Sustainable Urban Delivery Vehicle Selection in Vietnam: A Hybrid Multi-Criteria Decision-Making Approach

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ABSTRACT

E-commerce growth has intensified last-mile home delivery in dense urban areas, where operators must execute multi-stop tours under high stop density, volatile traffic, and tight delivery windows. In Vietnam, van procurement requires balancing the total cost of ownership, operational feasibility, and sustainability, while electrification is influenced by purchase incentives and charging availability. Although Multi-Criteria Decision-Making (MCDM) is widely used for vehicle appraisal, limited evidence exists regarding whether rankings remain stable across decision logics under Vietnam-specific operating conditions. This study derives criterion weights using the Fuzzy Analytic Hierarchy Process (Fuzzy AHP) and synthesizes four ranking methods through ensemble aggregation: the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), the VIseKriterijumska optimizacija I Kompromisno Resenje (VIKOR), the Preference Ranking Organization Method for Enrichment of Evaluations II (PROMETHEE II), and the Weighted Aggregated Sum Product Assessment (WASPAS). Seven urban delivery vans representing internal combustion and electric engines are evaluated, and robustness is assessed using systematic weight-perturbation scenarios and rank-agreement analysis. The results demonstrate strong cross-method agreement, with an electric van achieving the highest performance across all methods and perturbation settings. These findings provide Vietnam-specific evidence that electrification represents a robust procurement outcome under the evaluated criteria and decision structures.

Keywords-urban delivery vehicles; Fuzzy AHP; MCDM; sustainability

I. INTRODUCTION

Last-mile distribution is demanding because it must serve dispersed customers under high service expectations and substantial urban uncertainty [1]. Control becomes more difficult when shipments are fragmented into small orders executed as multi-stop tours with tight time windows, increasing routing complexity and service-time variability [2]. Cost-focused studies indicate that last-mile delivery materially affects overall logistics costs, and therefore warrants optimization; commonly cited cost drivers include failed deliveries, customer density, and process configuration [3]. Since these costs are structurally dependent on delivery-system configurations, substantial efficiencies can be realized through targeted operational redesign [4].

In Vietnam, platform-enabled commerce has increased reliance on home-delivery services, intensifying pressure on urban last-mile operations [5]. Under dense-city conditions, tour productivity and variability are significantly shaped by last-meter frictions—curb access, parking search, and stop-level dwell processes—rather than line-haul travel alone [6]. Related empirical work shows that commercial vehicle dwell time varies systematically with delivery-point and building characteristics, reinforcing the importance of curbside service processes in multi-stop operations [7]. More broadly, city logistics research indicates that congestion, curb constraints, and access restrictions reduce tour productivity and increase cost per delivery, making vehicle capability and operational fit central to service reliability and efficiency in urban distribution [8]. These constraints increase the variance of on-route and on-site times, complicating schedule adherence, capacity planning, and vehicle sizing decisions in dense urban delivery systems.

Beyond efficiency, urban delivery decisions are increasingly shaped by sustainability goals and environmental constraints. In urban freight distribution, congestion and stop-and-go driving patterns can reduce energy efficiency and increase carbon emissions per trip [9]. Electrifying urban freight fleets is often viewed as a practical pathway to reducing local emissions and noise [10]. However, the competitiveness of electric delivery vehicles is contingent on duty-cycle intensity, charging access, and total cost of ownership [11]. Charging availability and infrastructure placement further condition operational feasibility for freight transport, making infrastructure readiness a crucial enabling factor for electrification outcomes [12].

Given these operating characteristics, delivery vehicle selection can be formulated as a Multi-Criteria Decision-Making (MCDM) problem that must jointly evaluate economic cost, technical capability, operational suitability, and environmental impacts. The use of MCDM in logistics and supply-chain decisions is well documented in reviews on supplier evaluation and green supply-chain decision-making [13, 14]. Because criteria weights in such problems are commonly elicited from expert judgments, uncertainty and linguistic vagueness are unavoidable. Compared with the Analytic Hierarchy Process (AHP), the Fuzzy Analytic Hierarchy Process (Fuzzy AHP) better accommodates imprecise pairwise judgments expressed in linguistic terms. Fuzzy set theory provides a mathematical basis for representing such vagueness [15], and Fuzzy AHP derives criterion weights within an AHP hierarchy under imprecise judgments [16]. In applied decision contexts, Fuzzy AHP has been implemented in supply-chain supplier selection [17] and in broader engineering feasibility assessment [18], supporting its practicality as a weighting mechanism under imprecise judgments.

