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Research Article

Data-Driven Optimal Scheduling Algorithm of Human Resources in Colleges and Universities

Cong Liu

Department of Business Administration, Weifang University of Science and Technology, Shandong 262700, China

Correspondence should be addressed to Cong Liu; liucong@wfust.edu.cn

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At present, the development process of human resource management in Colleges and universities in China has gone through a period of time. In the whole process, the mode of human resource management in colleges and universities is gradually maturing, but there are also some problems. In this paper, data-driven stochastic optimal scheduling algorithm and robust optimal scheduling algorithm are used to model and analyze the human resources. Then, the two models are applied to the human resource management of Nanjing University and Southeast University. The data optimization results show that the robust optimal scheduling algorithm is helpful to the management of new teachers, while the random optimal scheduling algorithm can improve the management of teachers who have been in service for a long time, but there are still some disadvantages. If the combination of two data-driven scheduling algorithms is adopted, it can manage the human resources of colleges and universities well. In short, this paper provides some theoretical and experimental support for the specific application of data-driven human resources optimal scheduling algorithm in colleges and universities.

1. Introduction

With the rapid development of society and the gradual expansion of market economy, the competitiveness between colleges and universities is becoming more and more fierce [1]. Strengthening human resource management is not only conducive to the creation of talents, but also conducive to the rapid development of colleges and universities [2, 3].

With the reform of education system and the continuous progress of higher education, human resource management is important for universities at this stage, such as faculty incentive system, work analysis report, performance appraisal, personnel training and employment, etc. Meanwhile, some universities have also introduced many innovative teacher teams to drive the overall development of the school. These measures reflect the importance that colleges and universities attach to human resource management [4–6]. In addition, some colleges and universities still encourage teachers to carry out higher academic discussion and learning, and constantly improve the whole human resource management system. Although colleges and universities have made great contributions and reforms in human resource management, some problems are still inevitable. We need to analyze these problems and make relevant countermeasures.

In my opinion, the problems of human resource management are as follows [7–9]: (1) the performance appraisal index is unscientific. The core content of efficient human resource management is performance appraisal. In some universities, the appraisal system of many schools is difficult to determine, which also leads to the difficulty of evaluating the performance of many teaching staff in the teaching process and cannot improve the enthusiasm of teachers, affecting teachers' teaching quality. (2) The talent introduction mechanism is not perfect. The talent introduction mechanism is an important work of human resource management colleges and universities will hold recruitment fairs for personnel recruitment only if there is a teacher gap in one of their majors. Colleges and universities blindly introduce personnel when recruiting teachers and workers, without considering the majors of the school at all development. In addition, when introducing faculty, many colleges and universities often only pay attention to their diplomas, but do not consider their own value and strength. (3) The mobility of human resources is poor. Most colleges and universities are generally divided into three levels in the implementation of management. The first level is the school, the second level is the college, and the third level is the Department. Generally, the notice is issued by the school level, and then completed by the college and department, which leads to poor mobility of human resources. (4) Talent training is not in place. Some colleges and universities only attach importance to the introduction when recruiting personnel, but they often ignore the introduction and ignore the later training of teachers, resulting in imperfect human resources management.

The data-driven concept was first proposed by the United States and applied to the upgrading and improvement of complex production and operation systems. It believes that the data-driven optimization system should have the ability to obtain, process, and use data under real-time conditions, so as to improve the comprehensive benefits of operation [10]. To evaluate whether an optimization system is combined with the data-driven concept, we can evaluate the measurement from the following three aspects [11, 12]:

(1) Ways to obtain data: that is, to obtain relevant data in real life based on practical problems;

(2) Degree of using data: that is, the impact of the obtained data on system decision-making. Among them, effective data processing is the core and key of decision support system embedded in data-driven concept. At present, there are three basic means to optimize the design and improvement of human resources in colleges and universities: basic theoretical innovation, mathematical modeling and theoretical empirical application. With the in-depth research, popularization of data-driven concepts, Figure 1 shows the relationship between them has changed to some extent.

In the traditional scheduling system, the theory, modeling and demonstration are independent, separated and serial, and are weakly connected to each other; The data-driven scheduling system adds real-time information that can reflect the current real situation of the system in the process of scheduling plan formulation and implementation, so as to provide more accurate and reliable prediction and support for the decision-making of the system, so as to make the scheduling scheme closer to reality [13]. Through the interactive transmission of data, it gradually changes the relationship between modeling solution and empirical application from weak connectivity to strong connectivity. According to the variation characteristics of acquired data and the number of data feedback, the dispatching system can be divided into three categories [14–16].

1.1. Traditional Dispatching System (TDS). The traditional scheduling system relies on the solution of the optimal scheduling problem of human resources to formulate the scheduling plan. It knows all kinds of internal information of the depot and customers before the scheduling plan is formulated.

1.2. Single Feedback Scheduling System (SFSS). The single feedback scheduling system makes the scheduling plan based on the solution of the university human resources scheduling problem with single information feedback. Before making the scheduling plan, it can not only obtain internal information but also obtain information reflecting different colleges and universities. The given scheduling plan is the only feedback for decision-making combined with data.

1.3. Real Time Feedback Scheduling System (RFSS). The scheduling system relies on the data of multiple information feedback to optimize the solution of human resource scheduling problem and formulate scheduling plan. Based on the single feedback scheduling system, it increases the real-time acquisition of human resources data in colleges and universities to adjust the scheduling plan in real-time [17].

