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A Fuzzy TOPSIS approach for Ytterbium Supplier Selection

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Abstract
This article presents a fuzzy Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) approach to evaluating and selecting suppliers based on multiple decision criteria. The proposed method utilizes a fuzzified weighted normalized decision matrix to describe suppliers' performance in the form of triangular fuzzy numbers (TFNs). The fuzzy TOPSIS method enables the determination of ideal and anti-ideal supplier scenarios, creating a benchmark for expected performance across all decision criteria. By comparing suppliers to these ideal and anti-ideal scenarios, the method allows for a compromise in the decision process, considering all decision criteria and prioritizing those necessary for an improved decision process. The results of the study indicate that suppliers can be improved upon depending on their performance in preferred decision criteria, which may change over time due to logistics or policy adjustments on decision criteria. The fuzzy TOPSIS model determines the optimal supplier based on cumulative distances and closeness coefficients, providing a robust and reliable decision-making framework.
Keywords
Fuzzy TOPSIS, supplier selection, multiple criteria decision-making, triangular fuzzy numbers, cumulative distances, closeness coefficients Ytterbium suppliers.

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I. Introduction

Supplier selection represents a critical strategic decision in supply chain management, directly impacting organizational performance, cost efficiency, and competitive advantage. The complexity of modern supply chains, coupled with multiple conflicting criteria and uncertain information, necessitates sophisticated decision-making tools. Fuzzy TOPSIS has emerged as a powerful methodology for addressing these challenges, combining the traditional TOPSIS framework with fuzzy set theory to handle imprecise data and linguistic variables.The advent of quantum computing has spurred the discovery and development of novel elements, including Ytterbium, which plays a pivotal role in this emerging technology. Ytterbium's exceptional properties, such as low error rates, scalability, robustness, and rapid gate operations, make it an ideal component for quantum computing applications. Specifically, Ytterbium ions are leveraged in the development of ion trap quantum computers, where they are manipulated using electromagnetic fields and optical lattices for quantum simulation.The benefits of Ytterbium in quantum computing are multifaceted. For instance, Ytterbium-based quantum gates facilitate universal quantum computation, while its doped materials enhance superconducting qubit performance. The element's unique properties, including stable ions, low magnetic moment, narrow spectral lines, long coherence times, and natural abundance, render it particularly suitable for quantum computing.

These properties confer several advantages, such as stable energy levels, reduced magnetic noise, and improved quantum gate fidelity. Moreover, the narrow spectral lines and long coherence times enable precise control over quantum transitions and prolonged sustenance of quantum states. Ytterbium's applications in quantum computing are diverse, encompassing processors, metrology, simulations, error correction, and communication. Notably, Ytterbium-based systems facilitate secure quantum key distribution and mimic complex quantum phenomena in quantum simulation.

Ytterbium ions play a crucial role in quantum computing, serving as qubits for computation in quantum processing. Additionally, they enhance sensing and precision measurement, facilitating fault-tolerant quantum computing (Wael et al., 2019). Given the significance of Ytterbium in quantum computing, evaluating suppliers of this element is essential to ensure quality, reliability, cost-effectiveness, and timely delivery. The supplier selection process is critical in manufacturing, as it impacts the final product's quality. Key factors to consider include reliability, cost structure, delivery and lead times, technical capability and expertise, financial stability and creditworthiness, and customer service and support. Additional factors such as reputation and references, flexibility and adaptability, environmental and social responsibility, and regulatory compliance and certifications may also be relevant.

The supplier selection process typically involves defining requirements and specifications, researching and identifying potential suppliers, evaluating suppliers, and conducting site visits and audits if necessary. Monitoring and evaluating supplier performance is also crucial for continuous improvement. To ensure a quality Ytterbium supply for quantum computing, adopting best practices in supplier selection is essential. This includes developing a clear supplier selection strategy, establishing a cross-functional selection team, ensuring compliance with regulations and standards, using data-driven decision-making, evaluating suppliers' supply chain risk, and continuously monitoring supplier performance.

