# APPLICATION OF MULTIPLE-ATTRIBUTE DECISION-MAKING MODEL TO SELECT SUPPLIERS: IN THE CONTEXT OF SERVICE-ORIENTED MANUFACTURING PARADIGM

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**ABSTRACT:**

Effective evaluation of potential suppliers is made possible with the help of a proposed multiattribute decision-making model in this paper. The paper also proposes an index system for selecting suppliers in a service-oriented manufacturing setting and develops an evaluation matrix based on intervals. Due to the evaluation index's mixed attribute, we provide a technique to transform the mixed attribute value into an interval number. We employ a combination model based on the deviation function model and the interval relative entropy ranking approach to assess each potential provider, so removing subjectivity from the weight and allowing for more nuanced recommendations. Finally, a real-world scenario is presented to validate the feasibility and accuracy of the suggested decision-making framework.

**Keywords:** Application, Multiple-Attribute, Decision-Making, Service-Oriented, Manufacturing Paradigm

## 1. INTRODUCTION:

In the manufacturing industry, selecting the right supplier is a crucial task for companies, as the quality of raw materials, components, and services they receive directly impacts the quality of their own products. In a service-oriented manufacturing paradigm, where manufacturers are shifting from producing products to providing services, the supplier selection process is even more critical. This is because the suppliers' performance can directly affect the manufacturer's ability to deliver high-quality services to customers.

To ensure that the right supplier is selected, manufacturers often use multiple-attribute decision-making (MADM) models. These models help decision-makers evaluate suppliers' various attributes, such as quality, cost, reliability, and delivery time, and select the one that best meets their needs.[1]

This paper examines the application of MADM models to select suppliers in the context of a service-oriented manufacturing paradigm. The paper begins by providing an overview of MADM models and their use in supplier selection. It then describes the service-oriented manufacturing paradigm and explains how the shift from products to services affects the supplier selection process. Finally, the paper presents a case study of a manufacturing company that uses an MADM model to select suppliers in a service-oriented manufacturing paradigm.

Supplier selection is a critical decision that can have a significant impact on the performance and competitiveness of a manufacturing system. In the context of service-oriented manufacturing, selecting the right suppliers is even more important, as suppliers are expected to provide not only high-quality products but also customized services to support the manufacturing process. Multiple-attribute decision-making (MADM) models have been widely used to support supplier selection decisions. In this review article, we will discuss the application of MADM models to select suppliers in the context of service-oriented manufacturing.[2]

### 1.1 Overview of Multiple-Attribute Decision-Making Models

Multiple-Attribute Decision-Making (MADM) models are a type of decision-making tool that helps individuals and organizations make complex decisions involving multiple criteria or attributes. MADM models are particularly useful in situations where there are several potential options or alternatives, and each alternative has multiple attributes or criteria that need to be considered.

There are several different types of MADM models, each with its own strengths and weaknesses. Some of the most commonly used MADM models include:[3]

**i. Weighted Sum Model:** This model involves assigning weights to each criterion or attribute, and then evaluating each alternative based on its performance on each criterion. The weighted sum of each alternative's performance on all criteria is then calculated, and the alternative with the highest score is chosen.

**ii. Analytic Hierarchy Process (AHP):** AHP involves breaking down a decision problem into a hierarchy of criteria and sub-criteria, and then using pairwise comparisons to determine the relative importance of each criterion. AHP is particularly useful when there are multiple levels of criteria or attributes to consider.

**iii. Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS):** TOPSIS involves identifying an ideal alternative and a worst alternative based on all criteria, and then evaluating each alternative based on its distance from the ideal and worst alternatives. The alternative with the shortest distance from the ideal alternative is chosen.

**iv. ELECTRE:** ELECTRE involves using a set of decision rules to rank alternatives based on their performance on multiple criteria. ELECTRE is particularly useful when there are conflicting criteria or when some criteria are more important than others.

**v. Grey Relational Analysis (GRA):** GRA involves calculating the degree of similarity between each alternative and the ideal alternative based on each criterion. GRA is particularly useful when there is uncertainty or imprecision in the decision criteria.

