Sustainable Route Selection Using Fuzzy MCDM Techniques

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Abstract: Effective transportation route assessment is critical to transportation mobility, safety, and sustainability between urban cities. However, selecting the optimal route with consideration of sustainability is still a fresh challenge. This study aims to define the best pathway to utilize, taking into consideration several performance measures such as travel efficiency, safety, impact on the environment, and the quality of infrastructure between Baghdad and Fallujah. The methodology involves three phases, starting with creating an initial decision matrix that compares three assigned road routes with 12 criteria. The weight fuzzy judgment method (WFJM) was used to establish the relative significance of the twelve criteria for the assigned peak periods, considering the differences in the traffic patterns and priorities in the operations throughout the day. The roads were then ranked using the Multi-Objective Optimization by Ratio Analysis plus Full Multiplicative Form (MULTIMOORA) approach, which combines the Ratio System, Reference Point, and Multiplicative Form, followed by a Borda count to get the final ranking. Weighting outcomes suggested that speed limit, road condition, fuel consumption, and pollution were the most important variables during the AM period, whereas during the PM period, lighting and road condition were more significant. The MULTIMOORA findings showed that the Old Abu Ghuraib Route performed better in AM and PM versions and thus had a balanced score across all evaluation systems. The Karmah route and the Expressway No.1 segment had time-varying performance, whereby the Expressway had greater performance in the PM conditions. A sensitivity analysis provided validation of the robustness of the results. This paper provides information to policymakers and motorists on the best driving route selection between Baghdad and Fallujah for management and planning considerations.

1 INTRODUCTION

This study examines the main corridors that connect Baghdad and Fallujah (i.e., the segment of Expressway no. 1, Old Abu Ghuraib Road, and Karmah Road). Generally, the expressway links the main cities of Iraq, including the path from Umm Qasr Port in Basra, Nasiriyah, Al-Diwaniyah, Hillah, Baghdad, Fallujah, and reaching the Jordanian and Syrian borders in Ramadi, allowing both internal and foreign trade. The selected lengths of the Expressway no. 1, Old Abu Ghuraib Road, and Karmah Road are around 71.7, 66.1, 82.0 km, respectively, and the data collection was carried out in 2023. Figure 1 illustrates the selected routes for the study area. The introduction is divided into 6 sub-sections.

1.1 Motivation

Deciding on the best route for road users is one of the crucial aspects of transportation planning, as it directly impacts multiple technical, economic, and practical factors. A bunch of issues faced by road users can arise from traffic congestion, mainly in urban areas, such as stress, delays, and reduced productivity. Thus, to ensure driving with the minimum fuel consumption and the least amount of time, there is a need to develop superior route optimization algorithms that utilize real-time datasets, adaptive routing models, and predictive analytics [1]. In addition to the fuel prices increasing, environmental concerns make fuel efficiency essential for route selection to avoid and minimize unnecessary acceleration and braking [2].

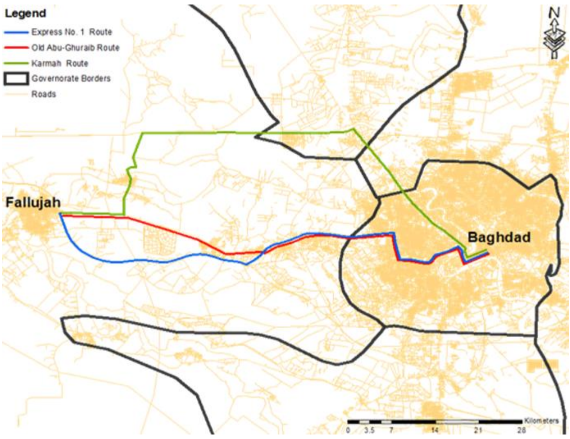

Figure 1: Road corridors connecting Baghdad and Fallujah.

Minimizing fuel consumption means less carbon emissions, which supports environmental preservation and aligns with government policies in addition to sustainable transportation enterprises [3]. Similarly, safety issues are regarded as a major criterion, since accidents can occur due to poor route selection with bad weather conditions, poor visibility, or due to the behavior of drivers [4]. Due to the varied drivers' preferences, some drivers select the shortest route while others prefer fascinating roads or highways for convenience [5]. Furthermore, efficient route optimization is crucial for businesses related to transportation, like ride-sharing, emergency services, and logistics [6], [7]. The traditional route selection models are primarily based on shortest path algorithms like A* Algorithm or Dijkstra's Algorithm. Hence, these traditional models do not constantly take into consideration factors like weather conditions, fuel consumption, road risks, and other cost factors. Due to these challenges, better route selection plays a crucial role in improving people's daily activities and supporting business benefits.

1.2 Problem Statement and Challenges

The decision-making issue of choosing the best transportation path between two cities is a complicated one because it includes the existence of several alternative paths and a broad variety of criteria that impact the final decision [8]. These requirements usually involve commuting time, safety, comfort, environmental effects, and dependability, among others. Not all criteria are of equal importance, and depending on the views of the decision-makers or the stakeholders, or their goals or limitations, they will place various weights on each criterion [9]. In addition, uncertainty as well as vagueness in the evaluation of criteria characterize the decision-making environment, making the process more difficult [10] , [11]. A primary concern is the reliability and availability of the dataset. Consistent and real-time datasets are crucial for Multi-Criteria Decision Making (MCDM) models' operation. Hence, such datasets are not consistently available across different spatial locations and transportation systems. Such complexity cannot be resolved using traditional single-criterion or intuitive methods because they cannot be used to effectively represent conflicting priorities, and they cannot be used to discover inconsistent and uncertain evaluations [12]. Therefore, a systematic and robust methodology that can combine various criteria, as they have different significance, and address the uncertainty, is urgently required to choose the most appropriate path between cities.

