

Article

Fuzzy Logic Approach for Evaluating Electromobility Alternatives in Last-Mile Delivery: Belgrade as a Case Study

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Abstract: This paper proposes a methodology based on the fuzzy approach, which provides decision-making support to the organizer of last-mile delivery (LMD) in selecting sustainable delivery models for a specific territory. Solving this task is essential to ensure that the delivery process is efficient and aligned with all three dimensions of sustainable development. The goal is to select the most suitable electromobility alternative for delivery implementation based on the characteristics of the requirements and the current circumstances. The proposed methodology involves the creation of a mechanism consisting of a series of fuzzy logic systems that will model expert opinions and produce a preference value as the output, defining the suitability of applying a particular LMD model. A specific methodological contribution is the creation of harmonized membership functions for fuzzy variables as a result of comparing symmetric and asymmetric membership functions aimed at achieving the most valid results. The results guide the delivery organizer in making the best decision when choosing from the analyzed models. The applicability and adequacy of the methodology are demonstrated through the results and analysis of a case study focused on the evaluation of electromobility alternatives in last-mile delivery in a part of the city of Belgrade. The obtained preference values, which range from 0 to 1 for all tested variants, are as follows within the interval: [0.481, 0.776] for e-motorcycles, [0.376, 0.564] for e-cargo bikes, and [0.5, 0.624] for e-scooters. The specific values of these indicators aim to support decision-makers in selecting a delivery model for a defined task based on the given constraints.

Keywords: last-mile delivery; fuzzy logic systems; harmonized membership function; city logistics; sustainability; electromobility; e-motorcycle; e-cargo bike; e-scooter



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1. Introduction

The modern business environment, along with the needs and habits of private consumers and the expansion of e-commerce, has led to a generation of many shipments within transportation systems. The core of the business operations of companies engaged in the transportation of shipments lies in their fast, efficient, and secure transfer from sender to recipient. The organization of shipment transfer encompasses a wide range of activities, as well as the use of various technical and methodological solutions. The market, along with various global procedures, prompts companies engaged in this field to strive to improve their business systems continuously. Shipment transfer systems are highly complex, typically possessing well-developed infrastructure and numerous individual factors that influence their functioning. The path to meeting customer needs and achieving business success involves continuous analysis of the market, global trends, regulations, and the company's internal systems, followed by appropriate and timely responses.

Global sustainability trends and specific regulations are prompting companies to align their operations toward a sustainable path. The European Commission (EC) is committed to achieving its Sustainable Development Goals by 2030. Still, progress is unsatisfactory, and significantly increased investments and actions are needed to meet the targets. The 2024 report indicates that the consequences of the pandemic, conflicts, and climate change have severely undermined progress [1]. The Commission has also adopted the goal of reducing greenhouse gas emissions by 90% by 2040, which is a crucial step toward achieving climate neutrality by 2050. These goals are part of the broader European Green Deal strategy, which aims for a sustainable economy and society while creating new jobs and enhancing the competitiveness of European companies [2,3]. The Commission integrates sustainable development goals into all legislative proposals and assessments to ensure their contribution to sustainability. In 2023, 46 out of 50 European Union (EU) programs supported the Sustainable Development Goals, and over 99% of the EU budget was directed toward programs aligned with these goals in coordination with member states [4]. In most of Europe, the transport sector still largely relies on fossil fuels, which significantly contributes to CO₂ and other pollutant emissions. Regarding total CO₂ emissions at the European Union level, 30% originates from transport, with road transport accounting for around 72% [5]. This mode of transport has been used by companies for years in domestic traffic to carry out last-mile delivery. Hence, it is no surprise that there is an ongoing trend among postal and other delivery companies to innovate their fleets, increasingly introducing electric vehicles and micromobility solutions such as e-scooters, e-cargo bikes, and the like. Consequently, new delivery models are emerging in operation, offering a higher sustainability level than the traditional approach, which involves deliveries using internal combustion engine vehicles. To improve the sustainability of the entire postal system, these models should be prioritized in operation; however, choosing delivery models also requires including other influential factors [6].

This paper specifically analyzes sustainable models for last-mile delivery, with the primary task being selecting the most suitable model based on delivery requirements and the conditions under which the delivery is carried out. Typically, various multi-criteria decision-making methods are applied in the literature for these tasks, which yield good results [7–10]. However, these approaches involve redefining the task for each model analysis, interviewing experts, processing data, and so on, which requires significant time that delivery organizers often do not have. For this reason, in this paper, we proposed a new methodology, the Fuzzy Delivery Model Selection (Fuzzy-DMS), which models expert reasoning and involves the creation of a mechanism consisting of a series of fuzzy logic systems. These systems ultimately provide a preference value that defines the suitability of applying a particular delivery model in a specific case. Creating the mechanism for determining delivery preferences is also long and complex. Still, once the mechanism is established, it can be used for an extended period until significant changes occur that may affect delivery efficiency. At any moment, after inputting the necessary data, the system provides results in a very short time. In addition to significantly reducing the time required to obtain a solution, applying the Fuzzy-DMS methodology also overcomes the challenge of organizing experts and the need for their constant availability during each decision-making task for selecting a delivery model. In this way, it improves the efficiency of the entire delivery organization process. A harmonized membership function is introduced by comparing symmetric and asymmetric functions to obtain more accurate results.

The applicability of the proposed approach is demonstrated through a case study on delivery organization in a part of the city of Belgrade. Specifically, for certain delivery requirements and in accordance with various constraints and conditions, three sustainable delivery models were analyzed based on the use of e-motorcycles, e-cargo bikes, and e-scooters. The obtained results and their analysis indicate that the developed mechanism of fuzzy logic systems provides logical and adequate solutions that align with the characteristics of the requirements and the key influential factors affecting the realization of the last-mile delivery (LMD) process.

In addition to the introduction, the paper consists of five more chapters. The second part presents a literature review appropriate for the analyzed topic, followed by a description of the Fuzzy Delivery Model Selection (Fuzzy-DMS) methodology within the materials and methods chapter. The fourth chapter provides the results of applying the proposed methodology and the corresponding analysis within the case study. The penultimate chapter highlights the key features of the approach in terms of applicability and limitations, followed by the concluding remarks.

2. Literature Review

Postal systems are complex, and the technological process of shipment transfer consists of several stages, each requiring efficiency and sustainability to ensure the overall system functions in this way. Continuous monitoring and improvement of all business activities and operations are necessary to establish such a system.

Last-mile delivery represents a phase of shipment transfer that is unique in many ways. It is, in fact, the most complex and costly stage in the technological process of shipment transfer [11–13]. Consequently, this phase is also the most sensitive to planning, and numerous authors have explored it from various perspectives. Most studies focus on addressing challenges arising from the expansion of e-commerce, improving sustainability, route optimization, location problems, or selecting delivery models [3,14].

Studies of this type are generally organization-oriented; however, those where customers provide their opinions are also highly significant, as they contribute to improving the shipment transfer process. For instance, in the study by [15], the authors explore consumer acceptance of three last-mile delivery methods, highlighting that ease of use and usefulness increase acceptance while costs limit it. Perceived sustainability (environmental, economic, and social) significantly impacts consumer preferences.

When it comes to the expansion of e-commerce and the concept of last-mile delivery, research varies widely. The presence of this topic in the literature is evident through numerous review papers. In the paper [16], innovative solutions that enhance last-mile delivery efficiency in Business-to-Consumer (B2C) e-commerce are reviewed and classified, highlighting key factors such as failed deliveries, customer density, and process automation. It also proposes directions for future research and offers solutions like parcel lockers, crowdsourcing logistics, and dynamic pricing to optimize delivery costs. In recent years, last-mile distribution in B2C e-commerce has brought new economic and environmental challenges, with limited attention to sustainability and greenhouse gas (GHG) emissions from freight transport. One of the initiatives emerging alongside the concept of e-commerce and LMD is the integration of delivery services with the installation or assembly of purchased goods. These components of commercial traffic in urban areas have not received adequate attention but have been unjustly marginalized, considering their potential [17]. The paper [18] reviews sustainability approaches in B2C deliveries, focusing on two key areas: logistics and consumer behavior, identifying benefits such as reduced costs, lower GHG emissions, and increased consumer engagement with sustainable options. Another interesting review paper [19] analyzes trends in sustainable last-mile delivery in urban areas within the context of e-commerce, examining the perspectives of various stakeholders such as residents, governments, and transport companies. A systematic literature review was conducted, employing both traditional methods and machine learning tools to identify key trends and relationships between these groups. The study highlights newer technological innovations like the Internet of Things (IoT) and autonomous vehicles and examines their impact on e-customer behavior and sustainable logistics.

The content of papers related to optimizing LMD routes is primarily focused on developing various algorithms [20–22]. The paper [23] proposes two levels of route optimization: the first involves designing routes for a fleet of vehicles from depots to a subset of satellites, and the second optimizes delivery from satellites to customers. The objective is to minimize total distribution costs, and the proposed solution is a hybrid genetic algorithm that efficiently explores the solution space, as confirmed by experiments on real-world

cases. There are also more complex LMD models that involve using different transportation modes for execution. In the study [24], the authors focus on a route optimization model in synchronized truck–drone operations, where drones depart from trucks, deliver packages to customers, and return for battery replacement and package retrieval. The model considers two delivery levels: the primary truck route from the main depot and the drone route, with the truck acting as a mobile intermediate depot. The objective is to minimize the total time for both trucks and drones to return to the depot, and the problem is solved using a mathematical model and two heuristic methods for larger problems.

When it comes to selecting a model for last-mile delivery, studies generally involve the application of multi-criteria decision-making methods [8,9,25]. A clear trend in the literature is that delivery models with a higher degree of sustainability are increasingly analyzed compared to traditional approaches. These models typically include electric vehicles, bicycles, e-cargo bikes, parcel lockers, autonomous vehicles, and similar alternatives. As models based on electromobility are increasingly mentioned and analyzed in the context of last-mile delivery (LMD), studies focusing on the assessment of the energy consumption of electric vehicles are simultaneously emerging, aiming to improve energy efficiency [26]. Multi-criteria decision-making approaches yield good results but require a certain amount of time to complete, as the task first needs to be structured. This involves selecting criteria and alternatives and forming a panel of experts. Expert opinions on the criteria and alternatives are then gathered, based on how the importance of each is calculated. The result of these approaches is a ranking of the alternatives. One of the most significant drawbacks of this approach is precisely the time required for its implementation, making it challenging to solve the task instantaneously. The proposed methodology in this paper significantly mitigates this limitation.

One of the most significant concepts integrated into last-mile delivery (LMD) is crowdsourcing, which involves engaging third parties in the delivery process [27–31]. Crowdsourcing is essential for last-mile delivery as it reduces costs by utilizing independent couriers, minimizing the need for a dedicated vehicle fleet. It also allows for greater flexibility and faster delivery, especially in urban areas, enabling same-day delivery options. Additionally, crowdsourcing reduces emissions by using couriers who are already traveling along specific routes, making the delivery process more environmentally friendly.

Analyzing the Web of Science (WoS) database [32], a considerable number of papers (589) include the term “last-mile delivery” in their titles, while 2244 papers appear when the term is searched across all fields. A total of 10 papers have both “last-mile delivery” and “fuzzy” in their titles, and a total of 50 papers when both terms are searched across all fields. Of the 589 papers with “last-mile delivery” in the title, 520 have been published since 2019, indicating a pronounced upward trend in the importance of this field over the past five years.

In Figure 1, a network visualization is presented, generated from the VOSviewer 1.6.19 software. As this paper focuses on the fuzzy approach for addressing a specific task within last-mile delivery, we analyzed papers (50) in which these two terms appear simultaneously when the search is conducted across all fields. The network shows the connections between keywords in these papers, arranged into three clusters. The main criterion for including keywords in the analysis was that they appear in at least four papers; based on this criterion, the total number of analyzed keywords is 24. The red cluster focuses on terms related to e-commerce, fuzzy clustering, frameworks, and supply chain management. This suggests that research in this area often addresses the structure and optimization of delivery systems within e-commerce. In this cluster, the term “last mile delivery” appears, reflecting the varied formatting used by individuals when referencing this term. The green cluster centers on logistics, sustainability, multi-criteria decision-making, and fuzzy sets, highlighting the importance of sustainability and decision-making based on multi-criteria methods and the fuzzy approach in last-mile delivery. The blue cluster includes terms such as vehicle-routing problem, traveling salesman problem, and urban logistics. This cluster

relates to optimization problems in logistics, particularly in urban areas, and indicates the technical challenges encountered in vehicle route optimization.

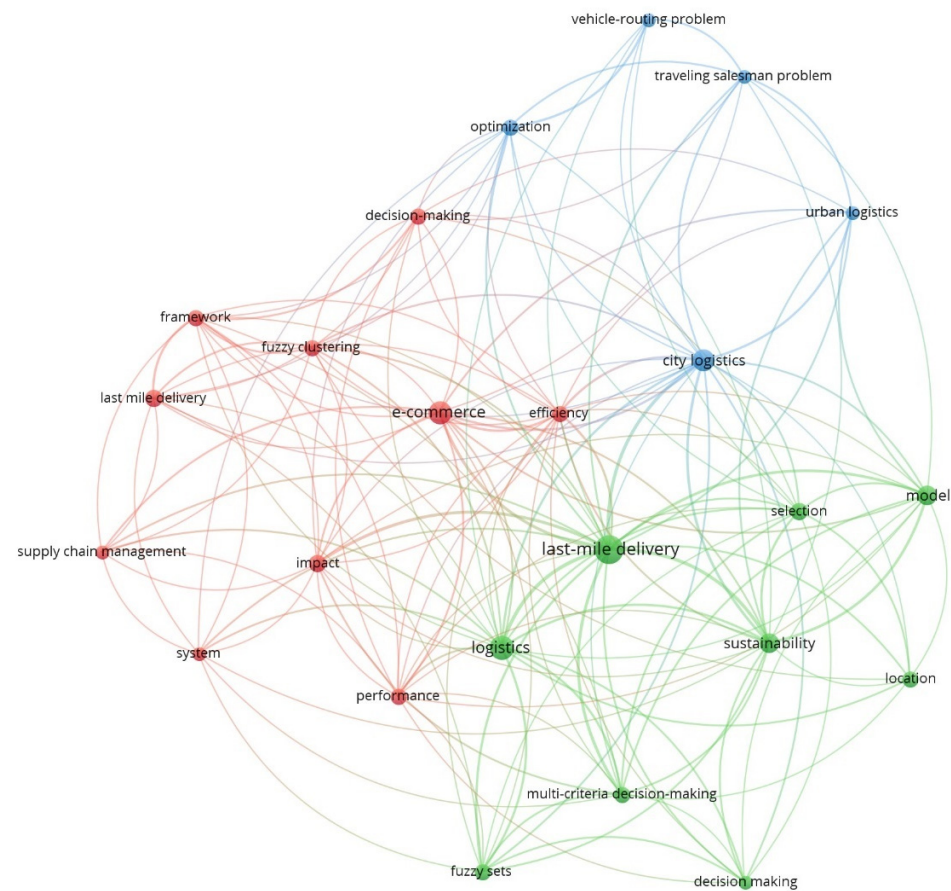


Figure 1. Bibliometric network of key terms associated with research utilizing the fuzzy approach in last-mile delivery.

It is evident from the figure that “last-mile delivery” is the central term, having the most connections with other terms, which makes it a key research focus. Additionally, “logistics” and “e-commerce” are also prominent terms with numerous connections to other concepts, underscoring their critical role in discussions on last-mile optimization. The connection between “fuzzy sets” and “multi-criteria decision-making” suggests that uncertainty theory and multi-criteria models are utilized for decision-making processes.

In line with the previous analysis, Table 1 will summarize the literature review, specifically papers in which the term “last-mile delivery” appears in the title while the term “fuzzy” is simultaneously present in the abstract. There are 20 such papers in the Web of Science database [32]. Through their approaches, methodologies, and applications, most of these studies directly or indirectly contribute to the advancement of sustainable development. Given that global trends have directed postal and other delivery systems toward continuous sustainability improvement, this is to be expected. However, here, we distinguish between studies that strongly emphasize this trend and those where it is not as prominent. Additionally, most studies involving the implementation of proposed solutions require the active participation of experts, which significantly increases the complexity of the organization and the time needed for their application. Based on the above, an analysis and comparison of the studies were conducted according to two criteria: a strong focus on sustainability—S and active participation of experts not required for every application—NE.

Table 1. The summary of the literature review—“last-mile delivery” in the title and “fuzzy” in the abstract.

