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RESEARCH ARTICLE

Dynamic Decision Making Process for Dangerous Good Transportation Using a Combination of TOPSIS and AHP Methods With Fuzzy Sets

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ABSTRACT Dangerous Goods Transportation in smart cities is one of the most intriguing topics that researchers are interested in to reduce the risks caused by hazardous events. This article proposes a novel technique to avoid hazardous events during the transportation of dangerous goods using real-time information provided by the cloud. This article applies Fuzzy Analytical Hierarchy Process - Technique for Order Preference by Similarity to Ideal Solution (AHP-TOPSIS) hybrid method for risk analysis applied to Dangerous goods transportation in a smart city. The article assumes that we have three criteria that dictate the choice of routs the vehicle follows: cost, duration, and risk. The main objective is to choose the best route through calculated weights assigned to the three criteria based on predefined pairwise comparisons. The study is done on both static and dynamic environments. In static environments, the decision is made and is followed prior to actions and no change of actions is made even if criteria values change. In dynamic environments on the other hand, the decision could change during the transportation process due to the change of the valuation the criteria contribute to. The study shows that risk is reduced and therefore safety is increased for the transportation of dangerous goods.

INDEX TERMS Supply chains, industry 4.0, best trajectory identification, dangerous good transportation, fuzzy AHP, fuzzy TOPSIS, multi-criteria decision making, risk evaluation.

I. INTRODUCTION

Supply chains are sets of actions and activities performed by organizations to deliver goods to customers [1]. As shown in Figure 1, a supply chain has 5 stages from suppliers to customers. Suppliers provide raw material, followed by procurement process then the production process takes place followed by the delivery process in which products are delivered to customers.

Like any big relatively new concept, Industry 4.0 does not have a unique agreed upon definition. However, most research defined it to be the result of integrating intelligence with all stages of the process [2]. In [3], industry 4.0 was defined to be the process of managing the cyber-physical production network that binds together ensuring: raw material supply, delivery to customers, logistics, factory operations and manufacturing operations. Figure 2 shows the structure of industry 4.0 as described in [3].

Industry 4.0 can be seen as a whole framework or digital organization [3], [4]. This framework integrates many modern techniques such as intelligent internet of things (IIoT) [5], [6]. big data [6], [7], wireless sensor networking [8], and automation [9], [10]. It also integrate the application of artificial intelligence in supply chains [11], [12], [13], [14], [15], and the analysis of everything with the objective to improve performance while making sure that customer is satisfied [16]. Figure 3 shows the basic technological requirements of industry 4.0.

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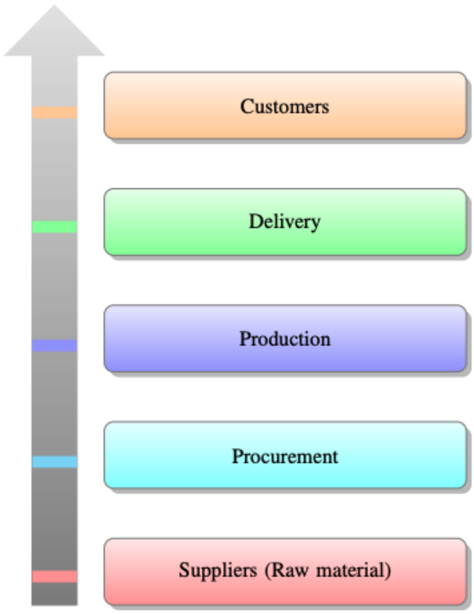


FIGURE 1. Simple supply chain model.

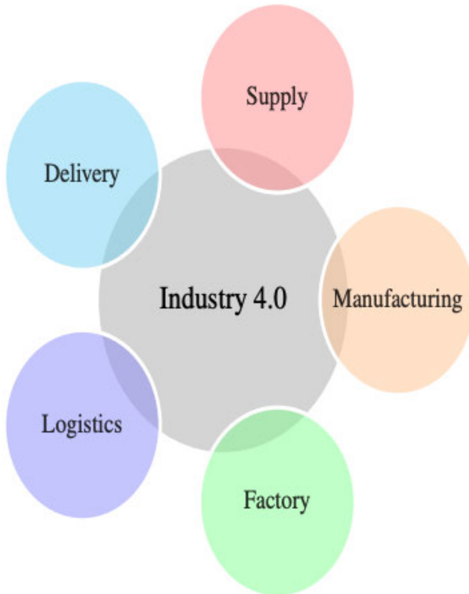


FIGURE 2. Components of Industry 4.0.

Supply chain 4.0 is a prerequisite for Industry 4.0. Supply chain 4.0 is a supply chain that respects the definition and constraints of industry 4.0 [4]. Supply chain 4.0 integrates intelligence with supply chain components for better planning and decision making. The objectives of applying intelligence to supply chain might change from one industry to another, however, regardless what the objectives are, Supply chain 4.0 definitely guarantees better performance in objective achievement compared to traditional supply chains [17].

As seen in Figures [1,2], delivery is an important stage in supply chains and Industry 4.0 in general. Delivering goods is not a trivial task. The process of goods delivery is a multi-criteria decision making (MCDM) process that aims to minimize *cost*, avoid *delays* and most importantly avoid *hazards* [18]. AHP [19] and TOPSIS [20] methods are the most used for MCDM problems. AHP method is especially suitable for weighing qualitative data and using pairwise comparison for each criteria [21]. The TOPSIS method has been implemented successfully to rank alternatives and take decision for different MCDM problems [22], [23], [24].

Avoiding or mitigating hazards related to DG shipment is a critical step in the delivery process since transportation presents high risk to human beings in the surrounding areas. Despite all activities of safety and security, risk exists and its level ranges from low/acceptable to high/unacceptable. This risk cannot be eliminated but it can be managed by reducing the quantity of loaded materials, changing the transport route, or the departure time [25]. Risk management involves a number of approaches, including the identification, evaluation and control of risk [26], [27], [28], [29], [30]. Generally, Risk evaluation uses two parameters: the likelihood of an incident and the severity of its outcome [31]. Those parameters depend on many inputs where some of them are uncertain. At this level, the shipment process becomes complex as it depends on three factors: cost, duration and risk level which is presented with uncertainty. The aim of this work is to propose an approach that optimizes the management of DGT delivery process. This approach uses a combination of AHP/TOPSIS methods with the integration of fuzzy models. It provides a dynamic and real-time ranking of alternative routes for the transportation process [32], [33].

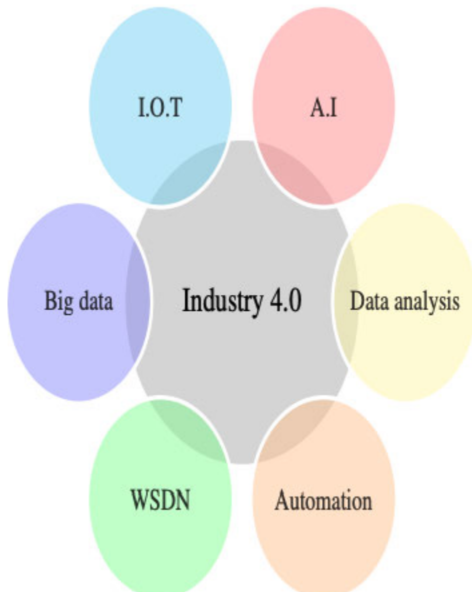


FIGURE 3. Technologies of Industry 4.0.

This paper is organized as follows: Section I introduces the paper and justifies the proposed work. Section II identifies the previous work that is related to the proposed model in this paper. Section III introduces the needed preliminaries for the reader to easily navigate through the paper. Section IV states the problem being solved in this paper and section V defines the objective of this work. Section VI specifies the contribution of this paper. Section VII presents the proposed model. Section VIII discusses the simulation and experiment results. Section IX concludes the paper.

II. LITERATURE SURVEY

In literature, many papers have been addressed the routing problem and some of them discussed the transportation of dangerous goods.

As for the risk assessment process, most of the scanned publications applied two parameters: likelihood and consequences, as effective factors that can have an effect on risk analysis [25], [34], [35], [36] and best trajectory selection for transportation [37], [38], [39]. Whereas, in order to optimize the dangerous goods transportation management (DGTM), it is important to take into account other factors than can have an effect on DGTM as trip duration and related cost. Therefore, the problem becomes a multi-criteria decision making (MCDM) problem [40], [41], [42], [43], [44]. And an appropriate method is needed for risk analysis of dangerous goods transportation to solve the interdependent issues in an effective manner.

MCDM methods have been used in several studies to analyze industrial risks [43], (e.g using the analytic network process and fuzzy linguistic approach [45], the best-worst method [46], the failure mode and effects analysis [47], [48]. Boateng et al. [49] defined a combined methodology of ANP and risk priority index to rank transportation risks.

In [50], authors focused on the mitigation of population exposure risk via production of truck-routes. To do so, they employed a single parameter metaheuristic algorithm. In [51], authors proposed a decision support system for assessing alternative distribution routes in the transportation of dangerous goods. This system considers three parameters: travel time, risk, and evacuation implications. In [52], authors discussed the problem of finding a set of non-dominated shortest paths in stochastic transportation networks using probability distribution approach. They divide the time horizon into many slots then considers a static analysis of the used parameters per time slot. In those work, authors assume that the inputs parameters are static and they didn't consider the uncertainty of the used parameters.

Many methods are proposed to solve multi-criteria decision making problems [53], [54], [55], [56]. Some MCDM methods have been used to determine the criteria weights, including the analytic hierarchy process (AHP) [57]. AHP method is especially suitable for weighting qualitative data with a crisp 9-point rating scale [58] and using pairwise comparison for each criteria [21]. It has been used in various research areas including evaluation, selection and forecasting [59], [60]. Also, AHP was used by Zayed et al. [61] to assess risks in Chinese highway construction and in [62] to evaluate potential risk of crane incidents in construction projects. Nonetheless, AHP has a main drawback while used with a large number of items to be determined and prioritized, as it can compare only a limited number of decision alternatives [58]. Another limitation of traditional AHP is that experts cannot truly express their judgments by the crisp values in the rating scale [63]. This issue can be solved by using Fuzzy set theory.

Technique for order preference by similarity to ideal solution (TOPSIS) [22] methods are well-known methods for MCDM problems [23], [24]. TOPSIS method is used by Zavadskas et al. [64], to propose a methodology for risk assessment in construction projects.

In most of the work in risk assessment, there is a difficulty in obtaining precise information, due to: insufficient data, the number of sources of data and the vague characteristics. Uncertainty analysis has been done in several studies to represent and propagate uncertainty in risk analysis [65], [66], [67], [68], [69]. Also, the application of the fuzzy set theory may systemically improve the ability of a MCDM to handle uncertainty [34], [70], [71], [72], [73], [74], [75], [76], and [77]. Fuzzy models are helpful for demystifying, assessing and learning about risks that are not well understood. Thus, several researchers integrate fuzzy set theory with MCDM methods to handle the uncertainty and complex problems involved in a decision-making environment [78], [79], [80], [81].

Zeng et al. [82] applied Fuzzy AHP method to prioritize the risk factor in construction projects. Shin et al. [83] used AHP and Fuzzy AHP at nuclear power plant to identify and assess probable risks. Such applications show that applying Fuzzy AHP method is more appropriate for risk evaluation [43].

Some authors proposed a hybrid model that consists of both methods AHP and TOPSIS [84]. Taylan et al. [85] proposed a hybrid model for risk assessment using Fuzzy AHP and TOPSIS. Kuo and Lu [86] used Fuzzy Multiple Attribute Decision-making (MADM) approach to assess risk of a metropolitan construction project.

Risk analysis can be done using many methods such as Monte Carlo Simulation [87], [88], [89], [90], [91], Event Trees [92] and [93], Fault Trees [94], [95], and [25], Dynamic Event trees [96], Markov models [97], Failure mode and Effective Analysis [76], [98], and [99], and Petri net [100], [101], [102], and [103].

Due to the importance of these products and the critical related risk, some researches are performed in order to evaluate risks and identify best trajectory to travel as in [104], [105], and [106].

III. PRELIMINARIES

This section introduces necessary preliminaries for the understanding of this paper. Different concepts are introduced in different subsections as seen below.

A. CRISP VS FUZZY VARIABLES

Before 1965, variables were always crisp. A crisp variable is a variable that has an exact value at any point of time. In 1965, Lotify Zadah introduced the concept of fuzziness and fuzzy logic [107]. The motivation behind proposing Fuzzy logic was mentioned in one of his famous quotes:

> "As complexity rises, precise statements lose meaning and meaningful statements lose precision"
>
> Lotfi A. Zadeh.

Concepts like **huge**, **gigantic**, **massive**, **tiny** and so on cannot be measured by single values, instead they represent a range in which values can be described as massive or tiny. Any of those concepts includes many crisp values and they are all linguistically described by the same concept.

Figure 4 shows the fuzzy variable on the left hand side where values fade the farthest they are from the center. On the right hand side of the figure, the variable is crisp where the value is always the same regardless where we are in the area where the variable is defined.

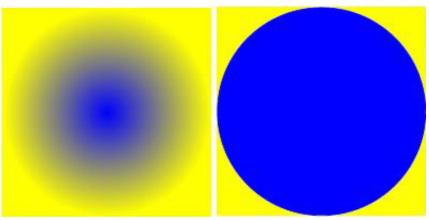


FIGURE 4. Fuzzy variables VS. Crisp variables.

B. MULTI-CRITERIA DECISION MAKING

Enabling decision making in any given system empowers it to become an active system with added value. Multi-criteria decision making (MCDM) is a process that makes use of relevant criteria through various types of methods to decide on a targeted result. MCDM methods are used in complex systems that contain expanded processes to handle uncertainty and converge onto the desired goal. The most prominent methods of MCDM are AHP, TOPSIS, ELECTRE, and Grey Theory [108]. The most commonly used methods are AHP and TOPSIS where each has been developed to accept fuzzy systems as well. These methods are called Fuzzy AHP and fuzzy TOPSIS.

C. AHP

Analytical hierarchy process (AHP) is a powerful method used to solve complex multi-criteria decision-making (MCDM) problems. In AHP, the hierarchical technique used aims to decompose a complex problem into levels of sub-problems. Each level represents a set of criteria relative to each sub-problem. The top level contains the Goal or the objective. The second level represents the set of relevant criteria. If those criteria can be divided into sub-criteria, then lower levels can represent this decomposition. Thus, the last level highlights the set of alternatives as shown in figure 5.

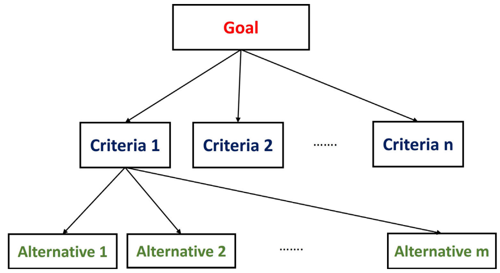


FIGURE 5. Hierarchy problem tree.

The analysis part of AHP is based on an additive weighting process, in which several relevant attributes are represented through their relative importance. The core of AHP is the comparison of different criteria represented in quantitative way (price, weight, or area) or even in qualitative manner (feelings, preferences, or satisfaction). This comparison is based on pairwise comparison rather than sorting, voting (e.g. assigning points) or the free assignment of priorities.

The basic AHP method does not take into account the uncertainty associated with the mapping of human judgment by perception, evaluation, improvement and selection. Figure 6 illustrates the main steps of AHP:

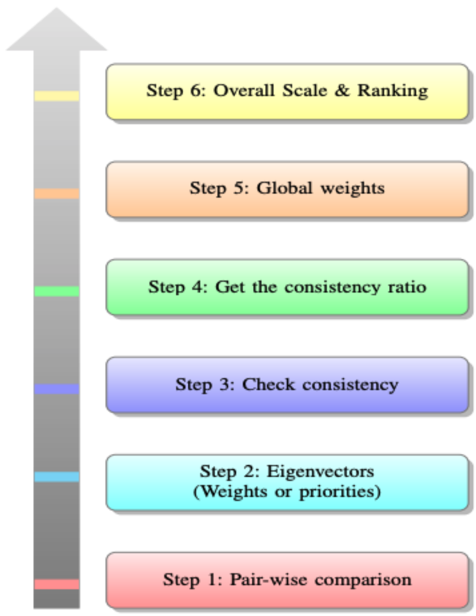


FIGURE 6. AHP steps.

