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E-commerce Logistics and Delivery Risk Management with Machine Learning and MCDM Methods

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Abstract

Machine learning techniques and fuzzy Multi-Criteria Decision Making (MCDM) are sophisticated methodology widely employed to support data analysis and decision-making in systems characterized by uncertainty and vagueness. Given the inherent imprecision present in real-world data, these approaches leverage fuzzy logic to effectively address ambi- guities and provide meaningful insights. In this thesis, we incorporate the machine learning technique with fuzzy cubic MCDM methods which helps to reduce the complexity in large scale MCDM problem. In particular the fuzzy C–Means algorithm is employed to reduce large data into meaningful clusters. Then these clusters are ranked and evaluated using MCDM techniques, specifically enhanced by fuzzy cubic numbers. The proposed algorithm allows decision-makers to effectively manage uncertainties inherent in decision-making processes that further improve the evaluation process including EDAS (Evaluation Based on Distance from Average Solution) and MAIRCA (Multi-Attributive Ideal-Real Comparative Analysis). Through the incorporation of fuzzy cubic numbers, these methods offer a precise evaluation that corresponds with the uncertainties and complexities of the real world. We also apply this proposed algorithm for risk assessment and mitigation in e-commerce logistics to find the best delivery routes for deliver different products. This hybrid strategy not only helps to identify delivery routes that best combine operational effectiveness and risk management but will also increase decision-making accuracy.

Introduction

Clustering is a core technique for grouping data points based on shared characteristics in machine learning. Standard approaches, such as *K*-Means, normally classify each point into exactly a single category. However, in practical appli- cations, data points often possess overlapping features, making it difficult to assign them exclusively to one category. The ambiguity or overlap of data points is quite common in many real-world applications (e.g. image segmentation, anomaly detection, pattern recognition).

Fuzzy logic is a mathematical framework for reasoning and decision-making in an uncertain, vague, or imprecise situ- ation. The flexibility of fuzzy systems allows them to deal with real-world data that is often composed of complex data in which exact information is typically not available. This concept of a fuzzy set is at the core of fuzzy logic, and its idea stems from a classical set by generalization, where elements of the classical set can only partially belong to the set, the idea was first proposed in (Zadeh et al., 1965). Fuzzy logic assign to each element a membership value ranging from 0 to 1, representing its level of association. It is very useful in many different fields, including control systems, decision-making, and data analysis, because of its ability to handle uncertainty and resemble human thinking. For instance, in industrial automation, fuzzy controllers process vague or imprecise inputs to make decisions that enhance system performance (Ross et al. , 2004).

Fuzzy *C*–means (FCM) is an unsupervised clustering algorithm that groups data points based on their similarities. FCM assigns each data point a membership score for each cluster, indicating how strongly it is related to each other, rather than grouping all the points into a single group (Bezdek et al., 1984). FCM can identify hidden or underlying patterns in data classification that traditional clustering techniques fail to recognize by employing fuzzy membership functions. In contrast, fuzzy MCDM approaches are designed to support decision-making where there are various conflicting criteria involved and the environment is vague or uncertain. Conventional MCDM methods tend to work with precise and certain data, which is not always realistic in practice because information tends to be imprecise or vague in real-life situations. Fuzzy MCDM techniques make easier and more reliable decisions in uncertain situations by using fuzzy sets to represent the uncertainty in weighting alternatives according to multiple criteria. Several fuzzy MCDM techniques are available for ranking alternatives and selecting the best alternative from fuzzy data, such as fuzzy TOPSIS (Tech- nique for Order Preference by Similarity to Ideal Solution), fuzzy AHP (Analytic Hierarchy Process), fuzzy VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje), etc. (Asemi et al., 2014).

Fuzzy MCDM is frequently used in domains where decisions frequently involve conflicting objectives, such as en- gineering, financial planning, and environmental management. These approaches provide a more flexible and useful method than traditional crisp techniques by using fuzzy numbers to represent subjective judgments. Because of this flexibility, fuzzy MCDM is particularly well-suited to real-world scenarios where uncertainty is necessary.

Fuzzy cubic numbers, as defined in(Prabu et al., 2024), are generalization of the traditional fuzzy number framework by adding the possibility and necessity functions in addition to the membership function. This provides a more thorough approach to handle uncertainty. Fuzzy cubic numbers provide a more accurate and complex representation of uncer- tainty than standard fuzzy numbers, which only use membership, by combining membership, possibility, and necessity. In particular, a more comprehensive and detailed uncertainty model is produced when the possibility function repre- sents the likelihood that an outcome will occur and the necessity function represents the extent to which that outcome is necessary for it to occur.

In decision-making, where membership degrees are unable to properly express uncertainty about what is possible, these fuzzy cubic numbers are very useful. In contexts like risk analysis, where the utility and worth of possible outcomes must be considered, these findings offer an effective framework for incorporating the possibility and necessity of mul- tiple outcomes. These fuzzy cubic numbers are significant for complicated decision cases because they might represent different aspects of uncertainty.(Fahmi, 2019). Fuzzy cubic numbers allow for the simultaneous consideration of ne- cessity and possibility of outcomes, which improves the representation and analysis of uncertain information, lowers uncertainty in the dimer decision outcome, and gives the decision-maker a better understanding of the risks and re- wards of different decisions. The detail of fuzzy cubic numbers can be seen in Akram & Ashraf (2023); Akram & Zahid (2023); Rashid & Akram (2018); Akram & Dar (2018); Ayman & Uzma (2022); Uzma et al. (2024); Uzma & Al- Shamiri (2024); Zahid & Akram (2023). When ambiguity and imprecision are present, two advanced methods that help make decisions and data analysis more clear are fuzzy C-means clustering (FCM) and fuzzy multi-criteria decision-making (MCDM). The combination of FCM and fuzzy MCDM can provide outstanding results in the domains of business, healthcare, and environmental management. Xu et al. (2020). In situations with decision-making problems involving large data sets, it can be extremely time-consuming and computationally intensive to consider every alterna- tive with respect to each criterion. The outcomes of fuzzy clustering MCDM can assist in identifying the clusters or subset of the data that is most relevant for the decision, thereby reducing the overall amount of work by a great deal. This helps the decision-making process by removing unnecessary computations and keeping the analysis relevant and centered on the most useful parts of the dataset. Overall, FCM used in conjunction with MCDM increases the efficiency of a process without impacting the decisions being made.

