Operational Research in Engineering Sciences: Theory and Applications
Vol. 6, Issue 2, 2023, pp. 34-51
ISSN: 2620-1607
eISSN: 2620-1747
DOI: https://doi.org/10.31181/oresta/060203

COMMERCIAL-OFF-THE SHELF VENDOR SELECTION: A MULTI-CRITERIA DECISION-MAKING APPROACH USING INTUITIONISTIC FUZZY SETS AND TOPSIS

Vikram Bali[1], Shivani Bali[2], Dev Gaur[3], Sita Rani[4], Raman Kumar[5*]

[1] JSS Academy of Technical Education, Noida, UP, India
[2] Jaipuria Institute of Management, Noida, India
[3] JSS Academy of Technical Education, Noida, UP, India
[4] Department of Computer Science and Engineering, Guru Nanak Dev Engineering College, Ludhiana, Punjab-141006, India
[5] Department of Mechanical and Production Engineering, Guru Nanak Dev Engineering College, Ludhiana, Punjab-141006, India

Received: 16 April 2023
Accepted: 02 July 2023
First Online: 26 July 2023

Research Paper

***Abstract**: Commercial-off-the-Shelf (COTS) component selection is considered a critical task in effectively developing a component-based software system (CBSS). COTS vendor selection involves selecting the right vendors who can provide reliable COTS components at a suitable price and on time. However, COTS vendor selection is commonly a multi-criteria decision-making (MCDM) issue" associated with many paradoxical criteria for which the decision maker's knowledge may be uncertain and ambiguous. This paper attempts to present "Intuitionistic Fuzzy Sets (IFS) combined with the technique for order preference by similarity to an ideal solution (TOPSIS) method" to appraise and choose the best COTS vendor under the environment of group decision making while considering reliability, delivery time, compatibility, vendor support and functionality as benefit criteria. In contrast, price and maintenance be the cost criteria. The considered case study demonstrated the presented case effectively.*

***Keywords:** COTS, Software, Vendor, Selection, Intuitionistic Fuzzy Sets (IFS), TOPSIS.*

---

*Corresponding author: sehgal91@yahoo.co.in (R. Kumar)
vikramgcet@gmail.com (V. Bali), ibsshivani@gmail.com (S. Bali), devgaur15@gmail.com (D. Gaur), sitasaini80@gmail.com (S. Rani)

1. Introduction

Component-based software systems (CBSS) are established by assimilating software components that are popularly known as commercial-off-the-Shelf (COTS) if purchased as a ready-to-use component from the market or an in-house built component if developed within the organization. CBSS is gaining significant attention in the industry as well as in academia. CBSS aims to select appropriate components for developing an effective software system (Gupta, Mehlawat, & Mahajan, 2019). This approach helps significantly reduce software development time by keeping costs under control. To control cost CBSS approach to software development is motivated. The two main methodologies for developing the CBSS are: Units can be either "developed from scratch" or "acquired from the suppliers available in the market". These readymade components are called COTS or pre-packaged software. These COTS components can be purchased from a wide range of suppliers. The property of COTS components is that they are used without any modifications. The major concern with these COTS components is that different suppliers are available for the COTS product in the market. Therefore, one must be careful when selecting the COTS products from these suppliers.

The integration of COTS products may face many challenges, including functional problems, compatibility issues, licensing issues, vendor issues, etc., even though the industry can gain these challenges' multiple potential advantages after deploying COTS products. Jha and Bali (2012) devised a method for selecting ideal components for a fault-tolerant commutable software structure to maximize entire system resilience while lowering overall costs. A chance-limited goal programming model was developed after treating the characteristics relating to component reliability and cost as random variables. Gupta, Mehlawat, and Verma (2012) have evaluated the fitness of the COTS component considering various parameters and calculated each COTS component's score. They have used the analytical hierarchy process technique in their models.

COTS vendor selection involves selecting the right vendors who can provide reliable COTS components at a suitable price and on time. COTS vendor selection is classically a "multi-criteria group decision-making problem" with numerous paradoxical criteria which make the decisions uncertain and ambiguous. The choice of COTS selection depends upon the goal of the Decision Maker (Badampudi, Wohlin, & Petersen, 2016). For instance, if the objective of a software development project is to minimize the total cost, then the decision-maker might select the most cost-effective COTS components. However, hardly any project works on single criteria. Decision-makers must consider all the relevant criteria and trade-offs while choosing COTS components for effective decision-making. The criteria may be project related (such as delivery time and price), process-related (such as functionality and compatibility), and non-technical criteria (such as vendor support & maintenance). According to Garg (2020), the COTS selection and ranking problem have been modeled as an MCDM problem that involves ranking the various criteria and an optimization model based on FMBDA. Tailor and Dhodiya (2020) developed a genetic algorithm-dependent amalgam technique with a fuzzy exponential membership function for the optimum COTS components' optimum fit. The choice in this suggested technique must define multiple ambition levels according to their preferences to create an effective allocation plan with variable geometrical features in the exponential basis functions. Mehlawat, Gupta, and Mahajan (2020) suggested that the software can be developed in phases and delivered to the client. The phase-wise development is possible with the help of COTS, and a case study for e-commerce application has been developed in work.

As COTS components are available with the multi-vendors, it becomes difficult to manually evaluate each alternate on multiple conflicting criteria. Therefore, this paper presents "Intuitionistic Fuzzy Sets (IFS) combined with TOPSIS method" to assess and choose the best COTS component under the environment of group decision making.

Many researchers (Bali & Madan, 2015) have contributed to COTS evaluation & selection. Adam et al. (2020) have developed a COTS-Based Real-Time System used for Pump Motor Control. Although many authors proposed various accumulation models for the COTS election process to maximize software reliability, few authors have worked on minimizing the cost of software development using the CBSS approach. Both single and multi-criteria optimization models were proposed. Most of the models developed for COTS selection include quantitative parameters, such as price, delivery time, reliability, etc., but many qualitative parameters, such as vendor support, maintenance, functionality, etc., have not been incorporated in the formulation of optimization models. This is one of the significant research gaps identified and the motivation. The author of this paper has proposed a framework that is useful in developing the Component-based software system. The paper presents a methodology used by the software industry dealing in with a component-based software system. The framework presented in this paper clearly explains the trade-off between different criteria while developing software with COTS components.

In the remaining paper, 'Section 2' highlights a literature review relevant to this study's topic and the methodology outlined in 'Section 3'. The technique is then shown using a case study described in 'Section 4'. Finally, 'Section 5' contains the final observations.

2. Literature Survey

A fuzzy set approach is applied when the judgment call phase is ambiguous. The notion of 'fuzzy set' is employed in various applications (Goguen, 1973). The inclusion of any item in the fuzzy set is a unique integer between 0 and 1. So, the membership of an item in classical set theory is specified by "yet if the item is a member of the set or not." It's a two-sided situation. The member of an item is explained using a method described using unit interval [0,1] in fuzzy set theory.

MCDM approaches are of great interest and have been in demand for the last two decades as they are helpful in decision-making involving multiple objectives (Sidhu et al., 2021). With the help of the MCDM method, one can evaluate and compare the different computing alternatives available to achieve a goal (Kumar et al., 2020; Kumar & Singh, 2020). Literature has numerous approaches to solving MCDM problems (Tzeng & Huang, 2011). In TOPSIS, a rank of units is defined by the difference in positive-ideal (PI) and negative-ideal (NI) distance. According to Garg and Kaur (2020), the extended TOPSIS method is also beneficial for assessing MCDM problems (Chodha et al., 2022). Therefore, the best alternative must be with the least and maximum distance from PI and N1 solutions, respectively (Kumar et al., 2022; Singh et al., 2022).

