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The Influence of Objective Weight Determination Methods on Electric Vehicle Selection in Urban Logistics

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Abstract: This study addresses the challenge of selecting appropriate electric vehicles for urban logistics, with a specific focus on the impact of various multi-criteria analysis methods on this complex decision-making process. The investigation utilizes a mixed methodology, combining objective weight determination methods, such as Entropy, CRITIC (Criteria through the Inter-Criteria Correlation), and MEREC (Method Based on the Removal Effects of Criteria), alongside standard deviation and a modified version of the standard deviation method. The Simple Additive Weighting (SAW) method was further employed for alternative ranking. Application of these methods across nine diverse Small Van vehicles, assessed according to 12 criteria, highlighted the paramountcy of Charge Time and Cargo Volume as factors bearing the most significant weight in decision-making. The Toyota Proace City Verso Electric L2 emerged as a superior choice under most conditions. Yet, the results varied when applying weights deduced through the MEREC method, leading to the ascendency of the Renault Kangoo E-Tech. The study underscores that the objective determination of criteria weights plays an influential role in the ranking of alternatives, hence, the requirement for decision-makers' subjectivity in the final choice, factoring in the unique attributes of individual companies. This research contributes to the understanding of how multi-criteria analysis can facilitate electric vehicle selection for urban logistics, playing a crucial part in reducing harmful urban emissions.

Keywords: Electric vehicles; Urban logistics; Objective weight determination methods; SAW method

1 Introduction

Evolution in market dynamics and increasing environmental conservation concerns have ushered in changes within the automotive industry. The advent of the 21st century's third decade has marked the onset of a new era dominated by electric cars (e-cars) [1]. E-cars are being increasingly adopted globally, in response to an uptick in environmental consciousness among drivers. This shift has spurred the auto industry to meet the evolving demand, resulting in a growing array of e-car models [2].

E-cars offer numerous advantages over traditional fossil fuel vehicles, primarily characterized by their superior energy efficiency and environmental impact [2]. Amid growing urban air pollution and noise challenges, governmental bodies are seeking effective solutions [3]. This has culminated in prohibitions on diesel engines in various urban environments [4], further enhancing the demand for both personal and commercial e-cars.

In parallel with the e-car industry's rapid growth, the development of logistics services utilizing these vehicles has been observed [5]. Such vehicles, besides their fundamental role in goods and people transportation, exhibit zero environmental impact – an increasingly pertinent feature in contemporary society [5]. It has been noted that fossil fuel vehicles consume more fuel within urban environments as compared to open roads [6], thereby significantly contributing to urban air pollution [7]. This is being addressed through the incorporation of e-cars into urban logistics, emerging as a critical segment within green logistics [8].

The importance of e-cars extends beyond environmental implications; they play a significant role in cost reduction within urban logistics. It has been posited that the last mile in urban logistics can be the most intricate and account for up to 28% of the total costs [3]. As a solution to this, e-cars are becoming increasingly instrumental for urban logistics firms.

The decision to select the appropriate e-car within urban logistics, especially those classified as Small Van vehicles, is highly dependent on their technical characteristics. This selection process falls under the multi-criteria decision-making (MCDM) problem, which involves the choice among several e-cars based on their distinct technical characteristics [9]. It is, however, imperative to understand the importance of these technical characteristics for the decision-maker.

In practice, there are two predominant approaches to determining the importance of these technical characteristics: the subjective and the objective approach [9]. A hybrid of these two approaches can also be employed. Based on these approaches, multi-criteria methods are bifurcated into subjective and objective methods for determining the criteria weight. While subjective methods allow the decision-maker to determine the criteria importance, objective methods calculate this importance based on alternative values, with more weight given to criteria with a greater dispersion in alternative values [10].

The objective determination of criteria importance was employed in this study, a decision grounded in the study's universal applicability rather than catering to specific firms and their subjective evaluations. This study, therefore, evaluates Small Van e-cars using their technical characteristics and examines how objective weight determination methods impact the final choice. The significance of this study manifests in several ways:

- Assisting decision-making in e-car selection for urban logistics,
- Analyzing the influence of objective weight determination on the final choice,
- Identifying the e-car with the most advantageous technical characteristics for urban logistics,
- Promoting green logistics in urban areas through e-car utilization.

By addressing these aspects, the study contributes to filling some gaps in existing research. First, it addresses the possibility of different weights for criteria when using objective methods, and how these weights might influence the final decision. Second, it provides a comprehensive evaluation of e-cars, taking into account their overall characteristics rather than isolated features. Lastly, in the face of increasing pressure to reduce pollution, especially in urban areas, this study advocates for the use of e-cars in urban logistics as a means to mitigate pollution.

2 Literature Review

The field of study under review is the application of electric vehicles (e-cars) in urban logistics and the use of methods for objective weight determination in the selection of these vehicles. These two intertwining areas can be dissected in the literature from two dimensions: the practical application of e-cars and the methodological framework for evaluating their selection.

The practical application of e-cars in urban logistics has been scrutinized under various lenses, with common concerns centering around the vehicles' single-charge range and battery charging systems [11]. Li et al. [11] has specifically focused on these concerns, suggesting the optimization of route planning as a solution. The positive impact of e-cars in urban logistics is documented by Duarte et al. [12], who present evidence of energy consumption reduction through e-cars in Lisbon city's urban logistics. Likewise, Settey et al. [13] have advocated for the deployment of e-cars in urban logistics, linking this to a decrease in city pollution, a concern heightened by the increased reliance on delivery services during the recent pandemic.

