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Comparative Investigation of Normalization Techniques and Their Influence on MCDM Ranking – A Case Study

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ABSTRACT

Urban traffic significantly contributes to air pollution, and its effects are expected to increase in the coming years. Environmental policy measures can help achieve long-term goals, in which new modes of mobility for residents can play a significant role. However, local-level decision-making is also crucial. In the face of economic volatility, cities must carefully decide on sustainable transportation expenditures that respect budget limitations and promote local air quality standards. To create a sustainable traffic strategy and address the rise in traffic demands due to increased passenger transport, the use of buses with alternative drive technologies and fuel options is becoming increasingly important in European cities. However, buses utilizing alternative drive technologies and fuel options have varying impacts on air pollution, and the required investments and expenses vary. To determine the appropriate propulsion technology and fuel for buses specifically in Nis, the analysis based on multiple criteria will be conducted using the CRITIC (Criteria Importance Through Intercriteria Correlation) and in the following TOPSIS (Technique for Order Performance by Similarity to Ideal Solution) methods according to the defined criteria. The CRITIC method utilizes different normalization types to compute weighting coefficients and analyze their effect on the alternative rankings. Additionally, Spearman's rank correlation coefficient will be used to examine the degree of correlation between the rankings of different alternative drive technologies and fuel options for buses, calculated through the TOPSIS method.

1. Introduction

The idea of sustainable development involves balancing a variety of different sectorial interests and priorities. Sustainability involves blending economic development with environmental responsibility and social progress, prioritizing human interests. Sustainable development aims to create a functional equilibrium between resource use and the social system's capacity to fulfill people's needs. It advocates for a quality life for everyone while introducing a sense of responsibility in resource disposal, representing a new ethical aspect of social development.

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Development represents a balance between resource consumption and nature's capacity to renew itself, thereby meeting the needs of future generations. It arises from the interplay of economics, technology, ecology, and social policy. In addition to the components of integral development, modern sustainable development encompasses the harmonization of environmental protection and enhancement with the needs of both present and future generations. This concept is based on intergenerational fairness and equality. The integration of ecological considerations arises from a growing awareness of the necessity to preserve the planet and its resources. Development fosters the adoption of new technologies and the use of renewable resources.

The primary causes of air pollution in cities are associated with the release of pollutants from fossil fuel combustion in transportation and energy production, industrial plants, waste disposal areas, and other sources. The main pollutants responsible for poor air quality in urban areas are nitrogen oxides (NO_X), soot, sulfur dioxide (SO_2), carbon monoxide (CO), fine particulate matter (PM), and volatile organic compounds (VOCs). The emission of CO_2, which impacts climate change through the "greenhouse" effect, warrants special attention.

A big problem in urban areas due to topological, climatic, and other conditions is the uneven distribution of pollutants, i.e. their concentration in certain areas, the so-called "hot spots" where there is an extreme increase in the concentration of certain pollutants. This happens in commercial areas, at traffic intersections, and on other regulated roads. People who live in the mentioned areas are extremely exposed to those influences.

To enhance urban mobility, the EU has set ambitious obligations to cut emissions, with specific greenhouse gas (GHG) reduction targets for member states, addressing public health concerns linked to air quality, aligning with EU air quality goals, ensuring fuel security, and promoting the transition to alternative energy sources [1].

Buses are essential to the operation of many public transport networks in Europe and constitute a key component of local transport fleets in most EU countries. According to data from Eurostat, the EU's statistical office, the age of around 50% of buses and trolleybuses in the EU are more than a decade old. As only a limited number of modern fleets comply with the Euro VI standard, buses remain a significant source of local pollution. Choosing a bus that is more energy-efficient, cleaner, or has reduced carbon emissions helps drive the decarbonization of urban transport and enhances air quality in urban areas. The shift toward alternative drive technologies and fuel options for city buses is a timely issue, as adopting clean vehicles will support the EU’s air quality targets [2]. According to the European Commission's initiative (European Clean Bus Deployment Initiative), the authorities of certain countries and cities have undertaken to buy buses with low emissions of exhaust gases. The governments of Norway, along with the cities of Athens, Paris, and Madrid, have plans to gradually eliminate diesel vehicles [3]. Also, cities (Copenhagen, London, Berlin, and Oslo) have announced their plans to stop buying buses powered by conventional diesel fuel. Conventional propulsion that has been in use for a long time in recent years has been technologically improved. The swift rise in environmental pollution, caused directly by the combustion of fossil fuels, has led to an increased focus on the advancement of propulsion systems and alternative fuels. Regulation 595/2009, related to the certification of vehicles and engines regarding pollutants from heavy-duty vehicles (Euro VI), has been applied starting in January 2014. This standard aims to reduce nitrogen oxide emissions by 80% and particulate matter (PM) emissions by 66% compared to the limits established by the Euro V standard, which was implemented in 2008 [4].

The rapid advancement of innovations aimed at enhancing the sustainability of public transport often surpasses the typical lifespan of a bus, posing significant challenges and financial burdens for decision-makers attempting to stay abreast of developments. Due to the longstanding reliance on diesel engines, diesel buses offer distinct advantages, including predictable efficiency, maintenance requirements, and operating costs.

Therefore, the question arises: what are the benefits of alternative drive technologies and fuel options, considering current environmental protection standards, when compared to conventional diesel-powered buses versus those utilizing alternative fuels?

A key strategy for significantly reducing harmful gas emissions is the gradual phase-out of vehicles powered by conventional fuels in urban areas. Given that sustainable urban transport necessitates increased reliance on cleaner public transport, a multi-criteria analysis of different alternative propulsion technologies and fuel options for public buses was conducted for Niš as a case study. The ranking results, evaluated from a sustainability perspective, can provide valuable insights to decision-makers at both global and regional/local levels in selecting the most suitable propulsion technology and fuel for buses.

The paper will carry out a quantitative and qualitative analysis of current alternative bus propulsion technology and fuel for the city of Nis, starting from the adopted criteria, using the multi-criteria TOPSIS method in which the criteria weight coefficients were derived using the CRITIC method, incorporating various types of normalization. The criteria used for ranking reflect the characteristics of alternative propulsion technologies and fuel options for buses, considering their impact on air pollution, noise generation, as well as the associated costs and energy consumption.

2. Background

The methods of multi-criteria analysis are conceptually not particularly complex, and in the formal sense, they are simpler to understand than classic single-criteria optimization. A large number of different methods of multi-criteria analysis can be found in the literature [5-11]. Depending on the method used, a ranking of alternatives, the best alternative, and a set of alternatives that meet certain conditions are obtained as a solution. Multi-criteria analysis enables the comparison of alternatives based on a set of criteria, by measuring the aspects by which the dimensions of the various possibilities under consideration can be characterized.

An important step in the application of multi-criteria methods is normalization. The effectiveness of normalization techniques is primarily understood through empirical studies that compare a limited range of methods. Extensive research on the influence of normalization approaches in ranking alternatives for multi-criteria decision problems has shown that certain techniques are more compatible with specific decision-making methods than others [12-14].

Normalization is not only an integral aspect of most multi-criteria ranking methodologies but also serves as the preliminary stage in unbiased prioritization techniques. These approaches are designed to assess the relative significance of criteria solely on the available data, making them particularly advantageous when the evaluator has no direct influence over the process. When determining the weighting coefficients, approaches based on the application of subjective or objective methods, as well as their combination can be highlighted.