"Intuitionistic fuzzy set" is an extension of conventional fuzzy set theory, which was proposed in 1986. In the Fuzzy system, the entity's membership is determined by an individual value ranging from zero to one. Nevertheless, the "degree of non-membership of an item in a fuzzy set is one minus the degree of membership" is not assured. As a result, IFS is an outgrowth of a fuzzy set with a degree of hesitancy. Gangwar, Bali, and Kumar (2020) compared the performance of LSTM and SVM in wind speed predictions. The researchers proposed many different techniques presented in the literature by the researchers for COTS selection. Carney and Wallnau (1998) suggested basic principles applicable to evaluating COTS structure. A good programming model considering multiple criteria was presented by Badri, Davis, and Davis (2001); Wei, Chien, and Wang (2005) suggested a framework for ERP systems using an AHP-based approach. COTS evaluation is an MCDM problem (Shyur, 2006). The author proposed a hybrid model of the ANP (Analytic Network Process) system integrated with modified TOPSIS. A two-phased decision support technique for COTS selection was proposed by Neubauer and Stummer (2007). These techniques can further be implemented for problems like the weighting criteria entropy method as suggested by Parveen, Arora, and Alam (2020).

Cortellessa, Marinelli, and Potena (2008) presented an optimization technique for "build-or-buy decisions" in COTS picking. Every part can be acquired as off-the-shelf (COTS) or produced in-house by the company. This method is known as the "build-or-buy" principle, and it directly impacts the software cost and the platform's ability to achieve its specifications. Gupta et al. (2009) suggested a fuzzy multi-objective boost model for a modular software application for COTS selection. The notion of intra-modular coupling density (ICD) has been included by Kwong et al. (2010) in an optimal model for software application picking. Choosing and evaluating COTS software is done in an ad-hoc manner (Couts & Gerdes, 2010). A paradigm for enterprise's COTS software enhancement, assessment, and assessment methods was addressed (Tarawneh et al., 2011). The author highlighted a few of the observations which must be addressed:

1. Identifying the systems that enable the acquisition and assessment of COTS software.
2. Establish significant criteria for the screening process and practical evaluation.
3. Suggest solutions to the misalignment between COTS qualities and client expectations.
4. Create an archive from previous selection instances to arrange facts to aid in decision-making.

In constructing the "fault-tolerant modular software system", Bali et al. (2014) offered multiple computational equations for component selection. Furthermore, the researchers utilized the build-or-buy strategy to design multi-objective optimization algorithms for selecting components. Kushwaha, Panchal, and Sachdeva (2020) proposed a method with its application for examining the risk assessment of cutting system in sugar mill industry situated in western Uttar Pradesh province of India. Milovanović et al. (2021) proposed model that can be used in practice to solve not only the problem of supplier selection, but also similar problems where the decision is made based on inaccurate data. This model seeks to reduce indecision and subjectivity in decision making. Gergin, Peker, and Kısa (2021) study object to select the most suitable supplier for a company engage in activities in the automotive supply industry.

Most of the approaches discussed above seem to address complex problems related to COTS selection. Several existing models discussed in the literature for COTS selection are based on quantitative criteria. However, many essential criteria can be expressed in qualitative terms that are incomplete and vague. Thus, fuzzy set theory is used for choosing COTS software products (Biswas & Gupta, 2019; Gupta et al., 2019;

Gupta et al., 2009; Gupta et al., 2012). IFS is a further development of fuzzy set theory. It is appropriate to handle decision-making challenges under uncertainty. Aggregation of experts' opinions is an important task for group decision-making evaluation. TOPSIS is a prevalent method in the MCDM domain. Many authors have proposed hybrid techniques for COTS selection by integrating TOPSIS with AHP or ANP (Shyur, 2006; Upadhyay, Deshpande, & Agrawal, 2010). Bali, Bali, and Madan (2019) has formulated an optimization model known as IFSOM. It is a two-level technique for COTS assessment and selection. They have shown that to develop CBSS, two stages are required. The first stage is the assessment of the COTS vendors, and the second phase is the selection. Researchers have discussed many hybrid techniques for COTS selection, but IFS integrated with the TOPSIS method was not considered. Therefore, the novelty of this work is to propose a hybrid approach, "IFS combined with TOPSIS method", to assess and choose the best COTS vendor in the ecosystem of group decision making. The fuzzy TOPSIS along with other techniques can be implemented with COPRAS (Kumari & Mishra, 2020) for hybrid MCDM problems by Dhiman and Deb (2020).

3. Methodology

Intuitionistic Fuzzy Sets (IFS) gives the interconnectedness of the COTS selection technique. This is stated in (Atanasov, 1986; Atanassov, 1989, 1994). An IFS is a strategy for dealing with ambiguous situations that extends the traditional Fuzzy Sets (FS) developed by Zadeh in 1965 (Zadeh, 1965). "A fuzzy set entity's membership is a single number between "0" and then one," according to fuzzy sets. Nonetheless, the "degree of non-membership for an item in a fuzzy set is one minus the degree for membership" is not guaranteed, as there may be some hesitancy by Kumari, Mishra, and Sharma (2021). As a result, IFS, an expansion of FS that includes the degree of hesitation, is suggested. So, the method "intuitionistic fuzzy set" is quite remarkable and is applied in the various decision-making fields.

3.1 Preliminaries

Few explanations of fuzzy sets, linguistic variables, and IFS are reviewed by Zadeh (1965), Atanasov (1986) and Zadeh (1975).

Definition 1: (Zadeh, 1965): "Assume set Z is non-empty. A *fuzzy set X* drawn from Z is presented as

$$X = \{\langle z, \mu_X(z)\rangle : z \in Z\} \tag{1}$$

Where $\mu_X(z): Z \to [0,1]$ states membership function for 'fuzzy set' X. The function value of $\mu_X(z)$ is termed as the grade of membership of z $\in Z$ in X."

Definition 2: (Atanassov, 1989): "Assume set Z is a non-empty set. And an intuitionistic fuzzy set X in Z is given by

$$X = \{\langle z, \mu_X(x), \nu_X(z)\rangle : z \in Z\}, \tag{2}$$

Where $\mu_X(z): Z \to [0,1]$ and $\nu_X(z): Z \to [0,1]$ with the condition $0 \le \mu_A(x) + \nu_X(z) \le 1$ for all $z \in Z$. The numbers $\mu_X(z), \nu_X(z) \in [0,1]$ represent the degree of membership and non-membership of z to X, respectively."

Definition 3: (Atanassov, 1994): "The third parameter of IFS is $\pi_X(z)$, is known as 'intuitionistic fuzzy index' or 'hesitation degree', whether z belongs to X or not

$$\pi_X(z) = 1 - \mu_X(z) - \nu_X(z) \tag{3}$$

It is seen that for every $z \in Z$:

$$0 \leq \pi_X(z) \leq 1 \tag{4}$$

If the value of $\pi_X(z)$ is small, knowledge about Z is more definite. If $\pi_X(z)$ is large, knowledge about z is more indefinite."

