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Sustainable Last-Mile Delivery Solution Evaluation in the Context of a Developing Country: A Novel OPA–Fuzzy MARCOS Approach

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Abstract: With the surge in e-commerce volumes during COVID-19, improving last-mile logistics is extremely challenging, specifically for developing economies, due to poor infrastructures, lack of stakeholders' cooperation, and untapped resources. In the context of Vietnam, there are certain solutions that can bring more efficient and sustainable last-mile logistics. In this paper, to evaluate and rank these potentially sustainable last-mile solutions (LMSs), we propose a novel hybrid multiple attribute decision-making (MADM) model that combines the Ordinal Priority Approach (OPA) and fuzzy Measurement of Alternatives and Ranking according to the COmpromise Solution (fuzzy MARCOS). Twelve sustainability factors of technical, economic, social, and environmental aspects were determined through a literature review and experts' opinions to employ the MADM approach. A case study evaluating five LMSs in Vietnam concerning their sustainable implementation is solved to exhibit the proposed framework's applicability. From the OPA findings, "efficiency", "costs of implementation and control", "voice of customer", "reliability", and "flexibility" are the topmost criteria when considering a new LMS implementation in the context of Vietnam. Moreover, sensitivity analysis and comparative analysis were performed to test the robustness of the approach. The results illustrate that the applied methods reach consistent solution rankings, where LMS-03 (convenience store pickup), LMS-02 (parcel lockers), and LMS-01 (green vehicles) are the best solutions in Vietnam. The study holds novelty in evaluating last-mile initiatives for Vietnam by utilizing a unique approach in the form of two novel MADM techniques, thus providing significant insights for research and applications.

Keywords: last-mile delivery; urban logistics; sustainability; MADM; conflicting criteria; OPA; fuzzy MARCOS

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1. Introduction

Last-mile delivery refers to the final leg of supply chain operations, the process in which a product arrives at the buyer's door from a distribution center. Along with the strong development of e-commerce after the COVID-19 pandemic, it is urgent for businesses to achieve a sustainable solution in last-mile delivery in logistics and supply chain management not only for quick and efficient shipments for retaining customer needs but also to optimize costs, increase profits, and reduce environmental impacts. Overall, the cost of last-mile delivery is astronomical; the last-mile cost can be up to 50% of the total logistics costs, although this share is highly sensitive [1]. The constantly expanding requirement for same-day delivery, outdated IT systems, and inadequate logistics visibility are just a few of the difficulties that make supply chain management and last-mile delivery operations the most expensive, not to mention increasing fuel prices. Requirements for efficient last-mile deliveries are also becoming increasingly stricter in urban environments and developing economies due to infrastructure planning, the perception of citizens, and especially environmental impacts, such as air pollution, traffic jams, and noise pollution [2]. The last-mile process must also be safe in the trend of epidemic prevention to ensure that the contact between the shipper and the consignee does not spread COVID-19 while maintaining the speed and quality of delivery services.

E-commerce in Vietnam boomed in the period 2015–2021, gradually becoming a popular channel for young people as the rate of using the internet and electronic devices reached 70% of the national population [3]. Overcoming difficulties caused by the COVID-19 pandemic, e-logistics continued to thrive in the context of the "new normal", growing even more impressively than before the pandemic. However, last-mile logistics in Vietnam are still very primitive due to the lack of a professional and well-covered infrastructure network. Monotonous last-mile delivery solutions leading to low delivery quality and high costs have not yet met customer requirements [4]. E-commerce businesses still have to use traditional last-mile solutions, mainly using motorbikes, which makes it difficult to fulfill e-commerce orders with diverse and constantly changing requirements and, at the same time, seriously affects the environment and the common sustainable development goals. In light of the fact that last-mile logistics bottlenecks continue to be a massive pain point in an increasingly competitive market, businesses in the Vietnamese logistics ecosystem are racing to develop new technologies and propose innovative last-mile solutions to increase parcel volume, expedite deliveries, and delight customers. Thus, the objective of this paper is to evaluate and rank innovative and potentially sustainable last-mile solutions (LMSs) that businesses can apply to streamline their e-logistics systems. Accordingly, the planning and implementation of each LMS are investigated in consonance with the principles of economic, social, and environmental sustainability from a developing country's perspective.

The evaluation of LMSs in the present investigation requires simultaneously considering various design criteria derived from the academic literature and field experts. Multiple attribute decision-making (MADM) techniques have appeared to be promising for this task. In this paper, two novel MADM methods, named the Ordinal Priority Approach (OPA) and Measurement of Alternatives and Ranking according to the COmpromise Solution in a fuzzy environment (fuzzy MARCOS), were merged to suggest a novel approach for LMS evaluation. Both methods are the newest MADM methods of objective decision-making that have been proven effective in solving MADM problems. OPA was proposed in 2020 by Ataei, Mahmoudi, Feylizadeh, and Li, and as the name suggests, the method solves MADM problems that can be structured through ordinal relations [5]. Recent studies have verified its soundness in solving MADM problems to define expert weights and evaluate attributes/alternatives simultaneously. While most subjective models for determining criterion/alternative weighting coefficients, such as FUCOM [6], BWM [7], and LBWA [8], that are based on comparisons in pairs of home matrix elements may impair the quality of the solution in the case of comparisons of more than eight criteria/alternatives, OPA eliminates the problem of a limited range of predefined scales by defining weighting criteria/alternatives based on predefined ranks. The technique objectively, flexibly, and effectively assists an evaluation process without concerns for pairwise comparisons, normalization, and completeness of data. MARCOS was introduced in 2020 [9] as an effective and strong technique that empowers the decision-making environment by handling many deficiencies of other MADM techniques, such as neglecting the relative importance of distances and exhausting calculations. The method considers different parameters based on the alternatives' performance to determine their final performance score using utility-based functions. Then, the extended version of MARCOS to consider parameters in an uncertain environment through triangular numbers (TFNs), i.e., the novel fuzzy MARCOS method, was developed by Stanković et al. [10].

To the best of the authors' knowledge, this attempt is the first study to integrate OPA and fuzzy MARCOS to demonstrate their robustness in precisely solving complex decision-making, evaluation, and assessment problems. We adopt this novel hybrid approach to take the advantages offered by both methods, designating OPA for weighting the considered criteria and fuzzy MARCOS for ranking the LMSs (alternatives).

2. Literature Review

In this section, we aim to build literature on two aspects, (1) LMSs development and evaluation as well as the design criteria, and (2) applications of MADM methods. Below, we review relevant studies and point out the gap in the literature.

2.1. Review of Initiatives, Solutions, and Technologies of Last-Mile Logistics and Their Evaluation Criteria

LMS development and assessment is an important research topic, and it receives wide attention since it provides meaningful information to various stakeholders, such as logistics providers, urban planners, and governments. In recent years, several efforts have attempted to reduce the negative impacts and improve the efficiency of last-mile delivery. A burgeoning stream of research has been devoted to the topic, with various measures, initiatives, and concepts of last-mile logistics has been defined. Tadić et al. [11] evaluated various measures and initiatives in urban last-mile logistics, including different categories of logistics centers, environmentally friendly vehicles, and standardized logistics units. Iwan et al. [12] analyzed the usability and efficiency of parcel lockers as a solution to last-mile delivery systems in Poland. Nocerino et al. [13] exhibited the efficiency of electric bicycles and electric scooters in delivering goods in urban areas and contributing to mitigating logistic impacts in urban areas instead of traditional combustion engine ones. Lebeau et al. [14] focused on determining the best LMS for the City of Brussels, considering various configurations of urban consolidation centers, their conjunction with different vehicle classifications, toll charges, and time access limits. Huang and Ardiansyah [15] focused on developing a solid initial crowdsourcing integration strategy. Kumar and Bharj [16] investigated a new solution for the home delivery of logistics in urban areas in India called "solar hybrid e-cargo rickshaw" as a feasible alternative to traditional vehicles regarding transportation cost reduction for perishable products and energy savings. Figliozzi [17] provides valuable insights into the last-mile logistics behind the efficiency of drones and ground delivery vehicles in terms of vehicle miles, energy consumption, and CO_2 emissions. Leyerer et al. [18] evaluated the efficiency of a hybrid LMS that integrates parcel lockers and electro-powered cargo cycles for the case of Hannover. Nakayama and Yan [19] created a methodology to analyze the accessibility of convenience stores and their potential contribution to solving the redelivery problem.

In this paper, some of the most analyzed initiatives, concepts, and technologies for last-mile delivery, which are the elements of the LMSs proposed, are green vehicles, parcel lockers, convenience store pickup, autonomous vehicles, and crowdsourcing. Table 1 shows the distribution of recent studies regarding the initiatives mentioned earlier. To evaluate these solutions, the authors mainly deal with the problems and analysis of the implementation of individual LMS in terms of their ability to achieve economic, social, and environmental sustainability from a developing country's perspective. In this direction, we try to evaluate previous studies to establish a viable set of criteria alongside the proposed hybrid MADM approach development, as displayed in Table 2.

Table 1. Review of initiatives, solutions, and technologies of last-mile logistics.

Authors	Green Vehicles	Parcel Lockers	Convenience Store Pickup	Autonomous Vehicles	Crowdsourcing Delivery
Tadić et al. (2014) [11]	v				
Iwan et al. (2016) [12]		v			
Wang et al. (2016) [20]					v
Nocerino et al. (2016) [13]	v				
Castillo et al. (2017) [21]					v

Table 1. *Cont.*

Authors	Green Vehicles	Parcel Lockers	Convenience Store Pickup	Autonomous Vehicles	Crowdsourcing Delivery
Vakulenko et al. (2018) [22]		v			
Yuen et al. (2018) [23]			v		
Lebeau et al. (2018) [14]	v				
Huang and Ardiansyah (2019) [15]					v
Karak and Abdelghany (2019) [24]				v	
Nakayama and Yan (2019) [19]			v		
van Duin et al. (2020) [25]		v			
Kumar and Bharj (2020) [16]	v				
Figliozzi (2020) [17]				v	
Leyerer et al. (2020) [18]		v			
Krstić et al. (2021) [26]	v	v		v	v
Gielens et al. (2021) [27]			v		
Zuniga-Garcia et al. (2022) [28]	v				

Note: the symbol "v" means last-mile technology used in the reviewed research.

Table 2. Review of evaluation criteria on LMS.

