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THE APPLICATION OF ARTIFICIAL INTELLIGENCE TECHNOLOGY IN HUMAN CENTERED MANUFACTURING IN INDUSTRY 5.0

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Abstract. In order to clarify the cognitive process of human beings and the influencing factors of human errors in the process of manufacturing capability evaluation, quantitatively analyze the reliability of human beings in the manufacturing process, and more accurately evaluate the manufacturing capability of production lines, the author proposes the application of artificial intelligence technology in human centered manufacturing in Industry 5.0. In response to the dynamic nature of data in the operation process of manufacturing production units and the varying importance of indicators to evaluation objects at different times, the author proposes an objective weighting method that combines indicator sensitivity with entropy weight method to solve the problem of existing weighting methods only considering the fluctuation of indicator data and ignoring the importance of evaluation indicators to all evaluated objects. The combination of subjective weights established by the Analytic Hierarchy Process (AHP) is used to obtain the final combination weight of indicators. At the same time, evaluate and analyze the factors that contribute to human error behavior to obtain the human reliability of the unit, and introduce it into the comprehensive evaluation of unit manufacturing capability. Based on the time series data in the evaluation, a time dimension factor combined with grey correlation analysis is introduced to conduct a dynamic comprehensive evaluation of unit manufacturing capacity in time series, and the production unit manufacturing capacity index is obtained. The example results show that 10 indicator data from the past 10 time periods were selected for evaluation, and the closer the time period, the more important the data is. The time factor for each time period is (0.0048, 0.0068, 0.0126, 0.0266, 0.0582, 0.0704, 0.1232, 0.1685, 0.2212, 0.3070). The unit capability value obtained through dynamic horizontal and vertical comprehensive evaluation is most consistent with the capability value obtained by the author's method. Under the four methods, although there are differences in the capacity values of each unit, the fluctuation is within a reasonable range, indicating that the author's evaluation method is reasonable and feasible. The feasibility and effectiveness of the evaluation method have been validated.

Key words: Human reliability, Manufacturing capability, Dynamic evaluation, Production line, Industry 5.0

1. Introduction. Human centric/centered manufacturing, also known as people-oriented manufacturing, abbreviated as human-centered manufacturing, mainly involves two subjects - humans and machines, as well as their relationship - human-machine relationship . With the emergence and development of new generation information and communication technology (ICT)/artificial intelligence (AI) technologies such as the Internet of Things, cloud computing, Cyber physical systems (CPS), big data, and deep learning, the arrival of Industry 5.0, which mainly relies on intelligent manufacturing, has been promoted. New types of operators - operator 5.0 and holographic perception intelligent connected autonomous intelligent machines have emerged. The human-machine relationship (especially human-machine interaction) has evolved from the initial physical direct interaction between a single person and a single machine to the system collaboration of virtual and real fusion between humans and objects. Human in the loop (HiL) is no longer limited to the physical loop, and concepts such as Human on the loop (HoL) and Human out of the loop (HofL) have emerged [1,2]. In fact, HiL, HoL, and HofL correspond to the physical space, information space, and social (community) space of human intelligent manufacturing, ultimately forming a trinity of autonomous social cyber physical production system (SCPPS); Especially the development of intelligent manufacturing in Human CPS (H-CPS) promotes the development of people-oriented intelligent manufacturing [3].

Compared with the world's advanced level, the manufacturing industry has problems such as being large but not strong. The gap in independent innovation ability, resource utilization efficiency, industrial structure level, informatization level, quality and efficiency is particularly obvious. The task of industrial intelligence transformation and upgrading and leapfrog development is urgent and arduous [4]. The continuous development

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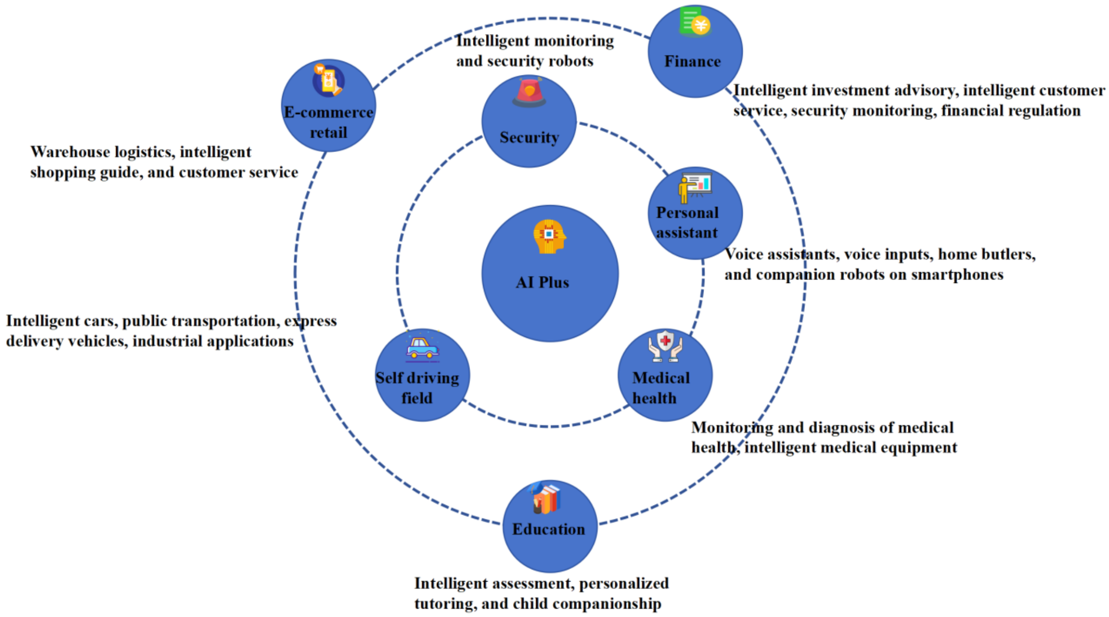