The key challenge is to identify and apply the MCDM method that models the complexity of transportation route choice accordingly. Although there are a number of methods of MCDM, they vary in their ability to address inconsistent judgments, uncertainty, and unequal weights of criteria [13]. The challenge is in selecting the method that will guarantee objectivity in the criteria weighting, create a reliable ranking of the alternatives, and make the decision-making process transparent [14]. The ability to balance between theoretical strength and practical application is a primary issue that should be resolved to help decision-makers come up with an optimal and evidence-based solution to the route selection.

1.3 Research Gap and Contribution

Despite the extensive use of MCDM methods in transportation planning [15], [16], the integration of further weighting and ranking approaches towards route evaluation has an obvious theoretical gap. In particular, though the weight fuzzy judgment method (WFJM) has proven to be very beneficial in dealing with inconsistency and uncertainty in decision-making processes [14], little has been done in the application of the method as a weighting mechanism in the transport sector. Likewise, even though such ranking techniques as Ratio Analysis plus Full Multiplicative Form (MULTIMOORA) have become popular due to their high strength and the capacity to provide consistent outcomes in a variety of perspectives, little has been done in the literature that would imply the integration of WFJM and MULTIMOORA into a single framework of evaluating transportation routes. A bunch of researchers have used MCDM methods. Nevertheless, there are still some gaps in using MCDM for selecting the best driving route. Also, both the evaluation and selection of the best route are still exhibiting some shortcomings, which need to be addressed comprehensively. For instance, when dealing with issues requiring well-structured and similar judgments, Analytic Hierarchy Process (AHP) excels due to its simplicity and hierarchical framework [17]. Nevertheless, since it depends on pairwise comparisons, its subjectivity could lead to mistakes and discrepancies, when the number of criteria increases.

In addition, previous studies have ignored real-time weather, traffic accidents, road closures, and traffic conditions [18]. By using traditional models, some researchers have oversimplified driver preferences by assuming equal values of distance and time for all drivers [19]. On the other hand, some modelers have failed to sufficiently integrate multiple conflicting criteria, when these models struggle to balance factors such as fuel consumption versus travel time or safety versus speed. Furthermore, few researchers have involved real users in validating the serviceability and efficiency of the projected models [20]. Last but not least, the appropriate scaling of large and complex road networks is crucial for route optimization, but it has been missed by some researchers [21], [22]. In order to address the gaps that have been mentioned previously, this research aims to integrate new strategies by making significant contributions:

1) For the first time, the current study used the WFJM model in the field of transportation.
2) The new formative decision matrix contains 12 criteria and 3 alternatives.
3) Integrating global sustainability goals by proposing MCDM systems that account for environmental impacts, such as fuel consumption and emissions.

1.4 Objectives

In order to align the route optimization methodology with the United Nations Sustainable Development Goals, the main objectives are (1) present a precise and reliable weight for 12 criteria and reduce the uncertainty. (2) Minimizing fuel consumption by choosing smoother routes reduces unnecessary stops and congestion, thereby lowering fuel costs and vehicle emissions. (3) The study also focuses on minimizing travel time by identifying the best route that allows drivers to reach their destination in the shortest travel time to achieve time savings, improve productivity, and reduce driver fatigue. (4) Besides, verifying the optimum driving route selection approach is crucial to utilize real-world datasets to determine the driver preferences and validate its practical feasibility.

1.5 Significance of the Study

The significance of research is to contribute to the enhancement of the decision-making process in transportation planning by combining the application of the WFJM and the MULTIMOORA. The integrated application of WFJM and MULTIMOORA would enable the decision-makers to attain uniformity and certainty in ranking the transportation routes, as well as to respond to the uncertainty and variability of the expert opinion. The integration of this method also adds to the literature, where these methods can help resolve the divide between theoretical rigor and applications. Practically, the paper provides a decision support instrument to the transportation authorities, urban planners, and policymakers to choose the best routes that can provide maximum efficiency, reduce their environmental impacts, and support the general societal interests. Moreover, considering the growing need to develop sustainable transportation systems globally, the methodology used in this work demonstrates how the crisis can be addressed with the help of scientific methods of decision-making to make the transport infrastructure more sustainable and resilient. In addition to the particular context of the three transport routes considered, there is the importance of delivering a framework that is reproducible and can be applied to other geographic areas, modes of transport, or infrastructure endeavors, where decisions made are not only evidence-based but also consistent with long-term development plans. Finally, this work showcases the power of our techniques, not only in providing the best possible route but also in building stakeholder trust, transparency and accountability in the decision-making processes of large-scale infrastructure projects.