Criteria Group	Criteria	References
Technical	Efficiency	Krstić et al. (2021) [26], Švadlenka et al. [29], Büyüközkan and Uztür [30], Awasthi and Chauhan [31], Szmelter-Jarosz and Rześny-Cieplińska [32], Tadić et al. [33], Wang et al. [34]
	Reliability	Krstić et al. (2021) [26], Švadlenka et al. [29], Awasthi and Chauhan [31], Wang et al. [35], Tadić et al. [36]
	Flexibility	Krstić et al. (2021) [26], Švadlenka et al. [29], Awasthi and Chauhan [31], Wang et al. [35], Tadić et al. [36]
	Possibility of implementation	Tadić et al. [11], Krstić et al. (2021) [26], Büyüközkan and Uztür [30]
	Traceability and information security	Büyüközkan and Uztür [30], Wang et al. [34]
Economic	Costs of implementation and control	Tadić et al. [11], Lebeau et al. [14], Krstić et al. (2021) [26], Švadlenka et al. [29], Büyüközkan and Uztür [30], Awasthi and Chauhan [31], Tadić et al. [33], Tadić et al. [36], Janjevic et al. [37]
Social	Consistency with urban planning	Tadić et al. [11], Lebeau et al. [14], Krstić et al. (2021) [26], Švadlenka et al. [29], Awasthi and Chauhan [31], Tadić et al. [36]
	Voice of customer	Wang et al. [35]
	Mobility	Tadić et al. [11], Krstić et al. (2021) [26], Tadić et al. [36], Janjevic et al. [37]
	Cooperation of stakeholders	Büyüközkan and Uztür [30]
Environmental	Air Pollution	Krstić et al. (2021) [26], Wang et al. [35], Tadić et al. [36]
	Energy savings	Tadić et al. [11], Krstić et al. (2021) [26], Tadić et al. [36]

2.2. Review of MADM Methods

In the literature on logistics and supply chain management, there are numerous examples of the implementation of different MADM methods, either alone or in integration with other methods, in a traditional or fuzzy environment. Li et al. [38] used fuzzy TOPSIS in the selection problem of logistics center locations. To evaluate green suppliers, Buyukozkan and Cifci [39] proposed a novel hybrid approach based on fuzzy DEMATEL, fuzzy ANP, and fuzzy TOPSIS. Wang et al. [35] used fuzzy AHP-VIKOR for the selection of the logistics providers. Krstić et al. [26] used fuzzy Delphi-VIKOR for the evaluation of sustainable last-mile solutions. Sawicka and Zak [40] applied ELECTRE for the ranking of the distribution system's redesign scenarios. Fuzzy AHP-WASPAS was employed in [34] to evaluate some key last-mile delivery companies in Vietnam regarding their sustainability performance.

In the recent literature, one can find examples of the two newly proposed OPA and MARCOS in many industries and in the field of logistics and supply chain management. The OPA method was applied to prioritize transport planning strategies for freight companies toward zero carbon emissions in [41]. Pamucar et al. [42] used OPA to rank the metaverse implementation alternatives for sustainable transportation systems. Mahmoudi et al. [43] used grey OPA for sustainable supplier selection in megaprojects. Stević, Pamučar, Puška, and Chatterjee [9] first proposed the MARCOS method in 2020 for sustainable supplier selection in healthcare industries. In 2021, Ecer [44] applied MARCOS for the performance assessment of battery electric vehicles based on ranking strategies. Pamucar et al. [45] used the proposed neutrosophic fuzzy MARCOS for the evaluation of alternative fuel vehicles for sustainable road transportation. Kovač et al. [46] proposed a spherical fuzzy MARCOS method for the assessment of drone-based city logistics concepts. Büyüközkan et al. [47] presented an integrated SWOT-based fuzzy AHP and fuzzy MARCOS methodology for digital transformation strategy analysis in the airline industry.

2.3. Position of This Study

From the review, it is deduced that ample studies on LMS selection are missing, especially in the developing country context. Keeping the same view, efforts have been made for the first time in the present study that takes the merits of two novel OPA and fuzzy MARCOS in order to identify the most sustainable LMS in Vietnam. On the one hand, the most important criteria have been identified with the aid of OPA. This recently developed method significantly reduces the time and computation costs for the decision-making process by not making use of the pairwise comparison matrix, decision-making matrix, and normalization methods that are common in many existing classical MADM methods [48]. By getting rid of collecting quantitative preferences and utilizing the order as its input, the judgments of dominance (i.e., ordinal information) between items are more accessible and accurate than exact ratios because it is more evident to judge which one is better. However, OPA cannot consider the uncertainties, which is a major concern for the decision-makers. While OPA succeeded in handling the existing drawbacks of MADM, it failed to consider the situations in which experts are not sure about his/her opinion, which, in this research, is related to determining the best alternatives. To handle these drawbacks, fuzzy MARCOS has been presented for selecting a sustainable LMS. Through the use of an algorithm for examining the connections between alternatives and reference points, fuzzy MARCOS revitalizes the MADM domain [10]. To make a solid choice, it incorporates the following factors: Determining the relationship between alternatives and fuzzy ideal/anti-ideal values, defining reference points (fuzzy ideal and fuzzy anti-ideal values), and defining the utility level of alternatives in relation to the fuzzy ideal and fuzzy anti-ideal solutions. Because the ratio approach and the reference point sorting approach's results were combined, the fuzzy MARCOS method's results are more reasonable. The fuzzy MARCOS method shows the significant stability and reliability of the results in dynamic conditions and robustness.

The use of fuzzy MARCOS in the literature is elaborated in the sections above, indicating that it can be effectively used in combination with OPA. However, the integration of OPA and fuzzy MARCOS has not yet been researched. Combining these methods can be a novelty that has not been studied in the state-of-the-art. Thus, there are two salient features that distinguish our research from existing studies. First, our study fills the gap in the MADM literature by combining OPA and fuzzy MARCOS methods for the first time, to the best of our knowledge, and second, investigating its advantages in a case study in the selection of LMSs from a developing country's perspective of Vietnam. Factors and initiatives in last-mile logistics were determined through the literature and experts' responses. Five solutions (green vehicles, parcel lockers, convenience store pickup, autonomous vehicles, and crowdsourcing delivery) are evaluated regarding their sustainable implementation under technical, economic, social, and environmental dimensions. Furthermore, a comprehensive sensitivity analysis and comparative analysis are provided, which illustrates the priority of the experts and even the priority of human judgment.

3. Materials and Methods

3.1. Ordinal Priority Approach (OPA) Method

The ordinal priority approach (OPA) is a novel development in multiple attribute decision-making (MADM). It has many advantages compared with other MADM methods; for example, it does not require pairwise comparison, a normalization procedure, averaging methods for integrating the expert's judgments, or data completeness [43]. In multi-criteria decision-making and group decision-making, decision-makers (DMs) are frequently asked to compare two components at a time [49–52]. DMs provide judgments based on their knowledge and experiences, thus forming a pairwise comparison matrix. Nevertheless, it can be difficult for them to provide numerical judgments that accurately indicate the ratios because of knowledge gaps. However, determining the relative dominance of two items (i.e., ordinal information) is much simpler. In the latter scenario, DMs only need to specify which item is superior, rather than specifying the extent of the difference. Further, to make the various scales of measurement comparable, normalization is commonly used. This would enable the necessary calculations to be made on the attributes' constituent parts [53]. Calculation errors would certainly happen if the incorrect normalization technique was chosen. It can be difficult to select the best normalization technique in some research studies [54]. Many MADM methods call for normalization, but OPA does not require it because it only uses the order as input information.

The OPA method is built based on the linear programming model, while the sets, indexes, and decision variables are presented accordingly as follows. The parameters of the OPA model should be provided by the experts.

The steps of the OPA method for criteria weighting include: first, identifying and ranking the experts based on their years of experience or academic degree; second, determining and ranking the attributes based on the expert's opinion; and third, solving the OPA models (1) and (2) to find the weight of attributes [5].

Sets	
I	Set of experts $\forall i \in I$
J	Set of attributes $\forall j \in J$
Indexes	
i	Index of the experts $(1, \ldots, p)$
j	Index of preference of the attributes $(1, \ldots, n)$
Decision variables	
Z	Objective function
${W_{ij}}^r$	Weight (importance) of jth attribute by ith expert at rth rank

The linear programming model is presented as follows.

Maximize Z

Such that

$$\begin{gathered} Z \le i\left(j\left({W_{ij}}^r - {W_{ij}}^{r+1}\right)\right) \forall i, j, r \\ Z \le ijW_{ij} \forall i, j \\ \sum_{i=1}^{p} \sum_{j=1}^{n} W_{ij} = 1 \\ W_{ij} \ge 0 \forall i, j \end{gathered} \quad (1)$$

where Z is unrestricted in sign.

After solving model (1), in order to calculate the weight of attributes, Equation (2) should be utilized.

$$W_j = \sum_{i=1}^{p} W_{ij} \forall j \quad (2)$$

The weight of the attributes calculated by the OPA model will be used to rank the alternative with fuzzy MARCOS in the next phase.

3.2. Fuzzy MARCOS Method

3.2.1. Preliminaries

Fuzzy set theory has emerged as the critical method for dealing with imprecision or vagueness in real-world issues. The fuzzy triangular numbers (TFN) can be described as (l, m, u), indicating the least likely (l), most promising (m), and largest conceivable (u) values in TFN. TFN can be defined as in Equations (3) and (4) below [55].

$$\left(\frac{a}{\widetilde{M}}\right) = \begin{cases} 0 & if\ a \leq l, 1\ if\ a = m \\ \frac{a-l}{m-l} & if\ l < a \leq m, \\ \frac{u-a}{u-m} & if\ m < a \leq u, \\ 0 & if\ a \geq u, \end{cases} \tag{3}$$

$$\widetilde{M} = \left(M^{o(y)}, M^{i(y)}\right) = [l + (m-l)y, u + (m-u)y], y \in [0,1] \tag{4}$$

where $o(y)$ and $i(y)$ denote the left and right sides, respectively, of a fuzzy number.

The following Equations (5)–(9), illustrate fundamental computations involving two positive TFNs [56], $\widetilde{M}_1 = (l_1, m_1, u_1)$ and $\widetilde{M}_2 = (l_2, m_2, u_2)$.

