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On the Ytterbium Suppliers Selection process: fuzzified weighted average based on left and right scores

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Abstract
The selection of reliable ytterbium suppliers is crucial for ensuring the quality and efficiency of quantum computing applications. This study proposes a novel approach for evaluating and selecting ytterbium suppliers using a fuzzified weighted average based on left and right scores. The proposed method integrates fuzzy logic and weighted average techniques to handle the uncertainty and imprecision associated with supplier evaluation criteria. The left and right scores are used to represent the lower and upper bounds of the fuzzy numbers, respectively. The results show that the proposed method can effectively evaluate and rank ytterbium suppliers based on multiple criteria, including quality, delivery, support, lead time, compliance flexibility technical capability and cost structure. The study provides a valuable decision-making tool for organizations seeking to select reliable ytterbium suppliers for their quantum computing needs.
Keywords
Ytterbium suppliers, supplier selection, fuzzified weighted average, left and right scores, fuzzy logic, quantum computing.

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I. Introduction

Ytterbium (Yb) has emerged as a crucial element in advancing quantum computing due to its exceptional properties. Its low error rates, scalability, robustness, and rapid gate operations make it particularly valuable for ion trap quantum computers. Yb ions are confined and manipulated within electromagnetic fields or optical lattices, enabling precise quantum simulations. The application of Ytterbium in quantum computing includes; provision of consistent energy levels as stable ions for reliable quantum operations, minimization of magnetic noise, gate fidelity improvement and decoherence reduction. Further, it allows for precise control over the quantum transitions by enabling sustained quantum states which is crucial for maintaining quantum information. Ytterbium is found in several components of quantum computing such as quantum processors, metrology, simulations, error correction and communication. The quantum metrology is important for enhancing sensing capabilities and precise measurement while they assist in modelling of complex quantum systems and processes. The error correction capabilities are advantageous in mitigating errors and improving the reliability of quantum computations while enabling secured quantum key distribution and communication protocols. Furthermore, Ytterbium-based quantum gates enable universal quantum computation, and Ytterbium-doped materials enhance the performance of superconducting qubits. These attributes position Ytterbium as a cornerstone element in the ongoing development of robust and scalable quantum technologies (Nop *et. al*., 2021).

The Ytterbium ions serve as qubits, the fundamental units of information in quantum computers. They also play a crucial role in enhancing sensing and precision measurements, and are essential for enabling fault-tolerant quantum computing (Wael *et al*., 2019). Considering the critical role of Ytterbium in quantum computing, meticulous supplier selection is paramount. This ensures the procurement of high-quality materials, reliable delivery, and cost-effectiveness. Key factors considered in supplier evaluation include:reliability andcost,delivery andlead times which is a function of timely and efficient delivery to meet project timelines. Another factor is the technical capability which is important as it demonstrated expertise in Ytterbium production and relevant technologies. Other factors include financial stability and customer service.

The process of selecting a supplier for Ytterbium, a crucial element in quantum computing, involves several key steps. First, it is essential to clearly define the requirements and specifications for Ytterbium. This is followed by researching and identifying potential suppliers. Next, suppliers are evaluated based on predefined criteria, and site visits and audits may be conducted as needed. Finally, the performance of the selected supplier is continuously monitored and evaluated for ongoing improvement.To ensure effective Ytterbium procurement, several best practices should be followed. Developing a clear strategy aligned with business objectives is crucial. This strategy should be developed by a cross-functional team with relevant expertise. Ensuring compliance with all relevant regulations and industry standards is also vital. Data-driven decision-making and supply chain risk assessment are additional critical factors to consider. Finally, continuous monitoring of supplier performance is necessary to ensure ongoing quality and reliability (Angara *et. al*., 2021).

The supplier selection process typically involves requirement definition in which there is a clear definition of the needs and specifications for the Ytterbium. The next stage is the supplier identification. This stage usually involves researching and identifying potential suppliers before evaluation and site visits and performance monitoring can commence. In order to achieve an effective Ytterbium procurement, a clear strategy on the supplier selection decision criteria that is aligned with the objectives of the business is needed before involving diverse teams with expertise in decision making. The MCDM models offer a structured and comprehensive approach to supplier selection. The benefits of using MCDM include; holistic Evaluation, improved decision quality, transparency and accountability and reduction of computational errors (Olabanji and Mpofu, 2022).