AHP can broadly be classified to be crisp AHP or Fuzzy AHP. Crisp AHP is when the scale of relative importance between every two criteria is represented by a single crisp value. This of course ignores the possibility of inaccuracy of different comparisons. Fuzzy AHP on the other hand, represents the scale of relative importance as a triangular fuzzy number which takes into consideration the possibility of representing the scale of relative importance in an uncertain way. This leads to a better decision making process since inaccuracies are being represented in the model itself.

We start below by demonstrating the crisp AHP method first then we show how the fuzzy AHP is being extended out of the crisp approach.

1) CRISP AHP

Below we show the crisp AHP in details demonstrated by examples.

- Step 1: Use a scale of relative importance like the one represented in table 1 to construct the pairwise comparison matrix for all the criteria in the levels of the hierarchy as shown in matrix A;

TABLE 1. Scale of relative importance.

Number	Description
1	Equal importance
3	Moderate Importances
5	Strong importance
7	Very Strong Importances
9	Extreme Importances
2, 4, 6, 8	Intermediate values
1/3, 1/5, 1/7, 1/9	Values for Inverse comparison

The pairwise comparison matrix A is a square matrix with a length of the number of criteria we have. If criteria is price, look, quality, and maintenance then matrix A will simply be a 4×4 square matrix. Matrix A is described as follows:

$$A = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ a_{21} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & & 1 \end{bmatrix}$$

Every item $a_{ij} \in A$ represents the pairwise comparison between two criteria. An example is if first criterion is speed and second criterion is price then a_{12}represents how important speed is with respect to price whereas a_{21}represents how important price is with respect to speed. This means that:

$$\forall a_{ij} \in A, a_{ij} = \frac{1}{a_{ji}} \tag{1}$$

This explains why the diagonal is always 1. It is because you are comparing the how important a criterion is with itself. This means that $i = j$ and therefor

$$\forall a_{ij} \in A \| i = j, a_{ij} = 1 \tag{2}$$

from equations 1 and 2, we fill matrix A as follows:

$$A = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ \frac{1}{a_{12}} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{1}{a_{1n}} & \frac{1}{a_{1n}} & \cdots & 1 \end{bmatrix}$$

After matrix A is filled, we proceed with the next step.

- Step 2: After building pairwise comparison matrix A, weights for every criterion needs to be calculated. The first step to achieve this is to calculate the mean. The mean could either be arithmetic mean or geometric mean. Arithmetic mean is obtained by calculating the sum vector S. Sum vector S is the sum of the columns of matrix A and it is calculated as follows:

$$\forall s_j \in S, a_{ij} \in A, s_j = \Sigma_{i=0}^{n} a_{ij} \tag{3}$$

where A is an $n \times n$ matrix, $1 \leq i \leq n$ and $1 \leq j \leq n$. Given matrix A in III-C1, vector S is:

$$S = \begin{bmatrix} s_1 & s_2 & \cdots & s_n \end{bmatrix}$$

where $1 \leq j \leq n$ and $s_j \in S$ is calculated according to equation 3.

Now arithmetic mean is calculated according to the following matrix:

$$A\prime = \begin{pmatrix} \frac{1}{s_1} & \frac{a_{12}}{s_2} & \cdots & \frac{a_{1n}}{s_n} \\ \frac{a21}{s_1} & \frac{1}{s_2} & \cdots & \frac{a_{2n}}{s_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{a_{1n}}{s_1} & \frac{1}{a_{1n}} & \cdots & \frac{1}{s_n} \end{pmatrix}$$

In other words, arithmetic mean is calculated as:

$$a'_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \tag{4}$$

After calculating the arithmetic mean matrix $A\prime$, we can now find the weight vector W where $W = \{w_1, w_2, \ldots, w_n\}$ as follows:

$$w_i = \frac{1}{n} \sum_{i=1}^{n} (a'_{ij}) \text{ for } 1 \leq i \leq n \text{ and } 1 \leq j \leq n \tag{5}$$

Geometric mean is calculated as follows:

$$r_i = (a_{i1} \otimes \cdots \otimes a_{ij} \otimes \cdots \otimes a_{in})^{\frac{1}{n}} \tag{6}$$

where $1 \leq i \leq n$ and $1 \leq j \leq n$ and r_i is the geometric mean of row number i. Now the weights based on the geometric mean are calculated as:

$$\omega_i = r_i \otimes (r_1 \oplus \cdots \oplus r_i \oplus \cdots \oplus r_n)^{-1} \tag{7}$$

where $1 \leq i \leq n$ and $1 \leq j \leq n$

Note: If many sources of information are available (k experts), matrices aggregate is needed using this equation:

$$\tilde{w_{ij}} = \frac{1}{k}(\tilde{w_{ij}^1} + \tilde{w_{ij}^2} + \cdots + \tilde{w_{ij}^k}) \tag{8}$$

As seen above, after the aggregation of the opinions of the experts, the geometric means and then the local weights in each level can be determined. The results are related to each level alone and after that the global weights of the criteria that considered as final criteria is computed. This is shown in table 2.

TABLE 2. Criteria weights.

Criteria weights	w_1	w_2	...	w_n	
	$c1$	$c2$	...	cn	Weighted sum value
$c1$	$1 * w_1$	$a_{12} * w_2$	...	$a_{1n} * w_n$	$\sum_{j=1}^{n}(a_{1j} * w_j)$
$c2$	$a_{21} * w_1$	$1 * w_2$	...	$a_{2n} * w_n$	$\sum_{j=1}^{n}(a_{2j} * w_j)$
...	...	..	..	..	
cn	$a_{n1} * w_1$	$a_{n2} * w_2$	...	$1 * w_n$	$\sum_{j=1}^{n}(a_{nj} * w_j)$

- Step 3: On this step, consistency index $C.I.$ is calculated. Consistency index is the most important measurement in this process and it is defined to be the index of the consistency of judgements across all pairwise comparisons.
  Consistency index is defined to be a function of λ_{max}, where λ_{max} is evaluated based on the following equation:

$$\lambda_{max} = \frac{\sum_{j=1}^{n} \frac{(\text{Weighted sum value})_j}{w_j}}{n} \tag{9}$$

  After calculating λ_max, we can proceed to calculate the consistency index as follows:

$$C.I. = \frac{\lambda_{max} - n}{n-1} \tag{10}$$

- Step 4: Calculate the consistency ratio $C.R.$ by dividing the consistency index $C.I.$ with a random index $R.I.$ as shown in equation 11. Random index is the consistency index of randomly generated pairwise matrix. Table 3 illustrates the random index table for up to 10 criteria. C.R. should be less than 0.1 to be considered as reasonably consistent and to be able to move to the next step.

$$C.R. = \frac{C.I.}{R.I.} \tag{11}$$

TABLE 3. Random index table.

n	1	2	3	4	5
R.I	0.00	0.00	0.58	0.90	1.12
n	6	7	8	9	10
R.I	1.24	1.32	1.41	1.45	1.49

- Step 5: Get the global weight for each criteria. For the criteria without parent-criteria, their global and local weights are equal. For sub-criteria, their global weight is equal to their local weight multiplied by the global weight of their parent.
- Step 6: Compute the overall score of each alternative i with respect to all criteria as follows:

$$Score_i = \sum_{j=1}^{n} a_{ij} * w_j, i = 1, 2, \ldots, m \tag{12}$$

2) FUZZY AHP

In AHP, we relied on the scale of relative importance to create the pair-wise comparison matrix for our problem. The scale contains crisp values to indicate the importance of the criteria. In fuzzy AHP, the scale is generated using triangular fuzzy numbers instead of crisp numeric values. As a result, we start this process with:

- Step 1: define the criteria matrix as follows:

$$\tilde{A} = \begin{bmatrix} 1 & \tilde{a_{12}} & \cdots & \tilde{a_{1n}} \\ \tilde{a_{21}} & 1 & \cdots & \tilde{a_{2n}} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{a_{n1}} & \tilde{a_{n2}} & \cdots & 1 \end{bmatrix}$$

  which is evaluated as follows:

$$\tilde{A} = \begin{bmatrix} 1 & \tilde{a_{12}} & \cdots & \tilde{a_{1n}} \\ \frac{!}{\tilde{a_{12}}} & 1 & \cdots & \tilde{a_{2n}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{1}{\tilde{a_{1n}}} & \frac{1}{\tilde{a_{2n}}} & \cdots & 1 \end{bmatrix}$$

  where:

$$\tilde{a_{ij}} \begin{cases} = 1, & \text{if } i = j \\ \in \left\{ \tilde{9^{-1}}, \cdots, \tilde{2^{-1}}, \tilde{2}, \cdots, \tilde{9} \right\} & \text{otherwise} \end{cases} \tag{13}$$

- Step 2: calculate the fuzzy geometric mean using equation 14:

$$\tilde{r_i} = (\tilde{a_{i1}} \otimes \cdots \otimes \tilde{a_{ij}} \otimes \cdots \otimes \tilde{a_{in}})^{1/n} \tag{14}$$

- Step 3: calculate the fuzzy weights of each criteria using equation 15:

$$\tilde{w_i} = \tilde{r_i} \otimes (\tilde{r_1} \oplus \cdots \oplus \tilde{r_i} \oplus \cdots \oplus \tilde{r_n})^{-1} \tag{15}$$

- Step 4: change the fuzzy weights to crisp numerical value (defuzzification) using the center of area method. The method requires getting the average of the lower, middle and upper values of the triangular fuzzy number.
- Step 5: continue the AHP steps 3-6 to finally get the overall score of each alternative.

D. TOPSIS

TOPSIS is a great technique for prioritizing and selecting one or more alternatives from a pool of possible alternatives based on a set of many different criteria [109]. TOPSIS was developed by [110]. It is used to choose an alternative that has the shortest distance from the positive-ideal solution and the farthest distance from the negative-ideal solution. TOPSIS solves a problem with alternatives $A_1, A_1, \cdots, A_m$ evaluated based on n criteria $C_1, C_2, C_3, \cdots, C_n$. It can be applied in two ways: Crisp and Fuzzy.

1) CRISP TOPSIS

TOPSIS method can be applied according to the following steps:

- Step 1: Establish the decision matrix for ranking: in the case of m alternatives and n criteria, the decision matrix is: $(X) = (x_{ij})_{m\times n}$;

$$\begin{array}{c} \\ A_1 \\ A_2 \\ \cdots \\ A_m \end{array} \begin{array}{c} \begin{array}{ccccc} c_1 & c_2 & c_3 & \cdots & c_n \end{array} \\ \begin{pmatrix} x_{11} & x_{12} & x_{13} & \cdots & x_{1n} \\ x_{21} & x_{22} & x_{23} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & x_{m3} & \cdots & x_{mn} \end{pmatrix} \end{array}$$

- Step 2: Normalize the decision matrix: the normalization process used in our research is based on getting the sum of each criteria (performance value) under all alternatives then divide the criteria value by that sum. For the decision matrix $X = (x_{ij})_{m\times n}$, the normalized matrix is $R = (r_{ij})_{m\times n}$, where:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m}(x_{ij})^2}} \tag{16}$$

- Step 3: Construct the weighted normalized decision matrix by multiplying the indices of the normalized matrix by the specific weight w of each criterion. To get the weight of each criteria, authors may use AHP method or Entropy method or even get the opinion of experts. Once the weight value is defined. The weighted normalized matrix is: $(V_{ij})_{m\times n}$ where $(v_{ij}) = w_j \times r_{ij}$. Since w_j is a crisp number, then $(v_{ij}) = w_j \times r_{ij}$ where w_j is the weight of the ith criterion for $i = 1, \cdots, m$ and $j = 1, \cdots, n$ and $\sum_{j=1}^{n}(w_j) = 1$.
- Step 4: Determine the positive and negative ideal solutions according to equations 17 and 18. **For benefit criteria:**

$$A^+ = \left\{v_1^+, v_2^+, \cdots, v_n^+\right\}, v_j^+ = max_i(v_{ij}) \tag{17}$$

For cost criteria:

$$A^- = \left\{v_1^-, v_2^-, \cdots, v_n^-\right\}, v_j^- = min_i(v_{ij}) \tag{18}$$

- Step 5: Determine the distance for each alternative (trajectory) from the ideal solutions by using equations 19 and 20. The distance for each alternative from positive and negative solutions can be calculated by the summation of the distances between the ratings of such alternatives under all criteria with the ideal solutions sets.

$$d_i^+ = \sqrt{\sum_{j=1}^{n} d(v_{ij} - v_j^+)^2} \tag{19}$$

$$d_i^- = \sqrt{\sum_{j=1}^{n} d(v_{ij} - v_j^-)^2} \tag{20}$$

- Step 6: Calculate the closeness coefficient of each alternative which can be obtained using equation 21. The alternative with the highest closeness coefficient represents the best alternative.

$$CC_i = \frac{d_i^-}{d_i^- + d_i^+} \quad i = 1, \cdots, m. \tag{21}$$

- Step 7: Rank the preference order. A large value of closeness coefficient CC_i^+ indicates a good performance of the alternative A_i. The best alternative is the one with the greatest relative closeness to the ideal solution.

2) FUZZY TOPSIS

Fuzzy TOPSIS method can be applied according to the following steps:

- Step 1: Establish the decision matrix for ranking: in the case of m alternatives and n criteria, the decision matrix is: $(\tilde{X}) = (\tilde{x}_{ij})_{m\times n}$, where $\tilde{x}_{ij} = (a_{ij}, b_{ij}, c_{ij})$;

$$\begin{array}{c} \\ A_1 \\ A_2 \\ \cdots \\ A_m \end{array} \begin{array}{c} \begin{array}{ccccc} c_1 & c_2 & c_3 & \cdots & c_n \end{array} \\ \begin{pmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \tilde{x}_{13} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \tilde{x}_{23} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \tilde{x}_{m3} & \cdots & \tilde{x}_{mn} \end{pmatrix} \end{array}$$

- Step 2: Normalize the decision matrix: the normalization process used in our research is based on getting the sum of each criteria (performance value) under all alternatives then divide the criteria value by that sum. For the decision matrix $\tilde{X} = (\tilde{x}_{ij})_{m\times n}$, the normalized matrix is $\tilde{R} = (\tilde{r}_{ij})_{m\times n}$, where:

$$\tilde{r}_{ij} = \frac{\tilde{x_{ij}}}{\sqrt{\sum_{i=1}^{m}(\tilde{x}_{ij})^2}} \tag{22}$$

- Step 3: Construct the weighted normalized decision matrix by multiplying the indices of the normalized matrix by the specific weight w of each criterion. To get the weight of each criteria, authors may use AHP method or Entropy method or even get the opinion of experts. Once the weight value is defined. The weighted normalized matrix is: $(\tilde{V_{ij}})_{m\times n}$ where $(\tilde{v}_{ij}) = w_j \times \tilde{r}_{ij}$. Since w_j is a triangular fuzzy number, then $(\tilde{v}_{ij}) = (S(\tilde{w}_j, 0)) \times \tilde{r}_{ij}$ where w_j is the weight of the ith criterion, $\sum_{j=1}^{n}(S(\tilde{w}_j, 0)) = 1$ and $S(\tilde{w}_j, 0) \geq 0$ for $j = 1, \cdots, n$.
- Step 4: Determine the positive and negative ideal solutions according to equations 23 and 24.

For benefit criteria:

$$A^+ = \left\{\tilde{v_1^+}, \tilde{v_2^+}, \cdots, \tilde{v_n^+}\right\}, \tilde{v_j^+} = max_i(\tilde{v_{ij}}) \quad (23)$$

For cost criteria:

$$A^- = \left\{\tilde{v_1^-}, \tilde{v_2^-}, \cdots, \tilde{v_n^-}\right\}, \tilde{v_j^-} = min_i(\tilde{v_{ij}}) \quad (24)$$

- Step 5: Determine the distance for each alternative (trajectory) from the ideal solutions by using equations 25 and 26. The distance for each alternative from positive and negative solutions can be calculated by the summation of the distances between the ratings of such alternative under all criteria with the ideal solutions sets.

$$d_i^+ = \sqrt{\sum_{j=1}^{n} d(\tilde{v_{ij}} - \tilde{v_j^+})^2} \quad (25)$$

$$d_i^- = \sqrt{\sum_{j=1}^{n} d(\tilde{v_{ij}} - \tilde{v_j^-})^2} \quad (26)$$

- Step 6: Calculate the closeness coefficient of each alternative which can be obtained using equation 27. The alternative with highest closeness coefficient represents the best alternative.

$$CC_i = \frac{d_i^-}{d_i^- + d_i^+} \quad i = 1, \cdots, m. \quad (27)$$

- Step 7: Rank the preference order. A large value of closeness coefficient CC_i^+ indicates a good performance of the alternative A_i. The best alternative is the one with the greatest relative closeness to the ideal solution.

