Training Path for Talents Engaged in Agricultural Product Supply Chain Management and the Assessment of Their Training Quality

https://doi.org/10.3991/ijet.v17i20.34523

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Abstract—The Supply Chain Management (SCM) of agricultural products (AP) is an important part of modern logistics, and cultivating talents with rich theoretical knowledge and practical operation skills of the SCM of agricultural products is particularly meaningful for China as a major agricultural country. However, at present, few studies have concerned about the training path for such talents, so to fill in this research blank, this paper studied the training path for AP-SCM talents and the assessment of their training quality, aiming to find and solve the defects in the existing training programs. At first, this paper proposed training path for AP-SCM talents and attained the conclusion that colleges and universities should pose requirements for AP-SCM talents from 9 training directions. Then, a prediction model was built for assessing the training quality of AP-SCM talents, and the specific model framework and modeling principles were given. At last, experimental results verified the effectiveness of the prediction made by the proposed model.

Keywords—agricultural product (AP), supply chain management (SCM), talents, training path, training program, training quality, assessment

1 Introduction

Referring to the concept of supply chain, for agricultural products, its supply chain also forms a network structure system with the core agricultural product enterprise as the center, and suppliers, farmers, wholesalers, retailers, and end users as participant subjects. Processes such as the purchase of raw materials, the production of agricultural products, and the sales and delivery of fresh agricultural product commodities could be realized within this network [1–12]. AP-SCM talents are the valuable resources for various enterprises involved in the supple chain of agricultural products, they can bring unique competitive advantages to these enterprises in the market [13, 14]. As social economy develops fast in recent years and the variety of commodities in the market is getting increasingly diversified, if supply enterprises of agricultural products want to catch up with the pace of the market and the times, they'll need to attract and recruit excellent management talents continuously [15, 16]. As dominants in the supply chain of agricultural products, AP-SCM talents will inevitably play a great role in the future development, and this requires the colleges and universities to formulate training programs from a long-term perspective, optimize the existing training mechanisms, and improve the training quality of AP-SCM talents, so that they could exert their capabilities in their work posts as soon as possible.

The selection of partners is an important factor in the SCM of fresh products, environmental protection is another factor but conventional suppliers haven't taken it into consideration. Scholar Wang [17] studied the optimal mathematical model of green partner selection which has four objectives of cost, product quality, green evaluation score, and time; the multi-objective genetic algorithm proposed in the paper searched for the optimal solution set using the weighted sum method, the constructed model introduced the supply chain network structure, and adopted the genetic algorithm to analyze the average Pareto optimal solution of these four objectives. Employing the SCM theories of fresh agricultural products, Feng [18] analyzed the problems existing in the procurement of the e-commerce SCM of fresh agricultural products, with the self-operated fresh agricultural products of Yihao Store as an example, the author constructed a procurement optimization model and an evaluation system for the e-commerce SCM of fresh agricultural products, and integrated the smart supply chain industry into the regional resource construction system; the paper also pointed out that cultivating talents for smart SCM is an urgent need for urban agglomerations to adapt to the adjustment and upgrading of industrial structure and pursue high-quality development. Huang et al. [19] applied literature analysis and business research to analyze the new features of smart supply chain and its new demands for human resources; then the authors used clustering, statistics, text data mining, and other data analysis methods to mine the data of the recruitment information of supply chain and logistics positions in enterprises located in the Yangtze River Delta and its surrounding areas, so as to figure out the requirement features of the human resource market of smart SCM talents. According to the data-based smart supply chain analysis methods and their applications in the smart supply chain, Meng [20] summarized a big data analysis ability system for talents engaged in smart SCM, which contains problem identification, data feasibility demonstration, data visualization, modelling, and result evaluation. Hong and Chen [21] argued that SCM originates from enterprise management practices; since there're certain similarities between the talent cultivation process in colleges and universities and the product manufacturing process in production enterprises, the idea of SCM could be used to instruct the talent cultivation process in colleges and universities to improve the talent cultivation efficiency.

After reviewing existing literatures, it's found that there're few studies on the training path of AP-SCM talents. In order to find out shortcomings in the current training programs for AP-SCM talents, this paper fully explored the features of different links, different subjects, and different job post requirements in the SCM of agricultural products, and proposed individualized talent training path based on the personal characteristics of AP-SCM talents. AP-SCM talents are the main impetus for the sustainable development of the SCM of agricultural products, and it is of practical significance to figure out the training path for them in the context of a market economic system with increasingly mature conditions.