Conversely, Bac and Erdem [14] caution about the limitations of e-cars, arguing for the necessity of planning optimal routes to increase delivery efficiency per charge. Following an economic angle, Yan et al. [5] put forward that e-cars' deployment in urban logistics is profitable, offering the Chinese experience as a case study. An alternative suggestion by Melo and Baptista [15] is the utilization of electric off-road bicycles in urban logistics for enhanced environmental and social impacts without efficiency reduction. In a bid to minimize environmental effects, Wang et al. [16] propose a combination of e-cars and fossil fuel vehicles, whereas Strale [8] pushes for the incorporation of e-cars into the broader framework of sustainable logistics.

Given the necessity to optimize urban logistics for total cost reduction and efficiency improvement, Muñoz-Villamizar et al. [17] champion the use of e-cars. Furthermore, research by Edel et al. [18] on lightweight solutions for e-cars' bodywork indicates that textiles could be ideal for manufacturing bodies for light logistics vehicles, compensating for battery-induced weight increases.

The second angle of the literature examines the methodological models for evaluating e-cars selection, with varying methods for determining criteria weights. Puška et al. [19] utilize a combination of the MEREC and CRADIS methods for e-cars selection, implementing the double normalization approach. Other research by Nguyen et al. [20] investigates e-cars' sales and market shares across 14 countries, employing the CRITIC method and the Gray Relation Analysis theory of grey systems. The Entropy method and TOPSIS method are used by Dwivedi and Sharma [21] in their assessment of different e-cars against various criteria to identify optimal performance.

Štilić et al. [22] evaluated e-cars for taxi services using SWARA, MSDM, and MABAC methods. Bączkiewicz and Wątróbski [23] applied a range of methods, including Entropy, Standard Deviation (SD), CRITIC, Gini coefficient-based, MEREC, Statistical Variance, CILOS, IDOCRIW, Coefficient of Variation, and Angle weighting methods using a Python library to determine criteria weight. The VIKOR method was then used to rank e-cars.

Thus, a thorough understanding of the existing literature underlines the increasing importance of e-cars in urban logistics and the diverse methodological approaches employed in their evaluation. This research contributes to this growing field by examining e-cars' technical characteristics and evaluating how objective weight determination methods influence final vehicle selection.

3 Methodology

In the quest to identify the most suitable electric vehicle (e-car) for urban logistics, a multi-step approach as depicted in Figure 1 was adhered to.

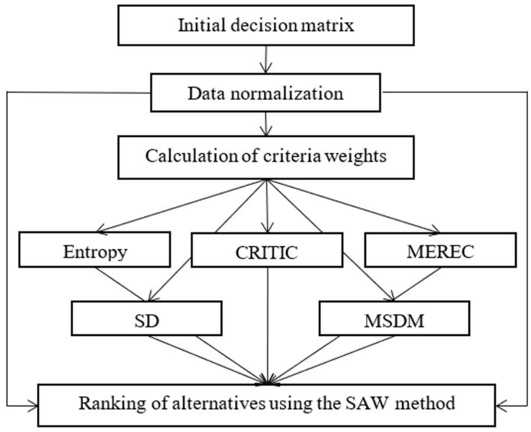

Figure 1. Research methodology

The initial stage involved defining alternatives and criteria to construct an initial decision-making matrix. Alternatives were narrowed down to Small Van e-cars, a selection process which resulted in a subset of the e-car market most aptly suited for urban logistics. Large van vehicles were omitted, focusing instead on Small Van delivery vehicles prevalent in the European market.

A database search of e-cars via ev-database.org yielded nine viable options, each priced below 45,000 Euros. The reasoning behind this budget cap stems from the need to identify vehicles within a price range accessible to a larger proportion of companies engaged in urban logistics [24]. The alternatives included: Renault Kangoo E-Tech (A1), Citroen e-Berlingo M (A2), Toyota Proace City Verso Electric L1 (A3), Peugeot e-Rifter Long (A4), Toyota Proace City Verso Electric L2 (A5), Peugeot e-Rifter Standard (A6), Opel Combo-e Life (A7), Citroen e-Berlingo XL (A8), and Opel Combo-e Life XL (A9).

The evaluation criteria were determined based on a comprehensive literature review and adapted to the specific needs of urban logistics vehicles. These are presented in Table 1.

Table 1. Criteria for selecting alternatives

ID	Criterion	Unit	Reference	Criterion Type
C1	Price	Euro	[19, 21–23]	cost
C2	Acceleration	s	[19, 21, 22, 25]	cost
C3	Top Speed	km / h	[19, 21–23, 25, 26]	benefit
C4	Range	km	[2, 19, 21, 22, 25, 26]	benefit
C5	Total Power	hp	[19, 22, 23]	benefit
C6	Useable Capacity	KW	[19, 21–23, 26]	benefit
C7	Charge Time	min	[2, 19, 22]	cost
C8	Fastcharge Time	min	[2, 19, 21, 22]	cost
C9	Vehicle Consumption	Wh / km	[2, 22, 25, 26]	cost
C10	Weight Unladen	kg	[19, 25]	benefit
C11	Max. Payload	kg	[25, 26]	benefit
C12	Cargo Volume	1	[19, 21, 22]	benefit

With the alternatives and criteria established, the initial decision-making matrix was formed. This matrix served as the foundation for the application of all Multi-Criteria Decision Making (MCDM) methods. The next phase involved data normalization. This process was necessary due to the variation in measurement units across different criteria and to establish a unified scale of values.