Utilizing the Multiple Criteria Decision Making (MCDM) methodology to assess and rank alternatives in multi-criteria decision-making problems is a logical and structured approach. Given that criteria with different units can't be directly compared, they need to be converted into a dimensionless form, for which various normalization techniques have been proposed. However, normalization techniques can significantly influence the final ranking of an MCDM method, potentially altering the best alternative and overall ranking. As a result, selecting an inappropriate technique may compromise the quality of the outcomes. There is no definitive agreement on the most effective normalization method.

It is crucial to consider both the final MCDM outcomes and the effectiveness of normalization techniques, as well as the data types (such as fuzzy or crisp), since both play key roles in MCDM and can directly influence the results. In the paper [15], the economic performance of G-20 countries, which encompass diverse data structures, was analyzed across ten different decision matrices over time. The authors employed ten distinct crisp-based MCDM methods—COPRAS, CODAS, MOORA, TOPSIS, MABAC, VIKOR (S, R, Q), FUCA, and ELECTRE III—to provide a comprehensive perspective. The paper explored the connections between two distinct real-world reference points and MCDM methods. The CODAS method demonstrated a strong correlation with both reference points during most periods. Additionally, the paper identified the optimal technique of normalization for CODAS method, with the maximum normalization technique outperforming alternatives such as min-max, vector, sum, and other ranking-based methods. The findings were highly consistent, leading to the recommendation of the "Maximum normalization-based fuzzy integrated CODAS procedure" for decision-makers to evaluate the financial performance of nations [15].

The paper [16] explores how normalization techniques can impact the relationship between MCDM methods and external factors. In other words, it examines how different normalization approaches affect the MCDM's connection to external reference points, aiming for a fair evaluation. The findings suggest that the most effective normalization technique may vary periodically. The authors suggest a versatile framework for selecting normalization methods in multi-criteria decision-making approaches, which can be adjusted to account for variations in financial data over time [16].

Therefore, selecting the appropriate normalization technique is crucial in decision-making problems. The study in [17] explores the influence of different normalization methods on the outcomes of the Combined Compromise Solution (CoCoSo) method across various scenarios. The findings suggest that improved precision, non-linear normalization, and linear normalization techniques can serve as viable alternatives to the Weitendorf linear normalization in the CoCoSo algorithm. In contrast, vector normalization and linear sum-based normalization techniques were deemed unsuitable for the CoCoSo method. This study represents the first attempt to evaluate the suitability of various normalization techniques for the CoCoSo method [17].

The paper [18] aims to highlight the advantages and disadvantages of various normalization techniques applicable to MCDM problems. To compare these techniques, fourteen different decision problem scenarios were analyzed. The results suggest that normalization techniques based on optimization are favored when the decision-maker aims to choose the alternative extreme value in the criteria. In contrast, reference-based normalization methods are more appropriate when ideal values for each criterion have been determined by the decision-maker. If the decision-maker perceives that the criterion values do not exhibit a consistent increase or decrease in terms of benefit or cost, non-linear normalization methods should be employed. In situations where conditions fluctuate, hybrid normalization techniques may be preferable. However, specific data structures, such as the presence of zero or negative values in the decision matrix, can restrict the applicability of certain methods. The choice of normalization technique may also be influenced by factors such as rank reversal, the range of normalized values, and uniformity in optimization across all criteria, and the precision of the results [18].

The RAWEC (Ranking of Alternatives with Weights of Criterion) method is a newly proposed multiple criteria decision making technique introduced in early 2024, which stand out due to its simplicity and minimal implementation steps [19, 20]. A unique feature of RAWEC is its simultaneous use of two data normalization approaches, setting it apart from most other MCDM methods. However, the method cannot be applied when there is at least one zero element in the decision matrix. The paper [21] addresses these limitations by exploring suitable data normalization methods to pair with RAWEC in various scenarios. The results highlight an alternative normalization approach capable of substituting the current method in RAWEC when the decision matrix contains zero elements [21].

The papers [22, 23] introduce an enhanced version of the CRiteria Importance Through Intercriteria Correlation (CRITIC) method. In the adapted CRITIC method (CRITIC-M), improvements are made to both the normalization of the decision matrix elements and the aggregation function used to process the normalized data. Modified normalization method minimizes discrepancies between normalized elements, leading to smaller standard deviations and offering a more objective representation of the relationships in the original decision matrix. Furthermore, the enhanced aggregation technique offers a broader perspective on the matrix data, resulting in more accurate weight values. The integration of fuzzy rough numbers helps to account for uncertainties within the CRITIC-M approach [23].

The outcomes of multi-criteria methods are influenced not only by the input data and weight coefficients but also by the type of normalization applied in the method being analyzed. Numerous studies [24, 25] explore the effects of altering the type of normalization on the results produced by multi-criteria methods. However, the effects of altering the normalization type within the CRITIC method on the resulting weight coefficient values, and their influence on the MCDM ranking performed using the TOPSIS method, which is the primary objective of this paper, have not been previously examined.

3. MCDM approach and Input Data discussion

3.1 CRITIC method

Conflicts between various criteria are a fundamental aspect of multi-criteria decision processes, representing the core of every decision-making scenario [26]. In cases of multi-dimensional decision analysis where criteria values of the alternatives are in complete agreement according to all criteria, the solution is obvious. However, when there is a conflict between criteria, addressing the multi-criteria problem requires the use of intricate methods to choose the preferred alternative or establish the ranking of the available options.

The CRITIC (CRiteria Importance Through Intercriteria Correlation) technique is widely recognized in the literature as one of the most prominent techniques for determining criteria weight coefficients. The method is employed to determine the objective weights of criteria, accounting for the intensity of contrast and conflict inherent in the structure of the decision problem. Classified as a correlational method, it relies on an analytical assessment of the decision matrix to extract the information embedded in the criteria used to evaluate the alternatives. To evaluate the contrast between criteria, the standard deviations of the normalized criterion values for each alternative, by column, are utilized, along with the correlation coefficients of all column pairs. Based on this analysis, it can be inferred that the higher the amount of information derived from a given criterion, the greater its relative importance in the decision-making process. This methodology fundamentally relies on the analytical review of the decision matrix to uncover the information within the criteria that facilitates the evaluation of the alternatives. The implementation of the CRITIC method involves the following steps [27, 28]:

i. Construct the preliminary decision matrix.
ii. Create the normalized adjusted matrix (linear max-min).