Fuzzy cubic numbers take the representation of uncertainty to a new level because fuzzy cubic numbers take into con- sideration three data dimensions as opposed to strictly lower, middle, and upper bounds. Since fuzzy cubic numbers are richer structures, they provide a better insight into membership values in the fuzzy c-means clustering process. With cubic numbers available in fuzzy c-means, there are added advantages when working with data consisting of ambiguous and complex membership values, which help to generate more accurate clusters based on real-world patterns.

The use of fuzzy cubic numbers also helps to improve the differentiation of overlapping clusters to provide a broader spectrum of memberships, which accordingly minimizes misclassifications of the membership values. The use of fuzzy cubic numbers gives greater flexibility in the boundary conditions of clustering by defining the cluster boundaries to potential complexity in such areas as data variability or non-linear behavior.

The aim of this paper is to develop a fuzzy MCDM technique using fuzzy cubic numbers, in combination with fuzzy *C*-means clustering to handle large number of alternatives. The approach of integrating the clustering process with the decision process is used by representing the uncertainty by fuzzy cubic numbers to give a more accurate and flexible modeling framework to handle imprecise information in decision-making. The effectiveness of fuzzy C-means cluster- ing methods and fuzzy MCDM methods as tools in decision-making processes under uncertainty has been validated. Combined with the methods in this paper the fuzzy cubic numbers make up a very powerful framework for solving com- plex decision-making problems (with a combination of necessary classification and evaluation). Fuzzy cubic numbers extend the facility in representing uncertainty to include possibility and necessity functions and thus provide a more fine-grained view of the decision environment. The potential for using this integration to assist in improving decision- making in, for example, environmental management, risk analysis, or strategic planning is great. Since there is an increasing need to handle uncertainty and imprecision in various industries, fuzzy C-means clustering, fuzzy MCDM, and fuzzy cubic numbers are likely to be used more and more.

The proposed integrated approach can be applied to environmental management in classifying different regions accord- ing to their environmental impact while assessing multiple criteria, including cost, feasibility, and ecological sustainabil- ity. In such a context, fuzzy cubic numbers provide decision-makers not only the possibility to assess the membership of the regions in some categories but also to consider such regions as the possibilistic or necessity of the outcomes under different policy scenarios. Thereby, a more complete and rigorous decision-making framework is produced that ac- counts for the interdependent ability of real-world problems. Table 1 provides an overview of various machine learning (ML) techniques and multi-criteria decision-making (MCDM) methods applied across different domains.

Table 1: Summary of MCDM and ML techniques

Authors	Methodology
Zhao et al. (2019)	Fuzzy C-means (FCM), Fuzzy Rough Feature Selection.
Hu, et al. (2019)	Federated Multi-View Fuzzy C-means
Amoozad Mahdiraji, et	Clustering. Hesitant Fuzzy Information, Mixed-
al. (2024)	Method Analysis.
Singh, et al. (2019)	Fuzzy AHP, Multi-Criteria Decision-Making (MCDM),
Muneeza et al.	GIS. Intuitionistic Cubic Fuzzy Numbers, Multi-Criteria
(2022) Wang, et al.	Decision-Making. Two-Stage Fuzzy MCDM Sustainable
(2021) Rezaee et al.	Last-Mile.
(2018) Bandeira et	Dynamic Fuzzy C-means, DEA, Artificial Neural Net-
al. (2018) Sheu et al.	works. Fuzzy Multi-Criteria Decision-Making.
(2004) Moslem et al.	Hybrid Fuzzy-Based Ap- proach.
(2024) Wang et al.	Decomposed Fuzzy MCDM.
(2014) Anand et al	Fuzzy-Based Customer Clus- tering, Hierarchical
(2023)	Structure. Fuzzy C-means, MAIRCA- MCDM
Rostamzadeh et al.	Method.
(2020)	Fuzzy ARAS, Decision- Making Approach.

The Fuzzy C-Means (FCM) and multi-criteria decision making (MCDM) methods constitute an efficient framework for dealing with uncertainty and imprecision in complex decision processes to solve many complex management problems. FCM can be used to cluster points with flexible classification where data points have different degrees of membership (for example, in image segmentation and anomaly detection). Fuzzy MCDM deals with conflicting criteria and fuzzy data in decision-making, providing a much more realistic way of dealing with real-world problems.

In addition, this approach can be enriched using the integration of fuzzy cubic numbers that incorporate not only mem- bership values but also possibility and necessity functions. The richer, more complete three-dimensional uncertainty representation that we provide here offers a better model for decision-making in complex, high-stakes situations like risk analysis and strategic planning. When we add these features into account, cubic numbers provide a more subtle view of the uncertainty leading to better decision accuracy and flexibility.

Increasing complexity and uncertainty in modern supply chains motivate the incorporation of fuzzy logic-based method- ologies, e.g. Fuzzy *C*-Means clustering, attribute risk formed Criteria Analysis (MARICA and EDAS) into e-commerce logistics research. Fuzzy logic-based methodologies are consistent with the improvement of e-commerce supply chain adaptability and resilience. By focusing on the uncertainties and complexities innate to logistics systems, these methods represent the basis for innovative solutions that promote efficiency and risk reduction as well as customer experience improvement. With growing consumer expectations and intricate global supply chains, the justification, and even the necessity for such advanced analytical techniques to be adopted in research is justified for the sustainable growth of e-commerce enterprises.

This work is structured as follows: In Section 2, essential definitions and findings are provided to develop the concept. In Section 3, the methods with cubic fuzzy numbers are explained. The applicaion in E- commerce is demon- strated in Section 4. In Section 5, results are discussed by the analysis of outcomes derived from cubic models. Lastly, the research findings and implication for future research are concluded in Section 6.

Preliminaries:

Definition 2.1:

(Klir et al., 1995) A fuzzy set is a mathematical concept used to deal with the idea of partial truth, where truth values can range from completely true to completely false. Rather than needing to

belong to a classical set, with elements either belonging to a set or not belonging to the set (0 or 1), a fuzzy set has degree of memberships between 0 and 1.

Definition 2.2:

(Al-Sabri et al., 2023) A cubic fuzzy number (CFN) is an enhancement of fuzzy numbers having the characteristics of an interval-valued fuzzy number and a fuzzy number. CFNs represent uncertainty in data more effectively by integrating an interval of possible values alongside a degree of fuzziness. This approach enables the more nuanced and representation of uncertainty. Mathematically, a cubic fuzzy number C is expressed as: $C = ([e, f], g)$ where, $[e, f]$ allows to capture the range in which the fuzzy number is supposed to lie, hence a domain of uncertainty.
g represents the degree of membership of each point $x \in [e, f]$ to the fuzzy set, how weak or strong it captures the membership of every element x in the fuzzy set.