For alternative appraisal and ranking, several established MCDM techniques are commonly employed. The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) evaluates each option by its distances to the ideal and anti-ideal solutions, yielding an intuitive, distance-based interpretation of the overall performance [19]. In logistics, TOPSIS has been applied to reverse-logistics service-provider selection in industrial settings [20]. VIseKriterijumska optimizacija I Kompromisno Resenje (VIKOR) identifies a compromise solution by balancing overall utility against individual regret under conflicting criteria [21], and transport-focused studies further demonstrate its applicability to multi-criteria prioritization problems [22]. The Preference Ranking Organization Method for Enrichment of Evaluations (PROMETHEE) builds pairwise preference relations and aggregates them into preference flows, supporting transparent interpretation of dominance relations in outranking evaluation [23]. PROMETHEE II yields a complete ordering by ranking alternatives according to the net outranking flow [24], and its broad applicability has been documented in methodological and application studies [25].

To enhance robustness beyond purely additive aggregation, the Weighted Aggregated Sum Product Assessment (WASPAS) combines weighted additive and weighted multiplicative utility structures [26]. In urban logistics contexts, WASPAS has been applied to last-mile delivery mode selection using real-life city data [27], and in logistics outsourcing, it has been used to assess third-party logistics providers under uncertainty through CRITIC–WASPAS frameworks [28]. Because normalization and aggregation mechanisms differ, rank reversals have been reported in TOPSIS-type evaluations, particularly when alternatives are closely matched or when criterion weights are highly uneven [29].

Most existing studies apply a single MCDM technique within a given case setting. Whether different ranking logics would yield consistent results when applied to the same setting, particularly in emerging-economy urban contexts, has received limited direct examination. This study addresses this limitation by: (i) integrating fuzzy weighting with four structurally different ranking logics within a rank-sum ensemble design, reducing dependence on any single aggregation mechanism; (ii) validating the ranking stability through calibrated preference thresholds and comprehensive sensitivity analysis; and (iii) empirically testing ranking consistency in a transitional electrification setting involving both Internal Combustion Engine (ICE) and Electric Vehicle (EV) alternatives in Vietnam.

II. MATERIALS AND METHODS

A. Alternatives and Evaluation Criteria

The experiment comprises seven urban delivery van models representative of the current logistics market in Vietnam, including four ICE vans (ICE-1 to ICE-4) and three electric vans (EV-1 to EV-3). This selection reflects the transitional decision context faced by operators who must assess incumbent ICE fleets alongside emerging electric options within a gradual electrification pathway. The evaluation criteria were developed to reflect the operational characteristics of dense urban delivery in Vietnam while remaining sufficiently comprehensive for cross-alternative comparison. Following expert consultation, eleven criteria (C1–C11) were finalized and grouped into major dimensions, including cost efficiency, technical capability, operational suitability, environmental impact, energy infrastructure readiness, and safety features. Detailed specifications of the alternatives and evaluation criteria are summarized in Table I.

Data acquisition followed a dual-stream protocol. Quantitative criteria (C1, C2, C4–C6, and C10) were compiled as baseline data from official technical specifications provided by Original Equipment Manufacturers (OEMs) and their authorized dealers operating in the Vietnamese market, with data accessed in December 2025. For analytical neutrality, vehicle alternatives were coded, and specific model names were not explicitly disclosed. As theoretical OEM specifications may not fully capture last-mile operational constraints, including curb access limitations and traffic-induced variability in energy consumption under dense urban conditions, qualitative criteria (C3, C7–C9, and C11) were incorporated into the evaluation framework. These qualitative indicators were assessed by a panel of six specialists, comprising two urban fleet managers, two logistics operation managers, and two supply chain consultants, each with over four years of direct professional experience in last-mile transport operations and fleet management in the Vietnamese market.

Experts employed a predefined 1–9 ordinal rating scale, where 1 represents the lowest relative evaluation assigned by the experts, and 9 represents the highest relative evaluation. The optimization direction of each criterion was subsequently incorporated within the MCDM computational procedures. To examine inter-expert agreement, the standard deviation of ratings was calculated for each criterion, yielding values ranging from 0.00 to 1.38. The relatively small standard deviations suggest consistent scoring across experts, thereby justifying the aggregation of individual ratings using the arithmetic mean to construct the group decision matrix.