Author(s) and Years	Research Focus	S	NE
Jiang et al. (2019) [33]	Analyzing the sustainability factors of rural last-mile delivery in China using Fuzzy Analytic Hierarchy Process (FAHP) and Interpretative Structural Modeling (ISM) to improve service quality and promote sustainable rural logistics.	x	x
Caggiani et al. (2020) [34]	Developing a Decision Support System (DSS) for optimizing e-cargo bike routes in last-mile delivery by balancing logistics performance with minimizing driver exposure to emissions, using a Fuzzy Inference System (FIS) for final route choice.	✓	x
Svadlenka et al. (2020) [8]	Providing an advanced decision-making approach for selecting the best sustainable LMD mode using Picture Fuzzy Sets (PFSs), hybrid criteria weighting, and a novel ranking method, with e-cargo bikes emerging as the optimal solution in a real-life context.	✓	x
Jiang et al. (2020) [35]	An integrated approach combines Fuzzy Comprehensive Evaluation (FCE) and an Interpretative Structural Model (ISM) to analyze and improve service quality evaluation indexes for rural last-mile delivery, focusing on enhancing the accuracy of goods arrival and timely customer service response for sustainable rural logistics development.	✓	x
Nur et al. (2020) [36]	Proposing an interval-valued inferential fuzzy Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method for multi-criteria decision-making to select the most appropriate drone for last-mile delivery, with results indicating smaller drones for urban areas and long-range drones for rural delivery needs.	✓	x
Wang et al. (2021) [37]	Evaluating the sustainability performance of last-mile delivery companies in Vietnam using a Fuzzy Multi-Criteria Decision-Making Framework (F-MCDM) that combines FAHP and Fuzzy Weighted Aggregated Sum Product Assessment (FWASPAS), with Grab Express identified as the top performer based on key criteria such as delivery time, order fulfillment, and decarbonization.	✓	x
Rashidzadeh et al. (2021) [38]	Assessing sustainability in the last-mile delivery of the blood supply chain by using drone technology through a multi-objective mathematical model and preemptive fuzzy goal programming, comparing drones with conventional vehicles to highlight their impact on CO ₂ emissions, costs, and social benefits.	✓	✓
Du & Wang (2021) [39]	Constructing an evaluation criteria system and a matching model using the fuzzy analytic hierarchy process (FAHP) to rank last-mile delivery methods based on customer preferences in different urban areas, validated through real-life applications in Chongqing, China.	x	x
Simić et al. (2021) [25]	Presenting an extension of the Weighted Aggregated Sum Product Assessment (WASPAS) method under the picture fuzzy environment to solve the last-mile delivery (LMD) mode selection problem, with a case study in Belgrade showing parcel lockers as the best LMD mode.	x	x
Peppel et al. (2022) [40]	Exploring future trends in the last-mile delivery (LMD) sector by conducting a Delphi-based scenario study for 2040, utilizing expert insights and fuzzy c-means clustering to project consumer behavior, delivery technologies, and service designs.	x	x
de Araújo et al. (2022) [41]	Investigating how logistics service expectations impact the urban last-mile delivery process using a multiple-criteria decision support system based on FAHP, results show cost and tracking as the most critical criteria and smart lockers as the best delivery method.	✓	x
Yilmaz & Demirel (2023) [42]	Evaluating six out-of-home last-mile delivery methods using the Hesitant Fuzzy Linguistic Term Sets approach to address uncertainty in expert opinions, with Click & Collect identified as the most sustainable option.	✓	x

Table 1. Cont.

Author(s) and Years	Research Focus	S	NE
Saha et al. (2023) [43]	Addressing the prioritization of zero-emission last-mile delivery (LMD) solutions using a novel multi-criteria group decision-making methodology with Dual Hesitant Fuzzy (DHF) sets and the Sustainable Decision-Making Approach for Ranking and Choosing Options (SDNMARCOS) method, with electric light commercial vehicles identified as the best solution.	✓	x
Wang et al. (2023) [44]	Evaluating sustainable last-mile solutions in Vietnam using a hybrid, multiple attribute decision-making model that combines the Ordinal Priority Approach (OPA) and fuzzy Making Approach for Ranking and Choosing Options (MARCOS) with convenience store pickup, parcel lockers, and green vehicles identified as the best solutions.	✓	x
Pamucar et al. (2023) [9]	Proposing a methodology for prioritizing crowdsourced last-mile delivery models using Sugeno–Weber nonlinear functions in a fuzzy environment, with a case study in suburban Belgrade.	x	x
Kara et al. (2024) [45]	Developing a Vehicle Routing Software (VRS) selection model for last-mile delivery (LMD) companies using Fermatean fuzzy sets and the hybrid Preference Selection Index Alternative Ranking Order Method Accounting For Two-Step Normalization (FFS-PSI-AROMAN) approach, with a case study in Turkey demonstrating its application and robustness.	✓	x
Moslem et al. (2024) [46]	Assessing the most suitable locations for parcel lockers in Dublin using a novel hybrid decision-making model that combines the Combinative Distance-based Assessment and Analytic Hierarchy Process (AHP) methods through Decomposed Fuzzy Sets, providing strategic insights for policymakers.	x	x
Ayyildiz & Erdogan (2024) [47]	Determining the challenges of using autonomous delivery robots (ADRs) in LMD by employing the Intuitionistic Fuzzy (IF) Pivot Pairwise Relative Criteria Importance Assessment (PIPRECIA) method combined with Political, Economic, Social, Technological, Environmental, and Legal (PESTEL) analysis, identifying key factors such as energy consumption, cybersecurity, and uncertain return on investment.	✓	x
Dai et al. (2024) [48]	Optimizing last-mile logistics in rural China through a truck–drone distribution model using the fuzzy C-means algorithm and genetic simulated annealing, aimed at reducing delivery time and costs while addressing rural infrastructure challenges.	x	✓
Kumbhani & Kant (2024) [49]	Exploring the benefits of drone-based last-mile delivery in India’s logistics sector by developing a hybrid framework using Spherical Fuzzy Analytic Hierarchy Process (SF-AHP), fuzzy C-means clustering, and Spherical Fuzzy Combined Compromise Solution (SF-CoCoSo) to rank benefits based on key enablers such as technology, infrastructure, and government regulations.	✓	x
Our study	A Fuzzy Delivery Model Selection (Fuzzy-DMS) methodology is proposed to determine the suitability of implementing electromobility LMD models based on a series of fuzzy logic systems. A case study was conducted in Belgrade, where delivery models such as e-motorcycles, e-cargo bikes, and e-scooters were analyzed.	✓	✓

The results are presented in the second and third columns. The results of the analysis unequivocally indicate that our study received a positive evaluation for both criteria. This status is shared by only one other study [38] among those analyzed; however, it involves a complex development and application process based on a multi-objective mathematical model and preemptive fuzzy goal programming. The simplicity of application directly impacts the efficiency of the delivery process organization, making it a significant advantage in practical terms.

The analyzed papers cover a wide range of topics focused on improving efficiency, sustainability, and optimizing last-mile delivery (LMD) logistics processes in the context of increasing consumer demands and the challenges posed by e-commerce and urban development. The primary focus of these studies is the application of advanced decision-making methods, such as fuzzy logic, multi-criteria analyses, and methods like FAHP, ISM, and TOPSIS, to identify the most suitable solutions for last-mile delivery. Special attention is given to innovative technologies like drones, autonomous robots, electric bikes, and crowdsourcing models, aiming to reduce greenhouse gas emissions, costs, and delivery time.

In urban areas, solutions like smart parcel lockers and route optimization are explored, while in rural areas, particular emphasis is placed on truck–drone distribution models to overcome challenges like poor infrastructure and low population density. Furthermore, the papers analyze the challenges of implementing new technologies, including energy efficiency, cybersecurity, and uncertain return on investment.

By combining theoretical models and case studies from various countries, such as China, Vietnam, Brazil, and Serbia, these papers provide practical guidelines and recommendations for logistics industry decision-makers, helping them identify the most effective strategies for the sustainable development of the LMD sector. In this way, the research offers a comprehensive overview of potential solutions and contributes to the adaptation of companies to increasingly demanding market conditions and societal expectations.

The methodology proposed in our research is based on the application of fuzzy set theory. Classical set theory is characterized by precise boundaries, clearly defining which element belongs to a set and which does not. However, in real-world situations, it is often difficult to determine clear boundaries and, consequently, whether an element belongs to a set or not. For example, consider set A representing “Short waiting time”. It is necessary to define the elements that belong to this set. People intuitively feel that, for instance, a waiting time of 6 min belongs more strongly to this set than a waiting time of 10 min. In other words, the statement that 6 min represents a short waiting time in a queue holds more truth than 10 min, even though both elements belong to the set [50].

From the basic principles of fuzzy set theory, fuzzy logic systems (FLS) have been developed, which aim to model human experience, intuition, and behavior in decision-making processes. In these systems, decisions or conclusions are made based on approximate reasoning, i.e., a fuzzy control algorithm that consists of a set of fuzzy rules [51,52]. These capabilities of fuzzy logic were crucial when choosing the approach on which the proposed Fuzzy Decision-Making System (Fuzzy-DMS) methodology is based. Fuzzy logic has also seen significant use in control systems and process management in traffic and transportation [53–59].

3. Materials and Methods

3.1. Fuzzy Delivery Model Selection—Fuzzy-DMS Methodology

In line with sustainable development trends and the efforts of companies engaged in the delivery of shipments to provide high-quality services while ensuring profitability, the continuous improvement of business processes is essential. This involves optimizing and enhancing efficiency, particularly in critical operations segments that may negatively impact the entire system. One of the key tasks for the organizer of postal shipment deliveries is the optimization of the most expensive and complex phase, which is the delivery to the end user. In this context, improving sustainability requires that the selection of the delivery model for a specific territory, based on concrete requirements and conditions, becomes one of the primary objectives. In this regard the paper proposes an approach for supporting the selection of a sustainable delivery model, the Fuzzy Delivery Model Selection (Fuzzy-DMS), based on fuzzy logic application. The broader methodological framework involves an algorithm (Figure 2) that comprises two main levels. The first level involves evaluating the alternatives in terms of meeting elimination criteria, while the second level, through the application of fuzzy logic, determines their suitability or preference for implementation in a specific case.

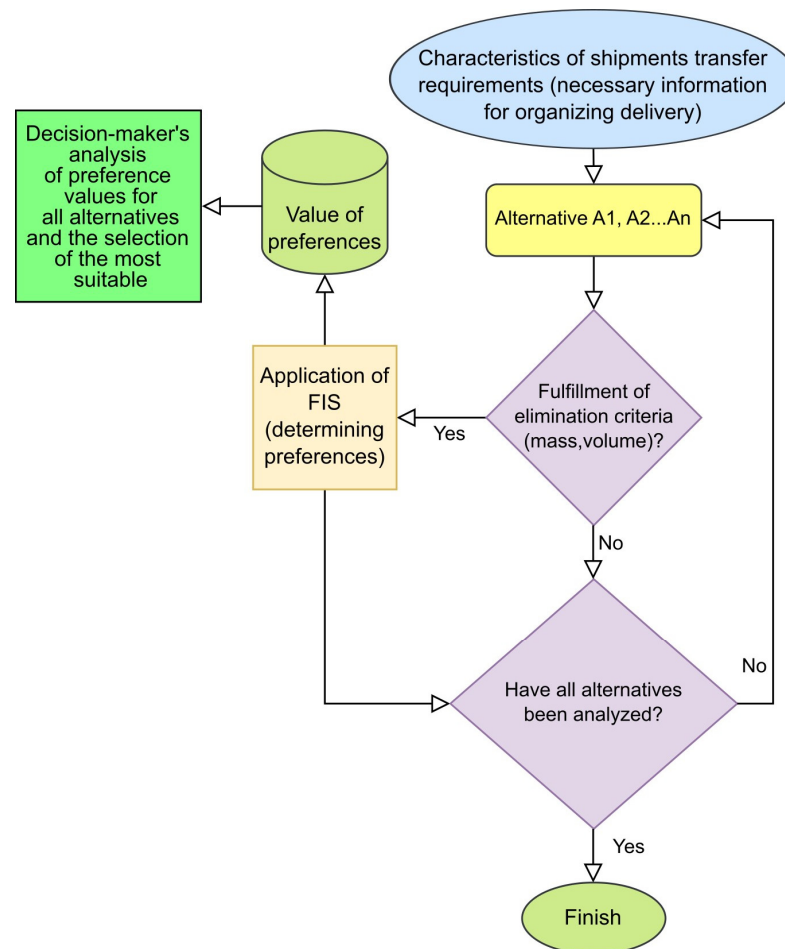


Figure 2. Graphical representation of the algorithm for the proposed methodology.

The proposed Fuzzy-DMS methodology can be presented through several steps:

- Step 1—this involves gathering and analyzing shipment delivery requirements, which originate from the users, and information that is useful and necessary for the decision-maker in organizing the delivery. Based on this information, and in accordance with its impact on a delivery organization, a set of influential factors is formed, which will also serve as input variables in the FLS;
- Step 2—this involves forming a set of delivery alternatives that are available in the observed area;
- Step 3—analysis of alternatives based on elimination criteria. In this step, alternatives that, due to their characteristics, do not support the weight and volume of the shipments to be delivered are removed from further analysis;
- Step 4—involves creating and applying an FLS, which will output a preference score indicating the suitability of applying the respective delivery model. A separate FLS is created for each alternative;
- Step 5—ensuring that all alternatives that have met the elimination criteria are analyzed in Step 4;
- Step 6—the final step involves the decision-maker's analysis of preference values for all alternatives.

In the first step, information is gathered about all the shipments that need to be delivered. The quantity and quality of input information and collected data are crucial for efficiently applying the methodology and obtaining adequate results. The automation and informatization of the postal system have made it possible to collect almost all information about shipments at the very entry into the system, either during acceptance by a postal

worker or upon entry into a processing center. As a rule, postal operators have developed information systems that maintain records for each shipment and all other related information, which is collected at different stages. Depending on the type of shipment acceptance, whether in the field by a courier or at a postal network unit, information about the shipment's destination, type, and weight can mainly be collected at this stage. Companies in this field generally have departments or teams dedicated to data management. Some relevant data may include the number of shipments and locations that need to be visited to complete the delivery. In reality, the values for the number of shipments and locations usually differ, with the number of shipments always being higher, as multiple shipments are often delivered to a single location. Based on this information, a suitable route can be formed for the courier to follow to meet the delivery requirements. This allows for a clear understanding of the route's characteristics, parking locations can be planned, and so on. The second set of information collected in this step relates to the physical characteristics of the shipments, specifically their weight and volume. This process can be challenging, but with investments in equipment such as 3D scanners, we can obtain additional physical characteristics that interest the transportation organization. Each delivery model, or the vehicle used in the process, has limitations concerning its load capacity and the space available for cargo. The third set of information can pertain to other factors that influence the organization of deliveries in the analyzed area, such as weather conditions, traffic characteristics, etc. The most important outcome of this step is identifying the set of influential factors for delivery organization, which will serve as input variables in the FLS for determining the preference and suitability of applying a specific delivery model.

The second step involves identifying the delivery models, or alternatives, that are currently in use in the observed area, as well as those that the company could potentially organize and implement in line with real-world conditions. The fundamental characteristics of each delivery model are determined by the features of the transport vehicle used for delivering shipments.

In line with the information from the previous two steps, the third step involves checking the basic, or elimination, criteria. This includes analyzing whether the alternative can meet the specific requirements, i.e., whether the transport vehicle used has sufficient load capacity and cargo space to transport all the shipments.

In the fourth step, an FLS is created and applied to determine the preference or suitability of the analyzed delivery alternative. The preference value is calculated for each alternative that meets the elimination criteria, which is ensured through verification in the fifth step. In the final step of the methodology, the decision-maker or delivery organizer analyzes the obtained preference values for all alternatives.

3.2. *Creating a Fuzzy Logic System for Determining Delivery Model Preference*

The FLS is the main mechanism of this methodology, which determines the preference, or suitability, of applying the analyzed delivery model in a specific case. It is necessary to define appropriate inputs for the FLS and fuzzy rules to obtain relevant results. Depending on the nature and characteristics of the inputs, the creation of fuzzy rules can be based on available data and expert opinions.

The delivery of shipments is a territorially dependent service, meaning that for areas with different characteristics, it may be necessary to define separate FISs for the same alternative. It is important to note that, to more precisely define the preference and account for potentially different fuzzy rules and input variable characteristics across different alternatives, creating a separate FIS for each alternative is recommended.

The founder of the theory of fuzzy sets is Professor Lotfi Zadeh. Following his initial works in this field, fuzzy sets and fuzzy logic have found widespread application in numerous areas. The fundamental characteristic of any fuzzy set is the membership function, which assigns each element a corresponding degree of membership to that fuzzy set. The degree of membership can range from 0 to 1. Based on this, a fuzzy set A can be defined as a set of ordered pairs: $A = \{x, \mu_A(x)\}$, where x is an element, and $\mu_A(x)$ is the

degree of membership of element x to set A . The higher the membership degree $\mu_A(x)$, the stronger the truth of the statement that element x belongs to set A . Figure 3 gives an arbitrary example of a membership function for fuzzy set A —“Short waiting time”. In this particular case, a waiting time of 9 min belongs to fuzzy set A —“Short waiting time” with a membership degree of $\mu_A(9) = 0.25$. It is logical and clear from the figure that values less than 9 min belong to this fuzzy set with a higher degree of membership, while values greater than 9 min belong to the set with a lower degree of membership.