Definition 2.3:

(Kuo et al., 2012) Let $\alpha =< [a, b], c >$ and $\beta =< [d, e], f >$ where $0 \le a,b,c,d,e,f \le 1$ be two cubic fuzzy numbers. Then the arithmetic operation +, ×, ÷ are defined on cubic fuzzy numbers as:

1. $\alpha + \beta =< [a + d, b + e], c + f >$.
2. $\alpha \times \beta =< [min(ad, ae, bd, be), max(ad, ae, bd, be)], cf >=< [ad, be], cf >$.
3. $\alpha \div \beta =< [min(\frac{a}{d}, \frac{a}{e}, \frac{b}{d}, \frac{b}{e}), max(\frac{a}{d}, \frac{a}{e}, \frac{b}{d}, \frac{b}{e})], \frac{c}{f} >=< [\frac{a}{d}, \frac{b}{e}], \frac{c}{f} >$.

Example 2.1. *Let $\alpha =< [0.2, 0.3], 0.5 >$ and $\beta =< [0.4, 0.6], 0.7 >$ be two cubic fuzzy numbers. Then*

$$\alpha + \beta =< [0.2 + 0.4, 0.3 + 0.6], 0.5 + 0.7 >=< [0.6, 0.9], 1.2 >$$

The value should not exceeds than 1 therefore we use the formula $(c + f - cf)$ to minimize the value from 1. Then

$$\begin{aligned} \alpha + \beta &= < [0.2 + 0.4, 0.3 + 0.6], 0.5 + 0.7 >=< [0.6, 0.9], 1.2 - (0.5)(0.7) >=< [0.6, 0.9], 0.8 > \\ \alpha \times \beta &= < [\min(0.08, 0.12, 0.12, 0.18), \max(0.08, 0.12, 0.12, 0.18)], 0.35 >= [0.08, 0.8], 0.35 > \\ \alpha \div \beta &= < [\min(\frac{0.2}{0.4}, \frac{0.2}{0.6}, \frac{0.3}{0.4}, \frac{0.3}{0.6}), \max(\frac{0.2}{0.4}, \frac{0.2}{0.6}, \frac{0.3}{0.4}, \frac{0.3}{0.6})], \frac{0.5}{0.7} >= [\frac{0.2}{0.4}, \frac{0.3}{0.6}], \frac{0.5}{0.7} > \\ \alpha \div \beta &= < [\min(0.5, 0.3, 0.75, 0.5), \max(0.5, 0.3, 0.75, 0.5)], 0.7 >= [0.3, 0.75], 0.7 > . \end{aligned}$$

Definition 2.4. **(?)** *Let $A =< [\mu_A^L(x_i), \mu_A^U(x_i)], \mu_A^F(x_i) >$ and $B =< [\mu_B^L(x_i), \mu_B^U(x_i)], \mu_B^F(x_i) >$ be two CFN then the normalized euclidean distance on cubic fuzzy numbers is defined as:*

$$dis(A, B) = \left[\frac{1}{2n} \sum_{i=1}^{n} (\mu_A(x_i) - \mu_B(x_i))^2 \right]^{\frac{1}{2}} .$$

Moreover,

$$dis(A, B) = \left[\frac{1}{2n} (\mu_A^L(x_i) - \mu_B^L(x_i))^2 + (\mu_A^U(x_i) - \mu_B^U(x_i))^2 + (\mu_A^F(x_i) - \mu_B^F(x_i))^2 \right]^{\frac{1}{2}} . \quad (1)$$

Example 2.2. *Let $A =< [0.2, 0.3], 0.5 >$ and $B =< [0.4, 0.6], 0.7 >$ be two cubic fuzzy numbers. Then*

$$dis(A, B) = \sqrt{\frac{1}{2(2)} (0.2 - 0.4)^2 + (0.3 - 0.6)^2 + (0.5 - 0.7))^2} = 0.206.$$

***K*-Means Clustering:**

K-means is a hard clustering algorithm that divides a dataset into K distinct groups based on the positioning of the centroids. It functions by associating each data point with the closest centroid, subsequently refining the centroids iteratively to minimize the variance within each cluster. The algorithm focuses on the minimization of the total sum of squared distances between the data points and the centroids of the clusters they are assigned to.

Fuzzy C-Means Clustering:

A clustering method called fuzzy C-Means (FCM) enables each data point to be partially associated with multiple clusters compared to just one, as is the case of traditional clustering methods. By allowing for possible overlap between clusters, this represents the data's complexities.The membership values, which indicate the degree to which each point is connected to the cluster, make up the weights.

BORDA Count method:

The Borda Count method is used to find out the highest ranked preferences among a list of alternatives that rank alternatives in several ways and assign scores according to their rankings, with alternatives ranked higher receiving higher scores. Adding up scores determines which alternatives are the most preferred on an overall basis, making it a good way to aggregate rankings on multiple criteria.

Step 1:

Assign the alternative that the decision maker prefers $n - 1$ points, and the least preferred option receives zero points.

Step 2:

Apply Step 1 again to the outcomes of each MCDM approach.

Step 3:

Calculate the BORDA score sum for each MCDM technique.

Step 4:

Determine the best alternative based on its highest BORDA score.

This process helps to identify the option with the strongest overall preference across multiple decision-making criteria.

Methodology

The Fuzzy *C*-Means algorithm is an unsupervised clustering algorithm that divides a dataset into C clusters, assign- ing each data point a membership value that reflects how strongly it belongs to each cluster. Unlike traditional clustering methods, such as *K*-means, which assign each data point to only one cluster, FCM assignment, meaning each data point can belong to multiple clusters to varying extents. Fuzzy cubic numbers provide a reliable method of encoding the un- predictability and dependability of data in datasets that contain noisy, imprecise, or incomplete information (such as sensor readings or expert evaluations). The Multi-Attributive Ideal-Real Comparative Analysis (MAIRCA) method is a multi-criteria decision-making (MCDM) approach used to evaluate and rank alternatives based on multiple conflict- ing criteria. MAIRCA focuses on comparing alternatives to both an ideal solution and a real solution, allowing for the assessment of deviations from the average performance of all alternatives.MAIRCA serves as an effective tool in Multi-Criteria Decision Making (MCDM), particularly when enhanced with fuzzy cubic numbers, allowing it to better handle complex and uncertain decision environments. In the similar way, the EDAS (Evaluation Based on Distance from Average Solution) method compares alternatives according to how far apart they are from the average solution. The foundation of this strategy is a decision matrix that shows how well each option performs across a range of criteria. Fuzzy cubic numbers significantly enhance the EDAS framework's capacity to manage ambiguity and complexity in decision-making, making it a powerful for real-world uncertainty issues.