In general, the traditional scheduling system makes a plan in advance and has no follow-up. The single feedback scheduling system is not only forward-looking but also comprehensive, while the real-time feedback scheduling system is upgraded on the basis of the single feedback scheduling system and has real-time dynamics.

The difference between the scheduling plan given by the three types of systems and the actual implementation benefits is shown in Figure 2.

Among them, the benefit gap between the TDS system scheduling plan and the actual situation is Δa, the SFSS system is Δb, and the RFSS system is Δc. When combined with static data, the benefit gap between the scheduling plan and the actual situation is narrowed by Δa-Δb, And as the dynamic data feedback process continues, this benefit gap will gradually narrow until $\Delta c \longrightarrow 0$.

As we all know, there are also many positive results in the scheduling problems research in different universities, However, the following problems deserve attention [18]: (1) the calculation accuracy of the model is low and the deviation is large, which brings some difficulties to the specific implementation; (2) the solution efficiency is low and the running time is long; (3) due to the lack of knowledge guidance, it is more limited in the selection of scheduling optimization objectives and rules and cannot comprehensively consider the scheduling performance indicators. Hou et al. [19] improves the representation method of traditional scheduling system, which is widely used in colleges and universities resources are used more and more widely. Ning et al. [20] studied the single feedback scheduling system, and discussed the methods of human resource optimization in detail. By defining the ontology of human resources in different colleges and universities, through the detailed study of the scheduling system, the real-time feedback scheduling system is selected, the human resources model is established, and the method of optimizing human resources management is put forward. Ning et al. [21] propose the traditional

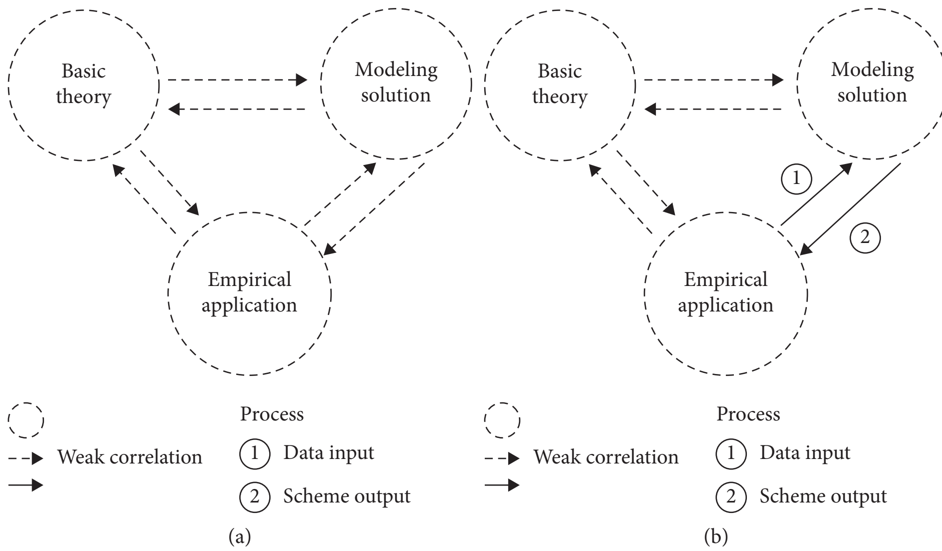

Figure 1: Components of dispatching system.

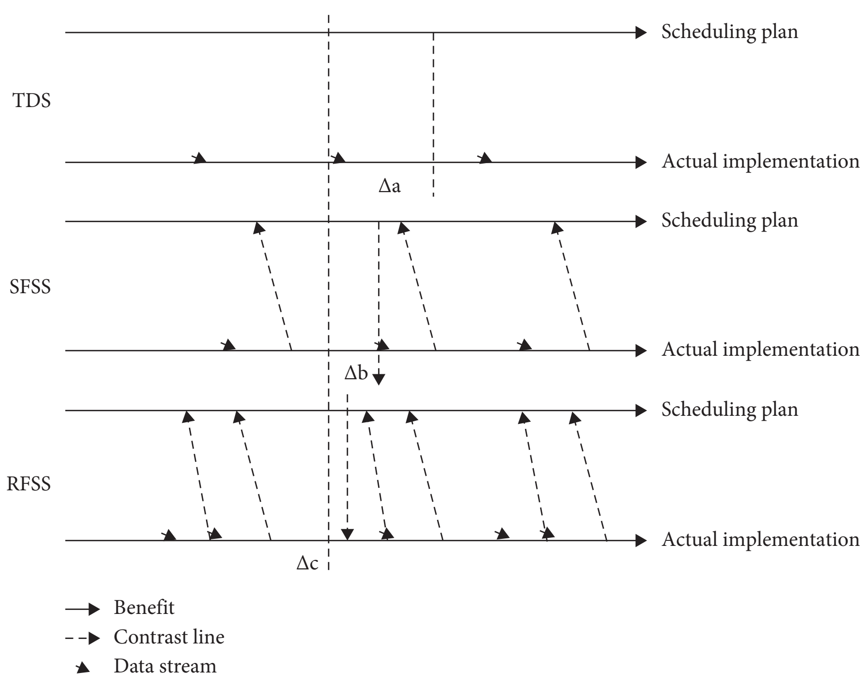

Figure 2: Gap between scheduling plan and actual implementation.

scheduling algorithm, binary regression model is combined to obtain the parameter learning model of adaptive scheduling rules to meet the needs of dynamic scheduling. Shang et al. [22] introduce the application of data-driven method in optimal power flow problem and do not deeply discuss the random variable modeling and corresponding optimization problem solving methods.