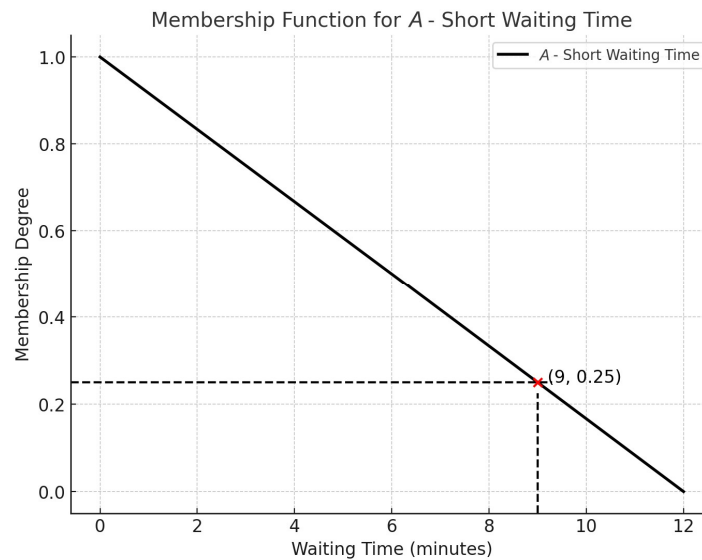


Figure 3. Membership function for fuzzy set A —“Short waiting time”.

Membership functions can take various shapes. Triangular and trapezoidal forms are most commonly used, but others, such as Gaussian and Bell curves, are also frequently utilized. Below are the mathematical representations of the most commonly used membership functions [50,56,60–62]:

- Triangular membership function:

$$\mu_A(x) = \begin{cases} 0, & \text{for } x \leq a \text{ or } x \geq c \\ \frac{x-a}{b-a}, & \text{for } a \leq x < b \\ \frac{c-x}{c-b}, & \text{for } b \leq x < c \end{cases}, \quad (1)$$

where $\mu_A(x)$ is the membership degree of value x to the fuzzy set A , a is the left boundary from which the membership begins to increase, b is the peak where the membership reaches its maximum (1), and c is the right boundary where the membership degree decreases to 0;

- Trapezoidal Membership Function:

$$\mu_A(x) = \begin{cases} 0, & \text{for } x \leq a \text{ or } x \geq d \\ \frac{x-a}{b-a}, & \text{for } a \leq x < b \\ 1, & \text{for } b \leq x < c \\ \frac{d-x}{d-c}, & \text{for } c \leq x < d \end{cases}, \quad (2)$$

where $\mu_A(x)$ is the membership degree of value x to the fuzzy set A , a and d are the trapezoid's endpoints where membership begins and ends, and b and c are the left and right points of the flat part of the trapezoid, where the membership remains at 1;

- Gaussian Membership Function:

$$\mu_A(x) = \exp\left(-\frac{(x-c)^2}{2\sigma^2}\right), \quad (3)$$

where c is the center, and σ is the standard deviation.

Determining membership functions is primarily based on experience, intuition, available facts, and knowledge about the observed phenomenon. It is important to note that exclusivity must be avoided when defining membership functions. This can be achieved by ensuring an overlap of their boundaries, thereby increasing tolerance [51].

The basic elements of every FLS are fuzzy rules, a fuzzifier, an inference engine, and a defuzzifier. Fuzzy rules represent the system's knowledge and form the rule base of the FLS. The rule base can be generated based on expert knowledge and experience, numerical data, or a combination of both approaches. The combined approach is based on numerical data typically obtained through measurement and linguistic information gathered from interviews. The combined approach for generating fuzzy rules is the most comprehensive, and it was developed by Wang & Mendel (1992) [63]. The rules are defined in an If-Then format:

If x_1 is A_1 AND x_2 is A_2 Then y is B

where x_1 and x_2 are input variables, A_1 and A_2 are fuzzy sets that define the degree of membership, and y is the output variable with fuzzy set B .

The Mamdani inference approach [64] was used in the paper, where α_i represents the activation degree of the i -th rule:

$$\alpha_i = \min(\mu_{A_1}(x_1), \mu_{A_2}(x_2)), \quad (4)$$

while the membership function $\mu_{B_i}(y)$ of the output fuzzy set B_i is calculated using the following formula:

$$\mu_B(y) = \max(\min(\alpha_i, \mu_{B_i}(y))). \quad (5)$$

The fuzzifier transforms precise input variables into fuzzy linguistic variables using the appropriate membership functions. Approximate reasoning translates fuzzy rules into fuzzy relations to arrive at a certain conclusion or result. The inference engine defines how the rules are combined. The final step is defuzzification, which aims to define or select a single value for the output variable. Defuzzification is usually conducted based on the following approaches (choices) and criteria: the smallest value with the highest degree of membership, the largest value with the highest degree of membership, the average value with the highest degree of membership, the center of gravity, etc. [65]. The most commonly used approach is the center of gravity principle [66,67]:

$$y = \frac{\int x \cdot \mu_A(x) dx}{\int x \mu_A(x) dx}, \quad (6)$$

where y represents the crisp output value and $\mu_B(y)$ is the membership function of the fuzzy output.

When the values are discrete, the formula is transformed into a sum because we cannot use integrals. Instead, we use the weighted sum of discrete points:

$$y = \frac{\sum_{i=1}^n x_i \cdot \mu_A(x_i)}{\sum_{i=1}^n \mu_A(x_i)}, \quad (7)$$

where x_i are the discrete values of the variable x , $\mu_A(x_i)$ are the membership function values for the corresponding discrete values x_i , and n is the number of discrete points.

In fuzzy logic systems, input and output variables often have membership functions that represent uncertain or imprecise information. Fuzzy entropy can help analyze the degree of uncertainty of a fuzzy variable. It is calculated using the following formula [68]:

$$H(A) = - \sum_{i=1}^n \mu_A(x_i) \log(\mu_A(x_i)) + (1 - \mu_A(x_i)) \log(1 - \mu_A(x_i)), \quad (8)$$

where $H(A)$ is the fuzzy entropy of fuzzy set A , $\mu_A(x_i)$ is the membership to fuzzy set A at point x_i , and n is the number of discrete points. Fuzzy entropy can be useful for identifying rules or variables with a high level of uncertainty. For example, high entropy indicates a need for further analysis or adjustment of the membership functions. On the other hand, low entropy suggests greater precision.

To enhance the validity of the obtained results and reduce the impact of expert subjectivity, we proposed introducing harmonized membership functions in this paper. As shown in Figure 4, a comparison is made between symmetric (blue function) and asymmetric (orange function) membership functions, resulting in the harmonized membership functions (green function). When considering the distances (a, b, c, d, e) of characteristic points from the axis passing through the top of the membership function, it is easy to verify the symmetry of each function. Asymmetric functions are typically those derived through expert collaboration or based on existing data, where the distances from the left and right boundaries to the axis passing through the top of the membership function differ. In symmetric functions, these distances are equal [69,70].

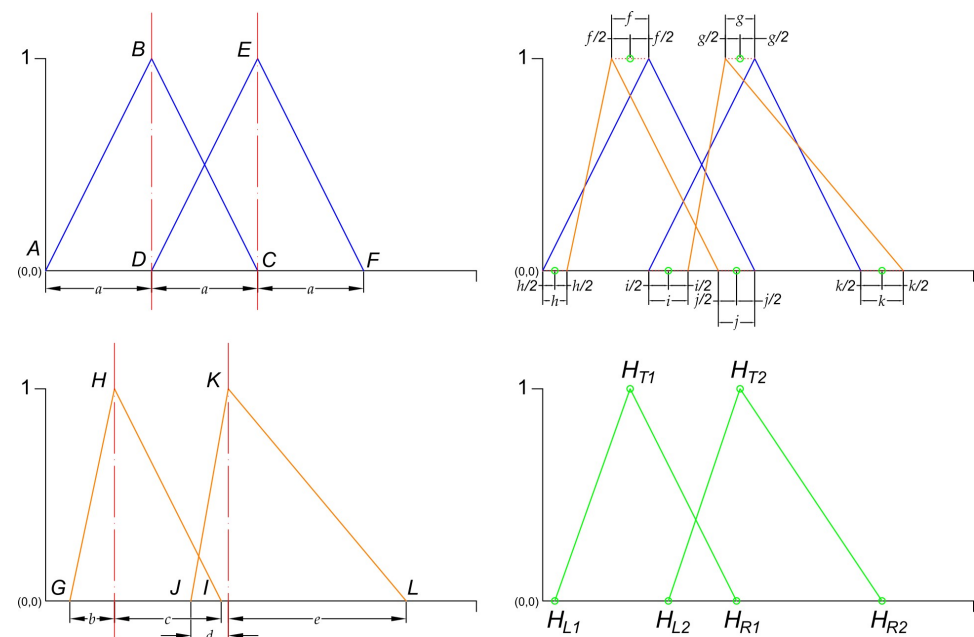


Figure 4. Formation of harmonized membership functions based on symmetric and asymmetric membership functions.

In creating the harmonized membership function, symmetric membership functions aim to moderate the impact of extreme values in the characteristic parameters of asymmetric membership functions, thereby reducing expert subjectivity. In this way, symmetric functions control and “draw” asymmetric functions toward symmetry. At the same time, the influence of asymmetric functions retains a certain level of expert subjectivity. The idea is to derive the characteristic values of the resulting function—the left boundary, right boundary, and top—as the arithmetic mean of the pairs of these parameters from both the symmetric and asymmetric functions (Figure 4). If we consider these characteristic values as points in a rectangular Cartesian coordinate system, with the origin at point $(0, 0)$, the

resulting parameter, for instance, H_{T1} , or the value of its x-coordinate, can be calculated based on the following formula:

$$x_{HT1} = \frac{x_B + x_H}{2}, \quad (9)$$

where x_B is the x-coordinate of point B , and x_H is the x-coordinate of point H . Based on this, the harmonized characteristic points are located at the midpoint between the corresponding characteristic points of symmetric and asymmetric membership functions, as illustrated in Figure 4.

When creating a fuzzy variable, it is first necessary to define the range of values and the membership functions, which will enable the determining of the degree of membership for each parameter value in a particular fuzzy set. This applies to every input and output variable in the fuzzy logic system. Fuzzy rules are created so that the system mimics expert reasoning, allowing the system to generate an output preference value, in this case, as close as possible to the value an expert would determine for every input value entered.

The range of values represents the set of expected values of the parameter being analyzed. If we take the example where the membership function that defines the fuzzy set is triangular, and if it is convex and normalized, then it represents a fuzzy number. In that case, it is necessary to define the left and right boundaries of the variable's value range, as well as the membership function for each fuzzy set (number), which includes defining the left and right boundaries and the peak—the value with the highest degree of membership, $\mu = 1$.

To determine the necessary parameters for modeling expert reasoning, it is essential to conduct appropriate research. The research plan depends on the nature of the parameter being observed, with the goal of defining the input and output variables of the FLS, i.e., the relationship between the parameter values and the corresponding fuzzy sets through membership functions. In general, an appropriate research process could consist of the following steps:

- Defining the range of values that the variable can take based on statistical indicators, expert opinions, or other appropriate determinants;
- Linguistic definition of fuzzy sets for the variable in accordance with expert opinions;
- Gathering expert opinions on the boundary values and the peak of the membership functions for each of the defined fuzzy sets;
- Analysis and processing of the obtained results, followed by the final definition of the membership functions for the fuzzy sets. Membership functions created in this way are primarily asymmetric, as their fundamental parameters are derived from expert opinions. Two additional steps need to be implemented to obtain harmonized membership functions;
- Creation of symmetric membership functions;
- Comparison of symmetric and asymmetric membership functions and creation of harmonized membership functions.

Additionally, in certain situations, depending on the nature of the variables, it may be necessary for the input to one FLS to be the generated output from another FLS.

The first step involves defining the range of values that the analyzed variable can take based on statistical indicators and subjective expert opinions. In the second step, it is necessary to define the fuzzy sets linguistically. Depending on the parameter being observed, some examples of fuzzy sets may include: "Very long service time", "Short waiting time", "High level of territorial accessibility", "Very low level of security", "Moderately developed service range", and similar. In the third step, the basic parameters of the membership functions are determined: the minimum and maximum values and the value with the highest degree of membership. Expert opinions (from experts and other relevant groups) are collected, as this is one way to obtain the most realistic indicators.

In the fourth step, through the analysis of the collected data, which typically involves averaging the values obtained from the responses, the basic parameters

of the membership functions for the fuzzy sets are defined. It is expected that the characteristic values being sought will cluster, and therefore, one of the principles for selecting a representative value from the group is applied (e.g., minimum value, maximum value, average value, etc.). It is clear that the membership functions of fuzzy sets for different variables will vary depending on the type of parameters, the collected data, and other factors. As previously mentioned, this method primarily results in the creation of asymmetric membership functions. In the fifth step, symmetric membership functions are created so that, in the sixth step, harmonized membership functions can be obtained, as explained in the methodology.

The output of the proposed FLS for the specified input parameter values represents the preference value. The range of values that preference can take is from 0 to 1, where 0 is the lowest and 1 is the highest value, corresponding to the highest level of suitability for exploiting the analyzed delivery model. The definition of fuzzy sets for the output variable can be achieved using the same approach. Certain variables can be defined depending on their nature or expert opinion so that the domain is divided into evenly distributed fuzzy sets, i.e., symmetric membership functions. To obtain the value of the output variable for defined values of the input variable—one that corresponds to the value based on expert reasoning—it is necessary to train the system and define fuzzy rules upon which conclusions about the output variable will be made. The fuzzy rule base includes all the rules within the FLS, which can be created based on expert opinions, numerical data, or a combination of both approaches [51,63,65].

4. Results

The following section presents the structure and results of the case study conducted in the territory of the city of Belgrade, aimed at demonstrating the applicability of the proposed methodology.

4.1. Case Study

In the case study, the proposed Fuzzy-DMS methodology was applied to the evaluation of electromobility delivery models in a part of the city of Belgrade, which is the capital of the Republic of Serbia, with an area of 322,268 hectares (the central urban area of the city covers 35,996 hectares) and a population of around 1.6 million people. The suitability of implementing various electromobility delivery alternatives in the specified part of the territory (Figure 5) was analyzed for specific delivery requirements. Figure 5 shows the location of the postal network unit from which deliveries are dispatched.

The creation of the fuzzy logic system involved a total of eight experts. Two experts are from academic institutions specializing in city logistics and postal services. The remaining six experts are from public and private postal operators: two are from development teams with expertise in developing modern delivery models, two experts are involved in the daily organization of shipment deliveries, and two are couriers responsible for executing delivery activities. The primary criteria for selecting the experts were their experience in the field, daily involvement, and role in activities related to the analyzed area. According to the authors, their expertise is adequate for addressing the task described below. Data was collected online as well as through traditional interviews.

Specifically, for the mentioned area of Belgrade, it is necessary to define FLSs that will determine the suitability of using available electromobility delivery models for specific cases and requirements, as explained in the methodological section.



Figure 5. The analyzed delivery territory.

The first step of the methodology involves collecting the necessary information to process the specific request. First, it was necessary to identify the key influential factors for delivery organization. The authors provided the experts with a list of the following five influential factors: route length, number of packages for delivery, number of delivery locations, estimated cargo space utilization, and degree of adaptation to weather conditions, with a request to select three they considered more important for further analysis than the remaining two. The limitation to three influential factors was defined for practical reasons, as these factors would serve as inputs to the Fuzzy Logic System (FLS) and directly affect its complexity. Each expert submitted a shortened list of three factors, resulting in the exclusion of number of packages for delivery and number of delivery locations from further analysis. In the discussion, one of the reasons cited was that a large number of packages does not necessarily imply significant weight or volume, and conversely, a small number of packages could have substantial weight and volume. For this reason, this parameter was deemed not particularly adequate for organizing delivery activities. On the other hand, the number of locations to visit or stops required for delivery is significant, primarily due to parking considerations. However, since the experts were familiar with the alternatives to be analyzed and the fact that parking requirements were similar for all of them, the consensus was that this factor would not significantly differentiate any of the analyzed alternatives. Thus, it was excluded from further analysis in this context. The following parameters have been identified as the key influencing factors for organizing delivery in the given case, and they will serve as input variables in the FLS:

- Route length is a significant factor as it influences the selection of appropriate delivery vehicles, especially in cases where the autonomy of electric vehicles must be considered. It also affects the time required for delivery, among other aspects;
- Estimated cargo space utilization—this represents the ratio between the total volume of shipments to be transported and the cargo space of the delivery vehicle. This parameter is significant, primarily from the perspective of improving sustainability, aiming for optimal cargo space utilization. To define this ratio, gathering information

on the volume of the packages is necessary. Additionally, information about the weight is required, as these are elimination criteria for the delivery alternatives being considered. If the load capacity and cargo space of a particular vehicle do not meet the requirements, the alternative based on that vehicle is excluded from further analysis;

- Degree of adaptation to weather conditions—this is a significant influencing factor in delivery organization, especially when it comes to sustainable delivery models that involve the use of transport vehicles sensitive to adverse weather conditions. Additionally, the exposure of couriers to weather conditions while using different vehicles is a crucial factor when organizing deliveries.