2 Proposal of training path for AP-SCM talents

The SCM of agricultural products has a high requirement for safe operation conditions, so the AP-SCM talents must have a thorough understanding of the biochemical characteristics, special importance, circulation and processing techniques, and logistic links of agricultural products; besides, since the transactions of agricultural products have significant random, seasonal, and regional features, the market of agricultural products is highly uncertain, and this requires the AP-SCM talents to fully consider the dispersed production and consumption of agricultural products, as well as their perishability and short shelf-life.

At the same time, the AP-SCM talents need to master the features and application scenarios of the five modes of AP-SCM: the AP-SCM centered on wholesale market, the AP-SCM driven by leading enterprises, the AP-SCM of "farmer + enterprise + association + retailer", the AP-SCM centered on professional cooperative organization, and the "farmer-supermarket docking mode" AP-SCM, and they should be able to apply and adjust between these modes flexibly during the actual operation process.

In current AP-SCM, the customization of agricultural product contracts and agreements is called contract agriculture. The purchase quantity, quality, and minimum protection price of the agricultural products are stipulated in the orders so that the enterprises, agents, and farmers have their respective rights and obligations, and are bound by the force of the law, and neither party could unilaterally breach the contract during the fulfillment process. Since the orders of agricultural products are signed before the planting, it is a kind of futures trade, so the AP-SCM talents need to make decisions that can solve the contradiction between small production and large market so that subjects in the SCM could avoid risks in production and operation to a certain extent.

AP-SCM talents should be able to make management decisions from the perspective of enterprises. In order to meet customer demands, they would require the agricultural products to have high quality and cheap price when assisting the enterprise to purchase the agricultural products. When placing orders, the AP-SCM talents will propose high-standard demands on the agricultural products produced by farmers so as to realize their own best interests, some may even help farmers build advanced production bases and guide them to carry out specialized, regional, diversified, and standardized production. Also, AP-SCM talents need to make management decisions from the perspective of farmers. For the purposes of meeting the requirements of the enterprise, fulfilling the contract, and gaining income, AP-SCM talents would instruct farmers to work their best to avoid unfavorable factors during production, thereby preventing them from suffering the loss caused by unqualified products

Through above analysis, this paper proposes that the colleges and universities should pose requirements for AP-SCM talents from nine training directions and require them to master and apply them deftly, the nine training directions include: logistics theory of AP, theories of AP-SCM, risk management of AP supply chain, green supply chain of AP, circulation and organization system of AP, preservation and maintenance of AP, transportation and distribution management of AP, cold chain logistics of AP, and e-commerce logistics of AP. The paragraph below gives the requirement details for AP-SCM talents in these nine directions.

In terms of the logistics theory of AP, AP-SCM talents are required to have the ability to sort out the relationship between AP logistics and supply chain, understand the effects of logistics on the management of AP in China, and know about the three intelligentization trends of AP logistics and supply chain; in terms of theories of AP-SCM, they should master the basic theories of AP-SCM, be able to analyze the structure of AP-SCM, and know about the resource integration and expansion of AP-SCM; in terms of the risk management of AP supply chain, they need to understand the conventional strategies of AP-SCM, be able to analyze the risks in the AP supply chain and propose appropriate and scientific strategies for coping with these risks; in terms of green supply chain of AP, they are required to have the basic knowledge of green supply chain, be able to analyze the collaborative mode of the green supply chain of AP, and realize the coordinated development of the green supply chain of AP and the agricultural ecosystem; in terms of the innovation of the circulation and organization system of AP, they should be able to analyze the effects of the circulation, organization, and operation of AP on the supply chain, give innovative ideas of the circulation and organization of AP, and innovate the organization system of AP wholesale markets; in terms of the preservation and maintenance of AP, they need to master the quality of AP in the existing supply chain, and adopt reasonable methods to process harvested products into commodities and maintain their quality during storage and transportation; in terms of the transportation and distribution management of AP, they should master the basic transportation and distribution states of AP, have certain abilities in AP transportation management, AP warehousing management, and AP delivery management; in terms of the cold chain logistics of AP, they are required to grasp the cold chain logistics process of AP and the cold chain logistics modes for three categories of AP; in terms of the e-commerce logistics of AP, they are also required to have a knowledge of the e-commerce logistics modes of AP, and be able to carry out the actual management works by referring to foreign and domestic AP e-commerce cases.

