Multicriteria Algorithms with Applications

Journal Homepage: sciencesforce.com/mawa

Multicriteria Algo. Appl. Vol. 4 (2024) 1–15

Paper Type: Original Article

A Hybrid Triangular Fuzzy SWARA-MAROCS Approach for Selecting Optimal and Smart Logistic Enterprise Based on IoT, Blockchain, and UAVs

Mai Mohamed [1,*], Amira Salam [1], Jun Ye [2], and Rui Yong [2]

[1] Faculty of Computers and Informatics, Zagazig University, Zagazig 44519, Sharqiyah, Egypt; Emails: mmgaafar@zu.edu.eg; sallam18@fci.zu.edu.eg.

[2] School of Civil and Environmental Engineering, Ningbo University, Ningbo, Zhejiang, China. Emails: yejun1@nbu.edu.cn; yongrui@nbu.edu.cn.

Received: 11 Dec 2023 **Revised**: 25 Mar 2024 **Accepted**: 27 Apr 2024 **Published**: 29 Apr 2024

Abstract

With the development of technology and the Internet of Things (IoT), the use of electronic commerce has become necessary. There are many logistical enterprises now use the IoT to support their delivery process via drones, due to the numerous advantages they offer over traditional methods. However they face some restrictions and security concerns, so blockchain technology was used to overcome these restrictions and follow up on the delivery process to meet the requirements of e-commerce. In light of this, choosing the most suitable logistics enterprises to meet the needs of customers in a given situation has become a challenging task for decision-makers. To facilitate this task, we have introduced a systematic approach that uses triangular fuzzy step-wise weight assessment ratio analysis (SWARA) and triangular fuzzy measurement of alternatives and ranking according to compromise solution (MAROCS) methods to evaluate and rank alternatives. Fuzzy SWARA is used to determine the weights of evaluative criteria, while Fuzzy MARCOS is used to rank alternatives and select the best of them. This method eliminates ambiguity and imprecision in the decision-making process.

Keywords: UAV, MCDM, IoT, Logistic, Blockchain, Fuzzy SWARA, Fuzzy MARCOS.

1 | Introduction

Recently, the number of users of e-commerce has increased greatly due to its benefits for both companies and consumers, which has contributed to the growth of productivity and improved efficiency of business operations [1, 2]. However, as the use of e-commerce has increased, it has become more complex than a traditional business. Therefore, managing the flow of goods, information, and resources from the production area to the consumption area has become crucial to improving the quality of commercial services. This process is called logistical services, and it is impossible to carry out any trade or process of transporting and manufacturing products without professional logistical support. Logistics include collecting information, transportation, inventory, storage, etc. [3-5]. Therefore, any enterprise needs to optimize these services to reduce cost and time. As a result of rapid change and advances in technology, it must be used technology and

Corresponding Author: mmgaafar@zu.edu.eg

https://doi.org/10.61356/j.mawa.2024.4241

their advantage to improve logistics. Thus, the organization can optimize its logistics efforts in several ways such as by using IoT.

E-commerce is strongly linked to the concept of the Internet of Things (IoT) [6, 7], as the Internet of Things is the connection of any device that has an on-off switch to the Internet and/or to each other, and it is considered a giant network of connected "things" (which also includes people), which forms the relationship between people and people, people and things, things and things which, IoT has the power to change the way we live our lives. In the near future, the technologies of (IoT, blockchain, and UAVs) can be used to optimize logistics. With the use of these technologies, an organization's logistics operations will be able to operate more efficiently, which will result in faster and better customer service.

Drones, which are considered an image of the Internet of Things, have been used for improving logistical services for e-commerce, whereas, drones have been used in air transport because of their advantages such as high payload, flexibility, environment friendly, cost-effective, etc. [8]. The drone delivery system is believed to have less environmental impact and is more efficient compared to traditional ground vehicle delivery methods. Moreover, taking into account the limitations of payload and fuel, the drone delivery system is considered to be the most suitable and effective option [9, 10]. Drone delivery has been utilized to deliver various parcels and offer logistical support to the military in war zones, as delivery by drone has overcome the problems of traditional military delivery methods [11]. Drones have proven effective in responding to natural disasters and providing humanitarian aid through logistics services, post-disaster product delivery, damage assessment, and monitoring [12]. The author proposed a model to ensure a reliable supply logistics distribution system by displaying the driving paths of vehicles and UAVs. Moreover, the UAV-vehicle cooperation is aimed at achieving energy conservation and pollution reduction targets, while saving operational expenses as compared to traditional logistics delivery [13].

When using drones for logistics transportation, certain limitations and security concerns have emerged. These limitations include disputes arising between the sender and the recipient due to issues such as lost packages, wrong delivery, denial, and others. To effectively resolve these problems, blockchain technology has been implemented. This technology ensures that packages are delivered correctly and safely, clarifies responsibility between the sender and the recipient, and tracks the entire delivery process to meet the requirements of e-commerce.

Blockchain is a technology that can record information and perform data operations with minimal human intervention. Where a block is a collection of all the transaction data that occurs during a specific time frame and once the sender and recipient agree on the outcome, the transaction records are finalized without any changes being made. It is designed in such a way that it is difficult to tamper with, hack, or manipulate the system. It has been applied to meet the requirements of electronic commerce, such as identity authentication, non-rejection of package delivery, or denial and control transactions between sender and recipient. The biggest advancement in the field of human credit is the marriage of economic management and information security technologies [14-17].

With the advancement of technology and the increased usage of the IoT, there are now numerous logistical enterprises that support delivery by drone. Each enterprise has its standards that distinguish it from the others. Hence, choosing the most suitable enterprise that meets the customer's needs has become a challenging and confusing task. Therefore, a systematic method must be adopted to facilitate the selection process. This research addresses the selection of logistics enterprises that support delivery by drone as a multi-criteria decision-making (MCDM) problem.

When faced with a set of choices, decision-makers can use MCDM technology to evaluate and prioritize each option based on various criteria or objectives. The MCDM helps to select the best option by taking into account multiple aspects. The author has proven the importance of using MCDM methods in decision-making for choosing machinery for use in ports, warehouses, city logistics, and intermodal transportation, by analyzing the scientific research used for MCDM methods, which includes: SWARA, ARAS, and MABAC [18]. The author employed MCDM techniques to evaluate road freight transport companies based on their assets. A combination of methods, including AHP for driver weighting, TOPSIS, COPRAS, SAW, PROMETHEE, and EDAS, were used to select the best alternative [19].

According to previous studies, using MCDM technology can help decision-makers make better-informed decisions. Therefore, our research aims to introduce a new model of MCDM in a fuzzy environment. This model will help decision-makers choose the most suitable logistical enterprises for drone delivery.