Before ranking, the criteria directions were standardized to ensure consistent interpretation across methods. Cost-type criteria were treated as minimization objectives (MIN), whereas benefit-type criteria were treated as maximization objectives (MAX). Accordingly, C1, C2, and C7 were coded as MIN criteria, whereas C3–C6 and C8–C11 were coded as MAX criteria. This MIN/MAX coding is used directly in TOPSIS, VIKOR, and WASPAS; in PROMETHEE II only, cost-type criteria are internally re-oriented to a benefit direction to ensure a consistent larger-is-better preference function.

TABLE I. CRITERIA AND ALTERNATIVE DATA FOR URBAN LAST-MILE DELIVERY VAN SELECTION IN VIETNAM

Code	Criterion	Unit	Direction	ICE-1	ICE-2	ICE-3	ICE-4	EV-1	EV-2	EV-3
C1	Total cost of ownership	USD	MIN	11,500	11,000	35,700	48,000	12,600	15,500	8,500
C2	Operating cost per km	USD/km	MIN	0.092	0.088	0.145	0.152	0.036	0.042	0.045
C3	Purchase financial incentives	Score (1–9)	MAX	4.50	5.17	2.17	2.00	8.17	5.33	4.83
C4	Payload capacity	kg	MAX	945	580	890	940	600	1,000	200
C5	Cargo compartment volume	m³	MAX	3.00	2.50	10.0	9.00	2.60	4.50	1.70
C6	Driving range per full fuel/energy charge	km	MAX	450	500	700	750	300	268	150
C7	Environmental impact	Score (1–9)	MIN	6.67	5.83	7.17	8.33	1.00	1.00	1.00
C8	Urban operational flexibility	Score (1–9)	MAX	7.17	8.67	2.33	3.17	7.67	6.33	8.17
C9	Energy infrastructure availability	Score (1–9)	MAX	9.00	9.00	9.00	9.00	7.83	3.83	3.33
C10	Warranty period	year(s)	MAX	2	3	3	3	5	2	2
C11	Safety and technology	Score (1–9)	MAX	3.33	4.67	6.50	6.83	7.67	5.83	2.17

B. Criterion Weighting Using Fuzzy AHP

Fuzzy AHP is used to derive criterion weights under ambiguity in expert judgments [15, 16]. Pairwise comparisons are represented by triangular fuzzy numbers $\tilde{a}_{jq} = (l_{jq}, m_{jq}, u_{jq})$, where $j, q = 1, \dots, J$ and J is the number of criteria. In this study, Chang's extent analysis method [30] was adopted due to its analytical simplicity and established applicability in multi-criteria decision contexts. Following this approach, the fuzzy synthetic extent value of the criterion j is computed as:

$$\tilde{S}_j = \left(\sum_{q=1}^{J} \tilde{a}_{jq}\right) \otimes \left(\sum_{j=1}^{J} \sum_{q=1}^{J} \tilde{a}_{jq}\right)^{-1} \tag{1}$$

The priority value of the criterion j is obtained from the minimum degree of possibility against all other criteria h $(h = 1, \dots, J;\ h \neq j)$:

$$d_j = \min_{h \neq j} V(\tilde{S}_j \geq \tilde{S}_h) \tag{2}$$

To verify judgment consistency, the aggregated fuzzy pairwise comparison matrix is defuzzified using the centroid method to obtain an equivalent crisp matrix. Consistency is then assessed on this crisp matrix using Saaty's consistency index and consistency ratio, and all matrices satisfy the commonly adopted threshold $CR < 0.1$ [31].

Finally, criterion weights are normalized as:

$$w_j = \frac{d_j}{\sum_{j=1}^{J} d_j} \tag{3}$$

The resulting w_j values are used as inputs to the subsequent alternative-ranking methods.

C. Alternative Ranking Methods

Let I denote the number of alternatives and J the number of criteria. The performance matrix is $X = [x_{ij}]$, where x_{ij} represents the performance of the alternative i with respect to the criterion j, and w_j is the corresponding criterion weight obtained from the Fuzzy AHP stage.

1) TOPSIS Method

TOPSIS ranks alternatives according to their distances from the Positive Ideal Solution (PIS) and the Negative Ideal Solution (NIS) [19]. The weighted normalized decision matrix is computed as:

$$v_{ij} = w_j \cdot \frac{x_{ij}}{\sqrt{\sum_{i=1}^{I} x_{ij}^2}} \tag{4}$$

For cost-type criteria, the definitions of the ideal and anti-ideal solutions are reversed. Accordingly, the ideal points for each criterion j are defined as:

$$\begin{cases} A_j^+ = \begin{cases} \max\limits_i v_{ij}, & j \in MAX \\ \min\limits_i v_{ij}, & j \in MIN \end{cases} \\ A_j^- = \begin{cases} \min\limits_i v_{ij}, & j \in MAX \\ \max\limits_i v_{ij}, & j \in MIN \end{cases} \end{cases} \tag{5}$$

The separation measures of the alternative i from the PIS and NIS are calculated as:

$$\begin{cases} D_i^+ = \sqrt{\sum_{j=1}^{J} (v_{ij} - A_j^+)^2} \\ D_i^- = \sqrt{\sum_{j=1}^{J} (v_{ij} - A_j^-)^2} \end{cases} \tag{6}$$

The closeness coefficient of the alternative i is defined as:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{7}$$

where $C_i \in [0,1]$, and larger values indicate higher preference.

