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A NOVEL COMBINATORIAL OPTIMIZATION STRATEGY WITH TOPSIS FOR SMART MANUFACTURING

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Abstract. This study proposes a novel optimization strategy that integrates the combinatorial assignment technique with the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), enhancing management efficiency in smart manufacturing. The combinatorial assignment method effectively addresses challenges in decision-making by integrating subjective and objective weight determination, ensuring a more balanced and rational weight distribution. Concurrently, the TOPSIS method facilitates ranking and selecting optimal solutions. Leveraging this integrated approach, the strategy efficiently evaluates employee performance, a critical component of smart manufacturing management. Results demonstrate that this method improves assessment accuracy and fairness, contributing to more effective management practices in the rapidly evolving manufacturing landscape.

Keywords: Novel optimization strategy, combinatorial assignment, TOPSIS, smart manufacturing

Mathematics Subject Classification 2010: 74P99

1 INTRODUCTION

With the continuous progress and broad application of technology, smart manufacturing technology is rapidly developing and becoming popular. By integrating various advanced systems and technologies, smart manufacturing effectively blends expert knowledge and worker skills to achieve efficient production [1]. Against this background, governments worldwide have introduced various policies to promote enterprise transformation and help revitalize the manufacturing industry through high technology [2]. Smart manufacturing shows significant advantages [3]. It not only optimizes the efficiency of resource allocation and improves production efficiency but also prompts the manufacturing industry to change from the traditional production mode to the high-value-added, service-oriented, intelligent manufacturing mode. This change has brought unprecedented development opportunities for the manufacturing industry, while injecting new kinetic energy into the sustained growth of the global economy. In the future, smart manufacturing will play a more critical role [4, 5, 6].

In realistic activities, smart manufacturing, with potential advantages, also brings a multitude of new challenges to enterprise management [7], particularly in task scheduling and employee management. Traditional approaches to managing production models, organizational structures, and operational processes have posed challenges in meeting the demands of smart manufacturing management [8, 9]. Therefore, optimizing management methods in response to production demands and resource constraints is necessary. It is a critical issue in the current smart manufacturing industry.

With this background, there are many optimization methods for enterprise management, such as genetic algorithms and particle swarm optimization. Although they have achieved some success in specific applications, it is limited to coping with complex, multi-objective, and multi-constraint management problems for smart manufacturing. For example, regarding resource allocation, although multi-objective optimization methods based on the non-dominated sorting genetic algorithm II (NSGA-II) provide adequate management support, they are computationally intensive in complex production environments [10]. In addition, improved multi-objective differential evolution algorithm (IMODEA) and PSO-GA hybrid algorithms are also limited in their adaptability in dynamic environments, especially in coping with complex dependencies in the production process, and it is often challenging to make timely adjustments to adapt to rapid changes [11, 12]. Moreover, single-objective optimization methods usually ignore the holistic factors of the manufacturing system [13]. Therefore, there is a strong need for current optimization methods to adopt hybrid optimization strategies to balance multiple objectives and effectively deal with uncertainty. Through a multi-objective optimization approach, multiple performance metrics within a manufacturing system can be more comprehensively considered and coordinated to achieve better system performance [14].

Although the management optimization methods of smart manufacturing enterprises have attracted widespread attention, the research on comprehensive management optimization for equipment, employees, and operation processes is still relatively insufficient, especially in the multi-objective optimization evaluation and optimal solution selection, which needs to be deepened. In addition, it is needed to improve the scientific evaluation of multiple indicators in smart manufacturing management. As these evaluation indexes are subject to the double influence of subjective and objective factors, it is crucial to integrate subjective and objective weights in the weights reasonably. At the same time, selecting a reasonable and feasible optimal program is conducive to efficiently managing the enterprise and production operation.

To this end, this paper proposes an optimization method that integrates combinatorial assignment and TOPSIS to optimize the management strategy. It uses process data and object characteristics to optimize the enterprise management process, improve production efficiency, and reduce operating costs. The combinatorial assignment method is a scientific method that integrates subjective and objective factors to determine the weights of indicators [15], which can effectively deal with multi-task and multi-resource allocation problems. TOPSIS can scientifically and accurately assess the advantages and disadvantages of the solutions by calculating the distance of each solution from the ideal solution and the negative ideal solution, and it has a strong interpretability [16]. Combining combinatorial assignment and TOPSIS is beneficial for achieving multi-task and multi-resource allocation optimization for enterprise management. The innovations of this paper are as follows:

1. Oriented to the demand for smart manufacturing enterprise management optimization, based on the combinatorial assignment to achieve the optimization of

the weight setting of the target indicators, the importance of the indicators can be effectively differentiated and can be adapted to the changes of the dynamic production demand.