Assume. Both J and K to be IFSs for set Z, then addition and multiplication operations are defined as below:

$$J \oplus K = \{\langle z, \mu_X(z) + \mu_K(z) - \mu_J(z)\mu_K(z), \nu_J(z)\nu_K(z)\rangle : z \in Z\} \tag{5}$$

$$J \otimes K = \{\langle z, \mu_J(z)\mu_K(z), \nu_J(z) + \nu_K(z) - \nu_J(z)\nu_K(z)\rangle : z \in Z\} \tag{6}$$

Definition 4: (Zadeh, 1975): "A variable is said to be linguistic if the values are represented with linguistic terms. Linguistic variables are useful in describing complex situations, and undefined by normal quantitative expressions".

In Tables 1 and Table 3, linguistic variables are presented as fuzzy numbers.

Table 1. Linguistics phrases for analyzing the importance of the technique and decision-making processes.

Linguistic terms	IFNs
Very Important (VI)	(0.90, 0.10)
Important (I)	(0.75, 0.20)
Medium (M)	(0.50, 0.45)
Unimportant (UI)	(0.35, 0.60)
Very Unimportant (VU)	(0.10, 0.90)

3.2 COTS Selection Process

The COTS selection process includes allowing different ratings to vendors depending upon the processing of decision-maker evaluation. Due to this, it becomes challenging for a decision-maker to give an accurate quality score for the criteria considered an alternative.

Let "$A = \{A_1, A_2, \ldots\ldots, A_m\}$ is a set of possible substitutes and $X = \{X_1, X_2, \ldots\ldots, X_n\}$ is criteria set".

Various steps for the Intuitionistic Fuzzy TOPSIS technique are given below (Boran et al., 2009):

Step 1: Allocating weights to the decision-makers.

Let there be "l be the experts or choice makers"; their influence is a linguistic variable expressed in 'intuitionistic fuzzy numbers.

Assume "$E_k=[\mu_k, \nu_k, \pi_k]$ is an intuitionistic fuzzy number to a rating of k^{th} expert". Then, the weight for k^{th}expert can be expressed as below (Boran et al., 2009; Rouyendegh, 2014):

$$\lambda_k = \frac{\left(\mu_k + \pi_k\left(\frac{\mu_k}{\mu_k+\nu_k}\right)\right)}{\sum_{k=1}^{l}\left(\mu_k + \pi_k\left(\frac{\mu_k}{\mu_k+\nu_k}\right)\right)} \tag{7}$$

$$\sum_{k=1}^{n}\lambda_k = 1$$

Step 2: Create an accumulated intuitionistic fuzzy decision matrix based on the expert's views.

Let "$R^{(k)} = (r_{ij}^{k})_{m\times n}$ is an intuitionistic fuzzy decision matrix of each expert". Then, a distributed, intuitionistic, fuzzy decision matrix combines all the expert views into a group view. The IFWA operant (Xu, 2007) is used to do this.

$R = (r_{ij})_{m\times n}$, Where

$$r_{ij} = IFWA_\lambda(r_{ij}^{(1)}, r_{ij}^{(2)}, \ldots.., r_{ij}^{(l)})$$

$$=\lambda_1 r_{ij}^{(1)} \oplus \lambda_2 r_{ij}^{(2)} \oplus \ldots.. \oplus \lambda_l r_{ij}^{(l)}$$

$$=\left[1-\prod_{k=1}^{l}\left(1-\mu_{ij}^{(k)}\right)^{\lambda_k}, \prod_{k=1}^{l}\left(\nu_{ij}^{(k)}\right)^{\lambda_k}, \prod_{k=1}^{l}\left(1-\mu_{ij}^{(k)}\right)^{\lambda_k} - \prod_{k=1}^{l}\left(\nu_{ij}^{(k)}\right)^{\lambda_k}\right] \tag{8}$$

where, $r_{ij} = (\mu_{Ai}(x_j), \nu_{Ai}(x_j), \pi_{Ai}(x_j)) \qquad (i = 1, 2, \ldots, m;\ j = 1, \ldots., n)$

The accumulated intuitionistic fuzzy decision matrix is represented as:

$$R = \begin{bmatrix} r_{11} & r_{12} & r_{13} & .. & r_{1n} \\ r_{21} & r_{22} & r_{23} & .. & r_{2n} \\ r_{31} & r_{32} & r_{33} & .. & r_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & r_{m3} & .. & r_{mn} \end{bmatrix} =$$

$$\begin{bmatrix} (\mu_{A1}(x_1), \nu_{A1}(x_1), \pi_{A1}(x_1)) & (\mu_{A1}(x_1), \nu_{A1}(x_1), \pi_{A1}(x_1)) & .. & (\mu_{A1}(x_1), \nu_{A1}(x_1), \pi_{A1}(x_1)) \\ (\mu_{A2}(x_1), \nu_{A2}(x_1), \pi_{A2}(x_1)) & (\mu_{A2}(x_1), \nu_{A2}(x_1), \pi_{A2}(x_1)) & .. & (\mu_{A2}(x_1), \nu_{A2}(x_1), \pi_{A2}(x_1)) \\ \vdots & \vdots & . & \vdots \\ (\mu_{Am}(x_1), \nu_{Am}(x_1), \pi_{Am}(x_1)) & (\mu_{Am}(x_1), \nu_{Am}(x_1), \pi_{Am}(x_1)) & .. & (\mu_{Am}(x_1), \nu_{Am}(x_1), \pi_{Am}(x_1)) \end{bmatrix}$$

Step 3: Determination of criteria weights

Let "$w_j^{(k)} = \left[\mu_j^{(k)}, \nu_j^{(k)}, \pi_j^{(k)}\right]$ is intuitionistic fuzzy number given by the k^{th} decision-maker to the criterion" X_j. By using the IFWA operator, the weights of the pattern are calculated as follows

$$w_j = IFWA_\lambda(w_j^{(1)}, w_j^{(2)}, \ldots\ldots, w_j^{(l)})$$
$$= \lambda_1 w_j^{(1)} \oplus \lambda_2 w_j^{(2)} \oplus \ldots\ldots \oplus \lambda_l w_j^{(l)}$$
$$= \left[1 - \prod_{k=1}^{l}\left(1-\mu_j^{(k)}\right)^{\lambda_k}, \prod_{k=1}^{l}\left(\nu_j^{(k)}\right)^{\lambda_k}, \prod_{k=1}^{l}\left(1-\mu_j^{(k)}\right)^{\lambda_k} - \prod_{k=1}^{l}\left(\nu_j^{(k)}\right)^{\lambda_k}\right] \quad (9)$$

$$W = \left[w_1, w_2, w_3, \ldots., w_j\right]$$

Where $w_j = (\mu_j, \nu_j, \pi_j);\ j = 1, 2, \ldots., n$

Step 4: Development of accumulated weighted intuitionistic fuzzy matrix of decisions.