For criterion maximization (benefit), the normalized values are determined using the following approach:

$$r_{ij} = \frac{a_{ij} - a_i^-}{a_i^+ - a_i^-} \tag{1}$$

For criterion minimization (cost), the normalized values are determined using the following approach:

$$r_{ij} = \frac{a_i^+ - a_{ij}}{a_i^+ - a_i^-} \tag{2}$$

Within formulations (1) and (2) members are representing the components of the preliminary decision matrix:

a_i^+ - the highest value of the given criterion among the alternatives, which means $a_i^+ = \max(x_1, x_2, \ldots, x_m)$ and

a_i^- - the lowest value of the given criterion among the alternatives., which means $a_i^- = \min(x_1, x_2, \ldots, x_m)$.

iii. Generate a criterion vector based on the given value r_{ij}, with each vector having a standard deviation σ_j.

$$\sigma_j = \sqrt{\frac{1}{n}\sum_{j=1}^{n}\left(r_{ij} - \overline{r_j}\right)^2} \tag{3}$$

where *n* - denotes the total number of criteria, $\overline{r_j}$ - the average value of the elements in the normalized matrix.

iv. Determine the correlation coefficient for the interdependence of each pair of criteria.

$$R_{ij} = \frac{n\sum r_j r_k - \sum r_j \sum r_k}{\sqrt{n\sum r_j^2 - \left(\sum r_j\right)^2} \cdot \sqrt{n\sum r_k^2 - \left(\sum r_k\right)^2}} \tag{4}$$

v. Determine the conflict measure of the criteria to the other criteria within the provided decision matrix.

$$\sum_{k=1}^{n}\left(1 - R_{jk}\right) \tag{5}$$

vi. Calculate the amount of information to each criterion.

$$C_j = \sigma_j \sum_{i=1}^{m}\left(1 - r_{ij}\right) \tag{6}$$

vii. Calculate the weighting coefficients by normalizing the C_j value.

$$w_j = \frac{C_j}{\sum_{j=1}^{n} C_j}, \; j = 1, \ldots, n \tag{7}$$

3.2 TOPSIS method

The mentioned method was introduced to tackle decision-making problems involving multiple criteria when there are no preferred or most important criteria [29]. The solution provided by the TOPSIS method is defined as the alternative that is maximally distant from the negative ideal and simultaneously closest to the ideal solution. Four key advantages of the TOPSIS method can be singled out: (1) principles underlying people's logical decision choices; (2) a single numerical value that allows for the evaluation or identification of both the optimal and least favorable alternatives; (3) a straightforward calculation procedure that is easily programmable; and (4) the ability to depict criterion values of preferred alternatives for all options on a polyhedron in any two-dimensional projection. This method has a significant application within the assessment of certain aspects of sustainable development [30-32].

When applying the TOPSIS method, it is vital to underscore the significance of choosing appropriate criteria for evaluating alternatives, as this complex and pivotal task has a profound impact on the final assessment outcomes. Another important step in applying the TOPSIS method is determining the weighting coefficients, which considerably impact the final result.

The steps involved in the TOPSIS method can be illustrated as follows [28, 29]:

Step 1: Construction of a normalized decision matrix

$$r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{m} a_{ij}^2}} \tag{8}$$

where r_{ij} represents the normalized performance of the i-th alternative in relation to the j-th criterion.

Step 2: Determination of ideal (A+) and negative ideal solutions (A^-). The ideal solution (A+) and the negative ideal solution (A^-) are determined using the formulas:

$$\begin{aligned} A^+ &= \left\{v_1^+, v_2^+, \ldots, v_n^+\right\} = \left\{\left(\max_i v_{ij} \,\middle|\, j \in J^{\max}\right), \left(\min_i v_{ij} \,\middle|\, j \in J^{\min}\right),\right\} \\ A^- &= \left\{v_1^-, v_2^-, \ldots, v_n^-\right\} = \left\{\left(\min_i v_{ij} \,\middle|\, j \in J^{\max}\right), \left(\max_i v_{ij} \,\middle|\, j \in J^{\min}\right),\right\} \end{aligned} \tag{9}$$

where J^{max} represents the criteria that are maximized, J^{min} the criteria that are minimized and v_{ij} represents the weight-normalized performance of the *i*-th alternative in relation to the *j*-th criterion, which is obtained by applying the following formula:

$$v_{ij} = w_j \cdot r_{ij} \tag{10}$$

Step 3: Calculating the distance of alternatives from the ideal and negative ideal solution.

The distance of the alternatives from the ideal and negative ideal solution is done using the following formulas:

$$\begin{aligned} d_i^+ &= \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^+\right)^2} \\ d_i^- &= \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)^2} \end{aligned} \tag{11}$$

Here, the deviation that each alternative has from the ideal positive and negative solutions is determined. The value should be as close as possible to the ideal positive solution and further away from the ideal negative solution. It would be best if each alternative had the same values as the ideal positive solution.

Step 4: Determining the relative proximity (S_i) of alternatives to the ideal solution.

The relative distance of the alternative a_j in relation to the ideal solution A^+ is defined as:

$$S_i = \frac{d_i^-}{d_i^+ + d_i^-} \tag{12}$$

The result based on this formula is $0 \leq S_i \leq 1$. When the alternative A_i is closer to the ideal solution, then the value of S_i is closer to unity. The best alternative is the one that is closest to or even occupies the value of one, and the other alternatives are ranked in descending order of value.

The best alternative is the one with the highest S_i and is determined using the formula:

$$A^* = \max_i \frac{d_i^-}{d_i^+ + d_i^-} \tag{13}$$

3.3 Analysis of the Input Data

Significant challenges associated with fossil fuels, which are non-renewable resources, include the rapid depletion of global reserves at a rate exceeding the discovery of new deposits, as well as the fact that the combustion of fossil fuels in vehicle engines releases the highest volume of greenhouse gases into the atmosphere compared to other energy sources used for vehicle operation. At today's level of technological development applied by buses, four main sources of energy are available: fossil fuels, biofuels, electricity, and hydrogen. The available options include various bus technologies that operate using either a single energy source or a combination of multiple energy sources (hybrid systems).

Buses utilizing compressed natural gas (CNG), second-generation biofuels, electricity, as well as hybrid systems combining electricity with hydrogen or diesel, are regarded as the most advanced and environmentally friendly solutions. Additionally, the implementation of Euro VI emission standards for fossil diesel buses has made these vehicles nearly comparable to alternative technologies in terms of emissions.

In terms of fossil fuels, buses can operate using diesel, compressed natural gas (CNG), liquefied natural gas (LNG), and liquefied petroleum gas (LPG). While LPG-powered buses were popular several years ago, it was found that substantial investments were required to develop the necessary infrastructure. Additionally, LPG caused damage to engine longevity, posing significant safety risks. Although LNG-powered buses offer an exceptionally high operational range, the substantial cost of refueling infrastructure makes them a less viable option for cities compared to CNG-powered buses [33].

The key advantages of utilizing biodiesel over conventional diesel can be assessed from strategic, economic, and environmental standpoints [34]. FAME (Fatty Acid Methyl Ester) is among the most commonly used first-generation biofuels for powering buses. When using pure FAME in place of fossil diesel, there is a 10% increase in NOX emissions for both passenger and commercial vehicles, along with a 48% decrease in carbon monoxide and a 47% reduction in particulate matter (PM) [35]. Current research and development efforts are focused on second-generation biofuels, particularly advanced biodiesel produced through the hydrogenation of vegetable oils or animal fats (Hydrotreating Vegetable Oil - HVO). "Second-generation" biofuels make use of non-food crops and agricultural waste, with their sustainable production being actively supported by EU policies.

Bioethanol is a liquid fuel primarily utilized in buses, often blended with diesel in significant proportions. While the energy consumption remains similar to that of conventional buses, bioethanol contains 60% less energy per unit, necessitating a higher fuel volume for buses to achieve the same performance [36].

Electric buses are regarded as the most environmentally friendly technologies currently available, generating zero local emissions and thus having the most significant effect on improving local air quality. The level of local emissions is primarily influenced by the method of electricity generation [37, 38].