Multi-Criteria Decision-Making (MCDM) models offer a structured and comprehensive approach to supplier selection. These models provide several benefits, including a holistic evaluation of multiple criteria, improved decision quality, increased transparency and accountability, and reduced error risk. MCDM models can be categorized into two main types: Multi-Attribute Decision Making (MADM) and Multi-Objective Decision Making (MODM) (Olabanji and Mpofu, 2020).In essence, effective Ytterbium supplier selection is critical for the success of quantum computing initiatives. By employing best practices and leveraging powerful tools like MCDM models, organizations can ensure they procure high-quality Ytterbium from reliable and trustworthy suppliers (Olabanji and Mpofu, 2022).

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 weighted average model to evaluate four different suppliers (Ayşegül and Adali, 2022; Badi and Pamucar, 2020).

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; Stevićet. *al*., 2020; Taş,*et. al*., 2021).

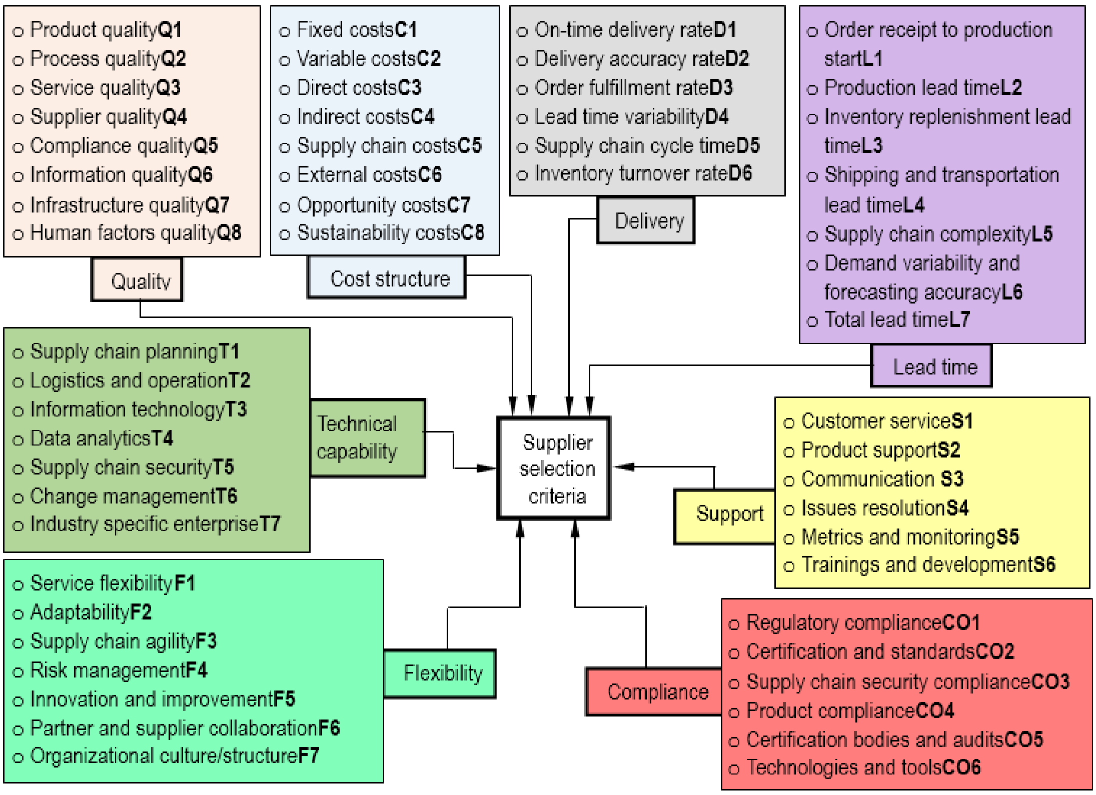

Fig. 1. Decision criteria and sub criteria considered for effective supplier selection

2.2 The Fuzzy Weighted average 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 (Olabanji, 2024).

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**)	$\frac{9}{2} \quad 5 \quad \frac{11}{2}$