Weights of the criteria were then determined using objective MCDM methods. In contrast to subjective ratings from experts, these methods offer an impartial analysis of the criteria weights. Five methods were employed to ascertain these weights objectively: Entropy, CRITIC, MEREC, SD, and MSDM. This study also aims to scrutinize the influence of these weights on the final decision, and thus provide a basis for future research.

The next step was to rank the alternatives using the SAW method. This method was chosen for its simplicity, having no additional steps that could potentially alter the ranking of alternatives. The ranking of alternatives was completed for all weights obtained via the aforementioned objective methods. Finally, an evaluation was conducted on how these weights impacted the final decision regarding the selection of the Small Van vehicle best equipped for urban logistics activities.

In summary, this study adopted a rigorous and objective approach to identify the most suitable e-car for urban logistics. The methodology encompassed the construction of an initial decision-making matrix, data normalization, and the objective determination of criteria weights using various methods. This systematic approach facilitated the generation of meaningful and valuable insights into the choice of Small Van e-cars for urban logistics.

3.1 Determination of Objective Weights

Five methods were employed in the determination of criteria weights: Entropy, CRITIC, MEREC, SD, and MSDM, all of which are classified as objective weight determination methods. These methods calculate the weight of a criterion by considering the values of alternatives for a particular criterion. Notably, no subjective influence on criteria weights is encountered in these methods. An exposition on each method's operational steps follows.

3.1.1 Entropy method

The Entropy method derives weight values of criteria from the Entropy Value. The greater the dispersion of the data, the higher the Entropy Value and, by extension, the criterion weight. This method's progression can be divided into several steps:

Step 1: Formation of the initial decision matrix, achieved through alternative evaluation via selected criteria. Technical characteristics of e-cars are utilised in evaluation. A similar initial decision matrix (Table 2) is applied across all methods since the results of all methods are calculated from the selected e-cars' values.

Step 2: Normalization of the initial decision matrix, an integral step in the calculation of each MCDM method [27]. To limit the impact of normalization, the same normalization—linear normalization type 1 (simple linear normalization)—is applied to all methods. Considering the initial decision matrix reveals that some criteria values should be minimized, e.g., price, acceleration, charging time, for which cost criteria normalization is used. Conversely, for the criteria of maximum speed, range, and power, benefit normalization is utilized, as these values should be maximized.

$$n_{ij} = \frac{x_{ij}}{x_{j\,\max}}, \text{ for benefit criteria} \tag{1}$$

$$n_{ij} = \frac{x_{j\,\min}}{x_{ij}}, \text{ for cost criteria} \tag{2}$$

Step 3: Determination of the Entropy Value (E_i). Here, natural logarithm values (ln) of all data in the normalized decision matrix are computed. These values are then multiplied by the normalized data, and the product is divided by the natural logarithm value of the number of alternatives (ln(n)).

$$E_i = \frac{\sum_{j=1}^{n} p_{ij} \cdot \ln p_{ij}}{\ln n} \tag{3}$$

Step 4: Determination of criteria weight values. The calculation of $(1 - E_i)$ is executed, and these values are aggregated across all criteria. The ultimate weight of the criteria is then calculated.

$$w_i = \frac{1 - E_i}{\sum_{i=1}^{m} (1 - E_i)} \tag{4}$$

Table 2. Initial decision matrix

	C1 Cost	C2 Cost	C3 Ben.	C4 Ben.	C5 Ben.	C6 Ben.	C7 Cost	C8 Cost	C9 Cost	C10 Cost	C11 Ben.	C12 Ben.
A1	39300	12.6	132	215	51	44.0	285	39	205	1870	575	542
A2	37790	11.7	135	205	100	46.3	450	26	226	1739	626	571
A3	37800	11.2	135	210	100	46.3	450	26	220	1739	626	597
A4	42440	11.7	135	200	100	46.3	450	26	232	1884	646	806
A5	40150	11.2	135	205	100	46.3	450	26	226	1813	582	850
A6	41240	11.7	135	205	100	46.3	450	26	226	1765	615	571
A7	43050	11.7	135	205	100	46.3	450	26	226	1764	626	571
A8	43640	11.7	135	200	100	46.3	450	26	232	1876	639	806
A9	44750	11.7	135	200	100	46.3	450	26	232	1884	582	806

3.1.2 CRITIC method

The CRITIC method ascertains the weight value of the criteria based on their deviations—represented as the standard deviation—and the interconnectedness of these criteria via correlation analysis. This method is composed of several steps, which are identical to the first two steps of the Entropy method.

Step 1: Formation of the initial decision matrix.

Step 2: Normalization of the initial decision matrix.

Step 3: Determination of the information amount. Here, the standard deviation value (σ) is first computed, and the interconnectedness value of the criteria is calculated through correlation analysis (r_{jk}). The value ($1 - r_{jk}$) is then calculated and summed for individual criteria. Finally, this value is multiplied by the standard deviation.

$$C_j = \sigma \sum_{k=1}^{m} (1 - r_{jk}) \tag{5}$$

Step 4: Calculation of criteria weight. The final criterion weight is calculated.

$$W_j = \frac{C_j}{\sum_{j=1}^{m} C_j} \tag{6}$$

3.1.3 MEREC method

The MEREC method establishes the objective weights of the criteria based on the value of the natural logarithm and the effects of removal. The method's steps are consistent with the first two steps in the previous methods.