This paper focuses on data-driven uncertainty modeling and optimal scheduling methods, and systematically combs the application status of data-based random optimization and robust optimization in human resource scheduling in colleges and universities. Firstly, the probability distribution modeling method of random variables based on data in stochastic optimization is introduced. Secondly, the data-driven uncertainty set modeling and its robust optimization problem solving methods are summarized. Then, the construction method of probability distribution fuzzy set based on data is described, and the corresponding modeling, solution method and application scenario in human resource scheduling are analyzed.

2. Data-Driven Optimization

2.1. Data-Driven Stochastic Optimization (DDSO). Stochastic optimization method is widely used to solve power system decision-making problems considering uncertainties. Typical stochastic scheduling problems of human resources in colleges and universities include stochastic OPF, stochastic economic scheduling, stochastic unit commitment, etc. Taking a commonly used stochastic unit commitment problem as an example, this paper expounds the modeling idea of stochastic optimal scheduling. Considering that the contents of different colleges and universities are different, and human resources need to be optimized for different colleges, the equation is as follows:

$$\min_{x\in X} g(x) + E_P\left(\min_{y\in\Omega(x,\xi)} f(y)\right), \tag{1}$$

where X is the stage 1 decision-making variable, indicating the talent distribution of human resources in different colleges; X is the feasible region of x; *g(x)* is the objective function of the first stage optimization problem; ξ is a random variable; P is the ξ probability distribution; y is the stage 2 decision variable; *f (y)* is the objective function of the second stage optimization problem; Ω(x, ξ) is the feasible region of y; and EP (·) indicates the expected value.

It can be seen from (1) that the human resource management depends on the specific implementation. *g(x)* is the objective function of the first stage optimization problem, which represents the distribution of human resources among universities. *f(y)* represents the distribution of human resources among colleges. For the stochastic optimization problem (equation (1)) through sampling random variables and scene reduction, typical operation scenarios and their corresponding probabilities are obtained, so that the stochastic optimization problem can be transformed into a scenario based optimization problem for solution, and the deterministic current human resources optimization conditions can be obtained. For other scheduling problems such as human resources and reserve optimization in colleges and universities, a stochastic optimization problem considering uncertain factors can be established in a similar way, and a deterministic scheduling scheme can be obtained.

In traditional stochastic scheduling, It is generally assumed that random variables obey a given probability distribution (for example, it is assumed that the personnel age error follows the normal distribution) to achieve the parameter modeling. Therefore, the parameter probability distribution models such as normal distribution and Weibull distribution are often difficult to accurately describe the uncertainty actual changes in factors. However, when adopting data-driven stochastic optimization, the improved modeling methods are mainly divided into the following categories: (1) nonparametric probability model, which does not limit the distribution characteristics and parameters of random variables, but obtains its statistical information from a sample of random variables. Compared with the parameter probability model, it has higher accuracy. (2) Stochastic process model, which is used to describe the change characteristics of random variables over time, and is often used for renewable energy generation power and load forecasting. (3) Artificial intelligence-based scene generation methods. Artificial intelligence methods have strong data feature mining capabilities. Based on existing data, they directly generate uncertain scenes that conform to temporal and spatial characteristics, instead of using the method of "probability distribution establishment-sample acquisition-scene reduction" to obtain typical scenes. Therefore, establishing a more accurate uncertainty factor model based on the actual data can improve the applicability of the decision-making scheme.

2.2. Data-Driven Robust Optimization (DDRO). Robust optimization uses the uncertainty set to represent its variation range, and seeks solutions with good performance for all implementations of uncertainty factors. Traditional robust optimization makes decisions directly according to the worst scenario in the uncertainty set, so the optimization results are highly conservative. The decision-making process of adaptive robust optimization (ARO) is adjusted based on the actual changes of random variables, and it has achieved good application results in the optimal management of human resources among different colleges and universities in recent years, which is worthy of our detailed analysis and research. The two-stage dispatching problem based on ARO can be expressed as

$$\min_{x\in X} g(x) + \max_{\xi\in U}\left(\min_{y\in\Omega(x,\xi)} f(y)\right), \tag{2}$$

where U is the uncertainty set of random variable ξ.

It can be seen from (2) that the setting of the uncertainty set significantly affects the robust optimization results. The commonly used is budget parameters, namely,

$$U = \left\{\begin{array}{c} \xi|\xi_i = \mu_i + \Delta\xi_i z_i - 1 \le z_i \le 1, \\ \sum_i |z_i| \le \Gamma, \quad \forall i \end{array}\right\}, \tag{3}$$

where ξ_i is the i-th random variable, μ_i is the expectation of ξ_i, $\Delta\xi i$ is the maximum change range of ξi. z_i is an integer variable, and G is the uncertainty budget parameter.

In the optimization problem with multiple random variables, only considering the upper and lower limits of the uncertain factors can hardly reflect the true range of changes, and the decision-making scheme is relatively conservative. Literature introduced other uncertainty set modeling methods, such as the ellipsoid uncertainty set considering the correlation of random variables. In recent years, some scholars have tried to mine the range of random variables from data, and proposed various methods to reduce the conservativeness of robust optimization.

2.2.1. Polyhedral Uncertainty Set. Ning et al. [23] finely modeled the polyhedral uncertainty set in robust scheduling. According to the human resource management between colleges and universities, combined with the management of new employees and old employees, and optimized the model. A data-driven dynamic uncertainty set is established as follows:

$$U = \left\{\xi_t | \underline{\xi}_t(\xi_{t-1}) \le \xi_t \le \overline{\xi}_t(\xi_{t-1}), \quad \forall t\right\}, \tag{4}$$

where ξ_t is the random variable at time t, $\overline{\xi}_t$ and $\underline{\xi}_t$ are the upper and lower limits of the random variable ξ_t at time t, which are related to the realization of the random variable at time t-1.