A prominent method for achieving effective supplier selection is by applying Multi-Criteria Decision-making Models (MCDM). MCDM ensures a holistic and comprehensive approach to evaluating criteria and sub-criteria, leading to a well-structured decision-making process, consideration of multiple perspectives, improved decision quality, and enhanced transparency and accountability. The application of MCDM models helps avoid common mistakes in supplier selection, such as focusing solely on price, overlooking quality, and neglecting to evaluate supplier risk. Effective utilization of supply chain tools and techniques, such as proposals and quotations, supplier scorecards, SWOT analysis, benchmarking, and supplier relationship management software, is also crucial. The benefits of applying MCDM models in supplier selection include evaluating multiple suppliers based on various criteria, achieving a balanced trade-off between competing criteria, and using a systematic method to aid decision-making (Olabanji and Mpofu, 2020; Olabanji and Mpofu, 2022). MCDM models can be broadly categorized into Multi-Attribute Decision Models (MADM) and Multi-Objective Decision Models (MODM).The Multi-Attribute Decision Making (MADM) methodology employs various tools to facilitate decision-making processes. These tools include the Weighted Sum Model (WSM), Analytic Hierarchy Process (AHP), Multi-Attribute Utility Theory (MAUT), Elimination and Choice Expressing Reality (ELECTRE), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE), and Simple Additive Weighting (SAW), among others (Olabanji and Mpofu, 2020; Olabanji and Mpofu, 2022).

The Fuzzy Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is a widely used Multi-Attribute Decision-Making (MADM) model that handles uncertain and imprecise data. The fuzzy TOPSIS method is particularly useful for evaluating alternatives with multiple criteria, where the data is fuzzy or uncertain. Compared to other MADM models, fuzzy TOPSIS offers several advantages. Firstly, it can handle fuzzy data, which is common in real-world decision-making problems. Secondly, it provides a simple and intuitive approach to evaluating alternatives, making it easier to understand and apply. Fuzzy TOPSIS has been widely applied in various fields, including supplier selection (Chen et al., 2006), logistics (Li et al., 2012), and finance (Wang and Elhag, 2006). Its ability to handle uncertain and imprecise data makes it a valuable tool for decision-makers. Further comparison to other MADM models, such as AHP (Analytic Hierarchy Process) and VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje), fuzzy TOPSIS offers several advantages. AHP is a widely used MADM model, but it requires a crisp pairwise comparison matrix, which can be difficult to obtain in real-world decision-making problems. VIKOR, on the other hand, provides a compromise solution, but it can be sensitive to the weights assigned to the criteria. In contrast, fuzzy TOPSIS provides a simple and intuitive approach to evaluating alternatives, making it easier to understand and apply. Additionally, it can handle fuzzy data, which is common in real-world decision-making problems (Wang et. al., 2006).

II. Methodology

The method applied in this article involves the identification of criteria and sub criteria needed for effective supplier selection of Ytterbium and application of the Fuzzy TOPSIS model to evaluate four different suppliers.

2.1 Identification of Criteria and Sub-Criteria for Optimum Supplier Selection

The criteria and sub criteria applied in this article is summarized in Fig. 1. Eight decision criteria are considered in this study. Each of these criteria are described and categorized by several sub-criteria that contributes to the relative importance of the main criteria in the decision process. This is necessary in order to obtain weights of the criteria and achieve a holistic decision process (Puška, *et. al*., 2020; Puška, *et. al*., 2021; Salimian, *et. al*., 2022; Stević*et. al*., 2020; Taş, *et. al*., 2021).