In general, MADM models can be very useful in helping individuals and organizations make complex decisions involving multiple criteria or attributes. However, it is important to choose the right MADM model for the specific decision problem, as each model has its own strengths and weaknesses.[4]

### 1.2 Service-Oriented Manufacturing

Service-oriented manufacturing (SOM) is a paradigm in manufacturing that focuses on providing value-added services alongside traditional manufacturing processes. The concept is based on the idea that customers not only want high-quality products but also require a range of services that add value to the product and meet their specific needs and preferences.

The shift towards SOM has been driven by several factors, including increasing competition in the manufacturing industry, changing customer demands and preferences, and advancements in technology. In today's market, customers expect more than just a product; they want a comprehensive solution that includes design, installation, maintenance, repair, and other services that meet their needs and preferences.[5]

SOM involves the integration of manufacturing processes with service processes to create a more comprehensive and customer-centric approach to manufacturing. This can involve developing new products that incorporate value-added services or providing customized solutions that meet specific customer needs. SOM also involves the use of technology to enable better communication and collaboration between manufacturers and customers, as well as the use of data analytics and predictive maintenance to optimize the performance of products and services.

The benefits of SOM are numerous, including increased customer satisfaction and loyalty, improved business performance, and enhanced competitiveness. By providing a more comprehensive solution that meets the specific needs and preferences of customers, manufacturers can differentiate themselves from their competitors and gain a competitive advantage in the market. SOM can also help to improve business performance by reducing costs, increasing efficiency, and improving quality.

### 1.3 Key Criteria or Attributes for Supplier Selection

When selecting suppliers for service-oriented manufacturing, several key criteria or attributes should be considered. These criteria can be broadly categorized into product-related and service-related criteria.

Product-related criteria include factors such as product quality, cost, delivery time, and reliability. In service-oriented manufacturing, it is important to select suppliers who can provide high-quality products that meet the customer's specific needs and preferences. This can involve customizing products to meet specific design requirements or providing specialized materials or components. Cost is also an important consideration, as service-oriented manufacturing tends to be more expensive than traditional manufacturing due to the added service components. Delivery time and reliability are also critical factors, as delays or defects in product delivery can have a significant impact on customer satisfaction and business performance.[6]

Service-related criteria include factors such as service quality, responsiveness, communication, and flexibility. In service-oriented manufacturing, suppliers are not only responsible for delivering high-quality products but also for providing excellent service that meets the needs of the customer. This can involve providing timely and responsive service, communicating effectively with the customer, and being flexible in adapting to changing customer needs and preferences.

### 1.4 Application of multiple-attribute decision-making model

Multiple-Attribute Decision-Making (MADM) models are a group of decision-making techniques that enable decision-makers to evaluate and rank multiple alternatives based on multiple criteria or attributes. MADM models are widely used in many fields, including engineering, economics, business, and healthcare, to support decision-making processes where multiple factors need to be considered.[7]

One important application of MADM models is supplier selection, which is a critical task for manufacturing companies that rely on suppliers to provide goods and services. Supplier selection is a complex process that requires consideration of multiple factors, such as quality, cost, delivery time, and service quality, among others. In the context of service-oriented manufacturing, supplier selection becomes even more complex as it involves evaluating suppliers based not only on the quality of the products they provide but also on the quality of the value-added services they offer, such as design, installation, and maintenance.

MADM models provide a systematic and structured approach to supplier selection by enabling decision-makers to evaluate and compare potential suppliers based on multiple criteria. By using MADM models, decision-makers can consider the relative importance of each criterion, assign weights to each criterion, and evaluate each supplier based on its performance on each criterion. The results of the MADM analysis can be used to rank suppliers and identify the best supplier(s) for the company's needs.

Overall, MADM models provide a powerful tool for decision-makers to support supplier selection and other decision-making processes where multiple factors need to be considered. By using MADM models, decision-makers can make more informed and rational decisions that consider all relevant factors, leading to better outcomes for the company.[8]

## 2.LITERATURE REVIEW

**Ali, K. and Zeynep, S., (2019)**Multiple-attribute decision-making (MADM) models provide a structured approach to evaluate and compare suppliers based on multiple criteria. One of the most widely used MADM models is the analytic hierarchy process (AHP). AHP involves decomposing a complex decision problem into a hierarchical structure of criteria and sub-criteria, and then using pairwise comparisons to determine the relative importance of each criterion. Another popular MADM model is the technique for order preference by similarity to ideal solution (TOPSIS), which involves identifying the ideal and anti-ideal solutions and then determining the relative distance of each alternative from these solutions. Other MADM models that have been applied to supplier selection include the weighted sum model, the weighted product model, and the grey relational analysis.[9]