Wang et al. [24] aimed at human resource scheduling and planning among colleges and universities, used kernel density estimation to establish the probability density function of the source load, and then constructed an uncertainty set containing budget parameters based on the quantile, namely,

$$U = \left\{ \begin{array}{c} \xi | F_i(\alpha) \leq \xi_i \leq F_i(1-\alpha), \quad \forall i, \\ \xi | \sum_i (1-\eta_i \mathrm{T})\mu_i \leq \sum_i \xi_i \leq \sum_i (1+\eta_i \mathrm{T})\mu_i \end{array} \right\}, \tag{5}$$

where $F_i(\alpha)$ is the quantile of ξ_i under the confidence level α and η_i is the relative deviation value of ξ_i. All the above parameters can be estimated by kernel density.

Considering the uncertainty of human resource optimization in colleges and universities, only one set may not be accurate enough to describe the variation range of uncertain factors. Therefore, Zhu et al. [25] use Dirichlet process hybrid model method to cluster wind power data, then establishes each cluster as a basic uncertainty set U_j, and finally represents the wind power uncertainty set as the union of all basic uncertainty sets.

$$U = U_1 \cup U_2 \cup \ldots \cup U_j \cup \ldots \cup U_J. \tag{6}$$

The basic uncertainty set $U_j (j = 1, 2, \ldots, J)$ is

$$U_j = \left\{ \xi_j | \xi_j = \mu_j + s_j \sqrt{\Psi_j} \Lambda_j \|\delta\|_\infty \leq 1, \quad \|\delta\|_1 \leq \Gamma_j \right\}, \tag{7}$$

where ξ_j is the random variable in the uncertainty set U_j and μ_j is the expectation of the random variable ξ_j. s_j and Ψ_j are the parameters of the j-th basic uncertainty set. Λ_j is the scale factor, δ is the random noise. $\|\cdot\|_\infty$ and $\|\cdot\|_1$ respectively represent infinite norm and 1-norm function. Γ_j is the uncertainty budget parameter of the uncertainty set U_j, and the fluctuation range of δ is controlled by Γ_j, thereby changing the uncertainty set size.

The robust optimization problem based on the uncertainty set ((7) is

$$\min_{x \in X} g(x) + \max_{j=1,2,\cdots,J} \left(\max_{\xi_j \in U_j} \left(\min_{y \in \Omega(x,\xi_j)} f(y) \right) \right). \tag{8}$$

Among them, the second stage optimization problem makes decisions for the worst scenario in all basic uncertainty sets.

2.2.2. Ellipsoidal Uncertainty Set. Yang et al. [26] established an ellipsoid uncertainty set considering the correlation of different universities in the optimization of human resources in universities, namely,

$$U = \left\{ \xi | (\xi - \mu_0)^T \sum_0^{-1} (\xi - \mu_0) \leq \Gamma \right\}, \tag{9}$$

where μ_0 is the expectation of the random variable ξ and Σ_0 is the covariance matrix of the random variable ξ.

Compared with the polyhedral set, the ellipsoid set considers the correlation between random variables, and is more suitable for optimal management of human resources among different universities and its data analysis. On the other hand, the uncertainty set of the ellipsoid is expressed as a quadratic constraint.

2.2.3. Constructing Uncertainty Sets Based on Scenarios. In addition to polyhedron and ellipsoid uncertainty sets, another common method is to construct uncertainty sets based on extreme scenes. Literature [44] proposed an adaptive uncertainty set modeling method based on extreme scenario screening. Firstly, based on the source load historical data of human resources among colleges and universities, an ellipsoidal uncertainty set is established, and several boundary points are selected as the initial extreme scenario. Then, the scale factor is introduced to expand the convex set with the initial extreme scene as the vertex until it covers all the data. Finally, the corrected uncertainty set is obtained. The established robust optimization problem can be expressed as a deterministic model based on extreme scenarios, namely:

$$\begin{cases} \max\limits_{\xi_n \in U_{\text{new}}} & \left(\min\limits_{x,y_n} f(x, y_n, \xi_n) \right) \\ \text{s.t.} & \begin{array}{l} A(x, y_n, \xi_n) = 0, \quad n = 1, 2, \ldots, N \\ B(x, y_n, \xi_n) \leq 0, \quad n = 1, 2, \ldots, N. \end{array} \end{cases} \tag{10}$$

Here ξ_n is the random variable in the nth extreme scene, U_{new} is the corrected extreme scene set, including N extreme scenes. y_n is the variable under the nth extreme scene. A(·) and B (·) is the constraint condition of the optimization model. The analysis of calculation examples shows that using the selected extreme scenes instead of the traditional uncertainty set to participate in the optimization decision-making, while ensuring the robustness of the decision-making scheme to reduce its conservativeness.

Another method of constructing uncertainty sets based on extreme scenes does not presuppose the shape of the uncertainty sets, but expresses the uncertain sets as the convex hull of the historical scene, namely,

$$U = \left\{ \xi | \xi = \sum_{n=1}^{N} \alpha_n \xi_n \sum_{n=1}^{N} \alpha_n = 1, \quad \alpha_n \geq 0 \right\}. \tag{11}$$

Here, α_n is the weight parameter of the nth extreme scene.

In my opinion, polyhedral uncertainty set can combine different factors to make data optimization more accurate. Ellipsoidal uncertainty set increases the connection between data and makes it compact, and constructing uncertainty set based on scene greatly reduces the conservative type of robust optimization and has good predictability.