E. RISK MANAGEMENT

Risk management is an applied scientific field that impacts any discipline posed by any risk. It constitutes a set of coordinated activities and procedures that focus on reducing risks with different priorities in a state or an organization [111]. The identification, assessment and prioritizing of risks are the main aspects of risk management that enable the monitoring, control and minimization of the frequency of severe and hazardous events [112]. Risk Management standards and models were created to provide stakeholders help in their decision process. These standards are: the Norm ISO 31000 and the ISO 73 guide. These systems of policies and practices are used to develop applications for risk identification, risk analysis, risk evaluation and risk treatment. The applications require elements of communication, consultation, establishing the context, monitoring and reviewing of risks [30], [113] [114], [115].

The implementation of this process starts with analyzing the risk by identifying the hazard sources or any related roots that can inflict property, people or environment calamities. To estimate the possible consequences of hazards, quotations grids and other simulation software are used in the steps after. In a similar approach, accident databases and expert judgments are used to approximate the accident occurrence probabilities. As a final step, risk analysis gives the characterization of the level of risk as well as the degree of confidence in the risk assessment.

Next, the attained risk level is compared to the decision criteria thresholds. The thresholds are derived from the context establishment step in the process. The comparison is important in studying the necessity of executing corrective measures. Risk control is defined as the process of diminishing probability of risk or severity of the damage incurred from a certain risk. Reducing the probability is considered as a prevention mechanism whereas reducing the severity is considered as a protection mechanism. Risk control can also be thought of as the group of actions taken to transfer risk or stop activities that lead to the risk.

Risk assessment represents one steps in the risk management process and it presents risk sources, vulnerable groups, and possible interventions. It enables policymakers to characterize the goals of the risk management programs and to define vulnerability reduction targets. As a general rule, risk can be presented as a function of two factors: *occurrence probability of an event* and *consequences related to it*.

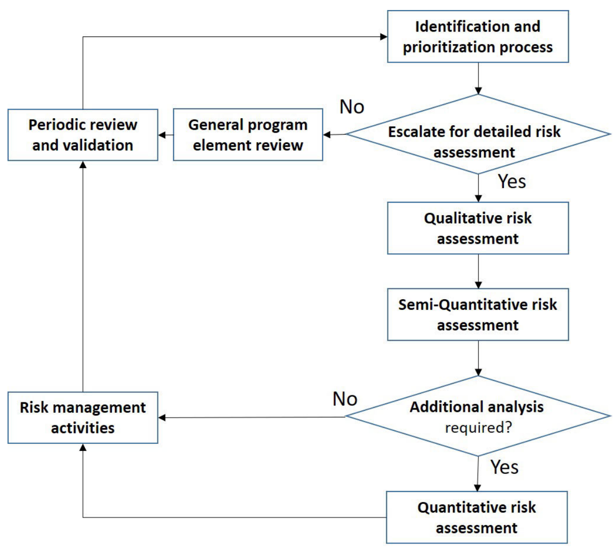


FIGURE 7. Risk Assessment Protocol.

A risk assessment protocol is shown in figure 7. First, the protocol dictates proceeding with the identification and prioritization processes. The prioritization gives the rank to movements that may result in a more detailed risk analysis [116]. In some cases, more detailed techniques in risk analysis are needed to identify, evaluate and mitigate the hazards of risks that require additional evaluation. Next, the process requires qualitative and semi-quantitative risk analysis for these types of risks [117]. Qualitative risk assessment [118] approximate the unwanted consequences by identifying possible accident scenarios and attempts. Historical experience and engineering judgment are used to describe and compare risks.

In some scenarios, systems might need more details than what is offered in the qualitative approach. In these cases, semi-quantitative evaluation can be used. The quantification of consequence, likelihood, and/or risk level are part of the semi-quantitative risk analysis technique. This technique is easily recognized by the majority of the people working on DGT systems. A semi-quantitative risk assessment can be done using risk indexes or a risk ranking matrix.

Further to using the semi-quantitative method, if the analyzed risks require more analysis details then a full quantitative risk analysis method is conducted. This method makes use of defined values of indicators to do risk assessment. The assessment is used to dynamically manage risks, identify and prioritize technology needs and decision making as well as evaluate regulatory alternatives [119].

The applications of risk assessment are many and can be utilized in systems such as: insurance systems [120], building fire evacuation systems [121], online shopping transaction systems [122], and food security systems [123]. Risk level can be evaluated through two elements. The first is the likelihood of the occurrence of a defined hazard P and the second is the severity of the consequences of the incident (number of fatalities η). This is described in equation 28. The classification shows four levels: high, moderate, low, and negligible risk regions as presented in table 4.

$$RiskLevel = f(Likelihood, Severity) \tag{28}$$

IV. PROBLEM STATEMENT

Shipment process is one of the key elements in any Supply Chain model. This process can be done in different modes such as: road, sea, air, or pipeline. Road shipment is the most critical mode as most accidents occur during road transportation. Any shipment of dangerous goods is described by two addresses: the source and the destination. Additional attributes are considered as the type and the quantity of goods. There are many available paths between the source and the destination. Each path is divided into several segments, where each one belongs to a specific area having its own characteristics such as: the population density and the weather conditions (see figure 8). In addition each segment has many parameters/attributes such as: number of lines, curve, slope, area, and type. Those characteristics/parameters served as inputs for the Risk assessment approach (see table 6).

The management of the delivery process focuses mainly on one traditional objective: finding the shortest length and/or the lowest cost of a route. This process is no longer valid in the case of DGT as such transportation represents serious threat to the population, the environment and properties in the traversed areas especially if any accident occurs during the transportation [124]. Those accidents may produce hazards such as fire, explosion, or toxic release that can generate severe outcomes with irreversible effects while impacting areas with high population density. It is crucial to avoid crossing such regions with consideration of the travel cost and duration. Thus, the optimization of DGT should consider many criteria such as the risk level, travel cost and the travel duration. Furthermore, some of the data used in risk assessment are uncertain and time-dependent (dynamic). So, Crisp and static methods cannot be used to tackle such inputs. Hence, a fuzzy model is required to handle this uncertainty.

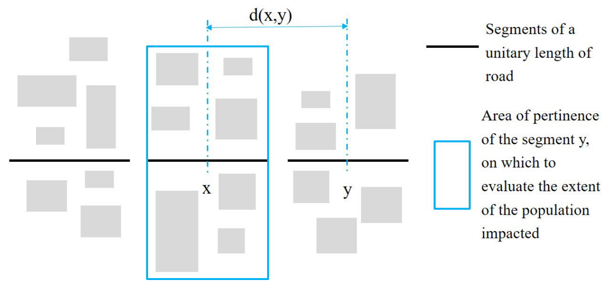


FIGURE 8. Network structure.

V. OBJECTIVE

The optimization of DGT is described as finding the best (optimal) trajectory to move dangerous goods from source to destination among a set of alternatives. It considers three main parameters which are: transport cost, transport duration, and transport risk level. As all of those are cost parameters, the objective function aims to reduce $\mathbb{V}$ where $\mathbb{V}$ is defined to be:

$$\mathbb{V} = \beta_1\mathbb{C} + \beta_2\mathbb{D} + \beta_3\mathbb{R} \tag{29}$$

where $\mathbb{C}$ is the cost in dollars of the trip, $\mathbb{D}$ is the time spent in the trip, and $\mathbb{R}$ is the risk that could be faced during the trip. Weights represent effectiveness of every factor in the total valuation $\mathbb{V}$. Note that the numbers written on edges between vertices represent the cost $\mathbb{C}$, duration $\mathbb{D}$ and risk $\mathbb{R}$ respectively.

VI. CONTRIBUTION

This work proposes a new dynamic approach for DGT management. This approach provides a real-time identification of the best route in dynamic environment. For the static environment, the assumption is that all the parameters have been calculated before the simulation and everything stays the same during the simulation. The proposed approach consists of several steps:

- Define a new model for risk assessment after a critical review of the available models.
- Evaluate the risk level, travel cost, and travel time related to every road segment.
- Propose a new method as a combination of AHP, TOPSIS methods and Fuzzy set.
- In the presence of an accident/ any change in the studied parameters after the departure of the truck, that may affect the ranking of the alternative trajectories, a real-time/dynamic evaluation of the best alternative will be done considering 2 different options: 1) having the ability of reconsidering the traversed paths/segments and

TABLE 4. Risk Level Classification.

	Severity of Harm			
Likelihood of occurrence	Catastrophic $\eta >= 100$	Serious $10 <= \eta < 100$	Moderate $1 <= \eta < 10$	Negligible $\eta = 0$
Very Likely $P >= 10^{-1}$	High	High	High	Moderate
Likely $10^{-5} <= P < 10^{-1}$	High	High	Moderate	Low
Unlikely $10^{-9} <= P < 10^{-5}$	Moderate	Moderate	Low	Negligible
Remote $P < 10^{-9}$	Low	Low	Negligible	Negligible

2) elimination of the traversed path with consideration of the remaining paths only in the dynamic evaluation.

As some of the studied parameters are uncertain, Fuzzy Logic is applied as a combination of two methods Fuzzy AHP and Fuzzy TOPSIS. Fuzzy AHP is used to identify the important weights of the criteria. Then, Fuzzy TOPSIS is used to select the best alternative using the criteria weights given by the Fuzzy AHP. In addition, a new model is proposed to analyze risks and determine the characteristics of each segment. Finally, the proposed model is illustrated and tested for an expedition of Dangerous goods in France. Tests were done in both static and dynamic environments then a comparison between them was carried on. Simulations to find the best route were done considering four options:

1) Each criteria was considered alone in the decision
2) A combination of all criteria was considered
3) An implementation of Fuzzy AHP
4) An integration of Fuzzy AHP-TOPSIS

Fuzzy set was implemented according to the below detailed equations and membership.

A. FUZZY SETS

A fuzzy set is a two-dimensional mapping function which defines how a certain variable belongs to that set. The Y-axis is called the **membership** of the variable. The variable has a membership of 1 if it completely belongs to the set and it has a membership of 0 if it does not belong at all. A variable is assigned a membership μ such that $0 \leq \mu \leq 1$ depending on how much it belongs to that set. X-axis is the value of the variable that determines how high or low the membership of that variable to that set is. Figure 9 shows a system of three fuzzy sets: **cold**, **Room Temp**, and **Hot**.

In Figure 9, the membership of fuzzy set **cold** can be expressed mathematically as follows:

$$\mu(x) = \begin{cases} 1 & 0 \leq x \leq 17 \\ \dfrac{21-x}{4} & 17 \leq x \leq 21 \\ 0 & x \geq 21 \end{cases}$$

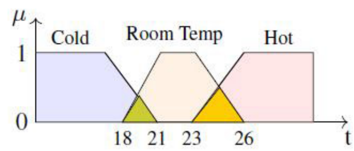


FIGURE 9. Fuzzy sets representing different temperature levels.

Using the same concept, we can find that fuzzy set **Room Temp** can be modeled as follows:

$$\mu(x) = \begin{cases} 0 & x \leq 18 \\ \dfrac{x-18}{3} & 18 \leq x \leq 21 \\ 1 & 21 \leq x \leq 23 \\ \dfrac{26-x}{3} & 23 \leq x \leq 26 \\ 0 & x \geq 26 \end{cases},$$

and fuzzy set **hot** can be modelled as follows:

$$\mu(x) = \begin{cases} 0 & x \geq 21 \\ \dfrac{x-23}{3} & 23 \leq x \leq 26 \\ 1 & x \geq 26 \end{cases}$$

If the value of x is 19 as an example, x will be both room temperature and cold. Those situations are discussed in Section VI-B.

In conclusion, a fuzzy set $\tilde{X}$ is defined by its membership function that can be any number between zero and one. Membership of 0 means that the value does not belong to set $\tilde{X}$, membership of 1 means that the value completely belongs to the set under consideration, and membership between 0 and 1 determines the degree of membership. The representation of the fuzzy set $\tilde{X}$ is:

$$\tilde{X} = \{(x, \mu_{\tilde{X}}(x)) : x \in X, \mu_{\tilde{X}}(x) \in [0, 1]\}. \quad (30)$$

So, in the pair $(x, \mu_{\tilde{x}}(x))$, the first element x belongs to the classical set X, and the second element $\mu_{\tilde{x}}(x)$ belongs to the interval [0, 1], called Membership function.

B. FUZZY LOGIC

Fuzzy logic is a rule-based decision process that seeks to solve problems where the system is difficult to model and where ambiguity, or vagueness is abundant between two extremes. With fuzzy logic, propositions can be represented with degrees of truthfulness and falsehood. For example, the statement, today is sunny, might be 100% true if there are no clouds, 50% true if it's hazy and 0% true if it rains all day.

Assume that we have fuzzy sets A and B, Fuzzy logic has the following operations:

1) Union: $A \cup B \equiv \mu_A \vee \mu_B$
2) Intersection: $A \cap B \equiv \mu_A \wedge \mu_B$
3) Complement $\bar{A} \equiv \bar{\mu_A}$ such that $\bar{\mu_A} = 1 - \mu_A$
4) Product $A.B \equiv \mu_{AB}$ such that $\mu_{AB} = \mu_A.\mu_B$
5) Sum $A+B \equiv \mu_{A+B}$ such that $\mu_{A+B} = \mu_A + \mu_B - \mu_A \mu_B$
6) Bounded Sum: $\oplus$
7) Bounded Difference: $\ominus$
8) Bounded Product $\odot$

C. TRIANGULAR FUZZY NUMBER

Triangular Fuzzy Number (TFN) is the most frequent fuzzy number used. It is a fuzzy number represented with three points as follows: $\tilde{X}$=(a,c,b). This representation is interpreted as membership functions and holds the following conditions:

- a to c is increasing function,
- c to b is decreasing function,
- $a \leq c \leq b$,
- it is represented by a graph (see figure 10).

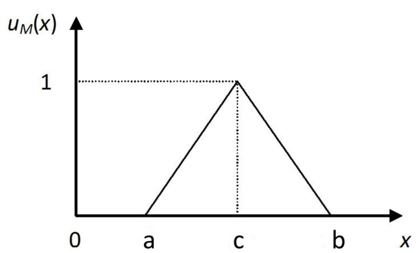


FIGURE 10. Triangular membership function.

The membership of the triangular fuzzy number is:

$$\mu_{(\tilde{A})}(x) = \begin{cases} \dfrac{x-a}{c-a} & \text{if } a \leq x \leq c, \\ \dfrac{b-x}{b-c} & \text{if } c \leq x \leq b, \\ 0 & \text{otherwise.} \end{cases} \quad (31)$$

In the literature, the simplified operations on the fuzzy values are often used when the membership functions are represented by regular triangular trapezes [125]. For example, let $\tilde{A}=(a_1,\ a_2,\ a_3)$ and $\tilde{B}=(b_1,\ b_2,\ b_3)$ be triangular fuzzy numbers. The simplified arithmetical operations on them are presented as follows: (for a_1, a_2, a_3>0 and b_1, b_2, b_3>0)

$$\tilde{A} + \tilde{B} = (a_1 + b_1, a_2 + b_2, a_3 + b_3) \quad (32)$$
$$\tilde{A} - \tilde{B} = (a_1 - b_3, a_2 - b_2, a_3 - b_1) \quad (33)$$
$$\tilde{A} \times \tilde{B} = (a_1 \times b_1, a_2 \times b_2, a_3 \times b_3) \quad (34)$$
$$\tilde{A} \div \tilde{B} = (a_1 / b_3, a_2 / b_2, a_3 / b_1) \quad (35)$$
$$A^{\tilde{-1}} = (a_1, a_2, a_3)^{-1} = (1/a_3, 1/a_2, 1/a_1) \quad (36)$$
$$d_{(\tilde{A},\tilde{B}} = \sqrt{\frac{1}{3}\left[(a_1 - b_1)^2 + (a_2 - b_2)^2 + (a_3 - b_3)^2\right]} \quad (37)$$

In fact, the result from the addition and the subtraction operations of two TFNs is also a TFN, while the result from the multiplication and the division of them is not. Thus, in this paper we used another approach to define the operation of fuzzy numbers. This approach is based on $\alpha - cuts$ representation and the arithmetic operations of intervals.

VII. PROPOSED MODEL

The risk assessment framework presented in this paper contains four phases which are:

- Declaring and identifying the risk types and factors
- Constructing the decision matrix
- Applying the fuzzy AHP to get the weight for the criteria (pairwise comparison)
- Apply Fuzzy TOPSIS method to rank the alternatives
- Selecting of the best alternative.