This section provides illustrations of the suggested integrated MCDM strategy based on fuzzy *C*-means, MAIRCA, EADAS, and BORDA Count methods employing fuzzy cubic numbers. Following is the breakdown of the our pro- posed algorithm for fuzzy cubic numbers:

Step 1. To Apply Fuzzy cubic C-means to given data.

Step 1a: Initialize Parameters Number of Clusters (C): Indicate the number of clusters.

Fuzziness Parameter (m): Choose a fuzziness factor, $m > 1$, that determines the degree of membership overlap. Higher values of m allow more overlap between clusters.

Threshold for Convergence: Set a threshold that will determine when the algorithm has converged.

Step 1b: Initialize data point Matrix. Create an initial matrix U, where each element represents the data point i. Create an initial cluster centers matrix with respect to number of clusters. This will be update iteratively.

Step 1c: Update Membership Degrees. For each data point, update its membership degree $\mu_{kj} =< [\mu^-_{kj}, \mu^+_{kj}], \mu^F_{kj} >$ for each cluster based on the distance between the point and the cluster center as follows

$$\mu_{kj} = \frac{1}{\sum_{i=1}^{C} \left(\frac{dis(<[x^-_k, x^+_k], x^F_k>, <[v^-_j, v^+_j], v^F_j>)}{dis(<[x^-_k, x^+_k], x^F_k>, <[v^-_i, v^+_i], v^F_i>)} \right)^{\frac{2}{m-1}}}, \tag{2}$$

where, $dis(< [x^-_k, x^+_k], x^F_k >, < [v^-_j, v^+_j], v^F_j >)$ is the normalized Eucledian distance from (1) between data point $< [x^-_k, x^+_k], x^F_k >$ and cluster center $< [v^-_j, v^+_j], v^F_j >$ is given as

$$dis(< [x^-_k, x^+_k], x^F_k >, < [v^-_j, v^+_j], v^F_j >) = \left(\frac{1}{2n} ((x^-_k - v^-_j)^2 + (x^+_k - v^+_j)^2 + (x^F_k - v^F_j)^2 \right)^{1/2}$$

Step 1d: Update Cluster Centers. Use the current membership matrix, calculate the center of each cluster v_j based on the weighted average of all data points, with weights given by membership degrees:

$$v_j = \frac{\sum_{k=1}^{n} (< [\mu^-_{kj}, \mu^+_{kj}], \mu^F_{kj} >)^m < [x^-_k, x^+_k], x^F_k >}{\sum_{k=1}^{n} (< [\mu^-_{kj}, \mu^+_{kj}], \mu^F_{kj} >)^m}, \tag{3}$$

where, $< [x^-_k, x^+_k], x^F_k >$ is a data point and n is the total number of data points.

Step 1e: Check for Convergence. After updating cluster centers and membership degrees, check if the difference between new and old values is less than the threshold ϵ. If not, repeat steps 3 and 4 until convergence.

Step 1f: Classification. Once convergence is achieved, data points can be classified by assigning each point to the cluster where it has the highest membership degree.

The algorithmic figure for Fuzzy cubic C-means and fuzzy cubic mcdm is given in the Figure 1:

Step 2: To apply fuzzy cubic MAIRCA Method on centroids A_i obtained in step 1.

Following are the steps of fuzzy cubic MAIRCA method on centroids A_i:

Step 2a: Forming the Initial Decision Matrix. Construct the initial decision matrix by organizing the performance values of all alternatives A_i against each criterion C_j.

Step 2b: Calculating Preference Values for Alternatives (PA_j). Assume there is no initial preference for any alternative. In this case, the priority for all criteria remains the same and can be calculated as follows:

$$P_{A_j} = \frac{1}{m}, \sum_{j=1}^{m} P_{A_j} = 1 \quad j = 1, 2, \ldots, n \tag{4}$$

where m is the number of alternatives.

Step 2c: Determining Elements of the Theoretical Rating Matrix (tp_{ij}). The elements of the theoretical rating matrix are calculated using the formula:

$$tp_{ij} = P_{A_j} \cdot < [w_j^-, w_j^+], w_j^F > \quad i = 1, 2, \ldots, m; \quad j = 1, 2, \ldots, n \tag{5}$$

Here,$< [w_j^-, w_j^+], w_j^F >$ represents the weight of the j-th criterion.

Step 2d: Determining Elements of the Real Rating Matrix (tr_{ij}). Calculate the elements of the real rating matrix based on whether the criterion is "benefit" (higher is better) or "cost" (lower is better):
For benefit criteria

$$tr_{ij} =< [tp_{ij}^-, tp_{ij}^+], tp_{ij}^F > \cdot \left(\frac{< [x_{ij}^-, x_{ij}^+], x_{ij}^F > -(< [x_i^-, x_i^+], x_i^F >)^-}{(< [x_i^-, x_i^+], x_i^F >)^+ - (< [x_i^-, x_i^+], x_i^F >)^-} \right) \tag{6}$$

For cost criteria

$$tr_{ij} =< [tp_{ij}^-, tp_{ij}^+], tp_{ij}^F > \cdot \left(\frac{(< [x_i^-, x_i^+], x_i^F >)^- - (< [x_i^-, x_i^+], x_i^F >)^+}{< [x_{ij}^-, x_{ij}^+], x_{ij}^F > -(< [x_i^-, x_i^+], x_i^F >)^+} \right), \tag{7}$$