3 Training quality assessment of AP-SCM talents

GRU neural network has outstanding advantages over other networks, but is disadvantages in initial parameter determination and structure optimization are obvious as well. In this case, this paper improved the GRU neural network based on Gravitational Search Algorithm (GSA) and Particle Swarm Optimization (PSO), and constructed a prediction model for assessing the training quality of AP-SCM talents, Figure 1 gives a diagram of the flow of the model, the specific steps are:

(1) Read the training quality assessment data of AP-SCM talents to be predicted;
(2) Pre-process the assessment data, and screen the feature variables;
(3) Optimize the GRU neural network respectively use GSA and PSO to attain optimal structural parameters of the GRU neural network, including the initial threshold, weight parameter, number of network layers, and the number of nodes in each layer.
(4) Predict the preprocessed assessment data based on the optimized GRU neural network;
(5) Output and save the prediction results of the training quality assessment of AP-SCM talents.

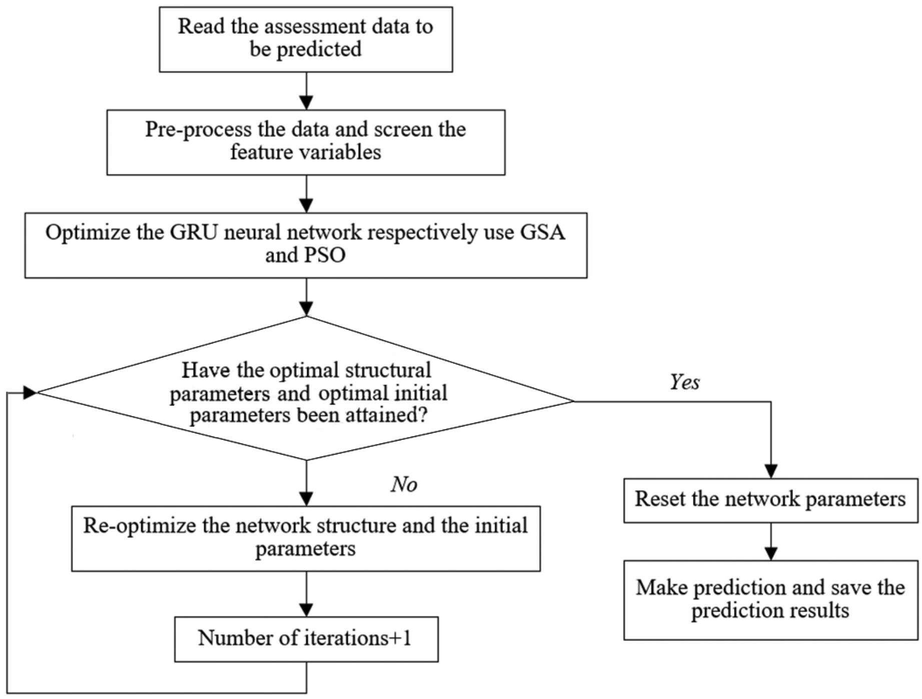

Fig. 1. Optimization flow of the GRU neural network

The model is described in detail below:

3.1 Structural parameter optimization algorithm

Assuming: $n_i(p)$ represents the ratio of the best and worst fitness in the iteration of the *i*-th particle; *M* represents the total number of particles; $FIT_i(p)$ represents the fitness of the *i*-th particle in the *t*-th iteration; then in the GSA, the formula for calculating the mass of each particle is:

$$N_i(p) = \frac{n_i(p)}{\sum_{j=1}^{M} n_j(p)},\ n_i(p) = \frac{FIT_i(p) - W(p)}{B(p) - W(p)} \tag{1}$$

Next, based on the best value *B* and the worst value *W* of the network optimization objective, the maximum and minimum values were attained:

$$\begin{cases} B(p) = max\{FIT_i(p)\} \\ W(p) = min\{FIT_i(p)\} \end{cases}, i = 1, 2, ..., M \tag{2}$$

$$\begin{cases} B(p) = min\{FIT_i(p)\} \\ W(p) = max\{FIT_i(p)\} \end{cases}, i = 1, 2, ..., M \tag{3}$$

Assuming: $S_{ij}(p)$ represents the Euclidean distance between particles; σ represents the lowest constant; $A_i^c(p)$ represents the c-dimensional positioning of the i-th particle in the p-th iteration; $H(p)$ represents the gravitational constant, then the gravity between any two particles could be calculated using the formula below:

$$G_{ij}^c(p) = H(p)\frac{N_i(p) \times N_j(p)}{S_{ij}(p) + \sigma}\left(A_j^c(p) - A_i^c(p)\right) \tag{4}$$

