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RESEARCH ARTICLE

Third-Party Logistics Provider Selection in the Industry 4.0 Era by Using a Fuzzy AHP and Fuzzy MARCOS Methodology

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ABSTRACT In the dynamic landscape of Industry 4.0, the selection of Third-Party Logistics Providers (3PLs) has emerged as a critical strategic decision for businesses seeking to optimize their supply chain operations. This paper aims to develop a new hybrid Multi-Criteria Decision-Making (MCDM) approach based on Industry 4.0 components for selecting the best 3PL provider by integrating Fuzzy Analytical Hierarchy Process (FAHP) and Fuzzy Measurement Alternatives and Ranking according to Compromise Solution (FMARCOS). The criteria for 3PL evaluation and selection are determined with respect to literature studies and experts' consultation. In the proposed approach, judgments of different experts are expressed by linguistic terms based on fuzzy numbers. The criteria weights are calculated by applying FAHP, then the ranking and selection of the best potential 3PL provider have been done using FMARCOS. A case study from a manufacturing company is illustrated. Finally, sensitivity analysis on the criteria weights and comparative analysis among MCDM methods (FMABAC, FWASPAS, FCOSOSO, FSAW, FCOPRAS, FTOPSIS and FVIKOR) are conducted for the validity of the results. The results indicate that the integrated FAHP and FMARCOS model offers a robust and adaptable framework for 3PL selection, enabling companies to navigate the complexities of Industry 4.0 with a strategic and informed approach. This research contributes to the evolving discourse on logistics optimization in the era of Industry 4.0 and provides practical insights for industry practitioners, academics, and policymakers.

INDEX TERMS Manufacturing, Industry 4.0, 3PL selection, FAHP, FMARCOS.

I. INTRODUCTION

The Fourth Industrial Revolution, often termed "Industry 4.0," stands as a monumental advancement in human progress. Emerged in 2011 from Germany's high-tech strategy, it epitomizes a fresh epoch of industrial evolution, characterized by the digitalization and automation of production processes [1]. This industrial revolution, commonly known as "Industry 4.0", represents the newest era of industrial transformation by introducing the digitalization of processes and the automation of production models [2]. Industry 4.0 envisions a realm of smart manufacturing, where machines and products harmoniously interact without human intervention [3], [4]. This gives rise to intelligent factory systems, encompassing astute machinery, devices, and logistics processes [5], [6], [7]. Industry 4.0 extends its transformative touch across the entire supply chain, fundamentally reshaping supply chain management (SCM). It leaves an indelible mark on retailers, operators, and other vital SCM components. The integration of Industry 4.0 into SCM bolsters the core elements—integration, operations, purchasing, and distribution—enhancing overall productivity [8]. This

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integration significantly diminishes lead times for product delivery, amplifies responsiveness to unforeseen disruptions, and elevates the quality of decision-making [9]. The outcome is a supply chain ecosystem marked by heightened efficiency, adaptability, and resilience. By amalgamating cutting-edge technology into the supply chain, Industry 4.0 ushers in a future where businesses operate with unprecedented precision and agility. As it continues to permeate industries, its impact on global commerce is poised to be profound, revolutionizing how goods move from production lines to the hands of consumers. Embracing Industry 4.0 is not merely a choice; it is a strategic imperative for enterprises aspiring to remain competitive in the dynamic landscape of modern commerce [10].

Logistics is at the core of supply chain operations, serving as the lifeblood that ensures products flow seamlessly from production to consumption [11]. In the context of Industry 4.0, logistics undergoes a profound transformation. Utilizing advanced technologies like Internet of Things (IoT), big data, autonomous automation, and artificial intelligence (AI) offer unprecedented visibility and control in logistics. This capability enables businesses to respond promptly and adapt flexibly to changing market conditions, striving for greater efficiency and effectiveness in their operations. More specifically, this empowers businesses to optimize routes, monitor shipments in real-time, and proactively respond to any disruptions [12]. Third-party logistics service providers (3PLs) play a pivotal role in this logistics revolution. They act as intermediaries, offering specialized expertise and resources to streamline the movement and storage of goods. With Industry 4.0, the expectations from 3PLs have evolved. Companies now seek partners who can leverage technology to provide data-driven insights, predictive analytics, and agile solutions. Equipped with advanced digital capabilities, 3PLs hold the key to significantly enhancing supply chain efficiency and responsiveness.

There are various examples of how Industry 4.0 technologies play key roles in the 3PL section. IoT sensors are integrated into transport vehicles, warehouse facilities, and inventory items to provide real-time visibility into their status and location [9]. This allows 3PL providers to track shipments, monitor temperature and humidity levels for perishable goods, and optimize routes for more efficient delivery. AI-powered algorithms analyze large volumes of historical and real-time data to predict demand, optimize inventory levels, and identify potential disruptions in the supply chain [13]. This helps 3PL providers to make data-driven decisions, minimize stockouts, and improve overall efficiency. Industry 4.0 has also introduced the use of autonomous vehicles and drones for last-mile delivery and warehouse operations [14]. These technologies enable 3PL providers to deliver goods faster, reduce delivery costs, and improve customer satisfaction by offering same-day or next-day delivery options. Blockchain technology ensures the integrity and security of transactions and data exchanges in the supply chain [15]. By leveraging blockchain, 3PL providers can create transparent and tamper-proof records of every transaction, reducing the risk of fraud, counterfeiting, and unauthorized access to sensitive information. Cloud computing and data analytics enable seamless collaboration and data sharing among supply chain partners, including manufacturers, suppliers, and customers [16]. This allows 3PL providers to access real-time data, optimize inventory management, and improve overall supply chain visibility and transparency. In addition, augmented reality (AR) and virtual reality (VR) technologies are used in warehouse operations for order picking, inventory management, and employee training [17]. By providing immersive and interactive experiences, these technologies help 3PL providers to improve accuracy, efficiency, and safety in warehouse operations. Beyond operational efficiency, Industry 4.0 also champions sustainability endeavors [18]. Through optimized routes and intelligent load management, it curtails fuel consumption and emissions. Additionally, real-time monitoring and adjustment of temperature-sensitive shipments minimize waste and spoilage. Furthermore, Industry 4.0 dissolves traditional boundaries between logistics and other supply chain functions, enabling seamless coordination across production, warehousing, and transportation. This synchronized ecosystem not only heightens overall efficiency but also augments customer satisfaction by ensuring swifter delivery times and more reliable service. As more and more companies seek more innovative solutions to achieve greater value for themselves and stakeholders, adequate evaluation and selection of 3PLs should be required for new business models that come with Industry 4.0 criteria.

Hence, it can be believed that the selection of a potential 3PL provider is a complex decision making procedure with the goal of reducing the preliminary set of 3PLs to the final choices. A high degree of uncertainty is associated with these decision-making processes, based on suitable multiple criteria, are taken into account of experts' reasoning and personal experience. The most popular tools for such complicated decision-making problems are multi-criteria decision-making (MCDM) tools, owing to the fact that these tools may quickly and effectively resolve evaluation issues that are complicated, poorly structured, and comprise numerous incompatible objectives or criteria [19]. More specifically, MCDM methodologies offer a viable solution for addressing the challenge of 3PL selection. MCDM techniques used in the research consider both qualitative and quantitative factors for the assessment of a set of 3PLs. Previous studies on 3PL selection considering both conventional factors and sustainability/green factors were based predominantly on criteria such as cost, relationship, services, quality, information and equipment systems, flexibility, delivery, professionalism, financial position, location, and concern for the environment (green policies, carbon emissions, pollution, waste, etc.) [20], [21], [22], [23], [24], [25], [26], [27], [28]. Moreover, while existing literature has explored 3PL selection extensively, both in crisp and fuzzy environment, there remains a need for further research encompassing a broader spectrum of criteria, diverse expertise, and linguistic variables, all of which should be viewed through the lens of Industry 4.0 advancements.

To handle the mentioned problem, this study aims to develop a new hybrid MCDM approach for the 3PL selection problem considering criteria appropriate to the characteristics of Industry 4.0. An integrated Fuzzy Analytical Hierarchy Process (FAHP) and Fuzzy Measurement Alternatives and Ranking according to Compromise Solution (FMARCOS) approach was proposed to decide the most suitable provider. For determining evaluation criteria of the 3PL selection in the context of Industry 4.0, a panel of experts is assembled in the first stage. Subsequently, the criteria are refined based on the review of the literature and experts' opinions from the Industry 4.0 perspective. The criteria weights are calculated by applying the FAHP method, then the ranking and selection of the best potential 3PL provider have been done using FMARCOS. The use of fuzzy logic allows the representation of uncertain and vague judgments commonly associated with the complexities of Industry 4.0 criteria. By incorporating fuzzy logic, the model can capture the inherent uncertainty in expert opinions on multiple factors, ensuring a more realistic representation of decision-making processes. Thus, the application of FAHP-FMARCOS contributes to the advancement of both theoretical understanding and practical implementation of Industry 4.0 principles by providing a robust methodology for decision support in complex and uncertain environments. A case study from a company in Vietnam that needs to choose a logistics providers is implemented. Lastly, a sensitivity analysis and a comparative analysis have been conducted to validate the accuracy and reliability of the created framework.

In order to overcome judgments based on unbalanced scales, imprecision, uncertainty, and decision makers' biases, fuzzy theory has been integrated with the AHP. Thus, FAHP makes the decision makers' linguistic evaluations more flexible and effective [29], [30], [31]. The benefits of FMARCOS, a new developed MCDM method [32], is as follows: (1) This method is simpler, more effective, and easier to sort and optimize than other MCDM methods such as TOPSIS, COPRAS, MABAC, SAW, ARAS, WASPAS, and EDAS. The method improves the accuracy and reliability of decision-making results even further. MARCOS performs better in large data sets and is better suited for solving multi-criteria models with more criteria. MARCOS differs from other methods in that it has a simpler algorithm that does not become more complex as the number of criteria or alternatives increases. (2) The MARCOS model is distinguished by its adaptability in analyzing expert preferences. The algorithm's flexibility is demonstrated by its ability to process expert preferences regardless of the scale used. (3) When it comes to ranking alternatives, the MARCOS method outperforms the TOPSIS method, which is based on similar principles, namely defining the distance of alternatives relative to reference points (ideal and anti-ideal alternatives). The FMARCOS method provides an algorithm for analyzing the relationship between alternatives and reference points in order to improve the robustness of MCDM in a fuzzy environment [33]. To provide a robust decision, FMARCOS integrates the following points: defining reference points (fuzzy ideal and fuzzy anti-ideal values), determining the relationship between alternatives and fuzzy ideal/anti-ideal values, and defining the utility degree of alternatives in relation to the fuzzy ideal and fuzzy anti-ideal solutions. The FMARCOS method produces more reasonable results due to the fusion of the ratio approach and the reference point sorting approach. FMARCOS demonstrates significant results stability and reliability in a dynamic environment.

The main contribution of this paper is to present a new hybrid model combining FAHP and FMARCOS for the 3PL selection problem in the perspective of Industry 4.0 levels in the context of linguistic evaluation. The originality of this paper is threefold: (1) This study is the first to consider Industry 4.0 factors in the 3PL selection problem under fuzzy environment. The research can provide valuable insights into the criteria of Logistics 4.0, more specifically, suitable indicators to evaluate the 3PL industry from the lens of Industry 4.0 towards sustainability. (2) Using the merits of both methods FAHP and FMARCOS, the proposed integrated approach can conveniently express the real condition of decision-making problem, providing better representation of experts' evaluation with simplified calculations. (3) A real case study of a manufacturing company in Vietnam that specializes in electronic components, smart devices, and other technology-related products was conducted which aims to implement heavily in innovative technologies to reduce costs, increase customer satisfaction and gain competitive advantage in the landscape. Furthermore, the implementation of sensitivity analysis and comparative analysis with other MCDM methods (FMABAC, FWASPAS, FCOSOSO, FSAW, FCOPRAS, FTOPSIS and FVIKOR) will allow decision-makers to test the method's stability. Findings can be effectively adapted to other sectors.