**Cevriye, G. and Didem, G., (2017)**Service-oriented manufacturing involves the integration of manufacturing and service activities to provide customized products and services to customers. The service component of service-oriented manufacturing includes activities such as customer needs analysis, product design and customization, and after-sales support. The manufacturing component involves the production and delivery of the customized products. The integration of manufacturing and service activities requires a different approach to supplier selection compared to traditional manufacturing. In service-oriented manufacturing, suppliers are expected to provide not only high-quality products but also customized services to support the manufacturing process.[10]

**Bei, W., and Hu, J., (2019)**constructed an AHP model reflecting the opinions of a wide range of specialists. The synthesis of priorities and the evaluation of consistency have been given careful thought, leading to the adoption of a well-researched approach. There is also a determined consistency ratio. There is a distinction between micro, mezzo, and macro enterprises. Based on the advice of the expert, a number of criteria for choosing a vendor have been established. The average matrix, the priority matrix, and the overall priority matrix have all been used to compare these criteria. According to the findings, the three most pressing issues in vendor selection for large-scale enterprises are trustworthiness of suppliers, product quality, and vendor experience.[11]

**Celebi, D. and Bayraktar, D., (2018)**using the multi-factor productivity analysis method data envelopment analysis (DEA), the authors propose a methodology for evaluating supplier performance. When combined with managerial performance ratings, the DEA model's efficiency metrics can classify groups of suppliers into four distinct buckets: high-performing, efficient suppliers (HE), low-performing, efficient suppliers (LE), and low-performing, inefficient suppliers (LI). In order to better the operations of providers in the HI, LE, and LI clusters, we identify effective benchmarks from the HE cluster. Conclusions and management ramifications are then examined.[12]

**Altuntas, B., and Cebi, F., (2017)**suggested a goal programming approach that can deal with the interactions between fuzzy values and decision makers in a straightforward manner. The extracted corresponding priority vector not only reflects the preferred information from the pairwise comparison values for a set of objects under a group decision making, but it is also the "best" reflect what a majority of the involved individuals prefer and is progressively less sensitive to realizations of the group conflicting judgment, all while taking into account the trade-off between optimizing group consensus and individual desirability or opinion. As an example of the usefulness and applicability of this research, we use a plant site selection dilemma.[13]

## 3.METHODOLOGY

A common multilevel, complex, and multiattribute decision-making issue, supplier selection in service-oriented manufacturing mode is often recast as a comparison and ranking problem with interval numbers.

In this study, we establish an evaluation criteria set for suppliers as:

$$P = \{p_1, p_2, \ldots, p_s, \ldots, p_m\} \, (s = 1, 2, \ldots, m),$$

the signal as $B = \{b_1, b_2, \ldots, b_t, \ldots, b_n\}\ (t = 1, 2, \ldots, n).$

In general, there are two kinds of indices: efficiency indices, which are rated higher when the assessment value is greater, and cost indices, which are rated lower when the evaluation value is lower. Allow the vector of index weights to $\omega = \{\omega_1, \omega_2, \ldots \omega_n\}$. Since t is a mystery and w is a measure of how significant each attribute index is, and $\sum_{t=1}^{n} \omega_t = 1.$

### 3.1. Construction of Interval Evaluation Matrix

Let Cst stand in for the precise integer, interval number, or fuzzy number that represents the value of the attribute for provider p under evaluation index b.

C = (cst)m x n is the first evaluation matrix, which is formed from these values.

The definition of the initial complex matrix C is

$$C = \begin{cases} c_{st} & \text{attribute value is the exact value,} \\ \left[c_{st}^{l}, c_{st}^{u}\right], & \text{attribute value is interval number,} \\ \left(c_{st}^{l}, c_{st}^{u}, c_{st}^{r}\right), & \text{attribute value is fuzzy number.} \end{cases} \quad \ldots\ldots\ldots 1$$

Decision-makers in the actual world would rather use figurative language than hard figures because of the complexity of the socioeconomic environment and the imprecision of human thought.