2) *VIKOR Method*

VIKOR produces a ranking index under conflicting criteria by balancing overall group utility and individual regret [21]. For each criterion j, the best value f_j^* and the worst value f_j^- across all alternatives are defined as:

$$\begin{cases} f_j^* = \begin{cases} \max\limits_i x_{ij}, j \in MAX \\ \min\limits_i x_{ij}, j \in MIN \end{cases} \\ f_j^- = \begin{cases} \min\limits_i x_{ij}, j \in MAX \\ \max\limits_i x_{ij}, j \in MIN \end{cases} \end{cases} \tag{8}$$

The group utility measure S_i and the individual regret measure R_i of alternative i are computed by:

$$\begin{cases} S_i = \sum_{j=1}^{J} w_j \frac{f_j^* - x_{ij}}{f_j^* - f_j^-} \\ R_i = \max\limits_j \left[w_j \frac{f_j^* - x_{ij}}{f_j^* - f_j^-} \right] \end{cases} \tag{9}$$

If $f_j^* = f_j^-$ for a criterion j, the corresponding normalized term is set to zero to avoid division by zero. Let $S^* = \min\limits_i S_i$, $S^- = \max\limits_i S_i$, $R^* = \min\limits_i R_i$, and $R^- = \max\limits_i R_i$. The VIKOR index is then obtained as:

$$Q_i = v \frac{S_i - S^*}{S^- - S^*} + (1 - v) \frac{R_i - R^*}{R^- - R^*} \tag{10}$$

where $v \in [0,1]$ reflects the decision strategy emphasizing group utility (v) versus individual regret (1-v). In this study, $v = 0.5$ is adopted to balance the two objectives, and alternatives are ranked in an ascending order of Q_i, with smaller values indicating higher preference.

3) *PROMETHEE II Method*

PROMETHEE is an outranking method that constructs preference relations through pairwise comparisons [23]. In this study, the PROMETHEE II variant is applied to obtain a complete ranking based on the net outranking flow [24]. For each criterion j, the preference for the alternative a over b is defined as:

$$P_j(a,b) = F_j\big(d_j(a,b)\big) \tag{11}$$

where the signed difference is computed as:

$$d_j(a,b) = \begin{cases} x_{aj} - x_{bj}, & j \in MAX \\ x_{bj} - x_{aj}, & j \in MIN \end{cases} \tag{12}$$

This formulation ensures that all criteria are expressed in a maximization orientation before applying the preference function. For quantitative criteria (C1, C2, C4, C5, C6, C10), the V-shape preference function (Type III) was adopted:

$$F_j(d) = \begin{cases} 0, & d \le 0 \\ \frac{d}{p_j}, & 0 < d \le p_j \\ 1, & d > p_j \end{cases} \tag{13}$$

where the strict preference threshold p_j was calibrated as the observed range across alternatives:

$$p_j = \max\limits_i x_{ij} - \min\limits_i x_{ij} \tag{14}$$

This data-driven calibration allows full discrimination within the empirical range, ensuring that the maximum observed performance gap corresponds to complete preference. In contrast, for qualitative criteria (C3, C7, C8, C9, C11), reflecting the ordinal nature of expert ratings, the usual preference function (Type I) was applied:

$$F_j(d) = \begin{cases} 0, & d \le 0 \\ 1, & d > 0 \end{cases} \tag{15}$$

The aggregated preference index between two alternatives a and b is computed as:

$$\pi(a,b) = \sum_{j=1}^{J} w_j P_j(a,b) \tag{16}$$

The positive, negative, and net outranking flows are then obtained as:

$$\begin{cases} \phi^+(a) = \frac{1}{I-1} \sum_{b \ne a} \pi(a,b) \\ \phi^-(a) = \frac{1}{I-1} \sum_{b \ne a} \pi(b,a) \\ \phi(a) = \phi^+(a) - \phi^-(a) \end{cases} \tag{17}$$

PROMETHEE II produces a complete ranking by sorting the alternatives in a descending order of $\phi(a)$; higher net flow values indicate a stronger overall preference.