Generally, the advantage of data-driven is that the quantity demand is low and the out-of-sample performance is better. However, because the statistical information (probability distribution, statistical moment, etc.) represented by the data is not considered in the uncertainty factor modeling process. Based on data-driven stochastic optimization, a more accurate uncertainty factor model can be established, but the optimization results are still relatively conservative, which is suitable for result analysis in a short time. Data-driven robust optimization makes use of the statistical information of random variables, which can improve the adaptability of decision-making schemes, and is suitable for solving the day ahead and day in scheduling problems that pay attention to safety for a long time. The data diagram of the two optimal scheduling algorithms is shown in Figure 3.

3. Results and Discussion

In this paper, the human resources of Nanjing University and Southeast University, two double first-class universities in Nanjing are selected for analysis, and then data-driven stochastic optimization and robust optimization are used for scheduling algorithm calculations, and the corresponding data is used to predict the management methods of human resources in universities.

Figure 4 shows the changes in human resource optimization data among different universities using a data-driven stochastic optimization scheduling algorithm. From this, it can be seen that the human resource optimization data between the two universities has changed drastically and the correlation is poor, indicating that the human resource management between the universities is poor and the structure of human resources is unbalanced. The main reasons may be: (1) some colleges and universities have a surplus of general teachers and a shortage of high-tech talents, a shortage of scientific research teachers and a surplus of teaching teachers, young teachers are overburdened and experts and professors are idle, and there are relatively many professional teachers in traditional subjects. (2) The structure of teachers and nonteachers is unreasonable. At present, there are generally bloated administrative institutions and low efficiency in colleges and universities, and there are more administrative staff and service personnel than teachers. This has caused the administrative department to overwhelm and overburden the work of teachers. The excessive expansion of the administrative management and logistics departments of colleges and universities has dispersed valuable education funds, diluted the teaching and scientific research-oriented school mission, and seriously affected the efficiency of schooling. (3) The internal structure of teachers is unreasonable. The current contradiction in the structure of teachers is prominently manifested as the proportion of teachers with high academic qualifications is too small: the proportion of teachers with high professional titles is too low, the age gap of teachers and the phenomenon of "inbreeding" are serious. (4) The quality of introduced talents is inconsistent, and the unified management of colleges and universities is not used, which hinders the development of colleges and universities to a certain extent. Therefore, the results of data-driven optimization show that it is necessary to change the allocation of human resources among universities, rationally arrange the distribution of human resources, increase the utilization rate of human resources, so as to "make the best use of things and people do their duty", promote the cultivation of talents in colleges and universities.

Figure 5 shows the optimized data values between different colleges obtained by using the data-driven robust optimal scheduling algorithm. It can be seen that the robustness optimization data of different colleges and universities are not the same. Through the comparative analysis of the school of chemistry, the school of physics, the school of art and the school of mathematics, the human resources of each college are different. Among them, for Nanjing University, the school of mathematics has the best human resources and Higher Teacher Allocation and management level. For Southeast University, the human resource management of the school of chemistry is better, followed by the school of mathematics, and the worst of the school of art, which shows that the school of art needs to further strengthen optimization of human resources. Data driven optimal scheduling algorithm can scientifically analyze the relevant data information of colleges and universities, so as to give a more comprehensive, objective and reasonable prediction, provide reference basis for colleges and universities to make decisions, make decisions more scientific and reasonable, and have higher practical value. Therefore, the impact of data-driven optimal scheduling algorithm is not single and short-term, but will have more far-reaching positive significance in a larger field. So we should actively establish an information-based human resource management mechanism, make overall arrangements and coordinated planning for various works, and strengthen the contact between different departments.

Figure 6 shows the data optimization ratio of human resources among different universities. It can be seen that the optimization ratio and correlation based on different data-driven scheduling algorithms are inconsistent. Among them, for the human resources in Southeast University, the rate of data-driven robustness optimization is higher, followed by Nanjing University. However, when both colleges and universities adopt data-driven stochastic optimization for scheduling algorithm, the optimization ratio and correlation are the worst, which shows that data-driven robust optimization is helpful to improve the management optimization of human resources. The universities should be actively established a teacher salary distribution system that can reflect their own advantages, meet the post characteristics and professional difficulties, and expect to attract, retain and motivate excellent talents through relevant system reform. In this way, teachers in different universities have different work enthusiasm. After the optimization of human resources, they can achieve the people-oriented management concept, reasonably optimize the performance appraisal, improve the incentive mechanism through the principles of performance distribution and distribution according to work, and evaluate according to the post category of teachers, discipline category of schools and teaching results, Material and spiritual rewards shall be given to the teaching staff through performance evaluation. In the assessment process, we must be fair, just and open. In the implementation, we should also make full use of this performance