Nearly all vehicle manufacturers are engaged in fuel cell research, yet most anticipate that fuel cell technology will not be commercially viable soon. While custom fuel cell and hydrogen vehicles are being developed, they are primarily intended for demonstration purposes. A notable example is the 27 fuel cell-powered buses involved in the EU project CUTE (Clean Urban Transport for Europe) [39, 40].

Hybrids, particularly series hybrids, provide the option of covering short distances using only electric power. This feature is especially beneficial in densely populated areas where low noise levels and minimal local emissions are essential for reducing pollution. For series hybrid buses, the advantages include significantly improved energy recovery during braking, the potential for substantial zero-emission range, and a solid foundation for transitioning to fully electric buses. The greatest savings, up to 30%, can be realized in highly congested urban traffic. Since the vehicle has two power units and the higher efficiency of the power units, the GHG emission is generally lower due to lower energy consumption.

Based on today's technical and technological solutions, the alternatives of propulsion systems and fuels that were considered in this research are are outlined in (Table 1). The bus comparison analysis is based on a standard 12-meter single-decker model, featuring an empty weight of 11500 kg and a capacity to accommodate between 80 and 100 passengers [41].

Table 1
Alternatives drive technologies and fuel options for buses [42]

Label	The name of the alternative
A_1	Bus with diesel engine (Euro V)
A_2	Bus with diesel engine (Euro VI)
A_3	Bus powered by compressed natural gas (CNG)
A_4	Biodiesel powered bus: first generation FAME
A_5	Biodiesel powered bus: second generation HVO
A_6	Bus powered by bioethanol
A_7	Electric bus with charging station
A_8	Electric bus with overnight charging
A_9	Trolleybus
A_{10}	Hydrogen/electric buses (hydrogen-powered vehicles)
A_{11}	Serial electric/diesel buses (hybrid vehicles)

The criteria were adopted based on the current offers of propulsion technology and fuels for buses and their characteristics not only from the aspect of air pollution and noise but also from the aspect of costs/investment and energy consumption. Operational, emission, and economic criteria taken for the evaluation of alternative propulsion systems and fuels of public urban passenger transport are given in Table 2.

Table 2
Criteria for evaluation of alternative drive technologies and fuel options for buses [42]

		Label	Criteria	Unit
Characteristics	Operational	f_1	Range	km
		f_2	Energy consumption	kWh/km
		f_3	Zero emission range	km
		f_4	Route flexibility	-
		f_5	Charging time	min
	Emissions	f_6	CO_2 emission	g/km
		f_7	NO_x emission	g/km
		f_8	PM_{10} emission	g/km
		f_9	Noise emission – stationary	dB
		f_{10}	Noise emission – pass	dB
	Economic	f_{11}	Vehicle price - investment costs	eur
		f_{12}	Total cost of ownership	eur/km
		f_{13}	Infrastructure - additional investment	eur

When creating the decision matrix (Table 3), it often happens that the criteria values for each alternative represent qualitative, not quantitative data. In these instances, a challenge emerges regarding how to compare qualitative and quantitative criterion values. To address this issue, the process of quantifying qualitative criteria is employed, which involves converting qualitative values into quantitative ones.

Table 3
The decision matrix [42]

	Criteria												
	Operational					Emissions					Economic		
	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}	f_{11}	f_{12}	f_{13}
	max	min	max	max	min	min	min	min	min	min	min	min	min
A_1	750	4.13	1	9	3	1000	3.51	0.10	80	77	220	2.1	1
A_2	750	4.13	1	9	3	834	1.1	0.03	80	77	220	2.1	1
A_3	375	5.21	1	9	3	1000	4.5	0.03	78	78	250	2.1	9
A_4	610	4.13	1	9	3	500	4.39	0.04	80	77	220	2.22	3
A_5	610	4.13	1	9	3	500	3.16	0.08	80	77	220	2.35	3
A_6	500	4.13	1	9	5	600	3.51	0.10	80	77	250	2.52	7
A_7	100	1.8	5	3	9	500	0	0	62	69	400	3.2	3
A_8	150	1.91	7	9	7	500	0	0	62	69	425	5.5	5
A_9	1000	1.8	9	3	1	500	0	0	62	72	300	3.1	9
A_{10}	300	3.2	9	9	5	1500	0	0	63	69	800	4.6	5
A_{11}	750	3.34	1	9	3	1000	3.51	0.10	69	73	270	2.4	1

There are several methods for this conversion, such as the ordinal scale, the interval scale, and the ratio scale. Since interval scales are most often applied, this method was used to translate qualitative values into quantitative ones. The range of scale ranges from 1 to 9 for "max" type criteria and from 9 to 1 for "min" type criteria. The values 0 and 10 are not included because the explicit extreme values of the observed criterion are not known.

4. Application of the Approach and Analysis of the Findings

The normalization process employed in multi-criteria methods transforms input data into numerical values that can be compared by standardizing them on a common scale [28]. Once the input data is collected, pre-processing is essential to ensure the criteria are comparable and appropriate for further analysis. In the literature, there are various methods for determining weight coefficients [43-47].

Input data, i.e. criteria values, need to be adjusted in some way. Namely, it is common to normalize the criteria values by reducing them to a value interval from 0 to 1 because different criteria are measured in different units, so if the criteria values were compared directly, the influence of some criteria would be ignored because of others that have a larger range of values. The normalization of criteria values eases the computational problems characteristic of different measurement units in the decision matrix.

The paper aims to perform an MCDM ranking of bus alternative drive technologies and fuel options for the city of Nis, using the TOPSIS method to the adopted criteria as a result of the application distinct normalization techniques within the CRITIC method used to calculate weighting coefficients (Figure 1).

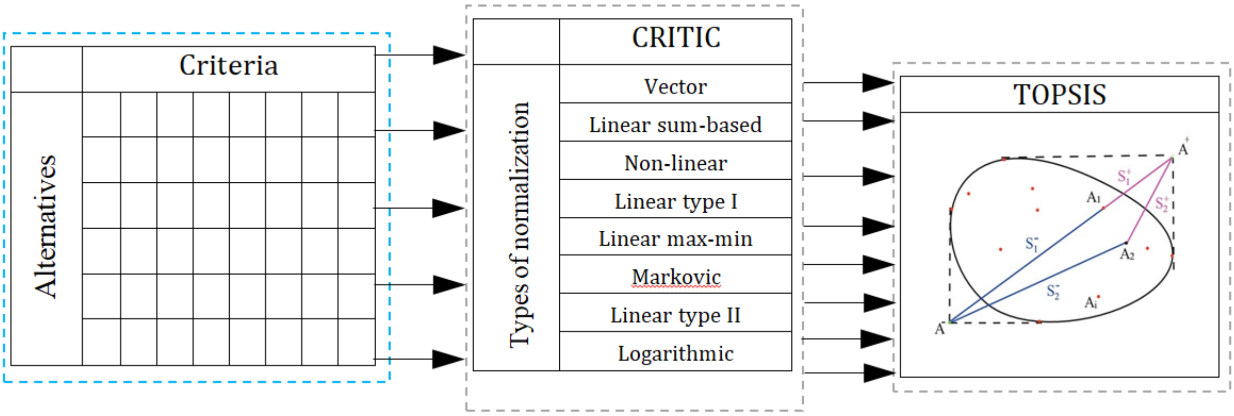

Fig. 1. Investigating the effects of changing the normalization type when calculating weight coefficients to ranking current bus alternative drive technologies and fuel options

In the initial stage of applying the CRITIC method for determining weight coefficients, the conventional use of linear max-min normalization was substituted, it was examined how vector, linear sum-based, non-linear, linear type I, Markovic, linear type II, and logarithmic normalization affect them (Table 4). In the research, given normalization formulas were applied, depending on whether a certain criterion needs to be minimized or maximized.