2. Breaking through the limitations of the traditional optimization methods and proposing an optimization method that combines the combinatorial assignment and TOPSIS to address the optimization of the smart manufacturing management strategy and improve the production efficiency.
3. Based on the optimization method proposed in this paper, optimizing employee management evaluation in manufacturing enterprises is realized, improving the scientificity of enterprise employee management.

The succeeding sections of this paper are arranged as follows. Section 2 constructs the structure of the management optimization strategy. Section 3 calculates the indicator weights based on combinatorial assignment, detailing the subjective and objective weight calculation. The ranking and selection of optimal solutions are based on the TOPSIS method in Section 4. Validation of the proposed method oriented to employee performance management is provided in Section 5, offering solid reassurance of the effectiveness of this approach. Finally, concluding reflections are provided in Section 6.

2 STRUCTURE OF THE MANAGEMENT OPTIMIZATION STRATEGY

In the context of smart manufacturing management, where the optimization needs are complex and dynamic, traditional single optimization methods often struggle to balance efficiency and quality [17]. This study's management optimization strategy, which combines a combinatorial assignment and the TOPSIS method, is designed with adaptability in mind. It constructs several critical indicators for multi-objective optimization in equipment management, employee management, and operation management, and the combinatorial assignment ensures the reasonable allocation of weights. This algorithm can flexibly adjust the weights of each index according to the needs of different management tasks, effectively differentiating the importance of each index and adapting to changes in dynamic production demand. The TOPSIS method is more capable of ranking in multi-objective decision-making [18], and the method is particularly suitable for multi-objective management optimization [19, 20]. Once the weights are determined, the TOPSIS method is introduced to analyze the indicators and sort the programs, ultimately helping to select the optimal management program. This adaptability provides an objective basis for managers to choose from, effectively comparing the management effect under different management strategies and reassuring them of its applicability in dynamic production environments.

In practice, this optimization strategy forms a flexible management optimization strategy through the synergy of the combinatorial assignment and the TOPSIS method. The combinatorial assignment is responsible for the dynamic allocation of weights to ensure the efficient application of management indicators. At the same time, TOPSIS provides managers with a clear basis for program selection. In the smart manufacturing environment, this synergistic mechanism effectively supports managers in achieving efficient and precise management optimization in a complex multi-task and multi-resource environment. The result is a significant improvement in production efficiency and management quality, offering a promising outlook for the potential benefits of the strategy.

3 CALCULATION OF INDICATOR WEIGHTS BASED ON COMBINATORIAL ASSIGNMENT

Multi-objective optimization problems for smart manufacturing management typically involve multiple objectives that must be optimized simultaneously. They are usually presented using multiple metrics, and due to their varying importance, these objectives are assigned different weights. A well-considered weight setting is crucial for optimizing and selecting management strategies. The weights are usually categorized into objective and subjective. Objective weights are typically derived from data and statistical methods, reflecting the inherent attributes or performance of the indicator itself. On the other hand, subjective weights rely more on individual or collective judgments and preferences. This study adopts a combinatorial assignment method to enhance the accuracy and reliability of multi-objective management optimization. The method rationalizes weight determination by integrating subjective and objective weights, resulting in a more comprehensive and accurate management evaluation system [21]. This hybrid approach combines managers' expert judgments with objective data insights, fostering a scientific and adaptable management process while ensuring equitable and robust weight allocation.

Determining subjective weights is a crucial part of the process. It reflects the decision maker's subjective perception of the evaluation indicators' importance. The study employs the rigorous ordinal relationship analysis to assess the subjective weights of performance evaluation indicators. This approach ensures that the weights are scientifically determined.

When making decisions, it is crucial to determine the subjective weights of indicators based on the importance of the evaluation target indicators. The ordinal relationship and difference-driven objective weighting methods demonstrate higher objectivity and convenience than the expert scoring and hierarchical analysis methods. The ordinal relationship method is preferred due to its simplicity and intuition, the advantages of smaller calculation amounts, and easy practical application.

At the same time, the study also emphasizes the determination of objective weights. Difference-driven objective weighting methods, especially the entropy weighting method and the pull-apart gearing method, rely on the actual evaluation data to determine the weights of each evaluation index. This method can more realistically reflect the characteristics and patterns of the data itself.