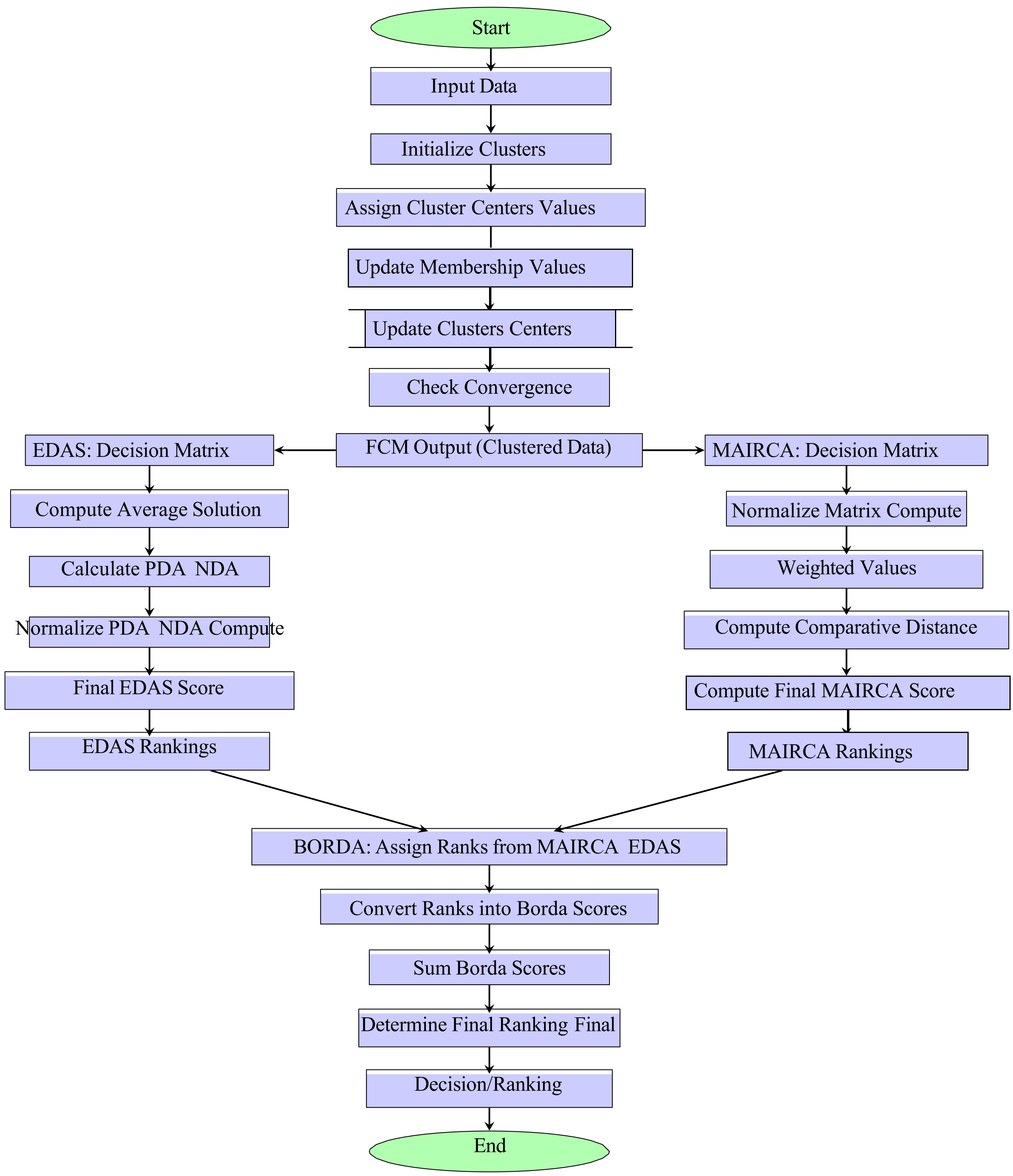

Figure 1: Fuzzy cubic *C*-Means with fuzzy cubic mcdm algorithm

where, $< [x_{ij}^-, x_{ij}^+], x_{ij}^F >$ is the value of the i-th alternative for the j-th criterion. $([\mathrm{x}_i^-, x_i^+], x_i^F >)^+$ is the best (maximum) value of the i-th criterion. $([\mathrm{x}_i^-, x_i^+], x_i^F >)^-$ is the worst (minimum) value of the i-th criterion.

Step 2e: Calculating the Total Gap Matrix (g_{ij}). The gap between theoretical and real ratings is determined as follows:

$$g_{ij} =< [tp_{ij}^-, tp_{ij}^+], tp_{ij}^F > - < [tr_{ij}^-, tr_{ij}^+], tr_{ij}^F > . \tag{8}$$

Step 2f: Determining Final Values of Criterion Functions (Q_i). The final value for each alternative is obtained by summing the total gaps for all criteria:

$$Q_i = \sum_{j=1}^{n} < [g_{ij}^-, g_{ij}^+], g_{ij}^F > . \tag{9}$$

This value represents the cumulative gap for each alternative.

Step 3: To apply fuzzy cubic EDAS method on centroids A_i obtained in step 1. Following are the steps of fuzzy cubic EDAS method on centroids A_i:

where, x_{ij} denotes the performance of alternative i under criterion j.

Step 3b: Calculate the Average Solution Matrix (AV). The average solution for each criterion is calculated by taking the mean of all alternatives for that criterion. This is done using the following equation:

$$AV_j = \frac{1}{m} \sum_{i=1}^{m} < [x_{ij}^-, x_{ij}^+], x_{ij}^F > \tag{10}$$

Here, AV_j is also a cubic number which represents the average value for criterion j.

Step 3c: Calculate Positive and Negative Distances. Next, the positive and negative distances are calculated for each alternative relative to the average solution, taking into account whether the criteria are benefit-based or cost-based. **For Benefit-Based Criteria:** The Average Positive Distance (PDA) and Average Negative Distance (NDA) are calculated as follows:

$$PDA_{ij} = \max \left(0, \frac{< [x_{ij}^-, x_{ij}^+], x_{ij}^F > - AV_j}{AV_j} \right) \tag{11}$$

$$NDA_{ij} = \max \left(0, \frac{AV_j - < [x_{ij}^-, x_{ij}^+], x_{ij}^F >}{AV_j} \right) \tag{12}$$

$$PDA_{ij} = \max \left(0, \frac{AV_j - < [x_{ij}^-, x_{ij}^+], x_{ij}^F >}{AV_j} \right) \tag{13}$$

$$NDA_{ij} = \max \left(0, \frac{< [x_{ij}^-, x_{ij}^+], x_{ij}^F > - AV_j}{AV_j} \right) \tag{14}$$

Step 3d: Calculate Weighted Total Distances for Each Alternative. The weighted positive and negative distance values for each alternative are then calculated by summing the individual distances across all criteria. These are computed using the following equations:

Step 3d: Calculate Weighted Total Distances for Each Alternative. The weighted positive and negative distance values for each alternative are then calculated by summing the individual distances across all criteria. These are computed using the following equations:

$$SP_i = \sum_{j=1}^{n} < [w_j^-, w_j^+], w_j^F > \cdot PDA_{ij} \quad (15)$$

$$SN_i = \sum_{j=1}^{n} < [w_j^-, w_j^+], w_j^F > \cdot NDA_{ij} \quad (16)$$

Where $< [w_j^-, w_j^+], w_j^F >$ represents the weight of criterion j.