4) *WASPAS Method*

WASPAS combines the Weighted Sum Model (WSM) and Weighted Product Model (WPM) to improve ranking stability [26]. Before aggregation, the decision matrix is normalized to obtain $x_{ij}^{(n)}$ according to the criterion type. For benefit-type criteria, $x_{ij}^{(n)} = x_{ij} / \max\limits_i x_{ij}$, whereas for cost-type criteria, $x_{ij}^{(n)} = \min\limits_i x_{ij} / x_{ij}$.

The WSM and WPM scores of the alternative i are computed as:

$$WS_i^{(1)} = \sum_{j=1}^{J} w_j x_{ij}^{(n)}, WS_i^{(2)} = \prod_{j=1}^{J} \left(x_{ij}^{(n)}\right)^{w_j} \tag{18}$$

The aggregated WASPAS score is then obtained by:

$$WS_i = \lambda WS_i^{(1)} + (1 - \lambda) WS_i^{(2)}, \lambda \in [0,1] \tag{19}$$

In this study, $\lambda = 0.5$ is adopted, and alternatives are ranked in a descending order of WS_i, with larger values indicating higher preference.

D. Ensemble Ranking and Agreement Assessment

To synthesize rankings produced by multiple MCDM methods and assuming equal importance among them, the rank positions of each alternative are aggregated into an overall rank sum. Let K denote the number of MCDM methods and let r_{ik} be the rank position of the alternative i under method k. The overall rank sum is defined as:

$$RS_i = \sum_{k=1}^{K} r_{ik} \tag{20}$$

The alternative with the smallest RS_i is considered the most preferred. Spearman's rank correlation coefficient is used to quantify the similarity between two ranking lists [32]:

$$\rho = 1 - \frac{6\sum_{i=1}^{I} d_i^2}{I(I^2-1)} \tag{21}$$

where d_i is the rank difference of the alternative i between the two methods. Values of ρ closer to 1 indicate stronger consistency. Similarly, Kendall's coefficient of concordance W is employed to assess overall agreement across K ranking lists [33]:

$$W = \frac{12S}{K^2(I^3-I)} \tag{22}$$

where $S = \sum_{i=1}^{I}(RS_i - \overline{RS})^2$, RS_i is the sum of the ranks of the alternatives i across the K methods, and $\overline{RS}$ is the mean rank sum. Larger W indicates higher concordance among the MCDM methods.

III. RESULTS AND DISCUSSION

A. Fuzzy AHP Results

The weighting process involved six domain experts performing pairwise comparisons across the eleven criteria using triangular fuzzy numbers mapped to Saaty's fundamental scale. The resulting individual fuzzy judgment matrices were aggregated into a group fuzzy comparison matrix using the fuzzy geometric mean operator. To verify judgment coherence, the aggregated fuzzy matrix was defuzzified via the centroid method to obtain an equivalent crisp comparison matrix, and the corresponding consistency ratio satisfied the accepted requirement (*CR*<0.1). Criterion weights were then derived following Chang's extent analysis procedure. Fuzzy synthetic extent values were first computed for each criterion, and pairwise degrees of possibility were evaluated to obtain the priority vector. The resulting weights were finally normalized according to (1)–(3) to ensure a unit-sum weight vector suitable for subsequent MCDM ranking.

The weight distribution shows that cost-related criteria receive the largest share of importance. The total cost of ownership (C1, 0.217) and operating cost per kilometer (C2, 0.165) are the two most influential criteria, jointly accounting for 38.2% of the total weight and indicating that economic efficiency is the primary decision driver in this setting. A secondary tier comprises payload capacity (C4, 0.105), warranty period (C10, 0.095), and purchase financial incentives (C3, 0.090), reflecting emphasis on operational utility and investment risk mitigation. Environmental impact (C7, 0.074) and energy infrastructure availability (C9, 0.066) receive moderate importance, indicating that sustainability-related considerations are present but remain secondary to direct cost drivers. The remaining criteria—cargo compartment volume (C5, 0.060), driving range (C6, 0.056), safety and technology (C11, 0.040), and urban operational flexibility (C8, 0.032)—have smaller weights and mainly provide additional differentiation among alternatives with similar performance on higher-weighted criteria.

