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Research Article

Analysis of Intelligent Optimization and Allocation of Human Resources in Media Operation Management

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Scientific and rational optimization of human resources allocation in media operation and management to maximize the economic and social benefits of enterprises is the top priority of the current media to strengthen human resources work. How to allocate human resources, adjust the structure of human resources, realize complementary advantages, and dynamically adapt to the needs of economic construction is a very important issue that must be carefully studied in the process of human resources development and management. In this article, a binary classification support vector machine method is proposed, which uses linear function calculation, and finally uses multi-skill model to solve performance experiments. The results show that the media operation management must reform the labor employment system, allocate the labor force scientifically and rationally, and make effective use of the media management labor resources; labor employment is a necessary means for the development and survival of enterprises. It is an important function of enterprise management to manage and utilize labor reasonably and effectively. Through optimal allocation and rational utilization, the human resource allocation in media operation management can reach a higher management level.

1. Introduction

In order to improve the efficiency and quality of business management system software development, we use the framework of Microsoft DotNet and explain how to implement the framework with key codes [1]. The talents who can promote the development of enterprises or carry out creative work in enterprises are the talents of business administration. This talent bears great social responsibility and is a hero in the market economy [2]. This article adopts two methods to combine enterprise management and expert system. The applicable fields are given, and the advantages of the new method are discussed [3]. The development of enterprises and the development direction of enterprises are managed by enterprises. Business administration plays a vital role in the sustainable development of enterprises. If an enterprise is not eliminated in its development, it is necessary to establish its own management mode [4]. Enterprise resource planning software is widely used in all kinds of enterprises, and the demand of implementing technology in colleges and universities is increasing. This article puts forward the methods that can reduce implementation failure and adopt corresponding measures. The research results show that adopting the best-proven model is the key to success [5]. With the accelerating development of global economy, our country has ushered in a very important period. If an enterprise wants to be recognized in the increasingly fierce competition, it must establish a good management system [6]. This article studies the effective methods and strategies of business administration. By strengthening management, system innovation, and talent innovation, the effectiveness of enterprise management can be achieved [7]. As an important organizational force in the process of enterprise development, enterprise managers play an irreplaceable role. Based on this, this article starts with the current situation of enterprise managers, and makes an in-depth discussion on the ability and training path that enterprise managers should have, hoping to be beneficial to enterprise managers [8]. In this article, a simulation optimization model of coal-fired logistics system in thermal power plant is established, and a detailed analysis is made on an example. The model reflects the bottleneck point and resource utilization rate macroscopically, and the research in this article has important practical significance for thermal power plants to formulate scientific and reasonable logistics system strategies, reduce costs, and improve competitiveness [9]. The special human resources, which have a profound impact on the development of colleges and universities and create social benefits, are a kind of pulling force on core resources produced by the combination of information resources, knowledge resources, and human resources. The intelligent resource system of colleges and universities is constructed from the perspective of optimizing, cultivating, and developing intelligent resources of colleges and universities [10]. In the manufacturing industry, resource-constrained multi-project allocation is very common. Therefore, we introduce particle swarm optimization algorithm to optimize the allocation of product resources. Finally, the network is optimized and the optimization results are given. These methods can be used to study the combination of similar complex network theories [11]. Human resource allocation is one of the most important links in project management. This article presents a new method of human resource allocation in project organization based on software architecture and social network [12]. Optimal allocation of project human resources is one of the most important aspects of project management. A human resource allocation method of project organization based on particle swarm optimization algorithm is proposed. According to the proposed method, we apply particle swarm optimization to find a feasible solution to the problem. The effectiveness of the algorithm is verified by an example of project human resource allocation [13]. This article introduces 12 methods of health human resources allocation, such as trend extrapolation method and health demand method, in order to provide reference for the allocation of health human resources on a more reasonable and scientific basis [14]. This article puts forward a multi-project human resource allocation method and designs a set of input-output indicators that can reflect the performance of human resource allocation. This method mainly uses data envelopment analysis model to evaluate the project progress of parallel multi-projects, dynamically adjust the allocation of human resources, and improve the performance of multi-projects, thus improving the resource utilization rate and the success rate of multi-projects [15]. Human resource development and management is an important field of demography research, but human resource research is not specialized in demography. In many other social science disciplines, human resources research is also concerned and valued, and there are many special studies from different disciplines. These achievements and the results of demographic research have merged into a batch of magnificent documents on human resource development and management. It is these valuable research documents that constitute the basis of exploring the problem of human resource allocation, and finally, form the theoretical basis of this article.

2. Main Influencing Factors of Human Resource Allocation

2.1. Political and Legal Factors. As far as the allocation of human resources in scientific research organizations is concerned, with the real-time revision and improvement of national or local human resources management policies and regulations, scientific research organizations need to implement the adjustment of corresponding management systems and detailed rules to ensure the legitimacy and standardization of their human resources allocation. For example, scientific research organizations need to adjust their human resources planning to implement the national requirements for the proportion of fresh graduates and non-fresh graduates, adjust the file management and labor relations management of on-the-job and non-on-the-job personnel to meet the changes in talent management system, and adjust their salaries and benefits to implement the changes of salary management policies. When scientific research organizations allocate human resources, the acquisition and use of human resources need to follow relevant policies and regulations.