Step 1: Formation of the initial decision matrix.

Step 2: Normalization of the initial decision matrix.

Step 3: Calculation of the overall performance of the alternatives (S_i). Here, the logarithmic values of the normalized matrix are computed using the natural logarithm (ln). The sum of these values is divided by the number of criteria (m), after which the value one (1) is added. The natural logarithm is then calculated from this result.

$$S_i = \ln\left(1 + \left(\frac{1}{m}\sum_j \left|\ln\left(n_{ij}^x\right)\right|\right)\right), \tag{7}$$

Step 4: Quantifying the Effects of Alternatives for Each Criterion. This stage diverges from the computation of overall alternative performance by excluding the specific value of the criterion under consideration for each alternative. The logarithmic values, apart from the value of the alternative associated with the examined criterion, are accumulated. For instance, if calculations are being made for n_{23}, the value for the third criterion for the second alternative is disregarded. This process facilitates the generation of a new matrix consisting of these elements.

$$S'_{ij} = \ln\left(1 + \left(\frac{1}{m}\sum_{k, k\neq j} \left|\ln\left(n_{ik}^x\right)\right|\right)\right), \tag{8}$$

Step 5: Calculation of the sum of absolute value deviations. In this step, the jth criterion's effect is removed, and the sum of the resulting values is calculated for the observed criterion.

$$E_j = \sum_i \left| S'_{ij} - S_i \right|, \tag{9}$$

Step 6: Calculation of criterion weights. Here, the value E_j is divided by the sum of all E_j values, leading to the determination of the weight of the criteria.

$$w_j = \frac{E_j}{\Sigma_k E_j} \tag{10}$$

3.1.4 Standard deviation

This method uses the standard deviation values for the criteria to calculate their weights. The steps for this method match the first two steps in the previous methods.

Step 1: Formation of the initial decision matrix.

Step 2: Normalization of the initial decision matrix.

Step 3: Calculation of the observed criteria's standard deviation value.

$$\sigma = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} \left(n_{ij} - \bar{n}_j\right)^2} \tag{11}$$

Step 4: Calculation of criteria weight. This is achieved by dividing the specific criterion's standard deviation value by the sum of all criteria's standard deviations. This is calculated according to the expression:

$$W_j = \frac{\sigma_j}{\sum_{j=1}^{m} \sigma_j} \tag{12}$$

3.1.5 Modified Standard Deviation Method

This method expands the standard deviation method by introducing the sum of criterion values into the calculation. This method follows the same initial steps as the previous methods.

Step 1: Formation of the initial decision matrix.

Step 2: Normalization of the initial decision matrix.

Step 3: Calculation of the observed criteria's standard deviation value.

$$\sigma = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} \left(n_{ij} - \bar{n}_j\right)^2} \tag{13}$$

Step 4: Calculation of individual criteria's sum of values. All normalized alternative values for individual criteria are summed. For each criterion, the sum of alternative values for the observed criterion is calculated.

$$S_i = \sum_{j}^{m} x_{ij} \tag{14}$$

Step 5: Calculation of the corrected standard deviation value. The standard deviation value is divided by the sum values of individual criteria in this step.

$$\sigma' = \frac{\sigma_i}{s_i} \tag{15}$$

Step 6: Calculation of criteria weight. This is done by dividing the individual corrected standard deviation values by the sum of these values.

$$W_j = \frac{\sigma' j}{\sum_{j=1}^{m} \sigma' j} \tag{16}$$

3.2 Application of the SAW Method

Upon determination of the objective weights of the criteria, the SAW method is deployed for ranking the alternatives. Recognized for its simplicity and brevity, the SAW method involves fewer steps than other multiple criteria decision-making (MCDM) methods. The following elucidates the sequence of steps undertaken:

Step 1: Generation of the Initial Decision Matrix: This is the first phase where the primary decision matrix is formulated.

Step 2: Normalization of the Initial Decision Matrix: This phase involves the standardization of the initial decision matrix.

Step 3: Intensification of the Normalized Decision Matrix: In this phase, multiplication is executed between the initial normalized decision matrix and the criteria weights, represented as:

$$v_{ij} = n_{ij} \cdot w_j \tag{17}$$

Step 4: Computation of SAW Method Values: The final phase includes the summation of the aggravated decision matrix for individual criteria, formulated as:

$$S_i = \sum_{j=1}^{n} v_{ij} \tag{18}$$

The initial three stages remain consistent across all MCDM methodologies. In contrast, the fourth stage involves an aggregation of the intensified normalized data for individual alternatives, subsequently forming the SAW method value. The alternative rendering the highest SAW method value is deemed as the superior-ranked alternative.

Expanding on the above, it is pertinent to note the significance of the SAW method in MCDM. With its emphasis on simplicity and reduced computational steps, the SAW method allows for efficient decision-making. It achieves this by simultaneously taking into account multiple criteria and their respective weights. This strength, combined with its ability to rank alternatives effectively, underscores its utility in the field of MCDM, particularly in scenarios where decision matrices can become complex.