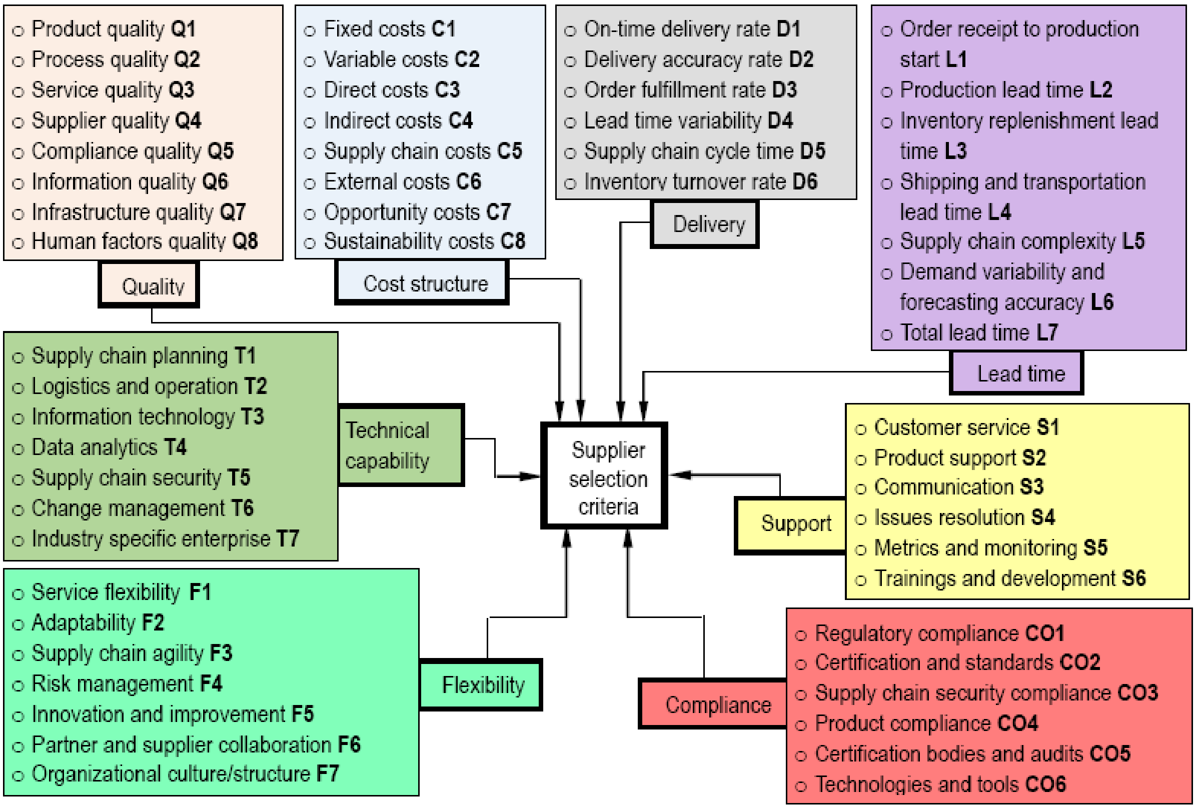

Fig. 1. Decision criteria and sub criteria considered for effective supplier selection

2.2 The Fuzzy TOPSIS Model

Considering the fact that the decision criteria and sub criteria are of different characteristics and dimensions, hence it may be difficult to quantify them with a crisp value. In view of this, a fuzzy number with the triangular membership function is applied by using a linguistic scale to represent the membership functions for the relative contributions of sub criteria to the main decision criteria and the relative availability of sub criteria in the Ytterbium suppliers as presented in Tables 1 and 2 respectively. the weight of the decision criteria and the performance of the suppliers relative to the sub criteria will form the fuzzified decision matrix which can then be normalized in order to obtain the normalized decision matrix

Table 1. Linguistic terms and TFNs for the importance of sub-criteria to main decision criteria

Relative contributions or importance of sub-criteria to main decision criteria	Triangular Fuzzy Numbers and membership function	Inverse of TFN
Equal Importance (**EIP**)	$1 \quad 1 \quad 1$	$1 \quad 1 \quad 1$
Low Importance (**LIP**)	$1 \quad \frac{3}{2} \quad 2$	$1 \quad \frac{3}{2} \quad 2$
Medium Importance (**MIP**)	$\frac{3}{2} \quad 2 \quad \frac{5}{2}$	$\frac{3}{2} \quad 2 \quad \frac{5}{2}$
High Importance (**HIP**)	$2 \quad \frac{5}{2} \quad 3$	$2 \quad \frac{5}{2} \quad 3$
Very high Importance (**VHP**)	$\frac{5}{2} \quad 3 \quad \frac{7}{2}$	$\frac{5}{2} \quad 3 \quad \frac{7}{2}$

Table 2. Linguistic terms and TFNs for the availability of sub-criteria in the operations of the Ytterbium suppliers