Based on the data collected during the acceptance phase and immediately after the arrival of shipments at the processing center, it is already possible to direct them toward delivery routes, where they are grouped, enabling the determination of the total weight and volume of shipments for a specific route. This data is essential for verifying elimination criteria as well as determining the degree of cargo space utilization. Additionally, at this stage, with the use of appropriate software, it is already possible to solve the routing problem, making the parameter related to route length known as well. It should be noted that weather data is available from various relevant sources, such as different hydrometeorological institutes. In this particular case, it is the Republic Hydrometeorological Service of Serbia. Based on the above, we can conclude that immediately after the arrival of shipments at the processing center, all the necessary information for applying the Fuzzy-DMS methodology is available. This enables the delivery process to be already fully organized by the time the shipments reach the final transfer phase, i.e., loading for delivery.

In this case study, data was collected from experts when defining the FLS variables, which will be discussed in more detail in the fourth step (Section 4.1.1), while the characteristics of the data used for testing are described in that chapter (Section 4.1.2).

From a sustainable development perspective, the selected variables touch upon all three dimensions. Specifically, increasing the “eco kilometers” traveled through sustainable models implies a reduced negative environmental impact. Improving the utilization of cargo space in transport vehicles enhances the efficiency of transport activities and optimizes the number of delivery trips, favoring vehicles with higher cargo utilization. This generally involves smaller cargo spaces and vehicles with a smaller negative impact on sustainability. Through the analysis of the last variable, the social aspect is partially covered, particularly regarding work in various weather conditions.

In the second step, electromobility delivery alternatives for the specified territory were identified. Since the goal is to select a sustainable delivery model, all the proposed alternatives are improvements to the traditional delivery approach in terms of sustainability dimensions. In this particular case, three alternatives were analyzed:

A1. By courier via e-motorcycles (BCM)—Delivery by e-motorcycle represents an improved variation of the traditional approach, where the courier uses a conventional motorcycle for deliveries. Depending on the model, their autonomy varies, ranging from approximately 30 to 100 km on a single battery charge. For the same reason, the weight limitation also varies, and it is usually between 30 and 150 kg. Additionally, regenerative braking helps return energy to the battery during braking, extending the overall range. These vehicles are particularly suited for executing delivery activities. In addition to the standard delivery bags carried by couriers, motorcycles can be equipped with cargo spaces in boxes, which are often modular and adaptable, with a typical capacity of around 100 L. The BCM model is popular in both rural and urban areas. Beyond postal deliveries, they are widely used today for food delivery as well;

A2. By courier via e-cargo bike (BCB)—Delivery using electric cargo bikes is an innovative and eco-friendly model. E-cargo bikes have electric drives and cargo space, allowing riders to cover greater distances and transport more shipments. One of the key limitations of this model has been the relatively smaller cargo space. However, this drawback has been largely mitigated with advancements in technological solutions. Modern e-cargo bikes now include significant cargo space, sufficient to accommodate many shipments [71]. The cargo space is organized on both the front and rear racks, using specialized boxes and trailers, and can exceed

200 L in volume. The weight limitation for e-cargo bikes depends on the model, but is usually between 50 and 200 kg. A notable feature of this delivery model is the possibility of extending the autonomy range, which for standard models is approximately 30 to 100 km (advanced models can exceed 150 km), by allowing the courier to provide additional power by pedaling. Importantly for the courier, most e-cargo bikes have multiple levels of electric assistance that can be adjusted based on the load and terrain, making the ride easier and reducing physical exertion. In some cases, these models include regenerative braking, which helps extend the range by returning energy to the battery during braking. Modern solutions also offer adequate protection from precipitation and wind;

A3. By courier via e-scooter (BCS)—This model involves courier shipment delivery, similar to the previous two models. Still, in this case, an e-scooter is used for delivery activities. The autonomy of e-scooters varies depending on the model, with standard models typically offering up to approximately 60 km of range. The cargo space is small, around 50 L, usually in the form of courier bags or mounted on the rear wheel or handlebars. The weight limitation for this delivery model is usually around 25 to 40 kg. Due to their compact size, e-scooters require much less parking space and offer high mobility. This makes it easier for couriers to find parking spots and complete deliveries quickly.

The proposed alternatives have significant differences, but they share one crucial characteristic—a positive impact on the sustainability of the overall delivery system. There are, of course, differences in the level and type of positive impact between the alternatives. Energy consumption, greenhouse gas emissions, and driving costs vary for each of the mentioned alternatives. Compared to the first two alternatives, e-scooters have a smaller cargo space but are more agile and require less parking space. All of the listed alternatives consume less energy and offer greater mobility than traditional delivery vehicles (e.g., pickup trucks using fossil fuels), so any shortfall in cargo space can be compensated by making deliveries in multiple iterations. In such cases, additional tasks must be addressed, such as dividing the shipments and the organization of couriers across multiple delivery iterations. Additionally, their high level of mobility allows for better access to alternative routes in case of traffic congestion.

In cases where the above models cannot perform delivery tasks due to insufficient technical characteristics, very poor weather conditions, etc., an Electric Light Commercial Vehicle (ELCV) is proposed. This also involves the traditional concept of delivery by couriers, but in this case, the delivery activities are performed using an ELCV. At first glance, this approach may not differ significantly from traditional delivery methods; however, using an electric vehicle means lower operational costs, greenhouse gas emissions, and noise levels. Additionally, ELCVs generally have smaller cargo spaces than traditional vans, usually around 3 to 5 cubic meters, which is sufficient for most delivery needs. The weight limitation for this delivery model is usually around 1000 to 1500 kg. Of course, models with larger cargo volume and load capacity are also available. Consequently, the cargo space utilization is higher than that of standard pickups with larger capacities. The range of these vehicles typically falls between 150 and 300 km.

Of the three mentioned delivery models, BCM and BCB are currently in use in the observed territory. Considering the growing trend in the use of various micromobility vehicles in delivery operations, it is expected that the third alternative, BCS, will soon be implemented as well.

In the third step, the alternatives are analyzed to assess whether they meet the elimination criteria. This study aims to demonstrate the usability of the proposed Fuzzy-DMS methodology, so this step is not the main focus. Nonetheless, its resolution in practice is straightforward. Specifically, the load capacity of the transport vehicle is compared with the weight and volume of the shipments that need to be delivered. If the vehicle's characteristics do not meet the specified criteria, the alternative utilizing that vehicle is excluded from further analysis. That alternative can only be considered in cases where delivery is carried out in multiple iterations, which involves solving additional tasks, as previously mentioned.

One of the significant challenges in the third step can be the process of gathering information. While information systems and automation in parcel processing are at a level where the weight of each shipment is easily accessible, determining the volume can be more challenging. Of course, this is not a problem when dealing with standardized packaging, as the volume of each package or container is already known. The complex volume-determining process applies to non-standard shipments, which are becoming increasingly common in delivery systems. Operators define standard packaging for their shipments, which users can use to pack their items. This packaging is available at the postal network units or postal shops. Some of the characteristic packaging includes plastic envelopes in A3 format, as well as boxes with dimensions of $250 \times 170 \times 100$ mm, $350 \times 250 \times 120$ mm, and similar. Due to the expansion of e-commerce, systems are increasingly handling a growing number of non-standard shipments with varying physical dimensions. A solution that simplifies this task is the application of modern technologies such as 3D scanners, which could scan each parcel during the initial processing steps, ensuring that this parameter is tracked for each shipment within the information system. Based on this information, the total volume of the shipments to be delivered can be easily calculated. Software for addressing the 3D bin-packing problem is often used in practice to support solving this task [72,73]. These tools provide results on cargo space utilization and a 3D model of the shipment packing plan. Package dimension limitations are defined by the postal operator depending on the type of service. For example, the public postal operator in Serbia has limited the dimensions of express shipments to $60 \text{ cm} \times 50 \text{ cm} \times 50 \text{ cm}$, meaning that packages exceeding these dimensions can only be accepted under a special agreement. However, as already emphasized, this study aims to demonstrate the usability of the proposed Fuzzy-DMS methodology; therefore, it is assumed that the alternatives meet the limitations regarding package dimensions and weight limitation for further analysis.

The fourth step involves creating and applying the FLS system, which will be presented in a separate chapter in the following sections.

4.1.1. Creating the FLS for Determining the Preference and Suitability of Applying the Corresponding Delivery Model

This step involves creating and applying an appropriate FLS to determine the preference and suitability of applying the corresponding delivery model. In this case, an FLS with three inputs and one output is proposed, as shown in Figure 6, where the inputs are I1, Route length; I2, Estimated cargo space utilization; and I3, Degree of adaptation to weather conditions, while the output is P—the preference for the suitability of the corresponding delivery model.

As mentioned, it is recommended that a separate FLS be created for each of the alternatives. In this specific case, we will have three FLSs:

- FLS1—BCM—Fuzzy logic system for determining the preference for applying model A1. By courier via e-motorcycles (BCM);
- FLS2—BCB—Fuzzy logic system for determining the preference for applying model A2. By courier via e-cargo bike (BCB);
- FLS3—BCS—Fuzzy logic system for determining the preference for applying model A3. By courier via e-scooter (BCS).

The following section will present the process of creating input and output variables for each of the FLSs. The Mamdani approach will be used in MATLAB R2024a/Fuzzy Logic Designer software [66] to create and test the FLS.

Creating Input and Output Variables for FLS1—BCM

As explained in the methodology, appropriate research will be conducted during the definition of variables in the FLS. The membership functions that define the fuzzy set will have a triangular shape and be convex and normalized so that they will represent a fuzzy number (Equation (1)). As emphasized in the methodology, in this case, it is necessary to define the left and right boundaries of the variable's value range, as well as each fuzzy set

(number), and the membership function (left and right boundaries; the peak—the value with the highest degree of membership $\mu = 1$).

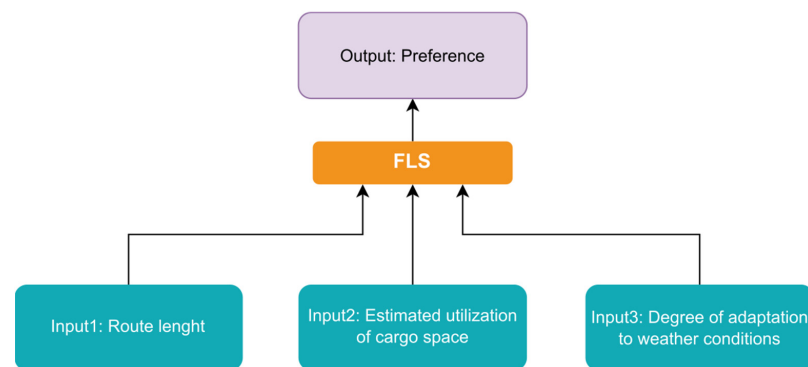


Figure 6. Structure of the proposed FLS.

Creating the Input Variable I1F1 Route Length

Data from the real system was obtained to determine the range of values for this variable, showing the shortest and longest routes in the analyzed area over the past year. These values are 2.9 km and 32.3 km, respectively. This information was presented to the experts, which indirectly influenced the range definition for this variable. Experts were advised that this parameter should partially include the influential factor of terrain configuration, as the driving characteristics of transport vehicles are not the same on flat versus hilly or undulating terrain. Five fuzzy sets were defined: Very short route—VSR, Short route—SR, Medium-length route—MLR, Long route—LR, and Very long route—VLR.

Experts were asked to provide answers to the following types of questions to define the boundaries of the fuzzy sets:

- The fuzzy set “Short route—SR” for an electric motorcycle is being analyzed. Please provide a value (in kilometers; the lowest and highest values in the previous year were 2.9 km and 32.3 km, respectively) for which you consider:
 - What represents the smallest value (left boundary) in the set SR?
 - What represents the highest degree of membership (peak) in the set SR?
 - What represents the largest value (right boundary) in the set SR?

The same question was posed to the experts for the remaining four fuzzy sets: VSR, MLR, LR, and VLR. The experts’ responses are presented in Table A1, Appendix A. An approach based on two comparison levels was applied for consistency checking. The first level involves comparing the characteristic values of each fuzzy set to ensure the following rule is satisfied: $LB < T < RB$, where LB represents the left boundary, T the top, and RB the right boundary of the fuzzy set. The second level involves comparing the characteristic values of adjacent fuzzy sets, where the fuzzy set that, according to the gradation of meaning, should be positioned closer to the axis representing the degree of membership must have lower corresponding characteristic values compared to the respective characteristic values of the next fuzzy set. Specifically, if the characteristic values of fuzzy set F1, which should logically be positioned closer to the defined axis, are LB1, T1, and RB1, and the characteristic values of the next fuzzy set F2 are LB2, T2 and RB2, the following relationship must be satisfied: $LB1 < LB2$, $T1 < T2$, and $RB1 < RB2$. Failure to meet any of these conditions disqualifies these responses from further analysis. It requires the expert to reevaluate their input with a suggestion to ensure consistency. This consistency-checking approach was also applied while creating other variables in the study.

It is important to note that for the fuzzy set VLR, the experts did not define a right boundary, just as they did not define a left boundary for the fuzzy set VSR. The reason is that all values greater than the peak of the fuzzy set VLR have a membership degree of 1, and all values lower than the peak of the fuzzy set VSR have a membership degree of 1. The processed results are shown in the following table (Table 2).

Table 2. Characteristics of the asymmetric (based on expert opinions) membership functions of the fuzzy sets for the variable I1F1 [km].

Fuzzy Set	Left Boundary	Top	Right Boundary
VSR	/	3.83	8.21
SR	5.15	9.14	14.24
MLR	10.06	16.45	22.74
LR	18.33	25.48	30.96
VLR	26.53	32.94	/

Based on the results from Tables 2 and A5, Appendix C, the variable I1F1 Route length was created (Figure 7). Harmonized membership functions, for all variables, were created based on the explanation provided within the methodology using Equation (9).

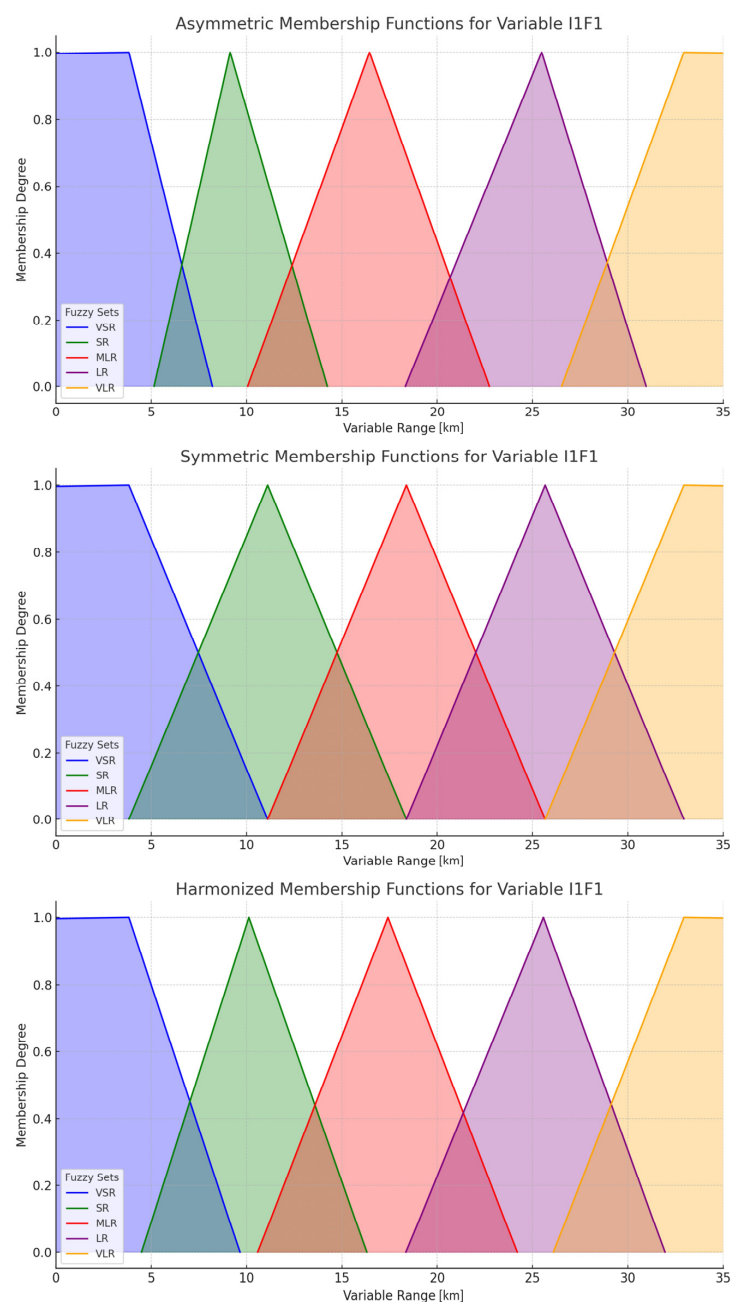


Figure 7. Input—I1F1 Route length.

Creating the Input Variable I2F1 Estimated Cargo Space Utilization

To demonstrate the applicability of the proposed methodology, we will assume that information on the volume and weight of each shipment is available. Regarding e-motorcycles, it is important to note that there are different variants, but they have approximately the same cargo space characteristics. The same applies to the remaining alternatives or delivery models being analyzed in the paper. The ratio of volumes defines cargo space, and the range of values the variable can take is from 0 to 1. Five fuzzy sets have been defined: Very low utilization level—VLU, Low utilization level—LU, Medium utilization level—MU, High utilization level—HU, and Very high utilization level—VHU. In agreement with the experts, the range of values was divided into equal intervals, ensuring overlap between the boundaries of the fuzzy sets to increase tolerance and avoid exclusivity. In accordance with this, the variable I2F1 Estimated cargo space utilization was created (Figure 8).