Our contribution: we presented two methods for MCDM in a fuzzy environment to evaluate and select the best logistic enterprise for the delivery process using drones. The first method is triangular fuzzy SWARA, which determines the weight of evaluation criteria for logistic enterprises in a fuzzy environment. It converts linguistic opinions into triangular fuzzy numbers during the assessment process. Triangular fuzzy SWARA is easy for experts to understand and apply, and it requires less computational time. The second method is triangular fuzzy MARCOS, which ranks the alternatives and selects the best one, based on the connection established between reference values and alternatives (ideal and anti-ideal alternatives).

The remaining parts of our research are provided below for processing purposes. In section 2, a proposed methodology in a fuzzy environment is described. In section 3, a case study for selecting the best logistic enterprise for the delivery process using drones is solved to demonstrate the method's applicability. In section 4, the managerial implications are presented. This research's conclusions and recommendations for the future are presented in Section 5.

2 | Methodology

This section outlines the primary structure of the Fuzzy SWARA and MARCOS methods. Figure 1 illustrates the framework of our model, represented as follows:

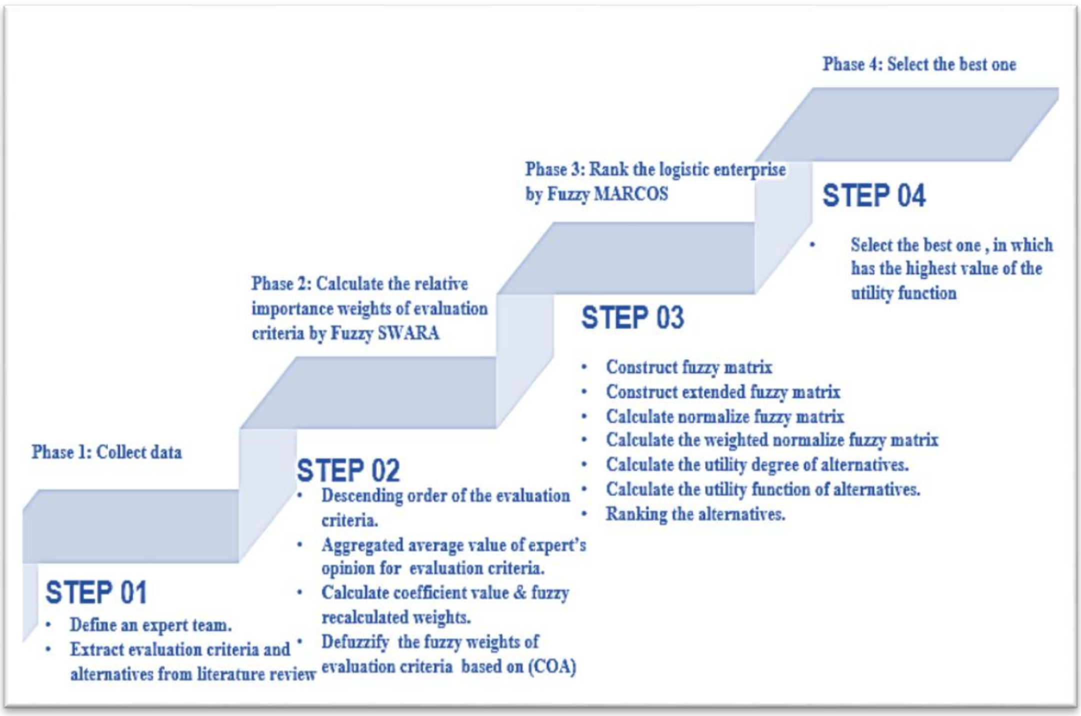

Figure 1. Framework of our model.

2.1 | Phase 1

Step 1: Define the expert team in terms of the problem domain, in which they have great experience and big knowledge in the problem domain.

Step 2: Define the evaluation criteria and alternatives based on the opinions of the expert's team.

2.2 | Phase 2

Step 3: Step-wise Weight Assessment Ratio Analysis that was introduced by [20] is one of the MCDM techniques being applied to estimate the evaluation criteria's weights. In this study, we apply the triangular fuzzy SWARA method in a fuzzy environment, according to the following steps:

Step 3.1: Order the criteria in descending order from most important to least important based on the expected opinions of the expert's team.

Step 3.2: Determine the relative importance ratio (S_j) for criteria j concerning the previous criterion $(j-1)$ by using linguistic terms, as displayed in Table 1, starting from the second criterion to the last one. After collecting the values of (S_j) from all experts on the expert's team, calculate the aggregation of the relative importance ratio (S_j^-) by using the arithmetic mean of the corresponding scores, $S_j^- = (S_j^{-l}, S_j^{-m}, S_j^{-u})$.

Step 3.3: Calculate the coefficient $(k^-{}_j)$ of comparative importance as follows:

$$k^-{}_j = \begin{cases} 1 & j = 1 \\ S_j^- + 1 & j > 1 \end{cases} \quad where\ k^-{}_j = (k^{-l}{}_j, k^{-m}{}_j, k^{-u}{}_j) \tag{1}$$

Step 3.4: Calculate the intermediate weight q_j as follows:

$$q_j = \begin{cases} 1 & j = 1 \\ \frac{q_{j-1}}{k^-{}_j} & j > 1 \end{cases} \text{ where } q_j = (q^l{}_j, q^m{}_j, q^u{}_j) \tag{2}$$

Step 3.5: Determine the relative importance weight of the criterion with the sum that is equal to 1, as follows:

$$w_j = \frac{q_j}{\sum_{k=1}^{n} q_j} \tag{3}$$

Since $w_j = (w^l{}_j, w^m{}_j, w^u{}_j)$, is triangular fuzzy relative importance weight and n is the number of criteria. Some essential algebraic operation definitions and fundamental of the important properties of triangular fuzzy sets are illustrated as Eqs. (4–7), Figure 2 shows, the membership function of triangular fuzzy numbers. Let $y1 = (l1, m1, u1)$ and $y2 = (l2, m2, u2)$ are two triangular fuzzy numbers (TFNs), then the functional rules of the two TFNs are shown as:

Fuzzy addition:

$$y1 + y2 = (l1 + l2, m1 + m2, u1 + u2) \tag{4}$$

Fuzzy subtraction:

$$y1 - y2 = (l1 - l2, m1 - m2, u1 - u2) \tag{5}$$

Fuzzy multiplication:

$$y1xy2 = (l1\ l2, m1\ m2, u1\ u2) \tag{6}$$

Fuzzy division:

$$y1/y2 = (l1\ /u2, m1/\ m2, u1/l2) \tag{7}$$

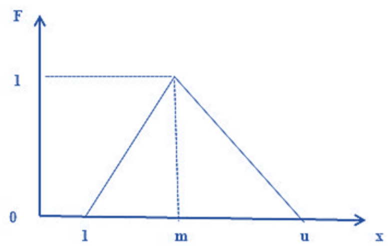

Figure 2. Membership function of (TFNs).

