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Research Article

Research on Demand Forecasting of Engineering Positions Based on Fusion of Multisource and Heterogeneous Data

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Aiming at the project demand forecasting problem based on multisource data fusion, a multisource heterogeneous data fusion model is established, and the unified quantitative representation method of heterogeneous data based on triangular fuzzy numbers is studied, and the ordered weighted average operator is used to integrate the preferences of decision-makers. A multisource heterogeneous data fusion algorithm that supports multiuser decision-making is designed. Based on the analysis of the internal and external environment of human resources in a company's engineering positions, this paper qualitatively analyzes and selects the factors affecting the demand for talents in key positions in a company based on the characteristics of demand influencing factors and finds out the quantifiable and influential factors from the representative factors of talent demand for key positions in a company. Using historical data, statistical methods are used to process the eight related factors of a certain company, which confirms the factors that have a greater impact on the demand for talents in key positions of a company and influences the demand for talents in key positions in companies of the same type. The identification of factors provides a basic argument for a company. According to the results of statistical analysis and the characteristics of existing data, two variables of factory output and time are selected to be used in regression analysis forecasting model and gray system forecasting model of a certain company to predict the demand for key talents of a certain company. The company finally adopts combined forecasting. The method determines the predicted value of the talent demand for a certain company's key positions. According to the results of demand forecasting and the current status of human resource management in a company, this article proposes a company's key position talent management planning measures, in order to provide a reference for the management of a company's key company position talents and ensure a company's key company positions in the future talent demand reserve.

1. Introduction

In the process of enterprise informatization construction, due to the phased, technical, and other economic and human factors of the construction of various business systems and the implementation of data management systems, enterprises have accumulated a large number of business data in different storage methods during the development process. Data fusion is the multilevel, multifaceted, multilevel processing and combination of multiple sets of sensor data obtained from the same target to generate new meaningful information. The sensor here is in a broad sense, generally referring to the relevant databases of various data acquisition systems. Data fusion is a processing method of multisource information. Simply put, data fusion is a comprehensive algorithm of multiple data. The purpose of processing is to reason and identify the obtained information and make estimates and judgments accordingly. By fusing multisensor data, confidence can be increased, ambiguity can be reduced, and system reliability can be improved [1–7].

Data fusion originated in the 1970s, initially out of military needs, and rapidly expanded to areas such as automatic control, medicine, intelligent buildings, and commerce in research. The analysis objects are also extended from physical goals to information goals and even cognitive goals. The theoretical basis of data fusion is information theory, detection and estimation theory, statistical signal theory, fuzzy mathematics, cognitive engineering, systems engineering, and so on. In 1986, Joint Directors of Laboratories established a function-oriented basic model and basic terminology, and in 1998, it was further improved. Although the JDL model is based on military proposals, it is also suitable for other application fields. The JDL model does not involve system structure. Bowman et al. extended this and proposed the concept of hierarchical data fusion tree, dividing the fusion problem into nodes [8–16]. Each node conceptually includes functions, such as data association, correlation, and evaluation. On this basis, Boss 6 colors further developed and proposed a set of modeling and simulation methods to realize the design of data fusion system, as can be seen in Figure 1, which mainly explains the whole system of data fusion system and its content.

Data fusion is essentially an integrated process of using computers to process, control, and make decisions on various information sources. The functions of the data fusion system mainly include detection, correlation, identification, and estimation. Data fusion can be divided into five levels: detection-level fusion, location-level fusion, attribute-(target recognition-) level fusion, situation assessment, and threat estimation. Related to this article is mainly the attribute -level fusion, also known as target-recognition-level fusion. It refers to the combination of target recognition data from multiple sensors to obtain a joint estimation of target identity. Attribute-level fusion uses multiple sensors to collect the data of the observed target, performs feature extraction and data combination, grouping the same target, and then using the content algorithm to synthesize the grouped data of the same target, and finally gets the joint attribute judgment of the target. That is, the type and category of the target are obtained. According to different fusion locations, attribute-level fusion is divided into three methods: decision-level fusion, feature-level fusion, and data-level fusion [17–20].

So far, researchers have proposed more than 30 data fusion models; the most cited is the JDL model of the US Department of Defense. Many mature applications of these models have appeared in the fields of target tracking, image fusion, and so on, but there are relatively few applications in data mining and natural language processing. Data fusion technology is an emerging interdisciplinary comprehensive theory and method. After decades of development, breakthrough progress has been made, but there are still many problems. For example, there is no unified definition, lack of systematic and complete basic theory, and so on. To sum up, in the face of the emerging scientific theory and method of data fusion, it is necessary to conduct in-depth systematic research on the existing data fusion technology and find its fit with the field of natural language processing from both theoretical and practical levels.

There are documents that have studied multisensor data fusion technology based on statistics and artificial intelligence methods and others that have studied the organization and management of multisource heterogeneous data in mobile geographic information systems and have established multisource heterogeneous data fusion models. The combination of sensor network and data fusion technology proposes a Kalman filter batch estimation fusion algorithm; some literature has studied the fusion method of massive multisource heterogeneous data in the Internet of Things environment and has been successfully applied in the process of target positioning and tracking. The literature has studied the intelligent maintenance decision-making architecture of the high-speed rail signal system based on heterogeneous data fusion, which has improved the accuracy and effectiveness of decision-making. Someone has studied the multisource heterogeneous data fusion technology in the construction of digital mines, ensuring that the construction of digital mines is in progress. The basic information platform is safe, stable, and efficient [21–25].