1.6 Literature Review

A bunch of interrelated factors influence the complex task of driving route selection, such as distance, traffic congestion, fuel consumption, safety considerations, travel time, and environmental impact. Consequently, in order to balance multiple criteria based on both system objectives and driver preferences, MCDM, one of the AI applications, has been used as a valuable framework [23], [24]. By considering both qualitative and quantitative criteria, MCDM sustains multiple processes of context-aware and informed decision making. Multiple studies have inspected the relevance of MCDM in transportation, especially in relation to the personalization and compliance of driver route choice systems [25]. In addition, the integration of MCDM with real-time traffic data alongside emerging technologies such as machine learning has surged its applicability in user-centric development and smart navigation systems [26].

MCDM includes a wide range of organized approaches intended for multiple conflicting purposes that should be simultaneously considered. For instance, one of the widely used techniques, AHP, simplifies decision complexity by using a hierarchical structure of both criteria and sub-criteria to determine relative importance over pairwise comparisons [27]. Another commonly used model, Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), allows the distinguishing between different alternative paths by ranking alternatives according to their geometric distance from anti-ideal and hypothetical resolution [28]. To categorize the alternatives that are employed to offer the optimal compromise among different requirements in a multi-dimensional space, the VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) model has also been utilized to emphasize compromise solutions [29]. Also, to compare multiple alternatives, ELimination and Choice Expressing REality (ELECTRE) models are another type of MCDM that uses ranking relationships, particularly in cases involving difficult-to-quantify preferences. Besides, fuzzy MCDM models incorporate fuzzy logic to account for both bias and ambiguity factors in real-world scenarios of transportation, like drivers' safety considerations and comfort [30]. The previously mentioned techniques are widely utilized in selecting the best driving route. Hence, decision-makers should take into consideration both qualitative and quantitative factors, which reflect the appropriate priorities and needs of road users [31]. For instance, Ekhlakov and Andriyanov [32] applied a MCDM approach by utilizing the AHP and TOPSIS for selecting the optimum driving route. Criteria such as distance, travel time, road traffic, safety, road type, road surface quality, travel cost, and weather conditions were included for modelling. Other criteria like selecting the shortest time, fastest speed, and safest conditions were selected to optimize the optimum driving routes by using MCDM methods such as AHP, Fuzzy AHP, TOPSIS, and Fuzzy TOPSIS [33]. Nevertheless, for the same purpose, Vrtagić et al., [34] utilized another type of criteria such as segemnt length, slope of road, speed limit, and accidents. Moreover, other bunch of researchers preferred to select criteria such as travel time, risk level, and travel cost combined with MCDM models such as AHP, Data Envelopment Analysis (DEA), TOPSIS for route optimization [35].

In order to address both qualitative and quantitative decision factors in route selection improvement across complex transportation networks, there is a crucial need for an integrated framework. For instance, Koohathongsumrit and Meethom [36] presented a hybrid MCDM model that integrates the TOPSIS, AHP, and DEA for problem addressing based on qualitative and qualitative criteria. Other researchers, such as Hassannayebi et al. [37], applied the ELECTRE and Condorcet models to estimate bus service reliability utilizing multiple performance indicators. This research highlights the usefulness of fuzzy logic in managing the essential imprecision and uncertainty of transportation datasets. Another type of MCDM models demonstrates the use of weighting systems, both objective and subjective, to enhance route selection under diverse network conditions. For instance, Nie et al. [38] combined Multi-Attribute Decision Making with heuristic path search to enhance vehicular safety messaging. Moreover, Huang et al. [5] demonstrated an approach to adaptive route endorsement. This model uses a historical navigation dataset for user conducting modelling by employing a Deep-Cross-Recurrent learning model, which integrates both LSTM and DCN-v2 styles.

On the other hand, fuzzy MCDM techniques stand out due to their capability to cope with imprecise input data and linguistic variables [39] . This is particularly useful for modeling consumer preferences, levels of comfort, or safety perceptions, which are often difficult to quantify using accurate quantitative measures. Fuzzy logic techniques enhance the accuracy and adaptability of decision models, allowing them to more accurately represent the real-world complexity [40]. While the ability to capture the fluctuation and unpredictability of the driving route selection based on human participation, both hybrid MCDM and fuzzy techniques are increasingly becoming the preferred approaches in transportation planning [41].

Recent studies of traffic planning have facilitated the integration of MCDM models with factors that directly impact drivers' route selection. Beyond basic geographic considerations, optimal route selection using MCDM models should encompass dynamic variables like emission levels, fuel consumption, traffic volumes, accident rates, and vehicle speeds. These criteria enhance drivers' awareness and support alternative driving route selection [42]. For instance, algorithm weights can be adjusted by assigning more weight to safety (i.e., high-risk zones) than economy (i.e., fuel consumption) depending on circumstances or user preferences. In addition, decision quality can be improved by integrating various criteria into MCDM preferences, especially under rapid and uncertain fluctuating traffic scenarios. By developing the optimality of the route and aligning with broader objectives, this study offers a robust foundation for transportation planning and superior navigation [43].

Unlike prior studies that have approached MCDM with limited criteria, this research presents a WFJM and MULTIMOORA models with 12 criteria, like travel time, accidents, and geometric design of routes in addition to other criteria that highly impact the mood of drivers for route selection.