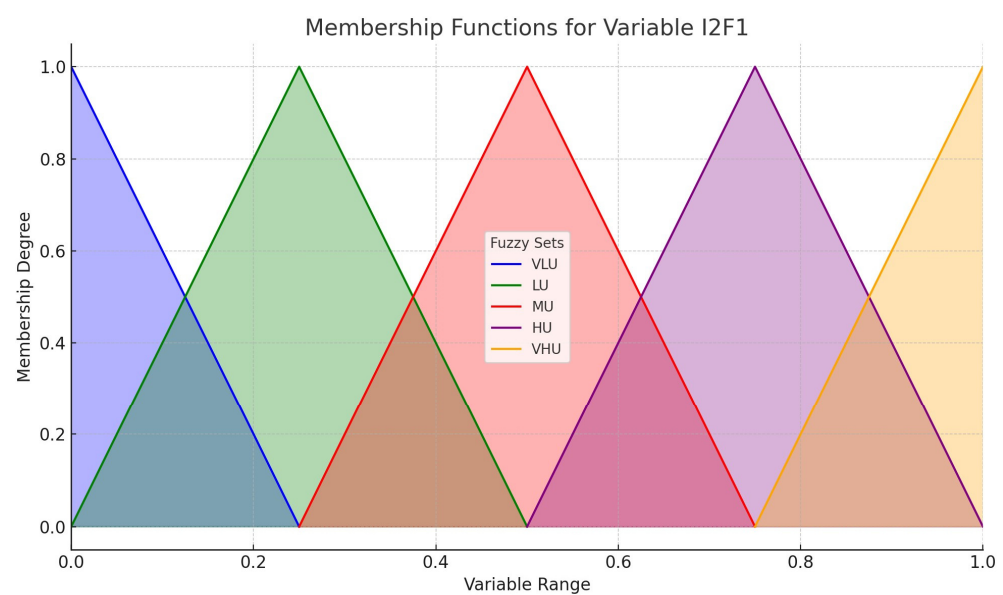


Figure 8. Input—I2F1 Estimated utilization of cargo space.

It should be noted that this variable has a universal character and will, therefore, be used in all three FLSs, with adjusted labels I2F2 and I2F3. The variation in cargo space capacity among the analyzed delivery models for the same requirements (shipment volume), will result in different impacts of this variable in each FLS. Specifically, in the case of a smaller cargo space where a certain shipment volume can be accommodated, the utilization will be at a higher level than in the case of a larger cargo space for the same requirements.

Creating the Input Variable I3F1 Degree of Adaptation to Weather Conditions

To determine the degree of adaptation to weather conditions, a separate fuzzy logic system, FLSW1, was created, the structure of which is shown in Figure 9. The output from this fuzzy logic system will serve as the third input, I3F1, in FLS1—BCM.

The following steps will outline the creation of the mentioned fuzzy logic system. As shown in the figure, the input variables in FLSW1 are I1FW1 Temperature and I2FW1 Precipitation. Experts were consulted for their creation, including two couriers from the base expert group, who were directly exposed to weather conditions in the field and could provide relevant insights. In addition, two additional experts participated in the study: one occupational safety engineer and one with a PhD in physical sciences specializing in meteorology.

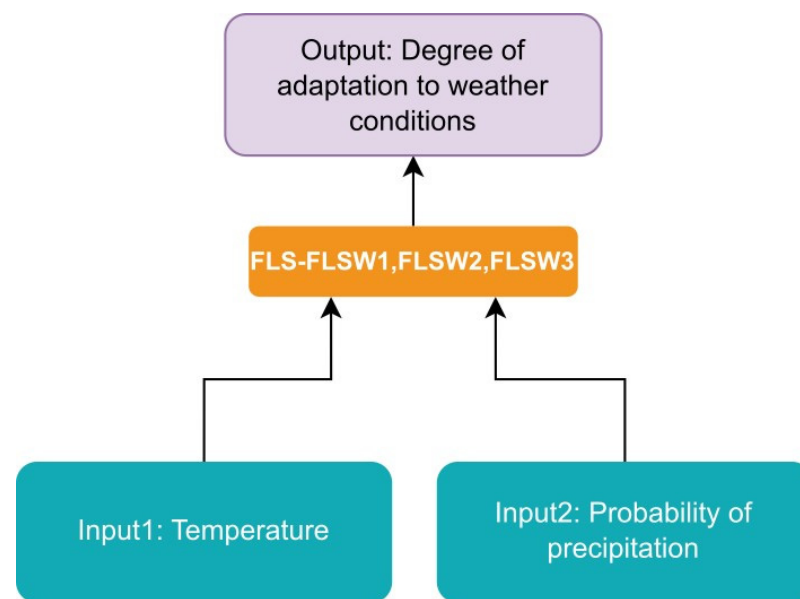


Figure 9. Structure of the FLSW for determining the degree of adaptation to weather conditions.

The variable I1FW1 Temperature is defined with five fuzzy sets: Very low temperature—VLT, Low temperature—LT, Medium temperature—MT, High temperature—HT, and Very high temperature—VHT. The following table (Table 3) presents the processed results obtained based on the opinions of the aforementioned expert group. The experts’ responses are presented in Table A4, Appendix B.

Table 3. Characteristics of the asymmetric (based on expert opinions) membership functions of the fuzzy sets for the variable I1FW1 [°C].

Fuzzy Set	Left Boundary	Top	Right Boundary
VLT	/	−6.75	3.50
LT	−3.25	4.75	9.50
MT	6.50	14.75	23.50
HT	19.75	27.50	32.50
VHT	29.75	35.75	/

Based on this data and data from Table A6, Appendix C, the variable I1FW1 was created (Figure 10). The obtained results will also be used to develop FLSs for the other two alternatives, namely FLSW2 and FLSW3 (Figure 9). The difference between these fuzzy logic systems, to adapt and provide more realistic results regarding the degree of adaptation to weather conditions for each alternative, will be reflected in certain rules that will differ, as concluded during the expert interviews. This approach ensures that the final solution accounts for the varying behavior of different transport modes under the same weather conditions.

In Serbia, there is no obligation to halt work in unfavorable temperatures. Accordingly, and considering the evident climate changes, we have approximately relied on the values defined by the experts during their input when determining the range of values for this variable.

The variable “Probability of precipitation” is defined as a percentage, meaning the range of values it can take is from 0 to 100. In this case, the percentages represent the probability of precipitation in a given region, although in some instances, it may also refer to the coverage of an area by precipitation. It is characterized by five fuzzy sets: Very low probability—VLP, Low probability—LP, Medium probability—MP, High probability—HP, and Very high probability—VHP. In agreement with the experts, the range of values was

divided into equal intervals, ensuring overlap between the boundaries of the fuzzy sets to increase tolerance and avoid exclusivity (Figure 11). Therefore, this variable has a universal character and will be used as I2FW2 for FLSW2, and as I2FW3 for FLSW3.

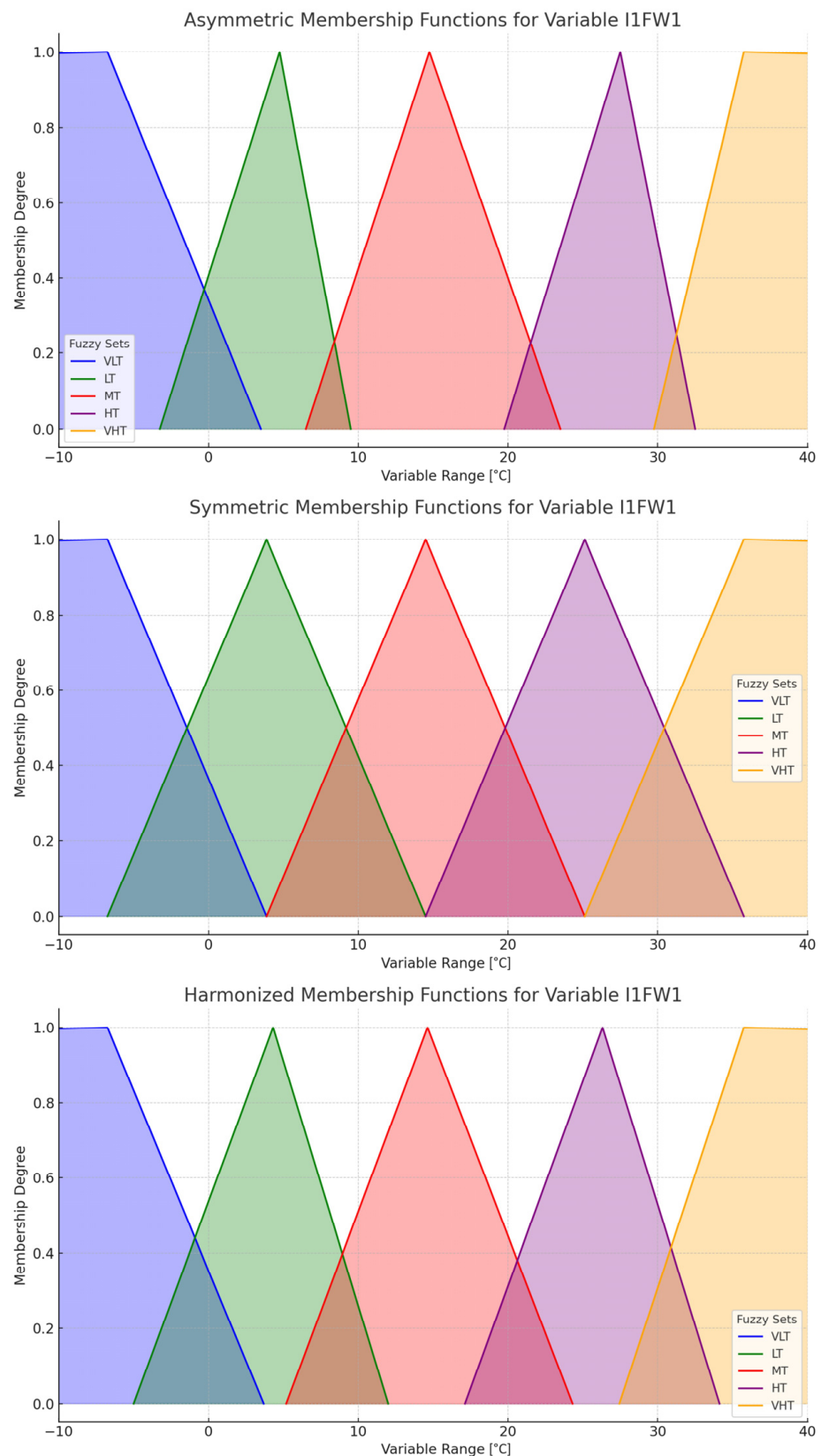


Figure 10. Input—I1FW1 Temperature.

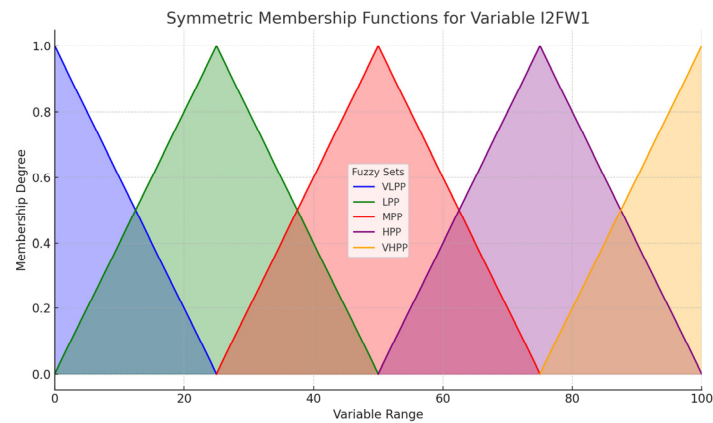


Figure 11. Input—I2FW1 Probability of precipitation.

The output variable, FLSW1, represents a value from 0 to 1, where 0 is the lowest and 1 is the highest degree of adaptation to weather conditions. Five fuzzy sets have been defined: Very low adaptation—VLA, Low adaptation—LA, Medium adaptation—MA, High adaptation—HA, and Very high adaptation—VHA. In agreement with the experts, the range of values was divided into equal intervals, ensuring overlap between the boundaries of the fuzzy sets to increase tolerance and avoid exclusivity. Following this, the variable O1FW1 Degree of adaptation to weather conditions was created (Figure 12).

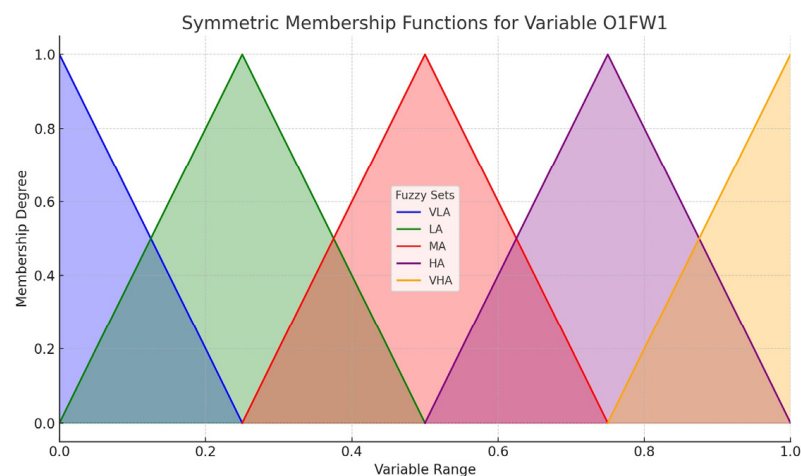


Figure 12. Output—O1FW1 Degree of adaptation to weather conditions.

It should be noted that this variable also has a universal character and will, therefore, be used in FLSW2 as O1FW2, and in FLSW3 as O1FW3. The output variables created in this way will serve as input variables in the main FLSs for determining the delivery model preference.

Creating the Output Variable P—Preference for Suitability of Applying the Corresponding Delivery Model

The preference, which reflects the suitability of the delivery model for exploitation, as mentioned in the methodology section, takes values from 0 to 1, and thus these boundaries define its value range. Five fuzzy sets have been defined: Very low preference—VLP, Low preference—LP, Medium preference—MP, High preference—HP, and Very high preference—VHP. In agreement with the experts, the range of values was divided into equal intervals, ensuring overlap between the boundaries of the fuzzy sets to increase tolerance and avoid exclusivity. Following this, the output variable P—preference for the suitability of applying the corresponding delivery model was created (Figure 13).

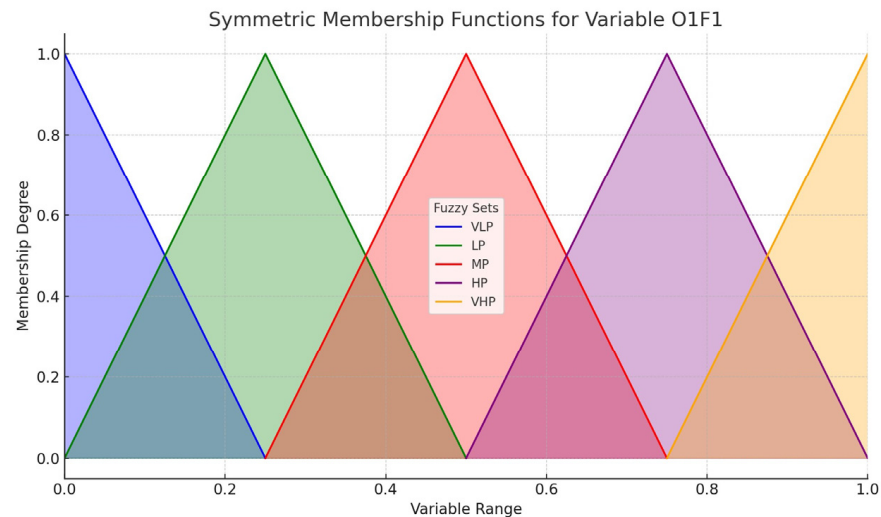


Figure 13. Output—O1F1 Preference.

It is clear that this variable also has a universal character and will therefore be used in FLS2—BCB with the label O1F2, and in FLS3—BCS as O1F3. Different preference values for various delivery models, even for the same delivery requirements, will be obtained thanks to differently defined I1F1, I1F2, and I1F3; different cargo space capacities; and different fuzzy logic systems for defining the degree of adaptation of the model to weather conditions (different rule bases for FLSWs, according to the characteristics of the delivery models).