2.2. Economic Factors. The continuous development and changes of global economic integration, national economic development situation, and economic system reform all affect the allocation of human resources, such as the fluctuation of human resources use cost, the investment of national finance to scientific research funds, and the change of human resources acquisition cost and supply in the market. The operating expenses of similar scientific research organizations come entirely from state finance, the increase or decrease of funds directly affects the investment in human resources of scientific research organizations. Whether the number of human resources actually available to organizations can increase and the quality of talent teams can be improved requires the support of a large amount of funds. Economic factors have a great influence on the allocation of human resources in scientific research organizations.

2.3. Sociocultural Factors. With the development and changes of the times, the diverse integration of foreign cultures, and the advancement of local cultures have changed people's traditional living habits, values, and professional activities. Emerging industries in the market provide more job types for job seekers to choose from. At the same time, job seekers show distinct individual differences in job selection, and their job-seeking intentions are no longer constrained by traditional job fields, but pay more attention to the realization of self-needs. The advantages of scientific research organizations, such as stable treatment and respected status, are gradually weakened in the current social and cultural environment. More and more job seekers follow their hobbies and choose careers, and the attraction of scientific research institutes to young talents is gradually reduced. The development and change of social culture to a certain extent increases the difficulty for scientific research organizations to make use of existing human resources and obtain new human resources.

2.4. Technical Factors. The improvement, upgrading, and perfection of various technologies related to production activities and organization management have brought great changes to the management of scientific research organizations. For example, the development of information technology has brought about the upgrading of various production and management equipment, data analysis technologies and methods. The progress of professional scientific research technology promotes the output speed of scientific research achievements, which leads to higher and higher requirements for the quality of human resources in scientific research organizations. Employees not only need to master new theories and technologies in their professional fields, but also need to know and even skillfully apply technologies in other related disciplines. Influenced by technical factors, scientific research organizations need to consider the quality level of employees more when allocating the number and structure of team human resources.

2.5. Development Strategies. The strategic objectives of state-owned scientific research organizations need to be consistent with the national science and technology development strategy and be adjusted accordingly. The change of strategic objectives of scientific research organizations drives the transformation of their functions and responsibilities, and determines a series of human resource management such as the adjustment of the overall structure of the organization, the division of departmental functions, the setting of grass-roots posts, and the allocation of specific personnel. Human resources allocation must serve the strategic objectives of the organization, otherwise, it will cause a huge waste of human resources value. Therefore, with the change in the development focus of scientific research organizations, the demand for human resources composition changes, and human resources allocation needs to be laid out in priority or key disciplines.

2.6. Funding for Scientific Research. The more scientific research funds of scientific research organizations and the larger the scale of investment funds for human resources management, it is possible to have funds to increase the number of human resources, improve the quality of human resources, optimize the structure of human resources, and promote the normal operation of organizations. Scientific research funds are also the source of employees' salaries and welfare. The higher the proportion of scientific research funds used for salary distribution, it will have the most direct incentive effect on improving employees' work enthusiasm. Only by relying on employees' labor scientific research organizations can they obtain greater scientific research benefits and economic benefits.

2.7. Establishment Constraints. The staffing quantity is determined by the higher level personnel department, and the total number of actual staffing personnel cannot exceed the limited staffing quantity. The staffing system directly affects the available amount of human resources and limits the number of newly added human resources. Under the condition that the increased staffing vacancy depends on the allocation changes such as retirement and resignation, the allocation and use of each staffing have an important impact on organizational development. Insufficient staffing limits the basic human resources of scientific research organizations, and the lack of sufficient human resources seriously hinders the normal operation of scientific research organizations.

3. Two-Class Support Vector Machine

3.1. Optimal Hyperplane. In statistical learning, VC dimension means that for a given data set with N samples, this data set has 2^N classification methods. If a given decision function set can classify all cases, the VC dimension of the function set is called N. It can reflect the generalization ability of the model.

The most important index to measure the algorithm is generalization ability. The stronger its ability, the higher the performance of the model on the test set. The generalization ability of the algorithm is defined as follows, as shown in the following formulas:

$$R(\alpha) \leq R_{\text{emp}}(\alpha) + \psi\left(\frac{N}{h}\right), \quad (1)$$

$$\psi\left(\frac{N}{h}\right) = \sqrt{\frac{h(\ln(2N/h)) - \ln(n/4)}{N}}, \quad (2)$$

where $\psi(N/N)$ is called the confidence range, h is the VC dimension, and N is the number of samples.

Structural risk minimization of support vector machine is realized by optimizing super layer. Given a hyperplane $w^T x + b = 0$. If the hyperplane can satisfy the following formula:

$$y = \begin{cases} 1, & w^T x + b \geq 1, \\ -1, & w^T x + b \leq -1. \end{cases} \quad (3)$$

Training samples can be divided into two categories, so this problem is called linearly separable. Let the interval between hyperplanes $w^T x + b = 1$ and $w^T x + b = -1$ be Δ. Then the hyperplane is a Δ-interval classification hyperplane. The relationship is shown in the following formula:

$$h \leq \min\left(\left[\frac{R^2}{\Delta^2}, n\right]\right) + 1, \quad (4)$$

where n is the dimension of the sample and R means that all the samples are enclosed in a sphere with radius R. The above formula shows that within a certain range, the interval is inversely proportional to the size of VC dimension, and the generalization ability of the model can be improved by increasing the classification interval. Looking at Figure 1, we can find that when the interval Δ is larger, the separability of unknown samples is better, and the samples with unknown labels can be classified correctly.