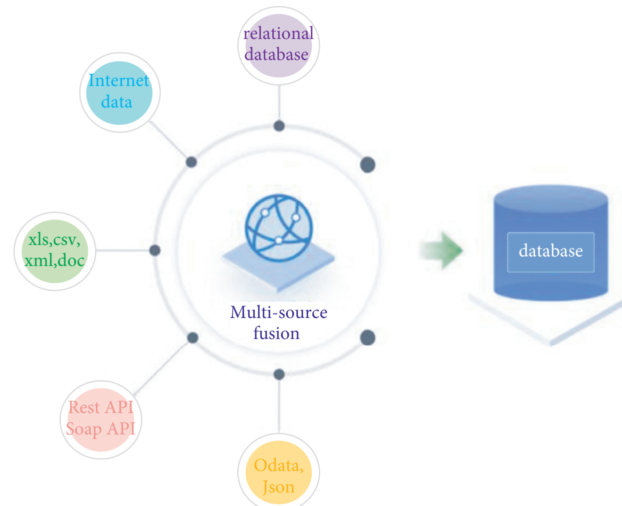

Figure 1: Data fusion system.

The type and structure of the fusion data is limited, and most work only incorporates an additional type of auxiliary information, which has domain limitations and sometimes relies on rules and expert knowledge and high labor costs. The more sufficient the auxiliary data is, the more comprehensive the hidden representation of users and items can be obtained. In the recommendation prediction, the rich feature relationship between the two can be integrated to obtain more accurate results. The structural dimensions of different data sources are also different, and the distribution of data is also very different, which also increases the difficulty of integrating more data in breadth. Including the adopted data management system is also very different; from simple file database to complex network database, they constitute the heterogeneous data source of the enterprise.

The fusion method is relatively preliminary, and the barriers between heterogeneous data have not been broken. In a related research, linear transformation is performed in the hidden semantic space of multisource data, and the method of adding and multiplying is used to integrate into the recommendation model, and it is impossible to fit the relationship between complex multisource heterogeneous data. To make matters worse, other auxiliary data may contain other information that has nothing to do with the recommendation. The mechanized fusion will introduce unnecessary noise, which will reduce the accuracy of the recommendation model. In addition, multisource data only supplements the characteristics of the recommendation model itself, and the feature information between each multisource heterogeneous data source also lacks in-depth interaction and cannot achieve synergistic effects [26–29].

In addition to numerical data, there are other description forms such as language or symbols. Various descriptions lead to the ambiguity, difference, and heterogeneity of the structure and semantics of the data information. On the other hand, the decision-making process needs to comprehensively consider various heterogeneous data and information and make final decisions through the fusion of data and information. Therefore, starting from the characteristics of heterogeneous data, this paper studies a multisource heterogeneous data fusion method that supports multiuser decision-making.

Human resource forecasting refers to the assumption of the human resource situation in a certain period of time in the future based on the evaluation and prediction of the enterprise, as shown in Figure 2. It mainly includes the forecast of the quantity and type of human resource demand for the future development of the enterprise; the forecast of the future human resource status of the enterprise; the forecast of the future industry competition situation; the forecast of the supply and demand relationship of social human resources. Experience forecasting method, current situation planning method, model method, expert discussion method, quota method, and top-down method are commonly used methods for human resource forecasting. At present, the research on the special field of enterprise human resource forecasting needs to be in-depth. In practical applications, it is necessary to further improve the accuracy and feasibility of the forecast and at the same time increase the forecast of ability and quality based on the forecast of the number of personnel. In addition, there are few applied researches on human resource forecasting methods in specific enterprises.

Figure 2: Human resource.

2. Multisource Heterogeneous Data Fusion Model

Human resource forecasting can be divided into human resource demand forecasting and human resource supply forecasting, including the dual meanings of foreseeing and measuring the future. When studying the status of a large-scale system, the status of each part of the system is usually judged first and then integrated to comprehensively judge the overall status. Therefore, a fusion method is needed to fuse the data of each part. Subsequently, multisource data fusion technology emerged, which can associate and combine data from multiple sensors, and integrate them together for a unified evaluation. According to the characteristics of the fusion algorithm, it can be summarized as data-level fusion, feature-level fusion, and decision-level fusion. Data-level fusion directly integrates the original log information obtained by the detector, and then, the fused data is processed in the next step. In this way, many details of the original data are retained, the amount of information lost is relatively small, and the granularity of fusion is relatively high. However, this fusion method is easily affected by the original data. When the original data is incomplete or the data stability is poor, it will directly affect the effect of the fusion, and the fused data must be homogeneous data. In addition, because many details in the original data are retained, the amount of calculation is relatively large and the processing cost is relatively high, which is not suitable for real-time fusion. This method has many applications in the field of image processing. Different from data-level fusion, feature-level fusion first performs data preprocessing and feature extraction on the data obtained by each detector and removes attributes that are weakly or irrelevant to the researched problem and then performs data extraction on the extracted feature data. Compared with the data-level fusion method, because the data fused by this fusion method is the data after feature extraction, the amount of data is small, the processing cost is low, the anti-interference ability is strong, the real-time performance is better, and heterogeneous data can be fused. Decision-level fusion first extracts the features of the original log information of each detector and analyzes and models it and then uses the single-source decision output from the model as a fusion factor to fuse, and the result of the fusion is the decision result of comprehensive multisource information. Compared with the other two fusion methods, this method has the smallest amount of data, so it has the best real-time performance and the lowest computational cost. And when the original data is unstable, the impact on fusion is minimal, and heterogeneous data can be fused. Enterprise human resources forecasting is a series of studies on the development trend, prospects, various possibilities, and consequences of enterprise human resources.