Assuming: H_0, P, and β respectively represent the maximum number of iterations, the initial gravity, and the decay coefficient, then the gravitational constant can be expressed as:

$$H(p) = H_0 e^{\frac{\beta p}{P}} \tag{5}$$

The resultant force $G_i^c(p)$ formed by the gravity of the particles can be calculated by the following formula:

$$G_i^c(p) = \sum_{j=1, j \neq i}^{M} rand_j G_{ij}^c(p) \tag{6}$$

Assuming: $\beta_i^c(p)$ represents the acceleration of the resultant force formed by the gravity of particles, then its calculation formula is:

$$\beta_i^c(p) = \frac{G_i^c(p)}{N_i(p)} \tag{7}$$

In the process of algorithm iteration, the velocity and position of particles need to be updated by $U_i^c(p)$, $A_i^c(p)$, and $\beta_i^c(p)$, the update formulas are:

$$U_i^c(p+1) = rand_i U_i^c(p) + \beta_i^c(p) \tag{8}$$

$$A_i^c(p+1) = rand_i A_i^c(p) + U_i^c(p) \tag{9}$$

There're nine training directions for the training quality assessment indexes of AP-SCM talents, however, when processing the high dimensional (9-dimension) space network optimization problem, the optimization effect of conventional GSA is not ideal enough, the search accuracy needs to be improved, and the defect of easily falling into local optimum should be solved. In this paper, the gravitational constant of the conventional GSA was adaptively adjusted based on the learning automaton, which was defined by a quadruple $\{\beta, \gamma, \varepsilon, P\}$ in this paper; assuming $\beta = \{\beta_1,\beta_2, \ldots,\beta_s\}$ represents the set of alternative actions; $\gamma = \{\gamma_1,\gamma_2, \ldots,\gamma_r\}$ represents the feedback values of the environment; $\varepsilon = \{\varepsilon_1,\varepsilon_2, \ldots,\varepsilon_s\}$ represents the vector of the probability of each action being selected; P represents the update strategy of the learning automaton, then Formula 10 describes the action selection process:

$$\varepsilon(m+1) = P\left[\beta(m),\gamma(m),\varepsilon(m)\right] \tag{10}$$

Assuming: s and β represent the reward parameters and φ represents the penalty parameter, when the learning automaton receives the reinforced signals, the state of the probability vector is updated based on Formulas 11 and 12 to attain beneficial responses.

$$\varepsilon_j(l+1) = \begin{cases} \varepsilon_j(l) + \beta \times \left(1-\varepsilon_j(l)\right), \ if\ i = j \\ \varepsilon_j(l) \times (1-\beta), \ if\ i \neq j \end{cases} \tag{11}$$

$$\varepsilon_j(l+1) = \begin{cases} \varepsilon_j(l) + (1-b), \ if\ i = j \\ \dfrac{\phi}{s-1} \times (1-\phi) \times \varepsilon_j(l), \ if\ i \neq j \end{cases} \tag{12}$$

Figure 2 gives the optimization algorithm flow of structure parameters.

3.2 Initial parameter optimization algorithm

The diversity of particle swarm has multiple effects on the conventional PSO such as the premature convergence and the local extreme values, therefore, this paper proposed a PSO based on the domain collision mechanism. Every time the particles search for the optimal solution, the algorithm will adjust their operation mechanism and introduce new particle interaction mechanism, so as to control of the diversity of the particle swarm and guide the search direction of the particles during the iteration process. The velocity and position of particles during movement are given by the following formulas:

$$U_{i,j}^{p+1} = \theta U_{i,j}^{p} + d_1 s_{1,i,j}^{p} \left(\overset{*p}{b}_j - a_{i,j}^{p} \right) + d_2 s_{2,i,j}^{p} \left(\overset{*p}{b}_j - a_{i,j}^{p} \right) \tag{13}$$