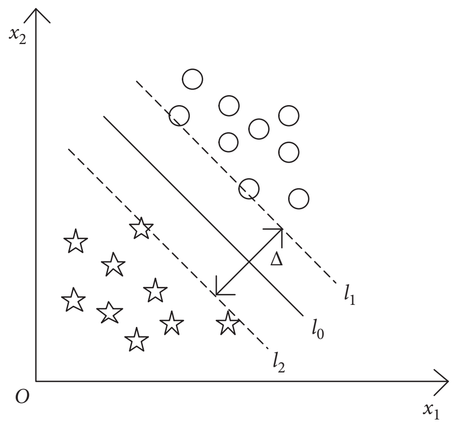

Figure 1: Schematic diagram of linearly separable optimal hyperplane.

3.2. Linear Support Vector Machine. As shown in Figure 1, the three classification hyperplanes are l_1, l_2 and l, respectively. l is in the middle of l_1 and l_2, and the hyperplane can be expressed by the following formulas:

$$l_1\colon w^T x + b = 1, \tag{5}$$

$$l_2\colon w^T x + b = -1. \tag{6}$$

Then the expression of the classification hyperplane in the middle is $w^T x + b = 0$.

Let x_i and x_j be any point on l_1 and l_2, then the distance Δ between l_1 and l_2 is the projection of the connecting line segment $x_i x_j$ to the normal vector w

$$d = w^T \frac{\left(x_i - x_j\right)}{\|w\|}. \tag{7}$$

Formula (8) is obtained by combining formula (5) with formula (6):

$$d = \frac{2}{\|w\|}. \tag{8}$$

In the linear separable problem, the expected risk is determined by the confidence interval. The smaller the confidence interval, the lower the expected risk. As shown in the following formula:

$$\begin{aligned} &\max_{w,b} \frac{2}{\|w\|}, \\ &w^T x_i + b \geq 1, \quad y_i = 1, \\ &\text{s.t. } w^T x_i + b \geq -1, \quad y_i = -1. \end{aligned} \tag{9}$$

Transform the objective problem into a convex form of the optimization problem, as shown in the following formula:

$$\begin{aligned} &\max_{w,b} \frac{\|w\|^2}{2}, \\ &\text{s.t. } y_i\left(w^T x_i + b\right) \geq 1. \end{aligned} \tag{10}$$

The Lagrangian function can be obtained by introducing the Lagrangian dual multiplier α, as shown in the following formula :

$$L(w, b, \alpha) = \frac{1}{2}\|w\|^2 + \sum_{i=1}^{N} \alpha_i \left(1 - y_i\left(w^T x_i + b\right)\right). \tag{11}$$

Formulas (12) and (13) can be obtained by calculating partial derivatives of w and b.

$$\frac{\partial L}{\partial w} = w - \sum_{i=1}^{N} \alpha_i y_i x_i = 0, \tag{12}$$

$$\frac{\partial L}{\partial b} = \sum_{i=1}^{N} \alpha_i y_i = 0. \tag{13}$$

By substituting formulas (12) and (13) into Lagrange function, the duality problem of the original equation is obtained, as shown in the following formula:

$$\begin{aligned} &\max_{\alpha} \left(\sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{N} \alpha_i \alpha_j y_i y_j x_i x_j \right), \\ &\text{s.t. } \sum_{i=1}^{N} \alpha_i y_i = 0, \\ &\alpha_i \geq 0. \end{aligned} \tag{14}$$

Assuming α^* is the optimal solution of the dual model, the normal vector of the decision equation is $w = \sum_{i=1}^{N} \alpha_i^* y_i x_i$, the offset is $b^* = y_j - w^T x_j j \in \left\{ j | 0 < \alpha_j^* \right\}$, and the final decision function is $f(x) = \text{sgn}(w^T * x + b^*)$.

In the nonlinear case, it will be transformed into the dual equation of the objective equation. The purpose of converting to a dual equation is to make the relationship between the samples of the objective equation become an inner product, which is convenient to be extended to nonlinear classification problems. When the linearity is indivisible, it may not be possible to realize that all the training samples are distributed on both sides, so that the empirical risk is zero.

In this case, a relaxation variable ξ can be introduced, which indicates the degree to which the training sample can be tolerated by "error" partition. The constraint condition becomes $y_i(w^T x_i + b) \geq 1 - \xi$, and the sum of the degrees of "error" division is $\sum_{i=1}^{N} \xi_i$. An effective method to solve the linear indivisibility of the support vector machine is to ensure the maximum gap and the small mismatch, and the objective equation is as follows:

$$\min_{w,b}\frac{\|w\|^2}{2}+C\sum_{i=1}^{N}\xi_i,$$
$$y_i\left(w^T x_i+b\right)\geq 1, \tag{15}$$
$$\text{s.t. } \xi\geq 0,\quad i=1,\ldots,N,$$

where C is the penalty coefficient. After introducing Lagrange multipliers α_i and β_i, the Lagrange equation is obtained as shown in the following formula:

$$L(w,b,\alpha,\beta)=\frac{1}{2}\|w\|^2+\sum_{i=1}^{N}\alpha_i\left(1-y_i\left(w^T x_i+b\right)\right)+C\sum_{i=1}^{N}\xi_i-\sum_{i=1}^{N}\beta_i\xi_i. \tag{16}$$