2.1. Multisource Heterogeneous Data Fusion Method. Data fusion is essentially the collaborative processing of data from multiple parties to achieve the purpose of reducing redundancy, comprehensive complementation, and capturing collaborative information. Data fusion is divided into data-level fusion, feature-level fusion, and decision-level fusion according to operation level. This paper studies the fusion of multiple data sources at the decision-making level, and its methods mainly include weighted average method, D-S evidence theory, and voting.

2.1.1. Weighted Average Method. Calculate the support value of each data source for decision-making, wi is the weight of data source i, and t_{ij} is the support of data source i to the j-th decision. This method judges the pros and cons of decision-making schemes according to the degree of support, which is easy to operate, and considers the importance of the data source and other characteristics, but the determination of the weight contains subjective factors.

2.1.2. D-S Evidence Theory. The space formed by all possible results of the object to be recognized is defined as the recognition frame D, and its subset is marked as 2D, and the definition is as follows:

$$m: 2^D \longrightarrow [0,1], \tag{1}$$

where

$$\begin{gathered} m(\Phi) = 0, \\ \sum_{A \subseteq 2^D} m(A) = 1. \end{gathered} \tag{2}$$

φ is the quasi-empty set, and then, m is the basic probability allocation function (BPAF) on 2^D, which actually assigns the trust degree of the subset of D based on the evidence.

In practice, different mi is often obtained for the same problem due to different evidences. After considering all the evidence, m can be obtained by the following formula:

$$m(A) = K^{-1} \sum_{\cap A_i = A} \prod m_i(A_i)(1 \leq i \leq n), \tag{3}$$

where

$$K = \sum_{\cap A_i \neq \phi} \prod m_i(A_i). \tag{4}$$

The D-S evidence theory is based on BPAF and can deal with the uncertainty caused by "not knowing." The disadvantage is that the elements in D must meet the mutually exclusive condition, and the calculation is complicated when there are too many BPAFs.

2.1.3. Voting Method. Consider each data source as a voter, and determine the pros and cons by comparing the number of votes obtained by each decision. The calculation method is

$$\mathrm{Sup}(a_i) = F\left[\mathrm{Sup}_j(a_i)\right]. \tag{5}$$

Among them, a_i is the i-th decision, and $\mathrm{Sup}(a_i)$ is the "number of votes"; $\mathrm{Sup}_j(a_i)$ is the support of the j-th data source for a_i. If it supports it, it is 1; otherwise, it is 0, and the function F can be defined as continuous add and sum. It is difficult to determine the BPAF for multisource heterogeneous data. The voting method cannot distinguish decisions with the same number of votes. Taking the preferences of decision makers into consideration, the OWA method is used to fuse the data in this article. The error is compared in Figure 3.

2.2. Multisource Heterogeneous Data Fusion Structure. The fusion structure of multiple data sources is shown in Figure 4. The data fusion process takes into account the characteristic factors expressing user needs and the reliability of information, uses context knowledge and domain knowledge, and uses voting to resolve data conflicts and other issues.

Aiming at the previously mentioned model, this paper designs a multisource heterogeneous data fusion structure model that supports multiuser decision-making. The data fusion engine in the model includes four modules: data warehouse, decision support calculation, OWA operator weight vector calculation, and data conversion and sorting. The specific descriptions are as follows. (1) The data warehouse implements data selection, feature extraction, and statistics operations: data integration, elimination of data heterogeneity and differences, and providing data sources for subsequent data processing. (2) The decision support calculation module obtains data of relevant dimensions from the data warehouse according to the decision attributes and calculates the impact of each data source on the decision: the support value s_{ij} (the support degree of the data source i for the j-th decision). (3) The OWA operator weight vector calculation module calculates the OWA weight wi according to the fuzzy semantic principle provided by the decision maker. The choice of fuzzy semantic parameters reflects the decision maker's: the preference attitude of the data source. (4) Data are converted and sorted according to the credibility or importance of the data source provided by the decision maker, combined with the OWA weight vector wi to convert sij and sort the converted results in order of size, and sort the result, which is calculated by summing the final decision value.