Addition:

$$\widetilde{M}_1 \oplus \widetilde{M}_2 = (l_1, m_1, u_1) + (l_2, m_2, u_2) = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \tag{5}$$

Subtraction:

$$\widetilde{M}_1 \ominus \widetilde{M}_2 = (l_1, m_1, u_1) - (l_2, m_2, u_2) = (l_1 - u_2, m_1 - m_2, u_1 - l_2) \tag{6}$$

Multiplication:

$$\widetilde{M}_1 \otimes \widetilde{M}_2 = (l_1, m_1, u_1) \times (l_2, m_2, u_2) = (l_1 \times l_2, m_1 \times m_2, u_1 \times u_2) \tag{7}$$

Division:

$$\frac{\widetilde{M}_1}{\widetilde{M}_2} = \frac{(l_1, m_1, u_1)}{(l_2, m_2, u_2)} = \left(\frac{l_1}{u_2}, \frac{m_1}{m_2}, \frac{u_1}{l_2}\right) \tag{8}$$

Reciprocal:

$$\widetilde{M}_1^{-1} = (l_1, m_1, u_1)^{-1} = \left(\frac{1}{u_1}, \frac{1}{m_1}, \frac{1}{l_1}\right) \tag{9}$$

3.2.2. Fuzzy MARCOS

Measurement of alternatives and ranking according to the compromise solution (MARCOS) is one of the MADM methods that are suitable for solving models with more criteria and alternatives. This method has three starting points, including reference points, the relationship between alternatives, and the utility degree of alternatives, which help DMs make a robust decision [10].

In addition, a fuzzy linguistic scale quantified into a triangular fuzzy number (TFN) is integrated into MARCOS (fuzzy MARCOS) to improve the robustness of MADM in a fuzzy environment. The calculation process of fuzzy MARCOS is shown in the following steps [10]. The geometric mean method is applied to do the aggregation of the linguistic judgment matrix of all experts for fuzzy MARCOS.

Step 1: Define an initial fuzzy decision-making matrix, including a set of n attributes (i.e., criteria) and m alternatives.

Step 2: Define an extended initial fuzzy decision-making matrix by introducing the fuzzy ideal $\widetilde{A}(ID)$ and anti-ideal $\widetilde{A}(AI)$ solutions.

$$\widetilde{X} = \begin{array}{c} \widetilde{A}(AI) \\ \widetilde{A}_1 \\ \widetilde{A}_2 \\ \cdots \\ \widetilde{A}_m \\ \widetilde{A}(ID) \end{array} \overbrace{\begin{bmatrix} \widetilde{x}_{ai1} & \widetilde{x}_{ai2} & \cdots & \widetilde{x}_{ain} \\ \widetilde{x}_{11} & \widetilde{x}_{12} & \cdots & \widetilde{x}_{1n} \\ \widetilde{x}_{21} & \widetilde{x}_{22} & \cdots & \widetilde{x}_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ \widetilde{x}_{m1} & \widetilde{x}_{m2} & \cdots & \widetilde{x}_{mn} \\ \widetilde{x}_{id1} & \widetilde{x}_{id2} & \cdots & \widetilde{x}_{idn} \end{bmatrix}}^{\widetilde{C}_1 \quad \widetilde{C}_2 \quad \cdots \quad \widetilde{C}_n} \tag{10}$$

The fuzzy $\widetilde{A}(ID)$ is an alternative with the best performance, while the fuzzy $\widetilde{A}(AI)$ is the worst alternative. Depending on type of the criteria, $\widetilde{A}(ID)$ and $\widetilde{A}(AI)$ are defined by applying Equations (11) and (12):

$$\widetilde{A}(ID) = \max_i \widetilde{x}_{ij} \; if \; j \in B \; and \; \min_i \widetilde{x}_{ij} \; if \; j \in C \tag{11}$$

$$\widetilde{A}(AI) = \min_i \widetilde{x}_{ij} \; if \; j \in B \; and \; \max_i \widetilde{x}_{ij} \; if \; j \in C \tag{12}$$

where B and C are sets of benefit and cost attributes, respectively.

Step 3: Determine the normalization of the extended initial fuzzy decision-making matrix, which is $\widetilde{N} = \left[\widetilde{n}_{ij}\right]_{m \times n}$ using Equations (13) and (14):

$$\widetilde{n}_{ij} = \left(n_{ij}^l, n_{ij}^m, n_{ij}^u\right) = \left(\frac{x_{ij}^l}{x_{id}^u}, \frac{x_{ij}^m}{x_{id}^u}, \frac{x_{ij}^u}{x_{id}^u}\right), j \in B \tag{13}$$

$$\widetilde{n}_{ij} = \left(n_{ij}^l, n_{ij}^m, n_{ij}^u\right) = \left(\frac{x_{id}^l}{x_{ij}^u}, \frac{x_{id}^l}{x_{ij}^m}, \frac{x_{id}^l}{x_{ij}^l}\right), j \in C \tag{14}$$

where elements x_{ij}^l, x_{ij}^m, x_{ij}^u, and x_{id}^l, x_{id}^u represent the elements of matrix $\widetilde{X}$.

Step 4: Determine the weighted fuzzy matrix $\widetilde{V} = \left[\widetilde{v}_{ij}\right]_{m \times n}$, which is calculated by multiplying matrix $\widetilde{N}$ with the fuzzy weight coefficients of the attribute $\widetilde{w}_j$ as follows.

$$\widetilde{v}_{ij} = \left(v_{ij}^l, v_{ij}^m, v_{ij}^u\right) = \widetilde{n}_{ij} \otimes \widetilde{w}_j = \left(n_{ij}^l \times w_j^l, n_{ij}^m \times w_j^m, n_{ij}^u \times w_j^u\right) \tag{15}$$

where $\widetilde{w}_j = \left(w_j^l, w_j^m, w_j^u\right)$ represents the elements of the fuzzy weight of the attribute.

Step 5: Calculate the fuzzy matrix $\widetilde{S}_i$ using Equation (16) below.

$$\widetilde{S}_i = \sum_{i=1}^{n} \widetilde{v}_{ij} \tag{16}$$

where $\widetilde{S}_i = \left(s_i^l, s_i^m, s_i^u\right)$ is the sum of the elements of the weighted fuzzy matrix $\widetilde{V}$.

Step 6: Calculate the utility degree of alternative $\widetilde{K}_i$ using Equations (17) and (18):

$$\widetilde{K}_i^- = \frac{\widetilde{S}_i}{\widetilde{S}_{ai}} = \left(\frac{s_i^l}{s_{ai}^u}, \frac{s_i^m}{s_{ai}^m}, \frac{s_i^u}{s_{ai}^l}\right) \tag{17}$$

$$\widetilde{K}_i^{+} = \frac{\widetilde{S}_i}{\widetilde{S}_{id}} = \left(\frac{s_i^l}{s_{id}^u}, \frac{s_i^m}{s_{id}^m}, \frac{s_i^u}{s_{id}^l} \right) \tag{18}$$

Step 7: Calculate the fuzzy matrix $\widetilde{T}_i$ using Equation (19):

$$\widetilde{T}_i = \widetilde{t}_i = \left(t_i^l, t_i^m, t_i^u\right) = \widetilde{K}_i^{-} \oplus \widetilde{K}_i^{+} = \left(k_i^{-l} + k_i^{+l}, k_i^{-m} + k_i^{+m}, k_i^{-u} + k_i^{+u}\right) \tag{19}$$

Then, a new fuzzy number, $\widetilde{D}$, is determined using Equation (20):

$$\widetilde{D} = \left(d^l, d^m, d^u\right) = \max_i \widetilde{t}_{ij} \tag{20}$$

Following that, it is necessary to de-fuzzy the number $\widetilde{D}$ using the expression $df_{crisp} = \frac{l+4m+u}{6}$, obtaining the number df_{crisp}.

Step 8: Determine the utility function in relation to the ideal $f\left(\widetilde{K}_i^{+}\right)$ and anti-ideal $f\left(\widetilde{K}_i^{-}\right)$ solutions using Equations (21) and (22):

$$f\left(\widetilde{K}_i^{+}\right) = \frac{\widetilde{K}_i^{-}}{df_{crisp}} = \left(\frac{k_i^{-l}}{df_{crisp}}, \frac{k_i^{-m}}{df_{crisp}}, \frac{k_i^{-u}}{df_{crisp}} \right) \tag{21}$$

$$f\left(\widetilde{K}_i^{-}\right) = \frac{\widetilde{K}_i^{+}}{df_{crisp}} = \left(\frac{k_i^{+l}}{df_{crisp}}, \frac{k_i^{+m}}{df_{crisp}}, \frac{k_i^{+u}}{df_{crisp}} \right) \tag{22}$$

Finally, calculate the defuzzification of $\widetilde{K}_i^{-}$, $\widetilde{K}_i^{+}$, $f\left(\widetilde{K}_i^{-}\right)$, and $f\left(\widetilde{K}_i^{+}\right)$ values using the same defuzzification formula.

Step 9: Determine the utility function of alternatives of $f(K_i)$ using Equation (23):

$$f(K_i) = \frac{K_i^{+} + K_i^{-}}{1 + \frac{1 - f(K_i^{+})}{f(K_i^{+})} + \frac{1 - f(K_i^{-})}{f(K_i^{-})}} \tag{23}$$

Step 10: Rank the alternatives based on the final values of the utility degree function. The alternative with the highest utility function value is most preferred.

A new linguistic scale for evaluating alternatives has been established in addition to the fuzzy MARCOS method, as indicated in Table 3. There are nine linguistic words specified, each with its own triangular fuzzy number.

Table 3. Linguistic scale for evaluating potential alternatives.

Symbol	Definition	Scale of Triangular Fuzzy Number
EP	Extremely poor	(1, 1, 1)
VP	Very poor	(1, 1, 3)
P	Poor	(1, 3, 3)
MP	Medium poor	(3, 3, 5)
M	Medium	(3, 5, 5)
MG	Medium good	(5, 5, 7)
G	Good	(5, 7, 7)
VG	Very good	(7, 7, 9)
EG	Extremely good	(7, 9, 9)

To summarize, this paper used a two-stage MADM model for evaluating sustainable last-mile solutions with a case study in Vietnam. First, the OPA method is applied to calculate the weight of attributes; then the fuzzy MARCOS method is utilized to rank the alternatives. A comparative analysis of the related MADM methods shows the applicability and robustness of the proposed model. The research framework is presented in Figure 1, which consists of two main stages: Attribute weighting with OPA and alternative ranking with fuzzy MARCOS.