4 Results

As previously stated, across all methodologies, identical normalization was applied to the initial decision matrix values (Table 1). The nature of certain criteria dictated the normalization technique employed, dependent on whether a criterion was of benefit or cost type. Consequently, expressions 1 and 2 were utilized. In the case of expression 1, the maximum value of a criterion was identified and subsequently, every value of that criterion was divided by this maximum. For expression 2, the minimum value of the criterion was ascertained, following which, this minimum value was divided by each individual value of the criterion. This resulted in the formation of a normalized initial decision matrix (Table 3). The normalized decision matrix serves as a cornerstone for calculating criteria weights and for compiling a ranking list of alternatives.

Table 3. Normalized decision matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
A1	0.962	0.889	0.978	1.000	0.510	0.950	1.000	0.667	1.000	0.930	0.890	0.638
A2	1.000	0.957	1.000	0.953	1.000	1.000	0.633	1.000	0.907	1.000	0.969	0.672
A3	1.000	1.000	1.000	0.977	1.000	1.000	0.633	1.000	0.932	1.000	0.969	0.702
A4	0.890	0.957	1.000	0.930	1.000	1.000	0.633	1.000	0.884	0.923	1.000	0.948
A5	0.941	1.000	1.000	0.953	1.000	1.000	0.633	1.000	0.907	0.959	0.901	1.000
A6	0.916	0.957	1.000	0.953	1.000	1.000	0.633	1.000	0.907	0.985	0.952	0.672
A7	0.878	0.957	1.000	0.953	1.000	1.000	0.633	1.000	0.907	0.986	0.969	0.672
A8	0.866	0.957	1.000	0.930	1.000	1.000	0.633	1.000	0.884	0.927	0.989	0.948
A9	0.844	0.957	1.000	0.930	1.000	1.000	0.633	1.000	0.884	0.923	0.901	0.948

Initially, the weight of the criteria is ascertained, followed by the development of a ranking list. The first technique employed for the determination of criteria weights is the Entropy method. This method utilizes the values of the natural logarithm, multiplying them with the normalized data. Subsequently, the respective values for each criterion are aggregated and divided by the total number of alternatives (ln(9)). In this manner, the Entropy Value is determined (Table 4). Following this, the value 1-E_i is computed, culminating in the calculation of the criteria weights. According to the results, criterion C7 (w = 0.133) was allocated the highest weight, succeeded by criterion C12 (w = 0.109), while criterion C6 (w = 0.066) was assigned the least weight.

Table 4. Calculating the weight using the Entropy method

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
E_i	-0.300	-0.162	-0.010	-0.185	-0.156	-0.022	-1.053	-0.123	-0.340	-0.161	-0.201	-0.677
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
$1 - E_i$	1.300	1.162	1.010	1.185	1.156	1.022	2.053	1.123	1.340	1.161	1.201	1.677
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
w_j	0.084	0.075	0.066	0.077	0.075	0.066	0.133	0.073	0.087	0.075	0.078	0.109

Subsequent to the Entropy method, the calculation of weights proceeds with the CRITIC method. Initially, the first and second steps mirror those in all other methods, followed by the calculation of standard deviation and the establishment of a connection between research criteria through correlation analysis. The correlation value is then subtracted from one, and a summation of these values for the criteria is performed. Next, the information value is computed, emerging as a product of previous calculations of the sum of reciprocal correlation and standard deviation. Ultimately, the weights of the criteria are determined based on the information value. In accordance with the results from the Entropy method, criterion C7 (w = 0.270) was assigned the highest weight, succeeded by criterion C12 (w = 0.269), while criterion C3 (w = 0.039) was attributed the least weight. Contrasting with the weights derived from the Entropy method, a wider dispersion in weights is observed in the results from the CRITIC method (Table 5), with larger deviations between the largest and smallest weights.

Table 5. Calculation of weights using the CRITIC method

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
σ	0.057	0.032	0.007	0.023	0.163	0.017	0.122	0.111	0.036	0.034	0.041	0.155
$\sum_{k=1}^{m}(1 - r_{jk})$	10.39	8.30	8.84	12.76	8.84	8.84	15.16	8.84	13.79	8.99	9.91	11.95
C_j	0.595	0.267	0.065	0.297	1.444	0.146	1.853	0.982	0.503	0.305	0.407	1.847
w_j	0.087	0.039	0.010	0.043	0.210	0.021	0.270	0.143	0.073	0.044	0.059	0.269

For the calculation of weights using the MEREC method, the computation initiates with the total performance value of alternatives (S_i), which is determined based on the natural logarithm of the normalized decision matrix. Following this, the sum is computed and divided by the total number of criteria, to which the value of one is then added. The natural logarithm is calculated from this resultant value. Next, the impacts of alternatives (S'_{ij}) are calculated for each criterion, paralleling the method used for the overall performance value, except this time applying the values specific to the criterion being calculated. Thereafter, the absolute value of the difference between these two values is sought, and the sums of those values for each criterion (E_j) are calculated, thereby determining the final weight of the criterion. The analysis reveals (Table 6) that criterion C7 (w = 0.285) received the most weight, followed by criterion C12 (w = 0.146), while criterion C9 (w = 0.029) received the least weight.