Fig. 1.1: Artificial Intelligence Technology

of new generation Internet, artificial intelligence, digital twins and other technologies has continuously injected strong power into the development of intelligent manufacturing. The excessive pursuit of informatization and digitization in production models can no longer meet the needs of complex operations such as flexible production workshops and personalized customization of users. The difficulties in intelligent manufacturing are becoming more prominent, so the production trend urgently needs to be changed, and human beings as a key factor cannot be ignored anymore [5]. The concept of Industry 5.0 has gradually attracted people's attention. As a continuation and supplement to Industry 5.0, Industry 5.0 not only focuses on optimizing industrial structure and improving automation levels, but also places people at the center of the manufacturing industry, allowing technology to actively serve and adapt to people, and paying more attention to human values and feelings. Human centered intelligent manufacturing should consider the safety and happiness of workers, dispel their concerns and concerns about the "machine replacement" brought about by the industrial revolution, and allow labor to return to the factory [6] (Figure 1.1).

2. Literature Review. In the blueprint of intelligent manufacturing, human-machine collaboration has become the mainstream mode of production and service. Due to the deep collaboration between humans and machines, the tasks and requirements of humans in intelligent manufacturing systems have undergone significant changes. Although humans no longer bear repetitive tasks, they remain the central link of the decision-making loop system and always occupy a dominant position. The deep connotation of human-machine collaboration is the integration of human-machine intelligence, which represents the need for humans and machines to jointly complete designated tasks. In the process of completing dynamic job tasks, the manufacturing system needs to keep pace with the staff, face dynamic job requirements, adapt resources and cooperate autonomously to achieve coordinated production. The intelligent manufacturing development theory of human cyber physical system (HCPS) proposed by Rannertshauser, P., clarifies a technological system dominated by physical systems (machines, robots, processing processes), information systems, and human decision-making [7]. By transferring part of human perception, analysis, and control functions through information systems, it can replace most of human physical and mental labor.

Compared with the automotive industry, manufacturing tasks and processes in fields such as aerospace, shipbuilding, and construction are too complex and require high assembly accuracy. Currently, manual operations are still relied upon, so it is necessary to conduct research on human-machine collaboration. Assisting humans with collaborative robots to complete complex tasks, maintaining optimal levels of mental and physical strength, and balancing the demand for cognitive resources in the brain with the supply of cognitive resources to the task, avoiding the negative impact of overload and underload on operators, reducing human burden, improving task execution efficiency and production safety. Froschauer, R. studied the relevant algorithms for controlling cooperative robots using electromyographic signals [8]. Romero, D. explored the effectiveness of guiding gestures in human-machine collaboration scenarios in the industrial field [9]. The "Intelligent Unit Production Line for Human Machine Collaboration" launched by Romero D integrates advanced technologies such as artificial intelligence, Internet of Things, and big data analysis. It aims to improve production efficiency, flexibility, and quality for multi variety and small batch production modes. Through mutual perception between humans and machines, ultra flexible production can be achieved on the same site through complementarity and assistance [10]. The "Intelligent Flexible Production Line Using Robots to Produce Robots" launched by Zhang R provides a stable and efficient reference sample for the human-machine cooperation application of collaborative robots in the industrial production field through modular design and collaborative production methods [11].

The author studies a dynamic evaluation method for unit level manufacturing capability based on information sensitivity at the unit level. Firstly, a production unit manufacturing capability evaluation model is established, and then human reliability issues are considered in the unit capability evaluation. Static grey correlation analysis is extended to dynamic decision-making, and indicator sensitivity weights are used to modify and assign weights, time dimension factors are introduced to obtain the unit's various capability values and comprehensive manufacturing capability values at each time step, based on time series data, the total manufacturing capability of each unit is obtained.

3. Research Methods.

3.1. Dynamic evaluation model for manufacturing capacity at the production unit level. During the production process of manufacturing system production units, each processing state will change with time, and the evaluation index values are also constantly changing. Therefore, the capacity value of the unit is dynamically changing at different times [12]. The static evaluation method mainly involves a two-dimensional evaluation of the decision object at a single moment, which only includes the decision space and the target space, and cannot reflect the characteristics over a period of time. Therefore, in addition to evaluating the decision space and target space dimensions, the production unit level manufacturing capacity also needs to be extended to consider time and space, that is, to dynamically evaluate the production unit level manufacturing capacity from the three dimensions of time, indicators, and goals [13].

In the process of evaluating unit capabilities, the focus is on the establishment of evaluation indicators and the generation of manufacturing capability evaluation results. In order to dynamically evaluate unit level capabilities, it is necessary to consider the indicator data of the entire time series. Let the decision solution set $U = \{u_1, u_2, \cdots, u_n\}$ consist of n manufacturing unit objects to be evaluated, the indicator set $P = \{p_1, p_2, \cdots, p_m\}$ consists of m evaluation indicators. The manufacturing indicator data from nearly N time points in the unit manufacturing process is used as the evaluation basis data. If the jth attribute value of the evaluation unit u_i at time point $t_k (k = 1, 2, \cdots, N)$ (or stage) is $p_{ij}(t_k)$, then the unit evaluation indicator data chronological list can be formed as shown in Table 3.1.

In the process of dynamically evaluating the manufacturing capacity of production units, it is necessary to first conduct a two-dimensional static evaluation at a fixed time, and then comprehensively evaluate the static evaluation results in the time dimension. For the evaluation of dynamic 3D space, commonly used 3D evaluation operators include Time Order Weight Average operator (TOWA) and Time Order Weighted Geometric Average operator (TOWGA) [14]. The time-series weighted average operator first evaluates at each time step, and then evaluates the time dimension; The temporal geometric mean operator evaluates the time dimension and then reduces it to evaluate the indicator dimension. The author uses a time-series weighted average operator to evaluate the manufacturing capacity of production units in three-dimensional space.