Relative Availability of sub-criteria in the operations of the Ytterbium suppliers	Triangular Fuzzy Numbers and membership function
Extremely Poor Performance (**ELP**)	$1 \quad 1 \quad 1$
Very LowPerformance (**VLP**)	$1 \quad \frac{3}{2} \quad 2$
LowPerformance (**LOP**)	$\frac{3}{2} \quad 2 \quad \frac{5}{2}$
Medium Low Performance (**MLP**)	$2 \quad \frac{5}{2} \quad 3$
Medium Performance (**MEP**)	$\frac{5}{2} \quad 3 \quad \frac{7}{2}$
Medium High Performance (**MHP**)	$3 \quad \frac{7}{2} \quad 4$
High Performance (**HGP**)	$\frac{7}{2} \quad 4 \quad \frac{9}{2}$
Very High Performance (**VHP**)	$4 \quad \frac{9}{2} \quad 5$
Extremely High performance (**EHP**)	$\frac{9}{2} \quad 5 \quad \frac{11}{2}$

Considering the weighted normalized performance value of the ith alternative supplier in terms of the nth decision criteria, the fuzzy positive (A^*) and negative (A^-) ideal solutions for the alternative supplier can be obtained from equations 1 and 2;

$$A^* = \left(v_1^*,\ v_2^*, \ldots\ldots\ v_n^*\right) \tag{1}$$

$$A^- = \left(v_1^-,\ v_2^-, \ldots\ldots\ v_n^-\right) \tag{2}$$

Where (v_n^*) is a vector TFN that is obtained from $v_n^* = \left(e,\ e,\ e\right)$ such that $e = \underset{i}{\text{Max}} \left\{E_{ik}^{"}\right\}$ (for $i = 1,\ldots\ldots n$ and $k = 1,\ldots\ldots j$). $E_{ik}^{"}$ is the upper value TFN in the column of the weighted normalized decision matrix. Similarly, (v_1^-) is a vector TFN that is obtained from $v_n^- = \left(f,\ f,\ f\right)$ such that $f = \underset{i}{\text{Min}} \left\{F_{ik}^{"}\right\}$ $e = \underset{i}{\text{Max}} \left\{E_{ik}^{"}\right\}$ (for $i = 1,\ldots\ldots n$ and $k = 1,\ldots\ldots j$). $F_{ik}^{"}$ is the lower value TFN in the column of the weighted normalized decision matrix (Olabanji and Mpofu, 2020).

The distance of each supplier from the positive ideal (d_i^*) and negative ideal (d_i^-) solution is needed for computation of the relative closeness of the alternative suppliers to the optimal supplier. This distance can be obtained from the ideal solutions;

$$d_i^* = \sum_{i=1}^{n} \frac{1}{3}\left[\left(\tilde{v}_{in},\ v_n^*\right)\right] \tag{3}$$

$$d_i^- = \sum_{i=1}^{n} \frac{1}{3}\left[\left(\tilde{v}_{in},\ v_n^-\right)\right] \tag{4}$$

The closeness coefficient (CC_i) represents the distances of the suppliers to the fuzzy positive ideal solution (A^*) and fuzzy negative ideal solution (A^-) simultaneously. This can be obtained from;

$$CC_i = \frac{d_i^-}{d_i^- + d_i^+} \tag{5}$$

In essence, the supplier with highest closeness coefficient represents the optimal supplier and itis close to the fuzzy positive ideal solution and far from fuzzy negative ideal solution(Olabanji and Mpofu, 2020).

III. Results and Discussions

3.1 Results

The weights of the decision criteria and responses on the performance of the supplier in terms of the criteria were obtained in the form of TFNs and this was used to develop a decision matrix. The elements of the decision matrix were normalized as presented in Table 3. The weighted normalized decision matrix presented in Table 4 was obtained by multiplying the normalized weights of the decision criteria with the performance of the suppliers in terms of the decision criteria. This is necessary in order to consider the weight of the decision criteria in the evaluation process. Further, the ideal and anti-ideal solutions that represents the best and worst TFNs membership function that the performance of the suppliers in all the decision criteria can be compared is presented in Table 5 as obtained from equations 1 and 2 respectively. The fuzzified distances of the suppliers to the ideal and anti-ideal solutions obtained from equations 3 and 4 respectively is presented in Table 6. These fuzzified distances provides a means of identifying the membership functions of the suppliers in terms of their performance in each of the decision criteria. In order to obtain the closeness coefficient and rank the suppliers, the cumulative distances of the suppliers in terms of their performance relative to each of the decision criteria is obtained as presented in Table 7 and the closeness coefficient and ranking is presented in Table 8.