The subsequent collection of algorithms exemplify the procedure. Algorithm 1 constructs the pairwise comparison matrix $\mathbb{PW}$. The algorithm takes a 2D array $\mathbb{A}$ as its input. For each row i in this array, the first element $\mathbb{A}[i][1]$ corresponds to the index of factor 1, the second element $\mathbb{A}[i][2]$ corresponds to the index of factor 2, and the third element $\mathbb{A}[i][3]$ represents the pairwise comparison between the factor with the index $\mathbb{A}[i][1]$ and the factor with the index $\mathbb{A}[i][2]$.

The computational complexity of Algorithm 1 is $\mathbb{O}(n)$. The algorithm takes as input comparison values, constructs a square matrix $\mathbb{PW}$, initializes the diagonal elements to 1, and then populates the matrix by assigning $\mathbb{PW}$[row][col] with the value stored in $\mathbb{A}$[index][3]. Additionally, it sets $\mathbb{PW}$[col][row] to the reciprocal of the value in $\mathbb{A}$[index][3]. It's important to note that in this context, the term "row" corresponds to the value stored in $\mathbb{A}$[index][1], and "col" refers to the value stored in $\mathbb{A}$[index][2], as indexing starts from 1.

Algorithm 2 outlines the fundamental AHP procedure. The algorithm receives the input of the pairwise comparison matrix $\mathbb{PW}$. This matrix is square in nature and is generated through the relationship (cross product) between factors and themselves.

Algorithm 1 Pairwise Comparison Matrix Formation ℙ𝕎

```
Require: 2D array 𝔸 that represents relationships between
    factors as integers, length as the number of factors.
Ensure: Pairwise comparison matrix formation ℙ𝕎
ℙ𝕎 ← array[length][length]
for index = 1 to length (𝔸) do
    row ← 𝔸[ index ][1]
    col ← 𝔸[ index ][2]
    if row == col then
        ℙ𝕎)[ row ][ col ] ← 1
    else
        ℙ𝕎[ row ][ col ] ← 𝔸[ index ][3]
        ℙ𝕎[ col ][ row ] ← 1/𝔸[ index ][3]
    end if
end for
return ℙ𝕎
```

Algorithm 2 Analytic Hierarchy Process (AHP)

```
Require: Pairwise comparison Matrix ℙ𝕎
Ensure: Wights Ω
for col = 1 to width (ℙ𝕎) do
    col-sum ← ∅
    for row = 1 to length (ℙ𝕎) do
        v ← ℙ𝕎[ row ][ col ]
        col-sum[ col ] ← col-sum[ col ] + v
    end for
end for
for col = 1 to width (ℙ𝕎) do
    for row = 1 to length (ℙ𝕎) do
        v ← ℙ𝕎[ row ][ col ]/ row-sum[ col ]
        ℙ𝕎[ row ][ col ] ← v
    end for
end for
for row = 1 to length (ℙ𝕎) do
    weights ← ∅
    v ← 0
    for col = 1 to width (ℙ𝕎) do
        v ← v + ℙ𝕎[ row ][ col ]/ row-sum[ col ]
    end for
    weights[row] ← v/ length (ℙ𝕎)
end for
return weights
```

Algorithm 2 generates the weights among various factors. It has a computational complexity of $\mathbb{O}(n^2)$. The procedure commences by calculating the sum for each column, with each column being associated with a specific factor. Following the computation of column sums, the pairwise matrix is transformed into a normalized matrix by dividing each column by its respective sum. Subsequently, the averages of each row are obtained by summing the elements in each row and then dividing that sum by the length of the row. This iterative process yields the weights for each individual factor.

After calculating factor weights using the AHP method, it is essential to verify the consistency of those weights. Algorithm 3 illustrates how this is done.

Algorithm 3 AHP Weight Consistency Check

```
Require: 1) AHP process output Weights
         2) Pairwise comparison Matrix ℙ𝕎.
         3) Random index vector ℝ.
Ensure: Consistency ratio
for col = 1 to width (ℙ𝕎) do
    for row = 1 to length (ℙ𝕎) do
        v ← weight [ col ] × ℙ𝕎[ row ][ col ]
        ℙ𝕎[ row ][ col ] ← v
    end for
end for
weighted-sum ← 0
for row = 1 to length (ℙ𝕎) do
    v ← 0
    for col = 1 to width (ℙ𝕎) do
        v ← v + ℙ𝕎[ row ][ col ]
    end for
    weighted-sum [ col ] ← v
end for
λ ← 0
for row = 0 to length (ℙ𝕎) do
    λ ← λ + weighted-sum [ row ]/ weights [ row ]
end for
λ ← λ/ length
Consistent Index ← (λ − length )/( length − 1)
Consistency Ratio ←
    Consistency Index /ℝ𝕀[ length ]
return Consistency Ratio
```

Algorithm 3 has a computational complexity of $\mathbb{O}(n^2)$. it takes as input the weights computed through the AHP procedure using Algorithm 2. Additionally, the algorithm is supplied with the pairwise comparison matrix $\mathbb{PW}$, which is generated by Algorithm 1. Furthermore, a random vector index denoted as $\mathbb{RI}$ is provided to the algorithm. The random index vector for the initial 9 random values is precisely defined in Table 5.

TABLE 5. Random index values for the first 9 factors.

n	1	2	3	4	5	6	7	8	9
$\mathbb{RI}$	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45

The initial row of Table 5 illustrates distinct values of n, signifying the count of various factors in each decision problem. In the subsequent row of Table 5, $\mathbb{RI}$ is represented, as the random index corresponding to the quantity of these distinct factors. The information within Table 5 implies that for a scenario involving n distinct factors, the associated random index should not surpass the value of $\mathbb{RI}[n]$.

The algorithm commences by multiplying the computed weights for each row with the corresponding values within that row. This yields a weighted pairwise comparison matrix. Subsequently, the summation of values in each row is carried out, resulting in the creation of a weighted sum vector. The consistency factor, denoted as λ, is calculated by summing all the values within the weighted sum vector. This λ represents the maximum attainable consistency factor.

The consistency index is then computed using the following equation:

$$\text{Consistency Index} = \frac{\lambda - \text{length}(\mathbb{PW})}{\text{length}(\mathbb{PW}) - 1} \tag{38}$$

Subsequently, the consistency ratio is determined through the subsequent process:

$$\text{Consistency Ratio} = \frac{\text{Consistency Index}}{\mathbb{RI}(\text{length})} \tag{39}$$

The consistency ratio serves as an indicator of the extent of deviation from the expected state. In simpler terms, a lower consistency ratio signifies a higher level of accuracy in the assigned weights. Conventionally, a typical consistency ratio falls below the threshold of 0.1, which serves as the standard benchmark. Thus, if the consistency ratio measures less than 0.1, it provides the green light to proceed with the decision-making process, employing the calculated weights.

Algorithm 4 executes the initial phase of the TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) process. This algorithm takes as input the AHP (Analytic Hierarchy Process) weights obtained from algorithm 2, the decision matrix denoted as $\mathbb{D}$, and the optimal decision vector represented by $\mathbb{B}$.

The decision matrix $\mathbb{D}$ is structured with rows corresponding to the various potential solutions and columns corresponding to the factors influencing the decision-making procedure. The optimal decision vector $\mathbb{B}$ is a vector with a length equivalent to the number of columns in the decision matrix.

Within algorithm 4, the information conveyed by $\mathbb{B}$ is pivotal. It guides the algorithm in determining whether the most desirable value for each factor is the maximum or minimum. In the scenario where $\mathbb{B}[1] = 1$, it signifies that selecting the maximum value for the first column in the decision matrix $\mathbb{D}$ is the superior choice. Conversely, the optimal selection for the solution would involve the minimum value of column 1 if $\mathbb{B}[1]$ holds any other value.

The best factor value is calculated according to the following equation:

$$\mathbb{I}_b[\text{ col }] = \begin{cases} max(\hat{\mathbb{D}}[col]) & \text{if } \mathbb{B} = 1, \\ min(\hat{\mathbb{D}}[col]) & \text{if } \mathbb{B} = 0. \end{cases} \tag{40}$$

The worst factor value is calculated according to the following equation:

$$\mathbb{I}_w[\text{ col }] = \begin{cases} min(\hat{\mathbb{D}}[col]) & \text{if } \mathbb{B} = 1, \\ max(\hat{\mathbb{D}}[col]) & \text{if } \mathbb{B} = 0. \end{cases} \tag{41}$$

Algorithm 4 Topsis Preprocessing

Require: 1) AHP weights
2) Decision matrix $\mathbb{D}$.
3) Best direction vector $\mathbb{B}$

Ensure: Weighted Decision Matrix $\hat{\mathbb{D}}$

Mean vector $\mathbb{U} \leftarrow \emptyset$
for col $= 1$ **to** width $(\mathbb{D})$ **do**
  $\mathbb{U}[\text{ col }] \leftarrow 0$
  for row $= 1$ **to** length $(\mathbb{D})$ **do**
    $\mathbb{U}[\text{ col }] \leftarrow \mathbb{U}[\text{ col }] + (\mathbb{D}[\text{ row }][\text{ col }])^2$
  end for
  $\mathbb{U}[\text{ col }] \leftarrow \sqrt{\mathbb{U}[\text{ col }]}$
end for
for col $= 1$ **to** width $(\mathbb{D})$ **do**
  for row $= 1$ **to** length $(\mathbb{D})$ **do**
    $v \leftarrow weight[\text{ col }]/\mathbb{U}[\text{ col }]$
    $\hat{\mathbb{D}}[\text{ row }][\text{ col }] \leftarrow \mathbb{D}[\text{ row }][\text{ col }] \times v$
  end for
end for
Ideal Best Vector $\mathbb{I}_b \leftarrow \{\emptyset\}$
Ideal Worst Vector $\mathbb{I}_w \leftarrow \{\emptyset\}$
for col $= 1$ **to** width $(\hat{\mathbb{D}})$ **do**
  $max \leftarrow -\infty$
  $min \leftarrow \infty$
  for row $= 1$ **to** length $(\hat{\mathbb{D}})$ **do**
    if $max < \mathbb{D}[\text{ row }][col]$ **then**
      $max \leftarrow \hat{\mathbb{D}}[\text{ row }][\text{ col }]$
    end if
    if $min > \hat{\mathbb{D}}[\text{ row }][col]$ **then**
      $min \leftarrow \hat{\mathbb{D}}[\text{ row }][\text{ col }]$
    end if
  end for
  if $\mathbb{B}[\text{ col }] == 1$ **then**
    $\mathbb{I}_b[\text{ col }] \leftarrow max$
    $\mathbb{I}_w[\text{ col }] \leftarrow min$
  else
    $\mathbb{I}_b[\text{ col }] \leftarrow min$
    $\mathbb{I}_w[\text{ col }] \leftarrow max$
  end if
end for
return $\hat{\mathbb{D}}, \mathbb{I}_b, \mathbb{I}_w$

Algorithm 4 commences by computing the mean value for each column within the decision matrix $\mathbb{D}$ and storing these averages in the vector $\mathbb{U}$. The dimensions of vector $\mathbb{U}$ align with the number of columns present in $\mathbb{D}$. Subsequently, the square root of each element in $\mathbb{U}$ is computed and recorded within the same vector $\mathbb{U}$.The computational complexity of Algorithm 4 is $\mathbb{O}(n^2)$.

Following this, each value within the decision matrix $\mathbb{D}$ undergoes a transformation. The transformation involves multiplying each value by its corresponding AHP weight, divided by the square root of the associated column average. The determination of the best and worst potential candidates is achieved by analyzing the maximum or minimum values in each column, guided by the optimal direction indicated in vector $\mathbb{B}$.

The outcomes provided by this algorithm consist of the normalized decision matrix denoted as $\hat{\mathbb{D}}$, as well as the vectors representing the best solution ($\mathbb{I}_b$) and the worst solution ($\mathbb{I}_w$).

Algorithm 5 has a computational complexity of $\mathbb{O}(n^2)$ and it represents a method centered around identifying a solution that minimizes the Euclidean distance from an ideal solution. The algorithm is formally named "Technique for Order Preference by Similarity to Ideal Solution," often referred to as Topsis. The input of algorithm 5 is the output of algorithm 4.

Algorithm 5 Topsis Process

Require: 1) Weighted decision making matrix $\hat{\mathbb{D}}$
2) Ideal best vector $\mathbb{I}_b$
3) Ideal worst vector $\mathbb{I}_w$

Ensure: Best Choice

$\Delta\mathbb{I}_b \leftarrow \{\emptyset\}$
$\Delta\mathbb{I}_w \leftarrow \{\emptyset\}$
for row $= 1$ **to** length ($\hat{\mathbb{D}}$) **do**
  $v_b \leftarrow 0$
  $v_w \leftarrow 0$
  for col $= 1$ **to** width ($\hat{\mathbb{D}}$) **do**
    $v_b \leftarrow v_b + (\mathbb{I}_b[\text{ col }] - \hat{\mathbb{D}}[\text{ row }][\text{ col }])^2$
    $v_w \leftarrow v_w + (\mathbb{I}_w[\text{ col }] - \hat{\mathbb{D}}[\text{ row }][\text{ col }])^2$
  end for
  $\Delta\mathbb{I}_b[\text{ row }] \leftarrow \sqrt{v_b}$
  $\Delta\mathbb{I}_w[\text{ row }] \leftarrow \sqrt{v_w}$
end for
Choices $\leftarrow \{\emptyset\}$
for row $= 1$ **to** length ($\Delta\mathbb{I}_b$ **do**
  $v_b \leftarrow \Delta\mathbb{I}_b[\text{ row }]$
  $v_w \leftarrow \Delta\mathbb{I}_w[\text{ row }]$
  Choices [row] $\leftarrow \frac{v_w}{v_b - v_w}$
end for
Best Choice Index $\leftarrow 1$
for row $= 2$ **to** length ($\Delta\mathbb{I}_b$ **do**
  if Choices [Best Choice Index] $<$ Choices [row] **then**
    Best Choice Index $\leftarrow$ row
  end if
end for
Best Choice $\leftarrow$ Choices [Best Choice Index]
return Best Choice

Algorithm 5 commences by initializing the sets for the closest and furthest Euclidean distance vectors ($\Delta\mathbb{I}_b$ and $\Delta\mathbb{I}_w$ respectively) as empty sets $\emptyset$. Subsequently, the Euclidean distance is computed for each item within a column, considering both the column's best and worst values. The vectors $\Delta\mathbb{I}_b$ and $\Delta\mathbb{I}_w$ are then updated to encompass the sum square error values for both the best and worst scenarios. The performance measure is subsequently computed for each option using the following equation:

$$\text{performance[row]} = \frac{\Delta\mathbb{I}_w[\text{row}]}{\Delta\mathbb{I}_b[\text{row}] + \Delta\mathbb{I}_w[\text{row}]} \tag{42}$$

The algorithm ends by returning the choice with the highest calculated performance.

The processes is detailed in the following subsections:

A. RISK ASSESSMENT PROCESS INITIALIZATION:

Risk factors are studied in risk assessment to show their significance and effect on the process. Some of the factors are attributes of risk amplification and mitigation, hazard attributes, or vulnerabilities attributes [126]. The latter being the attributes that have a direct impact on the population and the environment.

In our proposed method, to achieve the best possible route, the following categories are studied: 1) Travel Time, 2) Travel Cost and 3) Risk Level. The travel time and cost are analyzed in the next section. Risk Level is determined by studying the probability of the risk as well as its severity. The probability of the risk is affected by three factors (weather conditions, traffic density, and road characteristics). On the other hand, the severity of the incident is affected by the population density at the location of the incident.

Below is the description of the stated factors:

- Severity Characteristics: is measured by human severity and environment severity. The human severity can be determined according to the number of dead people, the number of injured people from the incident and the probability of occurrence of this incident.
- Traffic Condition: is described as Low intensity, Medium intensity, and High intensity.
- Road Characteristics: are represented by road slope, road curve, and road type.
- Weather Conditions: are categorized as Fine, Rain/Fog, and Snow/Ice

Random values of the discussed factors are introduced to show the related calculation of the process as shown in table 6. A discussion of this calculation is presented in section VIII to validate the efficacy of the proposed model.

B. CONSTRUCTING THE FUZZY DECISION MATRIX:

To build the fuzzy decision matrix, the following calculations are needed:

1) TRAVEL DURATION

The travel duration (TD) of a given segment i is calculated using equation 43. As shown in the equation, the weather condition (h_3) and the traffic characteristics (h_4) as well as the travelled distance determine the required time to go through the segment.

$$TD_i = \frac{length_i \times h_3 \times h_4}{meanspeed} \tag{43}$$

where $length_i$ is the distance between the start point and the end point of segment i. Based on this, the total travel duration

TABLE 6. Parameters of amplification and mitigation.