The normalized relative weights of the decision criteria and the normalized performance value of the ith alternative supplier in terms of the nth decision criteria are necessary for obtaining the normalized fuzzy weight and decision matrix. Since the normalized fuzzy weight matrix will satisfy the condition that $\sum_{i=1}^{n} W_{dA} = 1$, it is necessary to know that it will be separated from the normalized decision matrix under the FWA method. Hence the normalized fuzzy decision matrix and normalized fuzzy weights of decision criteria under the FWA method can be described as shown in equations 1 and 2. Two matrices that includes intervals of the left and right score can be constructed for the normalized fuzzy decision matrix and the fuzzy weights of the decision criteria. These intervals of the left and right scores will be of the form of equations 3 and 4. The value for the weighted average of each supplier can also be obtained in form of the intervals of the left and right scores. For ease of analysis, let $d_{ij} = \left[(L_S),(R_S) \right]_{ij} = \left[(L_S)_{ij},(R_S)_{ij} \right]$ and $w_j = \left[(L_S),(R_S) \right]_j = \left[(L_S)_j,(R_S)_j \right]$, then the FWA (θ_i) for alternative supplier d_{AC_i} can be obtained from equation 5.

$$\left(W_{Sf_n}\right)_N = \begin{pmatrix} \left(\tilde{B}^1_{sf_1}\right)_N & \left(\tilde{B}^2_{sf_1}\right)_N & \left(\tilde{B}^3_{sf_1}\right)_N & .... & \left(\tilde{B}^n_{sf_1}\right)_N \\ \left(\tilde{B}^1_{sf_2}\right)_N & \left(\tilde{B}^2_{sf_2}\right)_N & \left(\tilde{B}^3_{sf_2}\right)_N & \cdots & \left(\tilde{B}^n_{sf_2}\right)_N \\ \left(\tilde{B}^1_{sf_3}\right)_N & \left(\tilde{B}^2_{sf_3}\right)_N & \left(\tilde{B}^3_{sf_3}\right)_N & \cdots & \left(\tilde{B}^n_{sf_3}\right)_N \\ \vdots & \vdots & \vdots & & \vdots \\ \left(\tilde{B}^1_{sf_j}\right)_N & \left(\tilde{B}^2_{sf_j}\right)_N & \left(\tilde{B}^3_{sf_j}\right)_N & \cdots & \left(\tilde{B}^i_{sf_j}\right)_N \end{pmatrix} \tag{1}$$

$$\left(\tilde{W}_{dA}\right)_N = \left[\left(\tilde{W}_1\right)_N \quad \left(\tilde{W}_2\right)_N \quad \left(\tilde{W}_3\right)_N \quad \cdots \quad \left(\tilde{W}_n\right)_N \right] \tag{2}$$

$$\left[(L_S)\ ,\ (R_S) \right]_{(\tilde{W}_{sf})N} = \begin{bmatrix} \left[(L_S)\ ,\ (R_S) \right]_{11} & \cdots & \left[(L_S)\ ,\ (R_S) \right]_{12} & \cdots & \left[(L_S)\ ,\ (R_S) \right]_{1n} \\ \vdots & & \vdots & & \vdots \\ \left[(L_S)\ ,\ (R_S) \right]_{21} & \cdots & \left[(L_S)\ ,\ (R_S) \right]_{22} & \cdots & \left[(L_S)\ ,\ (R_S) \right]_{2n} \\ \vdots & & \vdots & & \vdots \\ \left[(L_S)\ ,\ (R_S) \right]_{j1} & \cdots & \left[(L_S)\ ,\ (R_S) \right]_{j2} & \cdots & \left[(L_S)\ ,\ (R_S) \right]_{jn} \end{bmatrix} \tag{3}$$

$$\left[(L_S)\ ,\ (R_S) \right]_{(\tilde{W}_{dA})N} = \left[\left[(L_S)\ ,\ (R_S) \right]_1 \quad \cdots \quad \left[(L_S)\ ,\ (R_S) \right]_2 \quad \cdots \quad \left[(L_S)\ ,\ (R_S) \right]_n \right] \tag{4}$$

$$\theta_i = \frac{\sum_{j=1}^{n} \left(w_j * d_{ij} \right)}{\sum_{j=1}^{n} w_j} = \frac{w_1 d_{i1} + w_2 d_{i2} + ... + w_n d_{in}}{w_1 + w_2 + ... + w_n} \ ;\ i = 1,...m \tag{5}$$