Based on the index time sequence list established in Table 3.1, at time $y_i(t_k) = \sum_{j=1}^{m} a_j p_{ij}(t_k), k = 1, 2, \cdots, n$, the comprehensive evaluation function of production unit iu based on the weighted model can be

Table 3.1: List of Index Time Series

unit	t_1				t_2				$\cdots$	t_N			
		$p_1, p_2, \cdots, p_m$				$p_1, p_2, \cdots, p_m$			$\cdots$		$p_1, p_2, \cdots, p_m$		
u_1	$p_{11}(t_1)$	$p_{12}(t_1)$	$\cdots$	$p_{1m}(t_1)$	$p_{11}(t_2)$	$p_{12}(t_2)$	$\cdots$	$p_{1m}(t_2)$		$p_{11}(t_N)$	$p_{12}(t_N)$	$\cdots$	$p_{1m}(t_N)$
u_2	$p_{20}(t_1)$	$p_{21}(t_1)$	$\cdots$	$p_{2m}(t_1)$	$p_{20}(t_2)$	$p_{21}(t_2)$	$\cdots$	$p_{2m}(t_2)$	$\cdots$	$p_{20}(t_N)$	$p_{21}(t_N)$	$\cdots$	$p_{2m}(t_N)$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$		$\vdots$	$\vdots$	$\vdots$	$\vdots$
u_n	$p_{n1}(t_1)$	$p_{n2}(t_1)$	$\cdots$	$p_{nm}(t_1)$	$p_{n1}(t_2)$	$p_{n2}(t_2)$	$\cdots$	$p_{nm}(t_2)$		$p_{n1}(t_N)$	$p_{n2}(t_N)$	$\cdots$	$p_{nm}(t_N)$

described as follows 3.1:

$$y_i(t_k) = \sum_{j=1}^{m} \alpha_j p_{ij}(t_k), k = 1, 2, \cdots, N; i = 1, 2, \cdots, n \tag{3.1}$$

In the formula, $\alpha = \{\alpha_1, \alpha_2, \cdots, \alpha_m\}$ is the weight corresponding to each evaluation indicator, and it satisfies the following equation 3.2:

$$\sum_{j=1}^{m} \alpha_j = 1, 0 \leqslant \alpha_j \leqslant 1 \tag{3.2}$$

For the calculation of indicator weights, it is usually necessary to pay attention to both people's subjective experience information and the information brought by objective data itself. Therefore, a combination of subjective weight and objective weight is used to assign weights to the indicators. If the subjective weight value is w' and the objective weight value is w", the combination weight of the indicators is as follows 3.3:

$$\alpha_j = \frac{w'_j * w_j"}{\sum_{j=1}^{m} w'_j * w_j"} (j = 1, 2, \cdots, n) \tag{3.3}$$

The author uses the sensitivity weight of indicators to adjust the objective weight, as the commonly used objective weighting method often only focuses on the fluctuation of the indicator's own data and does not pay attention to the impact of indicator changes on the overall indicator set. In order to more accurately reflect the weight of indicators, the author uses the sensitivity weight of indicators to adjust the objective weight. If the sensitivity weight of indicators is , the modified objective weight is as follows 3.4:

$$w_j" = \frac{w_j * w_r}{\sum_{j=1}^{m} w_j * w_r} \tag{3.4}$$

Due to the fact that the value of unit manufacturing capacity varies at different times in the time sequence, and the proportion of unit manufacturing capacity to the total manufacturing capacity of the production unit at different times in the time sequence is not the same [15]. Due to the influence of interference factors at certain times, the unit evaluation index data may experience abnormal mutations. In this case, the unit manufacturing capacity evaluation results obtained do not match the actual situation. Therefore, in order to avoid this situation, after conducting a two-dimensional static evaluation, different time factors can be assigned to the evaluation values at different times for comprehensive consideration, by using a time factor, the ability values at each time step are integrated into the total ability value at the time step. If the time factor at each moment is set to $v = \{v_1, v_2, \cdots, v_n\}$, then v should satisfy the following equation 3.5:

$$\sum_{j=1}^{N} v_j = 1, 0 \leqslant v_j \leqslant 1 \tag{3.5}$$

Therefore, the manufacturing capacity value of production unit v_i in the time sequence can be expressed as equation 3.6:

$$y_i = \sum_{k=1}^{N} y_i(t_k) * v_k \tag{3.6}$$

Based on the above research content, it can be concluded that for the dynamic evaluation of manufacturing capacity of production units, a two-dimensional evaluation should be conducted first in the time series table, and then a comprehensive manufacturing capacity evaluation of the unit should be conducted in the time dimension. In this process, the production data of the unit in the manufacturing process is updated in real-time in the time series table, which is used as a new data source for evaluating the manufacturing capacity of the unit. Therefore, the manufacturing capacity of the unit can be evaluated in real-time and dynamically. In order to establish a dynamic evaluation model for the manufacturing capacity of production units, providing support for subsequent dynamic evaluation methods.

The principle of the dynamic evaluation model for manufacturing capacity of production units is to first study and analyze the state change information during the manufacturing process of production units, including the status information of processing personnel during the manufacturing process of units. Based on the historical manufacturing task data of units, the evaluation data is standardized to form a unit capacity evaluation matrix [16]. The unit manufacturing data changes dynamically over time, and the importance of each indicator data to the overall evaluation indicator set may vary at different times, which may result in information redundancy. Therefore, the sensitivity of the indicator information is used to reflect the degree of influence of each indicator on the original indicator set information. Based on this, the indicator set is reduced in dimensionality, reducing redundant information, making the evaluation indicators more accurate, and further obtaining the sensitivity weight of the indicators. The sensitivity weight is used to correct the indicator weight, so that when assigning weights to indicators, not only the fluctuation of the indicator's own data is considered, but also the degree of influence of each indicator on the original indicator set information, at the same time, pay attention to the impact of indicator changes on the overall indicator set, obtain indicator weights, and combine grey correlation analysis to obtain the capability values of each unit's time series. Further introduce time factors, and finally obtain the total manufacturing capability values of each unit.