Table 4
Applied normalization techniques [42]

Type of normalization	For benefit criteria	For cost criteria
Vector	$r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{m} a_{ij}^2}}$	$r_{ij} = 1 - \frac{a_{ij}}{\sqrt{\sum_{i=1}^{m} a_{ij}^2}}$
Linear sum-based	$r_{ij} = \frac{a_{ij}}{\sum_{i=1}^{m} a_{ij}}$	$r_{ij} = \frac{1/a_{ij}}{\sum_{i=1}^{m} 1/a_{ij}}$
Non-linear	$r_{ij} = \left(\frac{a_{ij}}{a_j^{max}}\right)^2$	$r_{ij} = \left(\frac{a_j^{min}}{a_{ij}}\right)^3$
Linear type I	$r_{ij} = \frac{a_{ij}}{a_j^{max}}$	$r_{ij} = 1 - \frac{a_{ij}}{a_j^{max}}$
Linear max-min	$r_{ij} = \frac{a_{ij} - a_j^{min}}{a_j^{max} - a_j^{min}}$	$r_{ij} = \frac{a_j^{max} - a_{ij}}{a_j^{max} - a_j^{min}}$
Markovic	$r_{ij} = \frac{a_{ij}}{a_j^{max}}$	$r_{ij} = 1 - \frac{a_{ij} - a_j^{min}}{a_j^{max}}$
Linear type II	$r_{ij} = \frac{a_{ij}}{a_j^{max}}$	$r_{ij} = \frac{a_j^{min}}{a_{ij}}$
Logarithmic	$r_{ij} = \frac{ln(a_{ij})}{ln\left(\prod_{i=1}^{m} a_{ij}\right)}$	$r_{ij} = \frac{1 - \frac{ln(a_{ij})}{ln\left(\prod_{i=1}^{m} a_{ij}\right)}}{m-1}$

Based on Table 5, it can be concluded that the type of normalization has a significant impact on the values of the weighting coefficients calculated using the modified CRITIC method. Neither type of normalization gives the same values of weight coefficients as the type of normalization, linear max-min, which is officially used in the CRITIC method. However, the question arises, how does changing the type of normalization in the CRITIC method for obtaining weight coefficients affect the multi-criteria ranking solution implemented by the TOPSIS method?

Table 5
Weight coefficients outcomes obtained via distinct normalization techniques [42]

Criteria/Type	f_1	f_2	f_3	f_4	f_5	f_6
Linear max-min	0.07226	0.06133	0.08110	0.11722	0.06991	0.07643
Vector	0.09465	0.05016	0.12002	0.07425	0.10525	0.08022
Linear sum based	0.06836	0.06183	0.15467	0.05146	0.09390	0.05326
Non-linear	0.08094	0.10086	0.10397	0.13363	0.07334	0.12640
Linear type I	0.09262	0.05702	0.10245	0.11125	0.08833	0.07253
Markovic	0.09270	0.05711	0.10259	0.11133	0.08840	0.07260
Linear type II	0.09697	0.09772	0.15300	0.11969	0.08256	0.10594
Logarithmic	0.04485	0.01462	0.66215	0.09935	0.01747	0.00260

Table 5
Continued

Criteria/Type	f_7	f_8	f_9	f_{10}	f_{11}	f_{12}
Linear max-min	0.07841	0.08699	0.09025	0.08033	0.09468	0.09109
Vector	0.10855	0.12599	0.01842	0.00947	0.08882	0.12420
Linear sum based	0.16367	0.16250	0.01871	0.00810	0.04218	0.12135
Non-linear	0.00291	0.00291	0.06512	0.03505	0.13003	0.14484
Linear type I	0.11143	0.12386	0.02891	0.01317	0.08331	0.11512
Markovic	0.11155	0.12297	0.02896	0.01319	0.08336	0.11523
Linear type II	0.00100	0.05246	0.04301	0.02002	0.08850	0.13914
Logarithmic	0.09486	0.02010	0.00131	0.00055	0.01328	0.02883

It can be concluded that the application of different types of normalization, to calculate the weighting coefficients through the CRITIC method, has no effect on the best and worst alternatives, but has an effect on the ranking of the other alternatives. The weighting coefficients obtained by linear sum-based, vector normalization in CRITIC as well as by the Linear type II method give approximately the same ranking of alternatives within the application of the TOPSIS method (Table 6). The largest disagreement in ranking is given by the use of logarithmic normalization.

Table 6
Ranking of bus alternative drive technologies and fuel options (with different weighting coefficients) [42]

	TOPSIS							
	Vector	Linear sum based	Non-linear	Linear type I	Linear max-min	Markovic	Linear type II	Logarithmic
A_1	5	2	8	4	4	4	7	8
A_2	11	11	9	11	9	11	10	11
A_3	2	3	3	2	2	2	5	6
A_4	8	7	10	7	10	7	11	5
A_5	9	6	11	6	7	5	8	9
A_6	1	1	6	1	1	1	6	10
A_7	10	9	5	9	11	9	3	3
A_8	7	10	4	10	8	10	4	4
A_9	4	5	2	5	6	6	2	2
A_{10}	3	8	1	8	3	8	1	1
A_{11}	6	4	7	3	5	3	9	7

Employing the standard CRITIC method to derive weighting coefficients and the TOPSIS method to rank alternatives, the best-ranked alternative drive technologies and fuel options is A6 - Bus powered by bioethanol, while the worst-ranked alternative is A7 - Electric bus with charging station. The second and third ranked bus propulsion technology and fuel alternatives are A3 - Bus powered by compressed natural gas (CNG) bus and A10 - Hydrogen/electric bus.

In certain instances, specific values of the weighting coefficients for the chosen criteria do not yield the anticipated or desired results, necessitating an analysis of their effect on the outcome. Based on the weighting coefficient values derived from different normalization technique in Table 5 and the results of their application within the TOPSIS method (Table 6), it can be concluded that even a minor adjustment in the weighting coefficients significantly impacts the ranking of alternatives. In such cases, Spearman's rank correlation coefficient is utilized to assess and determine the degree of association between the solutions (rankings).

Spearman's correlation coefficient is used for the correlation of a relatively small number of data (maximum 30) whose properties cannot be expressed numerically, as well as for data that do not have a normal distribution. The value of the mentioned correlation coefficient can be within [-1, +1], where the first value represents an ideal negative correlation and the second an ideal positive correlation. The positive sign of the value of the correlation coefficient shows that both observed sets of rankings move in the same direction, i.e. there is a correlation, while when the sign is negative, one set of rankings increases and the other decreases, that is, the rankings are negatively correlated. If the correlation is equal to zero, it means that based on one set of rankings, nothing can be concluded about the other set of rankings, and there is no agreement between the sets, i.e., ranks are uncorrelated. Spearman's correlation coefficient can be calculated based on [48].

The values of the Spearman coefficients of the results of the ranking of the alternative drive technologies and fuel options for buses using the TOPSIS method (with different weighting coefficients) are shown in Table 7. The calculated correlation coefficient does not describe the correlation relationship, its strength, and direction, and does not depend on the numerical values between the observed values of ranking alternatives, but only between their relative relationships, i.e., ranks.