Step 3e: Normalize the Distances. The total positive and negative distances for each alternative are normalized as follows:

$$NSP_i = \frac{SP_i}{\max_i(SP_i)} \quad (17)$$

$$NSN_i = \frac{SN_i}{\max_i(SN_i)} \quad (18)$$

Here, NSP_i and NSN_i are the normalized positive and negative distance values for alternative i.

Step 3f: Calculate the Evaluation Score. The final evaluation score AS_i for each alternative is calculated by averaging the normalized positive and negative distances:

$$AS_i = \frac{1}{2}(NSP_i + NSN_i) \quad (19)$$

The evaluation scores AS_i will be between 0 and 1. The alternative with the highest evaluation score AS_i is considered the best, and the alternatives are ranked in descending order of their AS_i values.

Step 4: To apply BORDA count method on rankings obtained from Step 2 and Step 3. The final ranking of our proposed integrated technique is obtained by applying BORDA count method on rankings obtained from Step 2 and Step 3.

Application of Risk Assessment and Mitigation in E-Commerce Logistics Using Fuzzy C-Means Clustering and Hybrid MCDM Techniques:

As e-commerce continues to grow at a rapid pace, the problem of navigating through enormous delivery route networks, multiple fulfillment centers, and transportation systems under high variability and demanding customer ex- pectations comes to the fore. The ambiguous and imprecise data that characterize these systems usually make traditional risk management approaches unable to represent the data and relations, hence making fuzzy logic the best solution to address these challenges (Song et al., 2019) .

Multiple, interdependent factors, including traffic conditions, order demand, and inventory levels, fluctuate unpre- dictably in e-commerce logistics. FCM clustering allows for the classification of and prioritizing of risks within this complex environment by probabilistic membership values assigned to the data points. This capability permits a finer- grained analysis of risk zones to inform more reasoned decisions on resource allocation and logistical planning. Using FCM, researchers and practitioners can identify (most of) the high-risk areas which can then be pinpointed for more focused interventions to reduce disruptions and increase operational reliability.

Second, the need to evaluate the multiple criteria simultaneously when designing and implementing the logistics strate- gies is another critical motivation. The need for this is met by MARICA Multi-Criteria Decision Making and EDAS Evaluation Based on Distance from

Average Solution (MCDM) methods which account for conflicting considerations,

e.g. minimizing delivery costs and costs on the one hand and maximizing the satisfaction of the customer on achieving the delivery and guaranteeing timely delivery on the other hand. Using fuzzy logic, MARICA and EDAS incorporates human judgment and subjective preferences into the decision problem where often unavoidable tradeoffs exist in logis- tics operations simplifying the problem and making it operational [4]. As such, it is a valuable tool for the optimization of complex systems, where the application of traditional, deterministic methods does not lead to an answer.

In the framework of this research, 15 delivery routes within the limits of a major metropolitan region were chosen for this study, with order quantities ranging from 200 to 300 orders per day. Google Maps are used to produce the nec- essary spatial data by obtaining the geographic coordinates of each route's start and finish points. In order to reduce operational complexity variations and guarantee that the study's findings are clearly communicated, delivery routes with comparable order volumes are chosen. Routes with very low order quantities might not need sophisticated risk management techniques because they pose very little operational risk. Routes with abnormally high order volumes, on the other hand, might require unique risk mitigation techniques that are outside the scope of this study. The study intends to preserve uniformity in assessing risk variables like traffic congestion and delivery times by concentrating on routes with similar order quantities.

To demonstrate the consistency and breadth of the chosen routes, the geographic location information for each route's beginning and ending sites, along with their respective distances, is provided below in the form of cubic fuzzy numbers. This method guarantees that the outcomes of the risk assessment and clustering are significant and widely applicable to

Table 2: Geographic Coordinates of Routes

Routes	Traffic congestion	Order Quantity
RT001	< [0.6, 0.7], 0.8 >	< [0.3, 0.35], 0.4 >
RT002	< [0.4, 0.5], 0.6 >	< [0.1, 0.15], 0.2 >
RT003	< [0.1, 0.2], 0.3 >	< [0.4, 0.45], 0.5 >
RT004	< [0.2, 0.3], 0.4 >	< [0.6, 0.65], 0.7 >
RT005	< [0.3, 0.4], 0.5 >	< [0.7, 0.75], 0.8 >
RT006	< [0.8, 0.9], 1.0 >	< [0.2, 0.25], 0.35 >
RT007	< [0.5, 0.6], 0.7 >	< [0.15, 0.2], 0.25 >
RT008	< [0.7, 0.8], 0.9 >	< [0.45, 0.55], 0.65 >
RT009	< [0.5, 0.7], 0.8 >	< [0.75, 0.85], 0.9 >
RT010	< [0.4, 0.6], 0.7 >	< [0.3, 0.5], 0.55 >
RT011	< [0.3, 0.5], 0.7 >	< [0.1, 0.25], 0.45 >
RT012	< [0.2, 0.4], 0.6 >	< [0.15, 0.35], 0.4 >
RT013	< [0.1, 0.3], 0.5 >	< [0.8, 0.9], 0.95 >
RT014	< [0.6, 0.9], 1.0 >	< [0.75, 0.85], 0.95 >
RT015	< [0.7, 0.9], 1.0 >	< [0.6, 0.8], 1.0 >

actual logistical operations. The geographic coordinates of each routein relation to each criterion is provided in Table 2.

A potent technique for classifying delivery routes according to their risk profiles is fuzzy C-Means (FCM) clustering, which takes into account a number of factors, in this instance order volumes and traffic congestion. By enabling each data point (delivery channel) to belong to several clusters with varied degrees of membership, FCM deviates from conventional hard clustering algorithms. Because it accounts for the inherent unpredictability and overlap in route risk characteristics, this flexibility is especially beneficial for logistics risk management.

The coordinate information for each alternative delivery route for e-commerce products is determined using the Fuzzy C-Means Clustering Algorithm, as shown in Table 3. The decision matrix used by the MAIRCA and EDAS Methods is displayed in Table 4. Table 5 displays the outcomes of the decision-making techniques. While comparable rankings are derived from some of the techniques. For certain strategies, the choices are not arranged in the same sequence as for others. For example, the MAIRCA reference point is the best option (RT003), but for EDAS, the best option is the (RT002). Therefore, the obtained rankings must be merged according to dominance in order to examine the combined effect of the approaches on the alternative rankings.

Table 6 displays the outcomes of the Borda Count approach, which is applied to this combination.

