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Evaluation of Enterprise Lean Level Based on Fuzzy Multiple Subjective and Objective Weights

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Abstract

Aiming at the problem of weight determination in multi-attribute decision making, this paper proposes a method of index weight determination combining fuzzy subjective and comprehensive objective, and applies this method to evaluate the lean level of enterprises. First of all, the use of expert scoring method and entropy value method, fuzzy index correlation index weight determination method (CRITIC) and improved approach to ideal solution sorting method (improved TOPSIS) to determine the subjective and objective weight of each index, the subjective and objective weight combined to get the comprehensive weight; Then, TOPSIS method was used to rank the alternatives. H company ABC is discussed, the three production lines of the lean level evaluation as an example, the combination of single subjective and objective weight determination method and the proposed subjective, objective method to determine the weight of the combination of the comprehensive analysis of SPSS, verify the proposed subjective, objective weight determination method of combining the comprehensive accuracy and reliability.

Keywords

Trapezoidal Blur, Multi-Attribute Decision Making, Comprehensive Subjective and Objective Weight, Improved TOPSIS

1. Introduction

As a particularly important element in the field of decision science, multi-attribute decision making is a decision problem in which decision-makers choose an optimal scheme or prioritize it under the circumstance of considering multiple objective attributes. At present, there are endless overlapping solutions for multi-attribute decision making, and there are numerous solutions for weight distribution among common elements of methods, including ANP method (Jonathan Catron et al., 2013), CRITIC method (DIakoulakiI et al., 1995), entropy method (Abdel-Baset et al., 2019), VIKOR method (Liu Ziqi et al., 2020), TOPSIS method (Zeng et al., 2020) and prospect theory (Zhang & Fan, 2012). However, these methods are only subjective or objective methods to determine the weight, and ANP method is similar to analytic hierarchy process in that the decision or evaluation results mainly reflect the intention of the decision maker, while objective methods have their own limitations in data processing and cannot calculate the effective and reasonable weight of indicators.

Ervural and Zaim (2018) applied the multi-attribute decision making method to the research of energy planning, determined the scheme standard and weight by combining ANP method with SWOT analysis, and sorted the standards by fuzzy TOPSIS method. However, in this literature, the author only considered subjective weight. In other words, the weights obtained by ANP method are only taken as the weights of index ranking, thus ignoring the possible bias of decision makers in subjective consideration of evaluation indicators and other information. Reza Rostamzadeh et al. (2018) combined TOPSIS with CRITIC method model to build a model and apply it to the evaluation of multi-attribute risk indicators in a sustainable supply chain. However, in practical decision-making problems, complex decision-making background and decision-making alternative information will appear, which makes the single subjective or objective weight in the calculation of limitations. However, some research methods also provide new ideas for multi-attribute decision making. Dariusz Kacprzak (2018) extended TOPSIS method to ordered fuzzy number group decision making. In this paper, TOPSIS method was used twice. Firstly, the weight of decision maker was determined, and then the aggregate decision matrix was calculated for all group decision matrices provided by decision maker. On this basis, the extended TOPSIS method is used to sort the schemes again, and the optimal scheme is selected. In order to evaluate sustainable supply chain risk management, Abedl-Basset and Mohamed (2020) proposed a multi-criteria decision-making method combining TOPSIS and CRITIC method, and applied this model to telecom equipment companies to evaluate this model. Wang and Lin (2021) combined subjective and objective weight determination methods, thus determining the comprehensive weight method is worthy of attention.

To sum up, most of the existing literatures use single subjective or objective methods to determine the weight, and ANP method is similar to analytic hierarchy process in that the decision or evaluation results mainly reflect the intention of the decision-maker, while objective methods have their own limitations in data processing and cannot calculate effective and reasonable index weight. At present, although there are literatures combining subjective and objective, the limitations of methods cannot be overcome. After understanding all kinds of weight determination methods, this paper decided to combine subjective weight determination methods with multiple objective weight determination methods, trying to reduce the error rate of various methods, reflect the actual situation more directly, and solve the problem of enterprise lean level evaluation.

However, the method in this paper still cannot completely eliminate the limitations of subjective and objective methods, and can only reduce the error rate through comprehensive methods on the original basis. In addition, this paper takes enterprise lean level assessment as an example to discuss the decision-making method, so it focuses on the breadth of sample collection, and the number of samples needs to be improved.

In view of the above discussion, the basic thinking framework of this paper is established, as shown in Figure 1. This paper tries to construct a weight determination model for most comprehensive fuzzy MCDM problems by systematically and comprehensively applying fuzzy theory, subjective and objective weight synthesis method and TOPSIS method. First of all, the use of expert scoring method to determine the subjective weight of the indicators, the use of entropy method, fuzzy index correlation index weight determination method CRITIC and improve TOPSIS to determine the objective weight of the indicators, the subjective and objective weight combined to get the comprehensive weight; Then, TOPSIS method was used to rank the alternatives. Finally, taking the lean level assessment of three production lines ABC of H Company as an example, the accuracy and reliability of the weight determination method combining subjective and comprehensive objective proposed in this paper are verified.

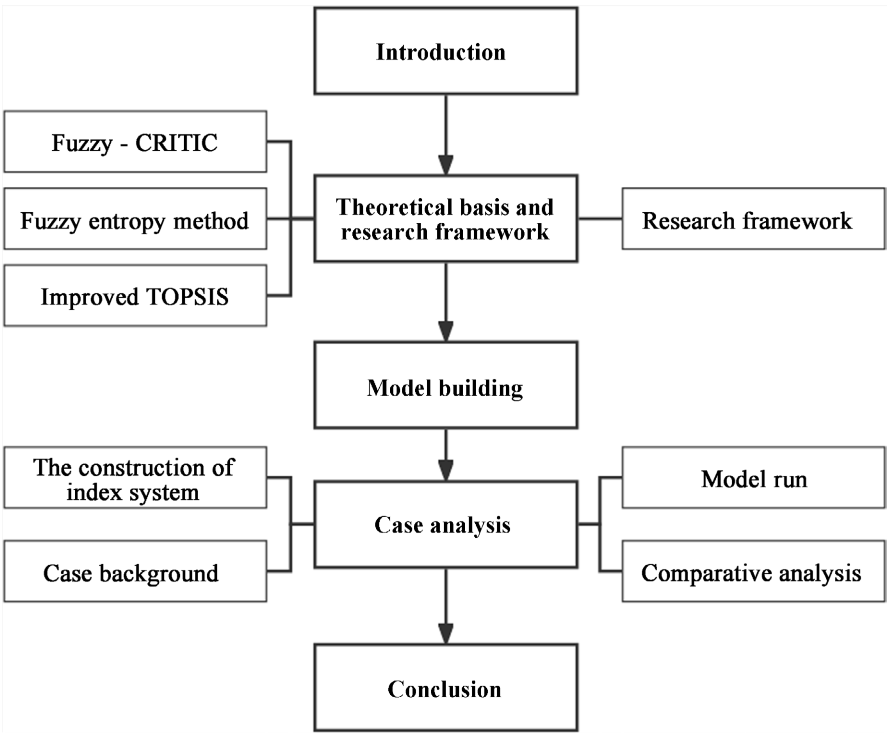

Figure 1. Basic idea frame diagram.