In the study, the ordinal relationship analysis is used to determine the subjective weights of the performance evaluation indicators, and the difference-driven principle is combined to determine the objective weights. This comprehensive method not only considers the subjective judgment of decision-makers but also makes full use of the actual data information, thus ensuring the comprehensiveness and accuracy of the evaluation results. With its strong scientific basis, such an empowerment method is expected to provide enterprises with a more valid and reasonable foundation for performance evaluation and thus promote continuous improvement and development.

3.1 Calculation of Subjective Weights of Performance Evaluation Indicators Based on the Ordinal Relationship Analysis

The ordinal relationship method is used to determine the subjective weights of indicators based on the importance of the evaluation target indicators [22]. Compared with the expert scoring and hierarchical analysis methods, the ordinal relationship method is more concise and intuitive and requires little calculation. With this regard, the ordinal relationship method is utilized to calculate the subjective weights of the evaluation indicators.

First of all, it is assumed that there are m evaluation indicators, which constitute the indicator set denoted as $\{x_1, x_2, \ldots, x_m\}$, and relevant definitions are presented based on the critical relationships between indicators.

Definition 1. If the degree of importance of an evaluation indicator is greater (or not less) than that of another indicator, it is denoted as $x_i > x_j$.

Definition 2. The set of evaluation indicators $\{x_1, x_2, \ldots, x_m\}$ can be ranked in decreasing order of importance for an evaluation objective.

$$x_1^* > x_2^* > \cdots > x_m^*. \tag{1}$$

If a series of crucial relationships are satisfied, this set of evaluation indicators establishes an ordinal relationship concerning that evaluation objective. Here, $x_1^*, x_2^*, \ldots, x_m^*$ is the ordinal relationship of the evaluation indicator.

With the ordinal relationship method, the steps for determining the subjective weights of the performance evaluation indicators are given as follows:

Step 1: Establish the ordinal relationships for the set of evaluation indicators $\{x_1, x_2, \ldots, x_m\}$.

1. The decision maker selects the most critical indicator from the set of indicators $\{x_1, x_2, \ldots, x_m\}$, denoted as x_1^*.
2. The decision maker then chooses the most important one from the remaining $m - 1$ indicators, denoted as x_2^*.
3. Repeat the above steps until all indicators have been sorted. After $m - 1$ selections, the remaining evaluation metrics is noted x_m^*.

4. The ordinal relation of the set of evaluation indicators $\{x_1, x_2, \ldots, x_m\}$ is denoted as:
$$x_1 \succ x_2 \succ \cdots \succ x_m. \tag{2}$$

Step 2: Determine the relative importance of neighboring indicators x_{k-1} and x_k.

Definition 3. The relative importance of the evaluation indicators x_{k-1} and x_k is r_k, i.e., the ratio of weights, expressed as:

$$r_k = w_{k-1}/w_k, \quad k = m, m-1, \ldots, 3, 2. \tag{3}$$

The assignment of this ratio r_k can be found in Table 1, which reflects the importance difference between two neighboring indicators.

The above steps can be used to obtain the subjective weights of each evaluation indicator, which will be used as the basis for subsequent portfolio assignments. The ordinal relationship analysis simplifies the weights calculation process and can more intuitively reflect decision-makers subjective judgment on the importance of evaluation indicators.

r_k	Explanation
1.1	Indicator x_{k-1} and x_k are of equal importance
1.3	Indicator x_{k-1} is slightly more important than indicator x_k
1.5	Indicator x_{k-1} is significantly more important than indicator x_k
1.8	Indicator x_{k-1} is intensely more important than indicator x_k
2.0	Indicator x_{k-1} is vitally more important than indicator x_k

Table 1. Assignment reference of r_k

As for the employees performance evaluation indicators, the production task completion rate is at the top of the list in descending order of importance. This indicator is the core standard for measuring the efficiency and output capacity of employees. The product once qualified rate follows closely, reflecting the staff's ability to control the quality of the products and the level of craftsmanship. The number of reworked or repaired products is in the third place, which reveals employees' error rate and problem-handling ability in the production process. Next is the failure time interval of intelligent welding robot, which reflects employees' ability to maintain intelligent equipment and their proficiency in operation. Then is the number of site management standard reached, which demonstrates the standardization and discipline of employees in the field work. The last one is the number of innovation suggestion adopted, which encourages the employees to actively participate in innovation and make suggestions for improvement, thereby promoting the enterprise's technological progress and process optimization.