Formulas (17)– can be obtained by calculating partial derivatives of w, b, and ξ_i:

$$\frac{\partial L}{\partial w}=w-\sum_{i=1}^{N}\alpha_i y_i x_i=0, \tag{17}$$

$$\frac{\partial L}{\partial b}=\sum_{i=1}^{N}\alpha_i y_i=0, \tag{18}$$

$$\frac{\partial L}{\partial \xi_i}=C-\alpha_i-\beta_i=0. \tag{19}$$

By substituting formulas (17)– into formula (16), the dual form of the original equation is obtained, as shown in the following formula:

$$\max_{\alpha}\left(\sum_{i=1}^{N}\alpha_i-\frac{1}{2}\sum_{i,j=1}^{N}\alpha_i\alpha_j y_i y_j x_i x_j\right),$$
$$\text{s.t.}\sum_{i=1}^{N}\alpha_i y_i=0, \tag{20}$$
$$0\leq\alpha_i\leq C.$$

3.3. Nonlinear Support Vector Machine. In reality, most data distribution is nonlinear. Generally speaking, one of the traditional machine learning algorithms to solve this kind of problem is to map nonlinear data to high-dimensional space and transform it into linear classification problem. However, this method will lead to dimensional disaster and increase computational complexity. The kernel function is a function satisfying the following formula:

$$K(x,z)=\langle\phi(x),\phi(z)\rangle, \tag{21}$$

where ϕ represents a mapping from x to Hilbert space F.

After introducing small-scale mapping in high-dimensional space for nonlinear problems, the original objective equation is transformed into the following equation:

$$\min_{w,b}\frac{\|w\|^2}{2}+C\sum_{i=1}^{N}\xi_i,$$
$$y_i\left(w^T\phi(x_i)+b\right)\geq 1, \tag{22}$$
$$\text{s.t. } \xi_i\geq 0,\quad i=1,\ldots,N.$$

In the objective equation, the dimension of w will become higher because of the dimension of $\phi(x_i)$, which leads to the increase of computation and even the inability to solve it. Therefore, the original objective equation is transformed into its dual form by introducing Lagrange multiplier, as shown in the following formula:

$$F=\max_{\alpha,\beta,\gamma}\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}y_i y_j\alpha_i\alpha_j K\left(x_i,x_j\right)$$
$$+\frac{1}{2}\sum_{s=1}^{u}\sum_{t=1}^{u}(\beta_s-\gamma_s)(\beta_t-\gamma_t)K(x_s^*,x_t^*),$$
$$+\sum_{i=1}^{N}\sum_{s=1}^{u}\alpha_i y_i(\beta_s-\gamma_s)K(x_i^*,x_s^*)-\sum_{i=1}^{N}y_i\alpha_i+\sum_{s=1}^{u}\beta_s-\sum_{s=1}^{u}\gamma_s,$$
$$F=\max_{\alpha,\beta,\gamma}\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}y_i y_j\alpha_i\alpha_j K\left(x_i,x_j\right)$$
$$+\frac{1}{2}\sum_{s=1}^{u}\sum_{t=1}^{u}(\beta_s-\gamma_s)(\beta_t-\gamma_t)K(x_s^*,x_t^*),$$
$$+\sum_{i=1}^{N}\sum_{s=1}^{u}\alpha_i y_i(\beta_s-\gamma_s)K(x_i^*,x_s^*)-\sum_{i=1}^{N}y_i\alpha_i+\sum_{s=1}^{u}$$
$$\beta_s-\sum_{s=1}^{u}\gamma_s,$$
$$\sum_{i=1}^{N}y_i\alpha_i+\sum_{s=1}^{u}\beta_s+\sum_{s=1}^{u}\gamma_s=0,$$
$$\text{s.t.}0\leq\alpha_i\leq C_1, i=1,\ldots,N,$$
$$0\leq\beta_s,\gamma_s\leq C_2, s=1,\ldots,u, \tag{23}$$

where $K(x_i,x_j)=<\phi(x_i),\phi(x_j)>$. Let α^* be the solution of dual problem, then the solved decision equation is $f(x)=\operatorname{sgn}(\alpha^* y_i K(x_i,x+b^*))$.

4. Analysis of Experimental Results

4.1. Multi-Skill Model Solution Performance Experiment. The data of 10 jobs (J10) and 20 job scales (J20) of RCPSP/max were used in this experiment, and 10 groups of data were selected for the experiment, the number of workers was $S=10$, and the skill level was $\text{SL}=0.6$. The experimental data are shown in Tables 1 and 2, where "N" indicates that the optimal solution has not been successfully obtained within the effective time range (300 seconds), "Obj" indicates the

Table 1: Multi-skill model for solving J10 with the shortest construction period.

	1	2	3	4	5	6	7	8	9	10
Obj	26	*N*	28	26	22	*N*	38	33	29	18
Time	0.37	—	0.53	0.73	0.48	—	0.44	0.16	1.12	0.89

Table 2: Solving J20 with multi-skill model of shortest construction period problem.

	1	2	3	4	5	6	7	8	9	10
Obj	*N*	*N*	*N*	40	72	65	65	50	*N*	*N*
Time	—	—	—	4.73	3.27	1.08	3.4	3.21	—	—

Table 3: Solving J10 by multi-mode model of shortest construction period problem.

	1	2	3	4	5	6	7	8	9	10
Obj	26	*N*	28	26	22	*N*	38	33	29	18
Time	3.79	—	17.86	39.62	31.87	—	16.65	14.49	66.08	23.21

Table 4: Solving J20 by multi-mode model of shortest construction period problem.

	1	2	3	4	5	6	7	8	9	10
Obj	*N*	*N*	*N*	40	72	65	65	50	*N*	*N*
Time	—	—	—	78.63	15.88	30.01	66.2	29.87	—	—

target value of solution, that is, the shortest construction period, and "Time" indicates the solution time, the same below.