II. LITERATURE REVIEW

Confronting the strategic decision of evaluating and selecting the best logistics provider, scholars have advocated for the applications of Multi-criteria Decision Making (MCDM) methods based on standalone and integrated use of fuzzy sets theory which allows these models to perform under uncertain decision-making processes. Furthermore, academics and professionals generally agree that the 3PL selection problem is a multi-criteria problem influenced by various factors, with a variety of quantitative and qualitative criteria for choosing an appropriate provider [34]. Table 1 provides a description of various 3PL evaluation criteria and MCDM methods used by numerous researchers.

Kannan et al. [35] introduced a framework combining Interpretive Structural Modeling (ISM) and fuzzy Technique for Order Preference by Similarity to Ideal Solution

TABLE 1. Summary of basic components of Industry 4.0.

Author(s)	Method	Criteria	Illustrative example
Bottani and Rizzi (2006) [20]	Fuzzy TOPSIS	Breadth of services, business experience, characterization of service, compatibility, financial stability, flexibility, performance, price, physical equipment and information systems, quality, strategic attitude, trust and fairness	A dairy product company
Kannan et al. (2009) [35]	ISM and fuzzy TOPSIS	Quality, delivery, logistics cost, rejection rate, technical/engineering capability, inability to meet future requirement, willingness and attitude	A battery manufacturin g company
Falsini et al. (2012) [26]	AHP, DEA and linear programming integration	Reliability of quality, speed of service, flexibility, cost, equipment, operators′ safety, and environmental safeguard	A company in Italy
Ho et al. (2012) [21]	QFD and fuzzy AHP	Cost, delivery, flexibility, quality, technology, risk and related sub-criteria	A supplier of hard disk components
Hsu et al. (2013) [36]	DEMATEL and ANP	Relationship, flexibility, information sharing, knowledge and skills, customer satisfaction, on-time rate, cost saving, flexibility in billing, labour union, loss of management control, and information security	A Taiwanese airline
Perçin and Min (2013) [25]	QFD, linear regression and MOP	Cost, timeliness, service quality, flexibility, and reputation	An auto part manufacturer
Singh et al. (2017) [22]	Fuzzy AHP and fuzzy TOPSIS	Transportation and warehousing cost, logistics infrastructure and warehousing facilitites, customer service and reliability, network management, material handling capabilities, quality control and inspection, automation of processes, innovation and effectiveness of cold chain processes, IT applications for tracking and tracing, flexibility of processes	Cold chain management for a health food manufacturin g company
Keshavarz Ghorabaee et al. (2017) [27]	Interval Type-2 fuzzy CRITIC and WASPAS	Expected cost, services, quality, flexibility, delivery, risk, and financial position	A home appliance manufacturer
Zarbakhshnia et al. (2018) [37]	Fuzzy SWARA and fuzzy COPRAS	Quality, cost, lead time, delivery and services, transportation, recycle, disposal, remanufacture and reuse, green technology capability, environment protection certification, eco-design production, health and safety, voice of customer, employment stability, operational and financial risk	An automotive company
Sremac et al. (2018) [55]	Rough SWARA and rough WASPAS	Vehicle fleet condition, financial stability, professionalization of drivers, cost of transport, application of risk mitigation measures, application of IT in transport organization, compensation for damages caused during transportation, reliability	A chemical company
Pamucar et ak. (2019) [24]	BWM, WASPAS, and MABAC with interval rough numbers	Services, logistics cost, information system, intangible, geographical location, and related sub-criteria	An electronics company
Vazifehdan and Darestani (2019) [23]	Fuzzy ANP, QFD, and SIR	Flexibility time, work experience, technology, risk, quality, social factors, company's green management, environmental pollution, economic factors, environmental laws, logistics industry, governmental green decision making, logistics costs and related sub-criteria	A petrochemical company

TABLE 1. ***(Continued.)*** **Summary of basic components of Industry 4.0.**

Wang et al. (2021) [38]	Fuzzy AHP and fuzzy VIKOR	Logistics cost, financial stability, IT and R&D systems, network management, quality of service, reliability and delivery time, flexibility and responsiveness, environmental pollution, ecological laws, green operation, health and safety, voice of customer, reputation, operational risk, and financial risk	A company in Vietnam
Yuan et al. (2022) [56]	Probabilistic linguistic DEMATEL-COPRAS	Cost of logistics, transportation and distribution time, customer service level, and storage level	A case study from e-commerce industry
Nila and Roy (2023) [28]	Fuzzy LOPCOW-FUCOM-DOBI	Cost of services, reputation, delivery reliability, technological expertise, geographical location, resource consumption, compliance with international organization for standardization, green distribution strategies, environmental protection policies, emission, effluents and waste generation, local community influence, equity labour sources, labour organization code, health and safety practices, and staff training	A food manufacturin g company

(TOPSIS) to select the best logistics provider for a battery manufacturing company in India. Falsini et al. [26] proposed a method that combines AHP, Data Envelopment Analysis (DEA) and linear programming (LP) for selecting 3PLs, focusing on three sectors in Italy, namely: industry and defense, perishable products, and consumer goods. Hsu et al. [36] developed an integrated model that combined Decision-Making Trial and Evaluation Laboratory (DEMATEL) and Analytic Network Process (ANP) for 3PL selection in a Taiwanese airline case. To select the best 3PL for Turkish auto part manufacturers, Perçin and Min [25] employed three methods: Quality Function Deployment (QFD), multi-objective programming (MOP) and fuzzy linear regression. A combined approach based on Interval Type-2 Fuzzy Sets (IT2FSs), the CRiteria Importance Through Inter-criteria Correlation (CRITIC) and Weighted Aggregated Sum Product ASsessment (WASPAS) methods was proposed in a study of Ghorabaee et al. [27] to evaluate 3PLs for a home appliance manufacturer. In a case study from automotive industry, Zarbakhshnia et al. [37] used fuzzy Step-wise Weight Assessment Ratio Analysis (SWARA) to weigh the evaluation criteria, and fuzzy COmplex PRoportional ASsessment of alternatives (COPRAS) was proposed to rank and select the sustainable logistics providers. Pamucar et al. [24] developed a new integrated interval rough number (IRN) approach based on the Best Worst Method (BWM) and Weighted Aggregated Sum Product Assessment (WASPAS) method along Multi-Attributive Border Approximation area Comparison (MABAC) to evaluate 3PL providers for an electronics company. Vazifehdan and Darestani [23] proposed a combinational approach using QFD, fuzzy ANP based on fuzzy DEMATEL and Superiority and Inferiority Ranking method (SIR) for a green logistics outsourcing problem in the petrochemical industry. Wang et al. [38] used the FAHP method and fuzzy vlsekriterijumska optimizacija i kompromisno resenje (FVIKOR) for a case study in Vietnam. Recently, Nila and Roy [28] developed an integrated MCDM framework based on triangular fuzzy numbers (TFN) that combines the LOgarithmic Percentage Change-driven Objective Weighting (LOPCOW), Full Consistency Method (FUCOM), and DOmbi Bonferroni (DOBI) methods for evaluating criteria and ranking alternatives for a case study of an Indian food manufacturing company' s optimal selection of 3PL providers.

As can be seen from the studies summarized in Table 1, studies on 3PL selection with elements of Industry 4.0 have been lacking. Furthermore, there is a complete lack of both the application of FMARCOS and the integration of FAHP and FMARCOS in the literature currently available for 3PL evaluation. Thus, this serves as our driving force behind conducting this study. Stević et al. [32] first proposed the MARCOS method in 2020 for sustainable supplier selection in healthcare industries. In 2021, Ecer [39] applied MARCOS for performance assessment of battery electric vehicles based on ranking strategies. Pamucar et al. [40] used proposed neutrosophic fuzzy MARCOS for the evaluation of alternative fuel vehicles for sustainable road transportation. Kovač et al. [41] proposed spherical fuzzy MARCOS method for assessment of drone-based city logistics concepts. Additional research that combines FAHP and FMARCOS is necessary to the best of our knowledge regarding a novel 3PL selection strategy in the Vietnamese context.

III. MATERIALS AND METHODS

Decision-making in the context of real-world problems, particularly when evaluating and selecting third-party logistics service providers, encompasses not only quantitative criteria such as cost and lead time but also qualitative factors like customer feedback and reputation. Fuzzy set theory proves invaluable in managing intricate decision-making problems entailing numerous interconnected variables. Within the scope of this paper, FAHP (fuzzy analytic hierarchy process) and FMARCOS (fuzzy measurement of alternatives and ranking according to the compromise solution) have been chosen from the array of available MCDM (multiple criteria decision making) models. These selections are based on the fact that they are integrated into decision-making software, facilitating effective decision-making by practitioners. The flow of the re-search is shown in Figure 1.

A. PRELIMINARIES

Fuzzy set theory has emerged as a crucial method for addressing imprecision or vagueness in real-world problems. The fuzzy triangular numbers (TFN) can be described as (l, m, u), indicating the least likely (l), most promising (m), and largest conceivable (u) values in TFN. TFN can be defined as in equations (1) and (2) below [42].

$$\left(\frac{a}{\tilde{M}}\right) = \begin{cases} 0 & if\ a < m, \\ \dfrac{a-l}{m-l} & if\ l \le a \le m, \\ \dfrac{u-a}{u-m} & if\ m \le a \le u, \\ 0 & if\ a > u, \end{cases} \tag{1}$$

$$\tilde{M} = \left(M^{o(y)}, M^{i(y)}\right) = [l + (m-l)\,y, u + (m-u)\,y]\,, y \in [0,1] \tag{2}$$

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

The following equations (3)–(7) illustrate fundamental computations involving two positive TFN [43], $\tilde{M}_1 = (l_1, m_1, u_1)$ and $\tilde{M}_2 = (l_2, m_2, u_2)$. Addition:

$$\tilde{M}_1 \oplus \tilde{M}_2 = (l_1, m_1, u_1) + (l_2, m_2, u_2) = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \tag{3}$$

Subtraction:

$$\tilde{M}_1 \ominus \tilde{M}_2 = (l_1, m_1, u_1) - (l_2, m_2, u_2) = (l_1 - u_2, m_1 - m_2, u_1 - l_2) \tag{4}$$

Multiplication:

$$\tilde{M}_1 \otimes \tilde{M}_2 = (l_1, m_1, u_1) \times (l_2, m_2, u_2) = (l_1 \times l_2, m_1 \times m_2, u_1 \times u_2) \tag{5}$$

Division:

$$\frac{\tilde{M}_1}{\tilde{M}_2} = \frac{(l_1, m_1, u_1)}{(l_2, m_2, u_2)} = \left(\frac{l_1}{u_2}, \frac{m_1}{m_2}, \frac{u_1}{l_2}\right) \tag{6}$$

Reciprocal:

$$\tilde{M}_1^{-1} = (l_1, m_1, u_1)^{-1} = \left(\frac{1}{u_1}, \frac{1}{m_1}, \frac{1}{l_1}\right) \tag{7}$$

B. FUZZY ANALYTIC HIERARCHY PROCESS (FAHP)

Table 2 illustrates that fuzzy triangular numbers represent the linguistic terms for both the pairwise comparison scale and the assigned fuzzy scale. The relative importance of the two criteria is assessed on a scale ranging from 1 to 9, using the linguistic variables provided. A tilde sign (∼) is used above the parameter symbol to denote uncertainty. Consequently, the following outlines the specifics of the FAHP process [44].

