Design and optimization of optimal performance allocation scheme based on multi-objective optimization model

Chenxuan Song, Zhaoqing Zhu, Yuantong Kong, Dongsheng Gao, Tong Fu,

Dongping Sheng*, Chun Su

Changzhou Institute of Technology, Changzhou, China

ABSTRACT

The performance evaluation of scientific and technological personnel is a key task in the field of scientific research. In response to this issue, research institutions need to establish a reasonable evaluation plan to promote the transformation and output of scientific and technological achievements, and improve the work enthusiasm and income level of scientific and technological personnel. This article discusses the performance evaluation and bonus distribution of scientific researchers, involving three issues: data quality processing, selection of performance evaluation methods, and design of bonus distribution plans. The first step is to identify and handle missing values and outliers in the dataset. By using the FIND function in MATLAB to identify missing values, it is possible to identify datasets without missing values. Secondly, Kolmogorov Smirnov (KS) test was used to determine the distribution of data, and the distribution of each indicator was determined through the q-q chart generated by SPSS PRO software and the KS test results. For normally distributed data, use box plots for outlier detection, and combine 1.5 times interquartile range standard and 3 o principle for outlier determination. Finally, handle outliers and remove inappropriate ones to ensure the quality and accuracy of the data, providing a reliable data foundation for subsequent analysis and modeling. In work one, the TOPSIS method is used for performance evaluation. Through data normalization and weight determination, the comprehensive evaluation value of scientific researchers is calculated to determine their performance ranking. In the bonus distribution plan, fair and reasonable bonus distribution is carried out according to the evaluation results of TPOSIS using the entropy weight method to ensure the objectivity and impartiality of the evaluation results. Work two requires ranking the four teams and implementing distribution according to work within the team. Using the entropy weight method to evaluate the performance of each team, combined with the performance of each member within the team, determine the best score combination to be submitted by each team and distribute it according to work to ensure the fairness and rationality of performance rewards. Work three aims to establish a multi-objective optimization model that maximizes the overall performance of the team while maintaining fairness and balance. Considering various constraints and the balance within the team, a genetic algorithm was used to solve the individual and team annual total performance of team members, achieving the optimization goals of team performance evaluation and bonus allocation.

Keywords: Performance Evaluation, Bonus Allocation, TOPSIS Model, Entropy Weighting Method, Multi-Objective Optimization, Genetic Algorithm

1 INTRODUCTION

In the field of scientific research, evaluating the performance of scientific and technological personnel is an important task that involves various considerations and policy guidance.

Science and technology management departments at all levels, such as the Ministry of Science and Technology, the Ministry of Education, etc., are committed to promoting the transformation and output of scientific and technological achievements through a series of documents and measures, emphasizing the construction of scientific research ethics, reducing the tendency to only focus on papers, and improving the income level of scientific and technological personnel. The performance evaluation policies of various scientific research units have also been continuously updated with the implementation of policies such as the Interim Measures for Performance Evaluation of Central level Scientific Research Institutions, which directly affect the determination of task priorities in the work plans of scientific researchers [1]. The formulation of a performance plan involves many factors, such as the total amount of performance allocation, limitations on the type and quantity of achievements, individual scores, subject differences, length of service and technical level, the training situation of the research institute, new project initiation and award situation, etc. In this context, it is necessary to develop appropriate performance allocation plans for scientific and technological personnel through modeling and data analysis, in order to promote the progress of scientific research and the improvement of talent cultivation. This article will analyze, model, and solve the following work.

Work one: Explain how to use the data in Attachment 1 to allocate the scientific research achievement rewards for 20 scientific research employees in 2023, how to adopt a reasonable performance allocation plan, and analyze its basis in detail.

Work two: In the context of a mathematics department in a certain university, there are four research teams, each consisting of five members, and the research results are produced in the form of teamwork. According to the performance reward plan, the first team can be allocated 35% of the total prize pool, followed by 28%, 22%, and 15%, respectively. Assuming the total prize pool is 1 million, and each team is only allowed to submit a maximum of 20 achievements, please arrange the types and quantities of submitted achievements reasonably based on the data in Attachment 2, and calculate the performance allocation results for each member in each team [2].