3. Multisource Heterogeneous Data Fusion Algorithm

3.1. Data Types and Their Characteristics. This technology has become a research hotspot in the fields of data processing, target recognition, situation assessment, and intelligent decision-making. Data can be described in terms of quantity and quality. The quantity is represented by numerical values, and the quality is described by linguistic variables. According to the different ways of data description, this paper divides the data into qualitative and quantitative types, focusing on the four types of descriptions of random variables, binary type, language level, and vocabulary terminology. The predicted values are compared in Figure 5. As can be found for these figures, the third one

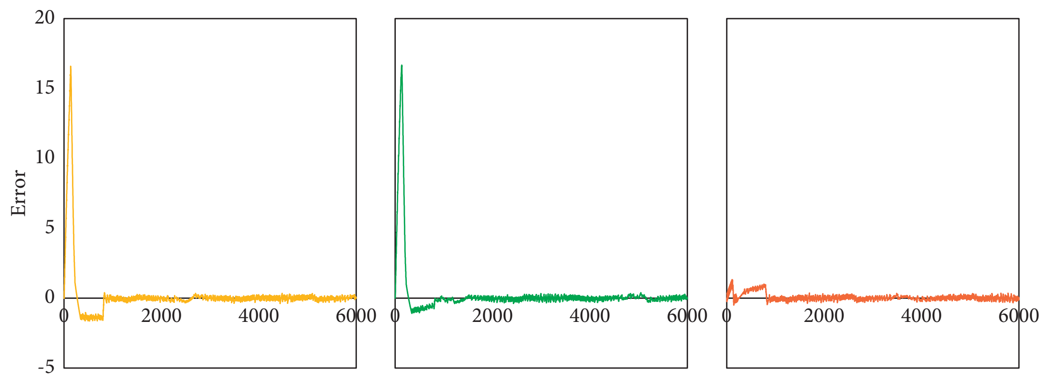

Figure 3: Error comparison.

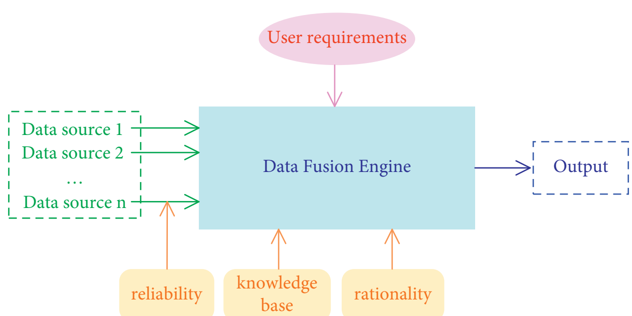

Figure 4: Multisource data source fusion structure.

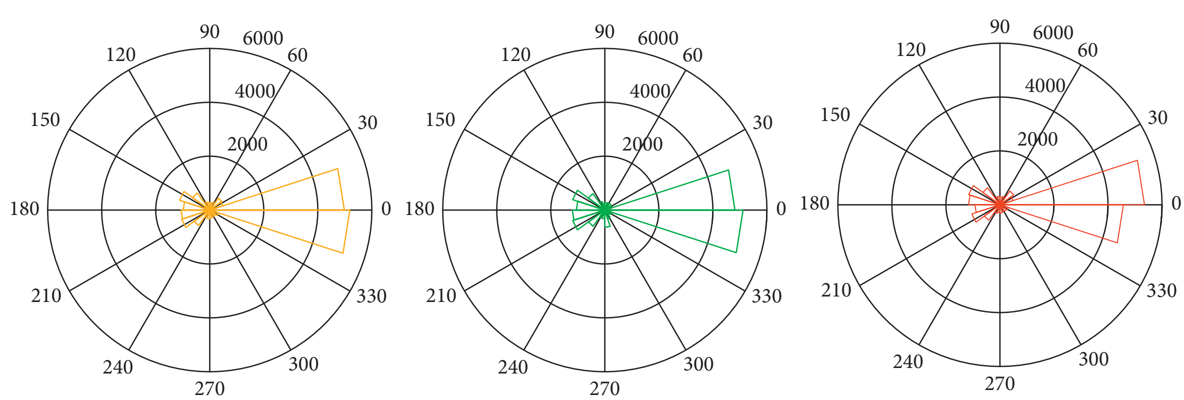

Figure 5: Value comparison.

exhibits the best performance of all, which is also consist with the previously mentioned analysis.

In the case of large samples, random variables follow a normal distribution. Binary data is used to describe the affirmation or negation of facts, and the value space is mostly {1, 0} or {True, False}. The data indicating the degree is generally expressed by Chinese adverbs of degree: very good, very poor, and so on. The degree level mostly uses 7 or 9 standards. The data based on the vocabulary term uses the vocabulary or term specified in the vocabulary space to give a qualitative description of things, and the number of vocabulary depends on the specific situation.

3.2. Support Calculation Based on Triangular Fuzzy Numbers. Taking into account the existence of ambiguity in the description of multisource data, triangular fuzzy numbers can be used to calculate the support value of the data for decision-making.

3.2.1. Conversion of Random Data. Suppose

$$x_0 = \mu - 3\sigma,$$
$$x' = \frac{x - x_0}{6\sigma}. \tag{6}$$

If the value of the random variable is larger, its support for decision-making is also greater. If the interval $[\mu - 3\sigma, \mu + 3\sigma]$ is divided into n equal parts, the conversion from random data to support can be defined as

$$s(x) = \begin{cases} (0,0,0), & x \le \mu - 3\sigma, \\ \left(\frac{i}{n}, x', \frac{i+1}{n}\right), & \frac{3\sigma i}{n} + x_0 < x \le \frac{6\sigma(i+1)}{n} + x_0, \\ (1,1,1), & x > \mu - 3\sigma. \end{cases} \quad (7)$$

If the value of the random variable is smaller, its support for the decision plan is greater, and then, the support is defined as

$$s'(x) = (\pi 1, 1, 1) - s(x). \quad (8)$$

3.2.2. Conversion of Binary Data. Binary data is described by 1 or 0. If the numbers of 1 and 0 in the data source are n and m, respectively, and the support is based on the value 1, and then, the support of the data source for decision-making is defined as

$$s(x) = \left(\frac{n}{n+m}, \frac{n}{n+m}, \frac{n}{n+m}\right). \quad (9)$$

3.2.3. Conversion of Degree Data. Generally speaking, 7 or 9 standards can be used to describe the quality of objects. This article adopts 7-level standards. The expression of degree adverbs can be divided into proportional type (the higher the efficiency, the better) and the inverse type (the higher the cost, the worse), and the degree of support for decision-making of each level can be quantified. The power in different situation is show in Figure 6, which shows the agreement between the prediction and the previously mentioned analysis in detail.