Step 3: The weighting coefficients of the evaluation indicators w_k are determined.

Combining the previous analysis and derivation, the weight coefficients can be calculated, and the specific formulas are given as follows (see Equations (4) and (5)).

$$w_m = \left(1 + \sum_{k=2}^{m} \prod_{i=k}^{m} r_i\right)^{-1}, \tag{4}$$

$$w_{k-1} = r_k w_k. \tag{5}$$

In order to differentiate the subjective weights from objective weights, the subjective weights are labeled, denoted as $W_1 = [w_{1,1}, w_{1,2}, \ldots, w_{1,m}]$.

3.2 Determination of the Objective Weights of the Performance Evaluation Indicators Based on the Difference-Driven Principle

The difference-driven objective assignment method focuses on using actual evaluation data to determine the weight of each evaluation indicator. This method involves two main techniques, i.e., the entropy weight and pull-apart methods. The entropy weight method determines the degree of dispersion of the data by assessing the entropy value of the indicators; a smaller entropy value means that the data are more dispersed and thus have a greater weight in the comprehensive evaluation [23, 24]. The pull-apart method determines the weight by maximizing the differences between the evaluation objects.

In this paper, a novel calculation method is proposed for the objective weights, which is driven by the differences in evaluation indicators. Specifically, an evaluation matrix $X = (x_{ij})_{n\times m}$ is constructed, covering n evaluation objects and m evaluation indicators (see Equation (6)). In this matrix, each element represents the rating received by a particular evaluation object under a specific evaluation indicator.

$$X = \begin{bmatrix} x_{11} & x_{12} & \ldots & x_{1m} \\ x_{21} & x_{22} & \ldots & x_{2m} \\ \ldots & \ldots & \ldots & \ldots \\ x_{n1} & x_{n2} & \ldots & x_{nm} \end{bmatrix}. \tag{6}$$

In the evaluation model, an evaluation matrix x_{ij} $(i = 1, 2, \ldots, n,\ j = 1, 2, \ldots, m)$ is set up, in which each element represents the specific evaluation value of object i under evaluation index j. To ensure a more accurate assessment, a positive ideal evaluation object is introduced, $X^+ = \left[x_1^+, x_2^+, \ldots, x_m^+\right]$, and it represents the object that has reached the optimal state in each evaluation index.

1. First, the maximum absolute difference is calculated, which is between the rated value x_{ij} of indicator i and its ideal value x_j^+. The ratio of this difference to the ideal value is denoted as a critical indicator Z_{1j}, as shown in Equation (7), reflecting the degree of deviation from the ideal state of that evaluated indicator at the individual level.

$$Z_{1j} = \max_i \left|\frac{x_{ij} - x_j^+}{x_j^+}\right|. \tag{7}$$

2. Next, the absolute difference between all the evaluated values of indicator i and the ideal value x_j^+ is summed and its mean value is calculated. The ratio of this average value to the perfect value is noted as shown in Equation (8), representing the deviation of this evaluation indicator from the ideal state at the overall level.

$$Z_{2j} = \sum_{i=1}^{n} \left| x_{ij} - x_j^+ \right| / \left(n \cdot x_j^+ \right). \tag{8}$$

Combining the information from these two aspects (Equations (7) and (8)), it is possible to assess each evaluation indicator's importance more comprehensively. When the value of these two ratios for a given indicator is significant, the indicator performs poorly in the actual evaluation, with this regard, it should be given more weight. Along these lines, the objective weights for each evaluation indicator are determined (see Equation (9)). $W_2 = [w_{2,1}, w_{2,2}, \ldots, w_{2,m}]$ is determined as:

$$w_{2j} = \frac{Z_{1j} + Z_{2j}}{\sum_{j=1}^{m} (Z_{1j} + Z_{2j})}. \tag{9}$$

3. Finally, after obtaining the subjective weights W_1 and the objective weights W_2, the geometric mean method is used to combine the two type weights, thus obtaining the combined weights for each evaluation indicator (see Equation (10)). This method considers the characteristics of subjective judgment and objective data, allocating more scientific and reasonable weights. $W = [w_1, w_2, \ldots, w_m]$, that is

$$w_j = \frac{\sqrt{w_{1j} w_{2j}}}{\sum_{j=1}^{m} \sqrt{w_{1j} w_{2j}}}. \tag{10}$$

The advantage of the combinatorial assignment method is that it combines the ordinal relationship analysis method with the difference-driven principle to effectively determine the subjective weights and objective weights of management indicators. This combinatorial assignment strategy solves the problem of subjectivity in weight allocation in the traditional method and improves the scientificity and accuracy of the management process.