Step 1: In order to generate the integrated fuzzy pairwise comparison matrix utilized in the FAHP calculation, we employ the geometric integration method as depicted in equation (8). $\tilde{l}_{ij}$ denotes the importance of the i^{th} criterion over the j^{th} criterion.

$$\tilde{M} = \begin{pmatrix} 1 & \tilde{l_{12}} & \cdots & \tilde{l_{1n}} \\ \tilde{l_{21}} & 1 & \cdots & \tilde{l_{2n}} \\ \cdots & \cdots & \cdots & \cdots \\ \tilde{l_{n1}} & \tilde{l_{n2}} & \cdots & 1 \end{pmatrix} = \begin{pmatrix} 1 & \tilde{l_{12}} & \cdots & \tilde{l_{1n}} \\ 1/\tilde{l_{12}} & 1 & \cdots & \tilde{l_{2n}} \\ \cdots & \cdots & \cdots & \cdots \\ 1/\tilde{l_{1n}} & 1/\tilde{l_{2n}} & \cdots & 1 \end{pmatrix} \tag{8}$$

$$\tilde{l_{ij}} = \begin{cases} \tilde{9}^{-1}, \tilde{8}^{-1}, \tilde{7}^{-1}, \tilde{6}^{-1}, \tilde{5}^{-1}, \tilde{4}^{-1}, \tilde{3}^{-1}, \tilde{2}^{-1}, \tilde{1}^{-1}, \tilde{1}, \tilde{2}, \tilde{3} \\ 1 \end{cases}$$

Step 2: The equation (9) is to determine the fuzzy geometric mean of each criterion.

$$\tilde{r}_i = \left(\prod_{j=1}^{n} \tilde{l_{ij}}\right)^{1/n} \ such\ that\ i = 1, 2, \ldots, n \tag{9}$$

where $\tilde{r}_i$ approximated by the fuzzy geometric mean, and $\tilde{l_{ij}}$ is a fuzzy comparison value generated by a panel of decision-makers based on the i^{th} criterion over the j^{th} criterion.

Step 3: The equation (10) is to determine the fuzzy preference weight for each criterion.

$$\tilde{w}_i = \tilde{r}_i \otimes (\tilde{r_1} \oplus \tilde{r_2} \oplus \ldots \oplus \tilde{r_n})^{-1} \tag{10}$$

where $\tilde{w}_i$ is the fuzzy weight of the i^{th} criterion.

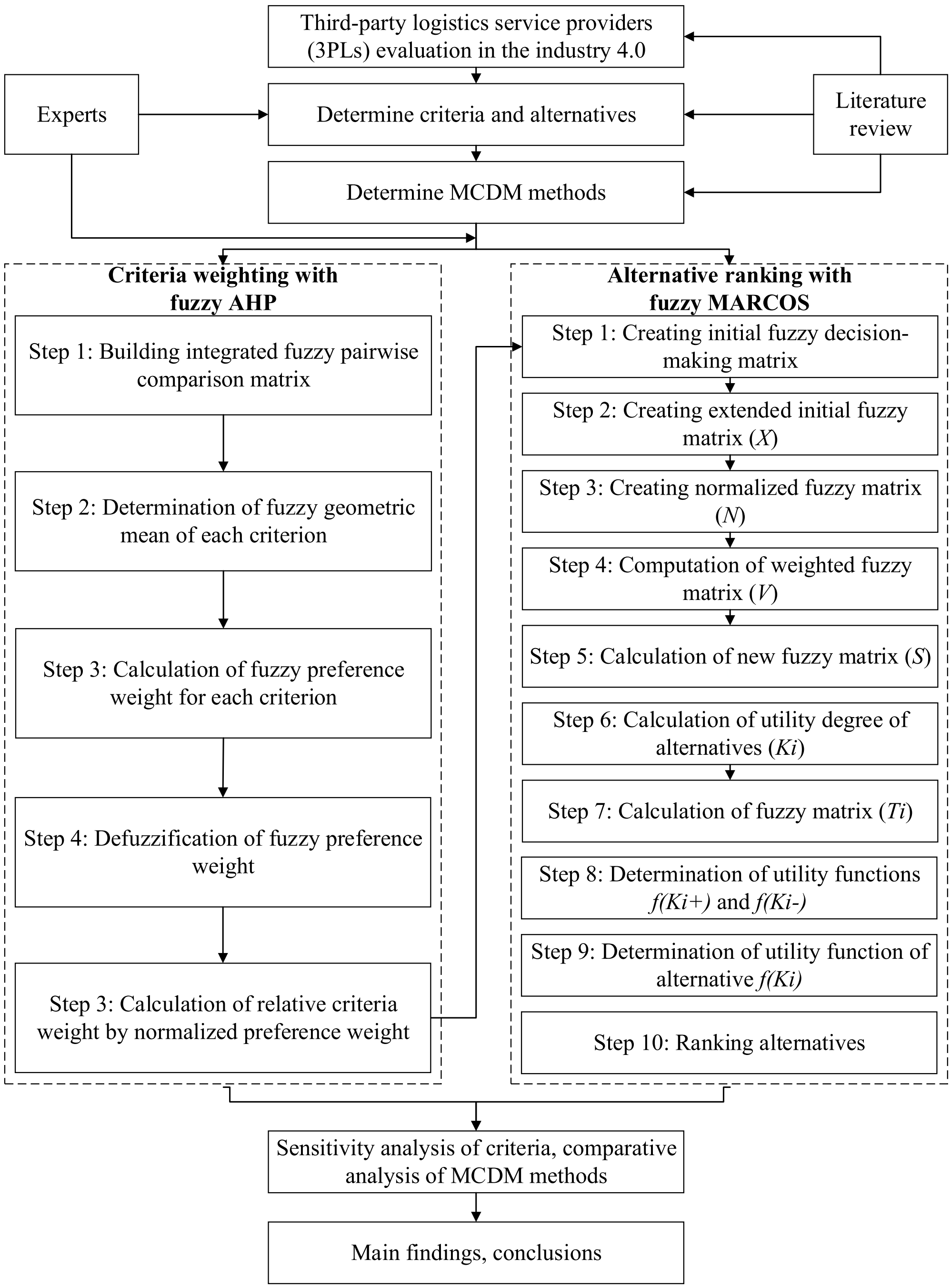

FIGURE 1. The research flow.

Step 4: To obtain a clear result, we need to defuzzify the fuzzy preference weights using the average weight criterion G_i, equation (11).

$$G_i = \frac{lw_i + mw_i + uw_i}{3} \tag{11}$$

where $\tilde{w}_i$ is the fuzzy weight of the i^{th} criterion, which can be presented as $\tilde{w}_i = (lw_i, m\, w_i, u\, w_i)$, such that $lw_i, m\, w_i, u\, w_i$ are the lower-bound, middle-bound, and upper-bound of $\tilde{w}_i$, respectively.

Step 5: The relative importance of each criterion, as determined by the normalized preference weight H_i, as seen by equation (12).

$$H_i = \frac{G_i}{\sum_{i=1}^{n} G_i} \tag{12}$$

C. FUZZY MEASUREMENT OF ALTERNATIVES AND RANKING ACCORDING TO THE COMPROMISE SOLUTION (FMARCOS)

In the context of multi-criteria decision-making (MCDM) scenarios, involving a defined set of criteria and a multitude of potential solutions, the employment of fuzzy measurement of alternatives and ranking based on compromise solutions

TABLE 2. Definition of the FAHP scale [44].

Fuzzy Set	Definition	Fuzzy Scale
$\tilde{1}$	Equal importance	(1, 1, 1)
$\tilde{2}$	Weak importance	(1, 2, 3)
$\tilde{3}$	Not bad	(2, 3, 4)
$\tilde{4}$	Preferable	(3, 4, 5)
$\tilde{5}$	Importance	(4, 5, 6)
$\tilde{6}$	Fairly importance	(5, 6, 7)
$\tilde{7}$	Very important	(6, 7, 8)
$\tilde{8}$	Absolute	(7, 8, 9)
$\tilde{9}$	Perfect	(8, 9, 10)

(FMARCOS) proves to be a valuable strategy for mitigating uncertainty. Decision-makers can enhance the stability of MCDM in fuzzy scenarios by adopting this approach, which is underpinned by three core elements: reference points, the interplay among choices, and alternative utility levels, as outlined in reference [33]. The FMARCOS procedure is detailed below.

Step 1: Identifying an initial fuzzy decision-making matrix including n criteria and m alternatives.

Step 2: Identifying an extended initial fuzzy decision making matrix by determining the fuzzy ideal $\tilde{A}(ID)$ and anti-ideal $\tilde{A}(AI)$ solutions, equations (13).

$$\tilde{X} = \begin{array}{c} \\ \tilde{A}(AI) \\ \tilde{A}_1 \\ \tilde{A}_2 \\ \cdots \\ \tilde{A}_m \\ \tilde{A}(ID) \end{array} \begin{array}{c} \overbrace{\begin{array}{cccc} \tilde{c}_1 & \tilde{c}_2 & \ldots & \tilde{c}_3 \end{array}} \\ \begin{bmatrix} \tilde{x}_{ai1} & \tilde{x}_{ai2} & \cdots & \tilde{x}_{ain} \\ \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \\ \tilde{x}_{id1} & \tilde{x}_{id2} & \cdots & \tilde{x}_{idn} \end{bmatrix} \end{array} \tag{13}$$

The fuzzy $\tilde{A}(ID)$ is an alternative with the best performance, while the fuzzy $\tilde{A}(AI)$ is the worst alternative. Based on the type of the criteria, $\tilde{A}(ID)$ and $\tilde{A}(AI)$ are defined by applying Equations (14) and (15):

$$\tilde{A}(ID) = \max_i \tilde{x}_{ij}\ ifj\ \in B\ and\ \min_i \tilde{x}_{ij}\ ifj \in C \tag{14}$$

$$\tilde{A}(AI) = \min_i \tilde{x}_{ij}\ ifj\ \in\ Band\ \min_i \tilde{x}_{ij}\ ifj\ \in C \tag{15}$$

where B and C are a set of benefit and cost criteria, respectively.