2. Theoretical Basis and Research Framework

2.1. Theoretical Basis

- **Fuzzy—CRITIC**

When measuring the weight of indicators, the comparison between indicators and the conflict between indicators are important factors that need to be considered. In the critic method, standard deviation is used to measure the comparison strength between indicators, and correlation coefficient is used to represent the degree of conflict between indicators. Suppose $\widetilde{x_{ij}} = \left(x_{ij1}, x_{ij2}, x_{ij3}, x_{ij4}\right)$ represents the fuzzy preference value of the *i*th scheme under the *j*th criterion $\left(i = 1,2,\cdots,n;\ j = 1,2,\cdots,m\right)$, $\widetilde{w_j^0} = \left(w_{j1}^0, w_{j2}^0, w_{j3}^0, w_{j4}^0\right)$ is the fuzzy objective weight of *j*th criterion, N is the set of non-beneficial criteria, B is the set of beneficial criteria. The process of determining fuzzy objective weight of indicators based on this method is summarized as follows.

Step 1: Decision matrix standardization processing.

$$x_{ijk}^{\mathrm{T}} = \begin{cases} \dfrac{x_{ijk} - x_{jk}^-}{x_{jk}^* - x_{jk}^-} & \text{if } j \in B \\ \dfrac{x_{jk}^- - x_{ijk}}{x_{jk}^- - x_{jk}^*} & \text{if } j \in N \end{cases} \tag{1}$$

$$\boldsymbol{x}_{jk} = \left(x_{1jk}^{\mathrm{T}} \cdot x_{2jk}^{\mathrm{T}} \cdots x_{njk}^{\mathrm{T}}\right) \tag{2}$$

where,

$$x_{jk}^* = \begin{cases} \max_i x_{ijk} & \text{if } j \in B \\ \min_i x_{ijk} & \text{if } j \in N \end{cases} \qquad x_{jk}^- = \begin{cases} \min_i x_{ijk} & \text{if } j \in B \\ \max_i x_{ijk} & \text{if } j \in N \end{cases} \tag{3}$$

x_{ijk}^{T} is the conversion value of the *k*th ($k = 1,2,3,4$) element of $\widetilde{x_{ij}}$, $\boldsymbol{x}_{jk}$ is the *k*th vector of the *j*th criterion, x_{jk}^* and x_{jk}^- are ideal and non-ideal values of the *j*th criterion and the *k*th element in $\widetilde{x_{ij}}$, respectively.

Step 2: Calculate the standard deviation σ_{jk} of each vector $\boldsymbol{x}_{jk}$.

Step 3: Construct four symmetric matrices of $m \times m$ dimensions, and the matrix elements are $r_{jj'}^k \left(j' = 1,2,\cdots,m; k = 1,2,3,4\right)$. The elements of this matrix are the linear correlation coefficients between vectors $\boldsymbol{x}_{jk}$ and $\boldsymbol{x}_{j'k}$.

One thing to note, if all the elements of A or B vectors are the same, we can assume that the elements are not correlated ($r_{jj'}^k = 0$).

Step 4: Calculate the information measure for each standard.

$$H_{jk} = \sigma_{jk} \sum_{j'=1}^{m} \left(1 - r_{jj'}^k\right) \tag{4}$$

Step 5: Determine the unsorted target weights.

$$w'_{jk} = \frac{H_{jk}}{\sum_{j'=1}^{m} H_{jj'}} \tag{5}$$

Step 6: Determine the weight of the fuzzy criteria.

$$w_{jk}^{0} = w'_{jk'} \tag{6}$$

where,

$$\begin{aligned} &k, k' \in \{1,2,3,4\} \\ &w_{j4}^{0} = \max_k w'_{jk} \\ &w_{j1}^{0} = \min_k w'_{jk} \end{aligned} \tag{7}$$

- **Fuzzy entropy method**

As an objective weighting method, entropy method can be used to judge the randomness and disorder degree of events and measure the dispersion degree of an index. In this method, the greater the dispersion degree of an index, the greater the influence of the index on the comprehensive evaluation. The specific implementation steps are as follows.

Step 1: Select the data and construct the fuzzy matrix ($\boldsymbol{X}$). m indicators and n samples are selected, and X_{ij} is the value of the jth indicator of the ith sample in the fuzzy matrix $(i = 1,2,\cdots,n;\ j = 1,2,\cdots,m)$.

Step 2: Data standardization processing.

Step 3: Calculate the proportion of the ith sample in the jth index. $(i = 1,2,\cdots,n;\ j = 1,2,\cdots,m)$.

$$P_{ij} = \frac{X_{ij}}{\sum_{i=1}^{n} X_{ij}} \tag{8}$$

Step 4: Calculate the entropy value of the jth index.

$$e_j = -k\sum_{j=1}^{m} P_{ij} \ln P_{ij} \tag{9}$$

where: $k > 0$, ln is the natural logarithm. In the formula, constant k is related to the number of samples. Generally, let $k = 1/\ln n$, then satisfy $0 \le e \le 1$.

Step 5: Calculate the difference coefficient of the jth index.

$$g_j = 1 - e_j \tag{10}$$

For the jth indicator, the greater the difference in the value of indicator X_{ij}, the greater the evaluation effect on the scheme, and the smaller the entropy value, that is, the larger the g_j, the more important the indicator.

Step 6: Calculate the index weight.

$$w_j = \frac{g_j}{\sum_{j=1}^{m} g_j} \qquad j(1,2,3,\cdots,m) \tag{11}$$

- **Improved TOPSIS method**

As an important method of uncertainty analysis, TOPSIS theory calculates the distance between each plan and the best plan and the worst plan, and uses the index of relative closeness as the standard of comprehensive evaluation. In order to make the decision scheme as close as possible to the positive ideal solution and far away from the negative ideal solution, and to fully mine the information in the data, this paper uses TOPSIS method under Lagrange method to determine the objective weight. The method is as follows.

$$\begin{cases} \min T = \sum_{i=1}^{n}\sum_{j=1}^{m}\left(r_{ij}-r_j^*\right)^2 w_j^2, \\ \text{s.t. } \sum_{j=1}^{m} w_j = 1, \\ w_j > 0,\ j = 1,2,3,\cdots,m. \end{cases} \tag{12}$$

where:

$r_j^* = \left\{\left(\max_i r_{ij} \mid j \in J\right) \text{or} \left(\min_i r_{ij} \mid j \in J'\right)\right\}$, J is a positive indicator, and J' is a negative index.