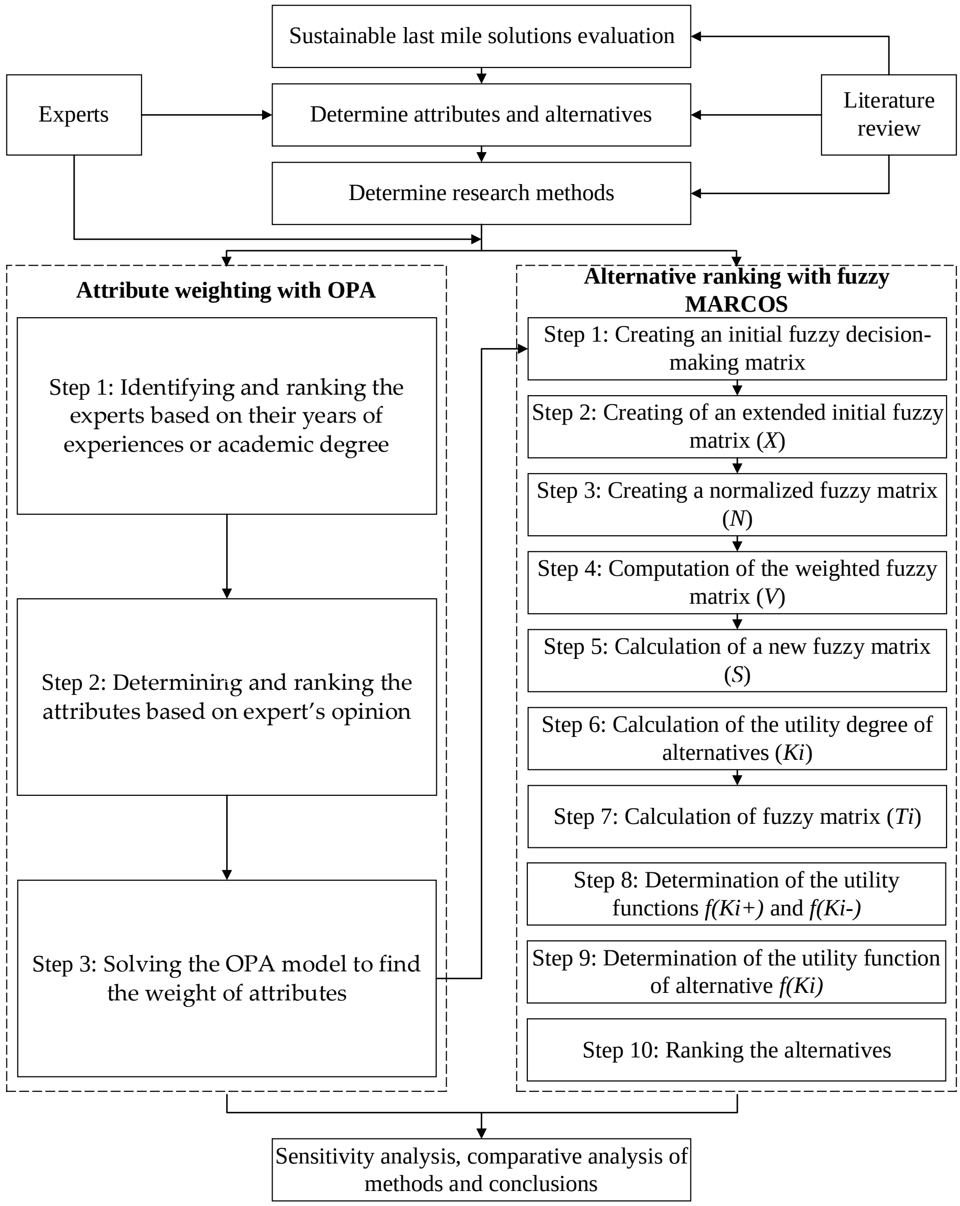

Figure 1. The research framework.

4. Evaluation of Sustainable LMSs for a Case Study in Vietnam

Following Section 3, the conducted case study is illustrated in this section to investigate the advantage of the OPA-fuzzy MARCOS research framework in LMS selection in Vietnam. There are various criteria for the evaluation, ranking, and selection of appropriate solutions for last-mile problems. While Section 4.1 describes the real-world case study, Sections 4.2 and 4.3 present the analytical results of the two main stages demonstrated in Figure 1.

4.1. Case Description

The criteria and alternatives were advised by interviews with experts. We focused on the transportation and logistics industry's perspective to provide an industry-internal view besides observations and relevant studies. As a result, four experts in the field of transportation, logistics, and supply chain management, based on their designated knowledge and expertise, as well as their capacity, willingness, and work experience, were invited to form a committee. Within discussion sessions, relevant content regarding the unique characteristics and needs of last-mile delivery in the developing country context of Vietnam, such as energy/emissions, customer behaviors, transport modes, supply chains' designs, etc., were considered to identify factors driving last-mile and potential solutions. The profiles of the four experts are provided in Table 4.

Table 4. Details of the four experts.

Expert	Work Experience	Education	Skilled Field
Expert 1	Between five and ten years	Doctoral	Logistics and Supply Chain Management
Expert 2	Between five and ten years	Master	Logistics and Supply Chain Management
Expert 3	More than ten years	Bachelor	Freight Forwarding
Expert 4	More than ten years	Bachelor	Transportation Planning

Based on the reviewed solutions in Table 1 and experts' knowledge, five innovative and potentially sustainable LMSs that are suitable in the context of Vietnam, especially for major cities such as Ho Chi Minh, Hanoi, and Danang, to name a few, are proposed as follows:

- **Green vehicles (LMS-01):** The adoption of an eco-fleet in last-mile delivery that runs on electric/hydrogen/hybrid motors instead of internal-combustion engines that generate power by burning a mix of fuel and gases. They can be all-electric vehicles (run solely on electricity) or plug-in hybrid electric vehicles (run partially on fuel and electricity). More specifically, eco-vehicles can be cargo bicycles, e-scooters, or battery-electric vans. This solution is to reduce the carbon footprint, minimize the impact of logistics on the environment, minimize fuel consumption significantly, reduce operating costs, and save time and cost on fleet maintenance.
- **Parcel lockers (LMS-02):** An unattended delivery system located at pre-selected locations. The system allows the receiving and delivering of parcels 24/7. Customers select a locker to receive their goods while doing their online shopping; then, they receive an email and a short message with a code to open a specific reception box. Packages can be delivered any time of the day or night and are safely stored until a convenient time for collection.
- **Convenience store pickup (LMS-03):** This model provides a service to help shoppers on e-commerce sites receive goods at convenience stores anytime. In Vietnam, especially in big cities, convenience store chains such as VinMart, Circle K, FamilyMart, and Ministop, whose coverage is gradually dense across the country and can be considered hubs, can serve as collection points. Depending on the sales website, this service is charged or not at a convenience store. In addition, not all products are eligible for convenience store pickup for various reasons, such as size.
- **Autonomous vehicles (LMS-04):** Through the use of aerial autonomous vehicles (drones), ground autonomous vehicles, and robots, a parcel is delivered to end-users at their doorsteps without human intervention.
- **Crowdsourcing delivery (LMS-05):** The outsourcing of logistics activities between a party wishing to outsource logistics activities and a community, individuals, or organizations on the other. These individuals and organizations can be a company or a citizen that can provide logistics services. Although logistics activities include storage, preservation, documents, packaging, loading and unloading, and transportation, the most common activity organized in the form of crowdsourcing is crowdsourced shipping and crowdsourced receiving. Crowdsourced shipping is when a non-professional

driver receives goods delivered to consumers. Crowdsourced receiving is when a third party provides short-term storage in cases where home delivery fails or the consignee does not want to receive the goods at that time or at home. This strategy aids logistics managers in lowering last-mile delivery costs while also addressing traffic and pollution issues. However, maintaining the safety of commodities and establishing confidence among the people engaged in this manner is a significant challenge.

To assess the proposed LMSs, it is possible to construct a broad set of criteria, but only those that are appropriate and consistent with sustainable principles are considered. As stated in Table 5, the criteria were chosen based on the literature research, experts' opinions, and the authors' field experience. The hierarchical tree for the evaluation process of LMSs is presented in Figure 2.

Table 5. Criteria explanation.

Criteria Group	Criteria	Explanation
Technical	Efficiency	It denotes the degree to which logistics activities in a solution have been rationalized, including indicators such as trip effectiveness, loading factor, volume of goods handled, fuel and energy utilization, the average traveled distance per delivery, overall delivery completion times, number of orders delivered on a route, etc.
	Reliability	It refers to the accessibility of services and goods, including metrics like on-time delivery rate (number of orders delivered on time), order accuracy, and damage rate of goods. Solutions such as drones are less reliable due to frequent delays and bottlenecks in bad weather conditions.
	Flexibility	It considers the possibility of the logistics system's responsiveness to unexpected changes in demand characteristics and unprecedented crises (such as COVID-19).
	Possibility of implementation	It refers to its conformity with the area's current urban planning. This criterion also considers the requirement for new laws, rules, and policies to govern the use of modern delivery technology (such as drones and autonomous cars), as well as the administrative procedures that must be followed before such solutions can be implemented.
	Traceability and information security	This factor is to ensure the safety of the products and customers' personal information.
Economic	Costs of implementation and control	It refers to the amount of investment required for the implementation and development of a solution, including infrastructures, operation, land and equipment acquisition, staff training, insurance, taxes, etc.
Social	Consistency with urban planning	It refers to what level a solution contributes to urban development in terms of the freeing of public spaces by efficient organization of goods and transport flows, causing areas to be more or less attractive.
	Voice of customer	It refers to customers' problems and customers' complaint rates for a solution.
	Mobility	It refers to changes in passenger and freight vehicle movement circumstances in the city as a result of the solution's implementation.
	Cooperation of stakeholders	When testing and implementing an innovative solution or disruptive change, such as the introduction of green vehicles or autonomous vehicles, accurate behavioral analyses based on stated preference methods are required to investigate stakeholders' acceptability and reactions.
Environmental	Air Pollution	It considers the impact of a modern solution on changes in harmful gas and particle emissions by delivery vehicles in the area.
	Energy savings	It evaluates the changes in energy consumption caused by the reduction in the number of delivery trucks and their more efficient usage as a consequence of the implementation of various initiatives.