4 RANKING AND SELECTION OF OPTIMAL SOLUTIONS BASED ON THE TOPSIS METHOD

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is a widely recognized decision analysis method that evaluates the distance between each alternative and the positive and negative ideal solutions [25]. Its core principle is ranking solutions by calculating their relative proximity to the ideal solution, which represents the optimal outcome, and the negative ideal solution, which represents the least favorable outcome [26]. TOPSIS has been widely used in various disciplines due to its intuitive and easy-to-understand, simple computation, and low requirement for data sample size. It is particularly advantageous in multi-dimensional and multi-scenario decision analyses, as it efficiently ranks numerous scenarios without imposing strict conditions on the sample data [27]. This capability allows TOPSIS to distinguish differences among alternatives clearly, making it a robust tool for complex decision-making tasks.

In this paper, the TOPSIS is adopted to construct an employee performance evaluation system, and a comprehensive and fair evaluation of employee performance is conducted more scientifically and objectively. In implementing the TOPSIS, the positive and negative ideal solutions are constructed, and the relative closeness between each employee's performance and these ideal solutions is calculated [28, 29]. It can provide scientific decision support for decision-makers and help to evaluate each employee's performance more accurately. Therefore, adopting the TOPSIS to construct the employee performance evaluation system is a wise and beneficial choice that will bring the enterprise a fairer and more transparent evaluation mechanism.

1. Standardization of the comprehensive evaluation matrix.

   Given the diversity of the indicators involved in the assessment process and their different types and scales, it is necessary to standardize the indicators' values to ensure the evaluation's accuracy and fairness. This process aims to eliminate the effects of differences in types and scales between indicators to construct a standardized evaluation matrix. The specific way of standardization is to convert each indicator value according to a particular mathematical formula so that it falls into a uniform value range, usually between 0 and 1, for subsequent comprehensive evaluation and comparison. This systematic process allows for a more objective analysis of indicators' relative importance. This instills confidence in the method's validity, providing a solid foundation for decision-making.

   Cost-based indicators:

   $$x'_{ij} = \frac{x_{ij} - \min_i\{x_{ij}\}}{\max_i\{x_{ij}\} - \min_i\{x_{ij}\}}. \tag{11}$$

   Effectiveness indicators:

   $$x'_{ij} = \frac{\max_i\{x_{ij}\} - x_{ij}}{\max_i\{x_{ij}\} - \min_i\{x_{ij}\}}. \tag{12}$$

2. Based on the comprehensive weight W of each indicator, the standardized evaluation matrix is weighted to obtain the canonical weighting matrix Z.

   $$Z = WX' = \begin{bmatrix} z_{11} & z_{12} & \cdots & z_{1m} \\ z_{21} & z_{21} & \cdots & z_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ z_{n1} & z_{n1} & \cdots & z_{nm} \end{bmatrix}. \tag{13}$$

A composite weighted value is assigned to each evaluation indicator for each object. This value, denoted as z_{ij} $(i = 1, 2, \ldots, n,\ j = 1, 2, \ldots, m)$, represents the combined assessment value of the j^{th} evaluation indicator of the i^{th} evaluation object after considering the weights. It is derived by multiplying the normalized values of the evaluation indicators with the corresponding weights. This step provides the critical data for determining the positive and negative ideal solutions and calculating the distance between each evaluation object and the perfect solution.

3. It is necessary to determine the positive ideal solution and negative ideal solution of each evaluation index. The positive ideal solution is the optimal value of each indicator, representing the ideal best state. In contrast, the negative ideal solution is the worst value of each indicator, representing the state that should be avoided [30, 31]. After determining the ideal solutions, the study will calculate the Euclidean distance between the indicator values of each evaluation object and these two ideal solutions. This calculation, which measures the proximity between each evaluation object and the ideal state, ensures a comprehensive evaluation and ranking. This thorough analysis not only provides a comprehensive evaluation and ranking, but also a deep understanding of the strengths and weaknesses of the evaluation objects, thereby offering robust support for decision-making.

$$S_i^+ = \sqrt{\sum_{j=1}^{n} \left(z_{ij} - x_j^+\right)^2}, \tag{14}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} \left(z_{ij} - x_j^-\right)^2}, \tag{15}$$

where S_i^+ denotes the Euclidean distance of the i^{th} evaluation object from the positive ideal solution. S_i^- denotes the Euclidean distance between the i^{th} evaluation object and the negative ideal solution.