Establishing Lagrange model:

$$L = \sum_{i=1}^{n}\sum_{j=1}^{m}\left(r_{ij}-r_j^*\right)^2 w_j^2 + \lambda\left(\sum_{j=1}^{m} w_j - 1\right) \tag{13}$$

Making $\partial L/\partial w_j = 0$, the objective weight of index $j(1,2,3,\cdots,m)$ can be obtained.

$$w_j = \frac{1}{\left\{\left[\sum_{j=1}^{m}\left(\frac{1}{\sum_{i=1}^{n}\left(r_{ij}-r_j^*\right)^2}\right)\right]\left[\sum_{i=1}^{n}\left(r_{ij}-r_j^*\right)^2\right]\right\}} \tag{14}$$

2.2. Research Framework

The research framework of this paper is shown in Figure 2.

3. Model Building

In this section, it is assumed that we have n alternative plans $\left(A = \{A_1, A_2, \cdots, A_n\}\right)$, m indicators $\left(C = \{c_1, c_2, \cdots, c_m\}\right)$ and k decision maker $\left(D = \{D_1, D_2, \cdots, D_k\}\right)$ to participate in the decision-making of indicators and plans. The following steps give the multi-attribute fuzzy decision making method.

Step 1: Construct the average decision matrix (X).

$$X = \left[\widetilde{x_{ij}}\right]_{n\times m} \tag{15}$$

where,

$$\widetilde{x_{ij}} = \frac{1}{k} \overset{k}{\underset{p=1}{\oplus}} \widetilde{x_{ij}^p} \tag{16}$$

Indicator $c_j(1 \le j \le m)$ is determined by decision maker $p(1 \le p \le k)$, and alternative performance value $A_i(1 \le i \le n)$ is determined by $\widetilde{x_{ij}^p}$.

Step 2: Construct subjective criteria weight matrix.

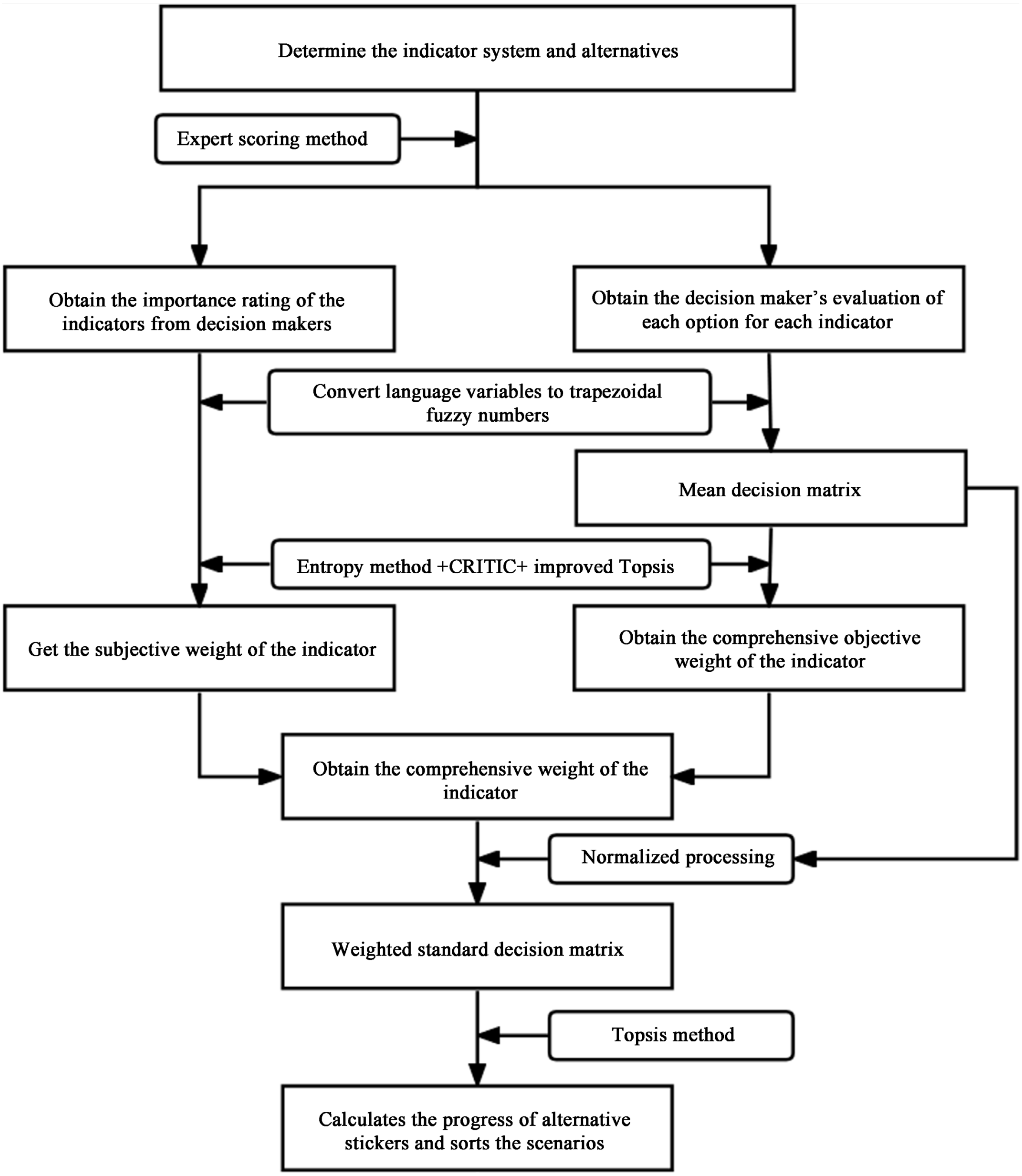

Figure 2. Research framework of the paper.

$$W = \left[\widetilde{w_j^s}\right]_{1\times m} \tag{17}$$

where,

$$\widetilde{w_j^s} = \frac{1}{k}\bigoplus_{p=1}^{k}\widetilde{w_{jp}^s} \tag{18}$$

The subjective weight of criterion $c_j\left(1\le j\le m\right)$ which is assigned by the *p*th decision-maker $\left(1\le p\le k\right)$ is donated by $\widetilde{w_{jp}^s}$.

Step 3: The normalized subjective weight of each index was calculated.

$$\widetilde{w_j^{sn}} = \widetilde{w_j^{s}} \Big/ k\left(\mathop{\oplus}_{j=1}^{m} \widetilde{w_j^{s}} \right) \tag{19}$$

Step 4: The objective weight of criteria is determined by using fuzzy CRITIC method, entropy method and improved TOPSIS method described in the previous section.