Step 3: Defining the normalization of the extended initial fuzzy decision-making matrix, which is $\tilde{N} = [\tilde{n}_{ij}]_{m\times n}$ using Equations (16) and (17):

$$\tilde{n}_{ij} = \left(n_{ij}^l, n_{ij}^m, n_{ij}^u\right) = \left(\frac{x_{ij}^l}{x_{id}^u}, \frac{x_{ij}^m}{x_{id}^u}, \frac{x_{ij}^u}{x_{id}^u}\right), \quad j \in B \tag{16}$$

$$\tilde{n}_{ij} = \left(n_{ij}^l, n_{ij}^m, n_{ij}^u\right) = \left(\frac{x_{id}^l}{x_{ij}^u}, \frac{x_{id}^l}{x_{ij}^m}, \frac{x_{id}^l}{x_{ij}^l}\right), \quad j \in C \tag{17}$$

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

Step 4: Establishing the weighted fuzzy matrix $\tilde{V} = [\tilde{v}_{ij}]_{m\times n}$, calculated by multiplying matrix $\tilde{N}$ with the fuzzy weight coefficients of the criteria $\tilde{w}_j$ as follows, equations (18).

$$\begin{aligned} \tilde{v}_{ij} &= \left(v_{ij}^l, v_{ij}^m, v_{ij}^u\right) = \tilde{n}_{ij} \otimes \tilde{w}_j \\ &= \left(n_{ij}^l \times w_j^l, n_{ij}^m \times w_j^m, n_{ij}^u \times w_j^u\right) \end{aligned} \tag{18}$$

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

Step 5: Computing the fuzzy matrix $\tilde{S}_i$ using Equation (19) below.

$$\tilde{S}_i = \sum_{i=1}^{n} \tilde{v}_{ij} \tag{19}$$

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

Step 6: Computing the utility degree of alternative $\tilde{K}_i$ using Equations (20) and (21):

$$\tilde{K}_i^- = \frac{\tilde{S}_i}{\tilde{S}_{ai}} = \left(\frac{s_i^l}{s_{ai}^u}, \frac{s_i^m}{s_{ai}^m}, \frac{s_i^u}{s_{ai}^l}\right) \tag{20}$$

$$\tilde{K}_i^+ = \frac{\tilde{S}_i}{\tilde{S}_{id}} = \left(\frac{s_i^l}{s_{id}^u}, \frac{s_i^m}{s_{id}^m}, \frac{s_i^u}{s_{id}^l}\right) \tag{21}$$

Step 7: To build the fuzzy matrix $\tilde{T}_i$, we use Equation (22):

$$\begin{aligned} \tilde{T}_i = \tilde{t}_i &= \left(t_i^l, t_i^m, t_i^u\right) \\ &= \tilde{K}_i^- \oplus \tilde{K}_i^+ = \left(k_i^{-l} + k_i^{+l}, k_i^{-m} + k_i^{+m}, k_i^{-u} + k_i^{+u}\right) \end{aligned} \tag{22}$$

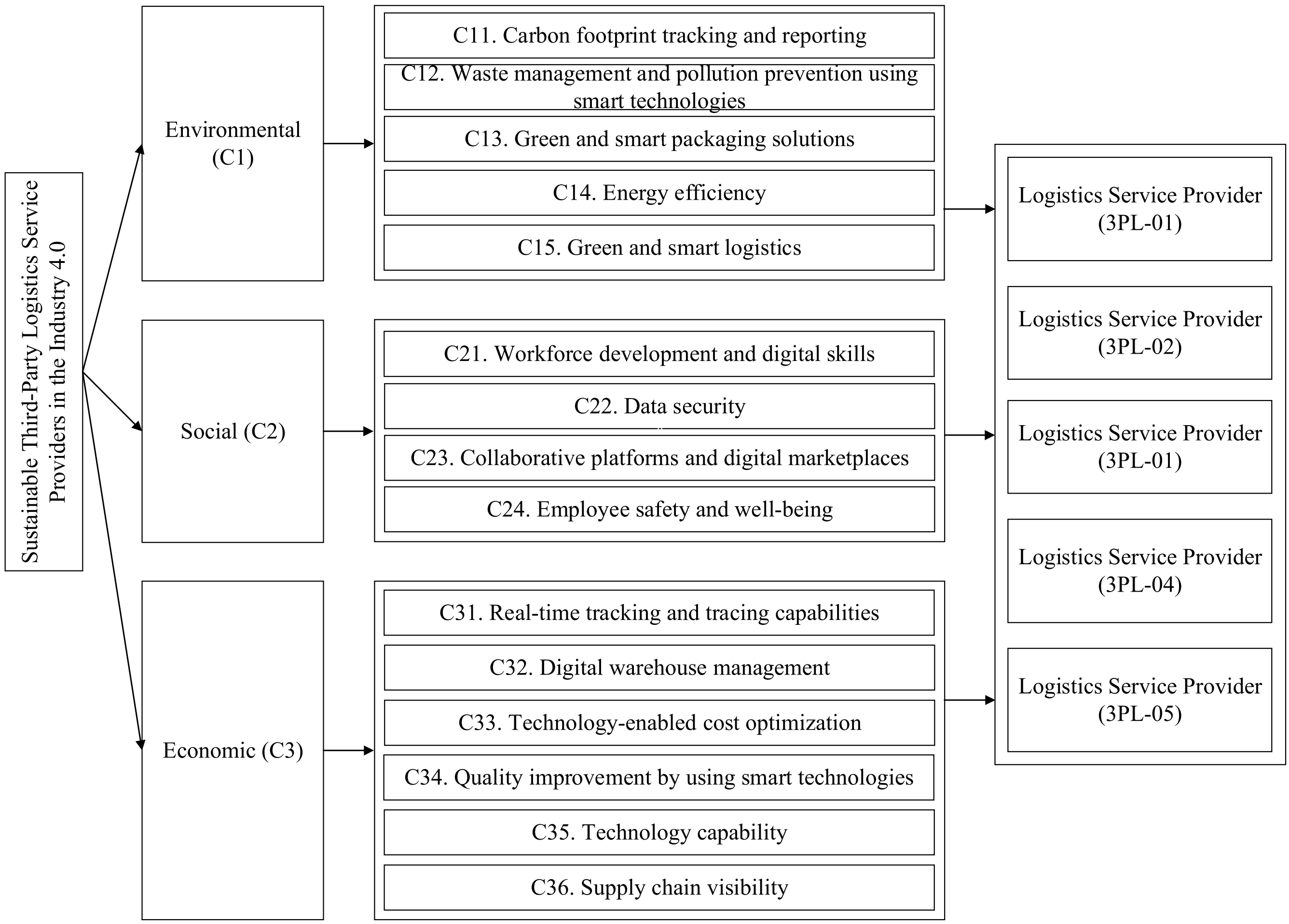

FIGURE 2. **The decision tree for evaluating 3PLs.**

Following that, a new fuzzy number $\tilde{D}$ is determined by equation (23):

$$\tilde{D} = \left(d^l, d^m, d^u\right) = \max_i \tilde{t}_{ij} \tag{23}$$

Then, it is necessary to defuzzify the number $\tilde{D}$ using the expression $df_{crisp} = \frac{l+4m+u}{6}$ obtaining the number df_{crisp}.

Step 8: Calculating the utility function to the ideal $f\left(\tilde{K}_i^+\right)$ and anti-ideal $f\left(\tilde{K}_i^-\right)$ solutions using Equations (24) and (25):

$$f\left(\tilde{K}_i^+\right) = \frac{\tilde{K}_i^-}{df_{crisp}} = \left(\frac{k_i^{-l}}{df_{crisp}}, \frac{k_i^{-m}}{df_{crisp}}, \frac{k_i^{-u}}{df_{crisp}}\right) \tag{24}$$

$$f\left(\tilde{K}_i^-\right) = \frac{\tilde{K}_i^+}{df_{crisp}} = \left(\frac{k_i^{+l}}{df_{crisp}}, \frac{k_i^{+m}}{df_{crisp}}, \frac{k_i^{+u}}{df_{crisp}}\right) \tag{25}$$

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

Step 9: Alternative utility functions $f\,(K_i)$ can be calculated with Equation (26):

$$f\,(K_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1-f\left(K_i^+\right)}{f\left(K_i^+\right)} + \frac{1-f\left(K_i^-\right)}{f\left(K_i^-\right)}} \tag{26}$$

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

As presented in Table 3, a new linguistic scale has been introduced for the evaluation of alternatives in conjunction with the FMARCOS method. This scale comprises a total of nine words, each of which is associated with its respective fuzzy triangular number.

IV. EVALUATION OF THIRD-PARTY LOGISTICS SERVICE PROVIDERS FOR A CASE STUDY IN VIETNAM

A. DESCRIPTION OF CASE STUDY

In this section, the data obtained from academic and industrial experts are analyzed. We conducted a case study of a manufacturing company in Vietnam that specializes in electronic components, smart devices, and other technology-related

TABLE 3. The linguistic of rating system for alternatives [33].

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

TABLE 4. Illustrates key sub-criteria according to main three criteria.

Main criteria	Symbol	Criteria
Environmental (C1)	C11	Carbon footprint tracking and reporting
	C12	Waste management and pollution prevention using smart technologies
	C13	Green and smart packaging solutions
	C14	Energy efficiency
	C15	Green and smart logistics
Social (C2)	C21	Workforce development and digital skills
	C22	Data security
	C23	Collaborative platforms and digital marketplaces
	C24	Employee safety and well-being
Economic (C3)	C31	Real-time tracking and tracing capabilities
	C32	Digital warehouse management
	C33	Technology-enabled cost optimization
	C34	Quality improvement by using smart technologies
	C35	Technology capability
	C36	Supply chain visibility

products. These products require sophisticated supply chain and logistics management. They involve high-tech manufacturing processes, frequent product iterations, and complex distribution networks, where efficient logistics operations are crucial for success. Thus, with a focus on innovation and adaptation to Industry 4.0 technologies, the company seeks to enhance its logistics and supply chain operations by selecting a 3PL that aligns with modern industry standards and digital transformation initiatives, considering the Industry 4.0 criteria. For this purpose, a panel consisting of 15 experts was designed to weigh the criteria and rank the 3PL providers. The selected experts have high-level education and working experience for more than 5 years in various domains including logistics and supply chain management, technology, industry-specific insights, and compliance. Each expert possesses a deep understanding of Industry 4.0 criteria and its relevance to the manufacturing sector. Also, face-to-face meetings to collect data make the survey reliable. Opinions of all experts were gathered to clarify the problem and discuss the evaluation criteria for 3PL selection in the Industry 4.0 context. Following this, the criteria are narrowed according to the literature studies and experts' opinions from the Industry 4.0 perspective. Table 4 illustrates key sub-criteria according to main three criteria: environmental, social and economic factors. The FAHP method is used to determine criteria's weights with the evaluation of experts. Then, based on the ranking of criteria, five potential 3PL providers {3PL-01, 3PL-02, 3PL-03, 3PL-04, 3PL-05} have been identified for further evaluation by FMARCOS. The decision tree for evaluating 3PLs is presented in Figure 2.

B. CRITERIA WEIGHTING USING FAHP

The FAHP method is employed to derive the weights for the criteria. All computations are conducted while assuming

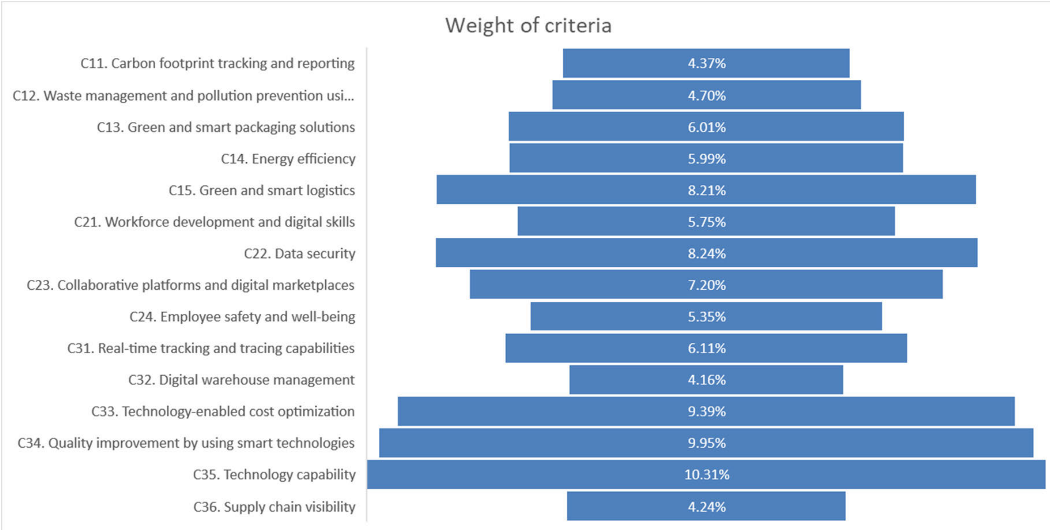

FIGURE 3. Criteria weighting of FAHP.