$$a_{i,j}^{p+1} = a_{i,j}^{p} + U_{i,j}^{p+1} \tag{14}$$

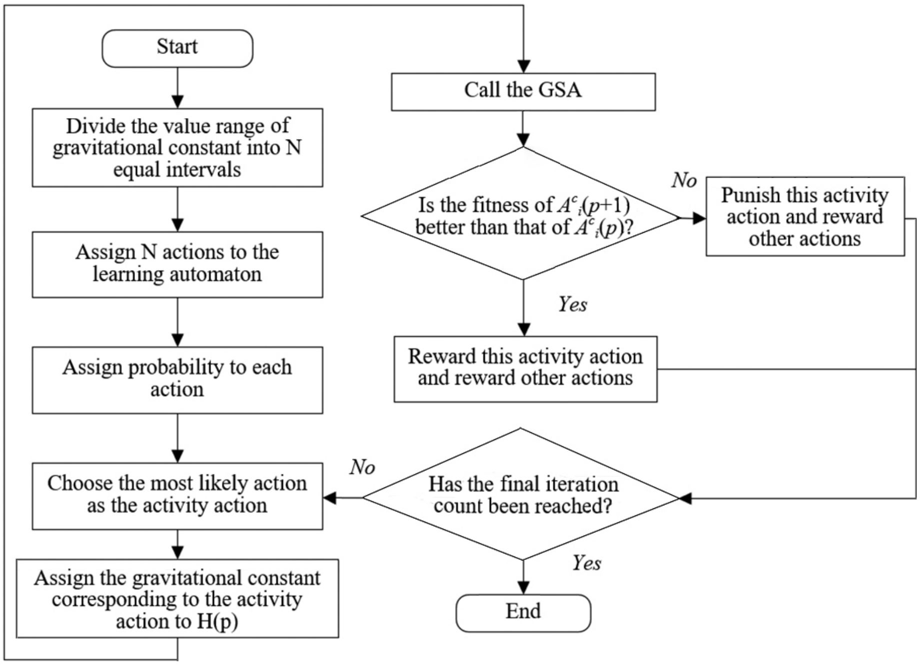

Fig. 2. Optimization algorithm flow of structural parameters

According to above formulas, $U^p_{i,j}$ represents the information carried by particle i; $b^p_{i,i}$ represents the local optimal position of particle i; $a^p_{i,i}$ represents the position of particle j; $b*^p_j$ represents the optimal position of particle j; parameter θ represents the inertia weight; $s^p_{1,ij}$ and $d^p_{2,ij}$ represent random numbers; d_1 and d_2 represent constant coefficients, according to Formula 13, the information carried by particle i includes parameters $\theta U^p_{i,j}$, $d_1 s^p_{1,ij}(b^{*p}_j - a^p_{i,j})$, and $d_2 s^p_{2,ij}(b^p_j - a^p_{i,j})$, which respectively represent the particle development state, the swarm cognition under swarm state, and the individual particle cognition under particle state.

The PSO based on domain collision mechanism plans fields with a radius of $S(p)$ around all particles in the swarm, if the domains of different particles overlap, then the particles are called the collision operator of each other. Assuming: G_i represents the fitness of particle i; G_j represents the fitness of collision operator; once two particles are judged to be a collision operator pair, then the particle with weaker search ability will execute the collision operation based on the following formula:

$$Collision_i^j = \begin{cases} \left(2S(p) - \left\| A_i - A_j \right\|\right) \dfrac{A_i - A_j}{\left\| A_i - A_j \right\|}, G_i > G_j \\ 0, G_i < G_j \end{cases} \tag{15}$$

Through the collision operation, the particle with weaker search ability will be bounced back to the position that is $2S(p)$ distance away from the particle with stronger search ability. In the PSO based on domain collision mechanism, with the accumulation of the count of iterations, the particle domain radius $S(p)$ decreases continuously. Assuming: M represents the size of dimension; L represents the size of the swarm; A'_V and A'_K respectively represent the upper and lower boundaries of the i-th variable; then the maximum initial domain radius of the particles S'_{max} can be calculated by the following formula:

$$S'_{max} = \frac{\sqrt[M]{\left(\prod_{i=1}^{M}\left(A_V^i - A_K^i\right)\right)/L}}{2} \tag{16}$$

In order to avoid the problem of domain overlap caused by unchanged particle positions at the beginning of the iteration, this paper set a domain radius that gradually decreases with the increase of the number of iterations:

$$S_{max} = \beta S'_{max} \tag{17}$$

Wherein β is the reduction coefficient of domain radius, which is a random value within the range of [0,1]. Assuming: G_i represents the fitness of current neighbor particle i; TB_j represents the fitness of local optimal position in the individual history of particle j, and the corresponding weight is represented by dividing the difference between G_i and TB_j by the square of the distance between G_i and TB_j; then, the individual historical local optimal position T*, which is the same for most particles, can be attained from the following formula:

$$T_j^* = \frac{\sum_{j(G_i > Tbest_j)}(T_j)(G_i - Tbest_j)/\left\|A_i - T_j\right\|^2}{\sum_{j(G_i > Tbest_j)}(G_i - Tbest_j)/\left\|A_i - T_j\right\|^2} \tag{18}$$