3.2. Optimization and weighting of evaluation indicators based on information sensitivity.

3.2.1. Optimization of evaluation indicators based on information sensitivity. In the evaluation of manufacturing capacity of production units, the data of evaluation indicators is constantly changing. During the evaluation process, a large amount of historical data needs to be combined for evaluation. The importance of each indicator data to the evaluation object may change at different times, and different indicator data may reflect the same information. That is, there may be information overlap between indicators, resulting in information redundancy. Some data information may be repeatedly emphasized during the evaluation, which may distort the evaluation results. Therefore, in the evaluation process, in order to avoid wasting calculation time on unnecessary data and make the evaluation results more accurate, it is necessary to reduce the dimensionality of the indicators.

Currently, principal component analysis, factor analysis, and other dimensionality reduction methods are still widely used in various fields such as comprehensive evaluation and pattern recognition. However, these methods still have some problems, such as difficulty in determining the economic meaning of principal components and non unique factor loading matrices. Moreover, most of these dimensionality reduction methods have not taken into account the degree of influence of indicators on the overall indicator set information, and may lose some information that has a significant impact on the overall indicator set during the dimensionality reduction process [17]. Therefore, based on the information sensitivity of the indicators, the author optimizes the dimensionality of the evaluation indicators to ensure that the retained indicator information has a significant impact on the original indicator set information and the degree of information overlap between the evaluation indicator sets is relatively low. Information sensitivity reflects the degree to which a certain indicator affects the information of the original indicator set. The greater the information sensitivity, the more important the indicator is in the original indicator system, and correspondingly, the more significant its impact on the evaluation results; On the contrary, it indicates that changes in indicators have a smaller impact on the evaluation results.

The dimensionality reduction of indicator data based on the information sensitivity of indicators is developed on the basis of principal component analysis dimensionality reduction method. The standardized data matrix of indicators is set as $X = (x_{ij})_{n\times m}$, among them, n represents the amount of indicator data, m represents the number of indicators, andamong them, n represents the amount of indicator data, m represents the number of indicators, and x_{ij} is the i-th data of the j-th indicator. The steps to reduce the dimensionality of the indicator using information sensitivity are as follows.

(1). Solve the principal component Z_i as follows 3.7:

$$Z_i = u_{i1}X_1 + u_{i2}X_2 + \cdots + u_{ij}X_j + \cdots + u_{im}X_m \tag{3.7}$$

In the formula, Z_i represents the i-th principal component, $X_j = (x_{1j}, x_{2j}, \cdots, x_{ij}, \cdots, x_{nj})$ is the value of the j-th indicator after Z-normalization of the indicator data, and u_{ij} is the j-th component of the orthogonal unitary eigenvector $u_i^T = (u_{i1}, u_{i2}, \cdots, u_{im})$ of the indicator correlation coefficient matrix $X^T X$.

(2). Calculate the variance contribution rate ω_i of principal component Z_i, as shown in equations 3.8 and 3.9:

$$|X^T X - \lambda_i E_m| = 0 \tag{3.8}$$

$$\omega_i = \lambda_i / \sum_{i=1}^{m} \lambda_i \tag{3.9}$$

Obtain the eigenvalues λ_i of the correlation coefficient matrix $X^T X$ through equation 3.9, and the variance contribution rate ω_i reflects the proportion of the information content of the i-th principal component Z_i to the information content of all original indicators.

(3). Calculate the cumulative variance contribution rate Ω_k as follows 3.10:

$$\Omega_k = \sum_{i=1}^{k} \omega_i \tag{3.10}$$

In equation 3.10, k represents the number of retained principal components. Usually, in principal component analysis, several principal components with a cumulative variance contribution rate of 70%∼90% and higher information content are retained. In order to approximate the original indicator set information, the author selects the relatively higher proportion of 90%, therefore, if the cumulative variance contribution rate of the first k principal components is $\geqslant \Omega_k 90\%$, the top k principal components with the highest variance contribution rate are retained.

(4). Solve the information sensitivity β_j of the jth indicator as follows 3.11:

$$\beta_j = \sum_{i=1}^{k} \omega_i |\partial Z_i / \partial X_j| \tag{3.11}$$

In the formula, $|\partial Z_i / \partial X_j|$ represents the sensitivity of the i-th principal component to changes in the size of the j-th indicator, that is, the magnitude of the change in information content of the i-th principal component caused by a small change in the j-th indicator, while the size of other indicators remains unchanged.

(5). Calculate the cumulative information content Γ_s, which reflects the cumulative content of the reduced indicators in the original indicator set. Assuming that the sensitivity of indicator information is arranged in descending order, the result is $\beta_1^* > \beta_2^* > \cdots > \beta_m^* >$, then s Γ solution is shown in formula 3.12:

$$\Gamma_s = \sum_{j=1}^{s} \beta_j^* / \sum_{j=1}^{m} \beta_j \tag{3.12}$$

Table 3.2: Description of Priority Relationship Matrix

A	B_1	B_2	$\cdots$	B_m
B_1	B_{11}	B_{12}	$\cdots$	B_{1m}
B_2	B_{20}	B_{21}	$\cdots$	B_{2m}
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
B_m	B_{m1}	B_{m2}	$\cdots$	B_{mm}

Generally, selecting to retain indicator information that can reach a cumulative information content of 70% to 90% for dimensionality reduction of the indicator set.

Reducing the dimensionality of indicators by determining their information sensitivity can compensate for the problem in principal component analysis where the load coefficient cannot reflect the importance of the indicators to the original indicator set, and reducing the dimensionality of information solely based on the load coefficient may be unreasonable [18]. By performing dimensionality reduction on indicator data, the pressure of evaluation calculations can be reduced without losing the original indicator set information, while further improving the final evaluation results.