Table 7
Spearman's correlation coefficients of the ranking bus alternative drive technologies and fuel options by the TOPSIS method (with different weighting coefficients) [42]

	Vector	Linear sum-based	Non-linear	Linear type I	Linear max-min	Markovic normalization	Linear type II	Logarithmic
Vector	1	0.7	0.61822	0.80912	0.92731	0.80911	0.64545	0.28191
Linear sum-based	0.70000	1	-0.03641	0.96364	0.74554	0.96371	0.01822	-0.26371
Non-linear	0.61819	-0.03640	1	0.11821	0.50911	0.11821	0.99011	0.77321
Linear type I	0.80910	0.96371	0.11823	1	0.84553	1	0.172727	-0.17273
Linear max-min	0.92730	0.74551	0.50911	0.84553	1	0.84553	0.52731	0.13641
Markovic	0.80910	0.96372	0.11823	1	0.84553	1	0.17273	-0.17273
Linear type II	0.64550	0.01822	0.99011	0.17273	0.52731	0.17273	1	0.78211
Logarithmic	0.28191	-0.26372	0.77321	-0.17287	0.13641	-0.17271	0.78211	1

From Table 7, it can be seen that the Spearman correlation coefficient of the ranking results with the values of the weighting coefficients obtained by linear max-min and vector normalization is quite close to the unit ρ=0.927273, which means that the relationship between these two rankings is positive and quite strong (Figure 2). There is also a strong correlation between the ranking with the values of the weighting coefficients obtained by linear max-min and linear type I and Marković normalization ρ=0.845455.

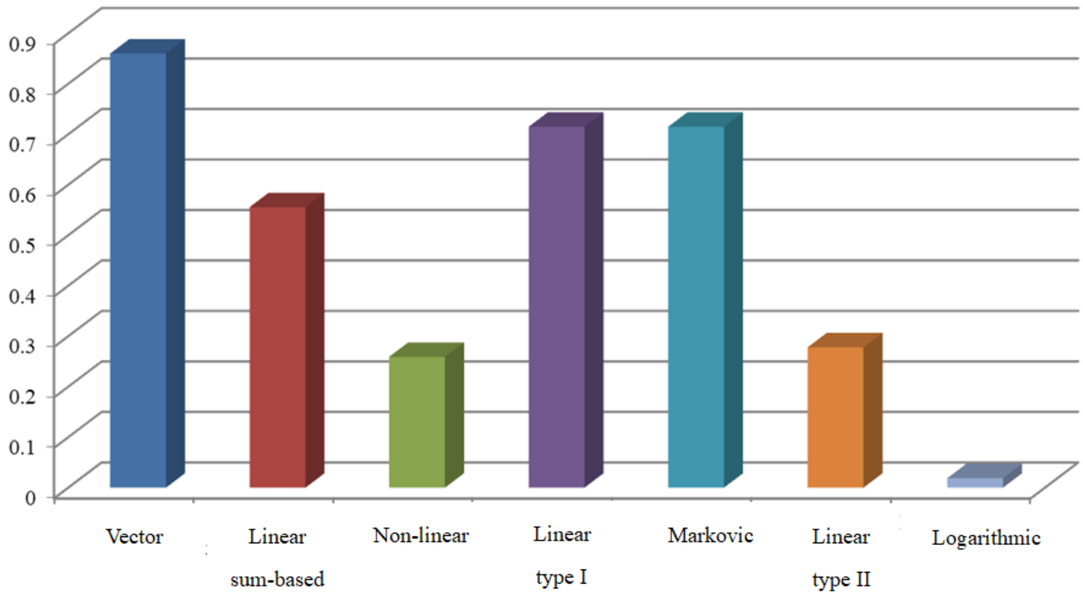

Fig. 2. Spearman's correlation coefficients of the ranking bus alternative drive technologies and fuel options [39] (Note: this figure was prepared by the authors)

Since the number of alternatives is n≥10, i.e. n=11 and to confirm the statistical significance of the obtained correlation coefficient, a t-test is applied which can be calculated based on [49], whose calculated values are shown in Table 8. The t-test value is compared with the theoretical values from the t-test table based on the calculated number of degrees of freedom. If the calculated value of t is greater than the value from the table, for the corresponding degree of freedom, it can be stated that the correlation coefficient is statistically significant, i.e. non-zero. Conversely, if the calculated value of t is less than or equal to the table value, the correlation coefficient is considered to be zero.

Table 8
T-test of the Spearman's correlation coefficients significance [42]

	Vector	Linear sum-based	Non-linear	Linear type I	Linear max-min	Markovic normalization	Linear type II	Logarithm
Vector	0	2.94059	2.35937	4.13024	7.43034	4.13024	2.53518	0.88117
Linear sum-based	2.94059	0	-0.10916	10.8186	3.35510	10.8186	0.05455	-0.81992
Non-linear	2.35937	-0.10916	0	0.35705	1.77443	0.35705	22.09661	3.65219
Linear type I	4.13024	10.81858	0.35705	0	4.74932	0	0.52609	-0.52609
Linear max-min	7.43034	3.35510	1.77443	4.74932	0	4.74932	1.86163	0.41295
Markovic	4.13024	10.81858	0.35705	0	4.74932	0	0.52609	-0.52609
Linear type II	2.53518	0.054554	22.0966	0.52609	1.86163	0.52609	0	3.76172
Logarithmic	0.88117	-0.81992	3.65217	-0.52609	0.41295	-0.52609	3.76172	0

A t-test determines whether the association between two rankings is statistically significant or not. The number of degrees of freedom is calculated by df = n-2, i.e. df = 9. The calculated values are compared with the limit values based on the number of degrees of freedom df = 9 in the t-test table (limit t (5%) =2.262, limit t (1 %) =3.250). As the calculated value of t=7.430337 (ρ=0.927273) is higher than the limit value for the selected null hypothesis probability (0.05 or 0.01) taken from the table, the correlation is convincing, i.e. there is a high statistical significance of the linear interdependence of the ranks of the observed alternatives. This can be concluded for the values t=4.749323 (ρ=0.845455), as well as for t=3.355100 (ρ=0.745455).

From the results obtained, it can be inferred that altering the normalization method in the CRITIC approach for determining weight coefficients and applying them in the TOPSIS method leads to a variation in the ranking of alternatives. Within the CRITIC method, the greatest statistical significance of the linear interdependence of the ranks of the observed alternatives was achieved by using vector then linear type I and Marković normalization instead of linear max-min normalization.

5. Conclusions

Public city passenger transport provides a service available to all users under pre-defined and known operating conditions. Its role is important for all cities, especially for solving traffic problems in central city areas.

Enhancing the organization and efficiency of cities and their transportation networks is a highly intricate and significant task, profoundly impacting every aspect of residents' lives. In the European Union, the achievement of the aims of sustainable development and life quality concerning transport systems is achieved through the conduct of a policy based on the principle of realizing the mobility of residents with limited use of passenger cars. One of the most important decisions in the process of planning efficient transport systems in cities concerns the choice of modes of transport, i.e. the subsystem of public passenger transport.

Planning and designing balanced urban transport systems, which would involve a systemic approach to resource organization and management, can satisfy the basic strategy of urban development. Above all, planning the development and improvement of the public passenger transport system can achieve this.