In the process of determining weights using the Standard Deviation (SD) method, it is crucial to compute the standard deviation (σ) values for all criteria, followed by weight calculation. Results (Table 7) reveal that the criterion C5 (w = 0.204) received the highest weight, closely followed by criterion C12 (w = 0.193), while criterion C3 (w = 0.009) received the lowest weight.

Conversely, the Modified Standard Deviation Method (MSDM) has an additional step where the sum of the criteria is calculated and the standard deviation value is divided by this sum. This approach diminishes the preference for criteria where the alternative values are closely aligned to unity, essentially the criteria lacking considerable dispersion. Results (Table 8) demonstrate that criterion C12 (w = 0.209) was allocated the most weight, followed by criterion C7 (w = 0.196), with criterion C3 (w = 0.008) receiving the least weight.

Once the weights of the criteria were derived using different methods, a comparative analysis was conducted prior to ranking the alternatives and examining the impact of the methodologies on this ranking. For easier comparison, a table listing the weights of the criteria for each method was created (Table 9).

The correlation analysis results for the weights of criteria, obtained through different methods, highlight that the strongest correlation is between the weights calculated by the CRITIC and MSDM methods (r = 0.9903). In contrast, the weakest correlation is observed between the weights computed via the Entropy and SD methods (r = 0.5474). From these findings (Table 10), it can be inferred that the results from the Entropy method exhibit the most significant deviation from the other methods, followed by the divergence of the MEREC method. To examine the implications of these weight variations, the SAW method was employed to generate a ranking of the alternatives.

Table 6. Calculation of weights using the MEREC method

						$\mathbf{S'_{ij}}$							
	S_i	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
A1	0.150	0.160	0.154	0.161	0.163	0.110	0.159	0.163	0.131	0.163	0.157	0.154	0.128
A2	0.086	0.093	0.090	0.093	0.089	0.093	0.093	0.055	0.093	0.085	0.093	0.091	0.060
A3	0.075	0.082	0.082	0.082	0.080	0.082	0.082	0.043	0.082	0.076	0.082	0.079	0.052
A4	0.076	0.073	0.079	0.082	0.076	0.082	0.082	0.043	0.082	0.072	0.076	0.082	0.078
A5	0.065	0.066	0.071	0.071	0.067	0.071	0.071	0.031	0.071	0.063	0.067	0.062	0.071
A6	0.095	0.096	0.100	0.103	0.099	0.103	0.103	0.065	0.103	0.095	0.102	0.099	0.070
A7	0.097	0.094	0.102	0.105	0.101	0.105	0.105	0.067	0.105	0.097	0.104	0.103	0.072
A8	0.079	0.073	0.082	0.085	0.079	0.085	0.085	0.046	0.085	0.075	0.079	0.084	0.081
$A9$	0.088	0.082	0.092	0.096	0.090	0.096	0.096	0.057	0.096	0.085	0.089	0.087	0.091
		C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
	A1	0.010	0.003	0.011	0.013	0.041	0.009	0.013	0.019	0.013	0.007	0.004	0.023
	A2	0.007	0.004	0.007	0.003	0.007	0.007	0.031	0.007	0.001	0.007	0.005	0.026
	A3	0.007	0.007	0.007	0.005	0.007	0.007	0.032	0.007	0.001	0.007	0.004	0.023
	A4	0.003	0.003	0.007	0.001	0.007	0.007	0.032	0.007	0.004	0.000	0.007	0.002
$\left\|S'_{ij} - S_i\right\|$	A5	0.001	0.006	0.006	0.002	0.006	0.006	0.034	0.006	0.003	0.002	0.003	0.006
	A6	0.001	0.005	0.008	0.004	0.008	0.008	0.030	0.008	0.000	0.007	0.004	0.025
	A7	0.002	0.005	0.008	0.004	0.008	0.008	0.030	0.008	0.000	0.007	0.006	0.025
	A8	0.005	0.003	0.007	0.001	0.007	0.007	0.032	0.007	0.004	0.000	0.006	0.002
	A9	0.006	0.004	0.008	0.002	0.008	0.008	0.031	0.008	0.003	0.001	0.001	0.003
		C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
E_j		0.042	0.039	0.068	0.034	0.098	0.066	0.265	0.077	0.027	0.039	0.039	0.136
w_j		0.046	0.042	0.073	0.037	0.106	0.071	0.285	0.082	0.029	0.042	0.042	0.146

Table 7. Calculation of weights using the standard deviation method

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**	**C11**	**C12**
σ	0.057	0.032	0.007	0.023	0.163	0.017	0.122	0.111	0.036	0.034	0.041	0.155
w_j	0.072	0.040	0.009	0.029	0.204	0.021	0.153	0.139	0.046	0.042	0.051	0.193

Table 8. Calculation of weights using the Modified Standard Deviation Method

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**	**C11**	**C12**
σ	0.057	0.032	0.007	0.023	0.163	0.017	0.122	0.111	0.036	0.034	0.041	0.155
S_i	8.298	8.632	8.978	8.581	8.510	8.950	6.067	8.667	8.211	8.633	8.540	7.200
σ'	0.007	0.004	0.001	0.003	0.019	0.002	0.020	0.013	0.004	0.004	0.005	0.021
w_j	0.067	0.036	0.008	0.026	0.187	0.018	0.196	0.125	0.043	0.038	0.047	0.209