Step 3.6: Convert the triangular fuzzy weight w_j into de-fuzzy weight according to the method of Center of Area (COA) [21], as follows:

$$w^{defuzz}{}_j = \frac{(w^u{}_j - w^l{}_j) + (w^m{}_j - w^l{}_j) + (w^l{}_j)}{3} \quad (8)$$

2.3 | Phase 3

Step 4: Applying the triangular fuzzy MARCOS (Measurement of Alternatives and Ranking according to Compromise Solution) method. The MARCOS method was introduced by [22]. It also measures the options and ranks them with respect to a compromise solution, which, determines utility functions based on the separation between anti-ideal and ideal solutions and their aggregations. In this study, we apply the MARCOS method in a fuzzy environment, which includes the following steps [23]:

Step 4.1: Constructing the initial fuzzy decision matrix (X^-):

Step 4.1.1: The linguistic decision matrices are initially created by experts and transformed into fuzzy matrices by using the linguistic scale in Table 1.

Step 4.1.2: Aggregate all fuzzy matrices into one fuzzy matrix by using the arithmetic mean of the corresponding scores $X_j^- = (x_j^{-l}, x_j^{-m}, x_j^{-u})$ according to the following formula:

$$X^- = \begin{bmatrix} (x^l{}_{11}, x^m{}_{11}, x^u{}_{11}) & \cdots & (x^l{}_{1n}, x^m{}_{1n}, x^u{}_{1n}) \\ \vdots & \ddots & \vdots \\ (x^l{}_{m1}, x^m{}_{m1}, x^u{}_{m1}) & \cdots & (x^l{}_{mn}, x^m{}_{mn}, x^u{}_{mn}) \end{bmatrix} \quad (9)$$

where m is the number of alternatives, n is the number of criteria x_{mn} is the value of the n criterion in m.

Step 4.2: Construct the extended fuzzy matrix by adding the fuzzy ideal alternative (AI) and the fuzzy anti-ideal alternative (AAI).

$$X^{exte} = \begin{matrix} A^-(AAI) \\ \vdots \\ A^-(AI) \end{matrix} \begin{bmatrix} X_{aa1}^- & \cdots & x_{aan}^- \\ \vdots & \ddots & \vdots \\ x_{ai1}^- & \cdots & x_{ain}^- \end{bmatrix} \quad (10)$$

where, $A^-(AAI)$ is the worst alternative and, $A^-(AI)$ is the best alternative, the fuzzy $A^-(AAI)$ and the fuzzy $A^-(AI)$ are determined as follows:

$$A^-(AAI) = \min(x_{ij}^-) \text{ if } j \in B, \text{ and } A^-(AAI) = \max(x_{ij}^-) \text{ if } j \in C \quad (11)$$

$$A^-(AI) = \max(x_{ij}^-) \text{ if } j \in B, \text{ and } A^-(AI) = \min(x_{ij}^-) \text{ if } j \in C \quad (12)$$

where B refers that the criteria belong to the maximize group, while C refers that the criteria belong to the minimize group.

Step 4.3: Calculate the normalized extended fuzzy matrix according to the following formula:

$$n_{ij} = \frac{X_{ai}}{x_{ij}} \text{ if } j \in C \quad (13)$$

$$n_{ij} = \frac{x_{ij}}{X_{ai}} \text{ if } j \in B \quad (14)$$

Step 4.4: Calculate the weighted normalized fuzzy matrix as follows:

$$V_{ij} = n_{ij} * w_j = (n_{ij}^l x w_j^l, n_{ij}^m x w_j^m, n_{ij}^u x w_j^u) \quad (15)$$

Where, w_j is the fuzzy weight of the criterion$j$.

Step 4.5: Calculation of the utility degree of alternatives, k_i as follows:

$$S_i = \sum_{i=1}^{n} V_{ij} \quad (16)$$

$$K_i^- = \frac{S_i}{S_{AAI}} \quad (17)$$

$$K_i^+ = \frac{S_i}{S_{AI}} \quad (18)$$

where, S_i is the sum of the values of the weighted fuzzy matrix V_{ij} and $= 1,2, \dots . m$.

Step 4.6: Calculation of fuzzy matrix T_i, as a follows:

$$T_i = K_i^- + K_i^+ = (k_i^{-l} + k_i^{+l}, k_i^{-m} + k_i^{+m}, k_i^{-u} + k_i^{+u}) \quad (19)$$

After that, determine a fuzzy number N as follows:

$$N = \max(t_i) = (n^l, n^m, n^u) \quad (20)$$

Then, $\text{def}\, N_{crisp}$ is obtained by de-fuzzify the fuzzy number N by de-fuzzify equation as follows:

$$\text{def}N_{crisp} = \frac{l+4m+u}{6} \quad (21)$$

Step 4.7: Calculation of the utility function of alternatives $f(k_i)$ according to the following formula:

$$f(K_i^-) = \frac{K_i^+}{\text{def}N_{crisp}} \quad (22)$$

$$f(K_i^+) = \frac{K_i^-}{\text{def}N_{crisp}} \quad (23)$$

$K_i^-, K_i^+, f(K_i^-)$ and $f(K_i^+)$ must be de-fuzzify firstly by using Eq. (21) then calculate the utility function of alternatives as:

$$f(k_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1 - f(K_i^+)}{f(K_i^+)} + \frac{1 - f(K_i^-)}{f(K_i^-)}} \quad (24)$$

Step 4.8: Ranking the alternatives by their $f(k_i)$

2.4 | Phase 4

Select the best alternative that has the highest value of $f(k_i)$.

Table 1. Linguistic scale and the fuzzy values for the evaluation criteria [24].

Linguistic Terms	Abbreviation	TFNs
Poor	P	(0.00, 0.00, 0.30)
Fair	F	(0.20, 0.35, 0.50)
Good	G	(0.40, 0.55, 0.70)
Very Good	VG	(0.60, 0.75, 0.90)
Excellent	E	(0.80, 1.00, 1.00)

3 | Case Study

Our research aims to conduct an experimental study that evaluates a proposed model for selecting the best logistics enterprise that uses the Internet of Things to support delivery by drones. We have four logistics enterprises, namely A1, A2, A3, and A4 that support delivery by drones, and a team of decision-makers consisting of four experts, each with experience and knowledge in a specific field. The challenge is to choose the best company out of the four alternatives to deliver a package from Cairo to Saudi Arabia while meeting e-commerce standards. This represents a difficult task for decision-makers.