Creating Input and Output Variables for FLS2—BCB

Creating the input variable I1F2 Route Length

The range of the BCB model is similar to that of the BCM model; however, due to certain differences in achieving mobility, energy consumption, and sustainability impact, the same parameter values from the BCM model were not used to obtain more accurate results. For this reason, there is also a difference in the definition of the membership functions of the fuzzy sets for this variable compared to the BCB model. One of the main reasons is that, due to the mobility characteristics of the transportation means, the travel characteristics differ for the analyzed alternatives. For instance, on a 25 km route, an e-scooter will consume a higher percentage of its battery than an e-motorcycle or an e-cargo bike. Furthermore, the physical and mental effort required from the courier varies depending on the means of transportation used. Therefore, it is necessary to evaluate the mentioned 25 km route individually for each transportation means and define the nature of the route for that specific means. For one vehicle, it might represent a long route; for another, it could be considered a medium-length route. For this reason, different fuzzy set parameters are used for the variables I1F1, I1F2, and I1F3. In this case, due to the similar performance of the alternatives, there are no significant deviations between the parameters. However, this approach enables more precise modeling of expert reasoning and a more realistic definition of the variable concerning the observed alternative. To clarify this approach, we can draw a parallel from everyday life: an object located at a height of 1.5 m is considered to be at a medium height for a person who is 2 m tall, while the same object is very high for a child who is 0.9 m tall.

The experts' responses are presented in Table A2, Appendix A. Based on data in Table 4 and from Table A7, Appendix C, the variable I1F2 was created (Figure 14). Table 4 shows the characteristics of the asymmetric membership functions of the fuzzy sets.

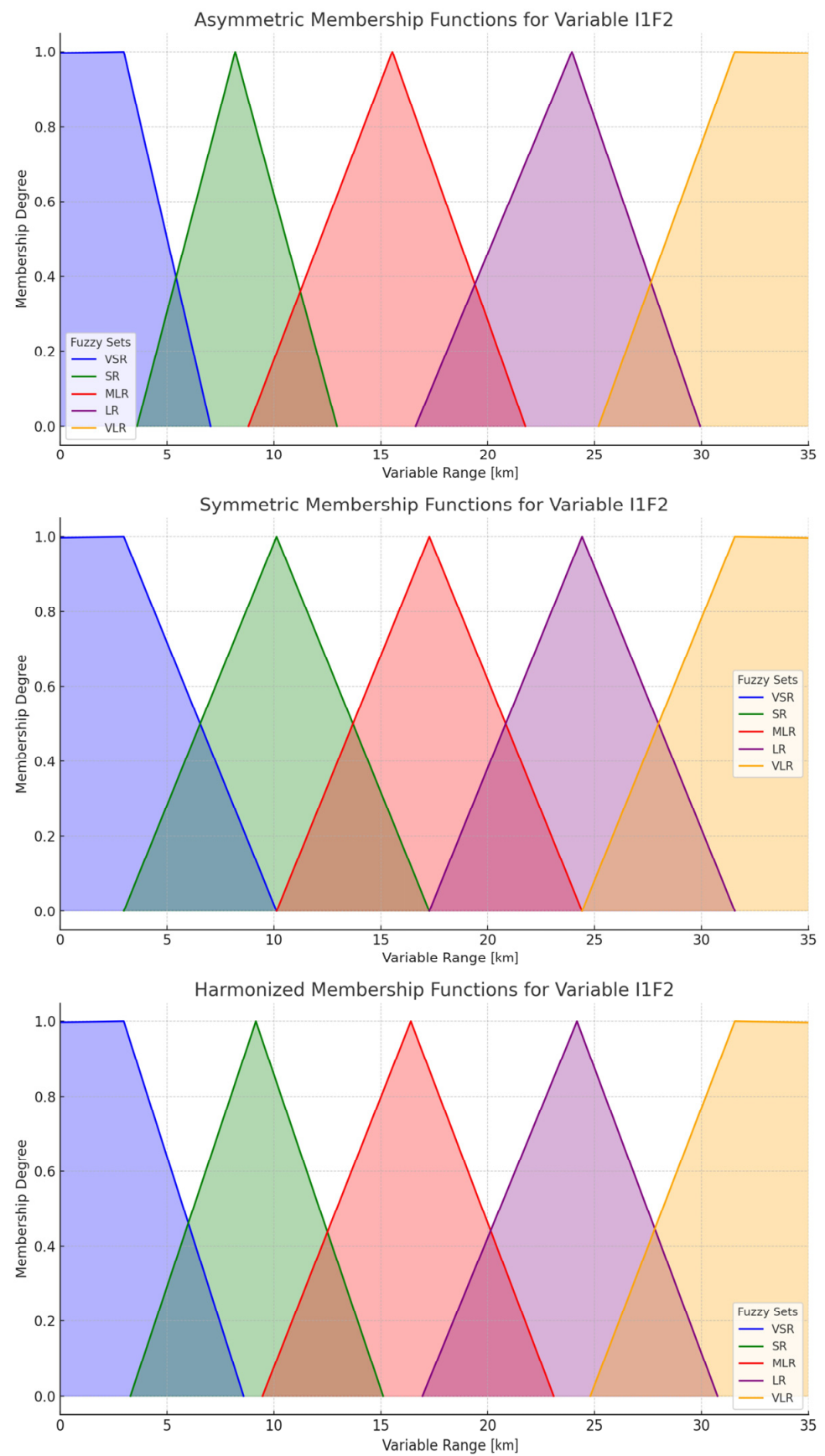


Figure 14. Input—I1F2 Route length.

Table 4. Characteristics of the asymmetric (based on expert opinions) membership functions of the fuzzy sets for the variable I1F2 [km].

Fuzzy Set	Left Boundary	Top	Right Boundary
VSR	/	2.98	7.04
SR	3.60	8.19	12.95
MLR	8.81	15.54	21.76
LR	16.63	23.94	29.94
VLR	25.19	31.56	/

The input variable I2F2, as already emphasized, corresponds to the created input variable I2F1 for FLS1—BCM. To define the input variable I3F2, FLSW2 was formed with the same structure as FLSW1, with differences in their rule sets due to the nature of the parameters, ensuring a more realistic output value.

Creating Input and Output Variables for FLS3—BCS

Creating the input variable I1F3 Route Length

For the BCS model, a similar explanation applies regarding the need to define inputs with different parameters, as was the case with the BCB model. Additionally, the BCS model has a significantly different range than the BCM and BCB models, which may lead to a slightly greater difference in this variable compared to the previous two. The experts' responses are presented in Table A3, Appendix A. Based on data in Table 5 and from Table A8, Appendix C, the variable I1F3 was created (Figure 15).

Table 5. Characteristics of the asymmetric (based on expert opinions) membership functions of the fuzzy sets for the variable I1F3 [km].

Fuzzy Set	Left Boundary	Top	Right Boundary
VSR	/	1.88	4.38
SR	2.13	5.06	9.75
MLR	4.69	10.94	17.46
LR	12.13	19.50	25.50
VLR	20.88	26.81	/

The input variable I2F3, as already emphasized, corresponds to the created input variables I2F1 and I2F2 for FLS1—BCM and FLS2—BCB, respectively. To define the input variable I3F3, FLSW3 was formed with the same structure as FLSW1 and FLSW2, with differences in their rule sets due to the nature of the parameters, ensuring a more realistic output value.

After creating the variables, fuzzy rule bases were developed for all the FLSs. Initially, the authors created the rule bases based on their knowledge and experience, then sent them to experts for corrections. They gathered expert opinions, adjusted the rule bases, and returned them to the experts. After three such iterations, the final fuzzy rule bases were obtained. It is important to note that the same groups of experts who participated in creating the variables were contacted for the main fuzzy logic systems for determining preference, as well as for the FLS systems for determining the degree of adaptation to weather conditions—FLSW.

The main FLS consists of 125 rules, which are the same for FLS1—BCM, FLS2—BCB, and FLS3—BCS. The difference between them, as described earlier, lies in the different parameters used when creating the fuzzy sets for the variables. The FLSW systems consist of 25 rules each, which differ due to the nature of the observed parameter.

The inference engine generates the output based on the established rule base when entering the input variable values. In this process, the software applies the principles defined by fuzzy set theory (Equations (4) and (5)). Defuzzification must be performed to obtain the final output

value, typically using the center of gravity approach (Equations (6) and (7)). The testing results will be presented in the following chapter.

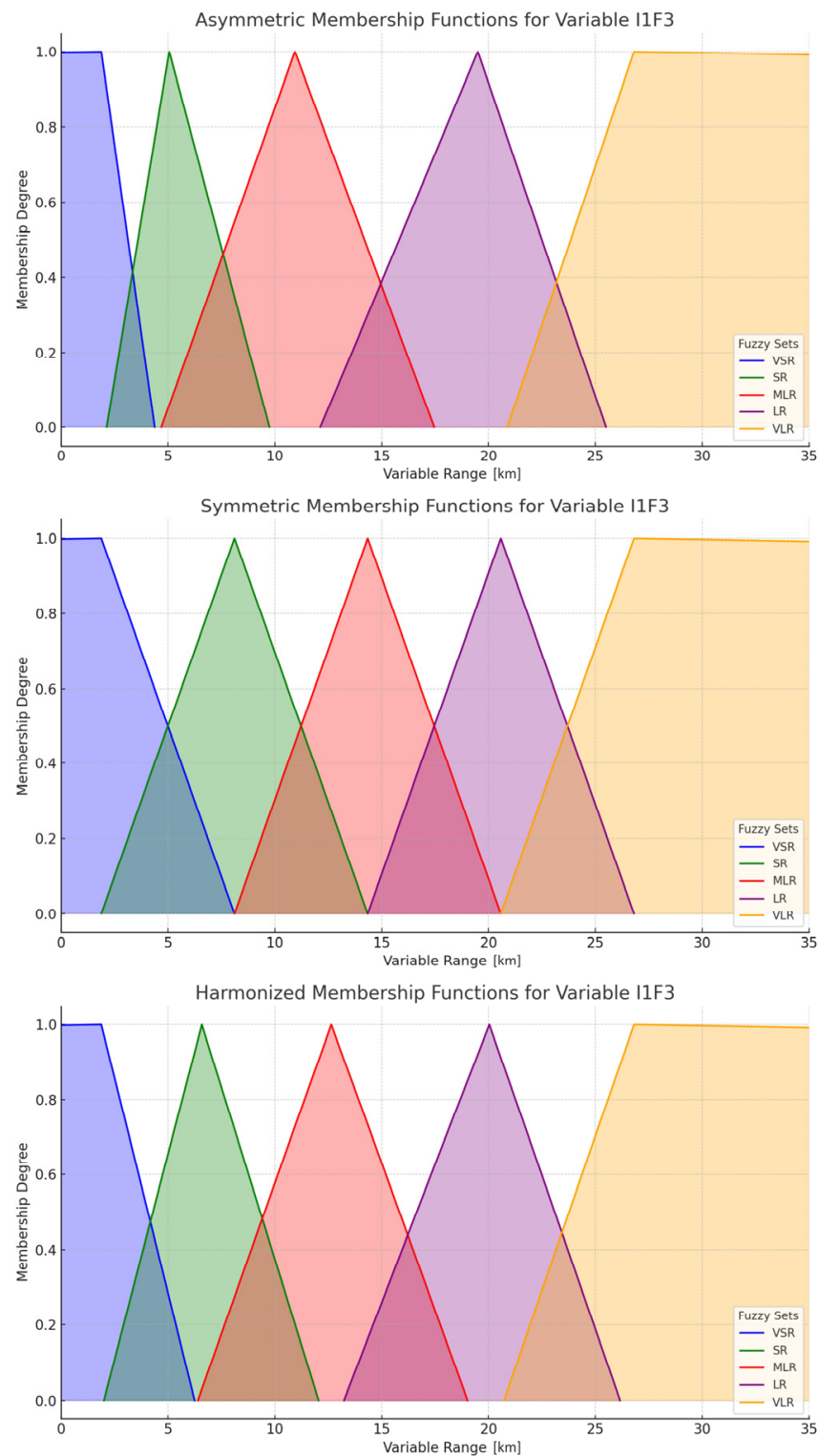


Figure 15. Input—I1F3 Route length.

4.1.2. Testing Results of the Fuzzy-DMS System with Discussion

The following section will present the testing results of the Fuzzy-DMS system, with the outcome being the determination of the preference for the suitability of applying a particular delivery model. Based on data collected from the real system, for a service that

ensures delivery between 12 PM and 7 PM the following day, a set of requirements was formed, which defined the parameters for the first two input variables for all three fuzzy logic systems: FLS1—BCM, FLS2—BCB, and FLS3—BCS. The data for the third variable in these FLSs was selected using a random method.

Postal and delivery systems, in general, are typically characterized by a wide range of services, a developed network, and infrastructure, thereby serving many users. Based on this, it is easy to conclude that many shipments pass through them. For the testing, data was selected partially at random from the real system, with an effort to ensure the most accurate assessment of the total volume of all shipments to be transported. This meant that only requests using standardized packaging were analyzed to facilitate a more straightforward calculation of total volume, as the system lacked a 3D scanner to provide this information for non-standard shipments. For the estimated utilization of cargo space, the ratio between the total volume of shipments to be transported and the cargo space volume was defined. For the cargo space volumes of the BCM, BCB, and BCS alternatives, values of 100 L, 200 L, and 50 L, respectively, were used. As for the data on temperature and probability of precipitation, i.e., for the fuzzy logic systems—FLSW, which produce the output for the degree of adaptation to weather conditions, these were defined by the authors. The goal of testing the Fuzzy-DMS system is to demonstrate its applicability, which justifies the adoption of certain parameters. When all input data from reality is known in specific situations, the results will align accordingly. Testing was conducted on fuzzy logic systems based on asymmetric membership functions, i.e., functions formed based on expert opinions, as well as on improved versions of the systems based on harmonized membership functions. In this way, the influence of symmetric membership functions on the final result was also indirectly tested.

The following tables (Tables 6–8) show the characteristics of the three test requests and the results obtained from the Fuzzy-DMS system. The values in parentheses for the “Temperature” and “Probability of precipitation” parameters (Table 6) represent additional values used to test the system. In this way, the sensitivity of the Fuzzy-DMS system to the parameter “Degree of adaptation to weather conditions” is demonstrated. The values in parentheses for the “Degree of adaptation to weather conditions” and “Preference” results correspond to these input parameters. Meanwhile, the parameters for route length and total shipment volume remain unchanged.

Table 6. Test 1.

Test 1 (Requests)	Route length [km]	Total shipments volume [l]	Temperature [°C]	Probability of precipitation [%]
	4.2	40	13 (−3)	60 (40)
Results—asymmetric (based on expert opinions) membership functions				
Alternative	Estimated utilization of cargo space	Degree of adaptation to weather conditions	Preference	
BCM	0.4	FLSW1	0.645 (0.355)	FLS1-BCM 0.641 (0.5)
BCB	0.2	FLSW2	0.534 (0.218)	FLS2-BCB 0.5 (0.456)
BCS	0.8	FLSW3	0.388 (0.109)	FLS3-BCS 0.57 (0.5)
Results—harmonized membership functions				
Alternative	Estimated utilization of cargo space	Degree of adaptation to weather conditions	Preference	
BCM	0.4	FLSW1	0.64 (0.35)	FLS1-BCM 0.637 (0.5)
BCB	0.2	FLSW2	0.53 (0.28)	FLS2-BCB 0.5 (0.5)
BCS	0.8	FLSW3	0.388 (0.176)	FLS3-BCS 0.624 (0.5)

Table 7. Test 2.

Test 2 (Requests)	Route length [km]	Total shipments volume [l]	Temperature [°C]	Probability of precipitation [%]	
	18.7 (10)	26	23	5	
Results—asymmetric (based on expert opinions) membership functions					
Alternative	Estimated utilization of cargo space	Degree of adaptation to weather conditions		Preference	
BCM	0.26	FLSW1	0.808	FLS1-BCM	0.481 (0.52)
BCB	0.13	FLSW2	0.808	FLS2-BCB	0.376 (0.43)
BCS	0.52	FLSW3	0.624	FLS3-BCS	0.5 (0.535)
Results—harmonized membership functions					
Alternative	Estimated utilization of cargo space	Degree of adaptation to weather conditions		Preference	
BCM	0.26	FLSW1	0.83	FLS1-BCM	0.482 (0.5)
BCB	0.13	FLSW2	0.83	FLS2-BCB	0.379 (0.47)
BCS	0.52	FLSW3	0.672	FLS3-BCS	0.52 (0.603)

Table 8. Test 3.

Test 3 (Requests)	Route length [km]	Total shipments volume [l]	Temperature [°C]	Probability of precipitation [%]	
	14	88 (70)	30	2	
Results—asymmetric (based on expert opinions) membership functions					
Alternative	Estimated utilization of cargo space	Degree of adaptation to weather conditions		Preference	
BCM	0.88 (0.70)	FLSW1	0.859	FLS1-BCM	0.776 (0.68)
BCB	0.44 (0.35)	FLSW2	0.859	FLS2-BCB	0.5 (0.5)
BCS	/	FLSW3	/	FLS3-BCS	/
Results—harmonized membership functions					
Alternative	Estimated utilization of cargo space	Degree of adaptation to weather conditions		Preference	
BCM	0.88 (0.70)	FLSW1	0.80	FLS1-BCM	0.757 (0.68)
BCB	0.44 (0.35)	FLSW2	0.80	FLS2-BCB	0.56 (0.56)
BCS	/	FLSW3	/	FLS3-BCS	/

If we analyze the results obtained based on fuzzy logic systems grounded in asymmetric membership functions, the results show that, for the defined requirements and conditions, the most suitable model is by courier via e-motorcycles (BCM). This outcome was expected and can be primarily explained by the highest level of adaptation to weather conditions and an approximately medium level of cargo space utilization.