As can be seen from the data in Tables 1 and 2, the multi-skill model aiming at the shortest construction period is ideal for solving small-scale problems (J10). With the increase of data scale (J20), the success rate of solving the model decreases, while the solving time increases. This is determined by the structure of the model itself. When the data scale increases, the number of variables and constraints of the model will increase geometrically, resulting in a sudden increase in the difficulty of solving the problem.

4.1.1. Multimodal Model Solution Performance Experiment. The solution data of multi-skill model is given before. For comparison, this section will give the solution of multi-mode model with the same data. The experimental data are shown in Tables 3 and 4.

As can be seen from the data in the table, the multi-mode model with the shortest construction period as the goal problem is effective in solving small-scale problems (J10). With the increase of data scale (J20), the success rate of solving the model decreases, while the solving time increases. The change rule is the same as that of the multi-skill model, and the reasons are basically the same.

As can be seen from the data in the table, the multi-mode model with the shortest construction period as the goal problem is effective in solving small-scale problems (J10). With the increase of data scale (J20), the success rate of solving the model decreases, while the solving time increases. The change rule is the same as that of the multi-skill model, and the reasons are basically the same.

Table 5: Comparison of solution results of two models for the lowest cost problem.

	1	2	3	4	5	6	7	8	9	10
Multimodal	26	26	26	26	26	26	26	26	26	26
Multi-skill	26	26	26	26	26	26	26	26	26	26

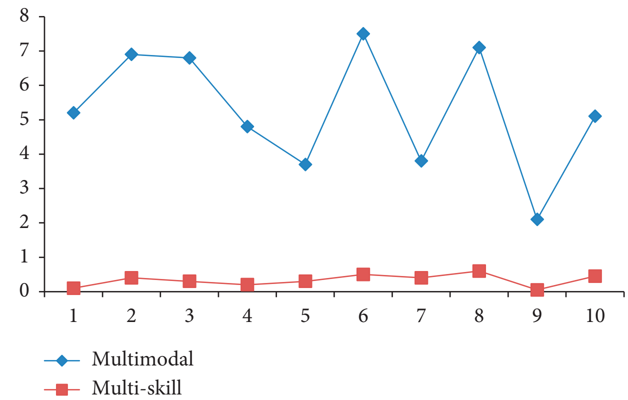

Figure 2: Performance comparison of two models for solving the shortest construction period problem.

4.1.2. Comparison of Solving Performance between Two Models. In the multi-skilled worker scheduling problem with the goal of the shortest construction period, two different mathematical models are introduced. Their structures are different, but they are all based on the same problem, so they should have the same solution results. In order to further compare the performance of the two models, a group of data with better solution effect in J10 data is selected, and 10 groups of data are randomly generated by simulation. Through the solution of the two models, the performance of the models is intuitively compared.

As can be seen from Table 5, among the 10 sets of data solved, the solution results of multi-mode model and multi-skill model are the same. See Figure 2 for specific solution performance comparison.

As can be seen from Figure 2, the solution effect of multi-skill model is obviously better than that of multi-mode model. Multi-model algorithm has poor stability and large error, so it cannot achieve accurate prediction in practical application. And the multi-skill model has a certain performance, in the media operation management of human resource management to achieve a better application.

By tracking and observing the CPLEX solution log, the number of constraints in multi-skill model is less than that in multi-mode model, and the amount of problem data increases after the transformation from multi-skill form to multi-mode form, which leads to the poor result of multi-mode solution, which has important reference value for further research in the future.

Table 6: Comparison of two solution methods of J10.

10	1	2	3	4	5	6	7	8	9	10
LB	26	*N*	28	29	22	*N*	38	33	29	18
LB^{min}	26	24	28	29	22	22	38	33	29	18

Table 7: Comparison of two solution methods of J20.

20	1	2	3	4	5	6	7	8	9	10
LB	*N*	*N*	*N*	40	72	65	65	50	*N*	*N*
LB^{min}	35	34	35	40	72	65	65	50	61	49

Table 8: Comparison of two solving methods for J30.

30	1	2	3	4	5	6	7	8	9	10
LB	89	73	*N*	*N*	82	68	70	81	*N*	*N*
LB^{min}	89	71	35	50	77	59	70	78	36	47

Table 9: Duration lower bound data for J10.

	1	2	3	4	5	6	7	8	9	10
Data 1	26	24	28	29	22	22	38	33	29	18
Data 2	26	24	28	29	22	22	38	33	29	18
Data 3	26	24	28	29	22	22	38	33	29	18

4.2. Analysis of Experimental Results of Multi-Skilled Worker Scheduling Problem Aiming at the Lowest Cost. After the experimental analysis of the multi-skilled worker scheduling problem aiming at the shortest construction period, the multi-skilled worker scheduling problem aiming at the lowest cost will be solved and analyzed.

4.2.1. Method for Solving Lower Bound of Construction Period. In the scheduling problem of multi-skilled workers with the goal of minimizing cost, the lower bound of construction period must be obtained first before further solution can be carried out. Because there is no data of project duration in RCPSP/max, the lower bound of project duration must be found first before the experimental study can be carried out. In the following, we will compare the effects of the model solution and the time limit solution method solved by Floyd–Warshall algorithm.