Table 9. Criteria weights according to individual methods

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**	**C11**	**C12**
ENTROPY	0.084	0.075	0.066	0.077	0.075	0.066	0.133	0.073	0.087	0.075	0.078	0.109
CRITIC	0.087	0.039	0.010	0.043	0.210	0.021	0.270	0.143	0.073	0.044	0.059	0.269
MEREC	0.046	0.042	0.073	0.037	0.106	0.071	0.285	0.082	0.029	0.042	0.042	0.146
SD	0.072	0.040	0.009	0.029	0.204	0.021	0.153	0.139	0.046	0.042	0.051	0.193
MSDM	0.067	0.036	0.008	0.026	0.187	0.018	0.196	0.125	0.043	0.038	0.047	0.209

Table 10. Correlation analysis of the weights of the criteria

	ENTROPY	**CRITIC**	**MEREC**	**SD**	**MSDM**
ENTROPY	1.0000	0.7838	0.8344	0.5474	0.6972
CRITIC	0.7838	1.0000	0.8055	0.9454	0.9903
MEREC	0.8344	0.8055	1.0000	0.6334	0.7625
SD	0.5474	0.9454	0.6334	1.0000	0.9790
MSDM	0.6972	0.9903	0.7570	0.9790	1.0000

To assess the influence of these weights, a ranking of alternatives was executed using the SAW method. The SAW method involves multiplying the normalized decision matrix by the weights, and the weighted data are then summed for individual alternatives. Using the Entropy method weights, the SAW calculation is demonstrated (Table 11). These results indicate minimal deviation across all alternatives, with alternative A5 scoring the highest (S5 = 0.893), and A1 the lowest (S1 = 0.849). Consequently, the alternatives are ranked, and when the weights of the criteria obtained by the Entropy method are applied, Toyota Proace City Verso Electric L2 (A5) presents the best indicators. Accordingly, the ranking order is determined for all weights obtained from the various methods.

Table 11. Results of the SAW method

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**	**C11**	**C12**	S_i
A1	0.081	0.067	0.064	0.077	0.038	0.063	0.133	0.049	0.087	0.070	0.069	0.050	0.849
A2	0.084	0.072	0.066	0.073	0.075	0.066	0.084	0.073	0.079	0.075	0.076	0.052	0.877
A3	0.084	0.075	0.066	0.075	0.075	0.066	0.084	0.073	0.081	0.075	0.076	0.055	0.887
A4	0.075	0.072	0.066	0.072	0.075	0.066	0.084	0.073	0.077	0.070	0.078	0.074	0.882
A5	0.080	0.075	0.066	0.073	0.075	0.066	0.084	0.073	0.079	0.072	0.070	0.078	0.893
A6	0.077	0.072	0.066	0.073	0.075	0.066	0.084	0.073	0.079	0.074	0.074	0.052	0.868
A7	0.074	0.072	0.066	0.073	0.075	0.066	0.084	0.073	0.079	0.074	0.076	0.052	0.866
A8	0.073	0.072	0.066	0.072	0.075	0.066	0.084	0.073	0.077	0.070	0.077	0.074	0.880
A9	0.071	0.072	0.066	0.072	0.075	0.066	0.084	0.073	0.077	0.070	0.070	0.074	0.871

Analytical results (Figure 2) reveal that weights obtained from the Entropy, CRITIC, SD, and MSDM methods yield identical ranking orders, with only the MEREC method differing. Applying these weights, the worst-performing alternative in the other methods yields the best results, while the ranking order of the other alternatives is shifted by one position. The reason lies in the technical specifications of the Renault Kangoo E-Tech (A1) vehicle, which has superior characteristics in criteria C1, C4, C7, and C9.

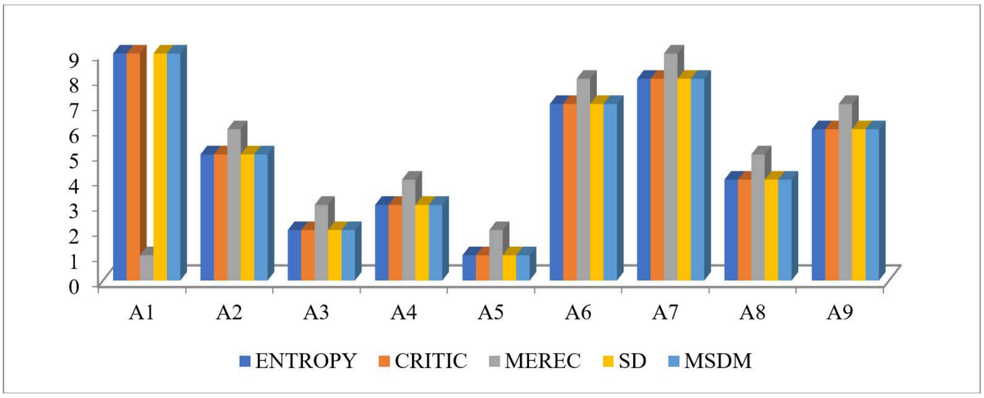

Figure 2. Ranking of alternatives using different criteria weights

Further analysis reveals the key criterion C7 received 2.5 times more weight than the second-ranked criterion, and 7.7 times more than the least-weighted criterion C4, using the MEREC method. As a result, the Charge Time criterion (C7) was emphasized. This vehicle possesses the shortest charging time among all others, which is 36.67% less than that of the other vehicles, thus rendering alternative A1 as the top-rated alternative, even though it was the lowest ranked in other weights.