Table 3. Normalized Fuzzified Decision matrix with weights of the decision criteria

SUPPLIERS	DECISIONCRITERIA																							
	QUALITY			DELIVERY			SUPPORT			LEAD TIME			COMPLIANCE			FLEXIBILITY			TECHNICAL CAPABILITY			COST STRUCTURE		
	0.65	1.09	1.67	0.59	1.00	1.70	0.65	1.00	1.54	0.64	1.00	1.57	0.64	1.00	1.57	0.62	0.96	1.49	0.65	1.00	1.55	0.64	1.00	1.57
S1	0.20	0.40	0.74	0.18	0.37	0.75	0.32	0.57	1.00	0.31	0.55	1.00	0.00	0.56	1.00	0.29	0.52	0.91	0.30	0.54	0.95	0.28	0.49	0.89
S2	0.25	0.51	0.89	0.24	0.48	0.92	0.28	0.50	0.89	0.29	0.51	0.91	0.31	0.55	0.98	0.31	0.55	0.97	0.31	0.55	0.96	0.30	0.55	1.00
S3	0.28	0.57	1.00	0.27	0.52	1.00	0.28	0.50	0.89	0.31	0.55	1.00	0.30	0.54	0.97	0.32	0.57	1.00	0.32	0.57	0.99	0.30	0.53	0.96
S4	0.19	0.39	0.71	0.21	0.42	0.84	0.29	0.53	0.93	0.27	0.47	0.85	0.31	0.56	1.00	0.29	0.51	0.91	0.29	0.52	0.92	0.29	0.51	0.93

Table 4. Weighted Normalized Fuzzified Decision matrix with weights of the decision criteria

SUPPLIERS	DECISIONCRITERIA																							
	QUALITY			DELIVERY			SUPPORT			LEAD TIME			COMPLIANCE			FLEXIBILITY			TECHNICAL CAPABILITY			COST STRUCTURE		
	0.65	1.09	1.67	0.59	1.00	1.70	0.65	1.00	1.54	0.64	1.00	1.57	0.64	1.00	1.57	0.62	0.96	1.49	0.65	1.00	1.55	0.64	1.00	1.57
S1	0.13	0.44	1.23	0.11	0.37	1.28	0.21	0.57	1.54	0.20	0.55	1.57	0.00	0.56	1.57	0.18	0.50	1.36	0.20	0.54	1.46	0.18	0.49	1.40
S2	0.16	0.55	1.49	0.14	0.48	1.57	0.18	0.50	1.37	0.18	0.51	1.43	0.00	0.31	0.98	0.09	0.29	0.89	0.09	0.30	0.91	0.08	0.27	0.89
S3	0.18	0.62	1.67	0.16	0.52	1.70	0.18	0.50	1.37	0.19	0.55	1.57	0.09	0.30	0.95	0.10	0.32	0.97	0.10	0.31	0.95	0.09	0.29	0.96
S4	0.12	0.42	1.18	0.11	0.37	1.28	0.19	0.53	1.43	0.17	0.47	1.33	0.09	0.30	0.97	0.09	0.29	0.90	0.09	0.30	0.91	0.09	0.27	0.89

Table 5. Ideal and Anti-Ideal solutions

	QUALITY			DELIVERY			SUPPORT			LEAD TIME			COMPLIANCE			FLEXIBILITY			TECHNICAL CAPABILITY			COST STRUCTURE		
Ideal Solution	1.67	1.67	1.67	1.70	1.70	1.70	1.54	1.54	1.54	1.57	1.57	1.57	1.57	1.57	1.57	1.49	1.49	1.49	1.55	1.55	1.55	1.57	1.57	1.57
Anti-Ideal Solution	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 6. Fuzzified distances of the alternative suppliers to the Ideal and anti-ideal solutions