B. Alternative Rankings Using MCDM Methods

The performance data of the alternatives were structured according to their optimization directions, as summarized in Table I, and integrated with the criterion weights derived from the Fuzzy AHP procedure. Four established MCDM methods—TOPSIS, VIKOR, PROMETHEE II, and WASPAS—were subsequently applied to evaluate and rank the seven delivery van alternatives. All computations, including matrix normalization, index calculation, and rank aggregation, were implemented in Python using standard numerical libraries. For illustration, a detailed numerical example is provided for TOPSIS, while the remaining methods were applied using the same input data and computational procedures, with their final indices and rankings reported accordingly.

1) TOPSIS Method

TOPSIS was implemented in accordance with (4)–(7). The calculation was carried out in four sequential stages: weighted normalization, identification of ideal solutions, separation distance evaluation, and closeness coefficient computation.

a) Stage 1: Weighted Normalization

The weighted normalized decision matrix v_{ij} was computed according to (4). Each criterion column was vector-normalized and multiplied by its corresponding weight.

For example, for EV-1 under C1 ($w_1 = 0.217$):

$$v_{EV\text{-}1,1} = w_1 \frac{x_{EV\text{-}1,1}}{\sqrt{\sum_{i=1}^{7} x_{i1}^2}}$$

$$v_{EV\text{-}1,1} = 0.217 \times \frac{12{,}600}{65{,}597.26} = 0.0417$$

The same operation was performed across all criteria and alternatives to obtain the complete weighted normalized matrix.

b) Stage 2: Determination of Ideal Solutions

The positive and NISs were determined using (5), based on the predefined optimization directions.

For C1 (a cost-type criterion), the ideal values are:

$$A_1^+ = \min_i v_{i1} = 0.0281 \textit{ (EV-3)}$$

$$A_1^- = \max_i v_{i1} = 0.1588 \textit{ (ICE-4)}$$

The corresponding ideal values for all criteria are summarized in Table II.

c) Stage 3: Separation Measures

The separation distances from the ideal and anti-ideal solutions were computed using (6). For EV-1, the squared deviations under C1 are:

$$(v_{EV\text{-}1,1} - A_1^+)^2 = (0.0417 - 0.0281)^2 = 0.000185$$

$$(v_{EV\text{-}1,1} - A_1^-)^2 = (0.0417 - 0.1588)^2 = 0.013712$$

Aggregating across all eleven criteria yields:

$$\sum_{j=1}^{11}(v_{\text{EV-1},j} - A_j^+)^2 = 0.001859$$

$$\sum_{j=1}^{11}(v_{\text{EV-1},j} - A_j^-)^2 = 0.024802$$

Taking square roots gives the separation measures:

$$D_{\text{EV-1}}^+ = \sqrt{0.001859} = 0.0431$$

$$D_{\text{EV-1}}^- = \sqrt{0.024802} = 0.1575$$

d) Stage 4: Closeness Coefficient and Ranking

The relative closeness to the ideal solution was computed using:

$$C_{\text{EV-1}} = \frac{0.1575}{0.0431+0.1575} = 0.7851$$

The same computational steps were applied to all alternatives to obtain their respective closeness coefficients and the induced ranking, as reported in Table III.

TABLE II. IDEAL SOLUTION VALUES FOR ALL CRITERIA

Criterion	**Direction**	A_j^+	A_j^-
C1	MIN	0.0281	0.1588
C2	MIN	0.0232	0.0981
C3	MAX	0.0557	0.0136
C4	MAX	0.0506	0.0101
C5	MAX	0.0399	0.0068
C6	MAX	0.0323	0.0065
C7	MIN	0.0052	0.0433
C8	MAX	0.0158	0.0043
C9	MAX	0.0293	0.0108
C10	MAX	0.0594	0.0238
C11	MAX	0.0207	0.0059

TABLE III. TOPSIS METRICS AND RANK

Alternative	D_i^+	D_i^-	C_i	**Rank**
EV-1	0.0431	0.1575	0.7851	1
EV-2	0.0586	0.1432	0.7096	2
ICE-2	0.0659	0.1363	0.6743	3
EV-3	0.0761	0.1542	0.6696	4
ICE-1	0.0726	0.1360	0.6519	5
ICE-3	0.1284	0.0722	0.3598	6
ICE-4	0.1631	0.0597	0.2679	7

2) VIKOR Method

For each criterion, the best and worst values were identified according to the predefined optimization directions (MIN/MAX) using (8). The group utility measure S_i and the individual regret R_i were computed using (9), and the compromise index Q_i was obtained from (10) with $v = 0.5$ to balance group utility and individual regret. Alternatives were ranked in an ascending order of Q_i, where smaller values indicate higher preference. The VIKOR results are summarized in Table IV.