Step 1: There are four experts in our assumption, namely expert1, expert2, expert3, and expert4. Each of them holds a PhD degree in a specific field of expertise. Expert1 holds a PhD degree in the Business Management field, expert2 holds a PhD degree in the Cyber Security field, expert3 holds a PhD degree in the E-Marketing field, and expert4 holds a PhD degree in the Machine Learning field. The experts will evaluate the judgment comparison of the main criteria based on their area of concern.

Step 2: The first step was to create a team of experts. Next, a series of interviews was conducted with this team to identify evaluation standards and narrow down potential logistic enterprise prospects. Four candidates were identified, namely $A1$, $A2$, $A3$, and $A4$. Evaluation criteria were extracted from previous literature, where six criteria were identified and listed in Table 2.

Step 3: Triangular fuzzy SWARA method to determine the evaluation criteria weight:

3.1 A team of experts arranges the evaluation criteria in descending order from most important to least important, as shown in Table 3, where mutual authentication is the highest priority, and fairness is the least important for evaluation criteria.

3.2 The relative importance ratio S_j is determined by the expert team using the linguistic terms from Table 1, as shown in Table 4. The aggregation of the relative importance ratio S_j^- is calculated according to TFNs by applying Eqs (4-7), as shown in Table 5.

3.3 To determine the final weight of the criteria, you need to follow a few steps. First, use Eq. (1) to calculate the coefficient $k^-{}_j$. Next, use Eq. (2) to determine the intermediate weight q_j for each criterion. After that, apply Eq. (3) to calculate the fuzzy weight w_j of the criteria. Finally, use Eq. (8) to convert the fuzzy weight into de-fuzzy weight $w^{defuzz}{}_j$ and get the final weight of the criteria. All these calculations are shown in Table 6. As shown in Figure 3, the Mutual authentication $C5$ is the highest criterion with a weight equal to 0.080768 and the lowest criterion is the Fairness $C2$ with weight equal to 0.0304.

Table 2. Criteria for evaluating logistic enterprise.

Criteria	Abbreviation	Description
Integrity	C1	It indicates that the data or information has not been tampered with and can be easily detected if any changes are made without permission [25]
Fairness	C2	The parties involved must participate in a transaction that is fair and equitable [26]
Arbitrative mechanism	C3	It is important to have a well-defined process in place to handle transaction disputes on time [27]
Non-refusal	C4	Neither the sender nor the recipient may reject the transaction [26]
Mutual authentication	C5	This method prevents unauthorized control of UAVs and remote data access [28]
Location Piracy	C6	The security of data transmission should be guaranteed and the network's defenses against privacy breaches should be strengthened [25]

Table 3. Order of evaluation criteria based on experts.

Criteria	Order
C5	1
C4	2
C6	3
C3	4
C1	5
C2	6

Table 4. The relative importance ratio in the form of the linguistic term.

	C5<>C4	C4<>C6	C6<>C3	C3<>C1	C1<>C2
expert 1	F	G	VG	G	F
expert2	G	G	G	F	P
expert3	VG	G	E	VG	F
expert4	F	VG	VG	G	G

Table 5. The aggregation of relative importance ratio S_j^-.

	C5<>C4	C4<>C6	C6<>C3	C3<>C1	C1<>C2
expert 1	(0.2,0.35,0.5)	(0.4,0.55,0.7)	(0.6,0.75,0.9)	(0.4,0.55,0.7)	(0.2,0.35,0.5)
expert2	(0.4,0.55,0.7)	(0.4,0.55,0.7)	(0.4,0.55,0.7)	(0.2,0.35,0.5)	(0,0,0.3)
expert3	(0.6,0.75,0.9)	(0.4,0.55,0.7)	(0.6,0.75,0.9)	(0.6,0.75,0.9)	(0.2,0.35,0.5)
expert4	(0.2,0.35,0.5)	(0.6,0.75,0.9)	(0.6,0.75,0.9)	(0.4,0.55,0.7)	(0.4,0.55,0.7)
S_j^-	(0.35, 0.5,0.65)	(0.45,0.6,0.75)	(0.55,0.7,0.85)	(0.4,0.55,0.7)	(0.2,0.3125,0.5)

Table 6. The weight of the criteria with the SWARA method.

Criteria	$s_{i\leftrightarrow j+1}$	$k^-{}_j$	q_j	w_j	$w^{defuzz}{}_j$
$C5$	-----	(1.00, 1.00, 1.00)	(1.00, 1.00, 1.00)	(0.43045, 0.383577, 0.2891815)	0.080768
$C4$	(0.35, 0.5,0.65)	(1.35, 1.5,1.65)	(0.606060, 0.6666, 0.740740)	(0.260883, 0.255718, 0.214211)	0.069682
$C6$	(0.45,0.6,0.75)	(1.45,1.6,1.75)	(0.34632034, 0.416666, 0.689655)	(0.149076, 0.159824, 0.199438)	0.070062
$C3$	(0.55,0.7,0.85)	(1.55,1.7,1.85)	(0.187200, 0.245098, 0.4449388)	(0.080582, 0.94014, 0.12867)	0.047367
$C1$	(0.4,0.55,0.7)	(1.4,1.55,1.7)	(0.11011, 0.1581277, 0.31781344)	(0.047401, 0.060654, 0.091907)	0.035053
$C2$	(0.2,0.3125,0.5)	(1.2,1.3125,1.5)	(0.0734118, 0.1204782, 0.264844)	(0.031601, 0.046213, 0.076589)	0.0304

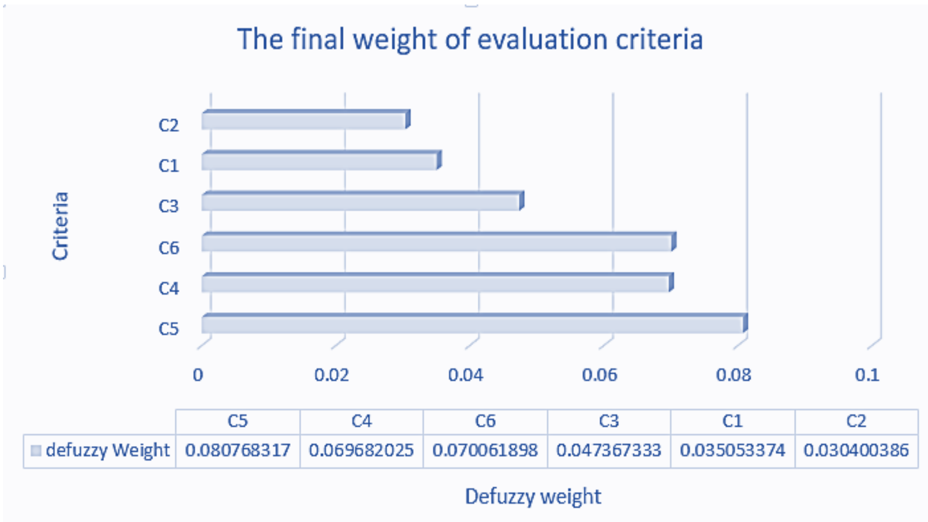

Figure 3. The final weight of evaluation criteria.