Extremely bad, very bad, bad, medium bad, medium, medium good, good, very good, extremely good (EB, VB, B, MB, M, MG, G, VG, EG) are a set of fuzzy linguistic values established to improve the accuracy of the experts' evaluation. Experts provide assessment data on qualitative criteria as fuzzy linguistic values that map to fuzzy numbers. Table 3.1 displays the mapping rules between the language variables and the triangular fuzzy number.

**Table 3.1: Fuzzy triangular numbers and the principles for mapping linguistic variables**

| No. | Linguistic evaluation value | Triangular fuzzy number |
|---|---|---|
| 1 | Extremely bad (EB) | (0.0, 0.1, 0.2) |
| 2 | Very bad (VB) | (0.1, 0.2, 0.3) |
| 3 | Bad (B) | (0.2, 0.3, 0.4) |
| 4 | Medium bad (MB) | (0.3, 0.4, 0.5) |
| 5 | Medium (M) | (0.4, 0.5, 0.6) |
| 6 | Medium good (MG) | (0.5, 0.6, 0.7) |
| 7 | Good (G) | (0.6, 0.7, 0.8) |
| 8 | Very good (VG) | (0.7, 0.8, 0.9) |
| 9 | Extremely good (EG) | (0.8, 0.9, 1.0) |

Many indicators used in the supplier selection process lack a definitive numeric value. The attribute value of each index is determined by the interval number, which is then used for analysis and assessment. In order to build the interval evaluation matrixE, we first convert the mixed attribute index into an interval number index based on the generalizability and operability of analysis and decision-making.

$$E = \left\| \left[ e_{st}^{l}, e_{st}^{r} \right] \right\|_{m \times n}. \qquad \ldots\ldots\ldots\ldots 2$$

The first version of the evaluation matrix E looked like this:

$$\left[ e_{st}^{l}, e_{st}^{r} \right] = \begin{cases} \left[ e_{st}, e_{st} \right], & \text{attribute value is the exact value,} \\ \left[ e_{st}^{l}, e_{st}^{u} \right], & \text{attribute value is interval number,} \\ \left[ \frac{\left( e_{st}^{l} + e_{st}^{u} \right)}{2}, \frac{\left( e_{st}^{u} + e_{st}^{r} \right)}{2} \right], & \text{attribute value is riangular fuzzy number.} \end{cases} \qquad \ldots..3$$

### 3.2. Normalization of the Interval Number Matrix.

The original indicators' attribute values should be normalized to prevent the impact of adopting various units and to lower variability. Applying ( 4 ) yields the normalized interval matrixU. One may use (5) to normalize a criteria where a bigger value indicates a better outcome, and (6) to normalize a criterion where a lower value indicates a better outcome.

$$U = \left\| \left[ u_{st}^{l}, u_{st}^{r} \right] \right\|_{m \times n}, \qquad \ldots..4$$

$$\begin{cases} u_{st}^{l} = \dfrac{e_{st}^{l}}{\sqrt{\sum_{s=1}^{m} \left( e_{st}^{r} \right)^2}}, \\ u_{st}^{r} = \dfrac{e_{st}^{r}}{\sqrt{\sum_{s=1}^{m} \left( e_{st}^{l} \right)^2}}, \end{cases} \qquad \ldots.5$$

$$\begin{cases} u_{st}^{l} = \dfrac{\left( 1/e_{st}^{r} \right)}{\sum_{s=1}^{m} \left( 1/e_{st}^{l} \right)^2}, \\ u_{st}^{r} = \dfrac{\left( 1/e_{st}^{l} \right)}{\sum_{s=1}^{m} \left( 1/e_{st}^{r} \right)^2}. \end{cases} \qquad \ldots6$$

### 3.3. Determination of Criteria Weight

This article uses a quantitative assessment methodology including expert rating of certain indicators. The field still lacks a theoretical and systematic foundation, making it difficult to ensure that assessment findings are reliable and objective. The deviation function model is utilized to establish the index weight, making it less arbitrary and more grounded in science and mathematics. The resulting weighting system is very objective.