Step 5: The normalized subjective weight is combined with the objective weight to calculate the total weight, as shown below.

$$\widetilde{\omega_j} = \rho \cdot \widetilde{\omega_j^{sn}} \oplus (1-\rho) \cdot \widetilde{\omega_j^{s}} \tag{20}$$

where,

$\widetilde{w_j^{s}}$ is the subjective weight of the normalized index, $\widetilde{w_j^{sn}}$ is the objective weight of the normalized index, and $\widetilde{w_j^{sn}}$ is the combination of three objective weight determination methods, namely:

$$\widetilde{w_j^{sn}} = \widetilde{w_j^{sn1}} + \widetilde{w_j^{sn2}} + \widetilde{w_j^{s3}} \tag{21}$$

Step 6: Normalized fuzzy average decision matrix.

$$\begin{gathered} R = \left[\widetilde{r_{ij}} \right]_{n\times m} \\ \widetilde{r_{ij}} = \left(\frac{x_{ij1}}{u_j}, \frac{x_{ij2}}{u_j}, \frac{x_{ij3}}{u_j}, \frac{x_{ij4}}{u_j} \right) \\ \widetilde{r_{ij}} = \left(\frac{l_j}{x_{ij4}}, \frac{l_j}{x_{ij3}}, \frac{l_j}{x_{ij2}}, \frac{l_j}{x_{ij1}} \right) \end{gathered} \tag{22}$$

where,

$$\begin{gathered} l_j = \min_i x_{ij1} \\ u_j = \max_i x_{ij4} \end{gathered} \tag{23}$$

Step 7: A weighted normalized fuzzy decision matrix is constructed.

$$\begin{gathered} Z = \left[\widetilde{z_{ij}} \right]_{n\times m} \\ \widetilde{z_{ij}} = \widetilde{w_j} \otimes \widetilde{r_{ij}} \end{gathered} \tag{24}$$

Step 8: Fuzzy negative ideal solution (FNIS) and fuzzy positive ideal solution (FPIS) are determined.

$$\begin{gathered} A^{+} = \left(v_1^{+}, v_2^{+}, \cdots, v_m^{+} \right) \\ A^{-} = \left(v_1^{-}, v_2^{-}, \cdots, v_m^{-} \right) \end{gathered} \tag{25}$$

where,

$$\begin{gathered} v_j^{+} = \begin{cases} \max_i z_{ij4} & \text{if } j \in B \\ \min_i z_{ij1} & \text{if } j \in N \end{cases} \\ v_j^{-} = \begin{cases} \min_i z_{ij1} & \text{if } j \in B \\ \max_i z_{ij4} & \text{if } j \in N \end{cases} \end{gathered} \tag{26}$$

Step 9: Calculate the distance of each alternative to FNIS and FPIS.

$$d_i^+ = \sum_{j=1}^{m} d\left(\widetilde{z_{ij}} \cdot v_j^+\right)$$
$$d_i^- = \sum_{j=1}^{m} d\left(\widetilde{z_{ij}} \cdot v_j^-\right) \tag{27}$$

Step 10: Calculate the relative proximity of each alternative and rank the alternatives in descending order of these values.

$$C_i = \frac{d_i^-}{d_i^- + d_i^+} \tag{28}$$

4. Case Analysis

In order to meet the diversified and personalized needs of customers and quickly respond to the dynamic changes of the market, the production mode of manufacturing enterprises has shifted from large-scale mass production to multi-variety and small-batch production (Wang Haonan et al., 2021). Multi-variety and small-batch manufacturing is more complex, production line changes are more frequent, and standard time setting is difficult, which brings new challenges to manufacturers in reducing costs, improving quality and productivity (Ku et al., 2020). In order to cope with these challenges, manufacturers are eager to find a better way to integrate lean production tools in the context of industry 4.0 (Rossini et al., 2019). At the same time, establishing an objective and reasonable evaluation system of lean production level has become an inevitable requirement for enterprises to implement and apply lean production (Pei Xiaobing & Jia Linlin, 2017).

4.1. The Construction of Index System

As a reflection of the application degree and implementation effect of lean production in enterprises, the level of lean production needs to be comprehensively analyzed from the perspective of the whole system engineering. Based on this, this paper constructs the evaluation system of enterprise's lean level from six aspects as first-level indicators: lean concept, lean management, organization and personnel, lean technology, flexibility level and continuous improvement.

The lean philosophy C1 can be divided into five secondary indexes $\{C11, C12, C13, C14, C15\}$, lean management C2 can be divided into five secondary indexes $\{C21, C22, C23, C24, C25\}$, organization and personnel C3 can be divided into four secondary indexes $\{C31, C32, C33, C34\}$, lean technology C4 can be divided into eleven secondary indexes $\{C41, C42, C43, C44, C45, C46, C47, C48, C49, C410, C411\}$, flexible level C5 can be divided into three secondary indexes $\{C51, C52, C53\}$, and the continuous improve C6 can be divided into four secondary indexes $\{C61, C62, C63, C64\}$.

4.2. Case Background

H company is a large state-owned manufacturing enterprise, its household refrigerator factory was established in October 2000, currently mainly produces household refrigerator, double temperature, commercial refrigerator series. After China's accession to the WTO, the influx of foreign home appliance enterprises has brought a serious impact on H Company. H Company has learned and implemented the idea of lean in an all-round way and committed itself to lean quality. The overall lean level is rising day by day, but the lean level of its subsidiaries and sub-lines has not been well tracked and evaluated. Therefore, in this paper, the H company uses the evaluation index system, the distribution of air-conditioner production factory in Qingdao ABC to evaluate the level of the lean production line, the auxiliary production line is A line, the main production output, less type complex lines, line B is more lines, production of large volume, batch C line is small models of large batch line.

Figure 3 shows the hierarchy of the problem and the final criteria and subcriteria.

4.3. Model Run

In this paper, the steps to achieve F-TOPSIS-CRITIC-Entropy method are as follows:

Step 1: The trapezoidal fuzziness in fuzzy set theory, that is, a quad array, is used to define the fuzzy number, and a language scale is determined for the importance of evaluation indicators and alternative scheme rating (Reza Rostamzadeh et al., 2018), as shown in Table 1.