Step 4: The triangular fuzzy MARCOS method to rank the alternatives and select the best of them:

4.1 The linguistic decision matrices are constructed based on experts' opinions as shown in Tables 7, 9, 11 and 13 then convert the linguistic matrices into fuzzy matrices using the linguistic scale in Table 1 as shown in Tables 8, 10, 12, and 14.

4.2 All fuzzy matrices are converted into one aggregated matrix according to the formula in Eq. (9) by using the arithmetic mean, as shown in Table 15.

4.3 The extended fuzzy matrix is constructed as the formula in Eq. (10) by adding the fuzzy anti-ideal alternative which is calculated by Eq. (11) and the fuzzy ideal alternative which is calculated by using Eq.

(12), as shown in Table 16, it should be noted that all evaluation criteria in our experimentation study belong to the maximum group.

4.4 The normalized fuzzy matrix is determined by using Eqs. (13) and (14), which are represented in two tables, namely Tables 17 and 18.

4.5 The weighted normalized fuzzy matrix is calculated by using Eq. (15), in which w_j is the fuzzy weight that we calculated before by fuzzy SWARA in Table 6, we represented the weighted normalized fuzzy matrix in Tables 19 and 20.

4.6 The sum of elements of the weighted fuzzy matrix s_i is calculated by using Eq. (16), as shown in Table 21.

4.7 The utility degree of alternatives K_i is calculated by using Eqs. (17) and (18), as shown in Table 22.

4.8 Fuzzy matrix T_i is calculated by using Eq. (19), as shown in Table 23. Then a new fuzzy number is created by using Eq. (20), then converted to $defN_{crisp}$ by using Eq. (21).

4.9 The utility function is to identify the ideal alternative$f(K^+{}_i)$ is calculated by Eq. (23), as shown in Table 24. Also, the utility function to identify the anti-ideal alternative$f(K^-{}_i)$ is calculated by Eq. (22) as shown in Table 25.

4.10 Both of (K^+), (K^-), $f(K^-i)$ and $f(K^{\mp}i)$ are de-fuzzified by Eq. (21), as shown in Table 26.

4.11 The utility function of alternatives is calculated by Eq. (24), as shown in Table 27.

4.12 Figure 4, shows the final rank of the alternatives, in which $A1$ is the best one with the highest value of $f(k_i)$ equal to 0.901417906, but $A3$ is the worst alternative with the lowest value of $f(k_i)$ equal to 0.112976366.

Table 7. The linguistic decision matrix by Expert 1.

	Max	Max	Max	Max	Max	Max
	C1	C2	C3	C4	C5	C6
A1	VG	G	G	E	E	VG
A2	F	F	F	G	G	F
A3	F	G	P	F	G	F
A4	G	G	G	VG	VG	G

Table 8. Decision matrix with TFNs by Expert 1.

	Max	Max	Max	Max	Max	Max
	C1	C**2**	**C3**	**C4**	**C5**	**C6**
A1	(0.60, 0.75, 0.90)	(0.40, 0.55, 0.70)	(0.40, 0.55, 0.70)	(0.80, 1.00, 1.00)	(0.80, 1.00, 1.00)	(0.60, 0.75, 0.90)
A2	(0.20, 0.35, 0.50)	(0.20, 0.35, 0.50)	(0.20, 0.35, 0.50)	(0.40, 0.55, 0.70)	(0.40, 0.55, 0.70)	(0.20, 0.35, 0.50)
A3	(0.20, 0.35, 0.50)	(0.40, 0.55, 0.70)	(0.00, 0.00, 0.30)	(0.20, 0.35, 0.50)	(0.40, 0.55, 0.70)	(0.20, 0.35, 0.50)
A4	(0.40, 0.55, 0.70)	(0.40, 0.55, 0.70)	(0.40, 0.55, 0.70)	(0.60, 0.75, 0.90)	(0.60, 0.75, 0.90)	(0.40, 0.55, 0.70)

Table 9. The linguistic decision matrix by Expert 2.

	Max	Max	Max	Max	Max	Max
	C1	C2	C3	C4	C5	C6
A1	E	VG	G	E	E	VG
A2	G	P	G	F	F	G
A3	P	F	F	P	G	F
A4	G	VG	VG	G	VG	G

Table 10. Decision matrix with TFNs by Expert 2.

	Max	Max	Max	Max	Max	Max
	C1	C2	**C3**	**C4**	**C5**	**C6**
A1	(0.80, 1.00, 1.00)	(0.60, 0.75, 0.90)	(0.40, 0.55, 0.70)	(0.80, 1.00, 1.00)	(0.80, 1.00, 1.00)	(0.60, 0.75, 0.90)
A2	(0.40, 0.55, 0.70)	(0.00, 0.00, 0.30)	(0.40, 0.55, 0.70)	(0.20, 0.35, 0.50)	(0.20, 0.35, 0.50)	(0.40, 0.55, 0.70)
A3	(0.00, 0.00, 0.30)	(0.20, 0.35, 0.50)	(0.20, 0.35, 0.50)	(0.00, 0.00, 0.30)	(0.40, 0.55, 0.70)	(0.20, 0.35, 0.50)
A4	(0.40, 0.55, 0.70)	(0.60, 0.75, 0.90)	(0.60, 0.75, 0.90)	(0.40, 0.55, 0.70)	(0.60, 0.75, 0.90)	(0.40, 0.55, 0.70)

Table 11. The linguistic decision matrix by Expert 3.

	Max	Max	Max	Max	Max	Max
	C1	C2	C3	C4	C5	C6
A1	E	VG	E	E	E	VG
A2	G	F	F	G	G	F
A3	F	F	F	P	G	P
A4	VG	VG	VG	G	G	G

Table 12. Decision matrix with TFNs by Expert 3.