TABLE 5. The triangular fuzzy weight of criteria of FAHP.

Criteria	Fuzzy Geometric Mean			Triangular Fuzzy Weight			Weight of criteria
C11. Carbon footprint tracking and reporting	0.4720	0.6811	1.0005	0.0207	0.0432	0.0927	0.0437
C12. Waste management and pollution prevention using smart technologies	0.4997	0.7276	1.0814	0.0220	0.0462	0.1002	0.0470
C13. Green and smart packaging solutions	0.6585	0.9532	1.3598	0.0289	0.0605	0.1260	0.0601
C14. Energy efficiency	0.6389	0.9395	1.3688	0.0281	0.0596	0.1268	0.0599
C15. Green and smart logistics	0.8761	1.3129	1.8602	0.0385	0.0833	0.1723	0.0821
C21. Workforce development and digital skills	0.6110	0.8932	1.3231	0.0269	0.0567	0.1226	0.0575
C22. Data security	0.8745	1.3187	1.8694	0.0384	0.0836	0.1732	0.0824
C23. Collaborative platforms and digital marketplaces	0.7804	1.1458	1.6296	0.0343	0.0727	0.1510	0.0720
C24. Employee safety and well-being	0.5877	0.8288	1.2233	0.0258	0.0526	0.1133	0.0535
C31. Real-time tracking and tracing capabilities	0.6678	0.9515	1.3934	0.0294	0.0604	0.1291	0.0611
C32. Digital warehouse management	0.4602	0.6348	0.9568	0.0202	0.0403	0.0886	0.0416
C33. Technology-enabled cost optimization	1.0074	1.4895	2.1350	0.0443	0.0945	0.1978	0.0939
C34. Quality improvement by using smart technologies	1.0884	1.5990	2.2362	0.0478	0.1014	0.2071	0.0995
C35. Technology capability	1.0983	1.6380	2.3455	0.0483	0.1039	0.2173	0.1031
C36. Supply chain visibility	0.4743	0.6513	0.9693	0.0208	0.0413	0.0898	0.0424

that all criteria provide benefits. The significance of each criterion is determined based on the input from 15 experts' opinions. The experts conveyed their opinions regarding the criteria by employing linguistic terms. The integrated fuzzy comparison matrix of FAHP is shown in Table 11 (Appendix).

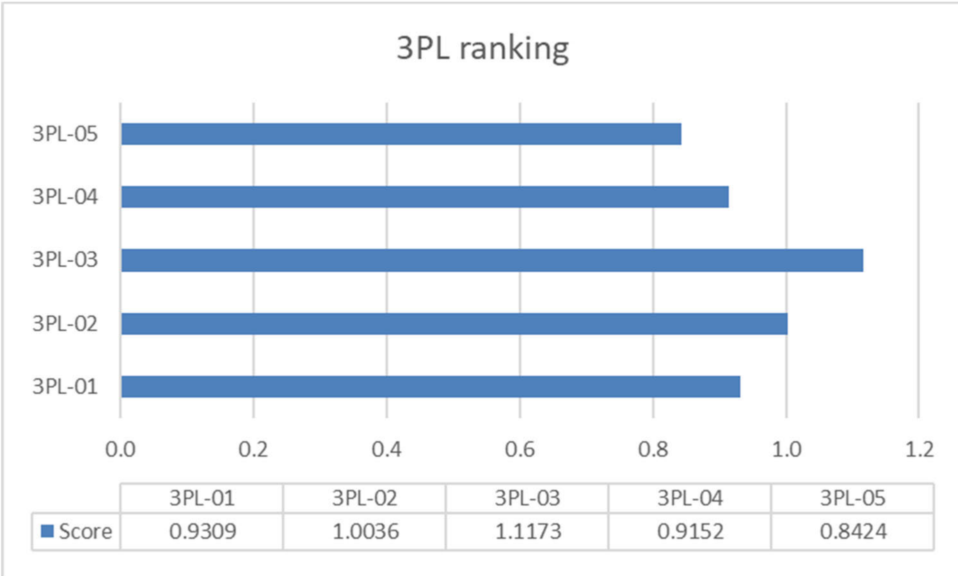

FIGURE 4. The final 3PLs ranking.

TABLE 6. Utility degree and fuzzy matrix of $\tilde{T}_i$.

Companies	Fuzzy $\tilde{S}_i$			Fuzzy $\tilde{K}_i^-$			Fuzzy $\tilde{K}_i^+$			Fuzzy $\tilde{T}_i$		
	l	m	u	l	m	u	l	m	u	l	m	u
A (AI)	0.3297	0.6954	1.4646									
3PL-01	0.3214	0.8362	2.1164	0.2195	1.2026	6.4194	0.1525	0.8362	4.4604	0.3720	2.0388	10.8799
3PL-02	0.3366	0.8699	2.1749	0.2298	1.2510	6.5971	0.1597	0.8699	4.5839	0.3895	2.1209	11.1809
3PL-03	0.3613	0.9076	2.2834	0.2467	1.3052	6.9261	0.1714	0.9076	4.8125	0.4182	2.2128	11.7385
3PL-04	0.3153	0.8356	2.0910	0.2153	1.2017	6.3426	0.1496	0.8356	4.4070	0.3649	2.0373	10.7496
3PL-05	0.2991	0.8020	2.0245	0.2042	1.1534	6.1407	0.1419	0.8020	4.2668	0.3461	1.9554	10.4075
A (ID)	0.4745	1.0000	2.1076	Dfcrisp MAX						3.5013		

Table 5 and Figure 3 present the results of the FAHP analysis. Based on the information provided, it can be seen that the top five impact criteria identified through the FAHP analysis are "Technology capability", "Quality improvement by using smart technologies", "Technology-enabled cost optimization", "Data security", and "Green and smart logistics", with the criteria weight at 0.1031, 0.0995, 0.0939, 0.0824, and 0.0821, respectively. These criteria hold particular significance in the evaluation of 3PLs in specific decision-making contexts. It's crucial to emphasize that the choice of specific criteria and their relative importance is contingent upon the unique context of the decision or project, and it may fluctuate in accordance with the goals and objectives of the decision-maker. FAHP aids decision-makers in taking into account a multitude of factors in the decision-making process, enabling them to arrive at more well-informed decisions through a thorough assessment of the relative importance of diverse criteria.

C. ALTERNATIVE RANKING USING FMARCOS

The FMARCOS method is implemented by utilizing the weights acquired through FAHP in order to identify the optimal 3PLs. Fifteen experts are invited to assess the linguistic

TABLE 7. Utility functions and final ranking of 3PLs.

Companies	Fuzzy $f\left(\tilde{K}_i^-\right)$			Fuzzy $f\left(\tilde{K}_i^+\right)$			K_i^-	K_i^+	$f(K_i^-)$	$f(K_i^+)$	$f(K_i)$	Rank
	l	m	u	l	m	u						
3PL-01	0.0436	0.2388	1.2739	0.0627	0.3435	1.8334	1.9082	1.3263	0.3788	0.5450	0.9309	3
3PL-02	0.0456	0.2484	1.3092	0.0656	0.3573	1.8842	1.9718	1.3705	0.3914	0.5632	1.0036	2
3PL-03	0.0490	0.2592	1.3745	0.0705	0.3728	1.9781	2.0656	1.4357	0.4100	0.5900	1.1173	1
3PL-04	0.0427	0.2387	1.2587	0.0615	0.3432	1.8115	1.8941	1.3165	0.3760	0.5410	0.9152	4
3PL-05	0.0405	0.2291	1.2186	0.0583	0.3294	1.7538	1.8264	1.2695	0.3626	0.5216	0.8424	5

TABLE 8. The weight of criteria in all scenarios.

Criteria	Base case	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7	Scenario 8	Scenario 9	Scenario 10	Scenario 11	Scenario 12	Scenario 13	Scenario 14	Scenario 15
C11	0.0437	0	0.0459	0.0465	0.0465	0.0476	0.0464	0.0477	0.0471	0.0462	0.0466	0.0456	0.0483	0.0486	0.0488	0.0457
C12	0.0470	0.0491	0	0.0500	0.0500	0.0512	0.0498	0.0512	0.0506	0.0496	0.0500	0.0490	0.0519	0.0522	0.0524	0.0491
C13	0.0601	0.0629	0.0631	0	0.0640	0.0655	0.0638	0.0655	0.0648	0.0635	0.0640	0.0627	0.0664	0.0668	0.0670	0.0628
C14	0.0599	0.0626	0.0628	0.0637	0	0.0652	0.0635	0.0653	0.0645	0.0633	0.0638	0.0625	0.0661	0.0665	0.0668	0.0625
C15	0.0821	0.0859	0.0862	0.0874	0.0873	0	0.0871	0.0895	0.0885	0.0867	0.0874	0.0857	0.0906	0.0912	0.0915	0.0857
C21	0.0575	0.0602	0.0604	0.0612	0.0612	0.0627	0	0.0627	0.0620	0.0608	0.0613	0.0600	0.0635	0.0639	0.0641	0.0601
C22	0.0824	0.0862	0.0865	0.0877	0.0877	0.0898	0.0875	0	0.0888	0.0871	0.0878	0.0860	0.0910	0.0915	0.0919	0.0861
C23	0.0720	0.0753	0.0756	0.0766	0.0766	0.0784	0.0764	0.0785	0	0.0761	0.0767	0.0751	0.0795	0.0800	0.0803	0.0752
C24	0.0535	0.0560	0.0562	0.0569	0.0569	0.0583	0.0568	0.0583	0.0577	0	0.0570	0.0558	0.0591	0.0594	0.0597	0.0559
C31	0.0611	0.0639	0.0641	0.0650	0.0650	0.0665	0.0648	0.0666	0.0658	0.0645	0	0.0637	0.0674	0.0678	0.0681	0.0638
C32	0.0416	0.0435	0.0437	0.0443	0.0443	0.0454	0.0442	0.0454	0.0449	0.0440	0.0443	0	0.0459	0.0462	0.0464	0.0435
C33	0.0939	0.0982	0.0986	0.1000	0.0999	0.1024	0.0997	0.1024	0.1012	0.0993	0.1001	0.0980	0	0.1043	0.1048	0.0981
C34	0.0995	0.1040	0.1044	0.1059	0.1058	0.1084	0.1056	0.1084	0.1072	0.1051	0.1060	0.1038	0.1098	0	0.1109	0.1039
C35	0.1031	0.1079	0.1082	0.1097	0.1097	0.1124	0.1094	0.1124	0.1111	0.1090	0.1098	0.1076	0.1138	0.1145	0	0.1077
C36	0.0424	0.0444	0.0445	0.0451	0.0451	0.0462	0.0450	0.0462	0.0457	0.0448	0.0452	0.0443	0.0468	0.0471	0.0473	0

variables employed in the evaluation of prospective 3PLs. In Appendix, Table 12, 13, and 14 presented the integrated fuzzy decision matrix of FMARCOS, the integrated normalized fuzzy decision matrix of FMARCOS, and the integrated