Create a normalized interval matrix U where d (u, u) represents the distance between elements u and ukt,

$$d(u_{st}, u_{kt}) = \frac{\sqrt{2}}{2}\sqrt{\left(u^l_{st} - u^l_{kt}\right)^2 + \left(u^r_{st} - u^r_{kt}\right)^2}. \quad \ldots 7$$

Denote by Dst (w) for the indicator b the difference between potential suppliers p and other suppliers.:

$$D_{st}(\omega) = \sum_{k=1}^{m} d(u_{st}, u_{kt})\omega_t, \quad (s = 1, 2, \ldots, m), (t = 1, 2, \ldots, n). \quad \ldots\ldots 8$$

Each potential supplier's total discrepancy from the mean is expressed by the following formula: D, (w):

$$D_t(\omega) = \sum_{s=1}^{m} D_{st}(\omega) = \sum_{s=1}^{m}\sum_{k=1}^{n} d(u_{st}, u_{kt})\omega_t, \quad (t = 1, 2, \ldots, n). \quad \ldots 9$$

Index weight vector selection ought to maximize the sum of index deviations relative to all potential vendors. So, let's set up the deviation function, shall we:

$$D(\omega) = \sum_{t=1}^{n} D_t(\omega) = \sum_{s=1}^{m} D_{st}(\omega) = \sum_{s=1}^{m}\sum_{t=1}^{n}\sum_{k=1}^{m} d(u_{st}, u_{kt})\omega_t. \quad \ldots 10$$

The Lagrange function is built in such a way as to maximize the deviation function:

$$L(\omega, \lambda) = \sum_{s=1}^{m}\sum_{t=1}^{n}\sum_{k=1}^{m} d(u_{st}, u_{kt})\omega_t + \frac{1}{2}\lambda\left[\sum_{t=1}^{n}\omega_t^2 - 1\right]. \quad \ldots 11$$

Determine a fractional derivative by

$$\left\{\frac{\partial L}{\partial \omega_t} = \sum_{s=1}^{m}\sum_{k=1}^{m} d(u_{st}, u_{kt}) + \lambda\omega_t = 0, \frac{\partial L}{\partial \lambda} = \sum_{t=1}^{n}\omega_t^2 - 1 = 0. \right. \quad \ldots 12$$

The best solution of w may be calculated by normalizing the weight vector:

$$\omega_t = \frac{\sum_{s=1}^{m}\sum_{k=1}^{m} d(u_{st}, u_{kt})}{\sum_{t=1}^{n}\left[\sum_{s=1}^{m}\sum_{k=1}^{m} d(u_{st}, u_{kt})\right]}, \quad (t = 1, 2, \ldots, n). \quad \ldots 13$$

**3.4. Construction of Weighted Standardized Decision Matrix.**

It is possible to create a weighted standardized decision matrix G using:

$$G = \left[g^l_{st}, g^r_{st}\right], \quad \ldots 14$$

Where

$$\begin{cases} g_{st}^{l} = \omega_t \cdot u_{st}^{l}, \\ g_{st}^{r} = \omega_t \cdot u_{st}^{r}. \end{cases} \quad \ldots 15$$

## 4. RESULT

Since the parts supplier of a service manufacturing enterprise frequently experiences issues during the service process, such as delayed delivery and unguaranteed quality, the enterprise must quickly select one of the four candidate parts suppliers following preliminary screening. Table 3 displays the four suppliers' past performance as well as the first judgment values from the experts.

Table 4.1 displays the result of using (2) and (3) to generate the interval decision matrix.

Attribute B is a monetary expense, while all the others are entirely advantageous. It is possible to get the normalized choice matrix by solving for x in (4-6). LINGO software can derive the attribute weight from Equations (7) and (13). The relevant tables are 4.2 and 5. Table 4.3 demonstrates how to calculate a weighted normalized decision matrix using equations (14) and (15).

Ideal points and negative ideal points for each characteristic are provided in Table 4.4 based on (16)-(18).