Assuming: EP represents the number of iterations, ψ_2 was set to be an adaptive parameter that increases with the increase of EP, then there is:

$$\psi_2 = \psi_2^{min} + \left(\frac{\psi_2^{max} - \psi_2^{min}}{MaxEP}\right) \times EP \tag{19}$$

Finally, the velocity update formula of the PSO based on domain collision mechanism is given by the following formula:

$$U_i(p+1) = U_i(p) + \psi_1(T_1^* - A_i) + \psi_2(H_i - A_i) + \psi_3 \sum_i Collision_i^j \tag{20}$$

3.3 The *GRU* neural network

The optimized GRU neural network model can be expressed as:

$$r_p^* = tanh\left(Q_r(s_p \oplus r_{p-1})\right) + V_r a_p + \phi_r \tag{21}$$

$$r_p = (1 - c_p) \oplus r_{p-1} + c_p \oplus r_p{}^* \tag{22}$$

$$c_p = \rho_{sig}(Q_r r_{p-1} + V_c a_p + \phi_c) \tag{23}$$

$$s_p = \rho_{sig}(Q_s r_{p-1} + V_s a_p + \phi_s) \tag{24}$$

Figure 3 gives a schematic diagram of the GRU neuron structure.

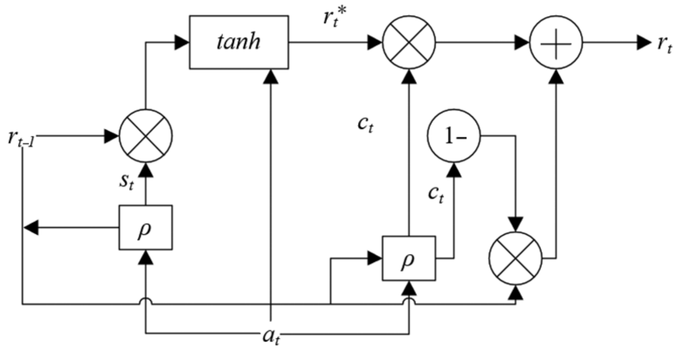

Fig. 3. Structure of the GRU neuron

4 Experimental results and analysis

Through analysis, this paper drew the conclusion that colleges and universities need to pose requirements for AP-SCM talents from 9 training directions (logistics theory of AP, theories of AP-SCM, risk management of AP supply chain, green supply chain of AP, circulation and organization system of AP, preservation and maintenance of AP, transportation and distribution management of AP, cold chain logistics of AP, and e-commerce logistics of AP). In order to attain effective prediction results of the training quality assessment of AP-SCM talents, at first, this paper pre-processed the data of assessment indexes corresponding to the nine directions. The data were subject to dimensionless processing based on logarithmic transformation to unify the units of the feature attributes of different assessment indexes.

Figures 4 and 5 give the actual data values and logarithmically transformed values of the training quality assessment indexes of AP-SCM talents, based on which the basic judgements on the data distribution of the training quality assessment indexes of AP-SCM talents could be made. According to Figure 1, the distribution of the data showed a significant inclination trend, and the prediction model cannot perform normal learning or give predictions based on this type of data, so at this time, the data need to be subject to logarithmic transformation. According to Figure 2, the logarithmically transformed data basically exhibited a normal distribution state, which met the prediction model's requirement for normal learning.