The public urban passenger transport system is a more efficient, cost-effective, economically viable, and environmentally friendly component of urban transportation. It serves as a key tool in promoting sustainable development and enhancing the quality of life in cities.

The modern concept and strategic framework for developing transportation systems emphasize the need for gradually transitioning these systems from their current suboptimal state to a more desirable one, in line with global trends and local capacities. This approach primarily focuses on promoting the evolution of balanced, integrated urban transportation systems and advancing public passenger transport, which is one of the most critical subsystems.

To determine the adequate propulsion technology and fuel for buses, specifically for the city of Nis, a multi-criteria analysis was performed using the CRITIC and TOPSIS methods based on the adopted criteria. The application of different types of normalization within the CRITIC method, which is used to calculate the weighting coefficients, aimed to analyze their impact on the ranking solutions of the alternatives. The application of Spearman's rank correlation coefficient made it possible to determine the degree of correlation between the ranking of alternative drive technologies and fuel options for buses using the TOPSIS method (with different weighting coefficients). The results indicated the greatest statistical significance of the linear interdependence of the ranks of the observed alternatives achieved by using vector normalization instead of the original linear max-min normalization in the CRITIC method.

By applying the CRITIC method to calculate the weighting coefficients and the TOPSIS method for ranking the alternatives, the highest-ranked propulsion technology and fuel alternative is A6 - Bus powered by bioethanol, while the lowest-ranked option is A7 - Electric bus with charging station.

The given/obtained data could provide valuable insights for refining existing and future traffic and transport development strategies in Niš, contributing to better air quality.

A substantial body of scientific research has focused on developing normalization models within multi-criteria ranking methodologies. However, a definitive determination regarding the most suitable technique remains elusive. Although many normalization approaches may appear to differ only slightly, these subtle distinctions can have a significant impact on the decision-making process.

An analysis was conducted to evaluate the effects of different normalization techniques in assigning weight coefficients, aimed at developing a multi-criteria analysis model for ranking contemporary alternative propulsion technologies and fuel options in the bus subsystem of public transport, based on their contributions to environmental quality in the selected urban setting.

Author Contributions

Conceptualization, N.P., V.J., M.P., B.N., and J.M.; methodology, N.P.; validation, N.P., V.J., M.P., B.N., and J.M.; investigation, N.P., V.J., M.P., B.N., and J.M.; writing—original draft preparation, N.P., V.J., M.P., B.N., and J.M.; writing—review and editing, N.P., V.J., M.P., B.N., and J.M. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

All data generated or analyzed during this study are included in this published article and its supplementary files. However, the reader may contact the corresponding author for more details on the data.

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Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

[1] Petrović, N., Bojović, N., Marinković, D., Jovanović, V., & Milanović, S. (2023). A two-phase model for the evaluation of urbanization impacts on carbon dioxide emissions from transport in the European Union. Tehnički Vjesnik, 30(2), 514–520. https://doi.org/10.17559/TV-20221018103946

[2] Ng, K.-W., & Tong, H.-Y. (2024). Comparisons of driving characteristics between electric and diesel-powered bus operations along identical bus routes. Sustainability, 16(12), 4950. https://doi.org/10.3390/su16124950

[3] European Commission. (n.d.). Clean transport. Retrieved January 10, 2025, from https://transport.ec.europa.eu/transport-themes/clean-transport_en

[4] European Union. (2009). *Regulation (EC) No 595/2009 of the European Parliament and of the Council of 18 June 2009*. Official Journal of the European Union. Retrieved December 29, 2024, from https://eur-lex.europa.eu/eli/reg/2009/595/oj/eng

[5] Petrović, N., Mihajlović, J., Jovanović, V., Ćirić, D., & Živojinović, T. (2023). Evaluating annual operation performance of Serbian railway system by using multiple criteria decision-making technique. Acta Polytechnica Hungarica, 20(1), 157–168. https://doi.org/10.12700/APH.20.1.2023.20.11

[6] Tadić, D., Lukić, J., Komatina, N., Marinković, D., & Pamučar, D. (2025). A fuzzy decision-making approach to electric vehicle evaluation and ranking. Tehnički Vjesnik / Technical Gazette. Accepted for publishing.

[7] Hamurcu, M., & Eren, T. (2022). Applications of the MOORA and TOPSIS methods for decision of electric vehicles in public transportation technology. Transport, 37(4), 251–263. https://doi.org/10.3846/transport.2022.17783

[8] Petrović, N., Marković, S., Nikolić, B., Jovanović, V., & Petrović, M. (2024). Evaluating alternative propulsion systems for urban public transport in Niš: A multicriteria decision-making approach. Journal of Engineering Management and Systems Engineering, 3(2), 72–81. https://doi.org/10.56578/jemse030202
[9] Sahoo, S. K., Choudhury, B. B., & Dhal, P. R. (2024). A bibliometric analysis of material selection using MCDM methods: Trends and insights. Spectrum of Mechanical Engineering and Operational Research, 1(1), 189–205. https://doi.org/10.31181/smeor11202417
[10] Tešić, D., Božanić, D., & Milić, A. (2023). A multi-criteria decision-making model for pontoon bridge selection: An application of the DIBR II-NWBM-FF MAIRCA approach. Journal of Engineering Management and Systems Engineering, 2(4), 212–223. https://doi.org/10.56578/jemse020403
[11] Komatina, N., Marinković, D., Tadić, D., & Pamučar, D. (2025). Advancing PFMEA decision-making: FRADAR based prioritization of failure modes using AP, RPN, and multi-attribute assessment in the automotive industry. Tehnički Glasnik / Technical Journal, 19(3).
[12] Milani, A. S., Shanian, A., Madoliat, R., & Nemes, J. A. (2005). The effect of normalization norms in multiple attribute decision making models: A case study in gear material selection. Structural and Multidisciplinary Optimization, 29(4), 312–318. https://doi.org/10.1007/s00158-004-0473-1
[13] Jahan, A., Bahraminasab, M., & Edwards, K. L. (2012). A target-based normalization technique for materials selection. Materials & Design, 35, 647–654. https://doi.org/10.1016/j.matdes.2011.09.005
[14] Jahan, A., Mustapha, F., Sapuan, S. M., Ismail, M. Y., & Bahraminasab, M. (2012). A framework for weighting of criteria in ranking stage of material selection process. The International Journal of Advanced Manufacturing Technology, 58(1), 411–420. https://doi.org/10.1007/s00170-011-3366-7
[15] Baydaş, M., Yılmaz, M., Jović, Ž., Stević, Ž., Özuyar, S. E. G., & Özçil, A. (2024). A comprehensive MCDM assessment for economic data: Success analysis of maximum normalization, CODAS, and fuzzy approaches. Financial Innovation, 10, 105. https://doi.org/10.1186/s40854-023-00588-x
[16] Baydaş, M., Eren, T., & İyibildiren, M. (2023). Normalization technique selection for MCDM methods: A flexible and conjunctural solution that can adapt to changes in financial data types. Necmettin Erbakan Üniversitesi Siyasal Bilgiler Fakültesi Dergisi, 5(Special Issue), 148–164. https://doi.org/10.51124/jneusbf.2023.54
[17] Ersoy, N. (2022). Normalization procedures for COCOSO method: A comparative analysis under different scenarios. Dokuz Eylül Üniversitesi İşletme Fakültesi Dergisi, 22(2), 217–234. https://doi.org/10.24889/ifede.974252
[18] Aytekin, A. (2021). Comparative analysis of the normalization techniques in the context of MCDM problems. Decision Making: Applications in Management and Engineering, 4(2), 1–25. https://doi.org/10.31181/dmame210402001a
[19] Puška, A., Štilić, A., Pamučar, D., Božanić, D., & Nedeljković, M. (2024). Introducing a novel multi-criteria ranking of alternatives with weights of criterion (RAWEC) model. MethodsX, 12, 102628. https://doi.org/10.1016/j.mex.2024.102628
[20] Petrović, N., Jovanović, V., Marković, S., Marinković, D., & Petrović, M. (2024). Multicriteria sustainability assessment of transport modes: A European Union case study for 2020. *Journal of Green Economics and Low-Carbon Development, 3*(1), 36–44. https://doi.org/10.56578/jgelcd030104
[21] Trung, D. D., Truong, N. X., Duc, D. V., & Bao, N. C. (2024). Data normalization in RAWEC method: Limitations and remedies. Yugoslav Journal of Operations Research. Advance online publication. https://doi.org/10.2298/YJOR240315020T
[22] Žižović, M., Miljković, B., & Marinković, D. (2020). Objective methods for determining criteria weight coefficients: A modification of the CRITIC method. Decision Making: Applications in Management and Engineering, 3(2), 149–161. https://doi.org/10.31181/dmame2003149z
[23] Pamučar, D., Žižović, M., & Đuričić, D. (2022). Modification of the CRITIC method using fuzzy rough numbers. Decision Making: Applications in Management and Engineering, 5(2), 362–371. https://doi.org/10.31181/dmame0316102022p
[24] Çelen, A. (2014). Comparative analysis of normalization procedures in TOPSIS method: With an application to Turkish deposit banking market. Informatica, 25(2), 185–208. https://doi.org/10.15388/Informatica.2014.10
[25] Ersoy, N. (2022). The influence of statistical normalization techniques on performance ranking results: The application of MCDM method proposed by Biswas and Saha. International Journal of Business Analytics (IJBAN), 9(5), 1–21. https://doi.org/10.4018/IJBAN.298017
[26] Arsu, T., & Ayçin, E. (2021). Evaluation of OECD countries with multi-criteria decision-making methods in terms of economic, social and environmental aspects. Operational Research in Engineering Sciences: Theory and Applications, 4(2), 55–78. https://doi.org/10.31181/oresta20402055a
[27] Milićević, M. R., & Župac, G. Ž. (2012). Objektivni pristup određivanju težina kriterijuma [Objective approach to determining criteria weights]. Vojnotehnički Glasnik, 60(1), 39–56. https://doi.org/10.5937/vojtehg1201039M