Table 3: FCM output routes

Routes	Traffic congestion	Order Quantity
RT001	< [0.456, 0.558], 0.658 >	< [0.136, 0.19], 0.24 >
RT002	< [0.663, 0.772], 0.872 >	< [0.422, 0.527], 0.618 >
RT003	< [0.778, 0.879], 0.979 >	< [0.21, 0.262], 0.357 >
RT004	< [0.106, 0.207], 0.307 >	< [0.4, 0.452], 0.502 >
RT005	< [0.499, 0.698], 0.798 >	< [0.744, 0.845], 0.895 >
RT006	< [0.255, 0.356], 0.456 >	< [0.647, 0.699], 0.749 >

The BORDA method is used in this study to integrate different MCDM techniques in order to get a consensus on the findings. Table 5 suggests that the alternatives are ranked differently by MAIRCA and EDAS. Certain MCDM strate- gies, for instance, evaluate criteria and alternatives pairwise, whereas other techniques compare criteria and alternatives with an ideal solution using distance-based metrics. Some approaches are more appropriate for quantitative criteria, while others may deal with fuzzy data or qualitative criteria. Certain approaches are more sensitive to the weights of the criteria, while others are more resilient to weight changes. Therefore, different MCDM approaches may have different strengths and limitations depending on the circumstances and the nature of the decision problem. Select the MCDM strategy that best fits the problem's characteristics and your decision-making goals. Researchers are thinking about

Table 4: Decision matrix for MAIRCA, EDAS methods.

Alternatives	Delivery Time	Cost efficiency	Products Availability	Customer Pride
RT 001	< [0.25, 0.35], 0.4 >	< [0.4, 0.45], 0.55 >	< [0.2, 0.3], 0.4 >	< [0.75, 0.8], 0.85 >
RT 002	< [0.1, 0.2], 0.35 >	< [0.2, 0.25]0.35 >	< [0.4, 0.5], 0.6 >	< [0.3, 0.35], 0.4 >
RT 003	< [0.35, 0.4], 0.45 >	< [0.15, 0.2], 0.25 >	< [0.1, 0.2], 0.3 >	< [0.5, 0.55], 0.6 >
RT 004	< [0.4, 0.5], 0.6 >	< [0.7, 0.75], 0.8 >	< [0.3, 0.35], 0.45 >	< [0.4, 0.45], 0.55 >
RT 005	< [0.5, 0.55], 0.6 >	< [0.65, 0.7], 0.75 >	< [0.5, 0.55], 0.65 >	< [0.5, 0.6], 0.65 >
RT 006	< [0.1, 0.15], 0.25 >	< [0.5, 0.6], 0.7 >	< [0.7, 0.75], 0.85 >	< [0.8, 0.9], 0.95 >

Table 5: The results of used methods.

Alternatives	MAIRCA	Ranking	EDAS	Ranking
RT 001	< [0.072, 0.086], 0.064 >	5	< [0.499, 0.53], 0.492 >	4
RT 002	< [0.101, 0.125], 0.118 >	2	< [0.358, 0.425], 0.51 >	1
RT 003	< [0.128, 0.129], 0.127 >	1	< [0.5, 0.5], 0.5 >	2
RT 004	< [0.069, 0.314], 0.11 >	3	< [0.341, 0.384], 0.482 >	5
RT 005	< [0.071, 0.286], 0.088 >	4	< [0.305, 0.354], 0.322 >	6
RT 006	< [0.011, 0.015], 0.004 >	6	< [0.5, 0.5], 0.5 >	3

employing a hybrid strategy that blends two or more MCDM approaches in order to overcome the unique drawbacks of each MCDM method or expand on its benefits. As a result, integrated and hybrid approaches decrease subjectivity in decision-making processes and yield more thorough and precise findings.

Table 6: The result of BORDA method.

Alternatives	MAIRCA		EDAS		BORDA	
	Ranking	Score	Ranking	Score	Score	Ranking
RT 001	5	1	4	2	3	5
RT 002	2	4	1	5	9	1
RT 003	1	5	2	4	9	2
RT 004	3	3	5	1	4	3
RT 005	4	2	6	0	2	6
RT 006	6	0	3	3	3	4

Figure 2 is the graphical representation of comparison analysis of used MCDM techniques.

Results and discussions

The placement of delivery routes is crucial for ensuring timely product distribution, as it greatly affects the overall efficiency and performance of the system. Key factors that influence route location decisions include:

Efficiency of FCM Clustering: A data-driven comprehension of risk considerations is made possible by the application of FCM clustering for delivery route classification. The strategy reduces delivery disruptions proactively by selecting low-risk routes.

MCDM's Value in Strategy Evaluation: MARICA MCDM shown to be successful in assessing intricate logistical situ- ations with several competing requirements. By considering variables like time, expense, and satisfaction, the approach offered a thorough and well-rounded foundation for making decisions.

Benefits to Operations and Strategy: The integration of FCM and MCDM enhanced logistical processes by: Reduc- ing Delays: By using low-risk routes, traffic and inventory problems caused fewer interruptions. Cost-cutting: Fuel consumption and operating expenses are decreased through effective route selection. Increasing Customer Loyalty: Recurring business and increased satisfaction are the results of on-time deliveries.