Factor	Details	Value
Road Curve	straight road (raduis 0)	1
h_1	curved road (>200 m)	1.3
	tightly curved road(<200 m)	2.2
Road Slope	plane road (gradient g=0%)	1
h_2	ascending road (g<5%)	1.1
	steeply ascending road (g>5%)	1.2
	descending road (g<5%)	1.3
	steeply descending road (g>5%)	1.5
Road Type	tunnel	0.8
h_5	bridge	1.2
Weather	fine weather	(0.7,1,1.3)
Conditions	rain/fog	(1.05,1.51.95)
h_3	snow/ice	(1.75,2.5,3.25)
Traffic	low intensity < 500 vehicles/hours	(0.56,0.8,1.04)
Characteristics	medium intensity<1250 vehicles/hour	(0.7,1,1.3)
h_4	with heavy traffic <125 lorries per day	
	high intensity>1250 vehicles/hour	(0.98,1.4,1.82)
	high intensity >1250 vehicles/hour	(1.68,2.4,3.12)
	with heavy traffic >250 lorries per day	

can be calculated for one trajectory using the following equation:

$$TD = \sum_{i=1}^{k} TD_i \tag{44}$$

where k is the number of segments for each trajectory.

2) TRAVEL COST

For each segment i, the travel cost can be calculated using equation 45.

$$TC_i = (TD_i \times (costliter/min) \times (cost/liter)) + (TD_i \times (costdriver/min)) + costtoll \tag{45}$$

Thus, the total travel cost for one trajectory is:

$$TC = \sum_{i=1}^{k} TC_i \tag{46}$$

3) ACCIDENT FREQUENCY

The frequency of an accident on the $j - esimo$ stretch [127] for each segment can be calculated using equation 47:

$$f_j = \gamma_j(\prod_{i=1}^{5} h_i) \times L_j \times n_j \tag{47}$$

where:

γ_j = frequency expected on the $j - esimo$ stretch of road [accidents km-1 per vehicle] [128]

L_j = road length [km]

n_j = number of vehicles [vehicles]

γ_0 = basic frequency [accidents km-1 per vehicle]

h_i = parameters of amplification / local mitigation

We use equation 48 to calculate the frequency of an accident on a trajectory T_r:

$$F(T_r) = f_1 + \sum_{j=2}^{k}(\prod_{i=1}^{j-1}(1 - f_i)) \times f_j \tag{48}$$

4) SEVERITY LEVEL (SL)

It is defined as a function of the Intensity Level (IL) and Vulnerability Level (VL):

$$SL = f(IL, VL) \tag{49}$$

- Intensity Level: The intensity levels of an event are estimated by recognizing the areas impacted by the accident. In the literature, many methods were suggested to calculate the impacted areas [124]. A straightforward approach is to draw circles around the center of the accident showing areas of lethal effect (A_1) and areas of irreversible effect (A_2). The truck position at the time of the accident is the center of all drawn circles representing the defined areas. The radius of the area is calculated based on the amount of hazardous material discharged from the truck. The amount of dangerous goods is defined by the interval [l,u]. Thus, four hazardous areas ($A_{11}, A_{12}, A_{22}, A_{21}$) can be plotted as shown in figure 11. ($A_{11} and A_{12}$) represent the areas of lethal effects whereas ($A_{22} and A_{21}$)) represent the areas of irreversible effects. The radius for each is determined by the following:

$$\begin{cases} A_{11} : R_{11} = l^{0.425} \times 3.12 \\ A_{12} : R_{12} = u^{0.425} \times 3.12 \\ A_{22} : R_{22} = l^{0.405} \times 4.7 \\ A_{21} : R_{21} = u^{0.405} \times 4.7 \end{cases} \tag{50}$$

- Vulnerability Level: There are two dimensions for the severity of an accident. As previously defined, the intensity level focuses on identifying the impacted areas. The second dimension focuses on the list of human and environmental assets in the impacted areas. The vulnerability level focuses on two factors:
  - Human Severity (HS): formed through two groups: Injured People (IP) and Dead People (DP). Let $|S|$ be the number of people in a circular area S. Thus, the number of DP is calculated as in equation 51

    $$\tilde{DP} = \{x \in [|A_{11}|, |A_{11}| + |A_{12} - A_{11}|]\}. \tag{51}$$

    Also, the number of IP is calculated as in equation 52:

    $$\tilde{IP} = \{x \in [|A_{22} - A_{12}|, |A_{22} - A_{12}| + |A_{21} - A_{22}|]\}. \tag{52}$$

  - Environment severity (ES): is determined based on the total number of parks and rivers in both A_{12} and A_{21}.

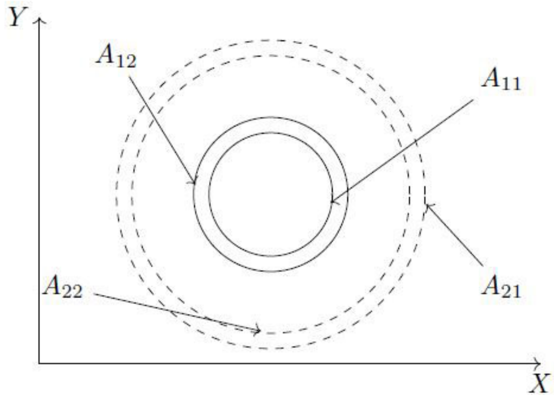


FIGURE 11. Four Hazardous Areas: two for lethal effects and two for irreversible effects.

5) BUILDING THE FUZZY DECISION MATRIX

To build the decision matrix and rank the given alternatives, the following is taken into consideration:

- For $Path = 1$ (after the first iteration), ($Alternative = 1$ $and\ Criteria = 5$), the decision matrix is a 1×5 matrix. This is presented in table 7.

TABLE 7. One Alternative.

	c_1	c_2	c_3	c_4	c_5
A_1	$\tilde{IP}_{11}$	$\tilde{DP}_{12}$	$\tilde{ES}_{13}$	$\tilde{TD}_{14}$	$\tilde{TC}_{15}$

- For $Path = m$ (after the final iteration), the decision matrix is a $m \times 5$ matrix. This is presented in table 8.

TABLE 8. m Alternatives.

	c_1	c_2	c_3	c_4	c_5
A_1	$\tilde{IP}_{11}$	$\tilde{DP}_{12}$	$\tilde{ES}_{13}$	$\tilde{TD}_{14}$	$\tilde{TC}_{15}$
A_2	$\tilde{Ip}_{21}$	$\tilde{DP}_{22}$	$\tilde{ES}_{23}$	$\tilde{TD}_{24}$	$\tilde{TC}_{25}$
A_3	$\tilde{IP}_{31}$	$\tilde{DP}_{32}$	$\tilde{ES}_{33}$	$\tilde{TD}_{34}$	$\tilde{TC}_{35}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
A_m	$\tilde{IP}_{m1}$	$\tilde{DP}_{m2}$	$\tilde{ES}_{m3}$	$\tilde{TD}_{m4}$	$\tilde{TC}_{m5}$

C. APPLYING FUZZY TOPSIS TO THE DECISION MATRIX:

To find the alternative with the highest relative closeness to the ideal solution, We use fuzzy TOPSIS. It is a solid method used for multi-criteria compromise programming. Once the method is applied to the fuzzy decision matrix then the following parameters are estimated for each alternative: d_i^+, d_i^-, and CC_i. This is shown in table 9.

TABLE 9. The Separation Measures and The Relative Closeness.

	d_i^+	d_i^-	CC_i
A_1	d_{11}	d_{12}	d_{13}
A_2	d_{21}	d_{22}	d_{23}
$\vdots$	$\vdots$	$\vdots$	$\vdots$
A_m	d_{m1}	d_{m2}	d_{m3}

D. SELECTING THE BEST ALTERNATIVE:

The alternative with the highest value of relative closeness is the best alternative. The higher the closeness coefficient CC_i^+ the better the performance of the alternative A_i is. Table 10 shows the ranking of the alternatives under the proposed system.

TABLE 10. Preference Ranking Versus Alternatives.

	A_1	A_2	A_3	A_4	$\ldots$	A_m
$Rank$	$Value_1$	$Value_2$	$Value_3$	$Value_4$	$\ldots$	$Value_m$

VIII. SIMULATION AND RESULTS

This section is dedicated to illustrate and discuss the simulation results. The simulator is built with Python. The simulator is composed of four components. The map which is an indirect graph and that is because of the assumption that the cost, risk and distance in any road segment (graph edge) is the same regardless which direction you are going. The correctness of this implementation is verified by testing several maps and getting all possible paths from a point to another. The algorithm is successfully avoiding circular paths for soundness and it is getting all possible paths from one point to another in a correct way and it finds the best path based on a predefined criteria.

The AHP Module is the implementation of the fuzzy version of the algorithm shown in Section III-C. The second module implements the Topsis algorithm shown in Section III-D. The correctness of two modules are verified by comparing the output of the two modules with known examples that are considered as benchmarks for the two algorithms and the output of the two implementations matched. The two modules (AHP and Topsis) are concatenated together to build the proposed model. This model determines the output of Fuzzy AHP (the weights) that is fed to Topsis for selecting the best path. Figure 12 shows the map that is used in the simulation. The objective is to move dangerous goods from V_{01} to V_{50}. The objective function is to reduce $\mathbb{V}$ defined in equation 29 where $\mathbb{C}$ is the cost in dollars of the trip, $\mathbb{D}$ is the time spent in the trip, and $\mathbb{R}$ is the risk that could be faced during the trip. Weights represent effectiveness of every factor in the total valuation $\mathbb{V}$. Note that the numbers written on edges between vertices represent the cost $\mathbb{C}$, duration $\mathbb{D}$ and risk $\mathbb{R}$ respectively.

Note that the cost of a path is calculated as follows:

$$\mathbb{C}_t = \Sigma_{i=1}^{n}\mathbb{C}(s_i) \quad (53)$$

where s_i is a segment number i, $1 \leq i \leq n$ that belongs to path p, $\mathbb{C}(s_i)$ is the cost of segment s_i and path p has a number of segments $\|p\| = n$.

Duration of a path is calculated as follows:

$$\mathbb{D}_t = \Sigma_{i=1}^{n}\mathbb{D}(s_i) \quad (54)$$

where s_i is a segment number i, $1 \leq i \leq n$ that belongs to path p, $\mathbb{D}(s_i)$ is the duration of segment s_i and path p has a number of segments $\|p\| = n$.

Risk of a path is calculated as follows:

$$\mathbb{R}_t = MAX(\mathbb{R}(s_i)) \tag{55}$$

where $\mathbb{R}_t$ is the risk of the whole path from source to destination, s_i is a segment number i, $1 \leq i \leq n$ that belongs to path p, $\mathbb{R}(s_i)$ is the risk of segment s_i and path p has a number of segments $\|p\| = n$.

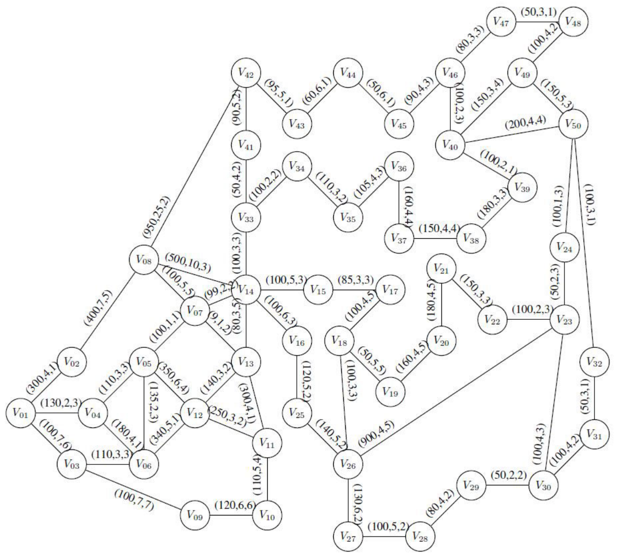


FIGURE 12. **Map used in the simulation. Numbers on arcs represent ($\mathbb{C}$, $\mathbb{D}$ and $\mathbb{R}$) defined in equation [29].**

Simulation is done for both static and dynamic environments starting from source vertex V_{01} to destination vertex V_{14}. A static environment is an environment that assumes that values of ($\mathbb{C}, \mathbb{D}, \mathbb{R}$) are fixed. In other words, the path that is being predetermined before the cargo leaves source to destination will not change since numbers do not change. In dynamic environments, on other hand, the values of the tuple ($\mathbb{C}, \mathbb{D}, \mathbb{R}$) can change in one or more path segments which means optimal paths could change by time. Path segments are edges between vertices as shown in figure 12.

This section is organized as follows: Subsection VIII-A1 presents the different path costs when the costs in dollars are the only criterion considered in the selection. It also shows the selected path with some statistics about the costs in dollars in the given map in Figure 12 when the environment is static.

Subsection VIII-A2 shows the different path duration. It also presents the selected path when the only criterion considered in the selection is the duration with some statistics about the duration in the given map in Figure 12 when the environment is static.

Subsection VIII-A3 highlights the different path risks. It also presents the selected path when the only criterion considered in the selection is the risk with some statistics about the duration in the given map in Figure 12 when the environment is static.

Subsection VIII-A4 demonstrates the different path valuations. It also selects the path with minimum valuation when all criteria are considered when the environment is static.

Subsection VIII-A5 manifest the selection of the minimum path using fuzzy AHP explained earlier.

Subsection VIII-A6 reveals the selection of the minimum path among all available paths using fuzzy AHP-Topsis method.

Subsection VIII-B1 presents the different path costs when the costs in dollars are the only criterion considered in the selection. It also shows the selected path with some statistics about the costs in dollars in the given map in Figure 12 when the environment is dynamic.

Subsection VIII-B4 shows the different path duration. It also presents the selected path when the only criterion considered in the selection is the duration with some statistics about the duration in the given map in Figure 12 when the environment is dynamic.

Subsection VIII-B3 highlights the different path risks. It also presents the selected path when the only criterion considered in the selection is the risk with some statistics about the duration in the given map in Figure 12 when the environment is dynamic.

Subsection VIII-A4 demonstrates the different path valuations. It also selects the path with minimum valuation when all criteria are considered when the environment is dynamic.

Subsection VIII-B5 manifest the selection of the minimum path using fuzzy AHP explained earlier.

A. STATIC ENVIRONMENT

This subsection pertains to experiments that operate under the assumption of a static environment, where costs, duration, and risks remain constant as defined initially, that is, all graph edges maintain the cost, duration, and risk values throughout the entire experiment with no change.

The map we use to simulate our static environment is shown in figure 12.

1) COST BASED PATH SELECTION

The term cost, interchangeably referred to as expenses in this context, signifies the tangible monetary outlay incurred during the journey. This includes but not limited to gas, driver wages and any other expenses for the trip. The objective is to move from vertex V_1 to vertex V_{50} with minimum cost. The experiment is based on A algorithm. From source V_1 to destination V_{50} there are 1725 different paths each with its own total cost. The different costs are shown below in figure 13.

In Figure 13, an illustration of various route expenses is presented. As previously indicated, the expenses are denominated in dollars and encompass the comprehensive transportation outlays. These encompass not only the driver's remuneration and fuel expenses but also factors such as mandatory trip maintenance and related costs.

The path with minimum cost in dollars (expenses) from source defined by vertex V_{01} to destination defined by

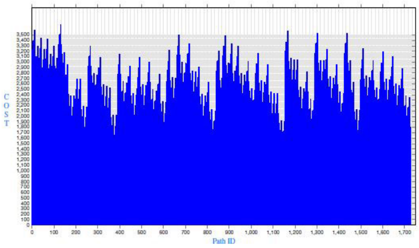


FIGURE 13. Path cost.

vertex V_{50} is:

$$V_{01} \rightarrow V_{04} \rightarrow V_{05} \rightarrow V_{07} \rightarrow V_{13} \rightarrow V_{14} \rightarrow V_{33} \rightarrow V_{41} \rightarrow V_{42} \rightarrow V_{43} \rightarrow V_{44} \rightarrow V_{45} \rightarrow V_{46} \rightarrow V_{40} \rightarrow V_{50} \tag{56}$$

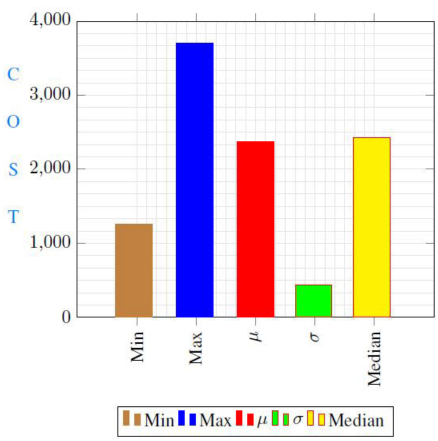


FIGURE 14. Min,Max,Mean μ,Standard deviation σ, and Median of route expenses.