4. Calculate the relative closeness of each evaluated object.

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-}. \tag{16}$$

In the formula, the relative closeness C_i of the i^{th} evaluation object is a key index, which reflects the similarity degree of the object with the positive ideal solution and the difference degree with the negative ideal solution. And then all evaluation objects are ranked according to the magnitude of this relative closeness, thus visualizing which objects are closer to the ideal and which are relatively poor.

5 VALIDATION OF THE PROPOSED METHOD ORIENTED TO THE EMPLOYEE PERFORMANCE MANAGEMENT

Employee management is a critical aspect of smart manufacturing organizations. Despite the significant changes brought about by automation, artificial intelligence, and robotics in employee work patterns and roles, effective employee management remains a core factor in driving innovation and maintaining productivity. The synergy between employees and smart devices is a trend and a necessity in the modern workplace. It is a crucial factor that can effectively enhance employee engagement, work enthusiasm, and motivation. Therefore, optimizing employee management in smart manufacturing enterprises and constructing a scientific and reasonable management logic are crucial.

Performance management is an essential part of employee management. It has moved beyond traditional supervision and appraisal to incorporate data-driven refinement. By analyzing employee performance data, performance management improves team efficiency and provides managers with decision support to optimize resource allocation. This study, which uses the employee performance management of a smart manufacturing enterprise as a case study, validates the practical application effect of the combinatorial assignment-TOPSIS method in the management of smart manufacturing enterprises. The method demonstrates its significant role in enhancing performance management and resource optimization through the scientific allocation of indicator weights and effective sorting decisions. It provides a new practical path for intelligent manufacturing management.

5.1 Design of Performance Evaluation System

Qingdao XJY Company was chosen as a representative and practical case study company. The company has continuously upgraded its production equipment in smart manufacturing, especially with the introduction of welding and stamping robots. It has significantly improved production efficiency and provided valuable data and practical examples to support the study. The validation will be carried out in the company's actual production environment, focusing on the performance of the welding robot management and collaboration specialists, ensuring the effectiveness and feasibility of the optimization strategy.

Furthermore, production line employees are the core force of production activities in manufacturing enterprises, and their work efficiency directly determine enterprises' economic benefits and market competitiveness. The study specifically examines the employees in the position for the welding management and coordination, and launches a detailed quantitative analysis to explore and optimize work performance.

To construct a comprehensive and scientific evaluation system, the study establishes a three-level evaluation index framework that considers employee performance across four key areas: efficient completion of production tasks, maintenance of stable operation of production equipment, assurance of production safety, and promotion of continuous innovation. These metrics aim to holistically assess the overall performance of employees within an intelligent manufacturing environment.

Finally, the TOPSIS method is employed to calculate each employee's relative closeness to the ideal solution by collecting their actual data on each work metric. This method not only integrates multiple aspects of employee performance but also ensures the objectivity and scientificity of the evaluation process, thereby providing the company with a more accurate and comprehensive assessment of the employee performance.

Such a performance evaluation system can help Qingdao XJY better understand employees' actual performance in the intelligent manufacturing environment, support the company's human resource management, and stimulate employees' motivation and innovation.

5.2 Establishment of Performance Evaluation System for Production Line Employees

The study carefully screens the evaluation indices according to the production objectives to construct a performance evaluation system for production line employees, that is widely applicable and meets the common needs of many intelligent manufacturing enterprises.

Based on in-depth connection with the heads of production departments and workshop supervisors, the study divides the work objectives of production line employees into three levels. The first-level goal emphasizes the efficient completion of production tasks, which is the core responsibility of the employees' work; the second-level goal focuses on guaranteeing the stable operation of production equipment to ensure the smoothness of the production process; and the third-level goal is dedicated to providing the safe production and continuous innovation to enhance the overall competitiveness and sustainable development of the enterprise.

Based on these hierarchical objectives, the study sets six specific appraisal indicators to comprehensively and objectively assess employees' performance. These indicators include:

- Production task completion rate: measuring the efficiency and accuracy of employees in completing production tasks within the specified time.
- Product once qualified rate: reflecting the level of product quality produced by employees and the ability of employees to control the production process.
- The number of reworked or repaired products: revealing the problems that may occur in the production process and the ability of employees to solve them.
- The failure time interval of intelligent welding robot: reflecting the staff's ability to maintain and manage the intelligent equipment and efforts to ensure the stable operation of production equipment.