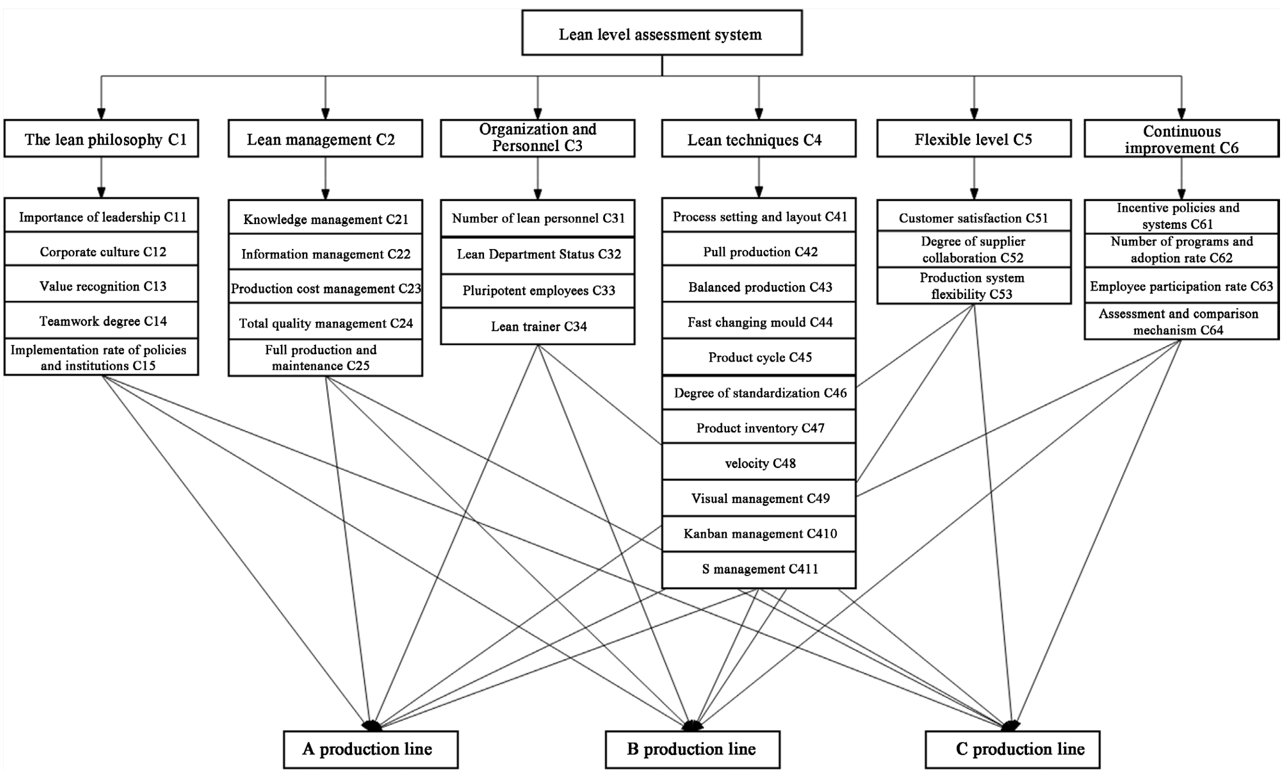

Figure 3. Problem hierarchy.

Table 1. Linguistic scales for importance and rating.

Importance language Scale	Trapezoidal fuzzy scale	Language rating Scale
Very low(VL)	(0, 0, 0.1, 0.2)	Very low (VP)
Low (L)	(0.1, 0.2, 0.2, 0.3)	Low (P)
The lower (ML)	(0.2, 0.3, 0.4, 0.5)	The lower (MP)
Medium (M)	(0.4, 0.5, 0.5, 0.6)	Medium (M)
The higher (MH)	(0.5, 0.6, 0.7, 0.8)	The higher (MG)
High (H)	(0.7, 0.8, 0.8, 0.9)	High (G)
Very high (VH)	(0.8, 0.9, 1, 1)	Very high (VG)

Step 2: Set up a decision-making team to grade the importance of indicators and the level of alternatives. The decision-making team of this paper consists of refrigerator production line expert group of H Company and lean production direction teachers of universities.

Step 3: The decision team's scoring results were converted into fuzzy numbers according to the index importance language scale, and the subjective criteria weight matrix is constructed by using Equation (18) to determine the subjective weight of each indicator. The normalized subjective weight table of each indicator is obtained by using Equation (19) and normalized, as shown in Table 2.

Step 4: The alternative rating language scale is converted into fuzzy numbers, and the average decision matrix is constructed by using Equation (15). Fuzzy entropy method, Fuzzy Critic and improved TOPSIS method are respectively used to determine the normalized objective weight of each alternative under each index with the help of MATLAB software. With the help of Equation (20) and (21), make $\rho = 0.5$, so as to determine the comprehensive weight and normalize it, and obtain the normalized comprehensive weight table of all alternatives as shown in Table 3.

Step 5: Equation (22) is used to normalize the average decision matrix, and the normalized decision matrix is obtained as shown in Table 4. Equation (24) is used to combine it with the weight of indicators and convert it into a weighted normalized decision matrix, as shown in Table 5.

Step 6: Fuzzy negative ideal solution (FNIS) and fuzzy positive ideal solution (FPIS) are calculated according to Equation (25), and the distance of each alternative is calculated using Equation (27), as shown in Table 6.

Step 7: Finally, according to Equation (28), the paste progress and ranking of each scheme are calculated, and the paste progress and ranking table of alternative schemes in Table 7 are obtained.

4.4. Comparative Analysis

In order to verify the accuracy of the ranking results of the method proposed in this paper and make the case analysis of the evaluation of lean level of the multi-attribute fuzzy decision model constructed in this paper more convincing, on

Table 2. Normalized subjective weight table of each index.

	Fuzzy weighted	Defuzzing	Normalized subjective weight
C11	(0.78, 0.88, 0.96, 0.98)	0.900	0.042
C12	(0.52, 0.62, 0.68, 0.78)	0.650	0.031
C13	(0.56, 0.66, 0.7, 0.8)	0.680	0.032
C14	(0.54, 0.64, 0.72, 0.82)	0.680	0.032
C15	(0.64, 0.74, 0.74, 0.84)	0.740	0.035
C21	(0.5, 0.6, 0.64, 0.74)	0.620	0.029
C22	(0.54, 0.64, 0.66, 0.76)	0.650	0.031
C23	(0.62, 0.72, 0.76, 0.84)	0.735	0.035
C24	(0.62, 0.72, 0.76, 0.86)	0.740	0.035
C25	(0.46, 0.56, 0.62, 0.72)	0.590	0.028
C31	(0.42, 0.52, 0.6, 0.68)	0.555	0.026
C32	(0.56, 0.66, 0.7, 0.78)	0.675	0.032
C33	(0.4, 0.5, 0.56, 0.66)	0.530	0.025
C34	(0.52, 0.62, 0.68, 0.76)	0.645	0.030
C41	(0.58, 0.68, 0.74, 0.82)	0.705	0.033
C42	(0.54, 0.64, 0.66, 0.76)	0.650	0.031
C43	(0.6, 0.7, 0.78, 0.86)	0.735	0.035
C44	(0.46, 0.56, 0.62, 0.72)	0.590	0.028
C45	(0.52, 0.62, 0.68, 0.76)	0.645	0.030
C46	(0.5, 0.6, 0.64, 0.74)	0.620	0.029
C47	(0.46, 0.56, 0.62, 0.72)	0.590	0.028
C48	(0.42, 0.52, 0.54, 0.64)	0.530	0.025
C49	(0.5, 0.6, 0.7, 0.8)	0.650	0.031
C410	(0.52, 0.62, 0.68, 0.76)	0.645	0.030
C411	(0.6, 0.7, 0.78, 0.86)	0.735	0.035
C51	(0.6, 0.7, 0.78, 0.86)	0.735	0.035
C52	(0.56, 0.66, 0.7, 0.8)	0.680	0.032
C53	(0.68, 0.78, 0.82, 0.88)	0.790	0.037
C61	(0.58, 0.68, 0.74, 0.82)	0.705	0.033
C62	(0.46, 0.56, 0.62, 0.72)	0.590	0.028
C63	(0.48, 0.58, 0.6, 0.7)	0.590	0.028
C64	(0.54, 0.64, 0.66, 0.74)	0.645	0.030

Table 3. Normalized comprehensive weight table of alternatives.