Once the accumulated intuitionist fuzzy judgment and parameters weights are collected, the weighted intuitionist fuzzy decision matrix is developed using the expression given below (Atanassov, 1989):

$$R \otimes W = \left\{\left\langle x, \mu_{Ai}(x).\mu_w(x), \nu_{Ai}(x) + \nu_w(x) - \nu_{Ai}(x).\nu_w(x)\right\rangle / x \in X\right\} \quad (10)$$

$$\pi_{Ai}.w(x) = 1 - \nu_{Ai}(x) - \nu_w(x) - \mu_{Ai}(x).\mu_w(x) + \nu_{Ai}(x).\nu_w(x) \quad (11)$$

Therefore, the aggregated intuitionistic fuzzy decision matrix can be expressed as follows:

$$R' = \begin{bmatrix} r'_{11} & r'_{12} & r'_{13} & .. & r'_{1n} \\ r'_{21} & r'_{22} & r'_{23} & .. & r'_{2n} \\ r'_{31} & r'_{32} & r'_{33} & .. & r'_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ r'_{m1} & r'_{m2} & r'_{m3} & .. & r'_{mn} \end{bmatrix} =$$

$$\begin{bmatrix} \left(\mu_{A1W}(x_1), \nu_{A1W}(x_1), \pi_{A1W}(x_1)\right) & \left(\mu_{A1W}(x_1), \nu_{A1W}(x_1), \pi_{A1W}(x_1)\right) & .. & \left(\mu_{A1W}(x_1), \nu_{A1W}(x_1), \pi_{A1W}(x_1)\right) \\ \left(\mu_{A2W}(x_1), \nu_{A2W}(x_1), \pi_{A2W}(x_1)\right) & \left(\mu_{A2W}(x_1), \nu_{A2W}(x_1), \pi_{A2W}(x_1)\right) & .. & \left(\mu_{A2W}(x_1), \nu_{A2W}(x_1), \pi_{A2W}(x_1)\right) \\ \vdots & \vdots & . & \vdots \\ \left(\mu_{AmW}(x_1), \nu_{AmW}(x_1), \pi_{AmW}(x_1)\right) & \left(\mu_{AmW}(x_1), \nu_{AmW}(x_1), \pi_{AmW}(x_1)\right) & .. & \left(\mu_{AmW}(x_1), \nu_{AmW}(x_1), \pi_{AmW}(x_1)\right) \end{bmatrix}$$

were, $r'_{ij} = (\mu'_{Ai}(x_j), \nu'_{Ai}(x_j), \pi'_{Ai}(x_j)) = (\mu'_{AiW}(x_j), \nu'_{AiW}(x_j), \pi'_{AiW}(x_j))$
$(i = 1, 2, \ldots, m;\ j = 1, 2, \ldots, n)$

Step 5: Find our intuitionistic fuzzy negative most ideal solution (IFNIS) and intuitionistic fuzzy positive-ideal solution (IFPIS).

The evaluation criteria for the TOPSIS method can be divided into two classes, i.e., benefit and cost. Let G_1 is the benefit and G_2 is the cost criteria, respectively. A^+ is an IFPIS and A^- is an IFNIS, which are presented below:

$$A^+ = \left[\left\{\begin{matrix} x_j, \left\langle\left(\max_i \mu_{Ai.W}(x_j) / g \in G_1\right), \left(\min_i \mu_{Ai.W}(x_j) / g \in G_2\right)\right\rangle, \\ \left\langle\left(\min_i \nu_{Ai.W}(x_j) / g \in G_1\right), \left(\max_i \nu_{Ai.W}(x_j) / g \in G_2\right)\right\rangle \end{matrix}\right\} \middle|\, i = 1, 2, \ldots, m\right] \quad (12)$$

$$A^{-}=\left[\left\{\begin{matrix} x_j,\left\langle\left(\min_i \mu_{Ai.W}(x_j)/g\in G_1\right),\left(\max_i \mu_{Ai.W}(x_j)/g\in G_2\right)\right\rangle, \\ \left\langle\left(\max_i \nu_{Ai.W}(x_j)/g\in G_1\right),\left(\min_i \nu_{Ai.W}(x_j)/g\in G_2\right)\right\rangle \end{matrix}\right\}\mid i=1,2,\ldots,m\right] \quad (13)$$

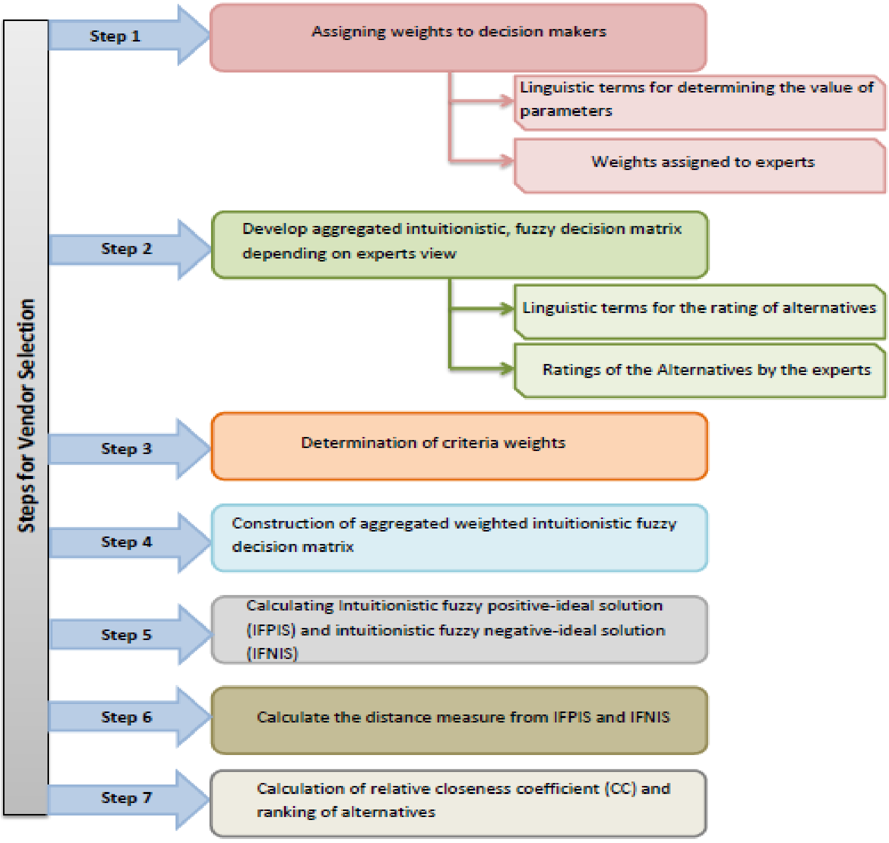

Figure 1. COTS Assortment Progression

Step 6: Calculate the distance measure from IFPIS and IFNIS

To measure the distance between IFPIS and IFNIS of each alternative, the intuitionistic separation measure utilizing normal Euclidean distance stated by (Szmidt & Kacprzyk, 2000) is presented as below:

$$S^{+}=\sqrt{\frac{1}{2n}\sum_{j=1}^{n}\left[\left(\mu_{Ai.W}(x_j)-\mu_{A^{+}.W}(x_j)\right)^2+\left(\nu_{Ai.W}(x_j)-\nu_{A^{+}.W}(x_j)\right)^2+\left(\pi_{Ai.W}(x_j)-\pi_{A^{+}.W}(x_j)\right)^2\right]} \quad (14)$$

$$S^{-}=\sqrt{\frac{1}{2n}\sum_{j=1}^{n}\left[\left(\mu_{Ai.W}(x_j)-\mu_{A^{-}.W}(x_j)\right)^2+\left(\nu_{Ai.W}(x_j)-\nu_{A^{-}.W}(x_j)\right)^2+\left(\pi_{Ai.W}(x_j)-\pi_{A^{-}.W}(x_j)\right)^2\right]} \quad (15)$$

Step 7: Calculation of relative closeness coefficient (CC_i) and ranking of alternatives here the relative coefficient of the closeness for every alternative possible for intuitionistic fuzzy ideal solutions is determined by the below-mentioned expression in Eq. (16).

$$CC_i = \frac{S_{i^-}}{S_{i^+} + S_{i^-}} \text{ where } 0 \le CC_i \le 1 \tag{16}$$

The alternative is closer to IFPIS as depicted by the bigger value of the corresponding closeness coefficient, and farther from IFNIS can be concluded. After determining each alternative's relative closeness coefficient (CCi), they are arranged according to the descending order. The most appropriate choice is the one with the most immense figure. The steps involved in the COTS selection process is given in Figure 1.