- The number of site management standard reached: demonstrating employees' professionalism and execution ability in site management.
- The number of innovation suggestion adopted: encouraging employees to actively put forward innovative suggestions and measures the adoption of their suggestions. This not only promotes the continuous innovation and development of the enterprise, but also underscores our commitment to staying ahead in the industry.

Through these specific and comprehensive assessment indicators (see Figure 1), it is possible to accurately assess the work performance of production line employees, thus providing the targeted training and incentive activities for the enterprise. More importantly, it would significantly improve the overall operational efficiency and market competitiveness of the enterprise, making it a valuable investment.

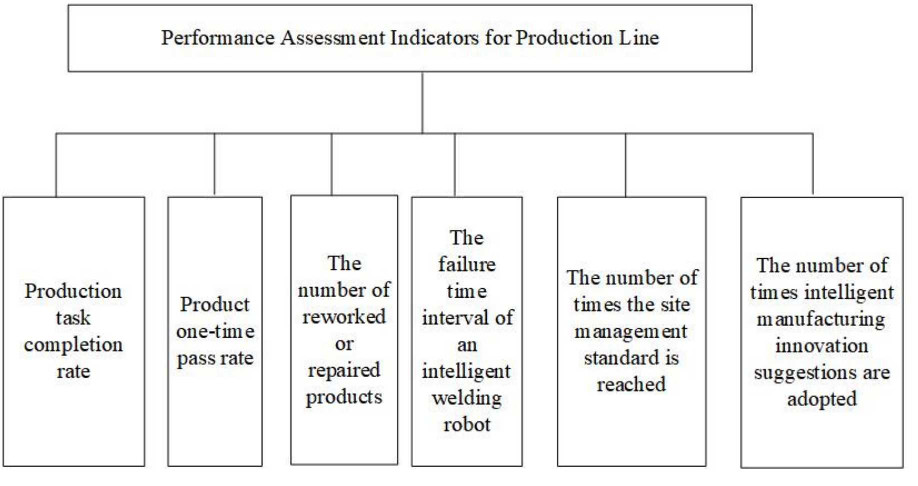

Figure 1. Performance assessment indicators for production line employees

5.3 Example of Quantitative Analysis Performance Evaluation

1. A scoring sheet for each evaluation indicator is developed for all participating employees. In Qingdao XJY company, the workshop chiefs give these monthly scores based on the employee's performance in managing and collaborating with the intelligent welding robots production process. This evaluation system can accurately measure each employee's performance, thus providing a more comprehensive analysis of operational data for the enterprise. Table 2 is shown for an example of the May 2024 evaluation index scoring table.

Evaluation indicators participant in an evaluation	Production task completion rate	Product once qualified rate	Number of reworked or repaired products	Failure time interval of intelligent welding robot (minutes)	Number of site management standard reached	Number of innovation suggestion adopted
Employee A	100 %	98 %	4	90	20	5
Employee B	98 %	98 %	4	120	21	2
Employee C	99 %	97 %	6	120	19	3
Employee D	95 %	98 %	4	140	20	1
Employee E	100 %	97 %	6	90	21	4
Employee F	97 %	96 %	8	130	20	3
Employee G	95 %	97 %	6	140	19	1
Employee H	96 %	97 %	6	130	19	1

Table 2. Scoring table for evaluation indicators

2. Calculate the combined weights of the six assessment indicators.

   (a) Calculate the subjective weights.
   Firstly, the indicators are ranked in order of importance, establishing ordinal relationships. And then the indicators are subjectively assigned values accordingly. The results of the assignment are shown below:

$$r_2 = w_1/w_2 = 1.1; \quad r_3 = w_2/w_3 = 1.3; \quad r_4 = w_3/w_4 = 1.5;$$

$$r_5 = w_4/w_5 = 1.8; \quad r_6 = w_5/w_6 = 2.0.$$

   Using Equations (4) and (5), the subjective weights of each evaluation indicator are accurately calculated as follows:

$$W_1 = [0.2888, 0.2625, 0.2019, 0.1346, 0.0748, 0.0374] .$$

   (b) Calculation of the objective weights.
   Based on the difference-driven principle, applying formulas (7), (8) and (9), the objective weights of each evaluation indicator are given as:

$$W_2 = [0.1049, 0.1201, 0.1713, 0.1375, 0.1538, 0.3124] .$$

   (c) Calculation of the combined weights.
   With the comprehensive consideration of the subjective weights and objective weights, based on formula (10), the comprehensive weights of each evaluation index are given as:

$$W = [0.1958, 0.1997, 0.2092, 0.1530, 0.1207, 0.1216] .$$

3. Determine the overall ranking of participants.

   Based on the TOPSIS, the positive and negative ideal solutions are first determined. On this basis, a scoring scale for the evaluation indicators from the superior leaders is introduced. The leaders scored the employees according to their actual performance, and then these scores are calculated and ranked, as shown in Table 3. Combining the monthly appraisal grades and performance coefficients of frontline production employees, as shown in Table 4, the appraisal results of each employee are derived. A comprehensive and systematic evaluation of the workshop participants is carried out using this method.

Subject of evaluation	Positive ideal solution distance D+	Negative ideal solution distance D−	Relative proximity C	Sorting results
Employee Object A	0.174	0.954	0.846	1
Employee Object B	0.418	0.788	0.654	3
Employee Object C	0.614	0.493	0.445	5
Employee Object D	0.708	0.663	0.484	4
Employee Object E	0.388	0.782	0.668	2
Employee Object F	0.808	0.308	0.276	6
Employee Object G	0.857	0.270	0.240	8
Employee Object H	0.790	0.290	0.268	7

Table 3. Comprehensive assessment results of participants

Appraisal level	Appraisal status	Coefficient of achievement
Grade A (excellent)	Efficient and outstanding	1.2
Grade B (good enough)	Completion in quality and quantity	1
Grade C (good)	Completion in quality or quantity	0.9
D (General)	Fundamentally complete	0.8
E (poor)	Far below expectations	0

Table 4. Monthly appraisal levels and performance factors for production employees

Based on the results of TOPSIS evaluation calculations, the positive ideal solution distance (D+), negative ideal solution distance (D-), and relative closeness (C) for each employee can be derived. From the ranking results, evaluation object A has the best performance, while evaluation object G has relatively poor performance. A detailed comparison of the indicator values was conducted to clarify whether the indicators of the selected scheme (evaluation object A) are superior to those of other schemes.

The analysis reveals that evaluation object A consistently achieves higher scores across key indicators, such as the production task completion rate, product once qualified rate, and innovation suggestion adoption rate, compared to other evaluations objects. For instance, object A has the highest production task completion rate, reflecting its superior efficiency in meeting production targets and a significantly higher product once the qualified rate, underscoring its excellence in maintaining quality standards. Furthermore, object A's performance in reducing rework and repair rates and ensuring minimal equipment downtime further solidifies its position as the optimal choice.

These findings not only validate the rankings generated by the TOPSIS method but also provide strong evidence that the indicators of the selected scheme are superior to those of the alternatives. Such a comprehensive analysis enhances the validity of the conclusions and ensures the robustness of the evaluation framework for managerial decisions like salary allocation and performance improvement strategies.

6 CONCLUSION

In this paper, an optimization strategy combining the combinatorial assignment-TOPSIS method was proposed for intelligent manufacturing management. The combinatorial assignment, which combines the ordinal relationship analysis method with the difference-driven principle, effectively determines management indicators' subjective and objective weights. With this method, this study solves the problem of subjectivity in weight allocation in the traditional method and improves management's scientificity and accuracy. In addition, based on the TOPSIS, the ranking of multi-objective indexes and the selection of optimal solutions are realized, thus reflecting employees' work performance and providing managers with more accurate support for managerial decision-making. Based on the proposed method, a practical application was conducted at the Qingdao XJY Company. The process involved empowering employees to make decisions and using the TOPSIS method to sort multi-objective indexes and select optimal solutions. This application realized the optimization of the performance evaluation management of the employees, verified the high efficiency of the combinatorial assignment-TOPSIS method, and improved the science and efficiency of the personnel management of this intelligent manufacturing enterprise.

The employee performance evaluation conducted in this study demonstrates the efficiency and practicality of the proposed combinatorial assignment-TOPSIS optimization method. Beyond its application to employee performance management, the methodology is highly generalizable and adaptable to other management processes in smart manufacturing and beyond. Integrating subjective and objective weighting ensures the method is flexible enough to accommodate diverse management scenarios, such as equipment optimization, resource allocation, and operational process improvement. Moreover, the method's inherent scalability makes it applicable to sectors outside manufacturing, such as logistics and service industries, where multi-objective decision-making is essential.

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