This example clearly demonstrates how methods used to determine objective weights of criteria can significantly impact the final alternative ranking. If tasked with deciding which e-car presents the best indicators, the evidence points towards the Toyota Proace City Verso Electric L2 (A5).

5 Discussion

Urban logistics exerts significant impacts on the environment, propelling the introduction of novel concepts such as e-cars, which serve to mitigate costs and air pollution associated with urban logistics [7]. However, the selection of e-cars necessitates an assessment of technical features such as battery capacity and range on a single charge. This multifaceted decision-making process involves the evaluation of numerous criteria, each of which contributes to the ultimate decision in a unique way. Assigning weights to these criteria enables more effective decision-making, with subjective methods relying on the expertise of decision-makers while objective methods use alternative values corresponding to individual criteria. The focus of the current research was to investigate how these objective weighting methods influence the final decision.

In the study, a total of nine small vans were evaluated against 12 criteria representing their technical characteristics. Data from ev-database.org was used to select Small Van type vehicles suitable for delivery purposes, and criteria significant to urban logistics were chosen. These criteria required the assignment of weights, which were determined using five different objective methods: Entropy, CRITIC, MEREC, SD, and MSDM. Each method possesses unique characteristics and procedures and uses different units of measure for criteria. Therefore, data normalization was employed to harmonize these criteria [19].

During the calculation of criterion weights, it was observed that Charge Time (C7) emerged as the most important criterion in three out of five methods. This was attributed to the large dispersion of alternative values for this criterion. Additionally, the charging time is crucial for urban logistics because once a battery is depleted, it must be recharged for the vehicle to continue operations, thus affecting logistics efficiency. Moreover, the larger the battery capacity, the longer the charging time required, making battery capacity another crucial factor. Cargo Volume (C12), indicating the amount of goods a vehicle can transport, was also considered significant.

The ranking of criteria weights varied across the different methods, and this was found to notably influence the final vehicle selection. Optimal routes are necessary for e-cars in urban logistics to compensate for their limitations [14]. The Simple Additive Weighting (SAW) method was applied using the obtained weights to select the most suitable vehicles. It was observed that four out of the five methods selected the Toyota Proace City Verso Electric L2 (A5) as the optimal vehicle. However, with the weights derived from the MEREC method, the Renault Kangoo E-Tech (A1) was ranked first, although it received the lowest rank when the other four weight sets were used. This was because the MEREC method gave more weight to the criteria where this vehicle performed best.

This study highlights the critical role of criteria weights in decision-making. Small variations in these weights could elevate the worst-performing vehicle to the top rank, especially in cases where vehicle characteristics are similar and lack significant deviations. Therefore, the weights of the criteria must be carefully considered as they dictate the decision-making process. Some studies have suggested combining objective and subjective weights to cater to the needs of alternative users, reducing subjectivity while respecting the input of decision-makers [22]. However, the present research did not incorporate subjective opinions from individual companies to maintain a more universal applicability, as focusing on specific companies may skew the decision-making process to their preferences rather than those of other stakeholders.

6 Conclusions

In the present investigation, the research objectives were effectively realized. The adopted methodology and resultant findings effectively served as decision-making support in the selection of e-cars for urban logistics. This support encompassed a blend of multiple MCDM methods aimed at assigning criteria weights and ranking alternatives. A comprehensive assessment of 12 criteria and 9 alternatives was undertaken to facilitate the optimal selection of e-cars for urban logistics. Concurrently, the influence of various methods for the objective determination of criteria weights on the final choice was scrutinized.

It was elucidated that the MEREC method manifested the greatest deviation from the rankings obtained via other methods. Consequently, the Toyota Proace City Verso Electric L2 (A5) emerged as the optimal e-car choice across other methods, owing to its superior technical characteristics for urban logistics. Conversely, the MEREC method ranked the Renault Kangoo E-Tech (A1) as the most favorable option. This was attributed to the significantly higher weights accorded to the criteria in which this vehicle showcased its best characteristics by the MEREC method.

These findings underscore the potential of such methodical selection processes to augment the implementation of green logistics within urban areas. This research highlights the importance of the criteria weights determination process in the decision-making context, proving it crucial to the final selection of e-cars. Thus, the importance of method selection is emphasized, as different methods may yield disparate results, underlining the necessity for careful consideration and potential combination of multiple methods for more accurate results.

By presenting a clear, replicable methodology for decision-making, this research may prove beneficial for further applications in e-car selection or similar contexts. Moreover, it contributes to the broader goal of sustainable urban development by providing a mechanism for promoting greener, more efficient urban logistics. This investigation showcases the potential for future research in this area, including the exploration of further objective weighting methods and their impacts on decision-making within the urban logistics context. The insights gained from this study can provide a valuable foundation for future investigations aimed at developing more sustainable logistics systems.

Author Contributions

Conceptualization, A.P.; methodology, A.P.; software, A.P. and A.Š.; validation, I.S. and A.Š.; formal analysis, A.P.; investigation, I.S.; resources, I.S.; data curation, A.P.; writing—original draft preparation, A.P., and I.S.;

writing—review and editing, I.S. and A.Š.; visualization, A.Š.; supervision, I.S.; project administration, A.P.; funding acquisition, I.S. All authors have read and agreed to the published version of the manuscript.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

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