**Table 4.1: Decision matrix with intervals**

| | *P*1 | *P*2 | *P*3 | *P*4 |
|---|---|---|---|---|
| $B_1$ | [0.90,0.90] | [0.95,0.95] | [0.80,0.80] | [0.85,0.85] |
| $B_2$ | [0.65,0.75] | [0.65,0.75] | [0.45,0.55] | [0.55,0.65] |
| $B_3$ | [0.15,0.15] | [0.25,0.25] | [0.18,0.18] | [0.16,0.16] |
| $B_4$ | [270,275] | [275,290] | [260,266] | [265,269] |
| $B_5$ | [0.70,1.20] | [0.60,1.10] | [0.50,1.00] | [0.45,0.85] |
| $B_6$ | [300,310] | [320,330] | [280,290] | [300,310] |
| $B_7$ | [0.98,0.98] | [0.97,0.97] | [0.96,0.96] | [0.99,0.99] |
| $B_8$ | [0.94,0.94] | [0.97,0.97] | [0.90,0.90] | [0.92,0.92] |
| $B_9$ | [0.87,0.87] | [0.96,0.96] | [0.88,0.88] | [0.93,0.93] |
| B10 | [0.75,0.85] | [0.65,0.75] | [0.65,0.75] | [0.45,0.55] |
| B11 | [0.75,0.85] | [0.65,0.75] | [0.55,0.65] | [0.55,0.65] |
| B12 | [0.55,0.65] | [0.65,0.75] | [0.45,0.55] | [0.55,0.65] |
| B13 | [0.65,0.75] | [0.55,0.65] | [0.55,0.65] | [0.55,0.65] |
| B14 | [0.65,0.75] | [0.75,0.85] | [0.65,0.75] | [0.55,0.65] |
| B15 | [0.55,0.65] | [0.65,0.75] | [0.65,0.75] | [0.75,0.85] |
| B16 | [0.65,0.75] | [0.75,0.85] | [0.65,0.75] | [0.55,0.65] |
| B17 | [0.75,0.85] | [0.55,0.65] | [0.55,0.65] | [0.55,0.65] |
| B18 | [0.65,0.75] | [0.75,0.85] | [0.65,0.75] | [0.55,0.65] |
| B19 | [0.55,0.65] | [0.65,0.75] | [0.45,0.55] | [0.55,00.65] |
| B20 | [0.90,0.90] | [1.30,1.30] | [0.70,0.70] | [0.80,0.80] |
| B21 | [430,430] | [520,520] | [380,380] | [370,370] |
| B22 | [0.65,0.75] | [0.75,0.85] | [0.55,0.65] | [0.45,0.55] |
| B23 | [0.65,0.75] | [0.65,0.75] | [0.55,0.65] | [0.55,0.65] |
| B24 | [0.75,0.85] | [0.65,0.75] | [0.55,0.65] | [0.45,0.55] |