3.2.2. Weighting of Evaluation Indicator Combination for Sensitivity Correction.

(1) Determination of subjective weight. In the process of weighting indicators, it is necessary to consider the importance of each indicator to the evaluation objectives based on the actual situation. Although subjective weighting carries a significant personal subjective color and the given weights may not conform to the changes in objective data, the evaluation process cannot ignore the decision-maker's view on the importance of the indicators. The subjective weighting method can effectively avoid the phenomenon of "important indicators having smaller weights and unimportant indicators having larger weights" that may occur in absolute objective weighting based on actual subjective conditions. Therefore, subjective weighting is crucial in the process of weighting indicators. The Analytic Hierarchy Process (AHP) is widely used in decision weighting, which is a weighting method that quantifies qualitative analysis problems by mathematizing people's thinking processes about complex systems [19]. The author subjectively assigns weights to unit capability evaluation indicators using the Analytic Hierarchy Process.

The Analytic Hierarchy Process (AHP) can transform a complex decision-making problem into a ranking problem of the evaluated object relative to the evaluation target. It first refines a complex decision-making problem into some constituent factors, and then further subdivides these factors until they cannot or do not need further subdivision. By doing so, a hierarchical structure can be established between various factors based on their subordinate relationships.

It can be specifically divided into the following steps:

Step 1: Establish a hierarchical structure. Based on the evaluation of unit manufacturing capability, the various factors that affect manufacturing capability are subdivided, and a hierarchical structure is formed based on the subordinate relationship between the factors [20].

In a hierarchical structure, there are generally three layers: target layer, criterion layer, and indicator layer. The targets of the two layers of indicators are often only related to some indicators in the lower layer, and the weights between indicators that do not have a connection between the upper and lower layers are 0.

Step 2: Establish a priority relationship matrix. Based on the established indicator hierarchy, establish the priority relationship matrix, also known as the judgment matrix, for the evaluation system. Compare the corresponding indicators in the upper and lower layers in sequence. The priority relationship matrix formed by the target layer and the criterion layer can be described in Table 3.2.

In the Table, B_{ij} represents the importance ratio scale of the indicators in criterion layer B relative to target layer A. Its value is generally determined using the 1-9 scale method based on people's intuitive judgment, as shown in Table 3.3, which shows the value pattern of B_{ij}. When B_{ij} takes numbers such as 2, 4, 6, and 8, it indicates that its importance is the middle value of adjacent levels.

Step 3: Consistency verification. After obtaining the judgment matrix, in order to make the final evaluation result reasonable, it is necessary to perform consistency judgment on it, and the judgment formula is shown in

Table 3.3: Proportional Scale of Relative Importance

Importance Level	B_{ij} value	Importance Level	B_{ij} value
i,j both elements are equally important	2		
Element is slightly more important than element j	4	The i element is slightly than the j element	1/4
The i element is significantly more important than the j element	6	The i element is significantly less important than the j element	1/6
The element i is much more important than the element j	8	The element i is much less important than the element j	1/8
The element i is extremely important than the element j	10	The element i is less important than the element j	1/10

Table 3.4: Average Random Consistency Index

Matrix order	1	2	3	4	5	6	7	8
RI	0	0	0.53	0.88	1.13	1.25	1.35	1.43
Matrix order	9	10	11	12	13	14	15	
RI	1.45	1.48	1.53	1.55	1.57	1.59	1.60	

equation 3.13.

$$CI = \frac{\lambda_{max} - m}{m - 1} \tag{3.13}$$

λ_{max} represents the maximum eigenvalue of the judgment matrix. If $\lambda_{max} = m$, that is CI=0, it indicates that the judgment matrix is completely consistent; On the contrary, if $CI \neq 0$, it indicates poor consistency. But this calculation process will become increasingly complex as the order of the judgment matrix increases. In order to make the calculation process relatively easy, the concept of random consistency ratio is introduced, it is the ratio of CI to RI, denoted as CR. The RI values of the 15th to 1st order judgment matrix are shown in Table 3.4. The following equation 3.14:

$$CR = \frac{CI}{RI} \tag{3.14}$$

If CR>1.0, then certain modifications should be made to the judgment matrix, and the above steps should be repeated until CR<0.10 is met, so there is no need to modify the judgment matrix.

Step 4: Sort by level. If CR<0.10, it is necessary to calculate the weight values of the relative importance order between the indicators in this layer and those in the previous layer in the judgment matrix.

Step 5: Overall hierarchical sorting. Repeat the operations from step 1 to step 4, from the top layer to the bottom layer, and calculate the eigenvalues and eigenvectors of each judgment matrix for each layer in turn, following the hierarchical structure. Then calculate the overall ranking of the hierarchy and calculate the relative weights of all indicators in the lowest layer relative to the target layer.

When the total ranking of all indicators $B_1, B_2, \cdots, B_m$ in the criterion layer is completed, the weights obtained are $b_1, b_2, \cdots, b_m$, if the single ranking result of a certain indicator c_j in layer C with respect to a certain indicator B_i in layer B is $c_1^i, c_2^i, \cdots, c_j^i, \cdots, c_n^i$, then the total ranking in layer C can be expressed as follows 3.15:

$$c_j = \sum_{i=1}^{m} b_i c_j^i (j = 1, 2, \cdots, n) \tag{3.15}$$

The overall hierarchical sorting still requires consistency testing. By following these steps and following the calculation steps above, the subjective weight value of the evaluation index can be obtained, which is denoted as W'.

(2) Sensitivity correction objective weight. Subjective weights often reflect the subjective preferences of decision-makers and cannot reflect the changes in objective data of indicators. If a certain indicator is very important but its data changes in each period are minimal, the impact on the evaluation object is relatively small; If a certain indicator has a low level of importance but has significant differences in data changes across different periods, it may have a significant impact on the evaluation results, therefore it needs to be given a higher weight. As an objective weighting method, the entropy weighting method determines the weight of each indicator based on the amount of information provided by its entropy value. The core idea is to reflect the importance of a certain indicator based on the degree of difference between its observed values. If the data difference of a certain indicator of each evaluated object is not too large, it indicates that the indicator has little effect on the evaluation system [21]. So it is inversely correlated with entropy value, while the importance of an indicator is positively correlated with entropy weight, that is, the larger the entropy weight, the more important the indicator is; On the contrary, the smaller the entropy weight, the less important the indicator is. Compared with other evaluation methods, entropy weighting method can avoid the interference of human factors in the weighting process of indicators, making the evaluation results more realistic.