SUPPLIERS	DECISIONCRITERIA																							
	QUALITY			DELIVERY			SUPPORT			LEAD TIME			COMPLIANCE			FLEXIBILITY			TECHNICAL CAPABILITY			COST STRUCTURE		
S1 (d+) *	1.54	1.23	0.44	1.59	1.32	0.42	1.33	0.97	0.00	1.38	1.02	0.00	1.57	1.00	0.00	1.31	0.99	0.13	1.35	1.01	0.08	1.39	1.08	0.17
S2 (d+) *	1.50	1.12	0.18	1.56	1.22	0.13	1.36	1.04	0.17	1.39	1.07	0.14	0.00	0.31	0.98	0.09	0.29	0.89	0.09	0.30	0.91	0.08	0.27	0.89
S3 (d+) *	1.48	1.05	0.00	1.54	1.18	0.00	1.36	1.04	0.17	1.38	1.03	0.01	0.09	0.30	0.95	0.10	0.32	0.97	0.10	0.31	0.95	0.09	0.29	0.96
S4 (d+) *	1.55	1.25	0.49	1.58	1.28	0.28	1.35	1.01	0.11	1.40	1.10	0.24	0.09	0.26	0.60	0.09	0.20	0.46	0.10	0.24	0.56	0.09	0.22	0.51
S1 (d-) *	0.13	0.44	1.23	0.11	0.37	1.28	0.21	0.57	1.54	0.20	0.55	1.57	0.00	0.56	1.57	0.18	0.50	1.36	0.20	0.54	1.46	0.18	0.49	1.40
S2 (d-) *	0.16	0.55	1.49	0.14	0.48	1.57	0.18	0.50	1.37	0.18	0.51	1.43	0.00	0.31	0.98	0.09	0.29	0.89	0.09	0.30	0.91	0.08	0.27	0.89
S3 (d-) *	0.18	0.62	1.67	0.16	0.52	1.70	0.18	0.50	1.37	0.19	0.55	1.57	0.09	0.26	0.61	0.08	0.18	0.39	0.10	0.23	0.51	0.09	0.21	0.44
S4 (d-) *	0.12	0.42	1.18	0.12	0.42	1.42	0.19	0.53	1.43	0.17	0.47	1.33	0.09	0.01	0.02	0.00	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.00

Table 7. Cumulative distances of suppliers

Suppliers	Decision criteria								Cumulative Distances
	QUALITY	DELIVERY	SUPPORT	LEAD TIME	COMPLIANCE	FLEXIBILITY	TECHNICAL CAPABILITY	COST STRUCTURE	
Supplier 1 d+	1.17	1.22	0.95	0.99	1.07	0.95	0.98	1.02	8.35
Supplier 2 d+	1.09	1.15	0.99	1.02	0.60	0.54	0.55	0.54	6.47
Supplier 3 d+	1.05	1.12	0.99	0.99	0.58	0.59	0.58	0.58	6.49
Supplier 4 d+	1.18	1.18	0.98	1.04	0.38	0.29	0.35	0.33	5.73
Supplier 1 d-	0.76	0.77	0.96	0.97	0.96	0.84	0.91	0.86	7.03
Supplier 2 d-	0.92	0.95	0.85	0.88	0.60	0.54	0.55	0.54	5.83
Supplier 3 d-	1.03	1.03	0.85	0.97	0.39	0.25	0.33	0.29	5.13
Supplier 4 d-	0.73	0.86	0.89	0.82	0.05	0.01	0.00	0.00	3.37

Table 8. Closeness Coefficient CC_i and Ranking of Suppliers

Suppliers	d^+	d^-	CC_i	***Ranking***
Supplier 1	8.35	7.03	0.46	2
Supplier 2	6.47	5.83	0.48	1
Supplier 3	6.49	5.13	0.44	3
Supplier 4	5.73	3.37	0.37	4