	The result of entropy method	The result of Critic method	The result of Topsis method	comprehensive weights	Normalized composite weight
C11	0.027	0.019	0.035	0.062	0.031
C12	0.031	0.022	0.028	0.056	0.028
C13	0.027	0.079	0.035	0.086	0.043
C14	0.027	0.079	0.035	0.086	0.043
C15	0.027	0.019	0.035	0.058	0.029
C21	0.031	0.022	0.028	0.055	0.028
C22	0.031	0.022	0.028	0.056	0.028
C23	0.031	0.022	0.028	0.058	0.029
C24	0.031	0.022	0.028	0.058	0.029
C25	0.031	0.081	0.028	0.084	0.042
C31	0.030	0.022	0.029	0.053	0.027
C32	0.030	0.022	0.029	0.056	0.028
C33	0.027	0.019	0.035	0.053	0.027
C34	0.031	0.022	0.028	0.056	0.028
C41	0.027	0.019	0.035	0.057	0.029
C42	0.032	0.023	0.028	0.057	0.028
C43	0.027	0.019	0.035	0.058	0.029
C44	0.027	0.019	0.035	0.055	0.027
C45	0.027	0.019	0.035	0.056	0.028
C46	0.072	0.098	0.018	0.108	0.054
C47	0.027	0.019	0.035	0.055	0.027
C48	0.031	0.055	0.028	0.069	0.035
C49	0.027	0.019	0.035	0.056	0.028
C410	0.031	0.055	0.028	0.072	0.036
C411	0.027	0.019	0.035	0.058	0.029
C51	0.027	0.019	0.035	0.058	0.029
C52	0.031	0.022	0.028	0.057	0.028
C53	0.028	0.020	0.032	0.058	0.029
C61	0.027	0.019	0.035	0.057	0.029
C62	0.027	0.019	0.035	0.055	0.027
C63	0.027	0.019	0.035	0.055	0.027
C64	0.072	0.042	0.018	0.081	0.040

Table 4. Normalized decision matrix.

	A	B	C
C11	(0.500, 0.600, 0.700, 0.800)	(0.800, 0.900, 1.000, 1.000)	(0.800, 0.900, 1.000, 1.000)
C12	(0.444, 0.556, 0.556, 0.667)	(0.556, 0.667, 0.778, 0.889)	(0.778, 0.889, 0.889, 1.000)
C13	(0.778, 0.889, 0.889, 1.000)	(0.556, 0.667, 0.778, 0.889)	(0.778, 0.889, 0.889, 1.000)
C14	(0.778, 0.889, 0.889, 1.000)	(0.556, 0.667, 0.778, 0.889)	(0.778, 0.889, 0.889, 1.000)
C15	(0.556, 0.667, 0.778, 0.889)	(0.778, 0.889, 0.889, 1.000)	(0.778, 0.889, 0.889, 1.000)
C21	(0.444, 0.556, 0.556, 0.667)	(0.556, 0.667, 0.778, 0.889)	(0.778, 0.889, 0.889, 1.000)
C22	(0.444, 0.556, 0.556, 0.667)	(0.556, 0.667, 0.778, 0.889)	(0.778, 0.889, 0.889, 1.000)
C23	(0.444, 0.556, 0.556, 0.667)	(0.556, 0.667, 0.778, 0.889)	(0.778, 0.889, 0.889, 1.000)
C24	(0.444, 0.556, 0.556, 0.667)	(0.556, 0.667, 0.778, 0.889)	(0.778, 0.889, 0.889, 1.000)
C25	(0.778, 0.889, 0.889, 1.000)	(0.444, 0.556, 0.556, 0.667)	(0.556, 0.667, 0.778, 0.889)
C31	(0.200, 0.300, 0.400, 0.500)	(0.800, 0.900, 1.000, 1.000)	(0.500, 0.600, 0.700, 0.800)
C32	(0.200, 0.300, 0.400, 0.500)	(0.800, 0.900, 1.000, 1.000)	(0.500, 0.600, 0.700, 0.800)
C33	(0.500, 0.625, 0.625, 0.750)	(0.625, 0.750, 0.875, 1.000)	(0.625, 0.750, 0.875, 1.000)
C34	(0.444, 0.556, 0.556, 0.667)	(0.556, 0.667, 0.778, 0.889)	(0.778, 0.889, 0.889, 1.000)
C41	(0.111, 0.222, 0.222, 0.333)	(0.778, 0.889, 0.889, 1.000)	(0.778, 0.889, 0.889, 1.000)
C42	(0.250, 0.375, 0.500, 0.625)	(0.500, 0.625, 0.625, 0.750)	(0.625, 0.750, 0.875, 1.000)
C43	(0.444, 0.556, 0.556, 0.667)	(0.778, 0.889, 0.889, 1.000)	(0.778, 0.889, 0.889, 1.000)
C44	(0.167, 0.333, 0.333, 0.500)	(0.667, 0.833, 0.833, 1.000)	(0.667, 0.833, 0.833, 1.000)
C45	(0.222, 0.333, 0.444, 0.556)	(0.778, 0.889, 0.889, 1.000)	(0.778, 0.889, 0.889, 1.000)
C46	(0.625, 0.750, 0.875, 1.000)	(0.500, 0.625, 0.625, 0.750)	(0.500, 0.625, 0.625, 0.750)
C47	(0.500, 0.625, 0.625, 0.750)	(0.625, 0.750, 0.875, 1.000)	(0.625, 0.750, 0.875, 1.000)
C48	(0.333, 0.500, 0.667, 0.833)	(0.667, 0.833, 0.833, 1.000)	(0.167, 0.333, 0.333, 0.500)
C49	(0.500, 0.625, 0.625, 0.750)	(0.625, 0.750, 0.875, 1.000)	(0.625, 0.750, 0.875, 1.000)
C410	(0.333, 0.500, 0.667, 0.833)	(0.667, 0.833, 0.833, 1.000)	(0.167, 0.333, 0.333, 0.500)
C411	(0.250, 0.375, 0.500, 0.625)	(0.625, 0.750, 0.875, 1.000)	(0.625, 0.750, 0.875, 1.000)
C51	(0.500, 0.625, 0.625, 0.750)	(0.625, 0.750, 0.875, 1.000)	(0.625, 0.750, 0.875, 1.000)
C52	(0.444, 0.556, 0.556, 0.667)	(0.556, 0.667, 0.778, 0.889)	(0.778, 0.889, 0.889, 1.000)
C53	(0.222, 0.333, 0.444, 0.556)	(0.778, 0.889, 0.889, 1.000)	(0.556, 0.667, 0.778, 0.889)
C61	(0.556, 0.667, 0.778, 0.889)	(0.778, 0.889, 0.889, 1.000)	(0.778, 0.889, 0.889, 1.000)
C62	(0.556, 0.667, 0.778, 0.889)	(0.778, 0.889, 0.889, 1.000)	(0.778, 0.889, 0.889, 1.000)
C63	(0.556, 0.667, 0.778, 0.889)	(0.778, 0.889, 0.889, 1.000)	(0.778, 0.889, 0.889, 1.000)
C64	(0.700, 0.800, 0.800, 0.900)	(0.800, 0.900, 1.000, 1.000)	(0.700, 0.800, 0.800, 0.900)