4. Case Study

Even during the strategy stage of the development process, evaluating and selecting COTS components based on functional and technical criteria is critical. To demonstrate the model suggested in this work, and the example of a medium-sized COTS-based software development company named XYZ was taken. The company has to develop customized software for a Business School.

The requirement elicitation Manager holds a series of meeting with the B-School stakeholders and gathers all the functional and non-functional requirements. After the requirement gathering phase, both parties prepared and mutually agreed upon an SRS. The Director, Manager, and the software development team decided to adopt a CBSS strategy for software development. Under this strategy, different components are assembled to form modules that form a complete software system. Depending upon the requirements gathered, the software to be developed goes through five modules.

These five modules were sufficient to fulfill all the requirements mentioned in the SRS. The different modules required for the B-school software were Finance, HR, Inventory, Exams, and Students. It was further decided that all the modules would be delivered to the client in one go. The company developed all the modules except the Exam module. The company did not develop the Exam Module due to a lack of time and technical ability. Therefore, the company purchased the COTS component for the Exam Module and had to select the appropriate software vendor.

An open tender with a due date was floated to various companies that wish to supply the exam module. The software development company holds an in-house meeting and decides that the Exam module software vendor will be finalized based on the seven criteria associated with the module. The seven criteria will be:

X_1 : Reliability

X_2 : Delivery Time

X_3 : Compatibility

X_4 : Vendor Support

X_5 : Functionality

X_6 : Price

X_7 : Maintenance Fee

Nine vendors submitted their quotations and participated in the bid for getting the contract for supplying the exam module. After a preliminary evaluation and a quick comparison of the nine competing vendors for the exam module, four vendors were chosen for final consideration. These four vendors were called alternatives and named an alternative (A1), alternative (A2), alternative (A3), and alternative A4. With this, the solution set of the vendor selection problem has been reduced from 09 to 04. These four vendors further participated in the evaluation process, and only one was selected. The complete process of the vendor selection is given in the subsequent section.

Steps for Software Vendor Selection

Step 1: Allocate weights to decision-makers. Table 1 offers the linguistic terms for determining the value of parameters and decision-makers. Then, using Eq. (7), the weights assigned to experts are obtained. Finally, the expert's importance and weights are given in Table 2.

Table 2. Decision maker's importance and their weights

	Expert 1	Expert 2	Expert 3
Linguistic Terms	Important	Medium	Very Important
Weight	0.356	0.238	0.406

Step 2: Develop accumulated intuitionistic, fuzzy decision matrix depending on experts' views. Table 3 represents linguistic terms to rate various alternatives.

Table 3. Linguistic terms to rate various alternatives.

Linguistic Terms	IFNs
Extremely Good (EG)/ Extremely High (EH)	(1.00, 0.00)
Very Very good (VVG)/ Very Very High (VVH)	(0.90, 0.10)
Very Good (VG)/ Very High (VH)	(0.80, 0.10)
Good (G)/ High (H)	(0.70, 0.20)
Medium Good (MG)/ Medium High (MH)	(0.60, 0.30)
Fair (F)/ Medium (M)	(0.50, 0.40)
Medium Bad (MB)/ Medium Low (ML)	(0.40, 0.50)
Bad (B)/ Low (L)	(0.25, 0.60)
Very Bad (VB)/ Very Low (VL)	(0.10, 0.75)
Very Very Bad (VVB)/ Very Very Low (VVL)	(0.10, 0.90)

Using Table 3, the alternative software vendor is assigned the ratings concerning each criterion by three experts shown in Table 4.

Table 4. Ratings of the alternatives

Criteria	Suppliers	Decision Makers			Criteria	Suppliers	Decision Makers		
		DM1	DM2	DM3			DM1	DM2	DM3
X1	A1	VG	G	G	X5	A1	F	G	MG
Reliability	A2	VG	G	VG	Functionality	A2	G	VG	G
	A3	G	G	VG		A3	G	G	G
	A4	G	VG	VG		A4	VG	VG	VVG
X2	A1	G	MG	F	X6	A1	MH	M	MH
Delivery Time	A2	MG	MG	MG	Price	A2	H	H	MH
	A3	MG	F	F		A3	MH	MH	H
	A4	VG	G	VG		A4	VH	VH	VH
X3	A1	F	G	MG	X7	A1	H	M	MH
Compatibility	A2	G	VG	G	Maintenance fee	A2	H	MH	H
	A3	G	G	MG		A3	MH	MH	H
	A4	VG	VVG	VVG		A4	H	H	VH
X4	A1	G	MG	F					
Vendor Support	A2	MG	G	MG					
	A3	MG	F	F					
	A4	VG	G	VG					

As shown below, the accumulated intuitionistic fuzzy decision matrix is built using Eq. (8).

$$
\begin{array}{cccccccc}
 & X_1 & X_2 & X_3 & X_4 & X_5 & X_6 & X_7 \\
R = & \multicolumn{7}{l}{\left[\begin{array}{ccccccc}
(0.740,0.156,0.104) & (0.605,0.292,0.103) & (0.596,0.302,0.102) & (0.605,0.292,0.103) & (0.596,0.302,0.102) & (0.578,0.321,0.101) & (0.619,0.278,0.103) \\
(0.780,0.118,0.102) & (0.600,0.300,0.100) & (0.728,0.170,0.102) & (0.626,0.272,0.102) & (0.728,0.170,0.102) & (0.663,0.236,0.101) & (0.679,0.220,0.101) \\
(0.746,0.151,0.103) & (0.538,0.361,0.101) & (0.663,0.236,0.101) & (0.538,0.361,0.101) & (0.700,0.200,0.100) & (0.644,0.254,0.102) & (0.644,0.254,0.102) \\
(0.769,0.128,0.103) & (0.780,0.118,0.102) & (0.872,0.100,0.028) & (0.780,0.118,0.102) & (0.849,0.100,0.051) & (0.800,0.100,0.100) & (0.746,0.151,0.103)
\end{array}\right]}
\end{array}
$$

Step 3: Determination of criteria weights Table 5 shows the relevance of the linguistic terms represented by the criteria.