Work three: With the severe economic situation and the improvement of the integrated technology evaluation system of industry, academia, research and application, expanding institutional income is an important incentive measure. The individual performance base and individual allocation budget indicators in the title have been provided, which are 40000, 25000, 15000, 10000 yuan and 320000, 200000, 100000, and 20000 yuan respectively. Assuming that the funding amount and achievement score can be allocated to members in the same group, the total achievement bonus is 100000 yuan. Please propose a suitable performance allocation plan to ensure the optimal overall performance of the target team, while balancing internal balance and fairness.

2 MODEL ASSUMPTION AND DATA PROCESSING

2.1 Model assumption

To ensure the establishment of the model and the rationality of the prediction results, we can make the following model assumptions:

- (1) The data source is reliable and authentic, and the validity of the data has been ensured through strict verification and review. Although there may be some outliers or extreme situations in the data, the frequency of these outliers is relatively low and will not have a significant impact on the overall model results.
- (2) In the process of establishing and solving the model, we assume that the mathematical methods and algorithms used are effective and applicable to solving the proposed problem.

(3) For missing values in the data, we have adopted reasonable processing methods such as interpolation, mean substitution, etc., and these processing methods will not cause significant deviation in the model's prediction results. By rewriting the model assumptions, we can better ensure the feasibility of the model and the accuracy of the prediction results, making the model more complete and credible.

2.2 Data processing

For the determination and handling of missing and outliers: We use the find function in Matlab to search for missing values in the dataset given, and obtain that there are no missing values in the data. Subsequently, we searched for outliers by verifying the distribution of the given dataset.

To determine how the data given is allocated, K-S test is used. K-S test is a non parametric test method suitable for comparing various types of distributions, especially for determining whether a dataset with small sample sizes or unclear population distribution conforms to a normal distribution. The basic principle is to compare the cumulative distribution function of the dataset with the theoretical distribution function, and determine the degree of difference between the two by calculating the maximum difference [3]. If the maximum difference is less than a critical value, the dataset is considered to conform to the theoretical distribution. Usually, a single sample K-S test is used to test whether the distribution of a dataset conforms to a known theoretical distribution. Whether the sample data with a known distribution comes from a known theoretical distribution. When there is not much difference between the empirical distribution of the observed dataset and the existing theoretical distribution, it can be concluded that the distribution of the existing dataset comes from a known distribution. As a distribution assuming zero, it is generally a normal distribution, uniform distribution, exponential distribution, etc.

The KS test result is generally a p-value. If the p-value is less than a significant level (usually 0.05), the null hypothesis is rejected, that is, two samples are considered to come from different distributions.

We use SPSS PRO to draw a q-q graph and perform KS test distribution on the dataset given to determine its distribution pattern. Through the q-q chart, we can conclude that most points seem to follow a trend line, indicating that most of the data is somewhat normal. However, there may be some deviations at both ends. To reduce the impact of this factor, we further use the ks function in Matlab for judgment.

Following the assumption of normal distribution (P value>0.05): For "SCI", "EI", "Chinese core", "invention patents", "other intellectual property rights", "horizontally received funds/10000 yuan", "talent plan", and "academic part-time work", if the P value is greater than 0.05, we believe it conforms to a statistically normal distribution [4].

Not following the assumption of normal distribution (P value<0.05). For "National Science and Technology Awards", "Provincial and Ministerial Science and Technology Awards", "Publication of Works", "National Standards/Norms", "Provincial or Industry Standards/Norms", "New Batch of National level Projects", "New Batch of Provincial and Ministerial level Projects", "Number of Graduate Students in Education", etc., the P-values are all below 0.05, indicating that the data in these columns are significantly different from the normal distribution. Therefore, the null hypothesis is rejected.