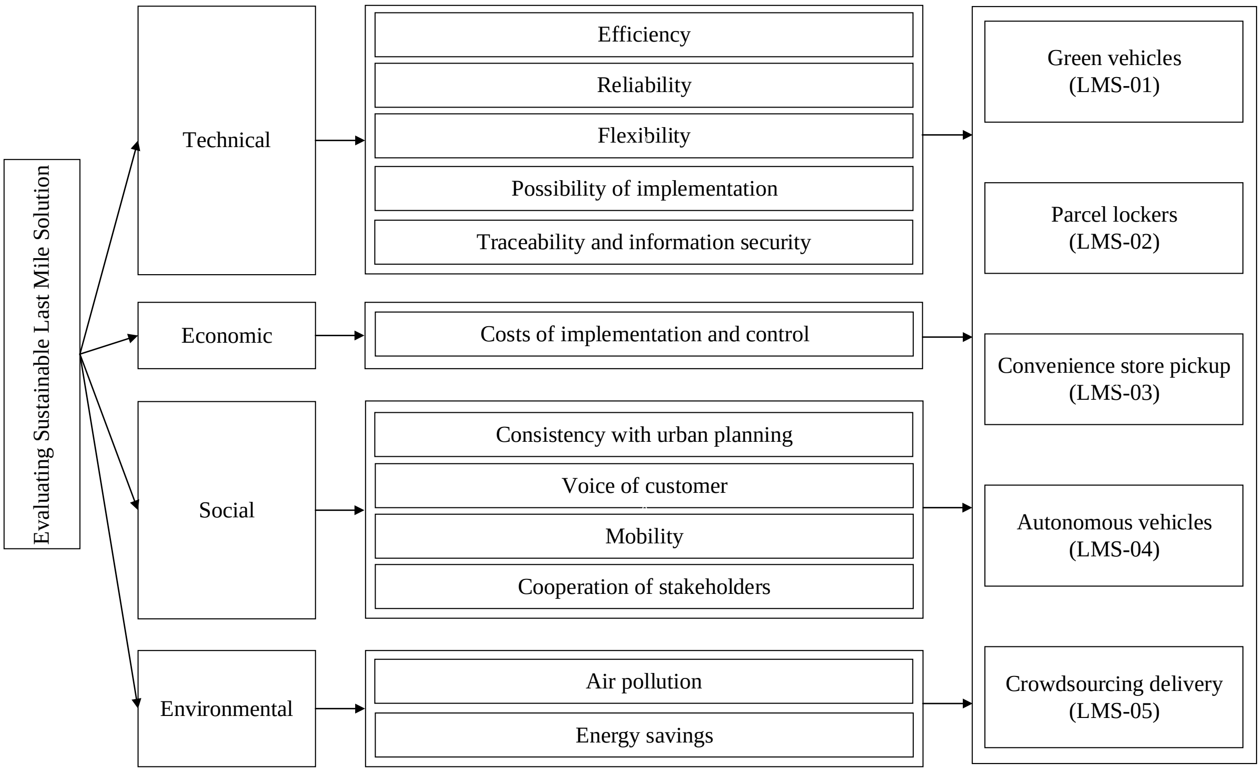

Figure 2. The decision tree for evaluating the last-mile solution.

4.2. Attribute Weighting with OPA

In this section, the OPA method is used to determine the weight of attributes. There are four main attributes, including technical (five sub-attributes), economic (one sub-attribute), social (four sub-attributes), and environmental (two sub-attributes). Experts are graded to improve the accuracy of judgments since their competence differs [5,43]. Based on the years of experience and academic degree, the expert's qualification and ranking are defined as follows: expert 1 > expert 3 > expert 2 > expert 4. The expert's opinions (i.e., in terms of ordinal numbers) regarding the last-mile solution in each attribute are presented in Table 6.

Table 6. The rank of attributes by each expert.

Main Attribute	Attribute	Cost (−)/Benefit (+)	Expert 1	Expert 2	Expert 3	Expert 4
Technical	Efficiency (Att-1)	+	1	1	2	1
	Reliability (Att-2)	+	3	7	3	5
	Flexibility (Att-3)	+	6	2	4	4
	Possibility of implementation (Att-4)	+	12	4	7	7
	Traceability and information security (Att-5)	+	10	6	5	6
Economic	Costs of implementation and control (Att-6)	−	4	3	1	2
Social	Consistency with urban planning (Att-7)	+	11	12	10	11
	Voice of customer (Att-8)	+	2	5	8	3
	Mobility (Att-9)	+	9	10	9	12
	Cooperation of stakeholders (Att-10)	+	7	8	6	8
Environmental	Air pollution (Att-11)	−	8	11	12	10
	Energy savings (Att-12)	+	5	9	11	9

Note: the symbol "+" represents the maximum attribute, "−" represents the minimum attribute.

In this paper, the OPA mathematical model is solved by Cplex studio (IDE 12.9.0), and the result of fuzzy MARCOS is obtained by Python 3.9 software. The optimal results from the OPA model are shown in Table 7. From the result, the OPAs weight of expert 1, expert 2, expert 3, and expert 4 are 0.4800, 0.1600, 0.2400, and 0.1200, respectively. Following that, in terms of attribute impact, efficiency (Att-1) is the most important attribute among the group of attributes ($w_{\text{Att-1}}$ = 0.2386). While consistency with urban planning (Att-7) is the least important among the group of attributes ($w_{\text{Att-1}}$ = 0.0153). The impact of attributes is visualized in Figure 3. The results show that the top five impact attributes are efficiency (Att-1), costs of implementation and control (Att-6), voice of customer (Att-8), reliability (Att-2), and flexibility (Att-3), so it needs more attention in considering the last-mile solution, especially in the Vietnam market.

Table 7. The weight of attributes from the OPA result.

Index	OPA Weight	Rank
Expert 1	0.4800	1
Expert 2	0.1600	3
Expert 3	0.2400	2
Expert 4	0.1200	4
Efficiency (Att-1)	0.2386	1
Reliability (Att-2)	0.1151	4
Flexibility (Att-3)	0.0989	5
Possibility of implementation (Att-4)	0.0399	9
Traceability and information security (Att-5)	0.0505	8
Costs of implementation and control (Att-6)	0.1553	2
Consistency with urban planning (Att-7)	0.0153	12
Voice of customer (Att-8)	0.1240	3
Mobility (Att-9)	0.0276	10
Cooperation of stakeholders (Att-10)	0.0544	6
Air pollution (Att-11)	0.0271	11
Energy savings (Att-12)	0.0533	7

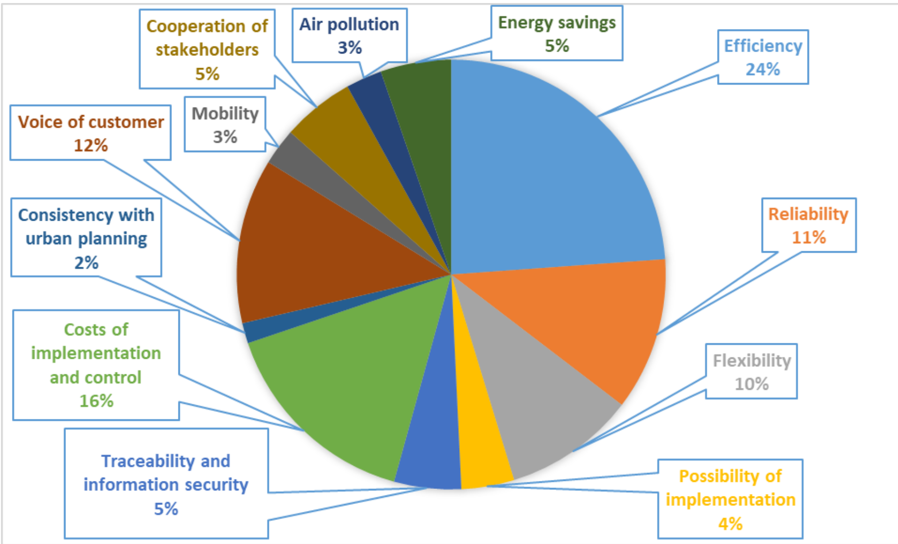

Figure 3. The impact weight of attributes from the OPA result.

4.3. Alternative Ranking with Fuzzy MARCOS

In this paper, a case study in Vietnam is used to test the proposed MADM model. A set of five possible last-mile solutions is determined by experts, which are green vehicles (LMS-01), parcel lockers (LMS-02), convenience store pickup (LMS-03), autonomous vehicles (LMS-04), and crowdsourcing delivery (LMS-05). According to the fuzzy MARCOS procedure, the fuzzy ideal $\widetilde{A}(ID)$ and anti-ideal $\widetilde{A}(AI)$ solutions corresponding to each attribute are defined. $\widetilde{A}(ID)$ is the highest value of each attribute while the lowest value is $\widetilde{A}(AI)$. Following that, the linguistic judgments matrix of experts, the integrated matrix, the normalized matrix, and the weighted normalized matrix for the fuzzy MARCOS method are presented in Tables A1–A4, respectively (Appendix A).

Table 8 shows the calculation of the utility degree and fuzzy matrix of $\widetilde{T}_i$. Finally, the final utility function value of alternatives is obtained. Using these values, the final ranking of the alternatives is derived. The value of utility functions and the final ranking of the alternatives are presented in Table 9. The results show that the top three last-mile solutions are convenience store pickup (LMS-03), green vehicles (LMS-01), and parcel lockers (LMS-02), ranking in the first, second, and third positions with the utility function scores of 0.7221, 0.5848, and 0.5188, respectively. Figure 4 displays the final last-mile solution ranking from the OPA-fuzzy MARCOS model.

Table 8. Calculating and summarizing the utility degree and fuzzy matrix of $\widetilde{T}_i$.

Solutions	Fuzzy $\widetilde{S}_i$			Fuzzy $\widetilde{K}_i^-$			Fuzzy $\widetilde{K}_i^+$			Fuzzy $\widetilde{T}_i$		
	l	m	u	l	m	u	l	m	u	l	m	u
$\widetilde{A}(AI)$	0.5755	0.5755	0.5755									
LMS-01	0.6455	0.7977	0.9447	1.1217	1.3862	1.6417	0.6455	0.7977	0.9447	1.7672	2.1839	2.5864
LMS-02	0.6028	0.7513	0.9261	1.0476	1.3056	1.6093	0.6028	0.7513	0.9261	1.6504	2.0570	2.5355
LMS-03	0.7102	0.8893	0.9763	1.2342	1.5453	1.6966	0.7102	0.8893	0.9763	1.9445	2.4346	2.6729
LMS-04	0.5376	0.7411	0.8748	0.9343	1.2879	1.5202	0.5376	0.7411	0.8748	1.4719	2.0290	2.3950
LMS-05	0.5257	0.7019	0.8596	0.9136	1.2197	1.4938	0.5257	0.7019	0.8596	1.4393	1.9215	2.3535
$\widetilde{A}(ID)$	1.0000	1.0000	1.0000								$df_{crisp} = 2.3926$	

Table 9. Value of utility functions and final ranking of the alternatives.