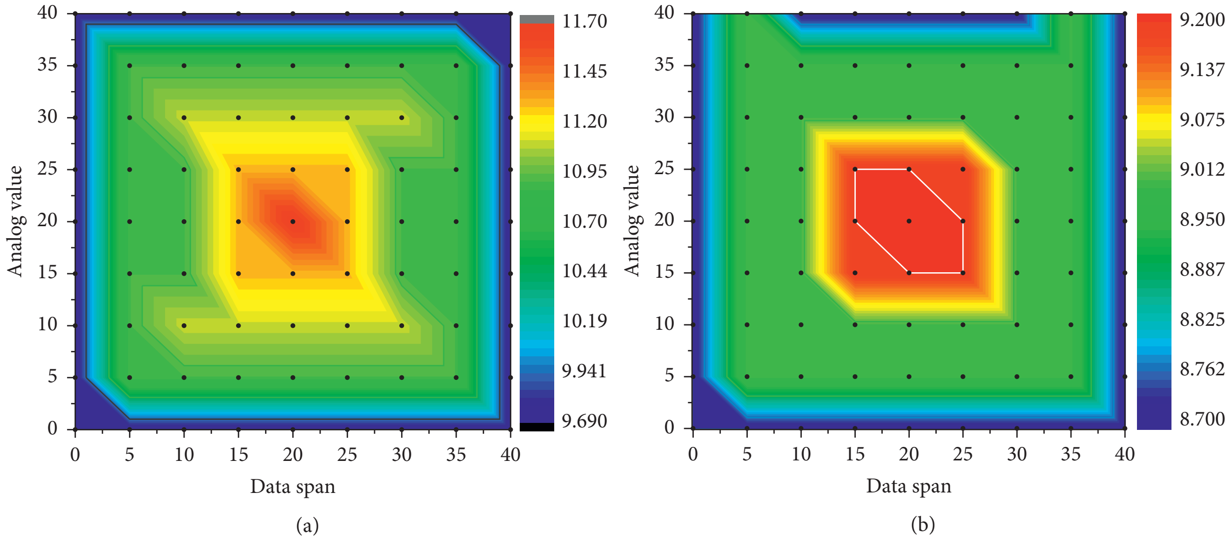

FIGURE 3: Changes in analog values driven by different data. (a) DDSO, (b) DDRO.

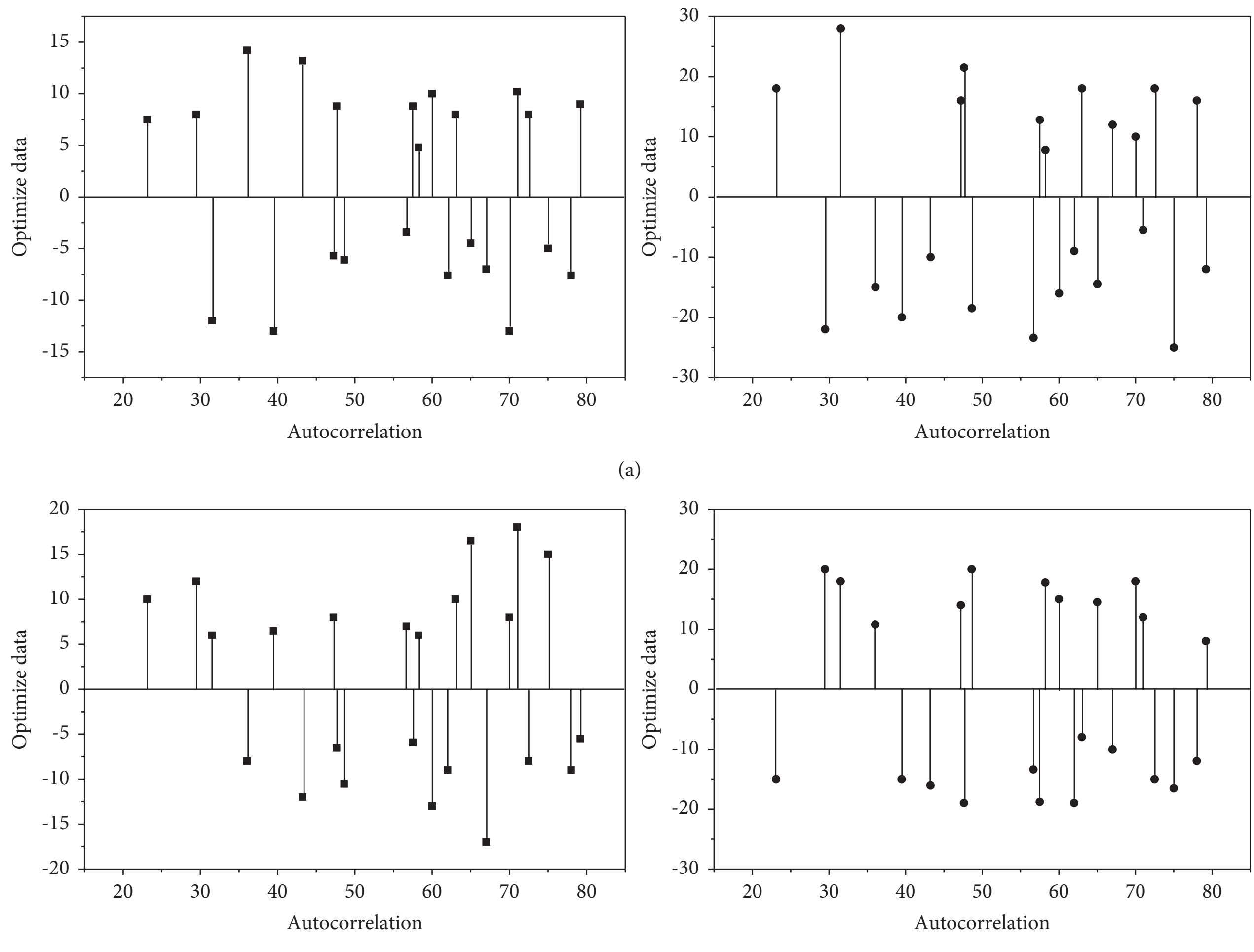

FIGURE 4: Changes of optimization data among different universities. (a) Nanjing University, (b) Southeast University.