From this, it can be concluded that most of the given dataset cannot be judged as normally distributed. Therefore, for data that conforms to a normal distribution, we introduce a box plot. The box plot does not need to be restricted by outliers and provides criteria for judging outliers. It is not affected by outliers and can intuitively determine the discrete distribution of the data. It also provides criteria for judging outliers, including 1.5 times interquartile range (1.5IQR), 3 times standard deviation, and upper and lower limits of the box plot. Using a box plot without

the need for data to follow a normal distribution, sort the detection data in descending order to obtain an ordered sequence, with the median M denoted as:

$$M = \begin{cases} X_{a+\frac{1}{2}} \\ x_n \\ \frac{1}{2} \left(\frac{2}{2} + X_{\left(1 + \frac{n}{2} \right)} \right) \end{cases}$$
 (1)

The criteria for determining outliers are:

$$X_1 > U + K \bullet IQR \mid X_1 < K \bullet IQR \tag{2}$$

Where, U represents the upper four quantiles, the interval [M, Xn] represents only 1/4 of the values in the sample greater than U, L represents the lower four quantiles, the median of the interval [X1, M] represents only 1/4 of the values in the sample smaller, LIQR is the interquartile distance, IQR=U-L, L step length, K=1.5.

Perform box plot inspection, use the boxplot function in MATLAB to generate a box plot and identify outliers. The outliers are often defined as values below Q1-1.5IQR or above O3+1.5IOR.

The 3 σ principle determines outliers: When the given dataset follows a normal distribution, 99.7% of the data falls within the range of three times the standard deviation of the mean. If the data falls outside the range of three times the standard deviation, we consider it an outlier. The formula for determining this outlier is:

$$P(|x - \mu| > 3\sigma) \le 0.003$$
 (3)

Where, x is a data point in the dataset, μ is the average of all data under the corresponding indicator of x, and σ is the standard deviation under the corresponding indicator.

By using the above two methods of outlier detection, we perform outlier detection on the data in the dataset and select inappropriate outliers for deletion. For example, there are 10 graduate students with relatively abnormal numbers [5].

According to the Opinions on Deepening the Reform of Graduate Education issued by the Ministry of Education, the National Development and Reform Commission, and the Ministry of Finance, it is clearly stipulated that supervisors can lead graduate students. Each supervisor generally admits no more than one doctoral student per session, and no more than four master's students per session. The number of teachers who serve as "double shoulders" generally does not exceed three. So for the situation of these ten people, we believe that this is not a data anomaly.

3 MODEL BUILDING AND ANALYZING

3.1 Model establishing and solving for work one

3.1.1 TOPSIS evaluation model based on entropy weight method

The TOPSIS method has high applicability in the performance evaluation of scientific researchers, with the characteristics of simple calculation, reasonable results, and flexible application. By weighting and comprehensively evaluating various indicators, the performance level of scientific researchers can be objectively evaluated, providing scientific basis for decision-making such as bonus distribution [6].

In our model, to normalize the indicators, we can adopt the following strategy: if all data of an indicator is denoted as uppercase X_i , and the elements are denoted as x_i .

Convert extremely small indicators to extremely large indicators:
$$\bar{x}_1 = \frac{1}{x_1} \text{ or } \bar{x}_1 = \max(\mathcal{X}) - \bar{x}_1 \tag{4}$$

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In our model, to normalize the indicators, we can adopt the following strategy: if all data of an indicator is denoted as uppercase X, and the elements are denoted as x_i .

Convert extremely small indicators to extremely large indicators:

$$\bar{x}_1 = 1 - \frac{|x_1 - x_{best}|}{\max(|x - x_{best}|)}$$
 (5)

Among them, x_{best} refers to the best value, and the two vertical lines represent the absolute value symbol. The denominator here calculates the value that deviates the farthest from the best value.

(3) Convert interval type indicators to extremely large indicators:

$$\bar{x}_1 = \begin{cases} 1 - \frac{\alpha - x_1}{M}, x_1 > a \\ 1, \\ 1 - \frac{x_1 - b}{M}, \quad x_1 > b \end{cases}$$
 (6)

Where, $M=\max\{a-\min(X), \max(X)-b\}$, a is bottom value, b is the top value.