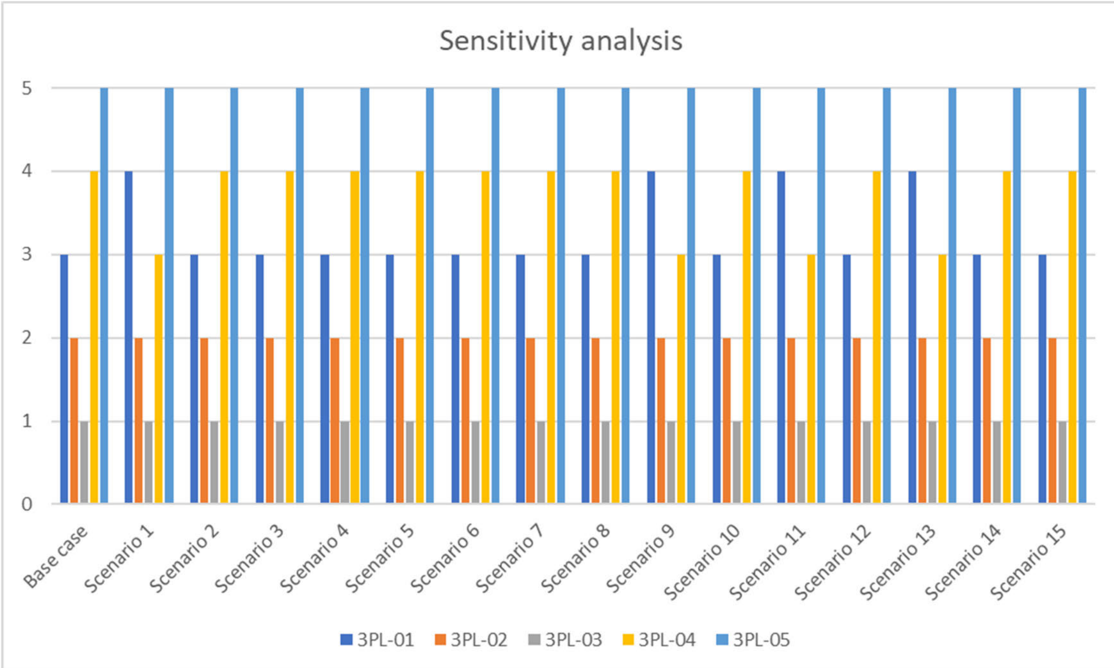

FIGURE 5. The ranking of 3PLs in all scenarios.

TABLE 9. The prospect value of 3PLs in all scenarios.

Companies	Base case	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7	Scenario 8	Scenario 9	Scenario 10	Scenario 11	Scenario 12	Scenario 13	Scenario 14	Scenario 15
3PL-01	0.9309	0.5741	0.5833	0.5880	0.6060	0.5891	0.5712	0.6113	0.5714	0.5686	0.5876	0.5815	0.5989	0.5594	0.5818	0.5806
3PL-02	1.0036	0.6446	0.6289	0.6382	0.6478	0.6485	0.6446	0.6221	0.6224	0.6378	0.6220	0.6193	0.6681	0.6344	0.6441	0.6427
3PL-03	1.1173	0.7070	0.7078	0.7082	0.7040	0.7025	0.7145	0.7039	0.7200	0.7134	0.7203	0.7104	0.7097	0.7095	0.7063	0.7094
3PL-04	0.9152	0.5895	0.5671	0.5293	0.5805	0.5847	0.5710	0.5711	0.5555	0.5728	0.5693	0.5926	0.5838	0.5936	0.5576	0.5630
3PL-05	0.8424	0.5169	0.5328	0.5250	0.5455	0.5486	0.5066	0.5471	0.4968	0.5254	0.4963	0.5353	0.4939	0.5199	0.5420	0.5344

weighted normalized fuzzy decision matrix of FMARCOS, respectively.

This paper conducts a case study of 5 logistics service providers in Vietnam, which are {3 PL-01, 3PL-02, 3PL-03, 3PL-04, 3PL-05}. Following the FMARCOS process, fuzzy ideal A~(ID) and anti-ideal A~(AI) solutions are defined for each criterion. A~ (ID) represents the highest value for each criterion, while the lowest value corresponds to A~(AI). Subsequently, the experts' linguistic judgments matrix and the integrated matrix for the FMARCOS method are computed. Table 6 displays the utility degree and fuzzy matrix of T~_i. Finally, the ultimate utility function of the 3 PLs is determined. Using these values, the final ranking of 3PLs is established. The utility function and the ultimate ranking of the 3PLs are presented in Table 7. The results indicate that the top three 3PLs are 3 PPL-03, 3PL-02, 3PL01}, occupying the first, second, and third positions, with utility function scores of 1.1173, 1.0036, and 0.9309, respectively. Figure 4 visualizes the final ranking of 3PLs derived from the FAHP and FMARCOS model.

V. RESULTS VALIDATION

A. SENSITIVITY ANALYSIS OF CRITERIA WEIGHT

In MCDM problems, the majority of input data tend to be dynamic, rather than continuous and stable. Consequently, sensitivity analysis plays a crucial role in aiding

TABLE 10. Comparative analysis of MCDM methods.

Companies	Fuzzy AHP and Fuzzy MARCOS		Fuzzy AHP and Fuzzy MABAC		Fuzzy AHP and Fuzzy WASPAS		Fuzzy AHP and Fuzzy CoCoSo		Fuzzy AHP and Fuzzy SAW		Fuzzy AHP and Fuzzy COPRAS		Fuzzy AHP and Fuzzy TOPSIS		Fuzzy AHP and Fuzzy VIKOR	
	Value	Rank	Value	Rank	Value	Rank	Value	Rank	Value	Rank	Value	Rank	Value	Rank	Value	Rank
3PL-01	0.9309	3	-0.0070	3	0.7684	3	5.2791	3	0.9383	3	91.75	3	0.0731	3	0.0683	2
3PL-02	1.0036	2	0.0362	2	0.7970	2	5.4678	2	0.9695	2	95.23	2	0.0755	2	0.0742	3
3PL-03	1.1173	1	0.1249	1	0.8397	1	5.9204	1	1.0183	1	100.00	1	0.0790	1	0.0000	1
3PL-04	0.9152	4	-0.0211	4	0.7602	4	5.1473	4	0.9290	4	90.88	4	0.0721	4	0.0930	4
3PL-05	0.8424	5	-0.0771	5	0.7296	5	4.7102	5	0.8963	5	87.64	5	0.0703	5	0.1239	5

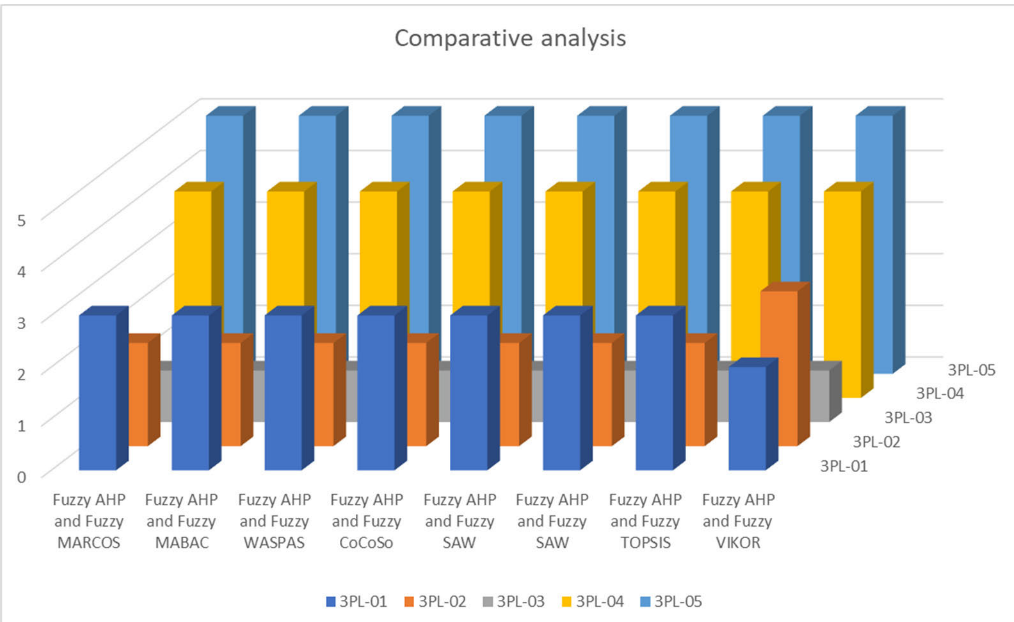

FIGURE 6. Comparison of proposed model with other MCDM methods.

the decision-making process. In this study, we employed sensitivity analysis within the context of MCDM problems. This approach allows us to assess the impact of altering the weights of one criterion, resulting in modifications to the problem's solutions. These changes encompass adjustments in the weighting of other criteria and shifts in the final ranking of alternatives [45].

To achieve this objective, we conducted a systematic removal of one criterion at a time, and examined its impact on the final ranking. Consequently, 15 scenarios were generated in the sensitivity analysis of criteria weights. Table 8 presents the criteria weights for all of these scenarios. The prospect values of the alternatives in each scenario are detailed in Table 9, and their respective rankings are visually depicted in Figure 5.

Significantly, it becomes apparent that although there are variations in the prospect values of the 3PLs, the final ranking remains consistent, with {3PL-01, 3PL-02} consistently

TABLE 11. The integrated fuzzy comparison matrix of FAHP.