Table 5. Weighted normalized decision matrix.

	A	B	C
C11	(0.015, 0.019, 0.022, 0.025)	(0.025, 0.028, 0.031, 0.031)	(0.025, 0.028, 0.031, 0.031)
C12	(0.012, 0.016, 0.016, 0.019)	(0.016, 0.019, 0.022, 0.025)	(0.022, 0.025, 0.025, 0.028)
C13	(0.034, 0.038, 0.038, 0.043)	(0.024, 0.029, 0.034, 0.038)	(0.034, 0.038, 0.038, 0.043)
C14	(0.034, 0.038, 0.038, 0.043)	(0.024, 0.029, 0.034, 0.038)	(0.034, 0.038, 0.038, 0.043)
C15	(0.016, 0.019, 0.023, 0.026)	(0.023, 0.026, 0.026, 0.029)	(0.023, 0.026, 0.026, 0.029)
C21	(0.012, 0.015, 0.015, 0.018)	(0.015, 0.018, 0.022, 0.025)	(0.022, 0.025, 0.025, 0.028)
C22	(0.012, 0.016, 0.016, 0.019)	(0.016, 0.019, 0.022, 0.025)	(0.022, 0.025, 0.025, 0.028)
C23	(0.013, 0.016, 0.016, 0.019)	(0.016, 0.019, 0.023, 0.026)	(0.023, 0.026, 0.026, 0.029)
C24	(0.013, 0.016, 0.016, 0.019)	(0.016, 0.019, 0.023, 0.026)	(0.023, 0.026, 0.026, 0.029)
C25	(0.033, 0.037, 0.037, 0.042)	(0.019, 0.023, 0.023, 0.028)	(0.023, 0.028, 0.033, 0.037)
C31	(0.005, 0.008, 0.011, 0.013)	(0.021, 0.024, 0.027, 0.027)	(0.013, 0.016, 0.019, 0.021)
C32	(0.006, 0.008, 0.011, 0.014)	(0.022, 0.025, 0.028, 0.028)	(0.014, 0.017, 0.020, 0.022)
C33	(0.013, 0.017, 0.017, 0.02)	(0.017, 0.020, 0.023, 0.027)	(0.017, 0.020, 0.023, 0.027)
C34	(0.012, 0.016, 0.016, 0.019)	(0.016, 0.019, 0.022, 0.025)	(0.022, 0.025, 0.025, 0.028)
C41	(0.003, 0.006, 0.006, 0.010)	(0.022, 0.025, 0.025, 0.029)	(0.022, 0.025, 0.025, 0.029)
C42	(0.007, 0.011, 0.014, 0.018)	(0.014, 0.018, 0.018, 0.021)	(0.018, 0.021, 0.025, 0.028)
C43	(0.013, 0.016, 0.016, 0.019)	(0.023, 0.026, 0.026, 0.029)	(0.023, 0.026, 0.026, 0.029)
C44	(0.005, 0.009, 0.009, 0.014)	(0.018, 0.023, 0.023, 0.027)	(0.018, 0.023, 0.023, 0.027)
C45	(0.006, 0.009, 0.012, 0.016)	(0.022, 0.025, 0.025, 0.028)	(0.022, 0.025, 0.025, 0.028)
C46	(0.034, 0.041, 0.047, 0.054)	(0.027, 0.034, 0.034, 0.041)	(0.027, 0.034, 0.034, 0.041)
C47	(0.014, 0.017, 0.017, 0.02)	(0.017, 0.020, 0.024, 0.027)	(0.017, 0.020, 0.024, 0.027)
C48	(0.012, 0.017, 0.023, 0.029)	(0.023, 0.029, 0.029, 0.035)	(0.006, 0.012, 0.012, 0.017)
C49	(0.014, 0.018, 0.018, 0.021)	(0.018, 0.021, 0.025, 0.028)	(0.018, 0.021, 0.025, 0.028)
C410	(0.012, 0.018, 0.024, 0.03)	(0.024, 0.030, 0.030, 0.036)	(0.006, 0.012, 0.012, 0.018)
C411	(0.007, 0.011, 0.015, 0.018)	(0.018, 0.022, 0.025, 0.029)	(0.018, 0.022, 0.025, 0.029)
C51	(0.015, 0.018, 0.018, 0.022)	(0.018, 0.022, 0.025, 0.029)	(0.018, 0.022, 0.025, 0.029)
C52	(0.013, 0.016, 0.016, 0.019)	(0.016, 0.019, 0.022, 0.025)	(0.022, 0.025, 0.025, 0.028)
C53	(0.006, 0.01, 0.013, 0.016)	(0.023, 0.026, 0.026, 0.029)	(0.016, 0.019, 0.023, 0.026)
C61	(0.016, 0.019, 0.022, 0.025)	(0.022, 0.025, 0.025, 0.029)	(0.022, 0.025, 0.025, 0.029)
C62	(0.015, 0.018, 0.021, 0.024)	(0.021, 0.024, 0.024, 0.027)	(0.021, 0.024, 0.024, 0.027)
C63	(0.015, 0.018, 0.021, 0.024)	(0.021, 0.024, 0.024, 0.027)	(0.021, 0.024, 0.024, 0.027)
C64	(0.028, 0.032, 0.032, 0.036)	(0.032, 0.036, 0.040, 0.040)	(0.028, 0.032, 0.032, 0.036)

Table 6. FNIS, FPIS and the corresponding distance with each scheme.