In second place is the by courier via e-scooter (BCS) model, primarily due to the very high level of cargo space utilization, although the level of adaptation to weather conditions is lower than the first alternative.

In last place, out of the three analyzed alternatives, is by courier via e-cargo bike (BCB). The reason lies in the very low level of cargo space utilization despite an approximately medium level of adaptation to weather conditions. Nevertheless, in this case, each of the alternatives fall within the upper part of the preference scale. One of the reasons for this is the short route length in this test case, allowing for some tolerance regarding the lower levels of cargo space utilization or adaptation to weather conditions. An additional analysis of the impact of weather conditions (data in parentheses) showed a certain drop in preference values for all the alternatives analyzed due to a significant temperature drop

from 13 °C to −3 °C. The decrease in preference was mitigated by a reduced probability of precipitation (from 60% to 40%). In this case, the BCM and BCS alternatives have the same preference value, while the preference for the BCB alternative is slightly lower.

The results from fuzzy logic systems using harmonized membership functions, that is, systems influenced by the symmetry of asymmetric membership functions yield slightly modified outcomes. This can be observed in both the degree of adaptation and preference levels. Regarding the impact of these changes on the selection of alternatives in the specific case, further analysis, which involves a drop in temperature and precipitation probability, shows that the preference for the BCB alternative has reached the level of the other two alternatives. In this scenario, all three alternatives have a preference value of 0.5.

The following table presents the data and results for the second test case. The value in parentheses for the “Route Length” parameter represents an additional value for which the system was tested. In this way, the sensitivity of the Fuzzy-DMS system to the “Route Length” parameter is demonstrated. The value in parentheses for the “Preference” results corresponds to this input parameter for each of the models. Meanwhile, the parameters for total shipment volume and weather conditions remain unchanged.

In this case, for asymmetric (based on expert opinions) membership functions, the results indicate that the most suitable alternative among the analyzed options is by courier via e-scooter (BCS). The primary reason lies in the significantly higher level of cargo space utilization compared to the other two alternatives. At the same time, the route length and degree of adaptation to weather conditions are adequately suitable for all three models. After additional testing and changing the route length to 10 km, with the same remaining parameters, the preference for all alternatives increased, although the preference order remained the same as in the case of the 18.7 km route length. These results are expected due to the shorter route length, while the lower cargo space utilization level limited the larger preference increase.

In this case, the impact of symmetry is also noticeable, particularly during testing for a shorter route of 10 km. It is easy to conclude that the difference in preference values between the BCA alternative and the second-ranked BCM has increased, which is significant for the final decision-maker. Additionally, the gap between the preferences of the BCB and BCM alternatives has narrowed.

The following table (Table 8) presents the data and results for the third test case. The value in parentheses for the “Total shipment volume” parameter represents an additional value for which the system was tested. In this way, the sensitivity of the Fuzzy-DMS system to changes in the “Estimated utilization of cargo space” parameter is demonstrated. Additionally, the value in parentheses for the “Preference” results corresponds to this input parameter for each of the models. Meanwhile, the parameters for route length and weather conditions remain unchanged. In this case, the BCS alternative is excluded from the analysis as it does not meet the elimination criteria.

In this test case, we have expected results for asymmetric (based on expert opinions) membership functions, which are primarily determined by cargo space utilization, as there is a clear advantage in favor of the BCM model. On the other hand, the route length and degree of adaptation to weather conditions are adequately suitable for both models. After additional testing and reducing the total shipment volume, there was a decrease in preference for the BCM alternative due to the reduction in cargo space utilization. On the other hand, the preference value for the BCB model did not change because the relevant threshold value, which would trigger such a change, was not exceeded.

When observing the results for FLSs with harmonized membership functions, the difference in preference values has decreased between the two observed models, which is especially noticeable in the test with a reduced total shipment volume. However, the difference remains evident and provides a clear suggestion to the decision-maker.

Compared to studies that addressed similar topics, the study conducted in this paper has certain similarities and differences. Firstly, they share the same or similar goal: to optimize a specific phase in the shipment transfer process, most often the last-mile delivery.

One significant difference is that most studies, methodologically speaking, focus on multi-criteria decision-making. The advantages of the proposed Fuzzy-DMS methodology have been highlighted in this regard. Some studies examine the same or similar alternatives, although the results concerning priorities or suitability for application differ. This is expected, as different areas were analyzed based on different criteria and approaches. Other studies analyzed in the literature review primarily focused on prioritizing alternatives from various categories rather than only those belonging to e-mobility, as is the case in this study. However, it is a fact, as the results indicate, that alternatives from the e-mobility category and, in general, alternatives considered sustainable, such as e-cargo bikes, drones, parcel lockers, etc., have been extensively researched and have ranked highly in various studies [8,25,36,38,44]. The result obtained in the study [43], which deals with prioritizing zero-emission LMD solutions, indicates that ELCVs are the best solution for the analyzed task. This very alternative has been suggested in our study as the most suitable option in cases where none of the three analyzed alternatives are feasible for exploitation. It is also recommended that electric cargo bikes be considered a viable mid-term solution.

In the context of future research directions, it is desirable to analyze the impact of Fuzzy entropy, as it can help assess the degree of uncertainty of a fuzzy variable (Equation (8)).

Analysis Based on Surface Graphs

The following section presents an additional analysis for FLS1—BCM, as the corresponding alternative—BCM, had the highest preference the most frequently during testing. Additionally, the fuzzy systems, FLS2—BCB and FLS3—BCS, have similar characteristics due to the same rule base being used, with the difference between these FLSs ensured by differently defined membership functions of the fuzzy sets. The analysis was conducted using surface graphs showing one output variable's dependence on two input variables. This type of graph is often used in the analysis of fuzzy logic systems to visualize the relationship between different input parameters and the corresponding output result. The colors on the surface represent various levels of the output variable, ranging from blue (low level) to yellow (high level) [59]. It can serve as a decision-making tool in planning and optimizing logistics operations. Figure 16 shows the dependence of preference on the input variables I1F1 Route length and I2F1 Estimated utilization of cargo space.

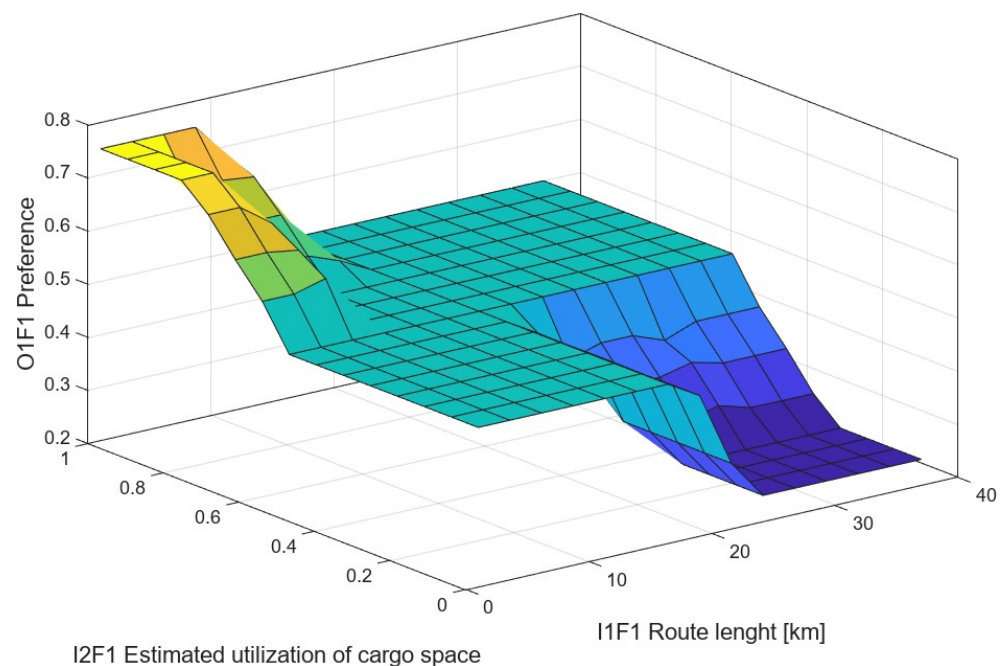


Figure 16. Surface plot of the FLS—Inputs I1F1, I2F1; Output O1F1.

From the graph, it can be concluded that short routes with high cargo space utilization can have a high preference, which is logical as these are desirable situations for performing delivery activities. On the other hand, long routes with low cargo space utilization are characterized by low preference, indicating undesirable or inefficient conditions. Additionally, a decreasing trend in preference can be observed as the route length increases. This suggests that long routes are generally less desirable, and from this perspective, one might consider dividing the territory into even smaller delivery segments than the existing regions. This would involve solving additional tasks, such as the allocation of packages and the organization of couriers, where a single courier could, if necessary, make multiple deliveries within the same area. In such cases, attention should be paid to the choice of the delivery model, which would imply the application of the proposed methodology. In certain situations, this might mean that a courier uses the BCB model for delivery in the first iteration and switches to the BCS model in the next, if it proves to be more suitable. Furthermore, when cargo space utilization is very low, the preference is low regardless of the route length.

Figure 17 shows the dependence of preference on the input variables I1F1 Route length, and I3F1 Degree of adaptation to weather conditions.

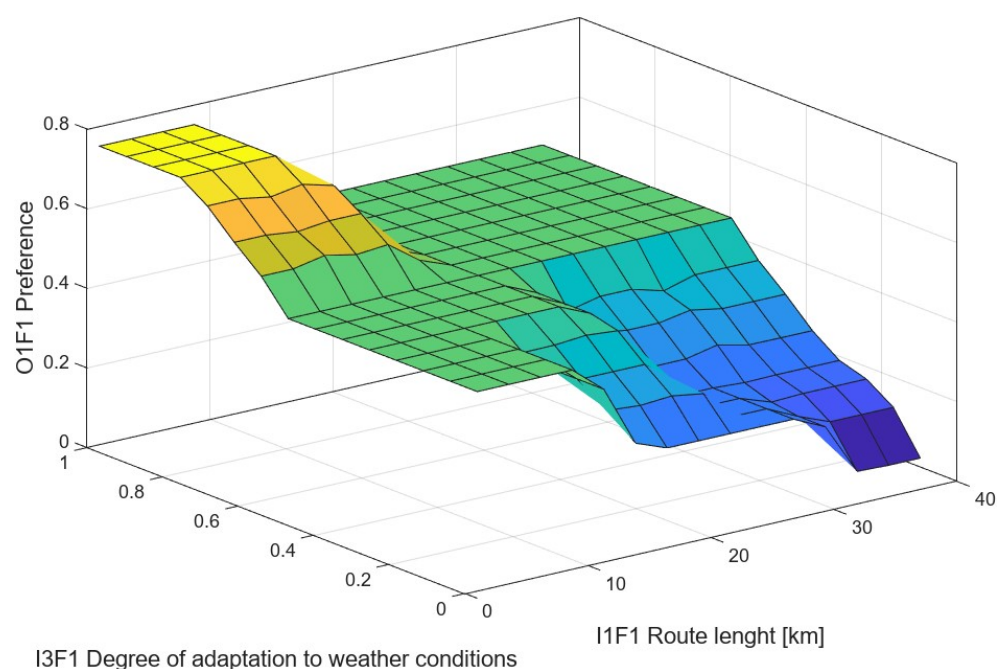


Figure 17. Surface plot of the FLS—Inputs I1F1, I3F1; Output O1F1.

The graph shows that preference is high when the adaptation to weather conditions is strong, indicating that the transportation process and delivery are more efficient and safer in favorable weather conditions. On the other hand, as the degree of adaptation decreases (below 0.5), the preference drops, confirming that poor weather conditions significantly impact the efficiency and safety of delivery. Regarding the impact of route length on preference, the same conclusion applies as in the previous analysis: using long routes can significantly reduce preference, regardless of the adaptation to weather conditions. This suggests that for long delivery routes and poor weather conditions, it may be necessary to consider engaging ELCV, as previously mentioned in the paper.

In the following section, Figure 18 graphically illustrates the dependence of preference on the input variables I2F1 Estimated utilization of cargo space, and I3F1 Degree of adaptation to weather conditions.

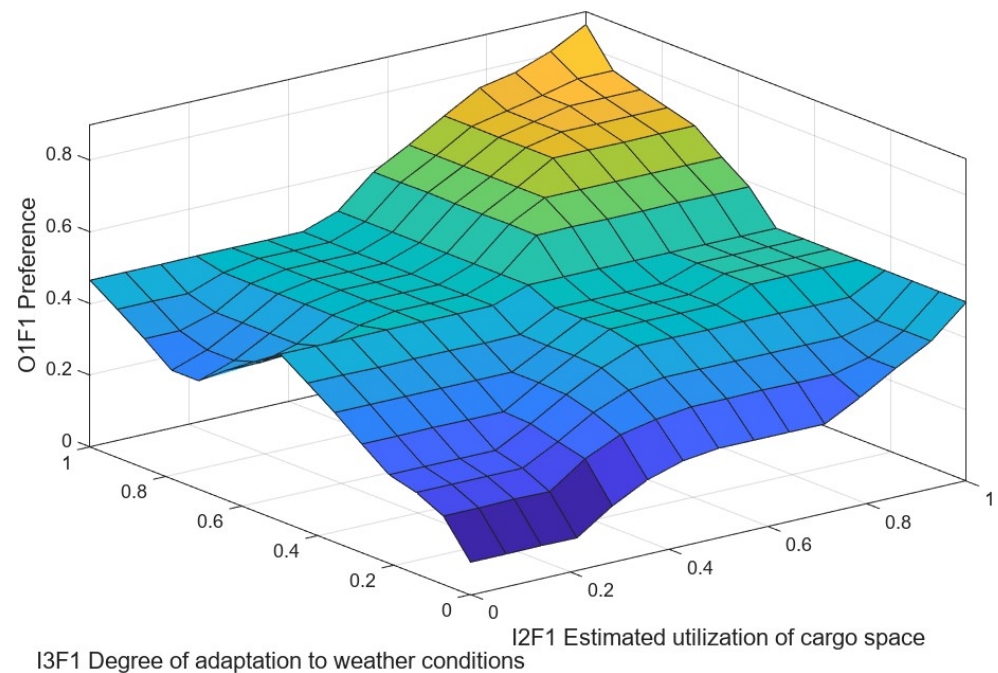


Figure 18. Surface plot of the FLS—Inputs I2F1, I3F1; Output O1F1.

In this case, it is easy to observe that as the degree of adaptation to weather conditions and cargo space utilization increases, the preference also rises. However, with low utilization, the preference remains low even with a high adaptation to weather conditions. Additionally, when the adaptation to weather conditions is low, the preference remains low regardless of cargo space utilization. This indicates that poor weather conditions and low cargo space utilization significantly negatively impact delivery efficiency.

Based on the results obtained from testing the created FLSs and the analysis conducted, it can be concluded that the proposed Fuzzy-DMS methodology provides usable results. The reason for this is that the formed FLS system models the reasoning of experts in this field, who encounter the same or similar tasks daily. In this way, their knowledge and experience, modeled through the FLS system, generate a preference that indicates the suitability of applying the appropriate sustainable delivery model for specific conditions and requirements. The additional enhancement of the validity of results provided by the proposed methodology is enabled by introducing harmonized membership functions resulting from the alignment of asymmetric and symmetric membership functions. Certainly, the preference value, the output of the proposed Fuzzy-DMS methodology, serves as additional information and support for decision-making. In this case, it is the organizer of delivery activities.

The final, sixth step of the methodology involves the decision-maker analyzing the preference values for all alternatives, after which they make the final decision. The penultimate fifth step in the methodology refers to ensuring that all alternatives undergo analysis, which is a straightforward task and was followed in our case study.

5. Applicability and Limitations of the Proposed Fuzzy-DMS Methodology

In the case study, it was demonstrated that the proposed methodology provides adequate results for the task at hand, which is determining the preference that defines the suitability of applying the appropriate delivery model for specific requirements and conditions. This model's flexibility is based on experts' active participation and ability to model their reasoning. This means that the more extensive the system's training, the higher the output results' adequacy level. Approaches based on multi-criteria analysis are commonly used to solve similar tasks and provide good results. Still, they require expert analysis to be conducted each time the suitability of a delivery model is determined.

However, in this case, it would mean that for every group of shipment delivery requests, a multi-criteria analysis would have to be carried out. This implies that multi-criteria analysis would be conducted at least once daily for a particular delivery area, which entails continuous expert involvement. With the proposed Fuzzy-DMS approach, expert reasoning is modeled through FLS and can be usable over an extended period, which is a significant practical advantage. The application of the methodology in this context involves collecting and inputting data into the FLS, while the final result of the inference machine, in the form of a preference value, is obtained immediately afterward. It is clear that this application is simpler compared to widely used multi-criteria decision-making methods, primarily because it does not always require the engagement of experts for every task, which can be organizationally- and time-demanding [25]. The efficiency of the methodology in terms of execution time represents a significant advantage in situations where decisions need to be made within very limited time frames. Additionally, introducing harmonized membership functions proactively addresses potential issues arising from expert subjectivity. This methodology can be easily adapted to address similar tasks as needed. This implies that the methodology is applicable to other delivery models not covered by the case study in this paper. Consequently, the transportation means analyzed could vary, ranging from conventional vans and e-vans, to other micromobility vehicles. The usability of the methodology is independent of the time availability of delivery, meaning it can be applied regardless of the type of service. The only time-related limitation concerns the duration required for collecting the necessary information. However, as previously mentioned in the study, collecting the needed information efficiently with an adequate information system makes the methodology applicable even for same-day delivery services. An additional advantage of the proposed methodology is its suitability for implementation through an appropriate application that could be developed, further enhancing the user experience and the efficiency of the delivery organization process.