2 METHODOLOGY

This study suggests an organized three-phase methodology to address complicated decision-making scenarios, including multiple and occasionally conflicting criteria. The first phase develops the judgment/decision matrix along with the assessment criteria, guaranteeing the appropriate illustration of both quantitative and qualitative factors. Assessment of the expert and theoretical basis for process fulfillment is regarded as assembly integration. The second phase applies the WFJM to estimate the relative importance of criteria. By integrating expert input with fuzzy set theory, WFJM efficiently addresses bias and vagueness, converting ambiguous judgements into reliable numerical values. The last phase of methodology consists of applying the technique of MULTIMOORA, an improved version of Multi-Objective Optimization by Ratio Analysis (MOORA) that integrates the ratio system, reference point, and entire exponential procedures into a single robust framework. Besides, MULTIMOORA utilizes WFJM-derived weights for thorough ranking of alternatives, reducing bias and improving decision reliability. To provide an unambiguous, rigorous, and responsive decision-making procedure suitable for intricate estimation scenarios in unpredictable situations, the combination of these steps is crucial to implement.

2.1 Decision Matrix

The established judgement/decision matrix for this research acts as a fundamental structure for organizing the methodological and assessing the multiple selected routes for the investigation aspect. It comprises two primary components, judgment criteria and alternatives. Each of these components performs a distinct yet complementary purpose throughout the process of decision-making. The alternatives demonstrate the main segments of selected roads for comparison facets. Three essential segments of roads were selected for this research, each with particular topographical, functional, and structural characteristics. An essential freeway through the regional roads network, the first, a selected road segment of Expressway No. 1, is characterized by high mobility and strict access control. The second route option, named locally as Old Abu Ghuraib Road, acts as a crucial urban road and is mainly utilized by road users to drive between Baghdad and Fallujah. The third option is the Karmah Road, a major local route that links multiple neighborhoods by combining both urban and rural elements of transportation.

The second component of the assigned criteria indicates an array of characteristics or performance indicators against which each option is assessed. During the MCDM analysis, there are two crucial terms that should have been taken into consideration through analysis: cost (C) and benefit (B). The cost illustrates the criteria when lower values are desired, indicating cost, effort, or adverse effects that should be minimized through the decision-making process. In contrast, benefit depicts any criteria when higher values are desired, signifying benefits, advantages, or even positive effects that ought to be maximized over the process of decision-making. The designated criteria were selected due to their rank in terms of traffic performance, overall safety, environmental sustainability, and infrastructure resilience. These criteria were established based on a dataset comprising real field measurements, traffic and accident records, professional road inspections, and environmental surveillance data. The assigned criteria consist of the length of each selected road segment and travel time, defined as the average time required to traverse a selected road segment under specific conditions. Density is also one of these criteria, which illustrates the number of vehicles within an assigned length of the road. The speed limit is also a crucial criterion when it is the maximum allowable speed that can be used by road users [44]. The rate of accidents is defined as the number of accidents per unit of time along a specified segment of the road [45]. The number of lanes and road surface conditions are also involved within the selected criteria at this study.

It is worth mentioning that the calculated criteria were collected during both selected peak AM (i.e., from 8:00 to 9:00 am) and PM (i.e., from 4:00 to 5:00 pm) periods. Each of these criteria was selected to reflect an imperative aspect of road performance, ensuring that the evaluation considered not only the efficiency of the trip, but also some factors such as safety, operational conditions, and environmental effect. By combining these multiple features into one neatly arranged decision matrix, this study presents a robust and unambiguous framework for elegant procedures of multicriteria decision making. This structure enables an organized assessment of different alternatives, besides improving the interpretation and consistency of analysis. These aspects are essential for establishing policies, infrastructure investment decisions, and further academic research on transportation system assessment.

The vital dataset utilized as criteria in this research consists of a bunch of key metrics. For instance, the reported number of accidents to law enforcement during a certain time period, by the length of the assigned road segment and the average speed of vehicles, was calculated by the floating car method. The selected data collection techniques guarantee accurate estimation, support successful transportation planning, and enable robust decision making.

Traffic density was performed manually by recording camera footage, when the observers review the recordings for vehicle counting passing through an assigned road segment during a specified time frame [46]. Consequently, traffic density was computed by dividing the number of observed vehicles by the length of the road segment. The determination of road condition was performed through site inspection, which offered an extensive estimation of pavement physical quality and related infrastructure.

Monitoring some factors, such as the existence of potholes, cracks, rutting, drainage efficiency, surface roughness, and shoulder conditions, was also performed within the inspection. The visual observations were frequently enhanced with defined assessment scales or indications of condition to recognize the extent and severity of deterioration [47].

The calculation of fuel consumption during peak hours was estimated by multiplying peak traffic volume, road segment length, and the number of peak traffic hours, then dividing by the assumed average fuel consumption efficiency factor for each vehicle (i.e., 10 km/l) [48]. The levels of pollution were estimated by using the road segment length, peak hours duration, and traffic volumes during peak hours. The latter values were multiplied by the CO_2 emission factor (i.e., 2.3 kg/l) and divided all by the average fuel efficiency of 10 km/l [49]. The resulting computation provides an estimate of the entire quantity of pollution that was generated during peak hours. This assists in understanding how traffic conditions impact the environment. Moreover, inspection surveys were conducted to identify all the remaining criteria, such as the existence of jersey barriers, the number of lanes, the presence of security checkpoints, and road lighting.