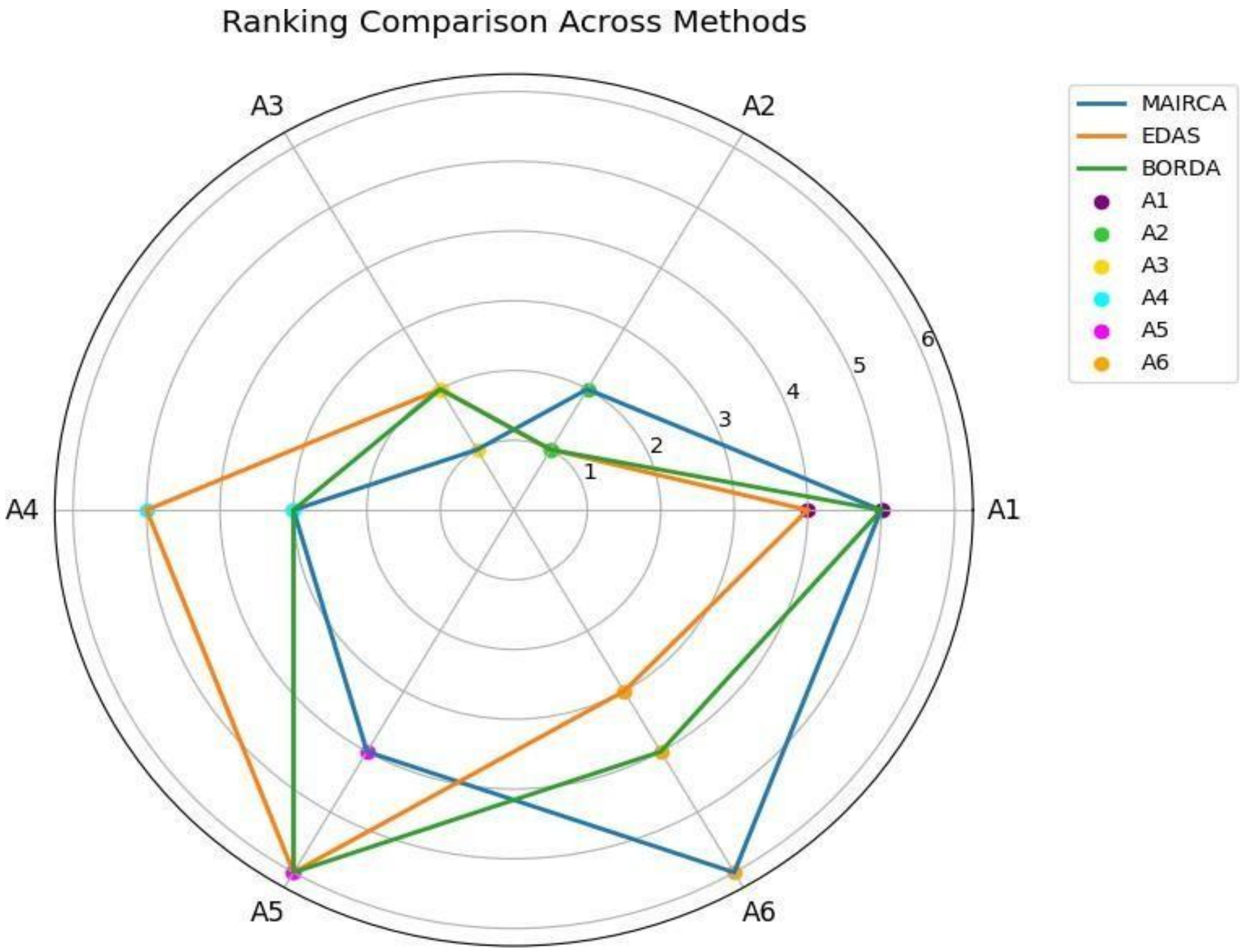

Figure 2: Representation of the results of the used method

To ensure timely deliveries and maintain customer satisfaction, e-commerce delivery route selection must consider mul- tiple factors, including cost efficiency, access to transportation infrastructure, proximity to distribution centers, traffic conditions, and regulatory requirements. In this study, we integrate the BORDA method with EDAS and MAIRCA approaches to reach a consensus on the optimal delivery route. Using the Fuzzy C-Means (FCM) algorithm on the dataset in Table 2, we derive optimized results presented in Table 3, which highlight the most efficient delivery route options by minimizing route complexity.

To make the selection process sharper, we utilize multi-criteria decision-making (MCDM) techniques applied to the different routes against a set of evaluation criteria. The MCDM applications produce different results as MAIRCA rates Route 3 as the most ideal whereas EDAS recommends Route 2. Therefore, in order to overcome the conflict between these two applications, Borda Count is used to normalize the rankings from both methods. The final ranking according to Borda count analysis reaffirms Route 2 as the most preferred option for providing on- time and reliable e-commerce delivery. A well-rounded evaluation of key factors such as delivery times, cost-efficiency, and the like including risk fac- tors such as congestion, route reliability, and possibly delayed deliveries confirm this conclusion. Route 2 is, among the others, most favorable for minimizing operational risks while guaranteeing timely delivery of shipments. The present findings highlight the necessity of implementing the efficient delivery routes selected within the e- commerce logis- tics maximizing customer satisfaction and building resilient supply chains. Multi-Criteria Decision Making (MCDM) methods provide a systematic and organized approach to the analysis of contrasting workable sites, leading to the iden- tification of the best one for distribution. This research makes the case that applying multiple MCDM methodologies leads to conclusions that are stronger and much more detailed than what one would achieve through single-method examples. The summarization of results generated by different MCDM methods would then be approached with the aid of the Borda method. The main objective of this combined strategy is to overcome the limitations that may arise from individual methods.This integrated approach offers a more reliable and accurate assessment of the available location alternatives by utilizing the advantages of each technique.

Conclusion

In conclusion, the results highlight the importance of complex computational methods in improving service quality, lowering risks associated with delivery, and improving supply chains' resilience. Providing useful tools and insights to help decision-makers navigate the complexities of delivery risk management, this study adds to the expanding body of research in e-commerce logistics. Decision-makers may arrive at more accurate conclusions in this approach, which also reduces computing complexity and time. The findings of this study offer a trustworthy model for delivery route selection with the goal of improving logistical efficiency. This research is particularly relevant in today's context, where social media use is widespread and online shopping has become the preferred mode of purchasing for many. In this way, e-commerce provides people with many benefits, such as ease of use, accessibility, and a variety of options for both customers and businesses. Customers can save time and effort by shopping whenever and wherever they want without having to go to physical stores. Access to a wide range of products, affordable prices, thorough reviews, and comparison tools that aid in well-informed decision-making are all advantageous to consumers. Moreover, by giving people a way to reach international markets without having to be physically present, e-commerce empowers people, particularly small business owners and entrepreneurs.Additionally, it helps create jobs in industries like logistics, digital marketing, customer service, and technology. E-commerce fills the gap by enabling access to goods and services that might otherwise be inaccessible to people in remote areas. As a result, both qualitative and quantitative evaluations are necessary when choosing the best delivery route. Through the integration of Multi-Criteria Decision Making (MCDM) and Machine Learning (ML) techniques, the framework presented in this study provides decision-makers with a com- prehensive tool for navigating advanced logistics challenges.

The proposed methodology holds potential for future research, offering decision-makers enhanced capabilities by in- tegrating MCDM with Machine Learning (ML) techniques. This combined approach allows for more informed, data- driven decision-making by uncovering deeper insights from complex datasets. It can be applied to a variety of decision- making contexts where multiple resources and predefined objectives must be balanced to achieve the most effective outcome. By adjusting the structure of evaluation criteria, the framework remains flexible and adaptable to different scenarios. Considering factors such as time, cost, and outcome quality, this approach provides decision-makers with a broader range of practical and well informed options.

Data Availability Statement:

There is no data used to support the findings.

Conflicts of Interest:

The authors declare that they have no conflicts of interest.

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