Table 5. The relevance of weight of the criteria

Criteria	Notations	DM1	DM2	DM3
Reliability	X_1	VI	VI	VI
Delivery Time	X_2	I	I	I
Compatibility	X_3	VI	I	VI
Vendor support	X_4	M	I	M
Functionality	X_5	VI	M	I
Price	X_6	M	I	M
Maintenance fee	X_7	M	I	M

To find out the weight of every criterion, the opinion of the experts on criteria were aggregated using Eq. (9).

$$
W_{\{X_1,X_2,X_3,X_4,X_5,X_6,X_7\}} = \begin{bmatrix} (0.900,0.100,0.000) \\ (0.750,0.200,0.050) \\ (0.876,0.118,0.006) \\ (0.576,0.371,0.053) \\ (0.787,0.189,0.023) \\ (0.576,0.371,0.053) \\ (0.576,0.371,0.053) \end{bmatrix}^T
$$

Step 4: Development of aggregated weighted intuitionistic fuzzy decision matrix

After parameter weights and alternatives ratings are calculated, the aggregated weighted intuitionistic fuzzy decision matrix is built using Eq. (10) in the following manner.

$$
\begin{array}{cccccccc}
 & X_1 & X_2 & X_3 & X_4 & X_5 & X_6 & X_7 \\
R' = & \multicolumn{7}{l}{\left[\begin{array}{ccccccc}
(0.666,0.240,0.094) & (0.454,0.434,0.113) & (0.522,0.384,0.094) & (0.348,0.555,0.097) & (0.469,0.434,0.097) & (0.333,0.573,0.094) & (0.356,0.546,0.098) \\
(0.702,0.206,0.092) & (0.450,0.440,0.110) & (0.637,0.268,0.095) & (0.361,0.542,0.097) & (0.573,0.327,0.100) & (0.382,0.520,0.098) & (0.391,0.510,0.099) \\
(0.671,0.236,0.093) & (0.404,0.489,0.107) & (0.581,0.326,0.093) & (0.310,0.598,0.092) & (0.551,0.352,0.097) & (0.371,0.531,0.098) & (0.371,0.531,0.098) \\
(0.692,0.215,0.093) & (0.585,0.294,0.121) & (0.764,0.206,0.030) & (0.449,0.445,0.106) & (0.668,0.270,0.062) & (0.461,0.434,0.105) & (0.430,0.466,0.104)
\end{array}\right]}
\end{array}
$$

Step 5: Get IFPIS and IFNIS.

Reliability, delivery time, compatibility, vendor support, and functionality are benefit criteria $G_1 = \{X_1, X_2, X_3, X_4, X_5\}$, whereas price and maintenance fee be the cost criteria $G_2 = \{X_6, X_7\}$. Then, intuitionistic fuzzy positive-ideal solution and intuitionistic fuzzy negative ideal solution are obtained as follows.

$$
A^+ = \left\{ \begin{array}{l} (0.702,0.206,0.092),(0.585,0.294,0.121),(0.764,0.206,0.030),(0.449,0.445,0.106), \\ (0.668,0.270,0.062),(0.333,0.573,0.094),(0.356,0.546,0.098) \end{array} \right\}
$$

$$
A^- = \left\{ \begin{array}{l} (0.666,0.240,0.094),(0.404,0.489,0.107),(0.522,0.384,0.094),(0.310,0.598,0.092), \\ (0.469,0.434,0.097),(0.461,0.434,0.105),(0.430,0.466,0.104) \end{array} \right\}
$$

Step 6: Calculate the distance measure from IFPIS and IFNIS

The intuitionistic separation measured using normal Euclidean distance along with results is shown in Figure 2.

Step 7: Calculation of relative closeness coefficient (CC_i) and ranking of alternatives.

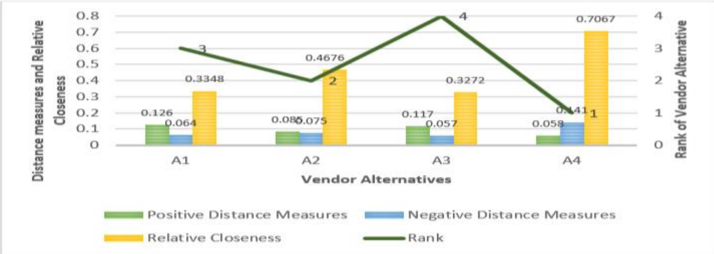

Figure 2. Distance measures, relative closeness coefficient, and rank of the alternatives

In the last step, the relative closeness coefficient for each possible alternative in the context of intuitionistic fuzzy ideal solutions is calculated using Eq. (16). Then the four alternatives were ranked in decreasing order of CC_i. For example, the higher value of 0.7067 of relative closeness of alternative vendor A4 assigned its first rank, followed by alternative vendor A2 with 0.3348. So, the vendor alternatives are ranked as A 4 > A 2 > A 1 > A 3; refer to Figure 2.

Sensitivity Analysis

For the comparison of the rankings obtained by the proposed methodology, sensitivity analysis is applied to investigate the relative closeness coefficient and the rank of alternatives (Kumar & Channi, 2022; Kumar et al., 2021). The sensitivity analysis allows the researchers to check whether any likely bias from a specific expert has significantly affected the results obtained (Vaid et al., 2022). It also helps to check the robustness and generalizability of the results obtained (Biswas & Gupta, 2019). For checking the robustness, we are testing the results by assigning different importance to the experts. First, Expert 1 was chosen; the linguistic importance (refer to Table 1) to this expert kept changing in every run of the sensitivity analysis while the weights assigned to the other two experts remained the same. The same procedure is followed with experts 2 and 3, as shown in Table 6. Table 7 presents a ranking of COTS vendors for the twelve-sensitivity analysis runs. We observe that the ranking remains the same for the 10 runs out of a total of twelve.

Table 6. The linguistic importance assigned to the experts during sensitivity analysis

	Expert 1	Expert 2	Expert 3
Original Solution	I	M	VI
Run 1	VI	M	VI
Run 2	M	M	VI
Run 3	UI	M	VI
Run 4	VU	M	VI
Run 5	I	I	VI
Run 6	I	VI	VI
Run 7	I	UI	VI
Run 8	I	VU	VI
Run 9	I	M	I
Run 10	I	M	M
Run 11	I	M	UI
Run 12	I	M	VU

Table 7. Ranking of COTS vendors for the twelve-sensitivity analysis runs

Vendors	OR	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12
A1	3	3	3	3	3	3	3	4	4	3	3	3	3
A2	2	2	2	2	2	2	2	2	2	2	2	2	2
A3	4	4	4	4	4	4	4	3	3	4	4	4	4
A4	1	1	1	1	1	1	1	1	1	1	1	1	1

**OR = Original Run; R_i = i^{th} Run*

It can be observed from Table 7 that the rankings of only two vendors, namely A1 and A3, in runs 7 and 8 are different in comparison to all the other sensitivity analysis runs. However, the top two ranks remain the same in all the 12 runs. Hence, we can say that there is no deviation from the results obtained in the original run and all the 12 runs. The top vendor in terms of ranking is A4 in all the twelve-sensitivity analysis runs performed.

5. Conclusion

This paper presents a solution to the MCDM for assessing and selecting COTS vendors by employing an intuitionistic fuzzy-TOPSIS approach. The paper begins with the introduction section laying the foundations with the terms and the concepts used in the work. Next, the review of the literature section summarizes the work done by other authors in the area of COTS, component-based software systems, and IFS. Finally, the methodology section presents and discusses the IFS-TOPSIS technique used in this paper. The work presented in the paper has got significant implications. It can be used as a guide to the software professionals developing component-based software systems. The formulated model gives an insight into the different criteria on which the CBSS is developed. The trade-off between different criteria can be visualized from the presented work.

In supporting their work, the authors have presented a case study in which four software vendors were chosen for evaluation based on seven different criteria. The ratings assigned to each alternative concerning each criterion, during the evaluation process, together with the weights of every criterion, the linguistic terms denoted by intuitionist fuzzy numbers were defined. The COTS vendor selection was made with the help of TOPSIS, and the alternatives were ranked as A 4 > A 2 > A 1 > A 3. Intuitionist fuzzy sets are best to address vagueness and ambiguity when considering various alternatives. Therefore, the TOPSIS approach integrated with IFS has a massive prospect of success in multiple-criteria decision-making scenarios. Further, this work can be extended by integrating IFS TOPSIS with the optimization model by making it a two-phase process. Hence, this would make the COTS selection process more robust. As written, the intuitionistic fuzzy TOPSIS method can also be used for the green supply selection problem (Rouyendegh, 2014; Rouyendegh, Yildizbasi, & Üstünyer, 2020). Sensitivity analysis was also performed to check possible bias, which could occur because of a particular expert, which may influence the reported findings.