2.2 WFJM Method

The WFJM approach is principally divided into five stages. The first stage is like other MCDM models, in which the input consists of different sets of m alternatives (i.e., A1, A2, …, Am) along with n preferences of criteria (C1, C2, …, Cn). The intersection of criteria and alternatives is characterized as a decision matrix. Besides, the second stage, standardization, comprises utilizing the knowledge of experts to classify criteria as either cost or benefit types. The next step applies a normalization formula to the assigned values [50].

$$c_{ij} = \frac{c_{ij} - \min_i x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \text{; for benefit criterion} \quad (1)$$

$$c_{ij} = \frac{\max_i x_{ij} - c_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \text{; for cost criterion} \quad (2)$$

The third stage comprises two steps: both expert identification and evaluation. The first step consists of selecting and recognizing professionals who have earned the confidence of their peers. In order to confirm availability and interest, selected experts were contacted via official email. The expert review and the development of an assessment form is regarded as the second step involved. In addition, this step comprises establishing an estimation form to gather expert input while ensuring its reliability and validity, which are of paramount importance.

The data transformation, the fourth stage, encompasses two steps. The first step involves identifying optimum values. There are three different classes of optimum values, regarded as the most feasible responses to this obligation. In some cases, the first group corresponds to higher values. For instance, considering the grades of students, higher values correspond to better performance. In contrast, in the second case, the smallest value is the optimal. For instance, in network security concerns, smaller values are preferable. At the very least, some cases consist of optimum values that fall approximately in the middle range, like blood pressure. Hence, the recommended approach is crucial for addressing issues associated with varying weights in MCDM models. (3) illustrates the ideal solution.

$$A^{*}=\{((\mathrm{max}_{i}x_{ij}|x\in X)\cdot(\mathrm{min}_{i}x_{ij}|x\in X)\cdot(J_{ij}\in I.J)\mid i=1.2.3\ldots.m)\}. \tag{3}$$

In this context, max denotes the best optimum feasible value based on the advantageous criteria, while min illustrates the best potential value based on non-benefit criteria, and j_{ij} identify the critical quantity. Ideally, the optimal value lies within the range between the most extreme and the least extreme values. The subsequent stage entails comparing the best selected options against other alternatives. The outcome is a comparison of the best potential outcome for each criterion with other alternatives for the same criterion. In order to determine the alternative's deviation from the ideal alternative, weights are applied to reflect relative importance. Five linguistic metrics were utilized for comparison: big difference, huge difference, slight difference, and no difference. (4) depicts the mentioned process.

$$\mathrm{Op}_{\mathrm{Lang}}=\left\{\left(\left(\tilde{x}_{ij}\otimes x_{ij}\mid j\in J\right).\middle|\, i=1.2.3\ldots.m\right)\right\} \tag{4}$$

In order to determine the best response and compare it to the other alternatives, ⊗ utilizes as the standard for comparison. The main theoretical basis for developing the assessment matrix is a comparison between the optimum and the alternative values under the same circumstances. Moreover, due to the development on the assessment matrix and evaluation within each criterion separately, the proposed system at this research has no inaccuracy.

Finally, the fifth stage involves employing the fuzzy function of membership. To improve the judgment matrix, the function of fuzzy membership is applied, followed by a defuzzification procedure. In order to ensure a logical procedure, these processes develop the practical precision and applicability of dataset usage. Nevertheless, imprecision and uncertainty may arise due to the challenges related to assigning weights to each criterion in MCDM models. Al-Hchaimi et. al [51] specified that utilizing fuzzy values instead of precise values enables better measurement of criterion significance, especially when addressing issues of fuzziness and ambiguity. Allowing decision-makers to express their viewpoint using linguistic variables is regarded as one of the benefits.

of Fuzzy Cognitive Systems (FCSs), especially when it enhances awareness and flexibility of experts. Moreover, for more realistic assessments of evaluated information, FCSs employ a boarder set of discrete points to present fuzziness and ambiguity in indeterminate concepts [52]. The theory of the fuzzy cloud can be defined using multiple classifications. The first definition, K is assumed as a qualitative concept belonging to a space Q. x ∈ Q is regarded as a random recognition of K, satisfying x ∼ N (Ex, En2), and En′ ∼N (En, He2). μT(x) ∈ [0, 1] is the convinced degree of x on K, which can be illustrated in equation (5):

$$\mu_{K}(x)=\exp\left(-\frac{(x-Ex)^{2}}{2(En')^{2}}\right) \tag{5}$$

The second definition states that D_1 = (Ex1, En1, He1) and D_2 = (Ex_2, En_2, He_2) as a random cloud, while the value of λ is regarded as an actual value. The following outlines the principle of arithmetic operations, which can be illustrated as follows.