Solutions	Fuzzy $f\left(\widetilde{K}_i^-\right)$			Fuzzy $f\left(\widetilde{K}_i^+\right)$			K_i^-	K_i^+	$f(K_i^-)$	$f(K_i^+)$	$f(K_i)$	Rank
	l	m	u	l	m	u						
LMS-01	0.2698	0.3334	0.3948	0.4688	0.5794	0.6861	1.3847	0.7968	0.3330	0.5787	0.5848	2
LMS-02	0.2520	0.3140	0.3871	0.4378	0.5457	0.6726	1.3132	0.7557	0.3159	0.5489	0.5188	3
LMS-03	0.2968	0.3717	0.4081	0.5158	0.6459	0.7091	1.5187	0.8739	0.3653	0.6347	0.7221	1
LMS-04	0.2247	0.3097	0.3656	0.3905	0.5383	0.6354	1.2677	0.7295	0.3049	0.5298	0.4792	4
LMS-05	0.2197	0.2933	0.3593	0.3818	0.5098	0.6244	1.2143	0.6988	0.2921	0.5075	0.4354	5

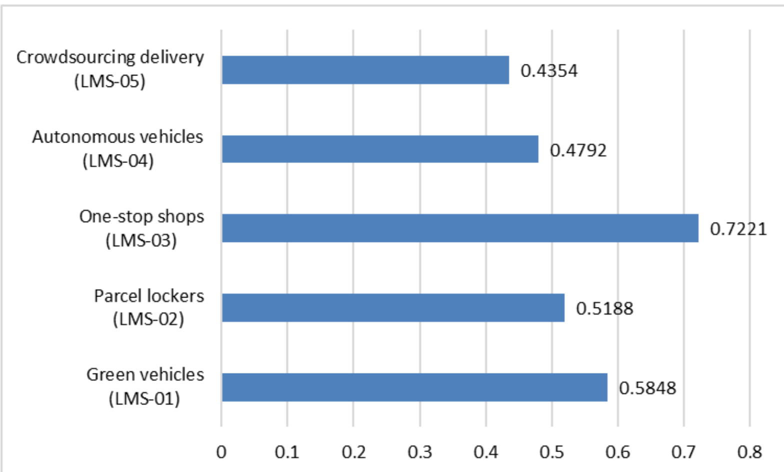

Figure 4. The final last-mile solution ranking of the proposed model.

5. Results Validation

5.1. Sensitivity Analysis of Attribute's Weight

The majority of input data in MADM problems is dynamic rather than continuous and stable. As a result, sensitivity analysis can successfully contribute to making appropriate decisions. In this study, we used the sensitivity analysis approach in MADM problems, where if the weights of one attribute change, we can identify changes in the problem's solutions. These changes include adjustments in the weighting of other attributes as well as changes in the final ranking of alternatives [57].

For this purpose, the removal of attributes one-by-one and its impact on the final ranking will be performed. Therefore, there will be 12 scenarios in the sensitivity analysis of the attribute's weight. The weight of attributes in all scenarios is shown in Table 10. The prospect value of alternatives in all scenarios is shown in Table 11, and their ranking is visualized in Figure 5. It can be seen that, while there are changes in the prospect values of the alternatives, the final ranking is unchanged, with convenience store pickup (LMS-03) as the optimal last-mile solution across all scenarios. The results of the sensitivity phase suggest that, in this case study, the alternative ranking is robust regardless of the change in the attribute's weight. Hence, the proposed OPA-fuzzy MARCOS model exhibits high stability and applicability.

Table 10. The weight of attributes in all scenarios.

Attributes	Base case	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7	Scenario 8	Scenario 9	Scenario 10	Scenario 11	Scenario 12
Att-1	0.2386	0	0.2696	0.2648	0.2485	0.2513	0.2825	0.2423	0.2724	0.2454	0.2523	0.2453	0.2520
Att-2	0.1151	0.1512	0	0.1277	0.1199	0.1212	0.1363	0.1169	0.1314	0.1184	0.1217	0.1183	0.1216
Att-3	0.0989	0.1299	0.1118	0	0.1030	0.1042	0.1171	0.1005	0.1129	0.1017	0.1046	0.1017	0.1045
Att-4	0.0399	0.0524	0.0450	0.0442	0	0.0420	0.0472	0.0405	0.0455	0.0410	0.0422	0.0410	0.0421
Att-5	0.0505	0.0663	0.0571	0.0560	0.0526	0	0.0598	0.0513	0.0576	0.0519	0.0534	0.0519	0.0533
Att-6	0.1553	0.2039	0.1755	0.1723	0.1617	0.1635	0	0.1577	0.1772	0.1597	0.1642	0.1596	0.1640
Att-7	0.0153	0.0201	0.0173	0.0170	0.0159	0.0161	0.0181	0	0.0175	0.0157	0.0162	0.0157	0.0162
Att-8	0.1240	0.1628	0.1401	0.1376	0.1291	0.1306	0.1468	0.1259	0	0.1275	0.1311	0.1274	0.1309
Att-9	0.0276	0.0363	0.0312	0.0306	0.0288	0.0291	0.0327	0.0280	0.0315	0	0.0292	0.0284	0.0292
Att-10	0.0544	0.0715	0.0615	0.0604	0.0567	0.0573	0.0644	0.0553	0.0621	0.0560	0	0.0560	0.0575
Att-11	0.0271	0.0357	0.0307	0.0301	0.0283	0.0286	0.0321	0.0276	0.0310	0.0279	0.0287	0	0.0287
Att-12	0.0533	0.0700	0.0602	0.0591	0.0555	0.0561	0.0631	0.0541	0.0608	0.0548	0.0563	0.0548	0

Table 11. The prospect value of alternatives in all scenarios.

Solutions	Base case	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7	Scenario 8	Scenario 9	Scenario 10	Scenario 11	Scenario 12
LMS-01	0.5848	0.6236	0.6739	0.6298	0.5793	0.5824	0.5463	0.5850	0.5193	0.5721	0.5691	0.5915	0.5669
LMS-02	0.5188	0.5757	0.5637	0.5528	0.5252	0.5177	0.4465	0.5227	0.4931	0.5119	0.4908	0.5206	0.5247
LMS-03	0.7221	0.6781	0.7030	0.7012	0.7194	0.7195	0.7655	0.7212	0.7436	0.7270	0.7368	0.7195	0.7269
LMS-04	0.4792	0.5679	0.5161	0.5209	0.4829	0.4780	0.3783	0.4790	0.4733	0.4783	0.4652	0.4705	0.4711
LMS-05	0.4354	0.5444	0.4539	0.4864	0.4406	0.4364	0.3351	0.4345	0.4244	0.4349	0.4204	0.4289	0.4215

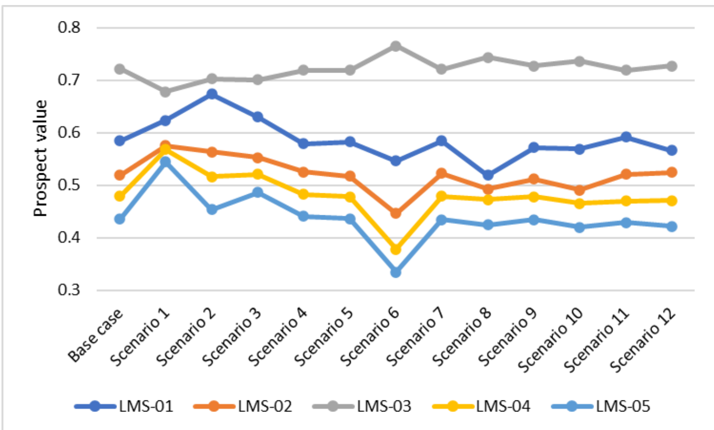

Figure 5. The ranking of alternatives in all scenarios.

5.2. Comparative Analysis of MADM Methods

In this phase of the results' validation, six different integrated fuzzy MADM methods are considered to check the result obtained by the proposed model (OPA-fuzzy MARCOS). The considered MADM methods are the fuzzy technique for order of preference by similarity to the ideal solution (fuzzy TOPSIS) [58], the fuzzy weighted aggregated sum product assessment (fuzzy WASPAS) [59], the fuzzy combined compromise solution (fuzzy CoCoSo) [60], the fuzzy simple additive weighting (fuzzy SAW) [61], the fuzzy multi-attributive border approximation area comparison (fuzzy MABAC) [62], and the fuzzy complex proportional assessment of alternatives (fuzzy COPRAS) [63]. The same weight of attributes is applied during the comparative analysis of MADM methods, and the obtained results are presented in Table 12. The comparison of OPA-fuzzy MARCOS with other MADM methods is depicted in Figure 6. The obtained results from different MADM methods show there is no difference in the ranking of the best alternative (last-mile solution). Convenience store pickup (LMS-03) is always ranked as the optimal supplier. Similar results obtained by all considered MADM methods confirm the results of the proposed model (OPA-fuzzy MARCOS).

Table 12. Result of the comparative analysis of MADM methods.