3.2 Discussions

Considering the fuzzified weighted normalized decision matrix in Table 6, a clear description of the performance of the suppliers with respect to the decision criteria can be obtained in the form of TFNs. Also, an interesting aspect of the fuzzy TOPSIS method is the determination of the ideal and anti-ideal supplier scenario in all the decision criteria. The identification of ideal and anti-ideal suppliers from the decision matrix creates a means of benchmarking what is expected from an ideal supplier considering all the decision criteria. However, it is not possible to have a supplier that will perform excellently in all the decision criteria and that is why it is an ideal scenario. Similarly, it is expected that all the suppliers must also overcome the anti-ideal scenario which contains poor performance in all the decision criteria. In essence, the fuzzy TOPSIS method will tend to compare all the suppliers considering the ideal and anti-ideal scenarios. Since it is not possible to have a supplier with excellent performance in all the decision criteria, there will be a compromise in the decision process such that some decision criteria will not be predominantly available in the supplier. It is worthwhile to note that such decision criteria are also important but the decision to prioritize the decision criteria has come to play in order to satisfy the criteria that are necessary for an improved decision process. Also, when there is a need to prioritize some other decision criteria, the alternatives which has the best performance in all these criteria can easily be identified. In essence, the TOPSIS model considers all the decision criteria in the aspect of the distances and cumulative distances to the ideal and anti-ideal scenario. The consideration of all the decision criteria will enable the decision-making team to know which of the suppliers that will be cheaper to engage with in terms of cost reduction of the Ytterbium and which of the suppliers to engage with in terms of Ytterbium with optimized cost and quality. Another observation from the results obtained in the TOPSIS model is that, none of the suppliers is performing close to the anti-ideal and ideal supplier. Although there TFN membership function have values in between these two ranges which means that all suppliers will tend to move closer to the ideal scenario while moving far from the anti-ideal instance. This implies that any of the suppliers can be improved upon depending on their performance in any of the preferred decision criteria because the weights of the decision criteria are subjected to change depending on the logistics and policy of the decision makers at the instance of purchase. In essence, that supplier “2” is the best in this example based on the data obtained does not imply that it will continue to be the best always. This may be due to improvement in the operations of other suppliers over time which will change their performance in the sub criteria or due to change in the preference of weights of the sub criteria and decision criteria. Considering the distances to the ideal and anti-ideal scenario and the determination of the cumulative distance and closeness coefficient, the TOPSIS model determined the optimal supplierrather than mere defuzzification. The TOPSIS model was also able to establish the level of performance of the suppliers relative to the expected performance of the ideal and anti-ideal supplier but a judgment on the optimal supplier from the set of alternative suppliers cannot be made because the closeness coefficient which is a function on how each of the supplier performs with respect to the ideal and anti-ideal scenario needs to be determined from the cumulative distances. Hence, the suppliers were ranked based on their scores in the closeness coefficient. An observation of the final values of the closeness coefficient showed that there is a closeness in the final values of the suppliers. This is an indication that the TOPSIS model did not apportion values to the suppliers but rather compared their performances in all the decision criteria and their closeness coefficient.

IV. Conclusion

Conclusively, the importance of identifying the best supplier from a set of alternative suppliers cannot be overstated because it will go a long way in controlling the price and quality of the final product. Aside from the issues of price and quality the decision-making process to select the optimal supplier also helps to strengthen the supply chain network. Hence more efforts and resources are needed to be put into action in the decision process for identification of optimal supplier for effective logistics process in the production system. This is necessary because it provides more information on the decision criteria associated with the suppliers and the Ytterbium product itself. In essence, considering the importance that is attached to the supplier section process, this article has presented fuzzy TOPSIS as a multicriteria decision making model which can be adopted as a tool for carrying out a robust decision process.

The fuzzy TOPSIS method, as demonstrated through the fuzzified weighted normalized decision matrix in Table 6, provides a comprehensive and systematic approach to evaluating and ranking suppliers based on multiple decision criteria. By establishing ideal and anti-ideal supplier scenarios, the method creates a benchmark for expected performance, enabling a compromise in the decision process. The TOPSIS model's ability to consider all decision criteria, prioritize those necessary for an improved decision process, and identify suppliers that offer the best performance in specific criteria, makes it a valuable tool for supplier selection.The results of the study indicate that suppliers can be improved upon depending on their performance in preferred decision criteria, which may change over time due to logistical or policy adjustments. This highlights the importance of continuous monitoring and evaluation of suppliers to ensure optimal performance. Ultimately, the TOPSIS model's determination of the optimal supplier based on cumulative distances and closeness coefficients provides a robust and reliable decision-making framework.The application of the fuzzy TOPSIS method in supplier selection has significant implications for organizations seeking to optimize their supply chain operations. By providing a systematic and comprehensive approach to evaluating and ranking suppliers, the method enables organizations to make informed decisions that balance competing criteria and priorities. Furthermore, the method's ability to accommodate uncertainty and imprecision in decision-making makes it particularly suitable for complex and dynamic supply chain environments.

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