	Max	Max	Max	Max	Max	Max
	C1	C2	**C3**	**C4**	**C5**	**C6**
A1	(0.80, 1.00, 1.00)	(0.60, 0.75, 0.90)	(0.80, 1.00, 1.00)	(0.80, 1.00, 1.00)	(0.80, 1.00, 1.00)	(0.60, 0.75, 0.90)
A2	(0.40, 0.55, 0.70)	(0.20, 0.35, 0.50)	(0.20, 0.35, 0.50)	(0.40, 0.55, 0.70)	(0.40, 0.55, 0.70)	(0.20, 0.35, 0.50)
A3	(0.20, 0.35, 0.50)	(0.20, 0.35, 0.50)	(0.20, 0.35, 0.50)	(0.00, 0.00, 0.30)	(0.40, 0.55, 0.70)	(0.00, 0.00, 0.30)
A4	(0.60, 0.75, 0.90)	(0.60, 0.75, 0.90)	(0.60, 0.75, 0.90)	(0.40, 0.55, 0.70)	(0.40, 0.55, 0.70)	(0.40, 0.55, 0.70)

Table 13. The linguistic decision matrix by Expert 4.

	Max	Max	Max	Max	Max	Max
	C1	C2	C3	C4	C5	C6
A1	VG	VG	E	E	E	E
A2	G	F	F	G	VG	G
A3	F	P	G	F	G	F
A4	G	G	VG	VG	VG	E

Table 14. Decision matrix with TFNs by Expert 4.

	Max	Max	Max	Max	Max	Max
	C1	C2	**C3**	**C4**	**C5**	**C6**
A1	(0.60, 0.75, 0.90)	(0.60, 0.75, 0.90)	(0.80, 1.00, 1.00)	(0.80, 1.00, 1.00)	(0.80, 1.00, 1.00)	(0.80, 1.00, 1.00)
A2	(0.40, 0.55, 0.70)	(0.20, 0.35, 0.50)	(0.20, 0.35, 0.50)	(0.40, 0.55, 0.70)	(0.60, 0.75, 0.90)	(0.40, 0.55, 0.70)
A3	(0.20, 0.35, 0.50)	(0.00, 0.00, 0.30)	(0.40, 0.55, 0.70)	(0.20, 0.35, 0.50)	(0.40, 0.55, 0.70)	(0.20, 0.35, 0.50)
A4	(0.40, 0.55, 0.70)	(0.40, 0.55, 0.70)	(0.60, 0.75, 0.90)	(0.60, 0.75, 0.90)	(0.60, 0.75, 0.90)	(0.80, 1.00, 1.00)

Table 15. Aggregated decision matrix with TFNs for all experts.

	Max	Max	Max	Max	Max	Max
	$\boldsymbol{C1}$	$C\mathbf{2}$	$\boldsymbol{C3}$	$\boldsymbol{C4}$	$\boldsymbol{C5}$	$\boldsymbol{C6}$
$\boldsymbol{A1}$	(0.7,0.875,0.95)	(0.55,0.7 ,0.85)	(0.6,0.775,0.85)	(0.8,1,1)	(0.8,1,1)	(0.65,0.8125,0.925)
$\boldsymbol{A2}$	(0.35,0.5,0.65)	(0.15,0.2625,0.45	(0.25,0.4 ,0.55)	(0.35,0.5 ,0.65)	(0.4,0.55 ,0.7)	(0.3,0.45 ,0.6)
$\boldsymbol{A3}$	(0.15,0.2625,0.45)	(0.2,0.3125,0.5)	(0.2,0.3125,0.5)	(0.1,0.175,0.4)	(0.4,0.55 ,0.7)	(0.15,0.2625,0.45)
$\boldsymbol{A4}$	(0.45,0.6 ,0.75)	(0.5,0.65 ,0.8)	(0.55,0.7 ,0.85)	(0.5,0.65 ,0.8)	(0.55,0.7 ,0.85)	(0.5,0.6625,0.775)

Table 16. Extended aggregated fuzzy matrix with TFNs.

	Max	Max	Max	Max	Max	Max
	C1	C**2**	**C3**	**C4**	**C5**	**C6**
AAI	(0.15,0.2625,0.45)	(0.15,0.2625,0.45)	(0.2,0.3125,0.5)	(0.1,0.175,0.4)	(0.4,0.55,0.7)	(0.15,0.2625,0.45)
A1	(0.7,0.875,0.95)	(0.55,0.7 ,0.85)	(0.6,0.775,0.85)	(0.8,1,1)	(0.8,1,1)	(0.65,0.8125,0.925)
A2	(0.35,0.5,0.65)	(0.15,0.2625,0.45	(0.25,0.4 ,0.55)	(0.35,0.5 ,0.65)	(0.4,0.55 ,0.7)	(0.3,0.45 ,0.6)
A3	(0.15,0.2625,0.45)	(0.2,0.3125,0.5)	(0.2,0.3125,0.5)	(0.1,0.175,0.4)	(0.4,0.55 ,0.7)	(0.15,0.2625,0.45)
A4	(0.45,0.6 ,0.75)	(0.5,0.65 ,0.8)	(0.55,0.7 ,0.85)	(0.5,0.65 ,0.8)	(0.55,0.7 ,0.85)	(0.5,0.6625,0.775)
AI	(0.7,0.875,0.95)	(0.55,0.7,0.85)	(0.6,0.775,0.85)	(0.8,1,1)	(0.8,1,1)	(0.65,0.8125,0.925)

Table 17. Normalized fuzzy matrix from [C1:C3].

	Max			Max			Max		
	C1			C**2**			**C3**		
	l	**m**	**u**	**l**	**m**	**u**	**l**	**m**	**u**
AAI	0.214285	0.3	0.4736842	0.2727272	0.375	0.5294117	0.3333333	0.4032258	0.58823529
A1	1	1	1	1	1	1	1	1	1
A2	0.5	0.5714285	0.6842105	0.3636363	0.375	0.5294117	0.4166666	0.516129	0.64705882
A3	0.214285	0.3	0.4736842	0.3636363	0.446428	0.5882352	0.3333333	0.4032258	0.58823529
A4	0.642857	0.6857142	0.4736842	0.9090909	0.446428	0.9411764	0.9166666	0.9032258	1
AI	1	1	1	1	1	1	1	1	1

Table 18. Normalized fuzzy matrix from [C4:C6].

	Max			Max			Max		
	C4			C5			**C6**		
	l	**m**	**u**	**l**	**m**	**u**	**l**	**m**	**u**
AAI	0.125	0.175	0.4	0.5	0.55	0.7	0.2307692	0.3230769	0.48648649
A1	1	1	1	1	1	1	1	1	1
A2	0.4375	0.5	0.65	0.5	0.55	0.7	0.4615384	0.5538461	0.64864865
A3	0.125	0.175	0.4	0.5	0.55	0.7	0.2307692	0.3230769	0.48648649
A4	0.625	0.65	0.8	0.6875	0.7	0.85	0.7692307	0.8153846	0.83783784
AI	1	1	1	1	1	1	1	1	1

Table 19. Weighted normalized aggregated fuzzy matrix from [C1:C3].