3) PROMETHEE II Method

Criterion-level preferences were derived using the Type I and Type III preference functions specified in (11)–(15). The aggregated preference index was calculated according to (16) by integrating these preference degrees with the corresponding Fuzzy AHP weights. The positive, negative, and net outranking flows were subsequently determined based on (17). Alternatives were ranked in a descending order of the net flow ϕ, where larger values indicate a stronger overall preference. The resulting PROMETHEE II metrics are outlined in Table V.

TABLE IV. VIKOR METRICS AND RANK

Alternative	S_i	R_i	Q_i	**Rank**
EV-1	0.1892	0.0535	0.0000	1
ICE-2	0.3980	0.0740	0.2852	2
EV-2	0.3535	0.0950	0.3021	3
ICE-1	0.4269	0.0950	0.3803	4
EV-3	0.4860	0.1050	0.4739	5
ICE-3	0.5772	0.1550	0.7241	6
ICE-4	0.6583	0.2170	1.0000	7

TABLE V. PROMETHEE II METRICS AND RANK

Alternative	ϕ^+	ϕ^-	ϕ	**Rank**
EV-1	0.4538	0.1290	0.3247	1
EV-2	0.3403	0.1945	0.1458	2
ICE-2	0.3056	0.1992	0.1064	3
ICE-1	0.2430	0.2588	-0.0158	4
EV-3	0.2677	0.3309	-0.0633	5
ICE-3	0.2167	0.4074	-0.1907	6
ICE-4	0.1902	0.4974	-0.3072	7

4) WASPAS Method

WASPAS integrates the WSM and the WPM. The WSM and WPM scores were computed using (18), and the aggregated WASPAS score (WS_i) was obtained using (19) with $\lambda = 0.5$ to balance the two components. Alternatives were ranked in a descending order of WS_i, where a higher value denotes superior performance. The WASPAS results are presented in Table VI.

TABLE VI. WASPAS METRICS AND RANK

Alternative	**WSM**	**WPM**	WS_i	**Rank**
EV-1	0.7971	0.7525	0.7748	1
EV-2	0.6650	0.6286	0.6468	2
ICE-2	0.5974	0.5452	0.5713	3
EV-3	0.6225	0.5196	0.5711	4
ICE-1	0.5843	0.5232	0.5537	5
ICE-3	0.4981	0.3986	0.4484	6
ICE-4	0.4874	0.3697	0.4286	7

C. Ensemble Ranking, Agreement, and Sensitivity Analysis

The four MCDM methods (TOPSIS, VIKOR, PROMETHEE II, and WASPAS) were assigned equal importance to avoid introducing subjective method priors when no defensible basis exists to privilege a single ranking logic. The ensemble ordering was therefore obtained using the rank-sum aggregation in (20), where a smaller RS_i denotes a more favorable alternative, and ties were retained when alternatives shared the same aggregate score.

As illustrated in Figure 1, the four methods yield highly concordant rankings, and EV-1 remains top-ranked under every method, indicating method-independent dominance. The main divergence arises at the second position: TOPSIS, PROMETHEE II, and WASPAS place EV-2 ahead of ICE-2, whereas VIKOR reverses this order. This pattern is consistent with VIKOR's regret-oriented compromise logic, which can favor an alternative with a stronger worst-criterion profile even when its overall compensatory performance is slightly lower. In the mid-tier, ICE-1 and EV-3 attain identical rank sums, indicating comparable competitiveness under equal method weights, whereas ICE-3 and ICE-4 consistently occupy the bottom positions, confirming that their inferiority is robust to the choice of the ranking method.

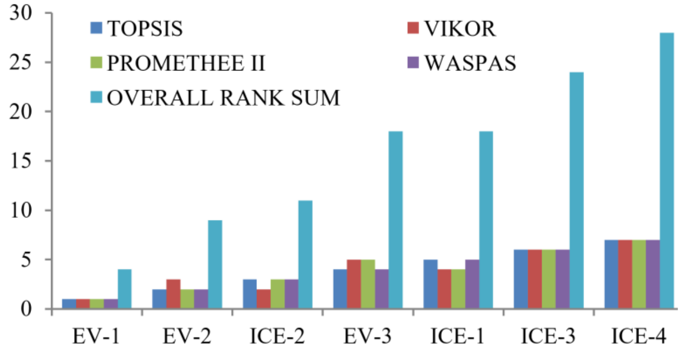

Fig. 1. MCDM ranking comparison and overall rank sum.