Certainly, there are also certain limitations to applying the Fuzzy-DMS approach. Some of them are highlighted below:

- There is a challenge in selecting experts. The reliance on expert knowledge for creating fuzzy sets and rules may introduce subjectivity;
- To apply the approach, gathering information about the volume of shipments included in the delivery request is necessary. In the case of standard packaging, the volume of each package is known, so this task is not complex. However, with the increasing number of non-standard packages in delivery systems, manually solving this task would be time-consuming and prone to errors. For this reason, 3D scanners are necessary in the system to provide accurate information efficiently. 3D scanners are still an expensive tool for verification and are not broadly available in delivery companies;
- In some situations, even though the volume criterion is satisfied, it is still not possible to fit all packages into the cargo space due to their dimensions. Each operator has appropriately defined package dimension limits for the type of services offered. On the other hand, transportation also has its specific limitations. This aspect requires particular attention when organizing deliveries. For example, the public postal operator in Serbia has limited the dimensions of express shipments to 60 cm × 50 cm × 50 cm, meaning that packages exceeding these dimensions can only be accepted under a special agreement. The weight limit per individual package for the same operator is 31.5 kg. For other services, the limits vary.
- There is the potential for complexity in defining membership functions and rule bases for new scenarios or delivery models, which may require substantial expert input;
- The most common service in delivery systems involves next-day delivery. As such, delivery organization is typically done a day in advance. In this regard, weather condition data, which can easily be retrieved from various sources, may be sensitive despite the high reliability of weather forecasting systems. If actual weather conditions significantly differ from those forecasted, the resulting preference may be inadequate,

affecting the choice of delivery model. However, this risk is not high, as with technological advances, weather forecasts, even several days ahead, are very reliable;

- Each alternative requires creating a separate fuzzy logic system to achieve accurate results. Depending on the circumstances, this can be a complex process;
- In some situations, the only available alternative may be excluded from the analysis due to elimination criteria. This impacts the overall delivery organization, requiring the division of shipments into smaller groups that match the available delivery models, resulting in multiple iterations by a courier or the use of different vehicles and couriers. This introduces various challenges, such as shipment distribution engaging additional labor and resources, which increases costs.

Despite these limitations, Fuzzy-DMS remains a valuable tool for delivery model selection in dynamic and complex environments.

6. Conclusions

The proposed Fuzzy-DMS methodology is based on applying fuzzy logic systems, which were created using expert opinions. In this way, it represents a mechanism that models expert reasoning in determining the suitability of a last-mile delivery model in line with specific requirements and circumstances. The final result of applying this approach is a preference that serves as a measure of suitability and supports decision-makers in the planning and organization of deliveries.

One of the main advantages of this methodology compared to others found in the literature, which are mostly based on multi-criteria decision-making, is that once the Fuzzy-DMS mechanism is created, it can be used for a longer period. By simply inputting values for the input variables and through the defined rule base, the desired output, i.e., the preference, is obtained. On the other hand, methods based on multi-criteria decision-making, which also provide good results, require a more complex application, as each analysis requires solving a multi-criteria task anew. Additionally, the introduction of harmonized membership functions, as a result of comparing symmetric and asymmetric membership functions, aims to enhance the validity of the obtained results by proactively addressing potential issues that may arise from expert subjectivity.

As part of the research, a case study was conducted in the city of Belgrade, demonstrating the applicability of the methodology. Specifically, three sustainable delivery models based on the use of e-motorcycles, e-cargo bikes, and e-scooters were analyzed. In accordance with sustainability principles and the specific task and circumstances, three key criteria influencing the level of suitability for applying the selected electromobility alternatives were defined, relating to route length, cargo space utilization, and adaptability to weather conditions. Testing was conducted, and for the defined tasks, the methodology provided results consistent with expert reasoning. The testing was conducted through three test scenarios for all three alternatives, based on two approaches: one involving asymmetric membership functions and the other involving harmonized membership functions. For the approach using asymmetric membership functions, preference values for all three alternatives range from 0.376 to 0.776. In contrast, this interval is slightly narrower for the harmonized membership functions approach, ranging from 0.379 to 0.757. This may indicate that harmonized membership functions provide more uniform results, reducing preference differences. The BCM delivery model has the highest preference value in both approaches, while the lowest preferences are associated with the BCB model. During testing, a sensitivity analysis was also conducted to examine the impact of changes in input variables on preference values. A drop in temperature from 13 °C to −3 °C, despite a reduction in the probability of precipitation from 60% to 40%, led to a decrease in the degree of adaptation to weather conditions for all alternatives, which indirectly caused a reduction in preferences. This clearly shows that unfavorable weather conditions negatively affect the preference for the analyzed delivery models. The test examples also confirmed that the more favorable the requirements or conditions, such as route length and cargo space utilization, the higher the preference values.

Additional analyses of the Fuzzy-DMS mechanism indicate its relevance in solving the designated task. Furthermore, the high level of flexibility allows for its adaptability and, therefore, its potential application for solving similar and related tasks.

Future research aims to enhance the methodology in defining membership functions by using metaheuristic algorithms to better model expert reasoning. For the same purpose, introducing expert prioritization based on their experience and response consistency may also be significant. Various tests will be conducted, including those with many input variables, to identify the most successful practices that will benefit future users. Regarding the improvement of applicability, the focus will be on developing an application that will enhance the accessibility and ease of use of the Fuzzy-DMS methodology in practice.

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Abbreviations

The following table present a list of abbreviations used in the study:

Abbreviation	Meaning
LMD	Last-Mile Delivery
EC	European Commission
EU	European Union
Fuzzy-DMS	Fuzzy Delivery Model Selection
B2C	Business-to-Consumer
GHG	Greenhouse Gases
WoS	Web of Science
FAHP	Fuzzy Analytic Hierarchy Process
ISM	Interpretative Structural Modeling
DSS	Decision Support System
FIS	Fuzzy Inference System
PFSs	Picture Fuzzy Sets
FCE	Fuzzy Comprehensive Evaluation
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
F-MCDM	Multi-Criteria Decision-Making Framework
FWASPAS	Fuzzy Weighted Aggregated Sum Product Assessment
WASPAS	Weighted Aggregated Sum Product Assessment
DHF	Dual Hesitant Fuzzy
SDNMARCOS	Sustainable Decision-Making Approach for Ranking and Choosing Options
OPA	Ordinal Priority Approach
MARCOS	Making Approach for Ranking and Choosing Options
VRS	Vehicle Routing Software
FFS-PSI-AROMAN	Fermatean Fuzzy Sets Preference Selection Index Alternative Ranking Order Method Accounting For Two-Step Normalization
AHP	Analytic Hierarchy Process
ADRs	Autonomous Delivery Robots
IF	Intuitionistic Fuzzy
PIPRECIA	Pivot Pairwise Relative Criteria Importance Assessment
PESTEL	Political, Economic, Social, Technological, Environmental, and Legal
SF-AHP	Spherical Fuzzy Analytic Hierarchy Process
SF-CoCoSo	Spherical Fuzzy Combined Compromise Solution

FLS	Fuzzy Logic System
Fuzzy DMS	Fuzzy Decision-Making System
BCM	By courier via e-motorcycles
BCB	By courier via e-cargo bike
BCS	By courier via e-scooter
ELCV	Electric Light Commercial Vehicle
I1F1	Input 1 Fuzzy Logic System 1
VSR	Very Short Route
SR	Short Route
MLR	Medium-Length Route
LR	Long Route
VLR	Very Long Route
LB	Left Boundary
T	Top
RB	Right Boundary
I2F1	Input 2 Fuzzy Logic System 1
VLU	Very Low Utilization Level
LU	Low Utilization Level
MU	Medium Utilization Level
HU	High Utilization Level
VHU	Very High Utilization Level
I2F2	Input 2 Fuzzy Logic System 2
I2F3	Input 3 Fuzzy Logic System 3
I3F1	Input 3 Fuzzy Logic System 1
FLSW1	Fuzzy Logic System for Weather Conditions 1
I1FW1	Input 1 Fuzzy Logic System for Weather Conditions 1
I2FW1	Input 2 Fuzzy Logic System for Weather Conditions 1
FLSW	Fuzzy Logic System for Weather Conditions
VLT	Very Low Temperature
LT	Low Temperature
MT	Medium Temperature
HT	High Temperature
VHT	Very High Temperature
FLSW2	Fuzzy Logic System for Weather Conditions 2
FLSW3	Fuzzy Logic System for Weather Conditions 3
VLPP	Very Low Probability
LPP	Low Probability
MPP	Medium Probability
HPP	High Probability
VHPP	Very High Probability
VLA	Very Low Adaptation
LA	Low Adaptation
MA	Medium Adaptation
HA	High Adaptation
VHA	Very High Adaptation
O1FW1	Output 1 Fuzzy Logic System for Weather Conditions 1
O1FW2	Output 1 Fuzzy Logic System for Weather Conditions 2
O1FW3	Output 1 Fuzzy Logic System for Weather Conditions 3
VLP	Very Low Preference
LP	Low Preference
MP	Medium Preference
HP	High Preference
VHP	Very High Preference
O1F1	Output 1 Fuzzy Logic System 1
O1F2	Output 1 Fuzzy Logic System 2
O1F3	Output 1 Fuzzy Logic System 3
I1F2	Input 1 Fuzzy Logic System 2

I1F3Input 1 Fuzzy Logic System 3

I3F2Input 3 Fuzzy Logic System 2

3DThree-Dimensional

Appendix A

The experts’ responses are presented in the following tables when creating variables I1F1, I1F2, and I1F3, where LB—left boundary, T—top, RB—right boundary.

Table A1. The experts’ responses—I1F1 [km].

I1F1		VSR			SR		MLR			LR			VLR		
Experts	LB	T	RB	LB	T	RB	LB	T	RB	LB	T	RB	LB	T	RB
E1	-	3	7	5	7.5	12.5	8	14	22.5	14.5	24	31	26	34.5	-
E2	-	3.5	8.5	6.7	9	13.3	10	16.5	23.4	20	27.5	34.5	27.5	35	-
E3	-	4.8	9	5	10.6	15	10.5	18	24	19	28	34	29	34.5	-
E4	-	3.8	6.2	4	7	9.8	7.5	12.6	18.5	17.5	22.8	28.2	26.2	32	-
E5	-	4	8.5	5	9	15	11	17	22	18	27	34	29	35	-
E6	-	4.5	10	6	11.5	16.5	12	19	26	18.5	26.5	30.5	25	31.5	-
E7	-	3	7.5	4.5	9.5	15.8	10.5	18.5	23.5	18.5	25	31	26.5	32	-
E8	-	4	9	5	9	16	11	16	22	17	23	28	23	29	-
Average	-	3.83	8.21	5.15	9.14	14.24	10.06	16.45	22.74	18.33	25.48	30.96	26.53	32.94	-

Table A2. The experts’ responses—I1F2 [km].

I1F2		VSR			SR		MLR			LR			VLR		
Experts	LB	T	RB	LB	T	RB	LB	T	RB	LB	T	RB	LB	T	RB
E1	-	2.5	6	3	7	11	7	13	21.5	13	22.5	29.5	24	33	-
E2	-	3	7	4.8	8	12.5	8.5	15.8	22.6	18.5	26.5	33	26.5	33.5	-
E3	-	3.5	7.5	3.5	9.5	13.5	9	16	23.5	18	27	32	28	34	-
E4	-	2.8	4.8	3	6	8.6	6.5	11.5	16.5	16.5	21.5	27	25.5	31	-
E5	-	3.5	7.5	3	7.5	13	10	16	21	16.5	23.5	33.5	27.5	33.5	-
E6	-	3	9.5	4.5	10.5	15.5	10.5	17.5	24.5	17	25	29	24	30.5	-
E7	-	2.5	6	3	9	14.5	9	17.5	22.5	17.5	24.5	29.5	25	30	-
E8	-	3	8	4	8	15	10	17	22	16	21	26	21	27	-
Average	-	2.98	7.04	3.60	8.19	12.95	8.81	15.54	21.76	16.63	23.94	29.94	25.19	31.56	-

Table A3. The experts’ responses—I1F3 [km].

I1F3		VSR			SR		MLR			LR			VLR		
Experts	LB	T	RB	LB	T	RB	LB	T	RB	LB	T	RB	LB	T	RB
E1	-	1	3	2	4	7.5	3	8.5	17	8.5	18.5	24.5	20	28	-
E2	-	1.5	3.5	2.5	4.5	9	4	10	18.2	14	22	29	22	27.5	-
E3	-	2.5	5.5	2.5	6	11	5.5	12.5	19	13.5	22	27.5	23.5	29	-
E4	-	2	2.5	2	3.5	6	3	8	12.5	11.5	16.5	23	20.5	26.5	-
E5	-	2.5	5	2.5	4	10.5	5.5	11	16.5	12	19.5	29.5	23	28.5	-
E6	-	2	6.5	2	7	12	6	12	19.5	13	21.5	25	20.5	26.5	-
E7	-	1.5	4	1.5	6.5	11	4.5	12.5	19	12.5	20	24.5	21.5	25.5	-
E8	-	2	5	2	5	11	6	13	18	12	16	21	16	23	-
Average	-	1.88	4.38	2.13	5.06	9.75	4.69	10.94	17.46	12.13	19.50	25.50	20.88	26.81	-

Appendix B

The experts' responses are presented in the following table while creating the variable "Temperature", where LB is the left boundary, T is the top, and RB is the right boundary.

Table A4. The experts' responses—Temperature [°C].

Temperature		VLT			LT			MT			HT			VHT		
Experts	LB	T	RB	LB	T	RB	LB	T	RB	LB	T	RB	LB	T	RB	
E1	-	−4	5	−2	7	11	8	15	22	19	25	30	28	35	-	
E2	-	−5	6	−2	4	9	7	16	23	20	27	32	30	34	-	
E3	-	−10	0	−5	3	8	6	13	24	18	28	33	30	38	-	
E4	-	−8	3	−4	5	10	5	15	25	22	30	35	31	36	-	
Average	-	−6.75	3.50	−3.25	4.75	9.50	6.50	14.75	23.50	19.75	27.50	32.50	29.75	35.75	-	

Appendix C

The following tables present the parameters defining symmetric and harmonized membership functions.

Table A5. Parameters of symmetric and harmonized membership functions—variable I1F1 [km].

Fuzzy Set	Left Boundary	Top	Right Boundary
Symmetric membership functions			
VSR	/	3.83	11.1075
SR	3.83	11.1075	18.385
MLR	11.1075	18.385	25.6625
LR	18.385	25.6625	32.94
VLR	25.6625	32.94	/
Harmonized membership functions			
VSR	/	3.83	9.65875
SR	4.49	10.12375	16.3125
MLR	10.58375	17.4175	24.20125
LR	18.3575	25.57125	31.95
VLR	26.09625	32.94	/

Table A6. Parameters of symmetric and harmonized membership functions—variable I1FW1 [°C].

Fuzzy Set	Left Boundary	Top	Right Boundary
Symmetric membership functions			
VSR	/	−6.75	3.875
SR	−6.75	3.875	14.5
MLR	3.875	14.5	25.125
LR	14.5	25.125	35.75
VLR	25.125	35.75	/
Harmonized membership functions			
VSR	/	−6.75	3.6875
SR	−5	4.3125	12
MLR	5.1875	14.625	24.3125
LR	17.125	26.3125	34.125
VLR	27.4375	35.75	

Table A7. Parameters of symmetric and harmonized membership functions—variable I1F2 [km].

Fuzzy Set	Left Boundary	Top	Right Boundary
Symmetric membership functions			
VSR	/	2.98	10.125
SR	2.98	10.125	17.27
MLR	10.125	17.27	24.415
LR	17.27	24.415	31.56
VLR	24.415	31.56	/
Harmonized membership functions			
VSR	/	2.98	8.5825
SR	3.29	9.1575	15.11
MLR	9.4675	16.405	23.0875
LR	16.95	24.1775	30.75
VLR	24.8025	31.56	/

Table A8. Parameters of symmetric and harmonized membership functions—variable I1F3 [km].

Fuzzy Set	Left Boundary	Top	Right Boundary
Symmetric membership functions			
VSR	/	1.88	8.1125
SR	1.88	8.1125	14.345
MLR	8.1125	14.345	20.5775
LR	14.345	20.5775	26.81
VLR	20.5775	26.81	/
Harmonized membership functions			
VSR	/	1.88	6.24625
SR	2.005	6.58625	12.0475
MLR	6.40125	12.6425	19.01875
LR	13.2375	20.03875	26.155
VLR	20.72875	26.81	/

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