$$D_{1}\pm D_{2}=\left(Ex_{1}\pm Ex_{2},\sqrt{En_{1}^{2}+En_{2}^{2}},\sqrt{He_{1}^{2}+He_{2}^{2}}\right) \tag{6}$$

$$D_{1}\times D_{2}=\left(Ex_{1}Ex_{2},|Ex_{1}Ex_{2}|\times\sqrt{\left(\frac{En_{1}}{Ex_{1}}\right)^{2}+\left(\frac{En_{2}}{Ex_{2}}\right)^{2}}\right.$$
$$\left.,|Ex_{1}Ex_{2}|\times\sqrt{\left(\frac{He_{1}}{Ex_{1}}\right)^{2}+\left(\frac{He_{2}}{Ex_{2}}\right)^{2}}\right) \tag{7}$$

$$\frac{D_{1}}{D_{2}}=\left(\frac{Ex_{1}}{Ex_{2}},\left|\frac{Ex_{1}}{Ex_{2}}\right|\times\sqrt{\left(\frac{En_{1}}{Ex_{1}}\right)^{2}+\left(\frac{En_{2}}{Ex_{2}}\right)^{2}},\left|\frac{Ex_{1}}{Ex_{2}}\right|\right.$$
$$\left.\times\sqrt{\left(\frac{He_{1}}{Ex_{1}}\right)^{2}+\left(\frac{He_{2}}{Ex_{2}}\right)^{2}}\right). \tag{8}$$

Table 1 illustrates the linguistic terms using FCS. In order to reach the optimum values for the estimation criteria $(w_1, w_2, \ldots, w_n)$ T of coefficient weights, the following steps are applied.

1) By combining equation 6 with the formally applied FCS formula, the fuzzification ratio dataset is determined, which can be denoted as A. For instance, the first criterion in the fuzzy representation can be illustrated as A_{C1}, and the second criterion is A_{C2}, which can be applied to the remaining criteria.
2) By applying the same procedure for all criteria, the summary of $\{A_{C1}, A_{C1}, A_{C1}\}/3$ can be utilized.
3) The obtained outcome of the above second step can be standardized by dividing it by the summation of the related results of the same

step, thereby providing the final criterion weight. Nevertheless, the weight should equal 1.0, as demonstrated in (9).

$$W = \left(\frac{\sum_{i=1}^{m} \frac{\left(\left(A_{cj}\right)\right)}{\left(\sum_{j=1}^{n} \left(A_{cj}\right)\right)}}{m} \right), \text{for } i = 1,2,3, \ldots m \text{ and } j = 1,2, \ldots n. \quad (9)$$

Table 1: Linguistic terms.

Linguistic terms	Numerical	Cloud value		
No_Difference (ND)	1	0.000	0.673	0.101
Slight_Difference (SD)	2	3.0988	0.453	0.068
Difference (D)	3	5.000	0.278	0.041
Big_Difference (BD)	4	8.262	0.579	0.086
Huge_Difference (HD)	5	10	0.673	0.101

2.3 MULTIMOORA Method

Through the analysis of ratios, a bunch of researchers have approached the optimization of the multi-objective optimization method (MOORA) [53]. In order to enhance its robustness, researchers extended this method by integrating a full multiplicative model with MOORA, known as MULTIMOORA [54]. This method has been applied in multiple domains of study, such as provincial assessments, cross-national evaluations, and investment management [55]. The MOORA method initiates with matrix X, where each entry x_ij indicates ith alternative associated with jth purpose (i = 1, 2,..,m; j = 1, 2..,,n). It involves two components: the ratio approach and the basis point approach. Brauers et al. [56] stated that the weighting methodology comprises two steps, depending on the relevance of outcomes. A bunch of other researchers have addressed the issue of normalization [57]. Moreover, other researchers have examined the issue of weighting [58]. The MULTIMOORA model focuses on internal standardization and treats all objectives equally. For instance, stakeholders associated with the topic might give a preference to a particular purpose. Hence, in order to depict a response on a target, either multiplying the dimensionless number, which reflects the response of the objective by an impact coefficient, or dividing the objective into multiple sub-objectives [59]. By comparing different options of objectives to different potential outcomes, MOORA's ratio system adjusts the dataset as illustrated in (10).

$$x_{ij}^{*} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^{2}}}, \quad (10)$$

X_{ij} Represents the ith alternative for the Jth objective. In general, these values range between 0 and 1. In addition, criteria may be included or excluded based on their optimal value (i.e., minimum or maximum).

The considered index for every selection is calculated by (11).

$$y_{i}^{*} = \sum_{j=1}^{g} x_{ij}^{*} - \sum_{j=g+1}^{n} x_{ij}^{*} \quad (11)$$

It is worth mentioning that g signifies the number of objectives that should be maximized. At this stage, each ratio is assigned a rank, where a higher index corresponds to a higher rank.

The reference point approach in the MOORA is directly related to the ratio system. According to the specified ratios, (11) is utilized to determine the Maximal Objective Reference Point vector. The Jth coordinate of the reference point is expressed as rj = max(ix) in the optimization context. Each coordinate of this vector specifies the minimum or maximum value of a specific objective. Subsequently, each component of the normalized response matrix is calibrated accordingly. In addition, the final ranking is determined according to the deviation between the reference point and the minimum and/or maximum Metric as illustrated in (12).

$$\min_{i} \left(\max_{j} \left| r_{j} - x_{ij}^{*} \right| \right). \quad (12)$$

Updating the MOORA method was enhanced by Kreinovich and Cheu [60] through the integration of a full Multiplication Form methodology. This method consists of both optimizing and reducing the sole exponential utility function. The dimensionless quantity is regarded as the practical utility of the ith alternative, as illustrated in (13).

$$U_{i}' = \frac{A_{i}}{B_{i}}. \quad (13)$$

According to (13), A_i is defined as Πig=1 xij; i = 1; 2 where m represents the invention of the purposes that belong to the ith alternative to be maximized with g = 1, …, n. Also, Bi = Πig=1 X_{ij} Illustrates the objective product of the ith that is minimized with n

– g, the number of indications that should be minimized. It is crucial to mention that the MULTIMOORA includes both the full multiplicative form and MOORA components (Ratio Systems and Reference Points) [61].