The standardization method is as follows: there is an object to be evaluated, and the positive matrix composed of M evaluation indicators (which have been normalized) is as follows:

$$X = \begin{bmatrix} X_{11} & X_{11} & \dots & X_{1m} \\ X_{11} & X_{22} & \dots & X_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ X_{n1} & X_{n2} & \dots & X_{nm} \end{bmatrix}$$
 (7)

Its gauge matrix is recorded as Z, and each element in Z is:

$$Z_{ij} = -x_{ij} / \sqrt{\sum_{i=1}^{n} x_{ij}^2}$$
 (8)

To determine if there are negative numbers in the Z matrix, another normalization method needs to be used for X. Normalize matrix X once to obtain the matrix, and the standardized formula is:

$$Z_{ij} = \frac{x_{ij} - \min\{X_{1j}, X_{2j}, \dots X_{nj}\}}{\max\{x_{1j}, x_{2j}, \dots x_{nj}\} - \min\{x_{1j}, x_{2j}, \dots x_{nj}\}}$$
(9)

Calculate the proportion of the ith sample under the jth indicator and consider it as the probability used in relative entropy calculation [7]. Assuming there is an object to be evaluated, m evaluation indicators, and the non-negative matrix obtained through the previous step of processing is:

$$\tilde{Z} = \begin{bmatrix} \tilde{Z}_{11} & \tilde{Z}_{12} & \dots & \tilde{Z}_{1m} \\ \tilde{Z}_{21} & \tilde{Z}_{22} & \dots & \tilde{Z}_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{Z}_{n1} & \tilde{Z}_{n2} & \dots & \tilde{Z}_{nm} \end{bmatrix}$$
(10)

We calculate the probability matrix P, where the calculation formula for each element in P_{ij} is as follows:

$$P_{ij} = \frac{\widetilde{z_{ij}}}{\sum_{i=1}^{n} \widetilde{z_{ij}}} \tag{11}$$

Calculate the information entropy of each indicator, calculate the information utility value, and normalize the weights of each indicator [8].

For the jth indicator, the formula for calculating its information entropy is:

$$e_{ij} = -\frac{1}{\ln n} P_{ij} \ln(P_{ij}) (j = 1, 2, ..., m)$$
 (12)

The larger the value of information utility, the more information will correspond to it. After normalizing the information utility value, we can obtain the entropy weight of each indicator:

$$W_j = dj \sum_{i=1}^m d_j \ (j = 1, 2, \dots, m)$$
 (13)

3.1.2 Model establishment and solution

After undergoing forward and standardized corrections, the remaining step is to construct scoring indicators. The final score is determined by the distance from a sample to the optimal and worst solutions, where the distance to the optimal solution is denoted as D+and the distance to the worst solution is denoted as D-.

Define maximum value:

$$Z^{+} = (Z_{1}^{+}, Z_{2}^{+}, ..., Z_{n}^{+})$$

$$= (max\{z_{11}, z_{21}, ..., z_{n1}\},$$

$$max\{z_{12}, z_{22}, ..., z_{n2}\}, max\{z_{1m}, z_{2m}, ..., z_{nm}\})$$
(14)

Define minimum value:

$$Z^{-} = (Z_{1}^{-}, Z_{2}^{-}, ..., Z_{n}^{-})$$

$$= (min\{z_{11}, z_{21}, ..., z_{n1}\},$$

$$min\{z_{12}, z_{22}, ..., z_{n2}\}, min\{z_{1m}, z_{2m}, ..., z_{nm}\})$$
(15)

Define the distance between the ith (i=1, 2,..., n) evaluation object and the maximum value

$$D_i^+ = \sqrt{\sum_{j=1}^m (Z_j^+ - z_{ij})^2}$$
 (16)

Define the distance between the ith (i=1, 2,..., n) evaluation object and the minimum value
$$D_i^- = \sqrt{\sum_{j=1}^m (Z_j^- - z_{ij})^2}$$
(17)

So, we can calculate the non-normalized score of the evaluation object:

$$s_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{18}$$

Based on the TOPSIS evaluation model, we obtained the ranking of 20 scientific research employees and established a proportional bonus distribution plan. For each researcher i, their performance score is S_i , and the total bonus pool is P [9]. The bonus amount that the researcher receives can be calculated according to the following formula:

$$G_i^2 = 2S_i^2 * \frac{P}{\sum_{i=1}^N S_i^2}$$
 (19)

According to the entropy weight method TPOSIS, the approximate results are allocated proportionally.