Using the entropy weight method to assign weights to indicators, the specific steps are as follows:

Let $X = (x_{ij})_{n \times m}$ be the data matrix of n evaluation sequences and m preprocessed evaluation indicators. Let H_j be the entropy value of the jth evaluation indicator, and then the entropy value H_j is as follows 3.16, 3.17:

$$H_j = -\frac{1}{ln(n)} (\sum_{i=1}^{n} f_{ij} ln f_{ij})(i = 1, 2, \cdots, n, j = 1, 2, \cdots, m) \tag{3.16}$$

$$f_{ij} = \frac{u_{ij}}{\sum_{i=1}^{n} u_{ij}} \tag{3.17}$$

According to the entropy value obtained above, the weight value of the indicator can be obtained as follows 3.18:

$$w_j = \frac{1 - H_j}{\sum_{j=1}^{m} (1 - H_j)} (j = 1, 2, \cdots, m) \tag{3.18}$$

The entropy weight method focuses on the magnitude of the fluctuation of the indicator's own data, with large data fluctuations indicating a greater impact on the evaluation results and small data fluctuations indicating a smaller impact on the evaluation results. However, it often overlooks the degree of influence of a certain indicator on the entire evaluation indicator set. The sensitivity of indicator information mentioned in the previous section reflects the degree of impact of indicator changes on the overall evaluation indicator set. Therefore, the weighting of indicators is based on their information sensitivity, and the calculation formula is shown in equation 3.19.

$$w_r = \beta_r / \sum_{j=1}^{m} \beta_j \tag{3.19}$$

After obtaining the sensitivity weights of the indicators, the weights obtained by the entropy weight method are modified to obtain more accurate objective weights of the indicators, significantly improving the accuracy of the evaluation results. Using the multiplication integration normalization method to combine the two, the calculation formula is as follows 3.20:

$$w_j" = \frac{w_j * w_r}{\sum_{j=1}^{m} w_j * w_r} \tag{3.20}$$

(3) Combination weighting. In the evaluation of manufacturing capacity in production units, the weight of indicators mainly includes two aspects: On the one hand, it is subjective weighting, which assigns weights to indicators by quantifying the decision-maker's subjective preference for the indicators; On the other hand, the weighting of indicators is based on their objective data, reflecting the usefulness of the amount of information that the objective data can provide during the evaluation process. Therefore, when assigning weights to indicators, one should not only consider one aspect of the weight, but should combine subjective and objective factors for combined weighting. The author uses a aggregation method with multiplication characteristics to aggregate subjective and objective weights, and obtains the final weight of the aggregated indicators as $w = (w_1, w_2, \cdots, w_m)$. Among them, equation 3.21 is as follows:

$$w_j = w'_j * w_j" / \sum_{j=1}^{m} w'_j * w_j" (j = 1, 2, \cdots, n) \tag{3.21}$$

4. Result analysis.

4.1. Example verification.

A certain manufacturing workshop has six production and processing units u_1, u_2, u_3, u_4, u_5, and u_6 responsible for the production and processing of workshop tasks. The production unit evaluation index system established earlier evaluates the manufacturing capacity of production units from the aspects of processing quality Q, processing flexibility F, manufacturing time T, processing cost C, environmental protection E, and human reliability P, selecting production and manufacturing data from nearly ten time periods of each unit to form the original unit evaluation index time series data Table, according to the author's proposed unit manufacturing capability evaluation method, the specific evaluation steps for its manufacturing capability are as follows.

Step 1. In the unit capability evaluation, the evaluation indicators are both benefit indicators and cost indicators. Formulas 3.1 and 3.2 are used to preprocess the original indicator data to obtain a standardized temporal decision matrix, which provides data support for subsequent evaluations [22].

Step 2. For the preprocessed indicator data, the impact of each indicator on the overall evaluation indicator set varies at different times, taking the most recent 10t as an example, calculate the information sensitivity B_j of each indicator according to formulas 3.7 to 3.11, and obtain the cumulative information content Γ_s of each indicator from formula 3.12. Then, perform dimensionality reduction on the indicators. The calculation results are shown in Table 4.1.

Generally, retaining indicator information with a cumulative information content of 65% to 95% can be achieved. The author chooses to retain information with a cumulative information content of 95%. According to Table 4.2, after sorting by sensitivity, the cumulative information content at indicator E3 reaches 88%. Therefore, at 10t, retaining indicator E3 and its previous indicator information is used to reduce the dimensionality of the indicator set.

Step 3. For the dimensionality reduction processed indicators, calculate the sensitivity weights of each indicator according to formula 3.19 as shown in Table 4.2.

Step 4. Based on the Analytic Hierarchy Process, subjectively assign weights to each indicator, and use formulas 3.16 to 3.20 to modify the entropy weights of each indicator using sensitivity weights to obtain the objective weights of the indicators. Finally, according to formula 3.21, obtain the combined weights of each indicator in indicator layer C relative to criterion layer B and relative to target layer A, as shown in Table 4.3.

Step 5. During the evaluation process, 10 indicator data from the past 10 time periods were selected for evaluation. The closer the time period, the more important the data is often, taking λ=0.4 here, we can obtain the time factor for each time step as v=(0.0048,0.00680.0126,0.0266,0.0582,0.0704,0.1232,0.1685,0.2212,0.3070)

Step 6. Determine the target sequence of each indicator, in order to obtain the capability values of each unit in terms of quality, time, and comprehensive manufacturing capability at each time step [23].