3.3. Data Fusion Algorithm. Suppose n decisions: $A=(A1, A2,...,An)$, m data sources: $S=(S1, S2,...,Sm)$, and the credibility (or importance) of each data source is pi. The data fusion algorithm is described as follows.

Step 1. Calculate the support of the data source for decision-making; extract data from the data warehouse, according to the different types of data and according to the previously mentioned method to convert it into the support for decision-making:

$$S_{ij} = \left(a_{ij}, b_{ij}, c_{ij}\right). \quad (10)$$

Among them, S_{ij} is the support degree of the i-th data source for the j-th decision target, and (a_{ij}, b_{ij}, c_{ij}) is the triangular fuzzy number representation of the support degree.

Step 2. Determine the weight vector of the OWA operator; select the appropriate fuzzy semantic quantization criterion according to the preference of the decision maker" and determine the corresponding parameter and value. The principle of fuzzy semantics is generally "majority," "at least half," or "as much as possible," and their parameter values are (0.3, 0.8), (0, 0.5), and (0.5, 1), which can be determined according to the parameters Fuzzy semantic quantization operator $f(x)$. According to $f(x)$, obtain the OWA weight vector $w=(w1, w2,..., wn)$; n is the number of data sources. Obtain the value of c.

Step 3. Convert s_{ij} according to the credibility (or importance) pi and support value s_{ij} of each data source; in order to use the OWA weight vector, each decision value needs to be converted according to p_i and s_{ij} and sorted in order of magnitude. The conversion method adopts the fuzzy judgment method. Assume

$$\begin{aligned} s_{ij\_\min} &= p_i s_{ij}, \\ s_{ij\_\max} &= p_i + s_{ij} - p_i s_{ij}, \\ s_{ij\_ave} &= \frac{n}{\sum_{i=1}^{n} p_i} p_i s_{ij}. \end{aligned} \quad (11)$$

Step 4. Fuse the data according to the OWA operator weight vector and the converted support, and calculate the final decision value of each decision:

$$s_j = \sum_{i=1}^{m} w_i b_{ij}, \quad j = 1, 2, \ldots, n. \quad (12)$$

Step 5. Make a decision based on the actual problem according to the decision value. The corresponding prediction is shown in Figure 7.

4. Forecast of Engineering Job Demand

Enterprise human resource demand forecasting is to predict human resources, which is a complex system, so, it must be completed based on a scientific forecasting model. This article has already sorted out the existing human resource demand forecasting models. In the qualitative and quantitative models of demand forecasting, each category contains many models with different forecasting focuses. To predict the needs of enterprise human resources, only those practical methods are scientific. After the previous analysis of the forecasting object and the internal and external human resources environment of the enterprise, the appropriate forecasting method can be determined according to the characteristics of the enterprise.

This article is a mid- and long-term forecast of the talent needs of a company's key positions. When choosing a forecasting method, it should be taken into account that due to the different degree of influence of internal and external factors, the results of the forecast of the talent demand for key positions will be different, so the main influencing

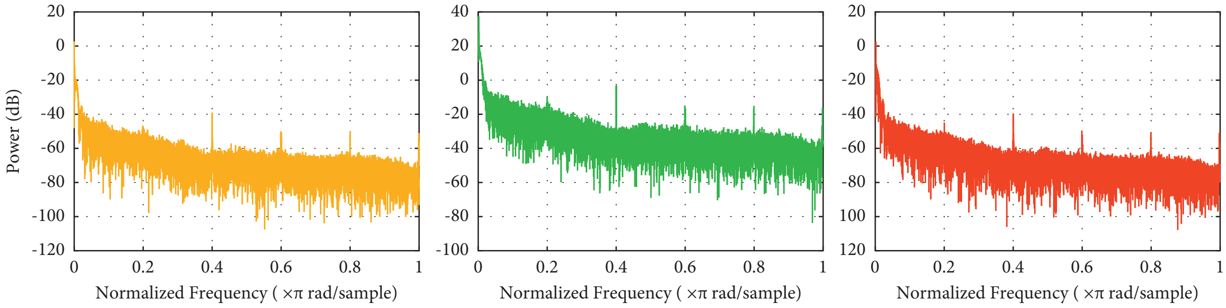

Figure 6: Power.