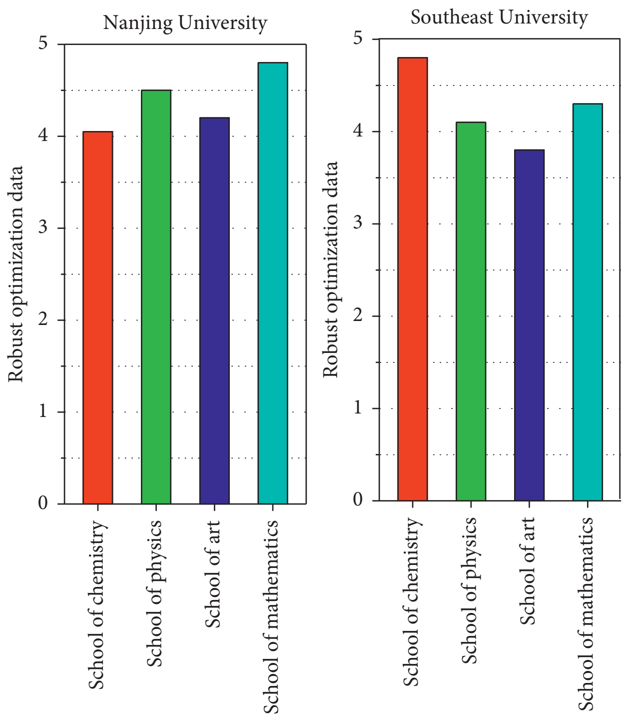

Figure 5: Data driven robust scheduling results among different schools.

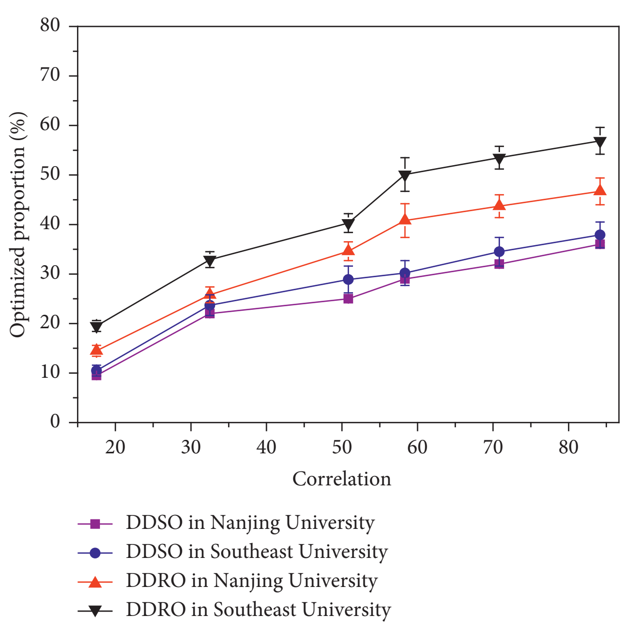

Figure 6: Optimal proportion of human resources driven by data among different universities.

reform mechanism to encourage faculty and mobilize their enthusiasm.

Figure 7 shows the optimization values obtained by data-driven random optimization. It can be seen that with the increase of simulation data, the random optimization values of the two universities tend to be stable, which shows that for

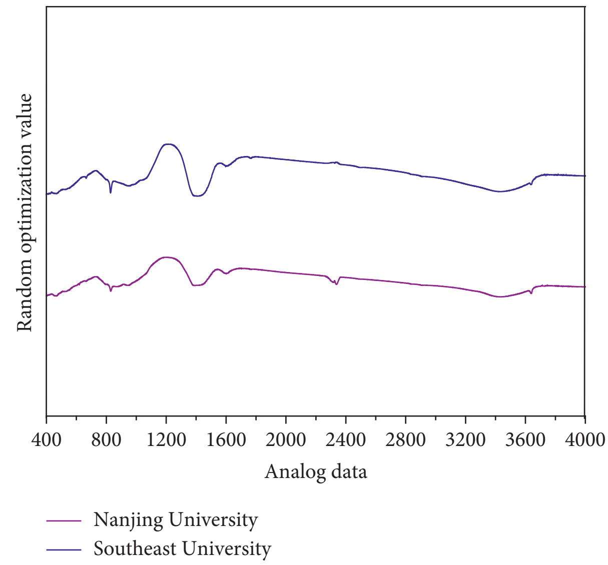

Figure 7: Random optimization values of different universities based on data-driven.

human resource management among different universities, after using the data-driven random optimization scheduling algorithm, human resources have an adaptive management period. At this time, the optimization values change greatly and fluctuate up and down. Then, with the continuous increase of simulation data, the optimized value reaches a good range. If data-driven robustness optimization is used for scheduling algorithm analysis, the results are shown in Figure 8. When the simulation data increases, the optimization value shows a gradual downward trend. When the simulation data reaches a certain value, the optimization value suddenly decreases, and then gradually becomes stable, which shows that the data-driven robust scheduling algorithm can be applied to early human resource management. When more than a certain number of years, the data-driven stochastic scheduling algorithm can be used, and the results are more accurate.

Therefore, the data-driven stochastic optimal scheduling algorithm can well predict the management of human resources. At the same time, strengthening human resource management in colleges and universities also needs to change the concept of human resource managers, improve their understanding and improve the whole management team. In the work, it is emphasized that managers should “not be perfunctory, establish a new awareness of human resource management”, and put the methods and measures in the right position. Therefore, colleges and universities should establish the management concept of “people-oriented”, tap school talents in the learning process, look out talents, and mobilize the initiative and enthusiasm of teaching staff, so as to improve the efficiency of efficient human resource management.