After obtaining the capability values at each moment, combined with the time factors obtained earlier, the total capability values in terms of unit processing quality, manufacturing time, etc., as well as the total manufacturing capability values, are shown in Table 4.4.

Table 4.1: Sensitivity of Indicator Information

Index	Sensitivity B_j	Sort by B_j	Accumulated information content Γ_s
Q1	0.297	Q1(0.299)	6.32%
Q2	0.16	F3(0.286)	12.32%
Q3	0.218	T2(0.274)	19%
Q4	0.224	T3(0.265)	23.61%
C1	0.255	C1(0.255)	28%
C2	0.156	T1(0.243)	35%
C3	0.172	Q4(0.225)	38.75%
F1	0.186	Q3(0.218)	43.32%
F2	0.208	P6(0.214)	47.81%
F3	0.286	F2(0.208)	52.11%
T1	0.242	P3(0.202)	56.41%
T2	0.275	P4(0.197)	60.51%
T3	0.267	E2(0.193)	64.51%
El	0.182	P2(0.188)	68.41%
E2	0.192	F1(0.186)	72.31%
E3	0.168	E1(0.183)	76.11%
P1	0.164	PS(0.175)	79.81%
P2	0.188	C3(0.175)	83.41%
P3	0.202	E3(0.167)	88%
P4	0.197	P1(0.164)	90.41%
P5	0.176	C2(0.157)	93.71%
P6	0.214	P7(0.153)	96.81%
P7	0.153	Q2(0.152)	100%

Table 4.2: Indicator Sensitivity Weights

Index	Q_1	Q_2	Q_3	C_1	C_2	F_1	F_2
Sensitivity weight	0. 404	0. 295	0.302	0. 598	0. 403	0. 274	0. 307
index	F_3	T_1	T_2	T_3	E_1	E_3	E_2
Sensitivity weight	0. 423	0. 308	0. 352	0. 343	0.337	0. 423	0.354
index	E_3	P_2	P_3	P_4	P_5	P_6	
Sensitivity weight	0. 313	0. 193	0. 208	0. 203	181	0. 218	

4.2. Result Analysis. The author first optimized the dimensionality of indicators based on their information sensitivity. The degree of influence of indicator data on the overall evaluation object may change at different times, and different indicator data may also reflect the same information. Repeated emphasis on the same information can generate redundancy and affect the evaluation results, reducing the dimensionality of indicator data based on indicator sensitivity can avoid problems such as difficulty in determining the economic meaning of principal components and non unique factor loading matrices compared to commonly used principal component analysis methods [24]. Compare the evaluation results of indicators after dimensionality reduction optimization with those without dimensionality reduction treatment, as shown in Figure 4.1.

From Figure 4.1, it can be seen that there is a certain difference between the unit capability evaluation results after dimensionality reduction and the evaluation results without dimensionality reduction, but the difference is not significant. The reason for the certain difference is that after dimensionality reduction of the indicator data, some redundant information is reduced, avoiding the same information from being repeatedly emphasized. The evaluation results of the two are basically consistent, which can prove that the author's dimensionality reduction processing of indicator data based on indicator sensitivity is reasonable and effective. The reduced data information can represent the overall data information and accurately evaluate manufacturing capabilities.

Table 4.3: Weight values of various indicator combinations

Criterion layer	Indicator layer	Subjective power	Objective rights	C-B combination weight	C-A combination weight
	Processing qualification rate	0.0702	0.553	0.628	0.1186
Processing quality Q	Shape machining accuracy	0.0582	0.255	0.25	0.0453
	Dimensional machining accuracy	0.0413	0.196	0.135	0.0245
	Raw material consumption cost	0.0745	0.556	0.645	0.1267
Processing cost C	Labor management fee	0.0515	0.446	0.355	0.0702
	Arrival of raw materials	0.0607	0.238	0.295	0.0438
Manufacturing flexible F	Equipment utilization rate	0.0476	0.18	0.186	0.0275
	Equipment failure handling	0.0443	0.574	0.53	0.0775
	response time	0.0575	0.303	0.294	0.0533
Manufacturing time T	Processing time	0.0658	0.434	0.483	0.0868
	Auxiliary processing time	0.0499	0.266	0.226	0.0405
	Solid waste pollution	0.0536	0.446	0.508	0.0727
Environmental Protection E	Waste gas pollution	0.0447	0.32	0.297	0.0426
	Waste liquid pollution	0.0368	0.246	0.192	0.0276
	Assignment difficulty	0.0535	0.165	0.187	0.0267
Human reliability	Homework guidance	0.0447	0.192	0.185	0.0268
	Work skills	0.0367	0.158	0.127	0.0178
	physiological function	0.0535	0.18	0.198	0.0279
	Assignment time	0.0447	0.316	0.305	0.0433

Table 4.4: Total Capacity Values of Each Unit

	u_1	u_2	u_3	u_4	u_5	u_6
Processing quality	0.567	0.705	0.574	0.668	0.565	0.588
Processing cost	0.64	0.546	0.585	0.66	0.694	0.648
Manufacturing flexibility	0.558	0.658	0.677	0.64	0.689	0.558
Manufacturing time	0.534	0.667	0.605	0.594	0.588	0.68
environmental protection	0.465	0.458	0.585	0.557	0.420	0.633
Human reliability	0.593	0.623	0.575	0.67	0.567	0.574
Manufacturing capability value	0.563	0.586	0.58	0.607	0.570	0.645

At the same time, the author uses the sensitivity weight of the indicators to modify the indicator weight obtained by the entropy weight method, which can solve the problem of existing weighting methods only considering the fluctuation of the indicator's own data and ignoring the importance of the evaluation indicator to the entire evaluated object. After weighting the indicators, considering the temporal dynamics of unit indicator values, the time factor combined with grey correlation analysis method is finally introduced to obtain the capacity values of each unit. Compare the evaluation results of the method adopted by the author with those obtained from three methods: fuzzy analytic hierarchy process, rough set theory, and dynamic comprehensive evaluation, as shown in Figure 4.2.