Using 10 groups of data in RPCPSP/max, the number of workers $S = 10$, skill level $SL = 0.6$, Tables 6–8 show the solution of the two methods under three data scales. In the table, "LB" is the lower bound of the problem duration obtained by solving the model, and "LB^{min}" is the lower bound of the relaxation problem duration obtained by solving the Floyd–Warshall algorithm.

From the data recorded in Tables 6–8, it can be seen that the success rate of solving the model under J10 data is 80%, and among the 8 groups of data that can be solved, the coincidence between LB and LB^{min} is 100%. The success rate of solving the model under J20 data is 50%, and the coincidence between LB and LB^{min} is also 100%. The success rate of solving J30 data is 60%, and the coincidence between LB and LB^{min} is only 20%.

It can be seen that the success rate of the model and the accuracy rate of Floyd–Warshall algorithm are both high for the problem with small data scale. With the increase of data scale, the success rate of the model and the coincidence degree of the two methods also decrease. The decrease of the success rate can be verified by the data in the previous section, and the decrease of the coincidence degree is probably due to the increase of the complexity of the priority relationship between tasks in the problem, which causes the target value of the model, the shortest duration LB, to fail to reach the lower bound LB^{min} of the relaxation problem obtained by Floyd–Warshall algorithm. However, when solving large-scale problems, the model cannot be solved completely, so the lower bound of relaxation problem obtained by Floyd–Warshall algorithm has obvious limiting effect on the lower bound of construction period.

4.2.2. Multi-Skill Model Solution Performance Experiment. In the multi-skilled worker scheduling problem aiming at the lowest cost, the mathematical model of the multi-skill problem is introduced firstly, and then the performance of the multi-skill model is tested. In order to ensure the accuracy of construction period constraints, J10 and J20 data in the previous section were selected, and three sets of random data were generated, respectively, with the number of workers $S = 10$ and the skill level $SL = 0.6$. Table 9 gives the lower bound of duration $LB^{min} = LB$ for 30 sets of data of J10 scale.

After getting the TE^{min} of the data, we can solve the scheduling problem of multi-skilled workers with the goal of minimizing the cost. Table 10 gives the solution data of the multi-skill model under J10 scale. The wage weight of workers is weight = 50, and the construction period constraint is uniformly set as $TE^{min} + 2$, the same below.

As can be seen from the above table, the multi-skill model with the lowest cost as the goal problem can successfully solve all the data of J10 scale selected. The specific solution performance is shown in Figure 3, and the running time unit is seconds, the same below.

It can be seen from Figure 3 that the multi-skill model can get the best solution in a very short time (1 second) when solving J10 scale problems with the lowest cost, and the solution effect is extremely ideal.

Next, the J20 scale problem is solved and analyzed. First, the lower bound of relaxation duration $TE^{min} = LB^{min}$ of J20 scale problem is given, as shown in Table 11.

After getting the TE^{min} of J20 work, the data is also solved, and the results are recorded in Table 12. "*N*" means that the optimal solution cannot be obtained within 300 seconds, the same below.

It can be seen from the above figure that when solving the multi-skilled worker scheduling problem aiming at the lowest cost, the multi-skill model can solve 18 groups of 30 groups of data at J20 scale, while the other 12 groups fail to find the optimal solution within 300 seconds.

4.2.3. Multimodal Model Solving Performance Experiment. The previous section gives the solution data of the multi-skill model, and this section will give the solution of the multi-

Table 10: Solving J10 data by multi-skill model of lowest cost problem.

	1	2	3	4	5	6	7	8	9	10
Data 1	16900	17100	18100	16350	19050	15400	16250	18350	15550	16450
Data 2	14800	13750	15050	14950	14100	13550	13350	16050	15100	14300
Data 3	15700	15800	15359	15250	14900	16200	15750	15450	14950	15500

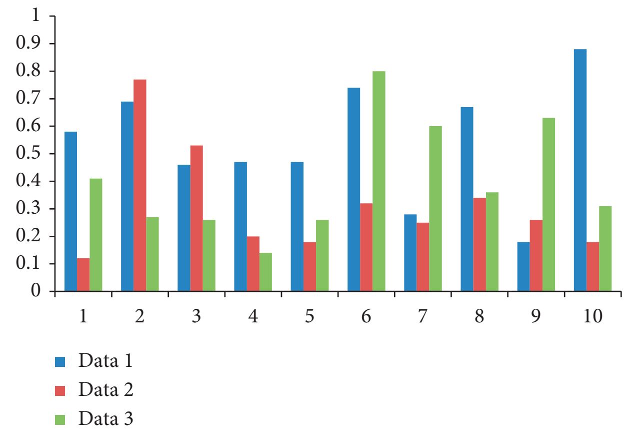

Figure 3: Multi-skill model for solving J10 performance with the lowest cost problem.

Table 11: Lower bound data of slack duration for J20.

	1	2	3	4	5	6	7	8	9	10
Data 1	35	34	35	40	72	65	65	50	61	49
Data 2	35	34	35	40	72	65	65	50	61	49
Data 3	35	34	35	40	72	65	65	50	61	49

Table 12: Solving J20 data by multi-skill model of lowest cost problem.

	1	2	3	4	5	6	7	8	9	10
Data 1	36400	*N*	36800	33300	38700	*N*	33100	32300	*N*	*N*
Data 2	35200	*N*	35700	33500	38800	*N*	32300	32700	*N*	*N*
Data 3	35000	*N*	37300	35100	36400	*N*	32100	31500	*N*	*N*

Table 13: Solving J10 data by multi-mode model of lowest cost problem.