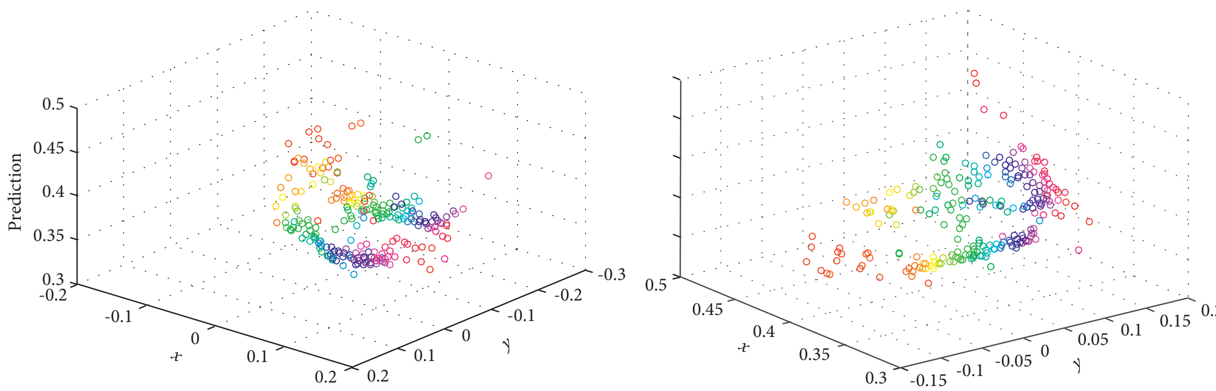

Figure 7: Prediction in different x and y.

factors need to be selected when forecasting. When predicting the total demand for talents, different variables are selected and a variety of forecasting schemes are used for forecasting, so that the information contained in various methods can be integrated to obtain more accurate forecasting values. Generally speaking, the selection of the method for forecasting talent demand for key positions in this article is mainly based on the following considerations.

(1) There are many factors that affect the demand for talents in key positions, but different factors sometimes have inherent correlations. Therefore, we should consider screening all factors to find out the main factors. In this way, we can consider using a few A variables to describe the nature of multiple variables.

(2) According to the data processing results, consider using one or more factors that have a greater impact on the demand for talents in key positions, and use mathematical models in statistical methods such as regression analysis and forecasting to predict the demand for talents, which will make the results more scientific, so as to obtain a better prediction effect.

(3) The development of enterprise human resources is a function with time as the basic variable. As time changes, the quantity and status of enterprise human resources are changing. Through the analysis of the internal and external environment of human resources of a company, it can be seen that the company is in a period of stable development, and the demand for talents in key positions has time continuity. Therefore, the time factor is an indispensable and important factor in the forecast of demand for talents in key position variable.

(4) Both theory and practical experience show that the combined forecasting method concentrates more relevant information and forecasting skills, so it can obtain better forecasting effects than single forecasting models, significantly improve the forecasting effect, and reduce the systematic error of the forecast. Therefore, this article will consider the use of combined forecasting methods to obtain the forecast value of the total demand for talents in order to reduce forecast errors and improve forecast accuracy.

Based on the previously mentioned considerations, this article will choose a quantitative forecasting method to predict a company's demand for key position talents and engineering professional and technical personnel (scarce talents) from 2006 to 2010. Comprehensive analysis and applicable methods are regression prediction model, gray system GM (1, l), prediction model, and combination prediction. This article will first use the first two methods to forecast the demand for talents in key positions and finally use the combined forecasting method to comprehensively process the results of the two forecasts and obtain the forecast value of the demand for key positions in a company. The x y variation is shown in Figure 8.

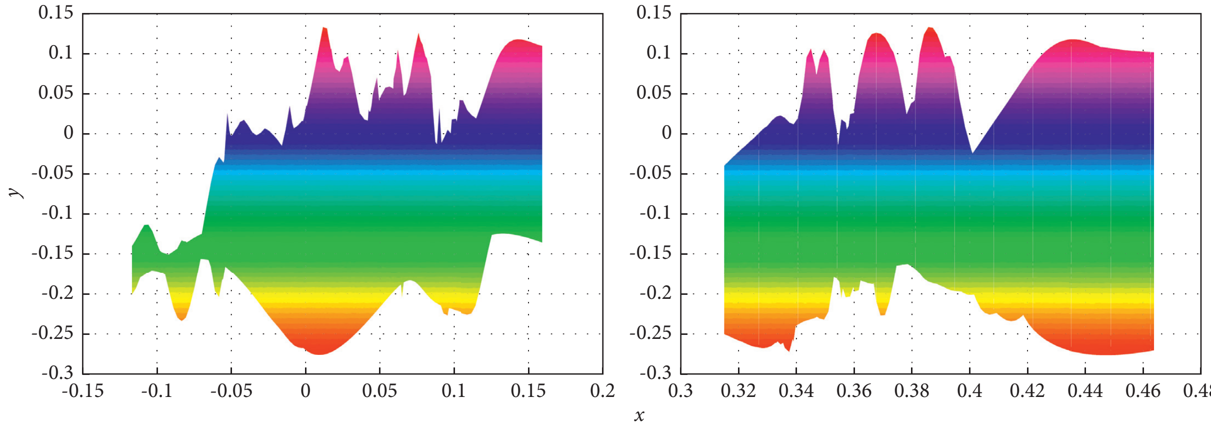

Figure 8: x and y variation.

Based on the analysis of the internal and external environment of a company's human resources, the preceding article qualitatively describes the factors that affect the talent needs of key positions. This qualitative analysis is only a preliminary identification of influencing factors and does not clarify the correlation and degree of influence on the number of talents in key positions. Therefore, it is necessary to carry out statistical analysis of various factors to find out the main factors affecting the demand for talents in key positions.