	OPA and Fuzzy MARCOS		OPA and Fuzzy TOPSIS		OPA and Fuzzy WASPAS		OPA and Fuzzy CoCoSo		OPA and Fuzzy SAW		OPA and Fuzzy MABAC		OPA and Fuzzy COPRAS	
	Value	**Rank**	**Value**	**Rank**	**Value**	**Rank**	**Value**	**Rank**	**Value**	**Rank**	**Value**	**Rank**	**Value**	**Rank**
LMS-01	0.5848	2	0.0576	2	0.6747	2	3.0777	2	0.6827	2	0.0724	2	0.9213	2
LMS-02	0.5188	3	0.0547	3	0.6445	3	2.8890	3	0.6470	3	0.0087	3	0.8970	3
LMS-03	0.7221	1	0.0628	1	0.7319	1	3.2264	1	0.7468	1	0.1409	1	1.0000	1
LMS-04	0.4792	4	0.0516	4	0.6027	4	2.6493	4	0.6080	4	−0.0563	4	0.8574	4
LMS-05	0.4354	5	0.0499	5	0.5803	5	2.4822	5	0.5877	5	−0.0878	5	0.8312	5

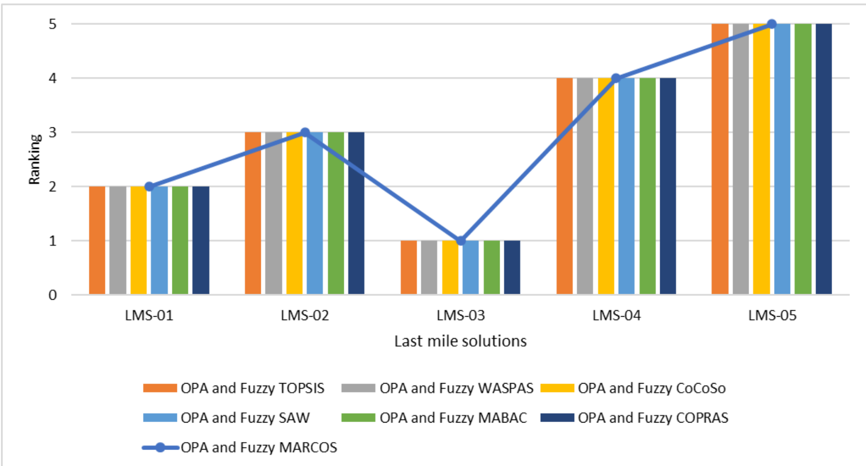

Figure 6. Comparison of OPA-fuzzy MARCOS with other MADM methods.

6. Discussion

6.1. Analysis of the Results

The proposed model's applicability is exemplified by solving the problem of LMS evaluation. Initially, a set of factors extracted from the literature review was discussed by the experts in the relevant fields of last-mile logistics to select the most influential criteria. Afterward, the OPA method was applied to obtain the weights of the criteria used in the assessment of the LMSs. As a result, factors such as efficiency, costs of implementation and control, voice of customer, reliability, and flexibility are some of the enabling factors that need to be investigated when launching a new LMS in the context of Vietnam.

The resulting LMS from the fuzzy MARCOS analysis is then recommended to employ these factors in order to be sustainable for the benefit of the country and its people in terms of urban logistics in particular. In the second step of the assessment, the fuzzy MARCOS method is used to rank the LMSs on the basis of the sustainability-enabling factors. Since evaluating the innovative solutions is more complex, and the experts' weighted criteria typically involve varied subjectivity and objectivity, we employ linguistic variables in the MARCOS method to express their judgments. In doing so, fuzzy MARCOS can reduce the inherent ambiguity or imprecision. Such integrated methodologies are thought to produce a more viable solution assessment decision. According to the final rankings, experts see room for improvement in Vietnam's final-leg logistics by implementing convenience store pickup, parcel lockers, and the use of green vehicles in last-mile delivery activities. Notice that these three LMSs are not ubiquitous in Vietnam, as door-to-door services now perform most last-mile deliveries with traditional vehicles.

The convenience store market is ever more competitive than before in Vietnam; more and more convenience stores appear in big cities, in densely populated areas, and are being expanded more in suburban areas. In 2021, 29% of customers shopped at convenience stores [64]. With the industry's growth, convenience store pickup is not only convenient for shoppers and shippers but also benefits the convenience stores as they can gain more customers for themselves. From the perspective of e-commerce retailers, the convenience store mode saves cost, improves efficiency, gains customers, and increases sales. From customers' perspectives, this solution saves time and makes time more flexible for them. From the social perspective, it optimizes resources and saves social costs.

The "parcel lockers" model has only been deployed in Hanoi and Ho Chi Minh City. In Vietnam, Lazada was the first e-commerce platform to deploy an automatic delivery service via smart lockers named "iLogic SmartBox" in 2019. Innovative solutions are highly appreciated when applying modern technology to logistics activities; customers can proactively receive goods without having to be in close contact with delivery staff or sellers. To use this delivery method, the buyer provides a shipping address. After receiving information about the delivery address, Lazada will suggest the nearest "iLogic SmartBox" lockers for buyers. Customers can choose to pay in advance via bank card or e-wallet. When the goods arrive in the cabinet, this platform will notify the customer via two methods: send a message to the registered phone number with an OTP code or send a QR code to the registered email address. Buyers can use OTP or QR to open the smart locker and receive the goods. This is also a contactless last-mile method, helping users feel secure buying goods at home during the COVID-19 epidemic. The solution has a lot of potential to be realized and expanded very soon.

The key advantage of "green vehicles" in comparison to the other solutions is by taking into account the process of implementing sustainable development goals of the nation in order to contribute to environmental protection and response to climate change when last-mile logistics is considered the most polluting segment in the entire supply chain network. This concept is most suitable in terms of the environment yet ensures the quality of logistics services. For example, the project using electric motorbikes called "Bentley E", implemented in 2022 by Vietnam Post Corporation, was the first project utilizing green vehicles in delivery. With a compact design suitable for the traffic system in Vietnam, green vehicle utilization, such as electric motorbikes, is a promising and suitable alternative in both rural and urban areas. Thus, this solution gains more importance in making a positive contribution to a comprehensive roadmap for environmentally friendly last-mile activities. However, the implementation of this solution is only more favorable if it receives consensus and close coordination from the government, ministries, agencies, and related businesses to be involved in the construction and development of appropriate infrastructure.

The methodology proposed for solving the defined problem has many advantages and can be applied to any decision-making problem. However, the criteria weighting process can be directed to the implementation of fuzzy sets theory in the OPA method that allows for an objective treatment of inaccuracies in expert estimates in the case of considering more complex factors, but in this paper, the traditional OPA could solve the real problem. The prescribed methodology also successfully identified the most promising sustainable LMSs in line with stakeholders' needs and the features of a growing nation like Vietnam. Such a method would be universal and possibly applicable to any city/country with comparable traits, as well as more new aspects and criteria, and the results would be more realistic.

6.2. Managerial Implications

To investigate the effectiveness of the proposed OPA-fuzzy MARCOS approach, the research was executed on a real-world case from the lens of a developing country, and then a practical study was conducted to select the best LMS. In terms of theoretical implications, the present study provides the development of a framework for the establishment of sustainable LMSs and an effective mathematical tool in the form of a hybrid MADM model, which can be used to solve problems in the field of logistics and any other industries. Meanwhile, the main practical implications are the determination of the set of the most influential criteria and solutions that could serve as a fruitful foundation for policy-making and plan development in Vietnam or any other locations with similar characteristics, as well as the application of the developed model for selecting sustainable solutions for city logistics and last-mile delivery by various DMs, especially e-commerce stakeholders, such as receivers (e-customers), shippers (producers, online retailers), residents, and government (local and national authorities), transport companies (couriers, freight forwarders, and express), to name a few.

7. Conclusions

In this study, a combination of OPA and fuzzy MARCOS was proposed and applied to a case study in a developing country where LMSs are evaluated in terms of their sustainable implementation. According to expert opinion and the literature review, we initially defined the essential factors for innovative LMS evaluation in the context of Vietnam to be sustainable in their overall performance. The OPA method was used for weighting the considered criteria and determining the degree of influence of these criteria over the decision process, which was then passed to and handled by the developed fuzzy MARCOS to recommend the final ranking of alternatives. Five potential LMSs were defined in line with the country's current state and development plans, logistics, and business environment. Since it is necessary to analyze their applicability in all aspects, twelve criteria are defined to obtain the best LMS in a sustainable manner and balanced economic, environmental, and social dimensions.

The novel hybrid OPA and fuzzy MARCOS is the main contribution of this paper. Furthermore, this research is the first attempt in the literature to evaluate the potentially sustainable LMSs in the case of a developing country. The approach is flexible, interactive, intelligent, and integrative and significantly reduces the time and computation costs for the decision-makers. The results confirmed the soundness of the proposed approach, which can be used by stakeholders of different industries with confidence.

For future research, other researchers are recommended to use the methods to investigate more factors in different logistics systems' characteristics or evaluate initiatives that combine two or more solutions. Methodologically, different enhanced MADM techniques, such as SPOTIS, COMET, SIMUS, or TOPSI-DARIA, should be considered to check the validity and consistency of the proposed approach [65]. Moreover, future studies should assess the similarity and expertise of ranking using appropriate coefficients (e.g., rw and ws) [66,67] to test the observation stability of the model.

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Appendix A

Table A1. The linguistic judgment matrix of experts for fuzzy MARCOS.

Code	Solutions	EP	VP	P	MP	M	MG	G	VG	EG
Efficiency (Att-1)										
LMS-01	Green vehicles						1	2	1	
LMS-02	Parcel lockers					1	1	2		
LMS-03	Convenience store pickup								1	3
LMS-04	Autonomous vehicles			1			1	2		
LMS-05	Crowdsourcing delivery			1		1	2			
Reliability (Att-2)										
LMS-01	Green vehicles		1			1	2			
LMS-02	Parcel lockers				1	1	2			
LMS-03	Convenience store pickup							1	1	2
LMS-04	Autonomous vehicles				1	1	2			
LMS-05	Crowdsourcing delivery					2	2			
Flexibility (Att-3)										
LMS-01	Green vehicles				1	1	1	1		
LMS-02	Parcel lockers					3	1			
LMS-03	Convenience store pickup							1		3
LMS-04	Autonomous vehicles			1		2	1			
LMS-05	Crowdsourcing delivery		1			3				
Possibility of implementation (Att-4)										
LMS-01	Green vehicles								3	1
LMS-02	Parcel lockers				1			1	2	
LMS-03	Convenience store pickup								2	2
LMS-04	Autonomous vehicles						2	2		
LMS-05	Crowdsourcing delivery					1	2	1		
Traceability and information security (Att-5)										
LMS-01	Green vehicles							2	1	1
LMS-02	Parcel lockers							3	1	
LMS-03	Convenience store pickup								2	2
LMS-04	Autonomous vehicles						1	1	2	
LMS-05	Crowdsourcing delivery					1		3		
Costs of implementation and control (Att-6)										
LMS-01	Green vehicles						3	1		
LMS-02	Parcel lockers					2	2			
LMS-03	Convenience store pickup							1	2	1
LMS-04	Autonomous vehicles				1	2	1			
LMS-05	Crowdsourcing delivery				1	2	1			
Consistency with urban planning (Att-7)										
LMS-01	Green vehicles							4		
LMS-02	Parcel lockers				1	1		2		
LMS-03	Convenience store pickup								3	1
LMS-04	Autonomous vehicles					1		2	1	
LMS-05	Crowdsourcing delivery					1		2	1	