From Figure 4.2, it can be seen that among the four methods, the unit capacity values obtained through dynamic horizontal and vertical comprehensive evaluation are most consistent with the capacity values obtained by the author's method. The capacity values obtained under rough set theory and fuzzy analytic hierarchy process have significant differences compared to these two methods, this is because rough set theory is a static evaluation method, while the method adopted by the author considers the temporal nature of the evaluation data. At the same time, fuzzy analytic hierarchy process is a subjective evaluation method, which has strong subjectivity and less attention to objective weights. Under the four methods, although there are differences in the capacity values of each unit, the fluctuation is within a reasonable range, indicating that the author's evaluation method is reasonable and feasible.

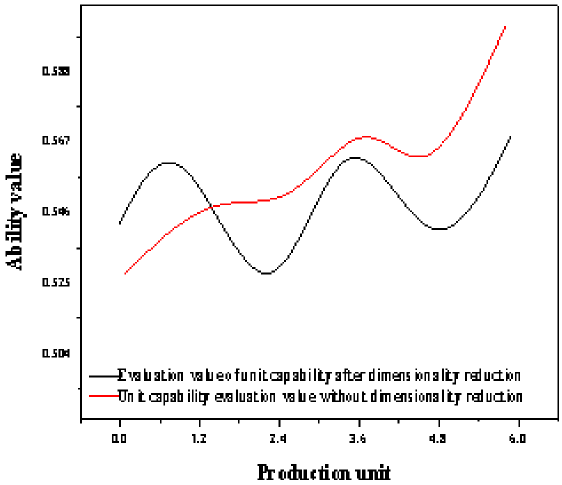

Fig. 4.1: Evaluation results of total manufacturing capacity of units before and after dimensionality reduction

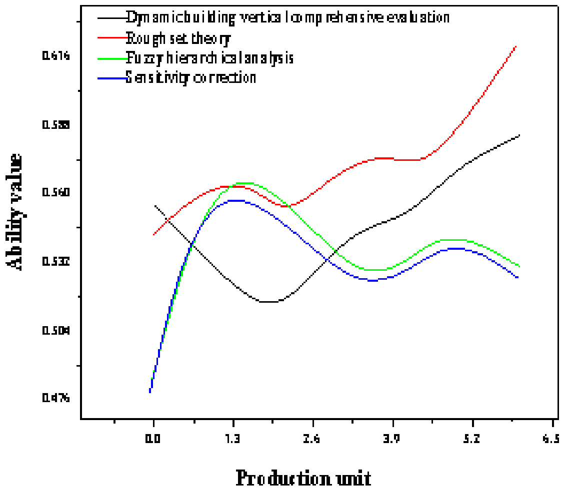

Fig. 4.2: Comparison of total manufacturing capacity values of units under different evaluation methods

In the evaluation process of unit manufacturing capability, the author analyzed the behavioral factors that affect human behavior in the manufacturing process, taking into account the role of human factors in the unit manufacturing process. By analyzing and evaluating the formation factors of each human factor behavior, the size of the unit's human reliability was obtained, and the unit manufacturing capability value was finally obtained by integrating factors such as unit time and quality. As shown in Figure 4.3, the figure reflects the ability values of each unit in processing quality, manufacturing flexibility, and other aspects. It can be seen from the figure that for production units with high human reliability, their ability in processing quality and

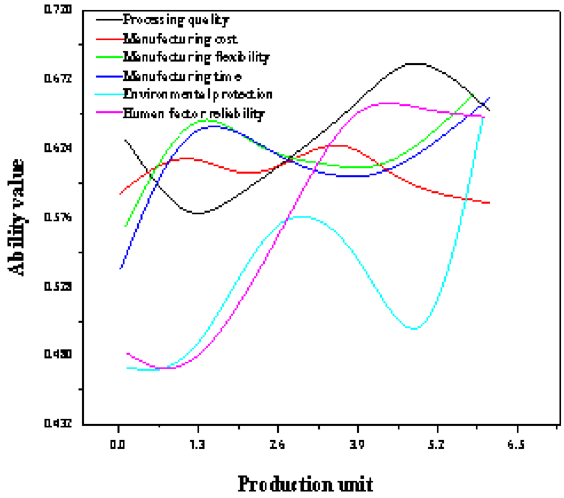

Fig. 4.3: Capability values of each unit in various aspects

manufacturing time is often higher, and the trend of change in the three is generally the same. In production and manufacturing, unreliable human behavior often leads to human error. Once a person makes an error, it often reduces their work efficiency and may also lower the production quality of the product to a certain extent. That is to say, human factors also have a certain impact on the unit manufacturing capacity. In the evaluation process of manufacturing capacity, the human factors in the production process cannot be ignored in order to obtain more accurate manufacturing capacity.

Evaluating the manufacturing capacity of production units can obtain the capability values of each unit in terms of processing quality, manufacturing flexibility, and other aspects. Therefore, workshop managers can timely grasp the production information of units, respond to weak links in unit production in a timely manner, and achieve optimal scheduling and complete production tasks on time.

5. Conclusion. The author established a manufacturing capacity evaluation model for production units. In response to the dynamic nature of data in the operation process of manufacturing production units and the varying importance of indicators to evaluation objects at different times, a combination of indicator sensitivity and entropy weighting method is proposed to objectively weight indicators, solving the problem of existing weighting methods only considering the fluctuation of indicator data and ignoring the importance of evaluation indicators to all evaluated objects. At the same time, in the process of unit manufacturing, humans are also an important component of the production unit, which can have a certain impact on the manufacturing capacity of the unit. Therefore, human reliability issues were considered in the unit capacity evaluation. Finally, the grey relational analysis method was used to obtain the various capabilities and comprehensive manufacturing capabilities of the unit at different times. Time dimension factors were introduced for time series data to obtain the total manufacturing value capabilities of each unit. Finally, the feasibility and effectiveness of the proposed evaluation method were verified through case analysis.

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