The path with maximum cost in dollars (expenses) from source defined by vertex V_{01} to destination defined by vertex V_{50} is:

$$V_{01} \rightarrow V_{02} \rightarrow V_{08} \rightarrow V_{07} \rightarrow V_{05} \rightarrow V_{12} \rightarrow V_{06} \rightarrow V_{03} \rightarrow V_{09} \rightarrow V_{10} \rightarrow V_{11} \rightarrow V_{13} \rightarrow V_{14} \rightarrow V_{33} \rightarrow V_{34} \rightarrow V_{35} \rightarrow V_{36} \rightarrow V_{37} \rightarrow V_{38} \rightarrow V_{39} \rightarrow V_{40} \rightarrow V_{46} \rightarrow V_{47} \rightarrow V_{48} \rightarrow V_{49} \rightarrow V_{50} \tag{57}$$

As previously indicated, the evaluation of each route encompasses the fusion of financial costs (expenditures), the duration required for travel between the starting point and the destination (duration), and the potential risks that cargo could encounter along specific routes (risk). In this experiment, the optimal route is chosen based solely on expenditures. Figure 14 presents a comparison among the minimum, maximum, and average costs of all routes. Note that the cost of a path is calculated as:

$$\mathbb{C}_t(P) = \int_{i=1}^{i=n} \mathbb{C}(E_i)\, \partial\, i, \quad iE_i \in P \tag{58}$$

where n is the number of edges in a path, $\mathbb{C}_t(P)$ is the expenses of path P, and $\mathbb{C}(E_i)$ is the expense of edge E_i such that edge E_i belongs to path P.

Figure 14 provides a statistical overview of the expense-focused route selection. The path with the lowest expenses amounts to 1264 units, while the one with the highest expenses reaches 3699 units. The average cost across all routes is 2372 units. The standard deviation is 440 units, and the median path registers expenses of 2428 units.

2) DURATION BASED PATH SELECTION

The concept of "duration" denotes the period of time consumed throughout the travel. The objective of the experiment is to traverse from vertex V_1 to vertex V_{50} in the least amount of time. The experiment is conducted utilizing the A^* algorithm. Along the path from source V_1 to destination V_{50}, there exist 1725 distinct routes, each characterized by its unique total duration. The varying duration are visualized in figure 15.

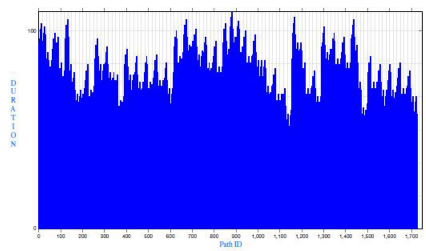


FIGURE 15. Path Duration.

Figure 15 provides a visual representation of diverse route duration. The route characterized by the shortest duration, originating at the vertex denoted by V_{01} and terminating at the vertex marked as V_{50}, is as follows:

$$V_{01} \rightarrow V_{04} \rightarrow V_{05} \rightarrow V_{07} \rightarrow V_{14} \rightarrow V_{15} \rightarrow V_{17} \rightarrow V_{18} \rightarrow V_{19} \rightarrow V_{20} \rightarrow V_{21} \rightarrow V_{22} \rightarrow V_{23} \rightarrow V_{24} \rightarrow V_{50} \tag{59}$$

The route exhibiting the maximum duration, starting at the source vertex identified as V_{01} and concluding at the destination vertex denoted by V_{50}, can be described as follows:

$$V_{01} \rightarrow V_{03} \rightarrow V_{09} \rightarrow V_{10} \rightarrow V_{11} \rightarrow V_{13} \rightarrow V_{12} \rightarrow V_{06} \rightarrow V_{04} \rightarrow V_{05} \rightarrow V_{07} \rightarrow V_{08} \rightarrow V_{14} \rightarrow V_{33} \rightarrow V_{41} \rightarrow V_{42} \rightarrow V_{43} \rightarrow V_{44} \rightarrow V_{45} \rightarrow V_{46} \rightarrow V_{47} \rightarrow V_{48} \rightarrow V_{49} \rightarrow V_{40} \rightarrow V_{50} \tag{60}$$

Displayed in Figure 16 is a comparative analysis involving the minimum, maximum, and average duration of all routes. It's worth noting that the computation of a path's cost adheres to the equation:

$$\mathbb{D}t(P) = \int_{i=1}^{i=n} \mathbb{D}(E_i)\, \partial\, i, \quad iE_i \in P \tag{61}$$

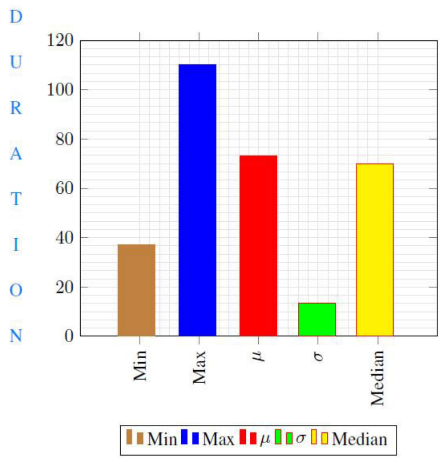


FIGURE 16. **Min,Max,Mean μ,Standard deviation σ, and Median of route expenses.**

Here, n represents the count of edges within a given path, $\mathbb{D}_t(P)$ signifies the duration associated with path P, and $\mathbb{D}(E_i)$ denotes the duration of edge E_i, which is a constituent of path P.

Figure 16 delivers a statistical summary of the route selection process centered on duration. The route characterized by the shortest duration encompasses 37 units, while the one marked with the longest duration extends to 110 units. The mean duration across all routes equates to 73 units. The standard deviation stands at 13.5 units, and the median path entails a duration of 70 units.

3) RISK BASED PATH SELECTION

The concept of ''risk'' denotes a measure of the difficulties and/or danger the cargo could face in some route. The objective of the experiment is to traverse from vertex V_1 to vertex V_{50} while avoiding risks as much as possible. The experiment is conducted utilizing the A^* algorithm. Along the path from source V_1 to destination V_{50}, there exist 1725 distinct routes, each characterized by its total risk. The varying risks are visualized in figure 17.

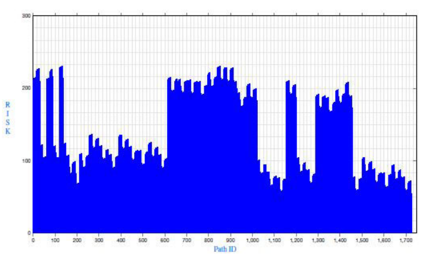


FIGURE 17. **Path Risks.**

Figure 17 illustrates a range of route risks. The path exhibiting the lowest level of risk, which begins at the vertex labeled as V_{01} and concludes at the vertex identified as V_{50}, can be described as follows:

$$V_{01} \rightarrow V_{04} \rightarrow V_{05} \rightarrow V_{07} \rightarrow V_{14} \rightarrow V_{16} \rightarrow V_{25} \rightarrow V_{26} \rightarrow V_{27} \rightarrow V_{28} \rightarrow V_{29} \rightarrow V_{30} \rightarrow V_{31} \rightarrow V_{32} \rightarrow V_{50} \quad (62)$$

The pathway demonstrating the highest degree of risk, commencing from the source vertex designated as V_{01} and culminating at the destination vertex denoted by V_{50}, can be outlined as follows:

$$V_{01} \rightarrow V_{02} \rightarrow V_{08} \rightarrow V_{07} \rightarrow V_{05} \rightarrow V_{12} \rightarrow V_{06} \rightarrow V_{03} \rightarrow V_{09} \rightarrow V_{10} \rightarrow V_{11} \rightarrow V_{13} \rightarrow V_{14} \rightarrow V_{33} \rightarrow V_{34} \rightarrow V_{35} \rightarrow V_{36} \rightarrow V_{37} \rightarrow V_{38} \rightarrow V_{39} \rightarrow V_{40} \rightarrow V_{46} \rightarrow V_{47} \rightarrow V_{48} \rightarrow V_{49} \rightarrow V_{50} \quad (63)$$

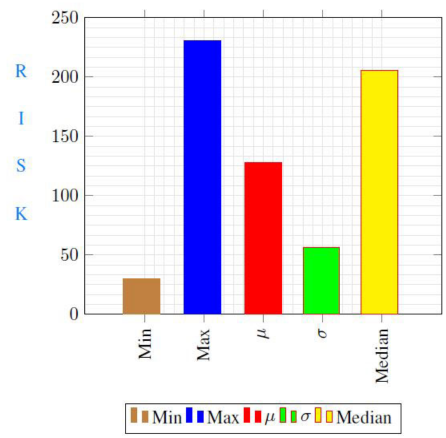


FIGURE 18. **Min,Max,Mean μ,Standard deviation σ, and Median of route expenses.**

Depicted in Figure 16 is a comparative examination encompassing the least, greatest, and mean risk assessments across all routes. It is important to highlight that the computation of a route's cost is governed by the following equation:

$$\mathbb{R}t(P) = \int_{i=1}^{i=n} 2^{\mathbb{R}(E_i)}\, \partial\, i, \quad iE_i \in P \quad (64)$$

In this context, the variable n represents the count of edges within a given path. $\mathbb{R}_t(P)$ denotes the level of risk associated with path P, and $\mathbb{R}(E_i)$ signifies the risk attributed to edge E_i, which constitutes a part of path P.

Figure 18 provides a statistical overview of the route selection process based on risk assessment. The route with the lowest risk is valued at 30 units, while the one with the highest risk spans 231 units. The average risk across all routes stands at 128 units. The standard deviation is 56 units, and the median path carries a risk measurement of 206 units.

4) VALUATION BASED PATH SELECTION

In this experiment, valuation based approach is adopted to select a path. Valuation is the fusion of cost, duration and risk.

The fusion is done according to the following equation:

$$\mathbb{V} = \eta_1 \times \mathbb{C} + \eta_2 \times \mathbb{D} + \eta_3 \times \mathbb{R} \tag{65}$$

η_1, η_2, and η_3 are scaling parameters. As seen in previous experiments, cost is in thousands, duration is mostly in tens while risk is mostly in hundreds. This makes the cost in dollar the dominant parameter for selecting the best path. This is why, scaling values is very important as a pre-processing phase before fusing those values together. The values of η_1, η_2, and η_3 are set according to the maximum magnitude of every factor. In this experiment, $\eta_1 0.1.\eta_2 = 1$ and $\eta_3 = 0.5$.

The objective of the experiment is to traverse from vertex V_1 to vertex V_{50} while maintaining minimum valuation $\mathbb{V}$. The experiment is conducted utilizing the A^* algorithm. Along the path from source V_1 to destination V_{50}, there exist 1725 distinct routes, each characterized by its total valuation. The varying valuations are visualized in figure 19.

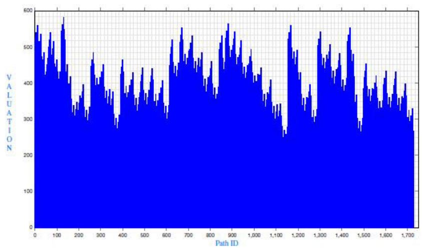


FIGURE 19. **Path Valuations.**

Figure 19 illustrates a range of route valuation. The path exhibiting the minimum valuation, which begins at the vertex labeled as V_{01} and concludes at the vertex identified as V_{50}, can be described as follows:

$$V_{01} \to V_{04} \to V_{05} \to V_{07} \to V_{14} \to V_{33} \to V_{41} \to V_{42} \to V_{43} \to V_{44} \to V_{45} \to V_{46} \to V_{40} \to V_{50} \tag{66}$$

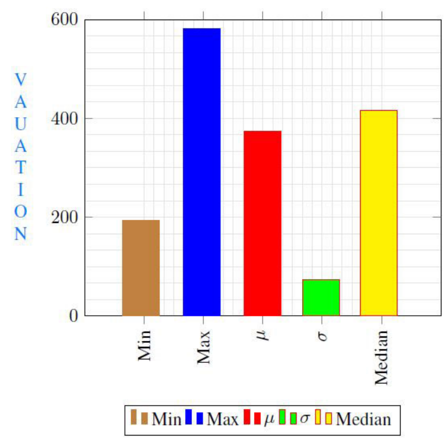


FIGURE 20. **Min,Max,Mean μ,Standard deviation σ, and Median of route expenses.**

The pathway demonstrating the maximum valuation, commencing from the source vertex designated as V_{01} and culminating at the destination vertex denoted by V_{50}, can be outlined as follows:

$$V_{01} \to V_{02} \to V_{08} \to V_{07} \to V_{05} \to V_{12} \to V_{06} \to V_{03} \to V_{09} \to V_{10} \to V_{11} \to V_{13} \to V_{14} \to V_{33} \to V_{34} \to V_{35} \to V_{36} \to V_{37} \to V_{38} \to V_{39} \to V_{40} \to V_{46} \to V_{47} \to V_{48} \to V_{49} \to V_{50} \tag{67}$$

Depicted in Figure 20 is a comparative examination encompassing the least, greatest, and mean risk assessments across all routes.

Figure 20 provides a statistical overview of the route selection process based on valuation assessment. The route with the lowest valuation is valued at 193 units, while the one with the highest valuation spans 581 units. The average valuation across all routes stands at 581 units. The standard deviation is 74 units, and the median path carries a risk measurement of 416 units.

5) AHP BASED PATH SELECTION

In subsection VIII-A4, the composite cost of the path was assumed to assign equal weights to different criteria. The division of the cost by a hundred dollars is solely intended for normalization purposes, rather than for assigning weights.

However, it's unrealistic to presuppose that all criteria carry the same degree of significance, and this is where the Analytic Hierarchy Process (AHP) comes into play. As previously observed, AHP computes weights based on predefined pairwise comparisons. These pairwise comparisons are illustrated in Figure 23.

In Figure 21(a), the pairwise comparison that signifies the relationship between cost in dollars $\mathbb{C}$ and duration $\mathbb{D}$. In this instance, cost is assessed as twice as significant as duration. Similarly, in Figure 21(b), pertains to risk $\mathbb{R}$ and cost in dollars $\mathbb{D}$, with risk being deemed three times more significant than cost. Figure 21(c) reflects the pairwise comparison between risk $\mathbb{R}$ and duration $\mathbb{D}$, wherein risk is considered four times more significant than duration. Applying AHP using those pairwise values produces the different coefficient values shown in Figure 21(d). These precise pairwise comparisons are outlined in the following table: Using pairwise comparison values shown in table 11

TABLE 11. **Pairwise comparisons among different criteria.**

	$\mathbb{C}$	$\mathbb{D}$	$\mathbb{R}$
$\mathbb{C}$	1	2	$\frac{1}{3}$
$\mathbb{D}$	$\frac{1}{2}$	1	$\frac{1}{4}$
$\mathbb{R}$	3	4	1

will give us the following weights:

$$\beta_1 = 0.24, \beta_2 = 0.15, \beta_3 = 0.61 \tag{68}$$

Equation 65 will modify to be:

$$\mathbb{V} = \beta_1 \times \eta_1 \times \mathbb{C} + \beta_2 \times \eta_2 \times \mathbb{D} + \beta_3 \times \eta_3 \times \mathbb{R} \quad (69)$$

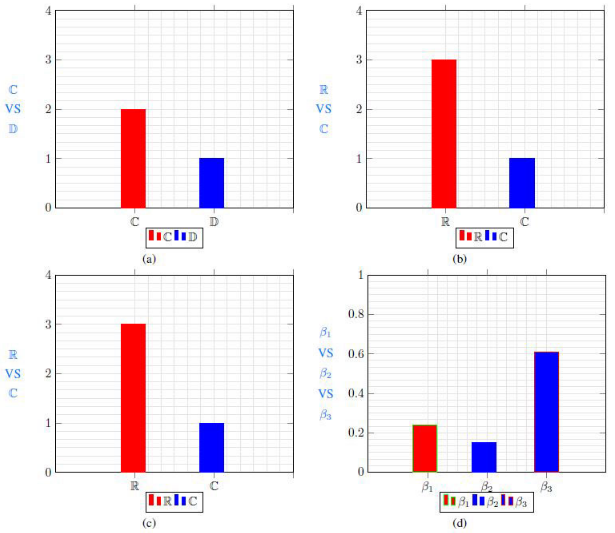


FIGURE 21. **Sub-figure (a) shows the pairwise comparison between cost $\mathbb{C}$ and duration $\mathbb{D}$. Sub-figure (b) shows the pairwise comparison between risk $\mathbb{R}$ and cost $\mathbb{C}$. Sub-figure (c) shows the pairwise comparison between risk $\mathbb{R}$ and duration $\mathbb{D}$. Sub-figure (d) shows values of weights β_1, β_2, and β_3 after applying the AHP process.**

The objective of the experiment is to traverse from vertex V_1 to vertex V_{50} while maintaining minimum valuation $\mathbb{V}$ calculated through AHP. Along the path from source V_1 to destination V_{50}, there exist 1725 distinct routes, each characterized by its total valuation. The varying valuations are visualized in figure 22.