3 RESULTS AND DISCUSSION

3.1 Results

According to the methodological approach described in the previous section, the analysis of the three main routes between Baghdad and Fallujah was conducted through a series of analytical stages. The results obtained for the selected road segments are presented below.

At the first stage, a decision matrix was constructed based on the selected evaluation criteria. This step was performed separately for the AM and PM peak periods to capture temporal variations in traffic conditions. The decision matrix is presented in Table A1 (Appendix) and serves as the basis for subsequent weighting and ranking procedures.

The weighting process was carried out using the WFJM method to determine the normalized importance of each criterion for both time periods (Figure 2). The results indicate that during the AM period, the most influential factors are speed limit (0.14245), road condition (0.11506), fuel consumption (0.11506), and pollution (0.11506), highlighting the importance of operational efficiency and environmental impact. Safety-related factors, such as accident frequency (0.07293) and road density (0.08748), also play a significant role due to congestion during morning hours. In contrast, factors such as checkpoints (0.03460) and jersey barriers (0.05830) have a lower impact.

In the PM period, the importance of lighting (0.17495) and road condition (0.11749) increases, reflecting greater concern for visibility and safety. While speed limit remains significant (0.11749), other factors such as road density, pollution, and fuel consumption show moderate influence. The increased weight of jersey barriers (0.08933) indicates higher safety requirements during evening travel. Overall, morning conditions emphasize efficiency, whereas evening conditions prioritize safety and visibility.

The ranking of alternatives was performed using the MULTIMOORA method. The evaluation combines three approaches—Ratio System, Reference Point, and Multiplicative Form—and aggregates the results using the Borda count (Table 2), ensuring a comprehensive and balanced decision-making process.

For the AM period, the Old Abu Ghuraib Route achieves the highest overall ranking with a Borda score of 8.0, despite not being the top performer in each individual method. This indicates consistent performance across all evaluation approaches. The Expressway Route and Karmah Route share the second position with equal scores.

In the PM period, the Old Abu Ghuraib Route maintains its leading position, confirming its stability across different time conditions. The Expressway Route ranks second, likely due to improved evening conditions such as lighting and traffic flow, while the Karmah Route ranks third due to less favorable conditions. Overall, the results demonstrate that the Old Abu Ghuraib Route is the most reliable and balanced option.

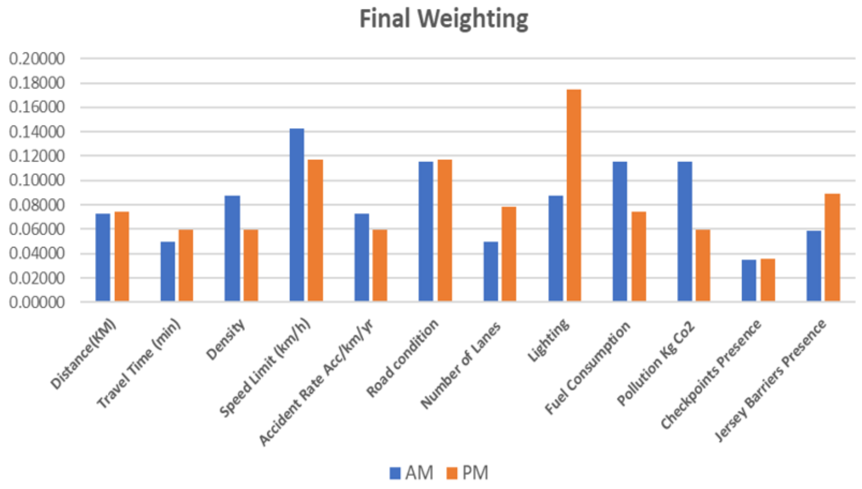

Figure 2: Final weight.

Table 2: Final rank.

Period	Path route	Ratio System	Reference Point	Multiplicative Form	Borda Score	Final Rank
AM	Expressway Route	1	3	1	5	2
	Old Abu Ghuraib Route	3	2	3	8	1
	Karmah Route	2	1	2	5	2
PM	Expressway Route	2	3	1	6	2
	Old Abu Ghuraib Route	3	2	3	8	1
	Karmah Route	1	2	2	5	3

3.2 Validation and Sensitivity Analysis

To verify the robustness and reliability of the obtained results, a sensitivity analysis was conducted (Figure 3). In this process, the weights of the evaluation criteria were systematically varied within a reasonable range, and the impact of these variations on the final ranking was examined.