Based on the qualitative analysis of the internal and external influencing factors of talents in key positions, this paper selects some representative indicators that can be quantified among the factors to study the contribution of each factor to the demand for talents in key positions and engineering and technical personnel of a company degree and inner law.

Through the correlation test, we found that the A djus te *d* R Squ *s* re (① value) among the total talents in key positions is closest to 1 and has three important factors in qualitative analysis: the annual output of raw coal, the resource recovery rate, and the annual output of clean coal. Among them, the correlation coefficient between the annual output of raw coal and the demand for talents in key positions is the largest, with a value of 0.907. The resource recovery rate is negatively correlated with the demand for talents in key positions, with a value of -0.75. The correlation between the annual output of products is also not very significant, and the correlation coefficient value is 0.772 after the correlation analysis and processing of each factor index by SPSS software. There is an asterisk next to the correlation coefficient value of the annual output of raw coal, which indicates that when the specified significance level is 0.0 5. The associated probability of the statistical test is less than or equal to 0.0 5 (shown as 0.013 in the table); that is, the annual output of raw coal is talents in key positions, which are significantly correlated and positively correlated.

Therefore, the results of data processing show that, among the selected factors, the factor that has the greatest impact on the demand for talents in a company's key positions is the company's annual output value. This result is also the basis for the next personnel demand forecast. Based on this conclusion, we will use regression analysis methods to predict talents in key positions, which is the basis for selecting regression prediction methods in this article.

Analyzing the correlation test results between engineering professional and technical personnel and indicators of various influencing factors, it can be known that there are no indicators that have an important influence on engineering professional and technical personnel in terms of qualitative analysis among the selected indicators. That is to say, there is no index suitable for the regression prediction of engineering and technical talents among the selected indicators, so this article will use the gray prediction model to predict such talents.

Although the current coal industry has a good momentum of development, due to the country's relevant regulations on coal production, excessive exploitation of resources is not allowed (mine production is not allowed to exceed its approved production capacity), which is why the planned annual production value tends to stabilize. This planned value will be reserved relative to actual production, so the predicted value obtained by using the regression prediction model will be slightly smaller than the actual demand. At the same time, based on the actual situation of a certain company, since some people engaged in extractive work will meet the requirements for relocating extractive positions for 25 years in the next two years, considering the number of gaps in this part of personnel, there will be additional extractive positions in 2008 and 2009 number of talents. Based on the previously mentioned reasons, it can be seen that a company's actual demand for talents in key positions will increase based on the combined forecast value.

In addition, through the previous analysis, we know that another aspect of a company's demand for talents in key positions is the demand for competence and quality. Combining the development goals of the mine's future development plan for the personnel's educational structure, it can be known that the proportion of professional and technical personnel will increase in the personnel structure of key positions, and the proportion of high-level scientific and technological personnel will also increase to a certain extent.

The purpose of forecasting is to meet the demand for personnel in key positions and improve labor productivity. Only by strengthening the management of talents in key positions, fully mobilizing the enthusiasm of these personnel, and improving the overall competence and performance of talents in key positions can the goal of improving the overall performance of the enterprise be achieved. Therefore, it is necessary to use the theory of human resource management and combine the actual situation of a company to formulate corresponding planning measures for the management of talents in key positions of a company, in order to achieve the role of management and incentives for talents in key positions and promote the steady development of the company.

5. Conclusion

This paper qualitatively analyzes and selects the factors affecting the talent demand of key positions; a certain unit finds the quantifiable and influential factors according to the characteristics of demand influencing factors. Representative factors of talent demand for key positions in a certain unit. Using historical data, statistical methods are used to process the eight related factors of a certain unit, which confirms the factors that have a greater impact on the demand for talents in key positions of a certain unit, affecting the demand for talents in key positions of the same type of enterprise. The identification of factors provides a basic argument for a certain unit. Hence, the following conclusions can be obtained.

(1) Based on the results of statistical analysis and the characteristics of existing data, two variables of factory output and time are selected to be used in regression analysis forecasting model and gray system forecasting model for a certain unit to predict the demand for talents in a key unit; a certain unit finally adopts a combination forecast. The method determines the predicted value of talent demand for a certain unit's key positions.

(2) Besides, according to the results of demand forecasting and the current status of human resource management in a certain unit, this article proposes talent management planning measures for key positions in a certain unit, hoping to provide a reference for the management of key talents in a certain unit and ensure a certain unit's key positions in the future talent demand reserve.

Data Availability

The dataset can be accessed upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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References

[1] Y. Yu, C. Yang, Q. Deng, T. Nyima, S. Liang, and C. Zhou, "Memristive network-based genetic algorithm and its application to image edge detection [J]," *Journal of Systems Engineering and Electronics*, vol. 32, no. 5, pp. 1–9, 2021.

[2] Y. Ishida and S. Hashimoto, "Asymmetric characterization of diversity in symmetric stable marriage problems: an example of agent evacuation," *Procedia Computer Science*, vol. 60, no. 1, pp. 1472–1481, 2015.

[3] P. Zoha and R. Kaushik, "Image edge detection based on swarm intelligence using memristive networks," *IEEE Trans. on CAD of Integrated Circuits and Systems*, vol. 37, no. 9, pp. 1774–1787, 2018.