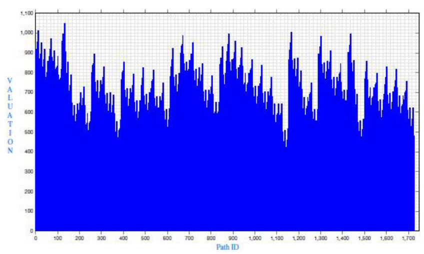


FIGURE 22. **Path Valuations through AHP Process.**

Figure 22 illustrates a range of route valuation. The path exhibiting the minimum valuation, which begins at the vertex labeled as V_{01} and concludes at the vertex identified as V_{50}, can be described as follows:

$$V_{01} \rightarrow V_{04} \rightarrow V_{05} \rightarrow V_{07} \rightarrow V_{14} \rightarrow V_{33} \rightarrow V_{41} \rightarrow V_{42} \rightarrow V_{43} \rightarrow V_{44} \rightarrow V_{45} \rightarrow V_{46} \rightarrow V_{40} \rightarrow V_{50} \quad (70)$$

The pathway demonstrating the maximum valuation, commencing from the source vertex designated as V_{01} and culminating at the destination vertex denoted by V_{50}, can be

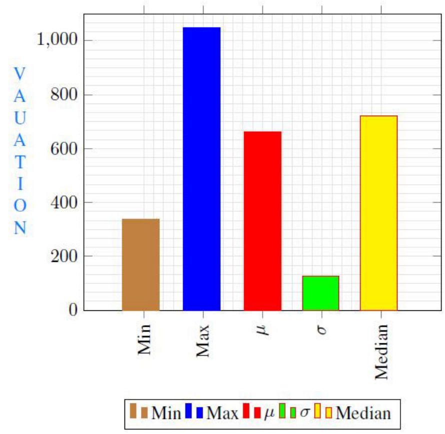


FIGURE 23. **Min,Max,Mean μ,Standard deviation σ, and Median of route expenses.**

outlined as follows:

$$V_{01} \rightarrow V_{02} \rightarrow V_{08} \rightarrow V_{07} \rightarrow V_{05} \rightarrow V_{12} \rightarrow V_{06} \rightarrow V_{03} \rightarrow V_{09} \rightarrow V_{10} \rightarrow V_{11} \rightarrow V_{13} \rightarrow V_{14} \rightarrow V_{33} \rightarrow V_{34} \rightarrow V_{35} \rightarrow V_{36} \rightarrow V_{37} \rightarrow V_{38} \rightarrow V_{39} \rightarrow V_{40} \rightarrow V_{46} \rightarrow V_{47} \rightarrow V_{48} \rightarrow V_{49} \rightarrow V_{50} \quad (71)$$

Figure 23 provides a statistical overview of the route selection process based on valuation assessment. The route with the lowest valuation is valued at 338 units, while the one with the highest valuation spans 1049 units. The average valuation across all routes stands at 661 units. The standard deviation is 128 units, and the median path carries a risk measurement of 723 units.

6) AHP TOPSIS BASED PATH SELECTION

This experiment uses the AHP Topsis merge methodology. As mentioned earlier, the weights are calculated using AHP and then weights get fed into Topsis to select the best path.

The objective of the experiment is to traverse from vertex V_1 to vertex V_{50} while maintaining minimum valuation $\mathbb{V}$. Along the path from source V_1 to destination V_{50}, there exist 1725 distinct routes, each characterized by its total valuation. The varying valuations are visualized in figure 24.

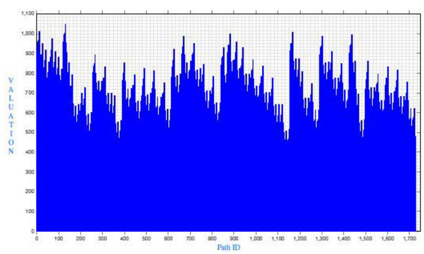


FIGURE 24. **Path Valuations through AHP/Topsis Process.**

Figure 24 illustrates a range of route valuation. The path exhibiting the minimum valuation, which begins at the vertex labeled as V_{01} and concludes at the vertex identified as V_{50}, can be described as follows:

$$V_{01} \rightarrow V_{04} \rightarrow V_{05} \rightarrow V_{07} \rightarrow V_{14} \rightarrow V_{33} \rightarrow V_{41} \rightarrow V_{42} \rightarrow V_{43} \rightarrow V_{44} \rightarrow V_{45} \rightarrow V_{46} \rightarrow V_{40} \rightarrow V_{50} \quad (72)$$

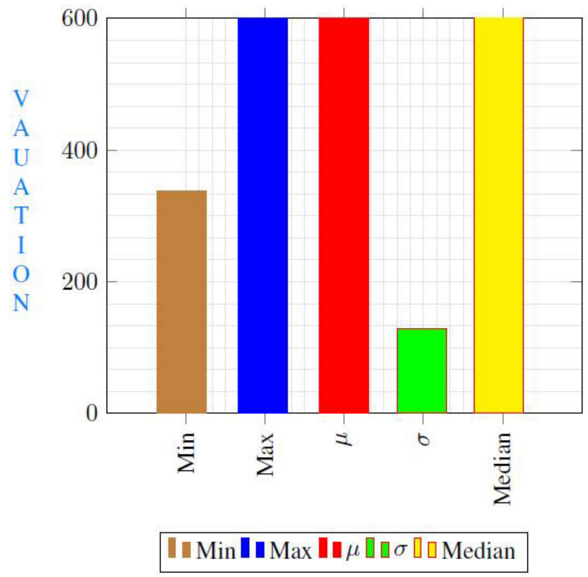


FIGURE 25. Min,Max,Mean μ,Standard deviation σ, and Median of route expenses.

The pathway demonstrating the maximum valuation, commencing from the source vertex designated as V_{01} and culminating at the destination vertex denoted by V_{50}, can be outlined as follows:

$$V_{01} \rightarrow V_{02} \rightarrow V_{08} \rightarrow V_{07} \rightarrow V_{05} \rightarrow V_{12} \rightarrow V_{06} \rightarrow V_{05} \rightarrow V_{12} \rightarrow V_{06} \rightarrow V_{03} \rightarrow V_{09} \rightarrow V_{10} \rightarrow V_{11} \rightarrow V_{13} \rightarrow V_{14} \rightarrow V_{33} \rightarrow V_{34} \rightarrow V_{35} \rightarrow V_{36} \rightarrow V_{37} \rightarrow V_{38} \rightarrow V_{39} \rightarrow V_{40} \rightarrow V_{46} \rightarrow V_{47} \rightarrow V_{48} \rightarrow V_{49} \rightarrow V_{50} \quad (73)$$

Depicted in Figure 20 is a comparative examination encompassing the least, greatest, and mean risk assessments across all routes.

Figure 20 provides a statistical overview of the route selection process based on valuation assessment. The route with the lowest valuation is valued at 193 units, while the one with the highest valuation spans 581 units. The average valuation across all routes stands at 581 units. The standard deviation is 74 units, and the median path carries a risk measurement of 416 units.

B. DYNAMIC ENVIRONMENT

In this section, we test our algorithms when the criteria change. In other words, the cost in dollars change due to the crookedness, the duration increases or decreases, or the risk changes.

The scenario of the simulator in this section is as follows: Transportation is from V_{01} to V_{50}. After the vehicle reaches V_{18}, criteria changes for the link from vertex v_{18} to vertex v_{19} from values described in Figure 12 to values shown in Figure 26 which means that the algorithm needs to find a better route from V_{18} to V_{50}.

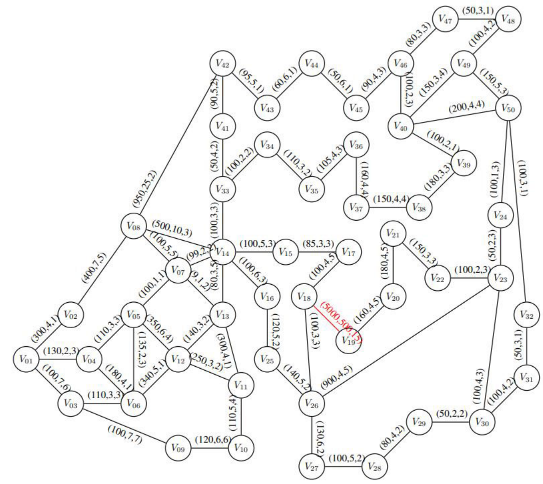


FIGURE 26. Map used in the simulation. Numbers on arcs represent ($\mathbb{C}$, $\mathbb{D}$ and $\mathbb{R}$) defined in equation [29].

The cost of rerouting is measured in this paper as follows:

$$\mathbb{C}(V_i, V_j) = \mathbb{C}(V_i, V_k) + \mathbb{C}(V_k, V_j) \quad (74)$$
$$\mathbb{D}(V_i, V_j) = \mathbb{D}(V_i, V_k) + \mathbb{D}(V_k, V_j) \quad (75)$$
$$\mathbb{R}(V_i, V_j) = max(\mathbb{R}(V_i, V_k), \mathbb{R}(V_k, V_j)) \quad (76)$$
$$\mathbb{V}(V_x, V_y) = \beta_1\mathbb{C}(V_x, V_y) + \beta_2\mathbb{D}(V_x, V_y) + \beta_3\mathbb{R}(V_x, V_y) \quad (77)$$
$$\mathbb{V}(V_i, V_j) = \mathbb{V}(V_i, V_k) + \mathbb{V}(V_k, V_j) \quad (78)$$

where V_i is the starting vertex (source / beginning of the trip), V_j is the ending vertex (destination / ending of the trip) and V_k is a vertex in the middle the vehicle is in when valued changed.

1) COST BASED PATH SELECTION

As mentioned earlier, we have three criteria for measuring the performance, the cost in dollars $\mathbb{C}$, the duration in hours $\mathbb{D}$ and the risk $\mathbb{R}$ as a number where 1 is no risk and more than 1 is how risky the road is. IN this subsection, we perform the experiment of choosing the best path where the only parameter of choice is the cost in dollars $\mathbb{C}$.As mentioned earlier, the experiment assumes that a dramatic change happens fur to an unexpected accident.

Figure 27 shows for sub figures. Each showing three bars. The yellow bar is the case when no change happens in the rout from V_{01} to V_{50}. This bar is the case of the static environment measure. The red bar represents the measure when an accident happens, yet, the vehicle does not change its predefined rout. The blue bar represents the measure when the vehicle changes it route based on the decision making process.

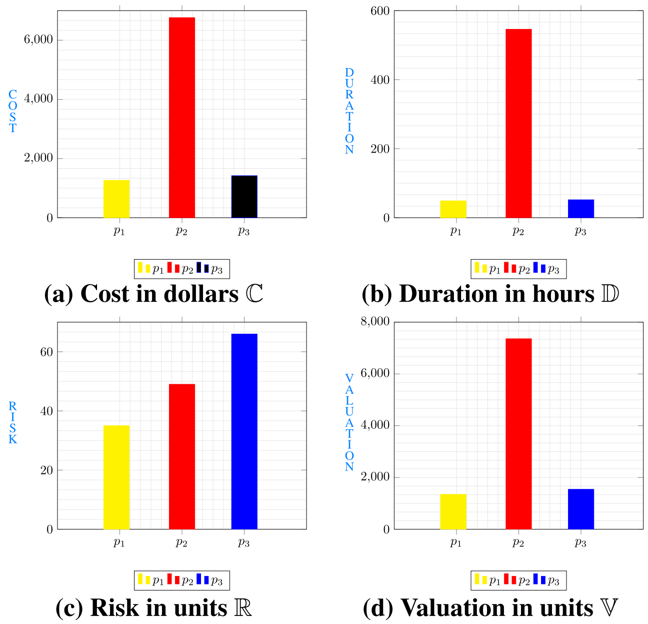


FIGURE 27. **Choosing path with minimum $\mathbb{C}$ in a dynamic environment.**

Figure 27(a) shoes the comparison of cost in dollars between the static environment cost illustrated by the yellow bar, the cost in dollars when the environment changes but the vehicle continued in the predefined path illustrated by the red bar and the cost in dollars when the environment changes and a new path is determined illustrated by the blue bar. The illustration in 28(a) shows that continuing in the predefined path will cost more than 535% of the original cost in dollars. It also shows that taking the new rout costs around 21% of the cost in dollars that would be spent if the vehicle continues in the predefined path. Due to the change in environment, the new path costs 12% more than the cost in dollars of the original path.

Figure 27(b) shows the duration of the three different paths. Continuing in the predefined path will take more than 11 times the time taken in the same path if the environment did not change. Taking the new path takes less than 10% of the time taken if the vehicle decides to continue in the predefined path. The new path takes 6% more of the time taken if the original path is followed with no accidents.

Figure 27(c) shows the risk levels in the three different paths. Continuing in the predefined path will have more than 146% of the risk of the same path if the environment did not change. Taking the new path takes less than 85% of the risk if the vehicle decides to continue in the predefined path. The new path takes 27% more of the risk if the original path is followed with no accidents.

Figure 27(d). shows the valuation in the three different paths. Valuation is calculated using equation 69 assuming that $\beta_1 = \beta_2 = \beta_3 = \eta_1 = eta_2 = \eta_3 = 1$.Continuing in the predefined path will have more than 546% of the valuation of the same path if the environment did not change. Taking the new path has 21% of the valuation if the vehicle decides to continue in the predefined path. The new path takes 14% more of the valuation if the original path is followed with no accidents.

2) DURATION BASED PATH SELECTION

In this subsection, we assume that the only criterion of choosing the path is the duration in hours $\mathbb{D}$. As mentioned earlier, the experiment assumes that a dramatic change happens due to an unexpected accident.

Figure 28 shows for sub figures. Each showing three bars. The yellow bar is the case when no change happens in the rout from V_{01} to V_{50}. This bar is the case of the static environment measure. The red bar represents the measure when an accident happens, yet, the vehicle does not change its predefined rout. The blue bar represents the measure when the vehicle changes it route based on the decision making process.

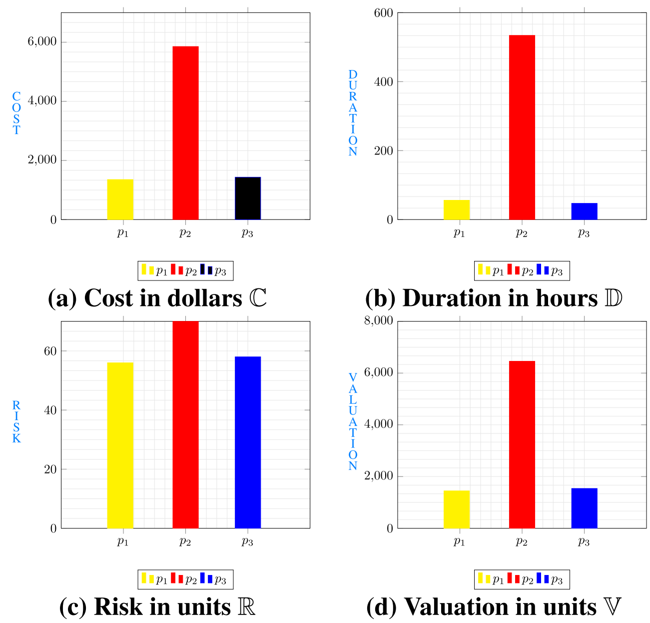


FIGURE 28. **Choosing path with minimum $\mathbb{D}$ in a dynamic environment.**

Figure 28(a) shows the comparison of cost in dollars between the static environment cost illustrated by the yellow bar, the cost in dollars when the environment changes but the vehicle continued in the predefined path illustrated by the red bar and the cost in dollars when the environment changes and a new path is determined illustrated by the blue bar. The illustration in 28(a) shows that continuing in the predefined path will cost more than 432% of the original cost in dollars. It also shows that taking the new rout costs around 24% of the cost in dollars that would be spent if the vehicle continues in the predefined path. Due to the change in environment, the new path costs 6% more than the cost in dollars of the original path.