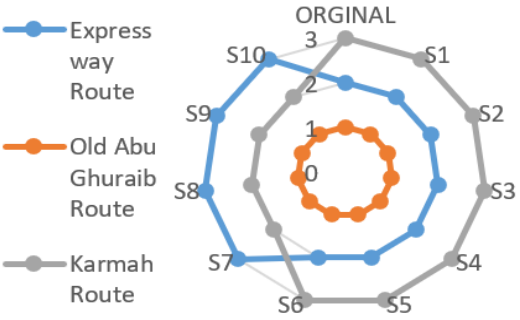

Figure 3: Sensitivity analysis.

The results show that the Old Abu Ghuraib Route consistently maintains the first position under both AM and PM conditions, even with significant changes in criteria weights. This stability indicates that the final decision is not overly sensitive to specific weighting schemes and confirms the robustness of the model.

Although minor ranking variations were observed for the Expressway and Karmah routes, these changes did not affect the overall ranking outcome. Therefore, the results obtained using the MULTIMOORA method can be considered reliable and consistent for decision-making purposes.

4 CONCLUSIONS

To utilize both the criterion dataset and expert judgement, a selected segment of Expressway No.1, the Old Abu Ghuraib Road, and the Karmah Road, regarded as the main social and economic arteries of road users between Baghdad and Fallujah, was subjected to thorough analysis in this study. Three methodological phases were taken into consideration for the complicated performance evaluation of the three selected routes (i.e., identification of the full set of criteria, assessing the significance of criteria by WFJM, and ranking the alternatives using MULTIMOORA approach.

Through three-phase integration, this study identified the route that operates best when the methodology is applied thoroughly and spatially accurately. Both AM and PM analyses of WFJM revealed temporal variations in the significance of the inspection criterion. For instance, during the AM period, environmental and operational factors like road condition, fuel consumption, speed limit, and pollution, combined with safety-related factors like accident frequency and traffic density, were the most significant. Conversely, the PM period emphasized visibility, safety, lighting, road condition, and the presence of jersey barriers as the most of significant criteria. Nevertheless, both environmental and traffic flow factors had an insignificant impact.

Based on MULTIMOORA analysis (i.e., ratio system, method of reference point, and Borda count aggregation for multiplicative form), the Old Abu Ghuraib Road was recognized as the ideal and the most reliable option for road users during both AM and PM circumstances. However, depending on the evaluation method and time period, both segments of Expressway No. 1 and the Karmah Road performed moderately but inconsistently. By confirming both stability and robustness of the final decision, the sensitivity analysis depicted that the Old Abu Ghuraib Road maintained its top ranking under different weighting conditions. Though all three selected routes are crucial for the regional transportation network, the Old Abu Ghuraib Road still performs best in terms of safety, operational efficiency, environmental impact, and infrastructural quality, despite temporal traffic variations.

Like others in the literature, this study has limitations. This paper studies only three selected routes that were evaluated based on the available data and assessment criteria. However, a high percentage of drivers between Baghdad and Fallujah utilize these three selected routes. In addition to the traditional MCDM frameworks, such as Weighted Product Method (WPM), AHP, and Analytic Network Process (ANP), could have been employed, but the selected method offers specific advantages when it processes the inconsistency, one of the main gaps over the MCDM methods. For future studies, the research recommends adding another fuzzy with the methods used in this research. Also, incorporating criteria such as seasonal variations, environmental data, and broader socioeconomic effects into the MCDM framework could further route optimization. Moreover, integrating multi-model transportation systems and last-mile interactions would offer a much thorough perspective on urban mobility.

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APPENDIX

Table A1 presents the decision matrix used in this study, summarizing the performance values of all three route alternatives across the selected criteria for both AM and PM peak periods. The matrix serves as the primary input for the WFJM weighting process and subsequent MULTIMOORA ranking analysis, ensuring a consistent and structured evaluation of route performance under varying traffic conditions.

Table A1: Decision matrix.

Criteria		AM		
		Expressway Route	Old Abu Ghuraib Route	Karmah Route
Traffic and performance	Distance (KM) (C)	71.7	66.1	82
	Travel Time (min) (C)	81	81	82
	Density (C)	High	Medium	Low
	Speed Limit (km/h) (B)	120	100	60
	Accident Rate (C) Acc/km/yr	0.89	0.83	0.28
Road Quality & Infrastructure	Road condition	Excellent	Good	Fair
	Number of Lanes (B)	3	3	1
	Lighting	Yes	No	No
Cost Considerations	Fuel Consumption (C) Liter	70389	15153	10557
Environmental impact	Pollution (C) Kg Co2	161895	34852	24281.1
Safety Features	Checkpoints Presence	Yes	No	No
	Jersey Barriers Presence	Yes	No	No
Criteria		PM		
		Expressway Route	Old Abu Ghuraib Route	Karmah Route
Traffic and performance	Distance(KM) (C)	71.7	66.1	82
	Travel Time (min) (C)	87	72	93
	Density (C)	High	Medium	Low
	Speed Limit (km/h) (B)	120	100	60
	Accident Rate (C) Acc/km/yr	0.89	0.83	0.28
Road Quality & Infrastructure	Road condition	excellent	Good	Fair
	Number of Lanes (B)	3	3	1
	Lighting	Yes	No	No
Cost Considerations	Fuel Consumption (C) Liter	111947	14492	10106
Environmental impact	Pollution (C) Kg Co2	257478	33332	23244
Safety Features	Checkpoints Presence	Yes	No	No
	Jersey Barriers Presence	Yes	No	No