[28] Dimitrijević, B. (2017). Višeatributivno odlučivanje [Multi-attribute decision making]. University of Belgrade – Faculty of Transport and Traffic Engineering.
[29] Hwang, C. L., & Yoon, K. (1981). Multiple attribute decision making: Methods and applications. Springer Verlag.
[30] Petrović, N., Živojinović, T., & Mihajlović, J. (2023). Evaluating the annual operational efficiency of passenger and freight road transport in Serbia through entropy and TOPSIS methods. Journal of Engineering Management and Systems Engineering, 2(4), 204–211. https://doi.org/10.56578/jemse020402
[31] Parashar, S., Bhattacharya, S., Titiyal, R., & Roy, D. G. (2024). Assessing environmental performance of service supply chain using fuzzy TOPSIS method. Health Services and Outcomes Research Methodology, 24, 46–72. https://doi.org/10.1007/s10742-023-00303-4
[32] Lin, H. (2024). Light pollution evaluation research based on the entropy weight method combined with the TOPSIS model. Transactions on Environment, Energy and Earth Sciences, 3, 514–522. https://doi.org/10.62051/c5cbhj73
[33] CIVITAS. (2013). Policy note: Smart choices for cities – Clean buses for your city. https://civitas.eu/sites/default/files/civ_pol-an_web.pdf
[34] Nikolić, B., Kegl, B., Milanović, S., Petrović, N., & Marković, S. (2023). Characteristics of biodiesel as a fuel for diesel engines. Innovative Mechanical Engineering, 2(3). http://ime.masfak.ni.ac.rs/Dokumenta/papers/v2n3/v2n3-6_Nikolic_et_al.pdf
[35] Kousoulidou, M., Fontaras, G., Mellios, G., & Ntziachristos, L. (2008). Effect of biodiesel and bioethanol on exhaust emissions (Report No. 08.RE.0006.V1). Aristotle University Thessaloniki, Laboratory of Applied Thermodynamics.
[36] Rutz, D., & Janssen, R. (2008). Biofuel technology handbook. WIP Renewable Energies.
[37] Birath, K., & Sjölin, L. (2007). Clean vehicles and alternative fuels: Trends and visions. NICHES Consortium.
[38] Kruchina, V. (2023). The possibility of electrification in public transport bus services. Acta Technica Jaurinensis, 16(4), 158–166. https://doi.org/10.14513/actatechjaur.00713
[39] European Commission. (2001–2006). Clean Urban Transport for Europe (CUTE) project. https://trimis.ec.europa.eu/project/clean-urban-transport-europe
[40] Fuel Cell Buses. (n.d.). Retrieved December 20, 2024, from https://fuelcellbuses.eu/
[41] CIVITAS. (2016). Policy note: Smart choices for cities – Alternative fuel buses. https://civitas.eu/sites/default/files/civ_pol-08_m_web.pdf
[42] Petrović, N. (2018). Managing the impacts of urbanization and transport modes on the environment quality [Doctoral dissertation, University of Belgrade, Faculty of Transport and Traffic Engineering].
[43] Damjanović, M., Stević, Ž., Stanimirović, D., Tanackov, I., & Marinković, D. (2022). Impact of the number of vehicles on traffic safety: Multiphase modeling. Facta Universitatis, Series: Mechanical Engineering, 20(1), 177–197. https://doi.org/10.22190/FUME220215012D
[44] Puška, A., Stojanović, I., & Štilić, A. (2023). The influence of objective weight determination methods on electric vehicle selection in urban logistics. Journal of Intelligent Management and Decision, 2(3), 117–129. https://doi.org/10.56578/jimd020302
[45] Mukhametzyanov, I. (2021). Specific character of objective methods for determining weights of criteria in MCDM problems: Entropy, CRITIC and SD. Decision Making: Applications in Management and Engineering, 4(2), 76–105. https://doi.org/10.31181/dmame210402076i
[46] Petrović, N., Jovanović, V., Petrović, M., Nikolić, B., & Pavlović, J. (2022). Evaluating the operation performance of the Serbian transport freight system by using multiple criteria decision-making technique. Engineering Today, 1(4), 33–40. https://doi.org/10.5937/engtoday2204033P
[47] Wang, C.-N., Le, T. Q., Chang, K.-H., & Dang, T.-T. (2022). Measuring road transport sustainability using MCDM-based entropy objective weighting method. Symmetry, 14(5), 1033. https://doi.org/10.3390/sym14051033
[48] Conover, W. J. (1980). Practical nonparametric statistics (2nd ed.). Wiley.
[49] Gopal, K. K. (2006). 100 statistical tests (3rd ed.). SAGE Publications.