**Table 4.2: Weighted indices and normalized decision matrices**

| | *P*1 | *P*2 | *P*3 | *P*4 | Weight |
|---|---|---|---|---|---|
| $B_1$ | [0.5132,0.5132] | [0.5418,0.5418] | [0.4562,0.4562] | [0.4847,0.4847] | 0.0256 |
| $B_2$ | [0.4779,0.6455] | [0.4779,0.6455] | [0.3308,0.4734] | [0.4044,0.5594] | 0.0503 |
| $B_3$ | [0.3967,0.3967] | [0.6611,0.6611] | [0.4760,0.4760] | [0.4231,0.4231] | 0.0760 |
| $B_4$ | [0.4860,0.5084] | [0.4609,0.4992] | [0.5025,0.5280] | [0.4969,0.5180] | 0.0108 |
| $B_5$ | [0.3348,1.0515] | [0.2869,0.9638] | [0.2391,0.8762] | [0.2152,0.7448] | 0.0694 |
| $B_6$ | [0.4834,0.5161] | [0.5156,0.5494] | [0.4511,0.4828] | [0.4834,0.5161] | 0.0177 |
| $B_7$ | [0.5025,0.5025] | [0.4974,0.4974] | [0.4923,0.4923] | [0.5077,0.5077] | 0.0046 |
| $B_8$ | [0.5038,0.5038] | [0.5199,0.5199] | [0.4824,0.4824] | [0.4931,0.4931] | 0.0111 |
| $B_9$ | [0.4776,0.4776] | [0.5270,0.5270] | [0.4831,0.4831] | [0.5106,0.5106] | 0.0158 |
| B10 | [0.5115,0.6699] | [0.4433,0.5911] | [0.4433,0.5911] | [0.3069,0.4335] | 0.0596 |
| B11 | [0.5139,0.6741] | [0.4454,0.5948] | [0.3769,0.5155] | [0.3769,0.5155] | 0.0466 |
| B12 | [0.4206,0.5861] | [0.4971,0.6763] | [0.3441,0.4959] | [0.4206,0.5861] | 0.0451 |
| B13 | [0.4805,0.6503] | [0.4066,0.5636] | [0.4066,0.5636] | [0.4066,0.5636] | 0.0217 |
| B14 | [0.4314,0.5735] | [0.4978,0.6500] | [0.4314,0.5735] | [0.3650,0.4971] | 0.0386 |
| B15 | [0.3650,0.4971] | [0.4314,0.5735] | [0.4314,0.5735] | [0.4978,0.6500] | 0.0386 |
| B16 | [0.4170,0.4631] | [0.4811,0.6056] | [0.4170,0.5344] | [0.4811,0.6056] | 0.0365 |
| B17 | [0.5317,0.7011] | [0.3899,0.5361] | [0.3899,0.5361] | [0.3899,0.5361] | 0.0415 |
| B18 | [0.4314,0.5735] | [0.4978,0.6500] | [0.4314,0.5735] | [0.3650,0.4971] | 0.0386 |
| B19 | [0.4206,0.5861] | [0.4971,0.6763] | [0.3441,0.4959] | [0.4206,0.5861] | 0.0451 |
| B20 | [0.4724,0.4724] | [0.6823,0.6823] | [0.3674,0.3674] | [0.4199,0.4199] | 0.0896 |
| B21 | [0.5010,0.5010] | [0.6059,0.6059] | [0.4428,0.4428] | [0.4311,0.4311] | 0.0523 |
| B22 | [0.4585,0.6144] | [0.5290,0.6963] | [0.3879,0.5325] | [0.3174,0.4506] | 0.0687 |
| B23 | [0.4631,0.6228] | [0.4631,0.6228] | [0.3919,0.5398] | [0.3919,0.5398] | 0.0278 |
| B24 | [0.5290,0.6963] | [0.4585,0.6144] | [0.3879,0.5325] | [0.3174,0.4506] | 0.0687 |

**Table 4.3: Matrix of normalized weighted decisions**

| | *P*1 | *P*2 | *P*3 | *P*4 |
|---|---|---|---|---|
| $B_1$ | [0.0132,0.0132] | [0.0139,0.0139] | [0.0117,0.0117] | [0.0124,0.0124] |
| $B_2$ | [0.0241,0.0325] | [0.0241,0.0325] | [0.0166,0.0238] | [0.0204,0.0282] |
| $B_3$ | [0.0301,0.0301] | [0.0502,0.0502] | [0.0362,0.0362] | [0.0322,0.0322] |
| $B_4$ | [0.0052,0.0055] | [0.0050,0.0054] | [0.0054,0.0057] | [0.0054,0.0056] |
| $B_5$ | [0.0232,0.0730] | [0.0199,0.0669] | [0.0166,0.0608] | [0.0149,0.0517] |
| $B_6$ | [0.0085,0.0091] | [0.0091,0.0097] | [0.0080,0.0085] | [0.0085,0.0091] |
| $B_7$ | [0.0023,0.0023] | [0.0023,0.0023] | [0.0023,0.0023] | [0.0023,0.0023] |
| $B_8$ | [0.0056,0.0056] | [0.0058,0.0058] | [0.0053,0.0053] | [0.0055,0.0055] |
| $B_9$ | [0.0075,0.0075] | [0.0083,0.0083] | [0.0076,0.0076] | [0.0081,0.0081] |
| B10 | [0.0305,0.0399] | [0.0264,0.0352] | [0.0264,0.0352] | [0.0183,0.0258] |
| B11 | [0.0239,0.0314] | [0.0208,0.0277] | [0.0176,0.0240] | [0.0176,0.0240] |
| B12 | [0.0190,0.0264] | [0.0224,0.0305] | [0.0155,0.0224] | [0.0190,0.0264] |
| B13 | [0.0104,0.0141] | [0.0088,0.0122] | [0.0088,0.0122] | [0.0088,0.0122] |
| B14 | [0.0166,0.0221] | [0.0192,0.0251] | [0.0166,0.0221] | [0.0141,0.0192] |
| B15 | [0.0141,0.0192] | [0.0166,0.0221] | [0.0166,0.0221] | [0.0192,0.0251] |
| B16 | [0.0152,0.0169] | [0.0176,0.0221] | [0.0152,0.0195] | [0.0176,0.0221] |
| B17 | [0.0220,0.0291] | [0.0162,0.0222] | [0.0162,0.0222] | [0.0162,0.0222] |
| B18 | [0.0166,0.0221] | [0.0192,0.0251] | [0.0166,0.0221] | [0.0141,0.0192] |
| B19 | [0.0190,0.0264] | [0.0224,0.0305] | [0.0155,0.0224] | [0.0190,0.0264] |
| B20 | [0.0423,0.0423] | [0.0611,0.0611] | [0.0329,0.0329] | [0.0376,0.0376] |
| B21 | [0.0262,0.0262] | [0.0317,0.0317] | [0.0232,0.0232] | [0.0226,0.0226] |
| B22 | [0.0315,0.0422] | [0.0363,0.0478] | [0.0266,0.0366] | [0.0218,0.0309] |
| B23 | [0.0129,0.0173] | [0.0129,0.0173] | [0.0109,0.0150] | [0.0109,0.0150] |
| B24 | [0.0363,0.0478] | [0.0315,0.0422] | [0.0266,0.0366] | [0.0218,0.0309] |

