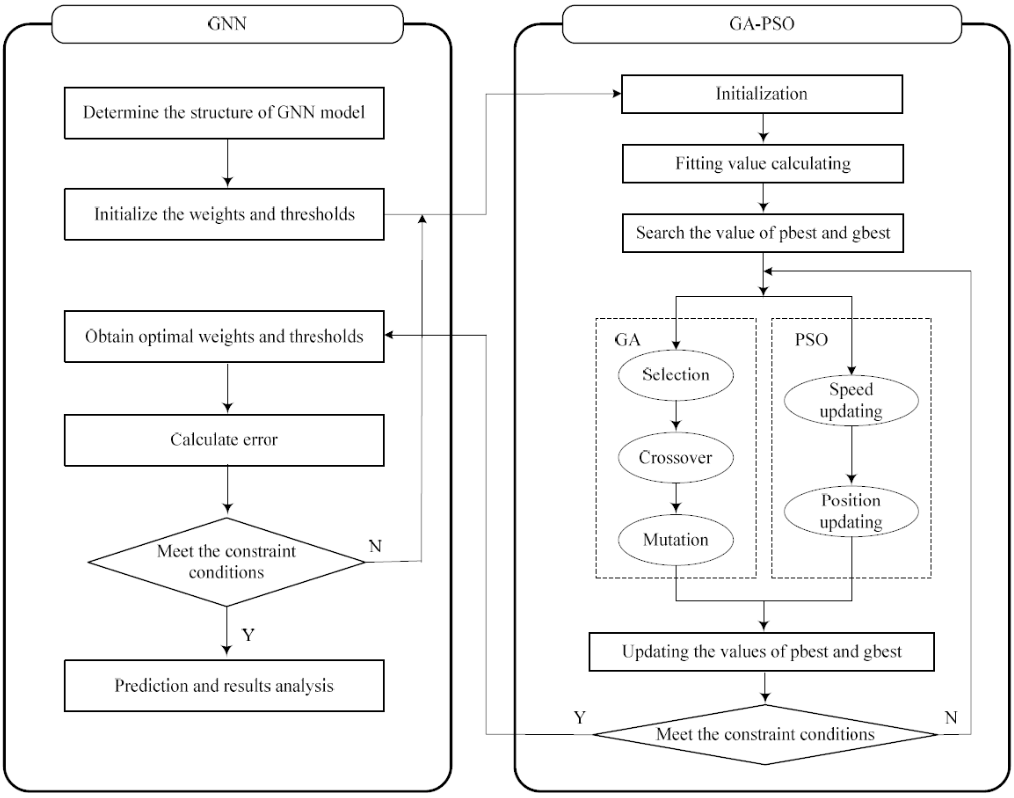

FIGURE 1. Main process of GNN model optimized by GA-PSO

3. Case Study.

3.1. Variable selection and factors determining. Industrial structure refers to the proportion and mutual correlation of interdependence and restriction between the industries. Reasonable industrial structure is crucial of developing a country's economy. Different industrial structure affects the choice of regional leading industries, determining the configuration of regional resources and economic benefits. The factors affecting industrial structure are various and complex. The proportion of added value of tertiary industry accounting for GDP is taken as the measuring index of industrial structure. In this paper, GNN model is used to forecast industrial structure which considers the nonlinear influence of many factors in order to make the prediction value closer to the actual value.

This paper sorts out the main factors from the perspective of supply and demand and the actuality of industrial structure in Jiangsu province. The factors of supply are labor input, capital input, scientific and technological level, and government's policy support. The factors of demand are consumption level, degree of foreign capital utilization and opening degree.

The data is derived from "Jiangsu Statistical Yearbook" and "Statistical Bulletin for National Economic and Social Development". From the collecting data, we select the data from 1990 to 2004 as training sample and the other 10 years as test sample, and use the GNN model optimized by GA-PSO for optimizing, training and prediction.

3.2. Prediction and results analysis. The initial parameters of GA-PSO are set as accelerating constants of c_1 and c_2 are 2, inertia weights of w_{start} and w_{end} are 0.9 and 0.4, and crossover and mutation probability p_c and p_m are 0.8 and 0.1. The number of the population of n is 40 and the maximum number of iterations of K is 500.

The eight parameters of GNN model are optimized by GA, PSO and GA-PSO. The change of the fitness values of optimal individual shows that the results optimized by

Table 1. Prediction of industrial structure and comparison

Year	Actual data	GA-GNN		PSO-GNN		GA-PSO-GNN	
		Prediction value	Error (%)	Prediction value	Error (%)	Prediction value	Error (%)
2005	35.80	33.32	6.93	36.21	1.15	37.06	3.52
2006	36.28	37.22	2.59	39.24	8.16	38.23	5.37
2007	37.36	35.92	3.85	38.99	4.36	38.08	1.93
2008	37.51	36.89	1.65	39.17	4.43	38.01	1.33
2009	39.47	37.56	4.84	41.06	4.03	38.65	2.08
2010	40.61	43.20	6.38	43.41	6.89	41.81	2.95
2011	42.21	40.68	3.62	43.29	2.56	42.11	0.24
2012	43.50	41.81	3.89	45.35	4.25	42.52	2.25
2013	44.66	45.40	1.66	46.27	3.61	45.03	0.83
2014	46.70	48.20	3.21	49.11	5.16	46.69	0.02

integration algorithm of GA-PSO are better than those optimized by a single algorithm. The results are shown in Table 1.

As can be seen from Table 1, in terms of the prediction error, the mean error of PSO-GNN model is 4.46% while that of GA-GNN model is 3.86% and that of GA-PSO-GNN model is only 2.05%. It demonstrates that GNN model optimized by GA-PSO has the most precise predicting results which fits the actual values accurately compared with GA-GNN and PSO-GNN. The integration algorithm of GA-PSO, which takes the advantages of GA and PSO, can describe the complex linear and nonlinear features. Hence, it significantly improves the prediction accuracy.

4. **Conclusions.** In this paper, GNN model is built which makes full use of the advantage of small samples in grey model and nonlinear feature in neural network. GNN model overcomes the shortcomings of a single model and makes a better prediction performance. To further improve the prediction precision, GA-PSO integration algorithm is proposed to optimize GNN model and related mathematics interpretation is done. The GNN model optimized by GA-PSO built in this paper fused effectively the advantages of grey model, neural network and optimization algorithm. A case study of industrial structure forecasting in Jiangsu province is used to validate the effectiveness of this model. The results show that, compared with GA-GNN and PSO-GNN model, GA-PSO-GNN model has higher prediction accuracy and is a reliable method for industrial structure prediction. GA-PSO-GNN model can be used for short-term and long time forecasting, and have extensive application in social and economic fields. The next research work will be carried out from the following two aspects. The first is the research on initialization method of weights and threshold of GNN model. The second is the research on application of GA-PSO in complex practical problems.

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