Figure 28(b) shows the duration of the three different paths. Continuing in the predefined path will take more than 14 times the time taken in the same path if the environment did not change. Taking the new path takes less than 8% of the time taken if the vehicle decides to continue in the predefined path. The new path takes 27% more of the time taken if the original path is followed with no accidents.

Figure 28(c) shows the risk levels in the three different paths. Continuing in the predefined path will have more than 125% of the risk of the same path if the environment did not change. Taking the new path takes less than 82% of the risk if the vehicle decides to continue in the predefined path. The new path takes 3% more of the risk if the original path is followed with no accidents.

Figure 28(d). shows the valuation in the three different paths. Valuation is calculated using equation 69 assuming that $\beta_1 = \beta_2 = \beta_3 = \eta_1 = eta_2 = \eta_3 = 1$. Continuing in the predefined path will have more than 446% of the valuation of the same path if the environment did not change. Taking the new path has 23% of the valuation if the vehicle decides to continue in the predefined path. The new path takes 6% more of the valuation if the original path is followed with no accidents.

3) RISK BASED PATH SELECTION

In this subsection, we assume that the only criterion of choosing the path is the risk in units $\mathbb{R}$. As mentioned earlier, the experiment assumes that a dramatic change happens due to an unexpected accident.

Figure 29 shows for sub figures. Each showing three bars. The yellow bar is the case when no change happens in the rout from V_{01} to V_{50}. This bar is the case of the static environment measure. The red bar represents the measure when an accident happens, yet, the vehicle does not change its predefined rout. The blue bar represents the measure when the vehicle changes it route based on the decision making process.

Figure 29(a) shows the comparison of cost in dollars between the static environment cost illustrated by the yellow bar, the cost in dollars when the environment changes but the vehicle continued in the predefined path illustrated by the red bar and the cost in dollars when the environment changes and a new path is determined illustrated by the blue bar. The illustration in 29(a) shows that continuing in the predefined path will cost more than 419% of the original cost in dollars. It also shows that taking the new rout costs around 27% of the cost in dollars that would be spent if the vehicle continues in the predefined path. Due to the change in environment, the new path costs 7% more than the cost in dollars of the original path.

Figure 29(b) shows the duration of the three different paths. Continuing in the predefined path will take more than 11 times the time taken in the same path if the environment did not change. Taking the new path takes less than 10% of the time taken if the vehicle decides to continue in the predefined path. The new path takes 11% more of the time taken if the original path is followed with no accidents.

Figure 29(c) shows the risk levels in the three different paths. Continuing in the predefined path will have more than

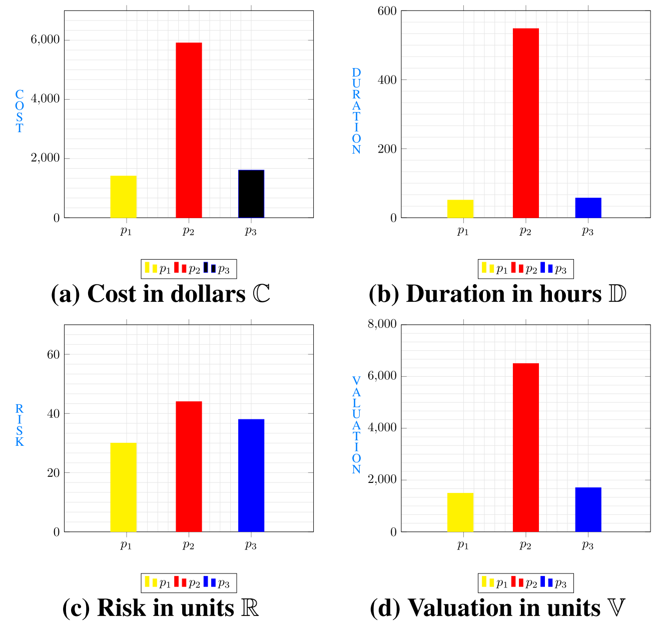


FIGURE 29. Choosing path with minimum $\mathbb{R}$ in a dynamic environment.

146% of the risk of the same path if the environment did not change. Taking the new path takes less than 86% of the risk if the vehicle decides to continue in the predefined path. The new path takes 26% more of the risk if the original path is followed with no accidents.

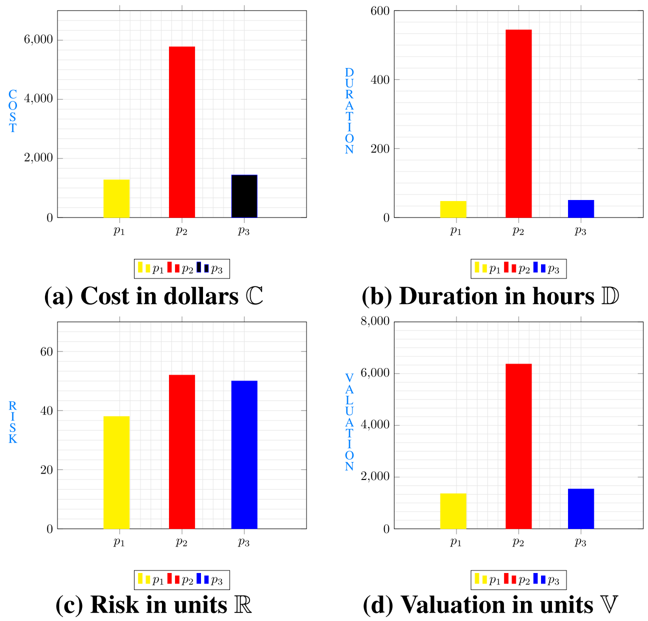
Figure 29(d). shows the valuation in the three different paths. Valuation is calculated using equation 69 assuming that $\beta_1 = \beta_2 = \beta_3 = \eta_1 = eta_2 = \eta_3 = 1$. Continuing in the predefined path will have more than 436% of the valuation of the same path if the environment did not change. Taking the new path has 26% of the valuation if the vehicle decides to continue in the predefined path. The new path takes 14% more of the valuation if the original path is followed with no accidents.

4) VALUATION BASED PATH SELECTION

In this subsection, we assume that the criterion of choosing the path is multi-criteria valuation $\mathbb{V}$ defined in equation 69. As mentioned earlier, the experiment assumes that a dramatic change happens due to an unexpected accident.

Figure 30 shows for sub figures. Each showing three bars. The yellow bar is the case when no change happens in the rout from V_{01} to V_{50}. This bar is the case of the static environment measure. The red bar represents the measure when an accident happens, yet, the vehicle does not change its predefined rout. The blue bar represents the measure when the vehicle changes it route based on the decision making process.

Figure 30(a) shows the comparison of cost in dollars between the static environment cost illustrated by the yellow bar, the cost in dollars when the environment changes but the vehicle continued in the predefined path illustrated by the red bar and the cost in dollars when the environment changes



(a) Cost in dollars $\mathbb{C}$ (b) Duration in hours $\mathbb{D}$ (c) Risk in units $\mathbb{R}$ (d) Valuation in units $\mathbb{V}$

FIGURE 30. **Choosing path with minimum valuation in a dynamic environment.**

and a new path is determined illustrated by the blue bar. The illustration in 30(a) shows that continuing in the predefined path will cost more than 453% of the original cost in dollars. It also shows that taking the new rout costs around 25% of the cost in dollars that would be spent if the vehicle continues in the predefined path. Due to the change in environment, the new path costs 13% more than the cost in dollars of the original path.

Figure 30(b) shows the duration of the three different paths. Continuing in the predefined path will take more than 12 times the time taken in the same path if the environment did not change. Taking the new path takes less than 9% of the time taken if the vehicle decides to continue in the predefined path. The new path takes 15% more of the time taken if the original path is followed with no accidents.

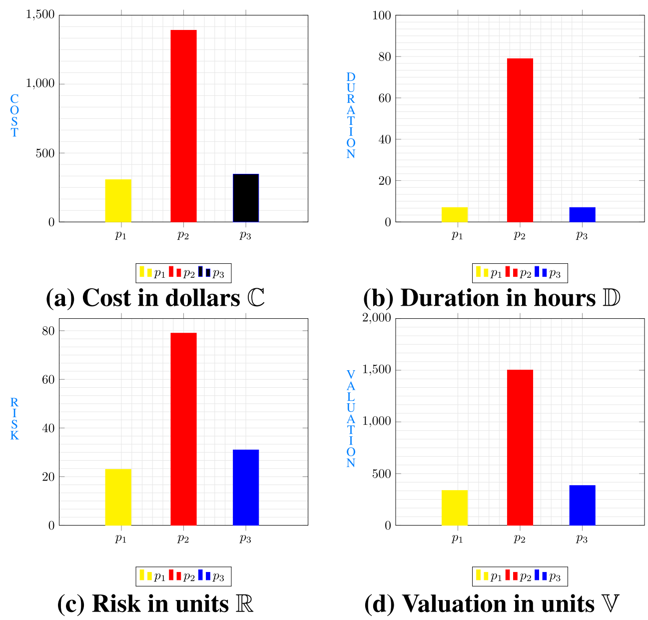
Figure 30(c) shows the risk levels in the three different paths. Continuing in the predefined path will have more than 136% of the risk of the same path if the environment did not change. Taking the new path takes less than 96% of the risk if the vehicle decides to continue in the predefined path. The new path takes 31% more of the risk if the original path is followed with no accidents.

Figure 30(d). shows the valuation in the three different paths. Valuation is calculated using equation 69 assuming that $\beta_1 = \beta_2 = \beta_3 = \eta_1 = eta_2 = \eta_3 = 1$. Continuing in the predefined path will have more than 469% of the valuation of the same path if the environment did not change. Taking the new path has 24% of the valuation if the vehicle decides to continue in the predefined path. The new path takes 13% more of the valuation if the original path is followed with no accidents.

5) AHP BASED PATH SELECTION

In this subsection, we assume that the criterion of choosing the path is the AHP based valuation $\mathbb{V}$. As mentioned earlier, the experiment assumes that a dramatic change happens due to an unexpected accident.

Figure 31 shows for sub figures. Each showing three bars. The yellow bar is the case when no change happens in the rout from V_{01} to V_{50}. This bar is the case of the static environment measure. The red bar represents the measure when an accident happens, yet, the vehicle does not change its predefined rout. The blue bar represents the measure when the vehicle changes it route based on the decision making process.



(a) Cost in dollars $\mathbb{C}$ (b) Duration in hours $\mathbb{D}$ (c) Risk in units $\mathbb{R}$ (d) Valuation in units $\mathbb{V}$

FIGURE 31. **Choosing path with minimum AHP-based $\mathbb{V}$ in a dynamic environment.**

Figure 31(a) shows the comparison of cost in dollars between the static environment cost illustrated by the yellow bar, the cost in dollars when the environment changes but the vehicle continued in the predefined path illustrated by the red bar and the cost in dollars when the environment changes and a new path is determined illustrated by the blue bar. The illustration in 32(a) shows that continuing in the predefined path will cost more than 445% of the original cost in dollars. It also shows that taking the new rout costs around 26% of the cost in dollars that would be spent if the vehicle continues in the predefined path. Due to the change in environment, the new path costs 14% more than the cost in dollars of the original path.

Figure 31(b) shows the duration of the three different paths. Continuing in the predefined path will take more than 11 times the time taken in the same path if the environment did not change. Taking the new path takes less than 8% of the time taken if the vehicle decides to continue in the predefined path. The new path takes the same time taken if the original path is followed with no accidents.

Figure 31(c) shows the risk levels in the three different paths. Continuing in the predefined path will have more than 139% of the risk of the same path if the environment did not change. Taking the new path takes less than 96% of the risk if the vehicle decides to continue in the predefined path. The new path takes 35% more of the risk if the original path is followed with no accidents.

Figure 31(d). shows the AHP based valuation in the three different paths. Continuing in the predefined path will have more than 445% of the valuation of the same path if the environment did not change. Taking the new path has 26% of the valuation if the vehicle decides to continue in the predefined path. The new path takes 14% more of the valuation if the original path is followed with no accidents.

6) AHP-TOPSIS BASED PATH SELECTION

In this subsection, we assume that the criterion of choosing the path is the AHP-Topsis based valuation $\mathbb{V}$. As mentioned earlier, the experiment assumes that a dramatic change happens due to an unexpected accident.

Figure 32 shows for sub figures. Each showing three bars. The yellow bar is the case when no change happens in the rout from V_{01} to V_{50}. This bar is the case of the static environment measure. The red bar represents the measure when an accident happens, yet, the vehicle does not change its predefined rout. The blue bar represents the measure when the vehicle changes it route based on the decision making process.

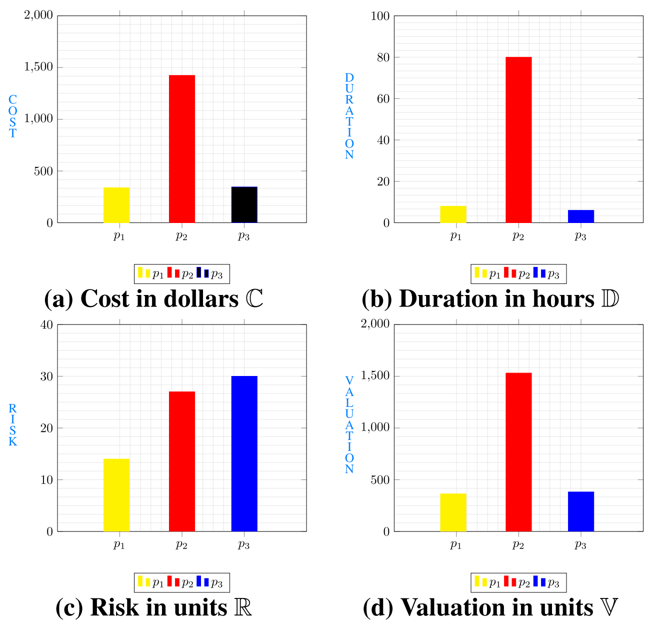


FIGURE 32. Choosing path with minimum AHP-TOPSIS based $\mathbb{V}$ in a dynamic environment.

Figure 32(a) shows the comparison of cost in dollars between the static environment cost illustrated by the yellow bar, the cost in dollars when the environment changes but the vehicle continued in the predefined path illustrated by the red bar and the cost in dollars when the environment changes and a new path is determined illustrated by the blue bar. The illustration in 32(a) shows that continuing in the predefined path will cost more than 425% of the original cost in dollars. It also shows that taking the new rout costs around 25% of the cost in dollars that would be spent if the vehicle continues in the predefined path. Due to the change in environment, the new path costs 6% more than the cost in dollars of the original path.

Figure 32(b) shows the duration of the three different paths. Continuing in the predefined path will take more than 11 times the time taken in the same path if the environment did not change. Taking the new path takes less than 8% of the time taken if the vehicle decides to continue in the predefined path. The new path takes the same time taken if the original path is followed with no accidents.

Figure 32(c) shows the risk levels in the three different paths. Continuing in the predefined path will have more than 240% of the risk of the same path if the environment did not change. Taking the new path takes less than 95% of the risk if the vehicle decides to continue in the predefined path. The new path has 138% risk of the original path if the original path is followed with no accidents.

Figure 32(d). shows the AHP based valuation in the three different paths. Continuing in the predefined path will have more than 420% of the valuation of the same path if the environment did not change. Taking the new path has 25% of the valuation if the vehicle decides to continue in the predefined path. The new path takes 6% more of the valuation if the original path is followed with no accidents.

IX. CONCLUSION

This work proposes a new dynamic model for the optimization of the transportation of Dangerous goods by road. It provides a real-time ranking of all the available paths between the two end points of the expedition (source and destination) by taking into account three parameters: the risk level, travel cost and travel duration. As some of the used parameters are uncertain, a combination of Fuzzy AHP and Fuzzy TOPSIS methods are proposed and used. The main advantage of the proposed model is that it considers any dynamic change in the used parameters during the simulation and ensures a revaluation and classification of the alternative paths to return the best path in real-time.

The model was tested on a graph containing 22 segments with more than 8 paths between origin and destination. Experimental results show that the AHP-TOPSIS model takes a decision that ensures satisfaction when pair comparisons defined by decision makers are fed to the system.

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