Table A1. *Cont.*

Code	Solutions	EP	VP	P	MP	M	MG	G	VG	EG
					Voice of customer (Att-8)					
LMS-01	Green vehicles							3	1	
LMS-02	Parcel lockers					1	2	1		
LMS-03	Convenience store pickup					3	1			
LMS-04	Autonomous vehicles					4				
LMS-05	Crowdsourcing delivery				1	2		1		
					Mobility (Att-9)					
LMS-01	Green vehicles							2	2	
LMS-02	Parcel lockers						2	2		
LMS-03	Convenience store pickup				1	1	1		1	
LMS-04	Autonomous vehicles				1	1	1	1		
LMS-05	Crowdsourcing delivery				1	1	2			
					Cooperation of stakeholders (Att-10)					
LMS-01	Green vehicles		1	1	2					
LMS-02	Parcel lockers		1		2	1				
LMS-03	Convenience store pickup	2		1	1					
LMS-04	Autonomous vehicles	1		1	2					
LMS-05	Crowdsourcing delivery	1		1	2					
					Air pollution (Att-11)					
LMS-01	Green vehicles						4			
LMS-02	Parcel lockers					2	2			
LMS-03	Convenience store pickup			1	1		2			
LMS-04	Autonomous vehicles			1	1		2			
LMS-05	Crowdsourcing delivery			1		1	2			
					Energy savings (Att-12)					
LMS-01	Green vehicles				1	2	1			
LMS-02	Parcel lockers		1		1	2				
LMS-03	Convenience store pickup			1	1	2				
LMS-04	Autonomous vehicles			1	1	2				
LMS-05	Crowdsourcing delivery				2	2				

Table A2. The integrated matrix for fuzzy MARCOS.

Solutions	Att-1			Att-2			Att-3			Att-4		
	l	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*
LMS-01	5.4388	6.4353	7.4539	2.9428	3.3437	5.2068	3.8730	4.7867	5.9161	7.0000	7.4539	9.0000
LMS-02	4.4006	5.9161	6.4353	3.8730	4.4006	5.9161	3.4087	5.0000	5.4388	5.2068	5.6637	7.2969
LMS-03	7.0000	8.4519	9.0000	6.4353	7.9373	8.4519	6.4353	8.4519	8.4519	7.0000	7.9373	9.0000
LMS-04	3.3437	5.2068	5.6637	3.8730	4.4006	5.9161	2.5900	4.4006	4.7867	5.0000	5.9161	7.0000
LMS-05	2.9428	4.4006	5.2068	3.8730	5.0000	5.9161	2.2795	3.3437	4.4006	4.4006	5.4388	6.4353
Solutions	**Att-5**			**Att-6**			**Att-7**			**Att-8**		
LMS-01	5.9161	7.4539	7.9373	5.0000	5.4388	7.0000	5.0000	7.0000	7.0000	5.4388	7.0000	7.4539
LMS-02	5.4388	7.0000	7.4539	3.8730	5.0000	5.9161	3.8730	5.2068	5.9161	4.4006	5.4388	6.4353
LMS-03	7.0000	7.9373	9.0000	6.4353	7.4539	8.4519	7.0000	7.4539	9.0000	3.4087	5.0000	5.4388
LMS-04	5.9161	6.4353	7.9373	3.4087	4.4006	5.4388	4.7867	6.4353	6.8525	3.0000	5.0000	5.0000
LMS-05	4.4006	6.4353	6.4353	3.4087	4.4006	5.4388	4.7867	6.4353	6.8525	3.4087	4.7867	5.4388
Solutions	**Att-9**			**Att-10**			**Att-11**			**Att-12**		
LMS-01	5.9161	7.0000	7.9373	1.7321	2.2795	3.8730	5.0000	5.0000	7.0000	3.4087	4.4006	5.4388
LMS-02	5.0000	5.9161	7.0000	2.2795	2.5900	4.4006	3.8730	5.0000	5.9161	2.2795	2.9428	4.4006
LMS-03	4.2129	4.7867	6.2997	1.3161	1.7321	1.9680	2.9428	3.8730	5.2068	2.2795	3.8730	4.4006
LMS-04	3.8730	4.7867	5.9161	1.7321	2.2795	2.9428	2.9428	3.8730	5.2068	2.2795	3.8730	4.4006
LMS-05	3.8730	4.4006	5.9161	1.7321	2.2795	2.9428	2.9428	4.4006	5.2068	3.0000	3.8730	5.0000

Table A3. The normalized matrix for fuzzy MARCOS.

Solutions		**Att-1**			**Att-2**			**Att-3**			**Att-4**	
	l	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*
LMS-01	0.6673	0.7895	0.9145	0.3868	0.4395	0.6844	0.4978	0.6153	0.7604	0.8773	0.9342	1.1279
LMS-02	0.5399	0.7258	0.7895	0.5091	0.5784	0.7776	0.4381	0.6427	0.6991	0.6526	0.7098	0.9145
LMS-03	0.8588	1.0370	1.1042	0.8458	1.0433	1.1109	0.8272	1.0864	1.0864	0.8773	0.9948	1.1279
LMS-04	0.4102	0.6388	0.6949	0.5091	0.5784	0.7776	0.3329	0.5656	0.6153	0.6266	0.7414	0.8773
LMS-05	0.3611	0.5399	0.6388	0.5091	0.6572	0.7776	0.2930	0.4298	0.5656	0.5515	0.6816	0.8065
Solutions		**Att-5**			**Att-6**			**Att-7**			**Att-8**	
LMS-01	0.7414	0.9342	0.9948	0.6309	0.8119	0.8832	0.6396	0.8954	0.8954	0.8202	1.0557	1.1241
LMS-02	0.6816	0.8773	0.9342	0.7464	0.8832	1.1402	0.4954	0.6660	0.7567	0.6636	0.8202	0.9705
LMS-03	0.8773	0.9948	1.1279	0.5225	0.5924	0.6862	0.8954	0.9534	1.1512	0.5141	0.7540	0.8202
LMS-04	0.7414	0.8065	0.9948	0.8119	1.0035	1.2955	0.6123	0.8231	0.8765	0.4524	0.7540	0.7540
LMS-05	0.5515	0.8065	0.8065	0.8119	1.0035	1.2955	0.6123	0.8231	0.8765	0.5141	0.7219	0.8202
Solutions		**Att-9**			**Att-10**			**Att-11**			**Att-12**	
LMS-01	0.8511	1.0070	1.1419	0.5605	0.7377	1.2534	0.5725	0.8015	0.8015	0.7719	0.9965	1.2316
LMS-02	0.7193	0.8511	1.0070	0.7377	0.8382	1.4241	0.6774	0.8015	1.0347	0.5162	0.6664	0.9965
LMS-03	0.6061	0.6886	0.9063	0.4259	0.5605	0.6369	0.7697	1.0347	1.3618	0.5162	0.8770	0.9965
LMS-04	0.5572	0.6886	0.8511	0.5605	0.7377	0.9524	0.7697	1.0347	1.3618	0.5162	0.8770	0.9965
LMS-05	0.5572	0.6331	0.8511	0.5605	0.7377	0.9524	0.7697	0.9107	1.3618	0.6793	0.8770	1.1322

Table A4. The weighted normalized matrix for fuzzy MARCOS.

Solutions		**Att-1**			**Att-2**			**Att-3**			**Att-4**	
	l	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*
LMS-01	0.1682	0.1990	0.2305	0.0470	0.0534	0.0832	0.0520	0.0643	0.0795	0.0369	0.0393	0.0475
LMS-02	0.1361	0.1829	0.1990	0.0619	0.0703	0.0945	0.0458	0.0672	0.0731	0.0275	0.0299	0.0385
LMS-03	0.2164	0.2613	0.2783	0.1028	0.1268	0.1351	0.0864	0.1135	0.1135	0.0369	0.0419	0.0475
LMS-04	0.1034	0.1610	0.1751	0.0619	0.0703	0.0945	0.0348	0.0591	0.0643	0.0264	0.0312	0.0369
LMS-05	0.0910	0.1361	0.1610	0.0619	0.0799	0.0945	0.0306	0.0449	0.0591	0.0232	0.0287	0.0340
Solutions		**Att-5**			**Att-6**			**Att-7**			**Att-8**	
LMS-01	0.0395	0.0498	0.0531	0.1035	0.1332	0.1448	0.0103	0.0145	0.0145	0.1074	0.1382	0.1472
LMS-02	0.0364	0.0468	0.0498	0.1224	0.1448	0.1870	0.0080	0.0108	0.0122	0.0869	0.1074	0.1271
LMS-03	0.0468	0.0531	0.0602	0.0857	0.0972	0.1125	0.0145	0.0154	0.0186	0.0673	0.0987	0.1074
LMS-04	0.0395	0.0430	0.0531	0.1332	0.1646	0.2125	0.0099	0.0133	0.0142	0.0592	0.0987	0.0987
LMS-05	0.0294	0.0430	0.0430	0.1332	0.1646	0.2125	0.0099	0.0133	0.0142	0.0673	0.0945	0.1074
Solutions		**Att-9**			**Att-10**			**Att-11**			**Att-12**	
LMS-01	0.0248	0.0294	0.0333	0.0322	0.0424	0.0721	0.0164	0.0230	0.0230	0.0248	0.0294	0.0333
LMS-02	0.0210	0.0248	0.0294	0.0424	0.0482	0.0819	0.0194	0.0230	0.0297	0.0210	0.0248	0.0294
LMS-03	0.0177	0.0201	0.0264	0.0245	0.0322	0.0366	0.0221	0.0297	0.0390	0.0177	0.0201	0.0264
LMS-04	0.0162	0.0201	0.0248	0.0322	0.0424	0.0548	0.0221	0.0297	0.0390	0.0162	0.0201	0.0248
LMS-05	0.0162	0.0185	0.0248	0.0322	0.0424	0.0548	0.0221	0.0261	0.0390	0.0162	0.0185	0.0248

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