Criteria	C11			C12			C13			C14		
C11	1.0000	1.0000	1.0000	0.4087	0.6132	0.9294	0.3421	0.4611	0.6988	0.4605	0.6910	1.0194
C12	1.0760	1.6309	2.4469	1.0000	1.0000	1.0000	0.4428	0.6598	1.0194	0.3073	0.4402	0.6988
C13	1.4310	2.1689	2.9231	0.9810	1.5157	2.2582	1.0000	1.0000	1.0000	0.4280	0.6300	0.9474
C14	0.9810	1.4473	2.1714	1.4310	2.2715	3.2542	1.0556	1.5874	2.3364	1.0000	1.0000	1.0000
C15	1.5695	2.5111	3.5166	1.1055	1.5874	2.3882	1.1055	1.6625	2.4836	0.8944	1.3711	2.0897
C21	0.6580	0.9221	1.3835	0.9810	1.4473	2.1714	0.5361	0.7813	1.2340	1.1578	1.8234	2.7455
C22	1.4310	2.3790	3.3842	1.1802	1.9247	2.8676	1.3046	2.0548	2.9106	1.7687	2.8297	3.8571
C23	1.5277	2.3522	3.2200	1.2125	1.9620	2.8131	1.6888	2.6484	3.5443	1.1269	1.6756	2.4943
C24	1.2457	1.8734	2.7241	1.0760	1.6309	2.4469	0.4020	0.5654	0.8898	0.4390	0.6322	0.9837
C31	1.2457	1.9097	2.8407	0.7725	1.1709	1.8001	0.5083	0.7262	1.0951	0.6371	0.9474	1.5253
C32	0.3275	0.4574	0.7632	0.5768	0.8570	1.3278	0.3023	0.4109	0.6467	0.4210	0.5994	0.9142
C33	1.1055	1.6625	2.4836	0.8540	1.2501	1.8903	1.1578	1.7080	2.5317	1.0000	1.5874	2.4662
C34	1.0760	1.6625	2.5516	1.0000	1.5874	2.4662	1.1895	1.8234	2.5828	1.2799	2.0000	2.8754
C35	1.1578	1.7888	2.6329	1.3046	2.0548	2.9106	1.3046	1.9620	2.8957	1.3046	1.9620	2.8957
C36	0.4159	0.5921	0.9574	0.6500	0.9657	1.4564	0.4295	0.5834	0.8394	0.3665	0.5017	0.7896
Criteria	C15			C21			C22			C23		
C11	0.2844	0.3982	0.6371	0.7228	1.0845	1.5198	0.2955	0.4204	0.6988	0.3106	0.4251	0.6546
C12	0.4187	0.6300	0.9046	0.4605	0.6910	1.0194	0.3487	0.5196	0.8473	0.3555	0.5097	0.8247
C13	0.4026	0.6015	0.9046	0.8103	1.2799	1.8654	0.3436	0.4867	0.7665	0.2821	0.3776	0.5921
C14	0.4785	0.7293	1.1181	0.3642	0.5484	0.8637	0.2593	0.3534	0.5654	0.4009	0.5968	0.8874
C15	1.0000	1.0000	1.0000	1.0444	1.6888	2.4042	0.9707	1.6125	2.3237	0.7085	1.0930	1.5874
C21	0.4159	0.5921	0.9574	1.0000	1.0000	1.0000	0.3371	0.4961	0.7875	0.3421	0.5057	0.8091
C22	0.4303	0.6201	1.0302	1.2699	2.0158	2.9669	1.0000	1.0000	1.0000	0.6077	0.9262	1.3451
C23	0.6300	0.9149	1.4114	1.2360	1.9775	2.9231	0.7435	1.0797	1.6456	1.0000	1.0000	1.0000
C24	0.5493	0.7665	1.1550	0.6422	0.9400	1.4782	0.4724	0.6621	1.0178	0.6422	0.9400	1.4782
C31	0.6207	0.8975	1.3738	0.6546	0.9657	1.5481	0.7881	1.1093	1.6572	0.8254	1.1936	1.7568
C32	0.4080	0.5763	0.9142	0.5181	0.7460	1.1469	0.4874	0.6574	0.9786	0.5057	0.7262	1.1783
C33	0.8944	1.3711	2.0897	0.9117	1.4087	2.1885	0.7579	1.1093	1.7235	1.1055	1.6625	2.4836
C34	0.5768	0.8183	1.2768	1.1802	1.9247	2.8676	0.5181	0.7460	1.1469	1.6438	2.4634	3.2200
C35	1.2699	1.9247	2.8529	0.9624	1.5039	2.2485	1.0000	1.5874	2.4662	1.3299	1.9775	2.8108
C36	0.3839	0.5319	0.8113	0.4130	0.5571	0.8394	0.5282	0.7665	1.2011	0.5532	0.7875	1.2244
Criteria	C24			C31			C32			C33		
C11	0.3671	0.5338	0.8027	0.3520	0.5236	0.8027	1.3103	2.1860	3.0530	0.4026	0.6015	0.9046
C12	0.4087	0.6132	0.9294	0.5555	0.8540	1.2944	0.7531	1.1669	1.7336	0.5290	0.8000	1.1709
C13	1.1238	1.7687	2.4875	0.9132	1.3771	1.9674	1.5463	2.4336	3.3082	0.3950	0.5855	0.8637
C14	1.0166	1.5819	2.2777	0.6556	1.0556	1.5695	1.0938	1.6684	2.3752	0.4055	0.6300	1.0000
C15	0.8658	1.3046	1.8206	0.7279	1.1142	1.6112	1.0938	1.7351	2.4508	0.4785	0.7293	1.1181
C21	0.6765	1.0639	1.5572	0.6459	1.0355	1.5277	0.8719	1.3404	1.9300	0.4569	0.7099	1.0968
C22	0.9826	1.5105	2.1169	0.6034	0.9015	1.2688	1.0218	1.5211	2.0516	0.5802	0.9015	1.3195
C23	0.6765	1.0639	1.5572	0.5692	0.8378	1.2115	0.8487	1.3771	1.9775	0.4026	0.6015	0.9046
C24	1.0000	1.0000	1.0000	0.3855	0.5441	0.8247	1.1770	1.8299	2.5557	0.3371	0.4961	0.7875
C31	1.2125	1.8378	2.5940	1.0000	1.0000	1.0000	0.8203	1.2556	1.7672	0.3060	0.3982	0.5921

TABLE 11. ***(Continued.)*** **The integrated fuzzy comparison matrix of FAHP.**

C32	0.3913	0.5465	0.8496	0.5659	0.7965	1.2191	1.0000	1.0000	1.0000	0.3241	0.4523	0.7319
C33	1.2699	2.0158	2.9669	1.6888	2.5111	3.2682	1.3663	2.2109	3.0855	1.0000	1.0000	1.0000
C34	1.5999	2.2188	2.7617	1.4986	2.3338	3.3172	1.7687	2.7019	3.5847	1.2799	1.9097	2.7649
C35	1.4310	2.3790	3.3842	1.4310	2.2715	3.2542	1.4986	2.3338	3.2061	0.4982	0.7124	1.1469
C36	0.5282	0.7665	1.2011	0.4618	0.6449	0.9906	0.4020	0.5654	0.8898	0.3084	0.4189	0.6175
Criteria		C34			C35			C36				
C11	0.3919	0.6015	0.9294	0.3798	0.5590	0.8637	1.0444	1.6888	2.4042			
C12	0.4055	0.6300	1.0000	0.3436	0.4867	0.7665	0.6866	1.0355	1.5384			
C13	0.3872	0.5484	0.8407	0.3453	0.5097	0.7665	1.1914	1.7141	2.3281			
C14	0.3478	0.5000	0.7813	0.3453	0.5097	0.7665	1.2664	1.9931	2.7284			
C15	0.7832	1.2221	1.7336	0.3505	0.5196	0.7875	1.2326	1.8801	2.6052			
C21	0.3487	0.5196	0.8473	0.4447	0.6650	1.0391	1.1914	1.7952	2.4212			
C22	0.8719	1.3404	1.9300	0.4055	0.6300	1.0000	0.8326	1.3046	1.8933			
C23	0.3106	0.4059	0.6084	0.3558	0.5057	0.7519	0.8167	1.2699	1.8078			
C24	0.3621	0.4507	0.6250	0.2955	0.4204	0.6988	0.8326	1.3046	1.8933			
C31	0.3015	0.4285	0.6673	0.3073	0.4402	0.6988	1.0095	1.5506	2.1655			
C32	0.2790	0.3701	0.5654	0.3119	0.4285	0.6673	1.1238	1.7687	2.4875			
C33	0.3617	0.5236	0.7813	0.8719	1.4038	2.0071	1.6195	2.3874	3.2427			
C34	1.0000	1.0000	1.0000	0.4844	0.7155	1.0592	1.4271	2.1445	2.8776			
C35	0.9441	1.3977	2.0645	1.0000	1.0000	1.0000	0.6765	1.0158	1.4974			
C36	0.3475	0.4663	0.7007	0.6678	0.9844	1.4782	1.0000	1.0000	1.0000			

emerging as the most suitable logistics service providers across all scenarios. The results of the sensitivity analysis phase suggest that, in this case study, the ranking of alternatives remains robust irrespective of changes in the criteria weights. Hence, the proposed FAHP and FMARCOS model demonstrate a high level of stability and applicability.

B. COMPARATIVE ANALYSIS OF MCDM METHODS

In this phase of results validation, eight distinct integrated fuzzy MCDM methods are taken into consideration to cross-verify the outcomes obtained through the proposed approach. The considered MCDM methods are the fuzzy multi-attributive border approximation area comparison (fuzzy MABAC) [46], the fuzzy weighted aggregated sum product assessment (fuzzy WASPAS) [47], the fuzzy combined compromise solution (fuzzy CoCoSo) [48], the fuzzy simple additive weighting (fuzzy SAW) [49], and the fuzzy complex proportional assessment of alternatives (fuzzy COPRAS) [50], the fuzzy technique for order of preference by similarity to ideal solution (fuzzy TOPSIS) [44], the fuzzy Vlsekriterijumska Optimizacija I KOmpromisno Resenje [51].

For the comparative analysis of various MCDM methods, identical criteria weights are utilized, and the resulting outcomes are detailed in Table 10. The comparison between FAHP and FMARCOS with other MCDM methods is illustrated in Figure 6. The results derived from different MCDM methods demonstrate that there is no notable disparity in the ranking of the top 3PLs. {3PL-03} consistently maintains its position as the preferred 3PL. This consistent outcome across all the considered MCDM methods serves to corroborate the results obtained from the proposed model.

VI. MANAGERIAL IMPLICATIONS

For businesses, choosing third-party logistics providers (3PLs) presents a significant decision-making challenge. Making this decision can help businesses stand out from the competition and be crucial to achieving their goals. It is crucial to proceed with caution and make sure that the appropriate 3PL partners are aligned. An intensive effort is being made to transform competitiveness, encourage innovation, improve flexibility, support individuality, and improve working conditions with the introduction of Industry 4.0. By putting the customer at the center of a digital platform, this transformation turns traditional supply chains into dynamic supply networks. Companies now have to set new standards and demands for their 3PL suppliers in order to align with Industry 4.0 deployment procedures.

Moreover, this paradigm shift has managerial ramifications for all industries. Although the suggested model is designed

TABLE 12. The integrated fuzzy decision matrix of FMARCOS.

Companies	C11			C12			C13			C14		
	l	m	u	l	m	u	l	m	u	l	m	u
3PL-01	5.2862	6.2219	7.3192	4.7729	5.4649	6.8428	3.9193	5.1093	6.0478	2.7597	4.0289	4.9382
3PL-02	3.8740	4.9959	6.0136	5.4062	6.3270	7.4428	5.7203	6.5799	7.7403	3.9395	4.8287	5.9828
3PL-03	5.2252	6.1185	7.2777	5.2252	6.2219	7.2777	4.8287	5.7203	6.8818	5.2252	6.0839	7.2777
3PL-04	2.9542	4.3597	5.1648	5.1648	6.3270	7.2365	3.2888	4.4107	5.4649	4.0760	4.9959	6.1185
3PL-05	4.8287	5.9828	6.8818	3.2888	4.7729	5.4649	3.1787	4.4107	5.3437	2.5648	3.8076	4.7729
Companies	C15			C21			C22			C23		
3PL-01	4.0082	5.1093	6.1500	4.6670	5.8501	6.7291	3.3057	4.2172	5.4062	4.0760	4.9959	6.1185
3PL-02	3.9395	5.1093	5.9828	3.6613	4.7215	5.7825	5.2862	6.2573	7.3192	4.0289	5.3481	6.0839
3PL-03	5.0502	6.1185	7.1163	4.0760	5.2862	6.1185	5.3481	6.1185	7.3608	3.4202	4.4622	5.5288
3PL-04	3.9395	4.9382	5.9828	4.2630	5.3437	6.3270	4.5144	5.7203	6.5444	4.4107	5.4062	6.4706
3PL-05	2.8553	4.0760	5.0502	5.1690	5.9828	7.1976	3.0722	4.2172	5.2252	4.5635	5.7203	6.6173
Companies	C24			C31			C32			C33		
3PL-01	4.7215	5.7203	6.7674	3.7881	4.8287	5.9137	4.5107	5.5288	6.5799	4.0082	5.2252	6.1500
3PL-02	3.9395	4.8287	5.9828	5.2862	6.2219	7.3192	6.1185	7.2777	8.1393	3.6613	4.8287	5.7825
3PL-03	4.0289	4.9959	6.0839	4.0760	4.8851	6.1185	4.7729	5.7825	6.8428	5.4062	6.3270	7.4428
3PL-04	4.2172	4.8287	6.2573	4.6670	5.4975	6.7291	2.3038	3.6801	4.5107	4.5635	5.4062	6.6173
3PL-05	3.2888	4.6130	5.4649	5.9828	7.0379	8.0040	2.6536	4.0289	4.8811	5.9828	6.9981	8.0040
Companies	C34			C35			C36					
3PL-01	5.2252	6.2573	7.2777	5.1093	5.8501	7.1568	4.8287	5.8501	6.8818			
3PL-02	4.7729	5.5889	6.8428	4.8287	5.8501	6.8818	4.1684	5.2252	6.2219			
3PL-03	4.9382	5.8501	6.9981	5.7203	6.4339	7.7403	5.1690	6.1185	7.1976			
3PL-04	3.4799	4.8247	5.6833	5.3437	6.6173	7.4007	5.7203	6.8818	7.7403			
3PL-05	4.4107	5.2862	6.4706	4.1203	4.8811	6.1867	3.3057	4.3633	5.4062			

for the manufacturing sector, given the widespread adoption of Industry 4.0 principles, its framework which takes Industry 4.0 technologies into account can be easily adapted to a variety of other sectors and industries. Because of Industry 4.0's

TABLE 13. The integrated normalized fuzzy decision matrix of FMARCOS.