	FNIS	FPIS	d_i^-			d_i^+		
			A	B	C	A	B	C
C11	0.015	0.031	0.006	0.013	0.013	0.011	0.003	0.003
C12	0.012	0.028	0.004	0.009	0.013	0.013	0.009	0.004
C13	0.024	0.043	0.015	0.009	0.015	0.006	0.013	0.006
C14	0.024	0.043	0.015	0.009	0.015	0.006	0.013	0.006
C15	0.016	0.029	0.006	0.010	0.010	0.009	0.004	0.004
C21	0.012	0.028	0.004	0.008	0.012	0.012	0.008	0.004
C22	0.012	0.028	0.004	0.009	0.013	0.013	0.009	0.004
C23	0.013	0.029	0.004	0.009	0.013	0.013	0.009	0.004
C24	0.013	0.029	0.004	0.009	0.013	0.013	0.009	0.004
C25	0.019	0.042	0.019	0.006	0.013	0.006	0.019	0.013
C31	0.005	0.027	0.005	0.019	0.012	0.018	0.003	0.010
C32	0.006	0.028	0.005	0.020	0.013	0.019	0.003	0.010
C33	0.013	0.027	0.004	0.009	0.009	0.010	0.006	0.006
C34	0.012	0.028	0.004	0.009	0.013	0.013	0.008	0.004
C41	0.003	0.029	0.004	0.022	0.022	0.022	0.004	0.004
C42	0.007	0.028	0.007	0.011	0.016	0.016	0.011	0.007
C43	0.013	0.029	0.004	0.013	0.013	0.013	0.004	0.004
C44	0.005	0.027	0.006	0.018	0.018	0.018	0.006	0.006
C45	0.006	0.028	0.006	0.019	0.019	0.017	0.004	0.004
C46	0.027	0.054	0.019	0.008	0.008	0.013	0.021	0.021
C47	0.014	0.027	0.004	0.009	0.009	0.011	0.006	0.006
C48	0.006	0.035	0.016	0.024	0.007	0.016	0.007	0.024
C49	0.014	0.028	0.004	0.010	0.010	0.011	0.007	0.007
C410	0.006	0.036	0.016	0.024	0.007	0.016	0.007	0.024
C411	0.007	0.029	0.007	0.017	0.017	0.017	0.007	0.007
C51	0.015	0.029	0.004	0.010	0.010	0.011	0.007	0.007
C52	0.013	0.028	0.004	0.009	0.013	0.013	0.009	0.004
C53	0.006	0.029	0.006	0.020	0.015	0.018	0.004	0.009
C61	0.016	0.029	0.006	0.010	0.010	0.009	0.004	0.004
C62	0.015	0.027	0.006	0.009	0.009	0.008	0.004	0.004
C63	0.015	0.027	0.006	0.009	0.009	0.008	0.004	0.004
C64	0.028	0.040	0.005	0.010	0.005	0.009	0.005	0.009

Table 7. Shows the schedule and ranking of alternative schemes.

Alternatives	Paste progress	Ranking
A	0.357	3
B	0.630	1
C	0.629	2

Table 8. The schedule and scheme ranking table obtained under each model.

Model Alternatives	Subject & entropy method		Subjective & Critic method		Subjective & Topsis method	
	Paste progress	Ranking	Paste progress	Ranking	Paste progress	Ranking
A	0.337	3	0.3774	3	0.330	3
B	0.639	2	0.6173	1	0.652	2
C	0.640	1	0.6167	2	0.658	1

the basis of obtaining the language scale of decision makers' evaluation of the importance of indicators and alternative schemes, The ranking results of TOPSIS model, which combines multiple objective (objective weight determination methods are mainly entropy method, CRITIC method and TOPSIS objective weight determination method) and subjective weight to determine the comprehensive weight, are compared with the TOPSIS model, which combines single objective and subjective weight to determine the comprehensive weight. The post progress obtained under each model and its ordering are shown in **Table 8**. According to the results, the ranking results obtained by combining subjective and CRITIC method to determine the weight are consistent with the ranking results obtained by subject-comprehensive objective method to determine the comprehensive weight, which are B-C-A; The other two subjective-objective methods determine the ranking results as C-B-A.

In order to make a comparative analysis and verify the correlation and reliability of the sorting results, SPSS was used in this paper to make a correlation analysis between the method of determining the comprehensive weight by combining subjective and comprehensive objective weight and the results by combining objective and subjective weight of the other three methods. The results are shown in **Figures 4-6**. The results show that the method of combining subjective and objective weight to determine the comprehensive weight is obviously correlated with the results obtained by the other three methods, which verifies the reliability of the ranking results. Therefore, the final ranking of the lean level of the production line is determined as B-C-A or C-B-A.

5. Conclusion

Taking the lean level assessment of three production lines of H Company as an

The correlation			
		Subjective - Comprehensive objective	Subject-entropy method
Subjective - Comprehensive objective	Pearson correlation	1	1.000**
	significant		0.004
	N	3	3
Subject-entropy method	Pearson correlation	1.000**	1
	significant	0.004	
	N	3	3
**.There was a significant correlation at 0.01 level (bilateral).			

Figure 4. Result comparison: subject-comprehensive objective weight & subject-entropy method.

The correlation			
		Subjective - Comprehensive objective	Subject-Critic method
Subjective - Comprehensive objective	Pearson correlation	1	1.000**
	significant		0.001
	N	3	3
Subject-Critic method	Pearson correlation	1.000**	1
	significant	0.001	
	N	3	3
**.There was a significant correlation at 0.01 level (bilateral).			

Figure 5. Result comparison: subject-comprehensive objective weight & subject-critic method.

The correlation			
		Subjective - Comprehensive objective	Subject-Topsis method
Subjective - Comprehensive objective	Pearson correlation	1	1.000**
	significant		0.012
	N	3	3
Subject-Topsis method	Pearson correlation	1.000**	1
	significant	0.012	
	N	3	3
**.There was a significant correlation at 0.01 level (bilateral).			

Figure 6. Result comparison: subject-comprehensive objective weight & subject-Topsis method.

example, this paper further optimized the weight determination problem in multi-attribute fuzzy decision making, and proposed the method of combining subjective and comprehensive objective to determine the weight. Compared with the weight determination methods proposed in previous studies, the accuracy and reliability of the proposed method are demonstrated.

The significance of this study is to solve the problems of fuzzy uncertainty of indicators in the process of multi-objective decision making, excessive influence of subjective factors on results, and limitations of single objective weight determination methods. At the same time, the paper establishes the evaluation index system of lean level in manufacturing industry and determines its comprehensive weight by combining subjective and objective methods, which also provides a more scientific and effective evaluation method for manufacturing enterprises to evaluate their internal lean level.

However, there are still some limitations in this paper. In the future research, we will try to establish ways and methods to overcome the limitations of the weight determination method itself, so as to better show the weight of the index itself. At the same time, in future studies, we will pay more attention to the breadth and depth of sample collection and enhance the compatibility between cases and reality.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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