Equation 5 is subject to

$$\begin{gathered} (L_s)_j \le w_j \le (R_s)_j,\ \ j = 1.....n \\ (L_s)_j \le d_{ij} \le (R_s)_j,\ \ j = 1.....n \end{gathered} \tag{6}$$

Also, since the components of the FWA for each of the supplier obtained in equation 5 is a function of the intervals of the left and right scores, then the FWA can be considered as lower and upper bound of a fractional programming model. In addition, since the FWA is a monotonically increasing function of d_{ij} which reaches it minimum and maximum at $d_{ij} = (L_S)_{ij}$ and $d_{ij} = (R_S)_{ij}$ respectively then the pair of fractional programming model can be presented as;

$$\theta_i^L = \text{Min} \frac{\sum_{j=1}^{n} \left(w_j * (L_S)_{ij} \right)}{\sum_{j=1}^{n} w_j} \text{ subject to } (L_s)_j \le w_j \le (R_s)_j,\ \ j = 1.....n \tag{7}$$

$$\theta_i^U = \text{Max} \frac{\sum_{j=1}^{n} \left(w_j * (R_S)_{ij} \right)}{\sum_{j=1}^{n} w_j} \text{ subject to } \left(L_s\right)_j \le w_j \le \left(R_s\right)_j, \; j = 1.....n \tag{8}$$

As presented by Mokhtarian, (2011), the fractional programming model presented in equations 7 and 8 can be transformed into a linear programming model using the transportation equations presented in equations 9 and 10. Based on this transportation equations, it is possible to rewrite equations 7 and 8 as presented in equations 11 and 12.

$$z = \frac{1}{\sum_{j=1}^{n} w_j} \tag{9}$$

$$t_j = z * w_j \quad j = 1.......n \tag{10}$$

$$\left(\theta_i\right)^L = \text{Min} \sum_{j=1}^{n} \left(t_j * (L_S)_{ij} \right) \text{ subject to } \sum_{j=1}^{n} t_j = 1$$
$$\left(z * (L_S)_{ij} \right) \le t_j \le \left(z * (L_S)_{ij} \right), \; j = 1.....n \tag{11}$$

$$\left(\theta_i\right)^U = \text{Max} \sum_{j=1}^{n} \left(t_j * (R_S)_{ij} \right) \text{ subject to } \sum_{j=1}^{n} t_j = 1$$
$$\left(z * (L_S)_{ij} \right) \le t_j \le \left(z * (L_S)_{ij} \right), \; j = 1.....n \tag{12}$$

In essence, the interval $\left[(\theta_i)^L, \; (\theta_i)^U \right]$ for each supplier can be generated from equations 11 and 12. An average of these two intervals is necessary for obtaining the weights of each supplier that can be used for ranking. The average value of the interval is obtained from equation 13.

$$\left(\theta_i\right)_{\text{average}} = \frac{(\theta_i)^L + (\theta_i)^U}{2} \tag{13}$$

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 TFNs and left and right scores for the decision criteria and evaluation of the suppliers was obtained (Table 5) in order to project a range of performance of all the suppliers with refence to the decision criteria. This provided an opportunity for identifying the interval of performance of the suppliers. Hence, the left and right scores of Fuzzified weighted average and ranking of the suppliers presented in Table 6 was obtained to show the performance and ratings of the suppliers.

3.2 Discussions

Considering the fuzzified weighted normalized decision matrix in Table 3, 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 weighted average method is the determination of interval of performance for the suppliers in terms of the decision criteria. The identification of these intervals creates a means of benchmarking what is expected from a supplier in any of the decision criteria. However, it is not possible to have a supplier that will perform excellently in all the decision criteria. Similarly, it is expected that all the suppliers must have good interval of performance in a considerable number of decision criteria. In essence, the fuzzified weighted average model tends to compare all the suppliers considering their interval values. 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, weighted average model employs the left and right scores in order to identify the range of performance expected from the Ytterbium suppliers relative to the decision criteria Another observation from the results obtained in the weighted average model is that, the supplier's performance can be glanced in a range for improvement. Although there TFN membership function have values in between these two ranges which means that all suppliers will tend to move closer to the upper limit while moving far from the lower limit. 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 "1" 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. Hence, the suppliers were ranked based on their scores in the overall weighted average. An observation of the final values of the weighted average showed that there is a closeness in the final values of the suppliers. This is an indication that the fuzzified weighted average model did not apportion values to the suppliers but rather compared their performances in all the decision criteria and their interval of performances.