3.2 Model establishing and solving for work two

Normalize each factor. For positive indicators:

$$Y_{ij} = \frac{X_{ij} - \min(X_i)}{\max(X_i) - \min(X_i)}$$

$$\tag{20}$$

For negative indicators:

$$Y_{ij} = \frac{\min(X_i) - X_{ij}}{\max(X_i) - \min(X_i)}$$
(21)

According to the definition of information entropy in information theory, the information entropy of a set of data is:

$$E_{j} = -\ln(n)^{-1} \sum_{i=1}^{n} p_{ij} \ln p_{ij} \left(\text{if } p_{ij} = 0, \text{ define } E_{j} = 0 \right)$$
 (22)

Calculate the information entropy of each indicator based on the calculation formula of information entropy, and calculate the weight of each indicator through information entropy:

$$\omega_{\mathbf{j}} = \frac{1 - E_{\mathbf{j}}}{K - \sum E_{\mathbf{j}}} \tag{23}$$

Calculate weights by calculating information redundancy:

$$D_j = 1 - E_j \tag{24}$$

Then calculate the weight of the indicators:

$$\omega_{j=} \frac{D_j}{\sum_{j=1}^n D_j} \tag{25}$$

The weights of various evaluation indicators for the four teams are calculated using the entropy weight method, and based on these weights, the specific results of the twenty best solution projects submitted by each group are selected [10]. The solution of the twenty best solutions is combined with the entropy weight method to obtain the total score of each team and the individual performance of each team member, as shown in Fig.1.

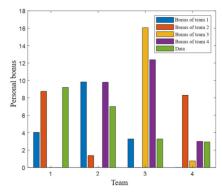


Fig.1: Personal bonus distribution

3.3 Model establishing and solving for work three

We calculate the performance of each member based on this formula and the individual performance base, individual allocation budget indicators, and total achievement bonus amount (100000 yuan) provided in the title. Considering the differences in individual performance bases and the allocation of funds by individuals.

According to the calculation results, the performance allocation of the target team members is as follows:

Item	Title	Annual personal funds received (10000 yuan)	Score	Performance (10000 yuan)
1	Positive height	34	8	46540.4
2	intermediate	10	7	16035.35
3	intermediate	0	97	48989.9
4	primary	0	0	0
5	deputy senior ranks	2	18	19090.91

Table 1: Performance Allocation of Target Team Members

In order to ensure the balance and fairness of the allocation plan, we have established an optimization model that maximizes the overall team performance while satisfying some constraints. A bonus distribution plan that reflects the contribution of each member to the team's results while maintaining internal harmony within the team.

Establish optimization goals: While pursuing maximum team performance, balance and fairness should also be taken into account.

$$Max \sum_{i=1}^{n} P_i \tag{26}$$

Where, P_i is the highest annual total performance for each individual.

Constraints:

(1) Because the total amount of bonus distribution is fixed, regardless of how the bonus is distributed within the group, the total amount remains unchanged, and the target team is constrained by the funds received:

$$\sum_{i=1}^{5} x_i = 46 \tag{27}$$

(2) Other team 1: Funding constraints upon receipt:

$$\sum_{i=1}^{5} y_i = 102 \tag{28}$$

(3) Due to the positive allocation amount:

$$\begin{cases} x_i > 0 \ (i = 1, 2 \cdots 10) \\ y_i > 0 \ (i = 1, 2 \cdots 10) \end{cases}$$
 (29)

- (4) Balance: Ensure that no member's bonus is significantly higher or lower than other members to maintain internal harmony within the team. We can achieve this by setting upper and lower limits for bonus distribution.
- (5) Ensuring that the performance of all members is not lower than a minimum and a maximum standard ensures that even members with smaller contributions can receive the most basic bonus distribution, thereby maintaining team relationships.

$$P_{max} \ge P \ge P_{min} \tag{30}$$

(6) Setting a ratio parameter R between the highest and lowest rewards can further control performance within the team, allocate differences, and promote greater fairness.

$$\frac{max(P)}{min(p)} \le R \tag{31}$$

(7) We consider the weight of professional titles: members with different professional titles can earn different bonuses due to their different experiences and contributions.