Companies	C11			C12			C13			C14		
	l	m	u	l	m	u	l	m	u	l	m	u
3PL-01	0.8423	0.9914	1.1663	0.7467	0.8550	1.0705	0.5867	0.7648	0.9053	0.4454	0.6503	0.7970
3PL-02	0.6173	0.7961	0.9582	0.8458	0.9898	1.1644	0.8563	0.9850	1.1587	0.6359	0.7794	0.9657
3PL-03	0.8326	0.9749	1.1597	0.8175	0.9734	1.1386	0.7228	0.8563	1.0302	0.8434	0.9820	1.1747
3PL-04	0.4707	0.6947	0.8230	0.8080	0.9898	1.1321	0.4923	0.6603	0.8181	0.6579	0.8064	0.9876
3PL-05	0.7694	0.9533	1.0966	0.5145	0.7467	0.8550	0.4758	0.6603	0.7999	0.4140	0.6146	0.7704
Companies	C15			C21			C22			C23		
3PL-01	0.6576	0.8383	1.0090	0.7630	0.9565	1.1002	0.5258	0.6707	0.8598	0.7235	0.8868	1.0861
3PL-02	0.6463	0.8383	0.9816	0.5986	0.7719	0.9454	0.8407	0.9952	1.1641	0.7151	0.9493	1.0799
3PL-03	0.8286	1.0039	1.1676	0.6664	0.8643	1.0003	0.8506	0.9731	1.1707	0.6071	0.7921	0.9814
3PL-04	0.6463	0.8102	0.9816	0.6970	0.8737	1.0344	0.7180	0.9098	1.0409	0.7829	0.9596	1.1485
3PL-05	0.4685	0.6687	0.8286	0.8451	0.9782	1.1768	0.4886	0.6707	0.8310	0.8100	1.0154	1.1746
Companies	C24			C31			C32			C33		
3PL-01	0.8231	0.9972	1.1797	0.5405	0.6890	0.8438	0.6284	0.7702	0.9166	0.5730	0.7470	0.8792
3PL-02	0.6867	0.8418	1.0429	0.7543	0.8878	1.0444	0.8523	1.0138	1.1338	0.5234	0.6903	0.8267
3PL-03	0.7023	0.8709	1.0606	0.5816	0.6971	0.8730	0.6649	0.8055	0.9532	0.7729	0.9045	1.0640
3PL-04	0.7352	0.8418	1.0908	0.6659	0.7844	0.9602	0.3209	0.5127	0.6284	0.6524	0.7729	0.9460
3PL-05	0.5733	0.8042	0.9527	0.8537	1.0042	1.1421	0.3697	0.5612	0.6800	0.8553	1.0004	1.1443
Companies	C34			C35			C36					
3PL-01	0.8356	1.0006	1.1638	0.7705	0.8822	1.0792	0.7121	0.8627	1.0149			
3PL-02	0.7632	0.8937	1.0943	0.7281	0.8822	1.0377	0.6147	0.7706	0.9176			
3PL-03	0.7897	0.9355	1.1191	0.8626	0.9702	1.1672	0.7623	0.9023	1.0615			
3PL-04	0.5565	0.7715	0.9088	0.8058	0.9979	1.1160	0.8436	1.0149	1.1415			
3PL-05	0.7053	0.8453	1.0347	0.6213	0.7361	0.9329	0.4875	0.6435	0.7973			

flexibility in terms of integration, this study provides insightful information to supply chain, innovation, and Industry 4.0 researchers in addition to economists, managers, IT specialists, and industry experts in a variety of fields.

TABLE 14. The integrated weighted normalized fuzzy decision matrix of FMARCOS.

Companies	C11			C12			C13			C14		
	l	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*
3PL-01	0.0175	0.0428	0.1081	0.0164	0.0395	0.1072	0.0170	0.0462	0.1140	0.0125	0.0388	0.1011
3PL-02	0.0128	0.0344	0.0888	0.0186	0.0457	0.1166	0.0248	0.0596	0.1459	0.0179	0.0464	0.1224
3PL-03	0.0173	0.0421	0.1075	0.0180	0.0449	0.1141	0.0209	0.0518	0.1298	0.0237	0.0585	0.1489
3PL-04	0.0098	0.0300	0.0763	0.0177	0.0457	0.1134	0.0142	0.0399	0.1030	0.0185	0.0481	0.1252
3PL-05	0.0160	0.0412	0.1016	0.0113	0.0345	0.0856	0.0138	0.0399	0.1008	0.0116	0.0366	0.0977
Companies	C15			C21			C22			C23		
3PL-01	0.0253	0.0698	0.1739	0.0205	0.0542	0.1348	0.0202	0.0561	0.1489	0.0248	0.0645	0.1639
3PL-02	0.0249	0.0698	0.1691	0.0161	0.0437	0.1159	0.0323	0.0832	0.2016	0.0245	0.0690	0.1630
3PL-03	0.0319	0.0836	0.2012	0.0179	0.0490	0.1226	0.0327	0.0814	0.2027	0.0208	0.0576	0.1481
3PL-04	0.0249	0.0675	0.1691	0.0187	0.0495	0.1268	0.0276	0.0761	0.1802	0.0269	0.0697	0.1734
3PL-05	0.0180	0.0557	0.1428	0.0227	0.0554	0.1442	0.0188	0.0561	0.1439	0.0278	0.0738	0.1773
Companies	C24			C31			C32			C33		
3PL-01	0.0213	0.0524	0.1337	0.0159	0.0416	0.1089	0.0127	0.0310	0.0812	0.0254	0.0706	0.1739
3PL-02	0.0177	0.0443	0.1182	0.0221	0.0536	0.1348	0.0172	0.0408	0.1005	0.0232	0.0652	0.1635
3PL-03	0.0181	0.0458	0.1202	0.0171	0.0421	0.1127	0.0134	0.0324	0.0845	0.0342	0.0855	0.2104
3PL-04	0.0190	0.0443	0.1236	0.0195	0.0473	0.1239	0.0065	0.0206	0.0557	0.0289	0.0730	0.1871
3PL-05	0.0148	0.0423	0.1080	0.0251	0.0606	0.1474	0.0075	0.0226	0.0603	0.0379	0.0945	0.2263
Companies	C34			C35			C36					
3PL-01	0.0400	0.1015	0.2411	0.0372	0.0917	0.2345	0.0148	0.0356	0.0911			
3PL-02	0.0365	0.0906	0.2267	0.0351	0.0917	0.2255	0.0128	0.0318	0.0824			
3PL-03	0.0378	0.0949	0.2318	0.0416	0.1008	0.2536	0.0159	0.0373	0.0953			
3PL-04	0.0266	0.0783	0.1883	0.0389	0.1037	0.2425	0.0176	0.0419	0.1025			
3PL-05	0.0337	0.0857	0.2143	0.0300	0.0765	0.2027	0.0102	0.0266	0.0716			

VII. CONCLUSION

The emergence of new technology forces businesses to adopt competitive tactics in order to thrive in the global marketplace. Businesses are prompted to match their operations with this disruptive wave by the advent of Industry 4.0 technologies. The choice of third-party logistics providers (3PLs) becomes extremely important in this situation. To fully utilize Industry 4.0, SCM solutions must be optimized. This is a critical aspect of the new era. The use of digitalization signals advancements in SCM efficiency in addition to a decrease in costs and risks. As a result, working with digitally-competent 3PL suppliers is becoming more and more important to businesses. This strategic alignment allows them to leverage the benefits of Industry 4.0 technologies for enhanced operational performance. The purpose of this study is to propose an integrated MCDM approach based on FAHP and FMARCOS to weigh the criteria and select the best 3PL provider.

By exhaustively reviewing the literature and consulting with experts, this research has determined three criteria, environmental, social, and economic, and 15 sub-criteria based on the Industry 4.0 components. While economic, environmental and social aspects of 3PL selection problem have been discussed in the previous studies, less attention has been paid to Industry 4.0. Our case study reveals that five different criteria, technology capability (C35), quality improvement by using smart technologies (C34), technology-enabled cost optimization (C33), green and smart logistics (C15), and data security (C22), are the most important factors from the Industry 4.0 window for 3PL selection. These criteria cover nearly 50% of the total weight for 3PL selection. Both methods proposed in the research (FAHP-FMARCOS) are proven to be effective for handling the 3PL selection problem in Industry 4.0 which can help businesses implement an integrated framework to prioritize and select suitable providers. It is observed that this new hybrid methodologies can also be practically capable of addressing the uncertainty of different real-life problems. A sensitivity analysis on the criteria weights and a comparative analysis among MCDM methods (FMABAC, FWASPAS, FCOSOSO, FSAW, FCOPRAS, FTOPSIS and FVIKOR) were performed to show the stability of the obtained results which increases the trustiness of the results. Consequently, the robustness and efficiency of the proposed framework have been proven, meaning that it can be applied by practitioners in various industries to address complex decision-making problems.

It is essential to recognize the limitations of this study. Firstly, the findings may lack generalizability across industries in different countries. Future research should broaden its scope to encompass various industries, thereby validating the effectiveness of the proposed framework in diverse supply chain contexts [52], [53]. Moreover, geographical variations may lead to different outcomes, necessitating a more globally inclusive perspective. Secondly, the prioritized criteria, influenced by expert opinions and literature, may be subject to varying interpretations among stakeholders. Subsequent studies could integrate a broader range of criteria that impact logistics and supply chain processes, thereby expanding the applicability of the approach across different sectors. Additionally, conclusions are contingent upon the opinions and judgments of experts, potentially changing with alterations in the expert panel. Hence, selecting the experts should be performed carefully to reduce the impacts of the experts' features. In the future, it would be beneficial to replicate the current study in diverse countries and regions, inviting experts from outside the country to participate in the expert group and comparing the outcomes. Lastly, Granular Computing [54] has emerged as a novel approach to Multi-Criteria Decision Making (MCDM) and decision-making problems. Exploring multi-granularity computing tools in MCDM could provide insights into addressing uncertainty and enhancing the robustness of decision-making processes by describing and processing vague, ambiguous, incomplete, and vast amounts of information.

APPENDIX

See Tables 11–14.

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