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. TFNs and left and right scores for the decision criteria and evaluation of the suppliers

	QUALITY			DELIVERY			SUPPORT			LEAD TIME			COMPLIANCE			FLEXIBILITY			TECHNICAL CAPABILITY			COST STRUCTURE		
Weight of decision criteria	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
	0.75		1.06	0.71		1.00	0.74		1.00	0.73		1.00	0.73		1.00	0.72		0.97	0.74		1.00	0.73		1.00
	0.13		0.26	0.12		0.25	0.13		0.25	0.13		0.25	0.13		0.25	0.12		0.24	0.13		0.25	0.12		0.25
Supplier 1	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
	0.33		0.69	0.29		0.67	0.42		0.78	0.41		0.78	0.36		0.78	0.38		0.73	0.40		0.76	0.38		0.74
Supplier 2	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
	0.40		0.77	0.36		0.75	0.38		0.73	0.38		0.74	0.24		0.59	0.24		0.55	0.25		0.56	0.23		0.55
Supplier 3	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
	0.43		0.81	0.38		0.78	0.38		0.73	0.40		0.78	0.25		0.58	0.26		0.59	0.26		0.58	0.24		0.57
Supplier 4	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	0.30	0.97	0.09	0.29	0.90	0.09	0.30	0.91	0.09	0.27	0.89
	0.32		0.67	0.33		0.71	0.39		0.75	0.36		0.72	0.25		0.58	0.25		0.56	0.25		0.56	0.23		0.55

Table 6. Left and right scores of Fuzzified Weighted Average and Ranking of the Alternative suppliers

	QUALITY		DELIVERY		SUPPORT		LEAD TIME		COMPLIANCE		FLEXIBILITY		TECHNICAL CAPABILITY		COST STRUCTURE		**Weighted Interval** $\left[(\theta_i)^L,(\theta_i)^U\right]$		**Weighted Average** $\left[\frac{(\theta_i)^L+(\theta_i)^U}{2}\right]$	***Ranking***
	0.13	**0.26**	**0.12**	**0.25**	**0.13**	**0.25**	**0.13**	**0.25**	**0.13**	**0.25**	**0.12**	**0.24**	**0.13**	**0.25**	**0.12**	**0.25**				
Supplier 1	0.33	0.69	0.29	0.67	0.42	0.78	0.41	0.78	0.36	0.78	0.38	0.73	0.40	0.76	0.38	0.74	0.37	1.47	0.92	1
Supplier 2	0.40	0.77	0.36	0.75	0.38	0.73	0.38	0.74	0.24	0.59	0.24	0.55	0.25	0.56	0.23	0.55	0.31	1.30	0.81	3
Supplier 3	0.43	0.81	0.38	0.78	0.38	0.73	0.40	0.78	0.25	0.58	0.26	0.59	0.26	0.58	0.24	0.57	0.33	1.34	0.83	2
Supplier 4	0.32	0.67	0.33	0.71	0.39	0.75	0.36	0.72	0.25	0.58	0.25	0.56	0.25	0.56	0.23	0.55	0.30	1.27	0.78	4

IV. Conclusion

Conclusively, the importance of identifying the best supplier from a set of alternative suppliers cannot be overemphasized 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 weighted average model as a multicriteria decision making tool which can be adopted for carrying out a robust decision process. The framework for the application of the weighted average model to selection of optimal supplier was developed based on its procedure in other areas of application and the model provided an excellent performance by identifying the best supplier considering its overall weighted average. Further work can also be carried out in the aspect of identifying the more sub criteria that can be used to characterize the decision criteria and also in the aspect of improving the computational process by developing a computer aided system where computations can be made easily for the decision process. this will go a long way in reducing computation fatigue.

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