[4] J. Pais, "Random matching in the college admissions problem," *Economic Theory*, vol. 35, no. 1, pp. 99–116, 2018.

[5] J. J. Jung and G. S. Jo, "Brokerage between buyer and seller agents using constraint satisfaction problem models," *Decision Support Systems*, vol. 28, no. 4, pp. 291–384, 2020.

[6] Y. Liu and K. W. Li, "A two-sided matching decision method for supply and demand of technological knowledge," *Journal of Knowledge Management*, vol. 21, no. 3, JKM-05-2016-0183, 2017.

[7] J. Byun and S. Jang, "Effective destination advertising: matching effect between advertising language and destination type," *Tourism Management*, vol. 50, no. 10, pp. 31–40, 2015.

[8] A. N. Nagamani, S. N. Anuktha, N. Nanditha, and V. K. Agrawal, "A genetic algorithm-based heuristic method for test set generation in reversible circuits," *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems*, vol. 37, no. 2, pp. 324–336, 2018.

[9] C. Koch and S. P. Penczynski, "The winner's curse: c," *Journal of Economic Theory*, vol. 174, pp. 57–102, 2018.

[10] C. K. Karl, "Investigating the winner's curse based on decision making in an auction environment," *Simulation & Gaming*, vol. 47, no. 3, pp. 324–345, 2016.

[11] D. Ettinger and F. Michelucci, "Creating a winner's curse via jump bids," *Review of Economic Design*, vol. 20, no. 3, pp. 173–186, 2016.

[12] J. A. Brander and E. J. Egan, "The winner's curse in acquisitions of privately-held firms," *The Quarterly Review of Economics and Finance*, vol. 65, pp. 249–262, 2017.

[13] Z. Palmowski, "A note on var for the winner's curse," *Economics/Ekonomia[J]*.vol. 15, no. 3, pp. 124–134, 2017.

[14] B. R. Routledge and S. E. Zin, "Model uncertainty and liquidity," *Review of Economic Dynamics*, vol. 12, no. 4, pp. 543–566, 2009.

[15] D. Easley and M. O'Hara, "Ambiguity and nonparticipation: the role of regulation," vol. 22, no. 5, pp. 1817–1843, 2019.

[16] P. Klibanoff, M. Marinacci, and S. Mukerji, "A smooth model of decision making under ambiguity," *Econometrica*, vol. 73, no. 6, pp. 1849–1892, 2005.

[17] Y. Halevy, "Ellsberg revisited: an experimental study," *Econometrica*, vol. 75, no. 2, pp. 503–536, 2017.

[18] D. Ahn, S. Choi, D. Gale, and S. Kariv, "Estimating ambiguity aversion in a portfolio choice experiment," *Working paper*, vol. 5, no. 2, pp. 195–223, 2019.

[19] T. Hayashi and R. Wada, "Choice with imprecise information: an experimental approach," *Theory and Decision*, vol. 69, no. 3, pp. 355–373, 2010.

[20] K. Zima, E. Plebankiewicz, and D. Wieczorek, "A SWOT analysis of the use of BIM technology in the polish construction industry," *Buildings*, vol. 10, no. 1, 2020.

[21] P. Sun, B. Liu, and T. Sun, "Injury status and strategies of female 7-a-side rugby players in Anhui Province," *Sports Boutique*, vol. 38, no. 3, pp. 72–74, 2019.

[22] P. Guild, M. R. Lininger, and M. Warren, "The association between the single leg hop test and lower-extremity injuries in female athletes: a critically appraised topic," *Journal of Sport Rehabilitation*, vol. 30, no. 2, pp. 1–7, 2020.

[23] U. G. Inyang, E. E. Akpan, and O. C. Akinyokun, "A hybrid machine learning approach for flood risk assessment and classification," *International Journal of Computational Intelligence and Applications*, vol. 19, no. 2, Article ID 2050012, 2020.

[24] Q. Liu, S. Du, B. J. van Wyk, and Y. Sun, "Double-layer-clustering differential evolution multimodal optimization by speciation and self-adaptive strategies," *Information Sciences*, vol. 545, no. 1, pp. 465–486, 2021.

[25] H. R. Medeiros, F. D. B. D. Oliveira, H. F. Bassani, and A. F. R. Araujo, "Dynamic topology and relevance learning SOM-based algorithm for image clustering tasks," *Computer Vision and Image Understanding*, vol. 179, pp. 19–30, 2019.

[26] Y. Deng, D. Huang, S. Du, G. Li, C. Zhao, and L. Jun, "A double-layer attention based adversarial network for partial transfer learning in machinery fault diagnosis," *Computers in Industry*, vol. 127, Article ID 103399, 2021.

[27] J. J. Chan, K. K. Chen, S. Sarker et al., "Epidemiology of Achilles tendon injuries in collegiate level athletes in the United States," *International Orthopaedics*, vol. 44, no. 3, pp. 585–594, 2020.

[28] W. Li, G. G. Wang, and A. H. Gandomi, "A survey of learning-based intelligent optimization algorithms," *Archives of Computational Methods in Engineering*, pp. 1–19, 2021.

[29] G. G. Wang, A. H. Gandomi, A. H. Alavi, and D. Gong, "A comprehensive review of krill herd algorithm: variants, hybrids and applications," *Artificial Intelligence Review*, vol. 51, no. 1, pp. 119–148, 2019.