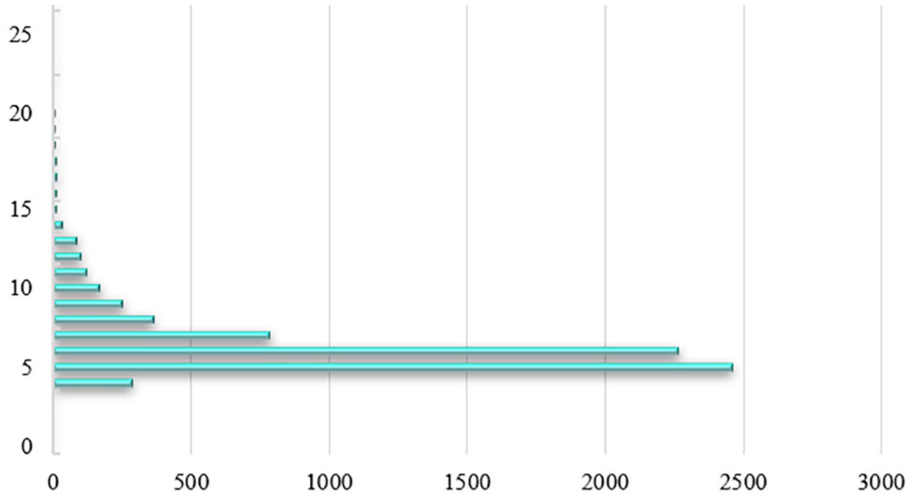

Fig. 4. Actual data of training quality assessment indexes of AP-SCM talents

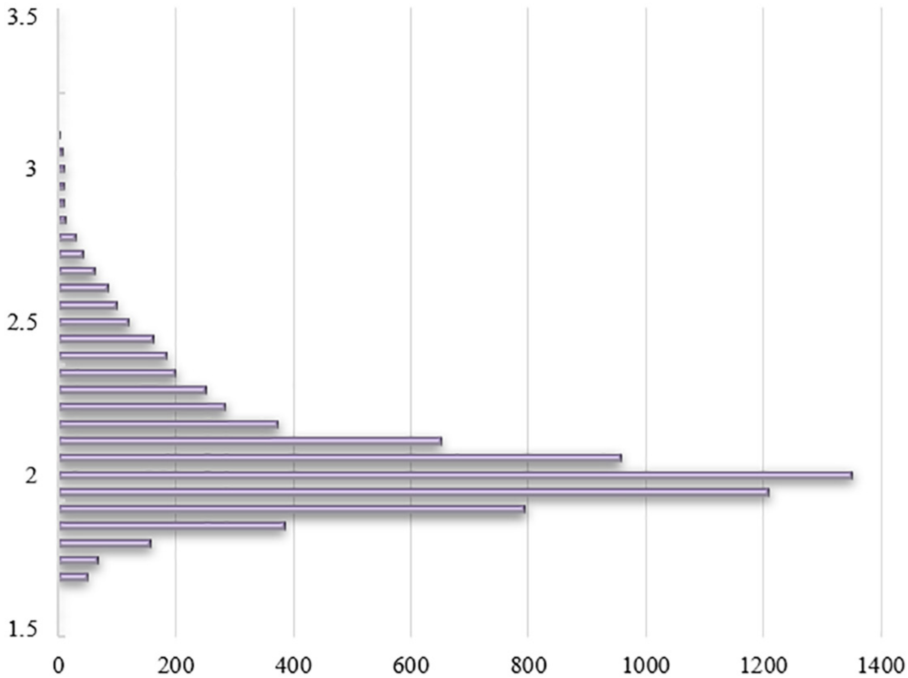

Fig. 5. The logarithmic transformation of the training quality assessment index values of AP-SCM talents

After completing the preprocessing of the data of training quality assessment of AP-SCM talents, for the 26 assessment criteria, namely the feature attributes of the nine training directions, the appropriate feature variables were screened to avoid the generation of direction operation results. Through the feature combination analysis of the data set of the training quality assessment of AP-SCM talents, the comparison of different assessment criterion features suggested that the relationship between some assessment criterion features and the talent training quality research was not clear and needs to be judged objectively. Based on the XGBoost algorithm of big data analysis and the assessment criterion feature variables screened by the *IV*-value, the calculation results of eigenvalues are given in Table 1.

Table 1. Calculation results of eigenvalues

Criterion No.	Feature Extraction	*woe*	*iv*	*IV*
1	2	–0.415	0.284	0.416
2	1	0.849	0.226	0.495
3	5	0.305	0.195	0.426
4	0.99	–2.691	0.14	0.402
5	3	0.114	0.135	0.415
6	8	0.825	0.195	0.436
7	1	–2.674	0.106	0.495
8	0.99	–0.938	0.374	0.462
9	6	0.284	0.129	0.259
10	2	0.063	0.114	0.220
11	7	–0.241	0.135	0.274
12	0.99	–1.632	0.269	0.262
13	8	–0.051	0.157	0.219
14	3	0.058	0.134	0.227
15	1	0.162	0.112	0.231
16	0.99	2.416	0.162	0.285
17	5	0.544	0.129	0.244
18	2	0.061	0.121	0.252
19	7	–0.235	0.147	0.224
20	8	0.645	0.195	0.436
21	2	–2.644	0.226	0.375
22	0.99	–0.918	0.324	0.452
23	7	0.615	0.245	0.426
24	1	0.379	0.616	0.505
25	4	0.315	0.225	0.486
26	0.99	–2.091	0.63	0.442