	1	2	3	4	5	6	7	8	9	10
Data 1	3.6	2	1.1	3.9	4	5.8	11.2	3.7	2.8	3.9
Data 2	4.3	8.4	9.2	5.9	2.9	4.3	11.5	4.3	3.1	4.8
Data 3	1.2	0.8	0.5	0.4	1.9	4.3	4	3.4	3.4	5.9

mode model under the same data. The experimental solution data of J10 scale is shown in Table 13, and "Id" indicates the 10 groups of problem data numbers generated by each group of RCPSP/max data.

As can be seen from the above table, like the multi-skill model, the multi-mode model can be completely solved at J10 scale. Figure 4 is a schematic diagram of the solution performance of the multi-mode model at J10 scale.

It can be seen from Figure 4 that the multi-skill model can get the best solution in a short time (12 seconds) when solving J10 scale problems with the lowest cost, and the solution effect is ideal.

For the J20 scale problem, the data in the previous section are also applied to solve the problem, and the solution results are shown in Table 14.

It can be seen from the above figure that when solving the multi-skilled worker scheduling problem aiming at the

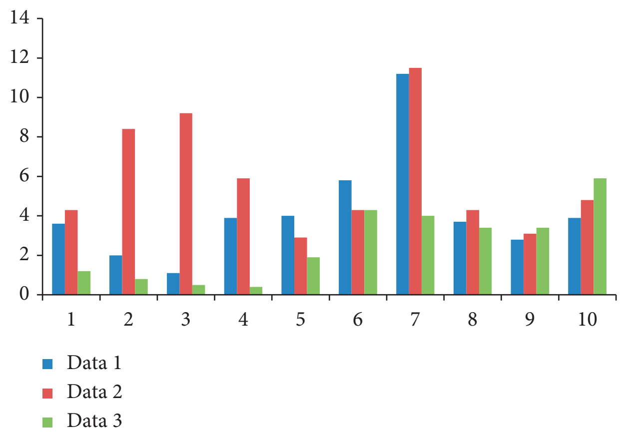

Figure 4: Multi-mode model for solving J10 performance of the lowest cost problem.

Table 14: Solving J20 data by multi-mode model of lowest cost problem.

	1	2	3	4	5	6	7	8	9	10
Data 1	*N*	*N*	*N*	33300	*N*	*N*	33100	*N*	*N*	*N*
Data 2	35200	*N*	35700	33500	*N*	*N*	32300	*N*	*N*	*N*
Data 3	*N*	*N*	37300	35100	*N*	*N*	32100	*N*	*N*	*N*

lowest cost, the multi-mode model can only solve 9 groups of 30 groups of data at J20 scale, and the other 21 groups fail to find the optimal solution within 300 seconds.

4.2.4. Comparison of Solving Performance between Two Models. In the multi-skilled worker scheduling problem aiming at the lowest cost, two different mathematical models are introduced. Their structures are different, but they are all based on the same problem, so they should have the same solution results. In order to compare the solving performance of the two models, a group of data with better solving effect in J10 data is selected, $TE^{min} = 26$, and 10 groups of data are randomly generated by simulation. The construction period constraint is uniformly set as $TE^{min} + 2$, the number of workers is $S = 10$, and the skill level is $SL = 0.6$. Through the solution of the two models, the performance of the models is intuitively compared. The specific solution data are shown in Table 15.

As can be seen from the above table, among the 10 sets of data solved, the solution results of multi-mode model and multi-skill model are the same. Specific solution performance pairs are shown in Figure 5.

As can be seen from Figure 5, the solution effect of multi-skill model is obviously better than that of multi-mode model. This rule is the same as the experimental results of the shortest construction period problem, and it is also determined by the characteristics of the model itself.

Multimodal model shows higher cost in the above operating cost, and the cost control is not stable and fluctuates greatly. Multi-skill model has good advantages in human resource cost control in media operation management, which can accurately predict costs and control expenses.

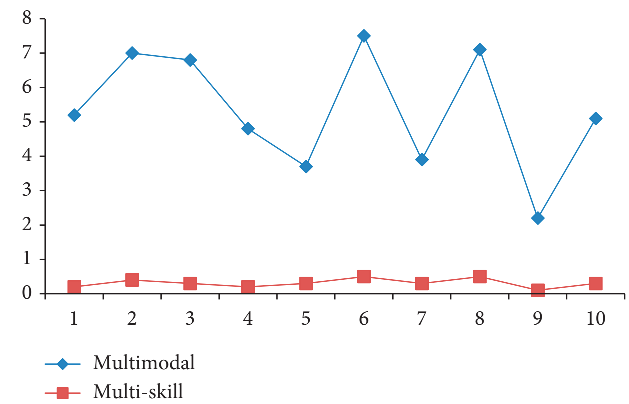

Figure 5: Performance comparison of two models for solving the lowest cost problem.

4.3. Analysis of the Influence of Simulation Data Parameters on Model Performance. The meaning of parameters such as work intensity WS, number of workers S and skill level SL has been discussed in Section 4.3. 1, but it is not known what impact the change of parameters will have on the performance of the model. For example, the influence of 8 available workers and 12 available workers in the project on the difficulty of scheduling, or the influence of workers' skill level on the operation of the model. Next, experiments will be carried out for the performance changes of the model under the condition of parameter changes.

We take the scheduling problem of multi-skilled workers with the goal of shortest construction period as an example. Compared with the multi-mode model, the multi-skill model has the same solution results in the lowest cost problem, but the multi-skill model still has better solution performance than the multi-mode model. Therefore, in order to validate this experiment more effectively, we choose to use multi-skill model for experimental analysis.