In summary, the optimization model we have established is as follows

$$\begin{cases} P_{i} \geq P_{min} \\ \frac{max(P)}{min(p)} \leq R \\ P_{i} = f(Title_{i}) \times P_{i} \\ \sum_{i=1}^{5} x_{i} = 46 \\ \sum_{i=1}^{5} y_{i} = 102 \\ \{x_{i} > 0 \\ y_{i} > 0 \end{cases} (i = 1, 2 \cdots 10)$$

$$(32)$$

For the multi-objective optimization model we have established, we use genetic algorithm to find the optimal solution. Through genetic algorithm, we can obtain the following results:

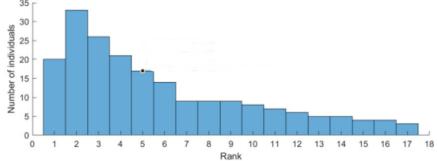


Fig.2: Genetic algorithm results

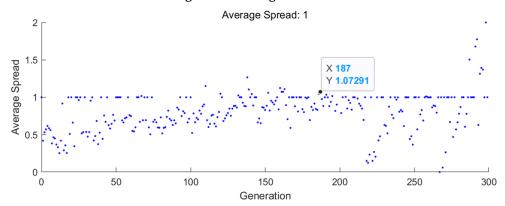


Fig. 3: Results based on genetic algorithm

Finally, we can calculate the total performance of the target team as 14370, the total performance of other team 1 as 13540, and the total performance of other team 2 as 13780. It not

only ensures the maximum overall performance of the target team, but also takes into account internal balance and fairness.

4 CONCLUSION

Data processing stage: To enhance the reliability of the established model, we have adopted various data processing methods to ensure the integrity and accuracy of the dataset. We used statistical methods and data visualization techniques, such as box plots and scatter plots, to identify and process outliers. Through data transformation and feature selection, we make the data have similar scales and distributions, and filter out the most relevant features for the model's predicted targets. Finally, we divide the dataset into training set, validation set, and testing set, which can ensure that the model has good generalization ability and stable performance. The entropy weight method TOPSIS evaluation model: The TOPSIS superiority and inferiority distance method model is a commonly used comprehensive evaluation method that can fully utilize the information of the original data, and its results can accurately reflect the differences between various evaluation schemes. Compared to Analytic Hierarchy Process, TOPSIS method is an evaluation model that solves the problem of known data in the decisionmaking level. This method is suitable for processing large amounts of data and is computationally simple and feasible. However, when dealing with the relationship between various data volumes, we need to use entropy weight method or analytic hierarchy process to determine the weights.

The principle of entropy weight method is that the smaller the degree of variation of an indicator, the less information it contains, and therefore the corresponding weight should be lower. This means that the data itself contains weight information, so the entropy weighting method is considered an objective method. However, after using this method, we still need to perform manual intervention to ensure that the obtained weights are reasonable. Overall, when data is known at the decision-making level, the TOPSIS model is a very suitable choice. Multi objective optimization model: with maximizing total performance as the objective function, and by setting corresponding constraints to ensure the rationality of individual performance within the team, thereby maintaining the balance and fairness within the team.

Work three uses genetic algorithm as the solution method for multi-objective optimization model: Genetic algorithm can simultaneously search for multiple candidate solutions in the solution space, and it performs more efficiently when dealing with large-scale problems. In addition, genetic algorithms have strong global search capabilities and can find the global optimal solution or a solution close to the optimal solution of the problem.

5 ACKNOWLEDGEMENTS

This work was Supported by Special Research Project on Teaching Reform(Grant No. 30120300100-23-yb-jgkt03).

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