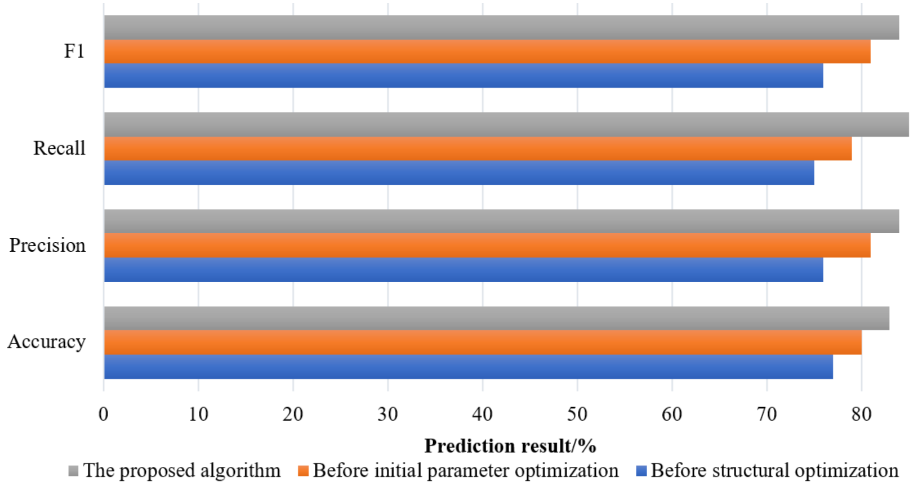

Fig. 6. Comparison of prediction results of different algorithms

Table 2. Comparison of prediction results of different algorithms

Model	Accuracy	Precision	Recall	F1
Before initial parameter optimization	78.41%	74.98%	71.54%	79.56%
Before structural optimization	81.54%	88.49%	79.48%	77.31%
The proposed algorithm	85.97%	90.47%	86.32%	85.91%

To verify the effectiveness of the GRU neural network optimized based on GSA and PSO, this paper compared the proposed model with the network model before the initial parameter optimization and the structural optimization, and the results of the comparative experiment are given in Figure 6 and Table 2.

According to Figure 6 and Table 2, compared with the network model before initial parameter optimization and structural optimization, the proposed model showed better performance in predicting the training quality of AP-SCM talents. The correct rate of the proposed model was 85.97%, which was 5.15% higher than the model before structural optimization, and 8.79% higher than the model before initial parameter optimization. The accuracy of the proposed model was 90.47%, which was 2.18% higher than the model before structural optimization, and 17.12% higher than the model before initial parameter optimization. The recall rate of the proposed model was 86.32%, which was 7.92% higher than the model before structural optimization, and 17.12% higher than the model before initial parameter optimization. The F1 value of the proposed model was 85.91%, which was 10% higher than the model before structural optimization, and 7.39% higher than the model before initial parameter optimization. The main reason of these attained results is that the initial parameters and structural parameters of the neural network obtained by the optimization algorithm adopted in this paper exerted a beneficial effect on the prediction performance of the model.

5 Conclusion

This paper studied the training path of AP-SCM talents and the assessment of their training quality. At first, this paper proposed the training path and attained the conclusion that colleges and universities should pose requirements for AP-SCM talents from 9 training directions. Then, this paper constructed a prediction model for assessing the training quality of AP-SCM talents, and gave the specific model framework and modelling principles. In the experimental results, this paper attained the actual values and logarithmically transformed values of the training quality assessment indexes of AP-SCM talents, and verified the effectiveness of the logarithmic transformation of the assessment data. After that, this paper also gave the calculation results of eigenvalues based on the XGBoost algorithm of big data analysis and the assessment criterion feature variables screened by the *IV*-value. At last, the prediction performance of the proposed model was compared with the network model before initial parameter optimization and structural optimization, and the results verified the effectiveness of the GRU neural network optimized based on GSA and PSO.

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Article submitted 2022-08-05. Resubmitted 2022-09-20. Final acceptance 2022-09-23. Final version published as submitted by the authors.