Firstly, a data file in J10 is extracted from RCPSP/max problem library, which is easy to calculate. For each combination of workers' number S from 9 to 12 and workers' skill level from 0.5 to 0.8, 5 groups of data are randomly generated. The table gives the solution results of these $4 \times 4 \times 5 = 80$ groups of data. Tables 16–19 show the variation of the solution time of the model with the skill level SL of workers when the number of workers S is different.

It can be seen that with the increase of S and SL, the solution efficiency of the model has a downward trend. In order to express this change trend more intuitively, Figure 6 is used to record the change of the solution effect of the model under the change of parameters.

As can be seen from Figure 6, When the skill level SL changes from 0.5 to 0.8, and when the number of workers S changes from 9 to 12, the performance of the model gradually decreases, which shows from the side that when the skill level of workers increases or the number of workers increases, the decision-makers have more decision-making space when scheduling, which will make the decision-making time longer and more difficult. Because the data of job demand for skills is transformed according to PSPLIB/max standard problem library, it is a constant, so no

Table 15: Performance comparison of two models for solving the lowest cost problem.

	1	2	3	4	5	6	7	8	9	10
Multimodal	16250	17250	16200	17800	17150	15600	18450	15350	16400	16800
Multi-skill	16250	17250	16200	17800	17150	15600	18450	15350	16400	16800

Table 16: Influence of SL on solution performance when $S = 9$.

SL	1	2	3	4	5	Ave.
0.5	0.53	0.69	0.62	0.66	0.69	0.638
0.6	0.36	0.37	0.64	0.56	0.67	0.52
0.7	2.04	0.47	0.5	0.42	0.47	0.78
0.8	0.58	0.37	2.07	0.78	1.78	1.116

Table 17: Influence of SL on solution performance when $S = 10$.

SL	1	2	3	4	5	Ave.
0.5	0.39	2.07	0.86	1.02	0.57	0.982
0.6	0.58	1.72	3.53	1.59	2.11	1.906
0.7	1.37	9.72	4.68	5.25	4.99	5.202
0.8	2.11	15.51	11.28	10.21	7.1	9.242

Table 18: Influence of SL on solution performance when $S = 11$.

SL	1	2	3	4	5	Ave.
0.5	0.3	3.9	1.45	1.98	0.99	1.724
0.6	1.01	4.74	5.85	3.11	3.78	3.698
0.7	0.72	3.73	6.56	6.1	5.36	4.494
0.8	0.92	66.18	34.35	18.18	9.1	25.746

Table 19: Influence of SL on solution performance when $S = 12$.

SL	1	2	3	4	5	Ave.
0.5	0.62	2.86	2.99	3.07	2.59	2.426
0.6	0.53	12.92	1.81	5.38	3.71	4.87
0.7	2.18	6.24	15.18	7.13	8.1	7.766
0.8	1.69	21.87	60.47	6.15	3.58	18.752

comparative experiment is carried out here. However, it can be speculated that when the work intensity WS increases, the demand for workers will also increase, which may also cause the difficulty of scheduling, which can be further studied in the future.

Based on the description of two different problems and each model, this article combines the relevant data of RCPSP/max in PSPLIB problem library, and relies on reasonable simulation generation, and obtains a data example suitable for this model. The correctness of the model is proved and the performance of the problem model is explored in-depth by designing contrast experiments between different models of each problem and other experiments, which further deepens the understanding of the problem and facilitates further research in the future.

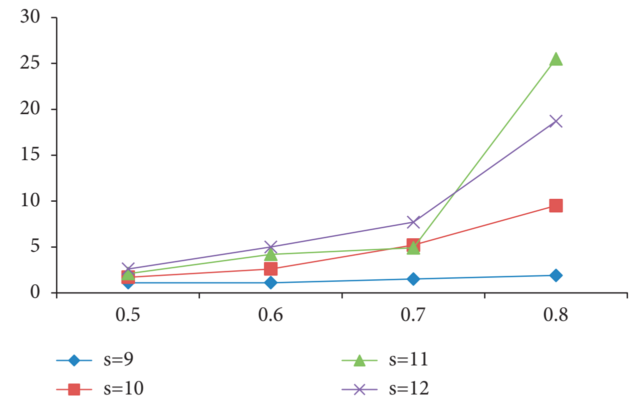

Figure 6: Solving performance data when parameters change.

5. Conclusion

As the supplier of institutional policies, the government should formulate necessary policies to ensure the healthy, orderly, and vigorous development of the human resources market. The human resource market urgently requires the government to change its functions, which is not to avoid government management, but to change the past planned management into macro-control. The government should change its functions from the aspects of management functions, means and main tasks, so as to create a good policy environment for human resources. The main functions of government macro-control include four aspects: first, formulate and implement macro-control policies, do a good job in infrastructure construction of human resources market, and create a good environment for human resources growth and development. The second is to cultivate the human resources market system, supervise the operation of the human resources market and maintain equal competition. The third is to adjust social distribution and organize social security; fourth, formulate and implement the strategy of human resources development to achieve the country's economic and social development goals. Under the circumstances of accelerating the construction of human resources market and further invigorating the flow of human resources, the government must improve and strengthen the management and supervision of the whole process of human resources market activities, create a fair, open and just competitive environment, and realize the standardized and orderly operation of the market.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding this work.

Acknowledgments

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