	Max			Max			Max		
	C1			C**2**			**C3**		
	l	**m**	**u**	**l**	**m**	**u**	**l**	**m**	**u**
WJ	0.04740099	0.0606542	0.09190692	0.03160066	0.04621272	0.0765891	0.08058169	0.094014	0.12866968
AAI	0.01015736	0.01819626	0.04353485	0.00861836	0.01732977	0.04054717	0.02686056	0.0379089	0.07568805
A1	0.04740099	0.0606542	0.09190692	0.03160066	0.04621272	0.0765891	0.08058169	0.094014	0.12866968
A2	0.0237005	0.03465954	0.06288368	0.01149115	0.01732977	0.04054717	0.0335757	0.0485234	0.08325685
A3	0.01015736	0.01819626	0.04353485	0.01149115	0.02063068	0.04505241	0.02686056	0.0379089	0.07568805
A4	0.03047207	0.04159145	0.04353485	0.02872787	0.02063068	0.07208386	0.07386655	0.0849159	0.12866968
AI	0.04740099	0.0606542	0.09190692	0.03160066	0.04621272	0.0765891	0.08058169	0.094014	0.12866968

Table 20. Weighted normalized aggregated fuzzy matrix from [C4:C6].

	Max			Max			Max		
	C4			C5			**C6**		
	l	**m**	**u**	**l**	**m**	**u**	**l**	**m**	**u**
WJ	0.26088322	0.2557181	0.21421119	0.43045731	0.38357715	0.28918511	0.14907613	0.15982381	0.19943801
AAI	0.0326104	0.04475067	0.08568448	0.21522866	0.21096743	0.20242958	0.03440218	0.05163539	0.09702389
A1	0.26088322	0.2557181	0.21421119	0.43045731	0.38357715	0.28918511	0.14907613	0.15982381	0.19943801
A2	0.11413641	0.12785905	0.13923727	0.21522866	0.21096743	0.20242958	0.06880437	0.0885178	0.12936519
A3	0.0326104	0.04475067	0.08568448	0.21522866	0.21096743	0.20242958	0.03440218	0.05163539	0.09702389
A4	0.16305201	0.16621677	0.17136895	0.2959394	0.26850401	0.24580734	0.11467394	0.13031788	0.16709671
AI	0.26088322	0.2557181	0.21421119	0.43045731	0.38357715	0.28918511	0.14907613	0.15982381	0.19943801

Table 21. The sum of elements of the weighted fuzzy matrix s_i.

Alternatives	$\mathbf{s_i = \sum_{i=1}^{n} v_{ij}}$		
	l	**m**	**u**
AAI	0.32787752	0.38078839	0.544908
A1	1	1	1
A2	0.466937	0.527857	0.65772
A3	0.33075	0.384089	0.549413
A4	0.706732	0.712177	0.828561
AI	1	1	1

Table 22. The utility degree of alternatives K_i

Alternatives	$\mathbf{K_i^- = \frac{S_i^-}{S_{AAI}}}$			$\mathbf{K_i^+ = \frac{S_i^-}{S_{AI}}}$		
	l	**m**	**u**	**l**	**m**	**u**
A1	1.835172	2.62613	3.049919	1	1	1
A2	0.856909	1.386221	2.005992	0.466937	0.527857	0.65772
A3	0.606984	1.008669	1.675666	0.33075	0.384089	0.549413
A4	1.296975	2.17591	2.527045	0.706732	0.712177	0.828561

Table 23. The fuzzy matrix T_i.

Alternatives	$\mathbf{T_i = K_i^- + K_i^+}$		
	l	**m**	**u**
A1	2.835172	3.62613	4.049919
A2	1.323846	1.914078	2.663712
A3	0.937734	1.392758	2.225079
A4	2.003706	2.888087	3.355607
New fuzzy number N	2.835172	3.62613	4.049919
$\mathbf{defN_{crisp}}$	3.564936		

Table 24. The utility function to identify the ideal alternative $f(K^{+}{}_{i})$.

Alternatives	$f(K^{+}{}_{i}) = \frac{K^{-}}{deffnumb}$		
	l	m	u
A1	0.514784092	0.736655803	0.855532817
A2	0.240371626	0.388848895	0.562700826
A3	0.170264998	0.282941613	0.470041074
A4	0.363814312	0.61036456	0.708861464

Table 25. The utility function to identify the anti-ideal alternative $f(K^{-}{}_{i})$.

Alternatives	$f(K^{-}{}_{i}) = \frac{K^{+}}{deffnumb}$		
	l	m	u
A1	0.28050998	0.28050998	0.28050998
A2	0.130980427	0.148069146	0.184496952
A3	0.092778763	0.107740882	0.154115902
A4	0.198245336	0.199772661	0.23241974

Table 26. Defuzzification for each (K^{+}), (K^{-}), $f(K^{-}i)$, $f(K^{\mp}i)$.

Alternatives	De-fuzzy (K^{+})	De-fuzzy (K^{-})	De-fuzzy $(f(K^{-}i))$	De-fuzzy $(f(K^{\mp}i))$
A1	1	2.564935553	0.71949002	0.28050998
A2	0.539347396	1.401297756	0.393078005	0.151292327
A3	0.402753463	1.052887391	0.295345421	0.112976366
A4	0.730666648	2.087943549	0.585689003	0.204959287

Table 27. the utility function of the alternatives.

Alternatives	$f(K_{i})$
A1	0.901417906
A2	0.238006608
A3	0.129536822
A4	0.504547811

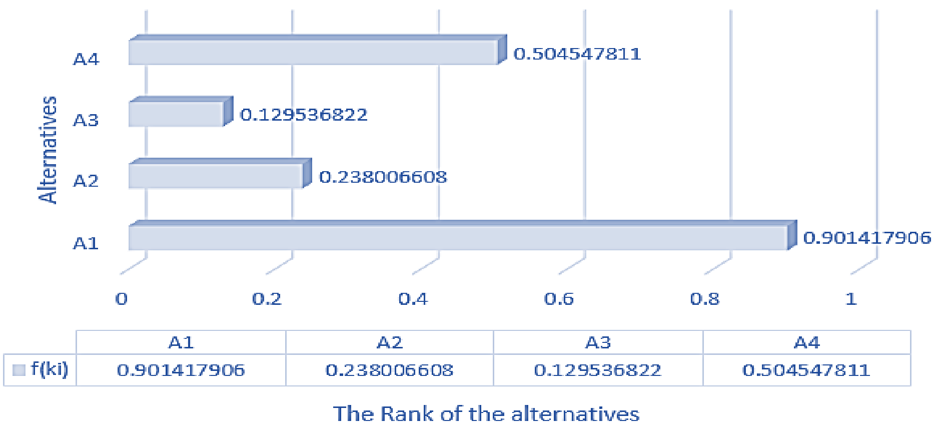

Figure 4. The rank of the alternatives based on fuzzy MAROCS.