Therefore, this work can be expanded by combining an optimization model with an objective function ranking and quantitative parameters as a set of constraints. The model would aim to maximize rankings obtained using the Fuzzy TOPSIS method. Hence, the new technique can be called a hybrid approach as it involves two phases – Fuzzy TOPSIS and optimization model for COTS selection. This work can further be extended by incorporating the build or buy strategy. The build or buy strategy makes the optimization models more robust and provides a competitive edge, especially in mission-critical systems.

References

Adam, G. K., Petrellis, N., Kontaxis, P. A., & Stylianos, T. (2020). COTS-Based Real-Time System Development: An Effective Application in Pump Motor Control. Computers, 9(4), 97. https://doi.org/10.3390/computers9040097

Atanasov, K. T. (1986). Intuitionistic fuzzy sets. Fuzzy sets and systems, 20(1), 87-96. https://doi.org/10.1016/S0165-0114(86)80034-3

Atanassov, K. T. (1989). More on intuitionistic fuzzy sets. Fuzzy sets and systems, 33(1), 37-45. https://doi.org/10.1016/0165-0114(89)90215-7

Atanassov, K. T. (1994). New operations defined over the intuitionistic fuzzy sets. Fuzzy sets and systems, 61(2), 137-142. https://doi.org/10.1016/0165-0114(94)90229-1

Badampudi, D., Wohlin, C., & Petersen, K. (2016). Software component decision-making: In-house, OSS, COTS or outsourcing-A systematic literature review. Journal of Systems and Software, 121, 105-124. https://doi.org/10.1016/j.jss.2016.07.027

Badri, M. A., Davis, D., & Davis, D. (2001). A comprehensive 0–1 goal programming model for project selection. International Journal of Project Management, 19(4), 243-252. https://doi.org/10.1016/S0263-7863(99)00078-2

Bali, S., Jha, P., Kumar, U. D., & Pham, H. (2014). Fuzzy multi-objective build-or-buy approach for component selection of fault tolerant software system under consensus recovery block scheme with mandatory redundancy in critical modules. International Journal of Artificial Intelligence and Soft Computing, 4(2-3), 98-119. https://doi.org/10.1504/IJAISC.2014.062815

Bali, V., Bali, S., & Madan, S. (2019). IFSOM: A Two-Phase Framework for COTS Evaluation and Selection. In Proceedings of 2nd International Conference on Communication, Computing and Networking (pp. 871-888). Springer. https://doi.org/10.1007/978-981-13-1217-5_86

Bali, V., & Madan, S. (2015). COTS Evaluation & Selection Process in Design of Component based Software System: An Overview and Future Direction. Global Journal of Computer Science and Technology, 15(6), 1-8. https://globaljournals.org/GJCST_Volume15/1-COTS-Evaluation.pdf

Biswas, B., & Gupta, R. (2019). Analysis of barriers to implement blockchain in industry and service sectors. Computers & Industrial Engineering, 136, 225-241. https://doi.org/10.1016/j.cie.2019.07.005

Boran, F. E., Genç, S., Kurt, M., & Akay, D. (2009). A multi-criteria intuitionistic fuzzy group decision making for supplier selection with TOPSIS method. Expert systems with applications, 36(8), 11363-11368. https://doi.org/10.1016/j.eswa.2009.03.039

Carney, D. J., & Wallnau, K. C. (1998). A basis for evaluation of commercial software. Information and Software Technology, 40(14), 851-860. https://doi.org/10.1016/S0950-5849(98)00099-8

Chodha, V., Dubey, R., Kumar, R., Singh, S., & Kaur, S. (2022). Selection of industrial arc welding robot with TOPSIS and Entropy MCDM techniques. Materials Today: Proceedings, 50, 709-715. https://doi.org/10.1016/j.matpr.2021.04.487

Cortellessa, V., Marinelli, F., & Potena, P. (2008). An optimization framework for "build-or-buy" decisions in software architecture. Computers & Operations Research, 35(10), 3090-3106. https://doi.org/10.1016/j.cor.2007.01.011

Couts, C. T., & Gerdes, P. F. (2010). Integrating COTS software: lessons from a large

healthcare organization. IT Professional, 12(2), 50-58. https://doi.org/10.1109/MITP.2010.59
Dhiman, H. S., & Deb, D. (2020). Fuzzy TOPSIS and fuzzy COPRAS based multi-criteria decision making for hybrid wind farms. Energy, 202, 117755. https://doi.org/10.1016/j.energy.2020.117755
Gangwar, S., Bali, V., & Kumar, A. (2020). Comparative analysis of wind speed forecasting using LSTM and SVM. EAI Endorsed Transactions on Scalable Information Systems, 7(25), e1. https://doi.org/10.4108/eai.13-7-2018.159407
Garg, H., & Kaur, G. (2020). Extended TOPSIS method for multi-criteria group decision-making problems under cubic intuitionistic fuzzy environment. Scientia iranica, 27(1), 396-410. https://doi.org/10.24200/sci.2018.5307.1194
Garg, R. (2020). A ranking model for the selection and ranking of commercial off-the-shelf components. IEEE Transactions on Engineering Management, 69(5), 2196-2204. https://doi.org/10.1109/TEM.2020.3001943
Gergin, R. E., Peker, İ., & Kısa, A. C. G. (2021). Supplier selection by integrated IFDEMATEL-IFTOPSIS Method: A case study of automotive supply industry. Decision Making: Applications in Management and Engineering, 5(1), 169-193. https://doi.org/10.31181/dmame211221075g
Goguen, J. A. (1973). LA Zadeh. Fuzzy sets. Information and control, vol. 8 (1965), pp. 338–353.-LA Zadeh. Similarity relations and fuzzy orderings. Information sciences, vol. 3 (1971), pp. 177–200. The Journal of Symbolic Logic, 38(4), 656-657.
Gupta, P., Mehlawat, M. K., & Mahajan, D. (2019). Multi-objective optimization framework for software maintenance, component evaluation and selection involving outsourcing, redundancy and customer to customer relationship. Information Sciences, 483, 21-52. https://doi.org/10.1016/j.ins.2019.01.017
Gupta, P., Mehlawat, M. K., Mittal, G., & Verma, S. (2009). A hybrid approach for selecting optimal COTS products. In International Conference on Computational Science and its Applications (pp. 949-962). Springer. https://doi.org/10.1007/978-3-642-02454-2_74
Gupta, P., Mehlawat, M. K., & Verma, S. (2012). COTS selection using fuzzy interactive approach. Optimization Letters, 6(2), 273-289. https://doi.org/10.1007/s11590-010-0243-5
Jha, P. C., & Bali, S. (2012). Optimal COTS selection for fault tolerant software system with mandatory redundancy in critical modules using consensus recovery block scheme under fuzzy environment. In 2012 International Conference on Recent Advances in Computing and Software Systems (pp. 273-280). IEEE. https://doi.org/10.1109/RACSS.2012.6212680
Kumar, R., Bhattacherjee, A., Singh, A. D., Singh, S., & Pruncu, C. I. (2020). Selection of portable hard disk drive based upon weighted aggregated sum product assessment method: A case of Indian market. Measurement and Control (United Kingdom), 53(7-8), 1218-1230. https://doi.org/10.1177/0020294020925841
Kumar, R., & Channi, H. K. (2022). A PV-Biomass off-grid hybrid renewable energy system (HRES) for rural electrification: Design, optimization and techno-economic-environmental analysis. Journal of Cleaner Production, 349, 131347. https://doi.org/10.1016/j.jclepro.2022.131347
Kumar, R., Dubey, R., Singh, S., Singh, S., Prakash, C., Nirsanametla, Y., Królczyk, G., & Chudy, R. (2021). Multiple-criteria decision-making and sensitivity analysis for selection of materials for knee implant femoral component. Materials, 14(8), 2084. https://doi.org/10.3390/ma14082084
Kumar, R., & Singh, S. (2020). Selection of vacuum cleaner with Technique for Order Preference by Similarity to Ideal Solution method based upon multi-criteriadecision-

making theory. Measurement and Control (United Kingdom), 53(3-4), 627-634. https://doi.org/10.1177/0020294019877524