Spearman's rank correlations among the MCDM methods, computed using (21), are uniformly high. TOPSIS and WASPAS exhibit perfect agreement, with a Spearman's correlation of 1.0000, whereas all other method pairs range from 0.9286 to 0.9643, indicating outstanding consistency with only minor local inversions. Kendall's coefficient of concordance, obtained via (22), also indicates strong overall agreement across the four methods, with W reaching 0.9688. This result suggests a high level of consistency in the induced rankings.

TABLE VII. ENSEMBLE RANKING RESULTS UNDER SENSITIVITY SCENARIOS

Scenario	EV-1	EV-2	ICE-2	ICE-1	EV-3	ICE-3	ICE-4
Base	1	2	3	4	4	6	7
C1 (+10%)	1	2	3	5	4	6	7
C2 (+10%)	1	2	3	5	4	6	7
C1 and C2 (+10%)	1	2	3	5	4	6	7
C1 (−10%)	1	2	3	4	4	6	7
C2 (−10%)	1	2	3	4	4	6	7
C1 and C2 (−10%)	1	2	3	4	4	6	7
C1 (+20%)	1	2	3	5	4	6	7
C2 (+20%)	1	2	3	5	4	6	7
C1 and C2 (+20%)	1	2	3	5	4	6	7
C1 (−20%)	1	2	3	4	4	6	7
C2 (−20%)	1	2	3	4	4	6	7
C1 and C2 (−20%)	1	2	3	4	5	6	7

A weight-perturbation sensitivity analysis was conducted using 13 scenarios, including the baseline case and 12 perturbed cases. The two most influential criteria (C1 and C2) were perturbed by $n \in \{10\%, 20\%\}$ under both increasing and decreasing settings (C1 ($\pm n\%$), C2 ($\pm n\%$), and C1 and C2 ($\pm n\%$)). After each perturbation, the weight vector was renormalized, and the ensemble ranking was recomputed. As summarized in Table VII, EV-1 remains ranked first in all scenarios, whereas EV-2 and ICE-2 stably retain the second and third positions, respectively. The only variation occurs within the mid-tier pair ICE-1 and EV-3. Under all weight-increase cases, EV-3 is ranked fourth and ICE-1 fifth, whereas under the baseline and all weight-decrease cases, they remain tied at fourth, except under the joint 20% decrease, where ICE-1 becomes fourth and EV-3 shifts to fifth. ICE-3 and ICE-4 remain unchanged at the bottom of the ranking, consistently occupying the sixth and seventh positions. Overall, these results indicate that the proposed Fuzzy AHP–MCDM framework is robust to reasonable variations in criterion weights.

From a managerial perspective, the dominance of cost-related criteria suggests that procurement should begin with an economic screen, using the total cost of ownership and operating cost as primary discriminators before considering secondary technical attributes. The leading electric van remains top-ranked under all tested weight-perturbation scenarios, suggesting that its advantage is not driven by a specific weighting profile. The comparatively weaker assessment of charging availability further indicates that deployment feasibility hinges on adequate depot charging capacity and consistent charging practices.

IV. CONCLUSION

Integrating fuzzy weighting with four ranking logics in an ensemble design produces stable rankings across model structures and moderate weight changes. By combining cross-method concordance testing with structured sensitivity analysis, the framework improves decision stability when alternatives exhibit closely competing performance profiles. The findings indicate that economic criteria primarily drive urban delivery fleet decisions. At the same time, feasibility-related factors, such as payload fit, warranty support, and charging readiness, determine practical implementability and operational risk in dense-city environments. The same alternative Electric Vehicle-1 (EV-1) remains ranked first under all four models and across all 13 perturbation scenarios. In contrast, mid-tier alternatives show greater sensitivity and should therefore be interpreted relative to specific operational requirements.

Despite these robust findings, a limitation concerns the qualitative evaluation process. The expert panel comprised six experienced industry professionals, which, although appropriate for specialized decision contexts, limits broader statistical representativeness. The present analysis relies on manufacturer-reported specifications. Collecting route-level operational data from urban fleets would improve empirical realism. Measuring last-meter frictions, traffic-induced energy variability, operational charging constraints, and grid reliability conditions would enable more realistic modeling of urban fleet electrification. In addition, a simulation-based weight sampling design could quantify ranking dispersion under broader uncertainty.

DECLARATION OF COMPETING INTERESTS

The authors declare no competing interests.

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DATA AVAILABILITY

All data required to support the findings of this study are provided within the manuscript. Any additional data can be made available by the corresponding author upon reasonable request.

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