4 | Managerial Implications

Since the choice process is a difficult and hard mission due to several conflicting criteria that exist nowadays, so we need an efficient and effective MCDM technique. Therefore, in this research, we present a fuzzy model to select the best logistic enterprise for the delivery process using drones. The presented model can be a dominant guide for firms, organizations, and governments to make precise decisions.

5 | Conclusion

We have suggested an integrated approach that combines two MCDM methods, namely SWARA and MARCOS in a fuzzy environment. This approach helps to evaluate and select logistical enterprises that offer logistical services using the IoT to support their delivery process via drones. This will assist decision-makers in choosing the best possible enterprises. The results of our experimental study have demonstrated the effectiveness of this model, which is also time-efficient. According to the study results, mutual authentication is the most preferred criterion among the other criteria, and the best alternative was chosen accordingly.

In the future, we will use the suggested model in several MCDM problems. Also, we tend to combine the proposed method with other methods such as AHP and TOPSIS.

Acknowledgments

The author is grateful to the editorial and reviewers, as well as the correspondent author, who offered assistance in the form of advice, assessment, and checking during the study period.

Author Contribution

All authors contributed equally to this work.

Funding

This research has no funding source.

Data Availability

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

References

[1] Tseng, Y.-y., W.L. Yue, and M.A. Taylor. The role of transportation in logistics chain. 2005. Eastern Asia Society for Transportation Studies.

[2] Yang, Z., Y. Shi, and H. Yan, Analysis on pure e-commerce congestion effect, productivity effect and profitability in China. Socio-Economic Planning Sciences, 2017. 57: p. 35-49.

[3] Gajewska, T. and D. Zimon, Study of the logistics factors that Influence the development of e-commerce services in the customer's opinion. Archives of Transport, 2018. 45(1): p. 25-34.

[4] Xing, Y., et al., The interface between retailers and logistics service providers in the online market. European Journal of Marketing, 2011. 45(3): p. 334-357.

[5] Vasić, N., et al., Satisfaction is a function of users of logistics services in e-commerce. Technology Analysis & Strategic Management, 2021. 33(7): p. 813-828.

[6] Singh, S. and N. Singh. Internet of Things (IoT): Security challenges, business opportunities & reference architecture for E-commerce. in 2015 International conference on green computing and internet of things (ICGCIoT). 2015. Ieee.

[7] Sun, C. and Y. Ji, For better or for worse: Impacts of IoT technology in e-commerce channel. Production and Operations Management, 2022. 31(3): p. 1353-1371.

[8] Ni, H., et al. Design of regional logistics system based on unmanned aerial vehicle. in 2018 IEEE 7th Data Driven Control and Learning Systems Conference (DDCLS). 2018. IEEE.

[9] Eun, J., et al., Mathematical investigation on the sustainability of UAV logistics. Sustainability, 2019. 11(21): p. 5932.

[10] Roca-Riu, M. and M. Menendez. Logistic deliveries with drones: State of the art of practice and research. in 19th Swiss Transport Research Conference (STRC 2019). 2019. STRC.

[11] Michalska, A. and K. Karpinska, Capabilities of the Unmanned Aerial Vehicles in Logistic Support. Safety & Defense, 2018. 4(1): p. 22-26.

[12] Estrada, M.A.R. and A. Ndoma, The uses of unmanned aerial vehicles–UAV's-(or drones) in social logistic: Natural disasters response and humanitarian relief aid. Procedia Computer Science, 2019. 149: p. 375-383.

[13] Li, H., et al., A Reliable Delivery Logistics System Based on the Collaboration of UAVs and Vehicles. Sustainability, 2023. 15(17): p. 12720.

[14] Arsova, M., Blockchain technology and its impact on logistic enterprise performance. Knowledge-International Journal, 2021. 46(1): p. 201-205.

[15] Britchenko, I., T. Cherniavska, and B. Cherniavskyi, Blockchain technology into the logistics supply. 2018.

[16] Datta, S., et al., BSSFFS: blockchain-based sybil-secured smart forest fire surveillance. Journal of Ambient Intelligence and Humanized Computing, 2022: p. 1-32.

[17] Datta, S., et al. Authentication and privacy preservation in IoT based forest fire detection by using blockchain–a review. in 4th International Conference on Internet of Things and Connected Technologies (ICIoTCT), 2019: Internet of Things and Connected Technologies. 2020. Springer.

[18] Jusufbašić, A., MCDM methods for selection of handling equipment in logistics: a brief review. Spectrum of Engineering and Management Sciences, 2023. 1(1): p. 13-24.

[19] Liachovičius, E., V. Skrickij, and A. Podviezko, MCDM evaluation of asset-based road freight transport companies using key drivers that influence the enterprise value. Sustainability, 2020. 12(18): p. 7259.

[20] Keršuliene, V., E.K. Zavadskas, and Z. Turskis, Selection of rational dispute resolution method by applying new step-wise weight assessment ratio analysis (SWARA). Journal of business economics and management, 2010. 11(2): p. 243-258.

[21] Sumrit, D., Supplier selection for vendor-managed inventory in healthcare using fuzzy multi-criteria decision-making approach. Decision Science Letters, 2020. 9(2): p. 233-256.

[22] Stević, Ž., et al., Sustainable supplier selection in healthcare industries using a new MCDM method: Measurement of alternatives and ranking according to COmpromise solution (MARCOS). Computers & industrial engineering, 2020. 140: p. 106231.

[23] Stanković, M., et al., A new fuzzy MARCOS method for road traffic risk analysis. Mathematics, 2020. 8(3): p. 457.

[24] Perçin, S., An integrated fuzzy SWARA and fuzzy AD approach for outsourcing provider selection. Journal of Manufacturing Technology Management, 2019. 30(2): p. 531-552.

[25] Mehta, P., R. Gupta, and S. Tanwar, Blockchain envisioned UAV networks: Challenges, solutions, and comparisons. Computer Communications, 2020. 151: p. 518-538.

[26] Chen, C.-L. and J.-J. Liao, A fair online payment system for digital content via subliminal channel. Electronic Commerce Research and Applications, 2011. 10(3): p. 279-287.

[27] Chen, C.-L. and M.-H. Liu, A traceable E-cash transfer system against blackmail via subliminal channel. Electronic Commerce Research and Applications, 2009. 8(6): p. 327-333.

[28] Chen, C.-L., et al., A secure public transport multimedia on demand system for VANET. Journal of Internet Technology, 2015. 16(7): p. 1177-1188.