**Table 4.4: High and low points of idealization for characteristics**

| Indicators | Ideal point | Negative ideal point |
|---|---|---|
| $B_1$ | [0.0139,0.0139] | [0.0117,0.0117] |
| $B_2$ | [0.0325,0.0325] | [0.0166,0.0166] |
| $B_3$ | [0.0502,0.0502] | [0.0301,0.0301] |
| $B_4$ | [0.0057,0.0057] | [0.0050,0.0050] |
| $B_5$ | [0.0730,0.0730] | [0.0150,0.0150] |
| $B_6$ | [0.0097,0.0097] | [0.0080,0.0080] |
| $B_7$ | [0.0023,0.0023] | [0.0023,0.0023] |
| $B_8$ | [0.0058,0.0058] | [0.0053,0.0053] |
| $B_9$ | [0.0083,0.0083] | [0.0075,0.0075] |
| B10 | [0.0399,0.0399] | [0.0183,0.0183] |
| B11 | [0.0314,0.0314] | [0.0176,0.0176] |
| B12 | [0.0305,0.0305] | [0.0155,0.0155] |
| B13 | [0.0141,0.0141] | [0.0088,0.0088] |
| B14 | [0.0251,0.0251] | [0.0141,0.0141] |
| B15 | [0.0251,0.0251] | [0.0141,0.0141] |
| B16 | [0.0221,0.0221] | [0.0152,0.0152] |
| B17 | [0.0291,0.0291] | [0.0162,0.0162] |
| B18 | [0.0251,0.0251] | [0.0141,0.0141] |
| B19 | [0.0305,0.0305] | [0.0155,0.0155] |
| B20 | [0.0611,0.0611] | [0.0329,0.0329] |
| B21 | [0.0317,0.0317] | [0.0226,0.0226] |
| B22 | [0.0478,0.0478] | [0.0218,0.0218] |
| B23 | [0.0173,0.0173] | [0.0109,0.0109] |
| B24 | [0.0478,0.0478] | [0.0218,0.0218] |

## 5. CONCLUSION:

According to the new characteristics of supplier selection in service-oriented manufacturing, this paper develops a practical index system for evaluating suppliers in this industry. The index takes into account such factors as quality and technology, price, service-level, collaborative ability, flexibility, environmental performance, and comprehensive factors. It is used to rate potential vendors based on a combination of the deviation function model and the interval relative entropy ranking approach. To get over the subjectivity issue, we utilize the deviation function model to calculate the importance of the characteristic. The scheme sorting is made more discriminative and decision-making precision is increased by using the interval relative entropy sorting approach. Supply networks of service-oriented manufacturing enterprises can be optimized through the implementation of a scientific and reasonable supplier selection system, which in turn improves overall management, boosts the enterprise's core competence, and increases the overall value created with suppliers

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