Figures 9 and 10 show the data-driven statistical analysis results of human resources optimization and simulation values of different data-driven optimal scheduling algorithms among different universities. It can be seen that for the two universities using data-driven random optimal

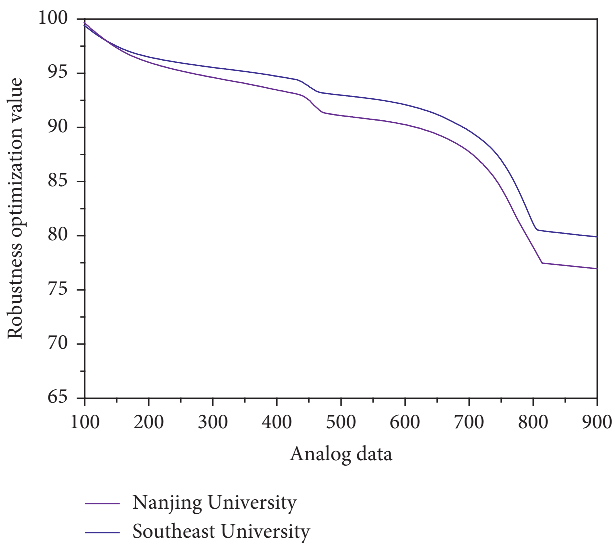

Figure 8: Robust optimization of different universities based on data-driven.

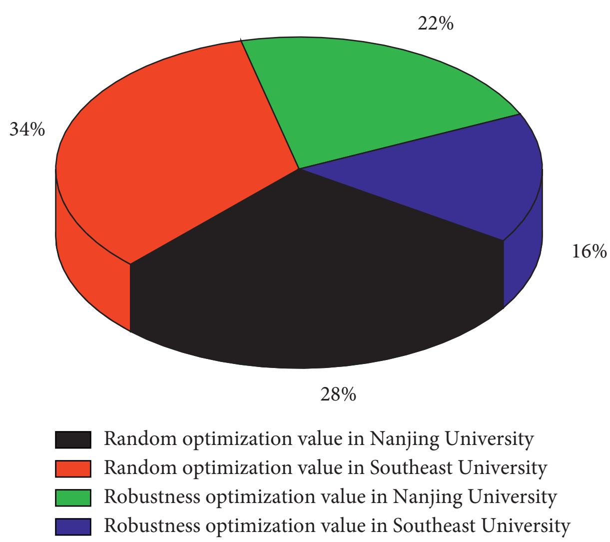

Figure 9: Data driven statistics of human resource optimization among different universities.

scheduling algorithm and robust optimal scheduling algorithm, the proportion is different. Among them, the random optimal scheduling algorithm of Southeast University accounts for a large proportion in human resource management, while the robust optimal scheduling algorithm of Nanjing University is higher. The main reason may be that there are many new employees in Southeast University. In the actual management process, random optimal scheduling algorithm will be selected, while there are few introduced talents in Nanjing University, and robust scheduling algorithm is better for modeling and analysis. Therefore, we can consider the combination optimization of the two data-driven scheduling algorithms, so as to better predict the optimal management of human resources. In general, human resource management in the universities is of great

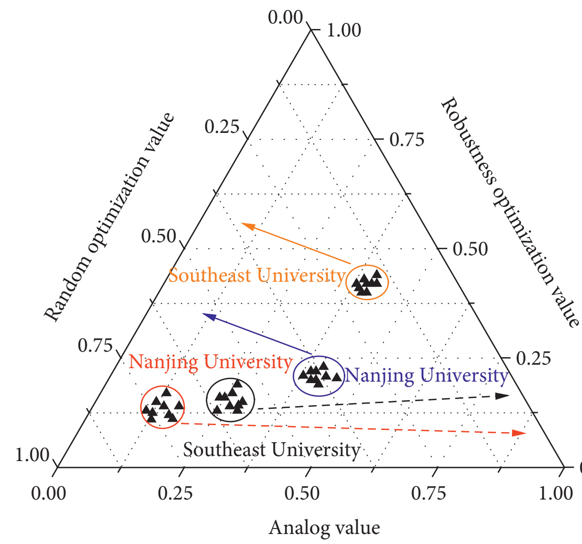

Figure 10: Simulation values of different data-driven optimal scheduling algorithms among different universities.

development and significance to both the school itself and the society, which can quickly promote the development of colleges and universities and improve the competitiveness. To strengthen the countermeasures of human resources management, we need to change the concept of managers, optimize the efficient allocation, increase the mobility of resources, reasonably improve the teacher performance appraisal system. Meanwhile, we should fully tap the potential of teachers, practice the concept of people-oriented, and promote the sustainable development of colleges and universities.

4. Conclusion and Outlook

In general, the article uses data-driven optimal scheduling algorithm for prediction and analysis, mainly including data-driven random optimal scheduling algorithm and data-driven robust optimal scheduling algorithm. Then, the modeling and calculation process of the two scheduling algorithms are discussed in detail, and two data-driven scheduling algorithm models are obtained. Next, the two scheduling algorithms are applied to two “double first-class universities” in Nanjing (Nanjing University and Southeast University), the article analyzes the effect of different optimal scheduling algorithms on the human resource management of the two universities. The results show that the robust optimal scheduling algorithm can be used for prediction and analysis for teachers with short entry time, while the stochastic optimal scheduling algorithm needs to be used for teachers with long entry time. After the optimization combination of the two scheduling algorithms, it is helpful to improve the efficiency Management of human resources.

Data Availability

The 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.

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