Kumar, R., Singh, S., Aggarwal, V., Singh, S., Pimenov, D. Y., Giasin, K., & Nadolny, K. (2022). Hand and Abrasive Flow Polished Tungsten Carbide Die: Optimization of Surface Roughness, Polishing Time and Comparative Analysis in Wire Drawing. Materials, 15(4), 1287. https://doi.org/10.3390/ma15041287

Kumari, R., & Mishra, A. R. (2020). Multi-criteria COPRAS method based on parametric measures for intuitionistic fuzzy sets: application of green supplier selection. Iranian journal of science and technology, Transactions of Electrical Engineering, 44(4), 1645-1662. https://doi.org/10.1007/s40998-020-00312-w

Kumari, R., Mishra, A. R., & Sharma, D. K. (2021). Intuitionistic fuzzy Shapley-TOPSIS method for multi-criteria decision making problems based on information measures. Recent Advances in Computer Science and Communications (Formerly: Recent Patents on Computer Science), 14(2), 376-383. https://doi.org/10.2174/2213275912666190115162832

Kushwaha, D. K., Panchal, D., & Sachdeva, A. (2020). Risk analysis of cutting system under intuitionistic fuzzy environment. Reports in Mechanical Engineering, 1(1), 162-173. https://doi.org/10.31181/rme200101162k

Kwong, C. K., Mu, L.-F., Tang, J. F., & Luo, X. G. (2010). Optimization of software components selection for component-based software system development. Computers & Industrial Engineering, 58(4), 618-624. https://doi.org/10.1016/j.cie.2010.01.003

Mehlawat, M. K., Gupta, P., & Mahajan, D. (2020). A multi-period multi-objective optimization framework for software enhancement and component evaluation, selection and integration. Information Sciences, 523, 91-110. https://doi.org/10.1016/j.ins.2020.02.076

Milovanović, V. R., Aleksić, A. V., Sokolović, V. S., & Milenkov, M. A. (2021). Uncertainty modeling using intuitionistic fuzzy numbers. Vojnotehnički glasnik/Military Technical Courier, 69(4), 905-929. https://doi.org/10.5937/vojtehg69-33301

Neubauer, T., & Stummer, C. (2007). Interactive decision support for multiobjective COTS selection. In 2007 40th Annual Hawaii International Conference on System Sciences (HICSS'07) (pp. 283b). IEEE. https://doi.org/10.1109/HICSS.2007.283

Parveen, T., Arora, H., & Alam, M. (2020). Intuitionistic Fuzzy Hybrid Multi-criteria Decision-Making Approach with TOPSIS Method Using Entropy Measure for Weighting Criteria. In Strategic System Assurance and Business Analytics (pp. 351-364). Springer. https://doi.org/10.1007/978-981-15-3647-2_26

Rouyendegh, B. D. (2014). Developing an integrated AHP and intuitionistic fuzzy TOPSIS methodology. Technical Gazette, 21(6), 1313-1319. https://hrcak.srce.hr/131324

Rouyendegh, B. D., Yildizbasi, A., & Üstünyer, P. (2020). Intuitionistic fuzzy TOPSIS method for green supplier selection problem. Soft Computing, 24(3), 2215-2228. https://doi.org/10.1007/s00500-019-04054-8

Shyur, H.-J. (2006). COTS evaluation using modified TOPSIS and ANP. Applied mathematics and computation, 177(1), 251-259. https://doi.org/10.1016/j.amc.2005.11.006

Sidhu, A. S., Singh, S., Kumar, R., Pimenov, D. Y., & Giasin, K. (2021). Prioritizing energy-intensive machining operations and gauging the influence of electric parameters: An industrial case study. Energies, 14(16), 4761. https://doi.org/10.3390/en14164761

Singh, S., Kumar, R., Kumar, R., Chohan, J. S., Ranjan, N., & Kumar, R. (2022). Aluminum metal composites primed by fused deposition modeling-assisted investment casting:

Hardness, surface, wear, and dimensional properties. Proceedings of the Institution of Mechanical Engineers, Part L: Journal of Materials: Design and Applications, 236(3), 674-691. https://doi.org/10.1177/14644207211054143
Szmidt, E., & Kacprzyk, J. (2000). Distances between intuitionistic fuzzy sets. Fuzzy sets and systems, 114(3), 505-518. https://doi.org/10.1016/S0165-0114(98)00244-9
Tailor, A. R., & Dhodiya, J. M. (2020). GA-Based Hybrid Approach to Solve Fuzzy Multi-objective Optimization Model of Multi-application-Based COTS Selection Problem. In Advanced Engineering Optimization Through Intelligent Techniques (pp. 75-86). Springer. https://doi.org/10.1007/978-981-13-8196-6_8
Tarawneh, F., Baharom, F., Yahaya, J. H., & Ahmad, F. (2011). Evaluation and selection COTS software process: The state of the art. International Journal on New Computer Architecture and Their Application (IJNCAA), 1(2), 344-357. https://oaji.net/articles/2015/544-1430918871.pdf
Tzeng, G.-H., & Huang, J.-J. (2011). Multiple attribute decision making: methods and applications. CRC Press. https://doi.org/10.1201/b11032
Upadhyay, N., Deshpande, B. M., & Agrawal, V. P. (2010). Integrated decision approach for COTS selection. International Journal of Decision Sciences, Risk and Management, 2(3-4), 165-177. https://doi.org/10.1504/IJDSRM.2010.037481
Vaid, S. K., Vaid, G., Kaur, S., Kumar, R., & Sidhu, M. S. (2022). Application of multi-criteria decision-making theory with VIKOR-WASPAS-Entropy methods: A case study of silent Genset. Materials Today: Proceedings, 50, 2416-2423. https://doi.org/10.1016/j.matpr.2021.10.259
Wei, C.-C., Chien, C.-F., & Wang, M.-J. J. (2005). An AHP-based approach to ERP system selection. International journal of production economics, 96(1), 47-62. https://doi.org/10.1016/j.ijpe.2004.03.004
Xu, Z. (2007). Intuitionistic fuzzy aggregation operators. IEEE Transactions on fuzzy systems, 15(6), 1179-1187. https://doi.org/10.1109/TFUZZ.2006.890678
Zadeh, L. A. (1965). Fuzzy sets. Information and Control, 8(3), 338-353. https://doi.org/10.1016/S0019-9958(65)90241-X
Zadeh, L. A. (1975). The concept of a linguistic variable and its application to approximate reasoning-III. Information Sciences, 9(1), 43-80. https://doi.org/10.1016/0020-0255(75)90017-1