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Neutrosophic model for vehicular malfunction detection

Marwa Elshahawy [1] *, Nada A. Nabeeh[1], Ahmed Aboelfetouh[1] and Hazem M. El-Bakry[1]

[1] Information Systems Department, Faculty of Computers and Information Sciences, Mansoura University, Mansoura 3551 6, Egypt; marwamelshahawy@gmail.com , nadaadel@mans.edu.eg , elfetouh@gmail.com , elbakry@mans.edu.eg

* Correspondence: Marwa ELshahawy (marwamelshahawy@gmail.com)

Abstract: The internet of vehicular things (IOVT) is an important modern technology that offers many advantages and facilities; however, if vehicular malfunctions are not detected in a timely manner, it may cause many dangers and serious accidents. To achieve safe self-driving vehicles, safety and security measures must be taken. In this work, a safety and security model are proposed to evaluate the level of vehicular malfunctions and determine the corresponding danger in terms of road safety. The proposed model presents the optimal actions and alternatives for self-driving vehicles to avoid crises. The objective of this study to develop a hybrid model for multicriteria decision-making problems using neutrosophic theory to handle vehicular malfunctions that occur in the IOVT environment under uncertain conditions and conflicting information. In addition, the technique for order of preference by similarity to the ideal solution is used to prioritize the corresponding alternatives in the case of vehicular malfunction. A case study considering four likely vehicular defects is presented to ensure the applicability and availability of the proposed model.

Keywords: internet of vehicular things (IOVT), vehicular malfunction detection, multi-criteria decision making (MCDM), neutrosophic theory, analytical hierarchy process (AHP), TOPSIS.

1. Introduction

Self-driving vehicles have become one of the most important technological advances in the world [1]. To reduce risks that result from vehicles, self-driving vehicles are expected to be relied upon in more countries and cities [2]. By 2040, 40% of vehicles are expected to be self-driving [3]. According to the World Health Organization, many people at risk of serious injury or death each year from accidents due to undiscovered vehicular defects [4]. The problem of defect detection in vehicles, especially while driving, is the target of this study, with the aim of preventing accidents on the road based on statistics regarding the causes of accidents. This paper proposes the most important problems that may cause accidents, which are classified into four categories depicted in Figure 1.

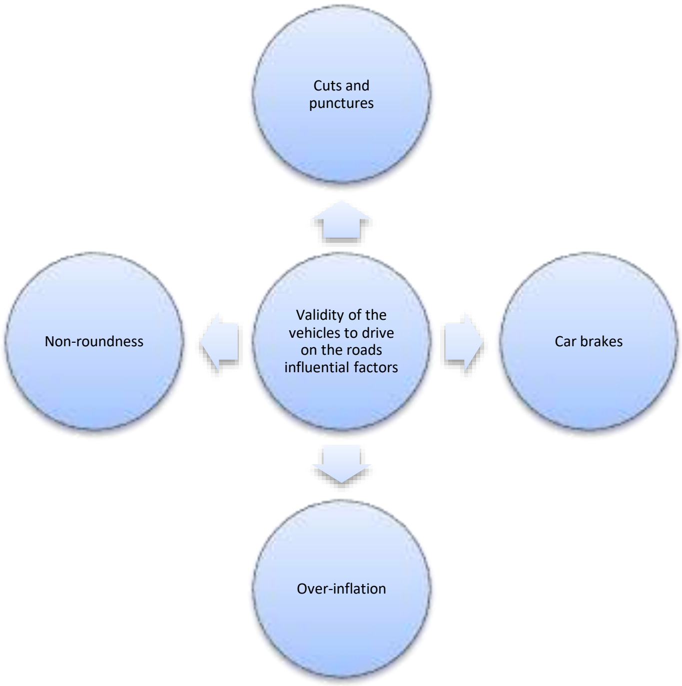

Figure 1. Factors and obstacles that influence the roadworthiness of vehicles.

Tires are important sources of vehicular risks and accidents. Hence, three of the problems considered in this study are related to tires: 1) overinflation, when the pressure exceeds the normal range [5],[6]; 2) non-roundness, deformations or extensions of the tire [7]; and 3) cuts and punctures, which can occur if the vehicle drives over hazards on the road [8]. The fourth problem is related to brakes [9]. Malfunctions and defects of the brakes can cause vague and inconsistent information for self-driving vehicles [1], which may lead to difficulty in making consistent and accurate driving decisions.

This paper discusses some of the defects that affect vehicles depending on internet of vehicular things (IOVT) technology by integrating multicriteria decision-making (MCDM) method, analytical hierarchy process (AHP), neutrosophic sets, and the technique for order of preference by similarity to ideal solution (TOPSIS) based on intelligent techniques [10]. AHP is among the most popular methods to deal with complicated MCDM problems [11] and can be summarized as a process of decomposition, calculating the weights for the decision criteria, and finally calculating the priority for alternatives [11]. This classical AHP method can determine the priorities for criteria and is also able compare and grade alternatives, but it is unable to handle ambiguous information [10] and the Saaty comparison matrix cannot determine whether it is in a consistent or inconsistent state because it has no systemic methodology [10]. To overcome this problem, fuzzy AHP (FAHP) combines fuzzy set theory and AHP [12]. This method can handle conflict, but decision makers cannot determine the membership function permanently. This paper proposes a neutrosophic technique combined with AHP to help decision makers handle uncertainty and determine influential factors to better handle vehicular defects. The neutrosophic set is expressed as truth, falsity, and indeterminacy (T, I, F) membership [13]. Based on this, uncertainty, conflict, and vague and incomplete information can be handled. TOPSIS methods, including AHP TOPSIS, depend on classifying alternatives into two parts: positive and negative solutions, where the optimal solution is the solution near the set of positive solutions that is farthest from the set of negative solutions [10,14]. This proposed model examined four risks that could affect self-driving vehicles that rely on IOVT technology to determine the optimal action that must be taken at the right time. IOVT is a network of vehicles that contain software, sensors, and other important techniques and among the most influential factors in autonomous vehicles [15,16]. This paper aims to achieve the following objectives:

1. Determine whether IOVT can overcome vehicular problems and accidents.
2. Discuss some defects and malfunctions that may affect vehicles and lead problems and accidents.
3. Assess the influence of criteria in attempt to help experts and decision makers reach optimal solutions.
4. Propose solutions to deal with MCDM problems.
5. Propose a hybrid model that integrates AHP, neutrosophic models, and TOPSIS to recommend the best option out of three proposed alternatives.
6. Apply the proposed framework in a case study of self-driving vehicles that depend on IOVT.
7. Conduct a sensitivity analysis to ensure the robustness and reliability of decision-making by IOVT.

The next sections of this paper are as follows. Section 2 presents a literature review. Section 3 introduces the framework of this study. Section 4 presents the methodology of the proposed model. Section 5 concludes the paper with insights obtained from this work and future considerations.

2. Literature Review

Many researchers have suggested the importance of the internet of things (IOT) to connect devices via the internet, and IOVT has become one of the most important modern technical developments in the era in both academic and industrial fields [17]. The rapid development of the intelligent transportation system (ITS) helps to provide utilities to consumers, including safe traffic management [18].

The daily use of roads causes some dangers for drivers [19]. There are many causes of vehicle accidents arising from a lack of experience in dealing with emergency situations. These situations include tire problems, such as overinflation, cuts and punctures, and non-roundness, as well as problems with the vehicle's brakes [20]. IOVT helps to predict these malfunctions in a timely manner and make an appropriate decision to avoid accidents. Many recent studies on vehicular defect detection in intelligent transportation systems introduce risk assessment of vehicles to propose a theoretical basis to prevent accidents that results from vehicular malfunctions [21]. In [22], a unified diagnostics service protocol (UDS) proposes a semiautomatic approach to brake pedal testing and diagnostics. In [23], radiography is used to detect defects in vehicle tires, and [24] describes three vehicular defects, including changes in tire pressure. Effective methods have been developed to detect aquaplaning detection using a small group of sensors, stability-based electronic control, and drive torques [5]. In [25], IOT and deep learning are combined to produce an integrated self-diagnostic system for self-driving vehicles. In [17] discuss federated learning issue and aims to develop IOVT applications which is characterized by confidentiality and security. IOT and ITS have been merged to improve the efficiency and effectiveness of ITS. Information about malfunctions that vehicles may be exposed may be incomplete and uncertainty [26]. The authors of [27] propose techniques to handle uncertainty when predicting crashes in self-driving vehicles.

MCDM methods have become an important issue for decision makers, as they are used to prioritize criteria and alternatives to help solve the problems of uncertainty and incomplete information [11]. In addition, several studies have been presented based on fuzzy sets. For example, [28] presents a theory of sets to manage uncertainty, and [4] presents an FAHP method to evaluate the roadworthiness of vehicles. When AHP methods are integrated with fuzzy techniques, they can better handle uncertainty information, but they still cannot handle indeterminate values. FAHP is very convenient for evaluating alternatives. FAHP can evaluate the current state of the vehicle, but it has some limitations. For example, when input data are expressed in linguistic terms depending on the experience and opinions of decision makers, it cannot obtain actual relations between the criteria and alternatives [11]. MCDM methods use neutrosophic sets to offer solutions under ambiguous and conflicting information by proposing truth, indeterminate, and falsity (T, I, F). In [29], MCDM with single value neutrosophic sets is proposed to calculate values between options and available choices. The neutrosophic set proposes three membership functions to calculate the weights of criteria and alternatives and choose the optimal alternative, and its integration with TOPSIS is a new development to enable the selection of an ideal choice [30]. In [31] researchers present a realistic empirical example of Starbucks company to develop strategies for its development and uses a model that combines AHP and Neutrosophic theory. In [32] researchers present a model that combines AHP and Neutrosophic theory. In [33] researchers discuss the problem of choosing the best learning management system (LMS) because there are many (LMS) available in the marketplace therefore, decision -making to choose the best system is a multi-criteria problem. so, this research applies neutrosophic AHP method. The main contribution of this study is the application of the MCDM method using a neutrosophic set, AHP, and TOPSIS to produce an effective model that can handle the problems of IOVT.

3. Framework

The integration of AHP, MCDM, neutrosophic, and TOPSIS techniques is an effective way to help decision makers face the problems of uncertainty and confusion of information to make appropriate decisions. Neutrosophic and TOPSIS methods have been used in recent studies to help determine ideal solutions. AHP is a method to solve confusion and complex problems [34] and is characterized by its simplicity, as it decomposes problems into subproblems [35]. This study proposes the integration of AHP and neutrosophic techniques to analyze the factors that influence the safety of vehicles [36]. The resulting system outputs a warning if defects or malfunctions are detected based on multiple data sets obtained from sensors in the tires, which are connected to each other and the warning system using IOT [37].

This section describes four main criteria that cause vehicular malfunctions, which may lead to injuries and accidents. Tires are a major source of problems that result in accidents; therefore, tires must be replaced or repaired as soon as a problem is detected to avoid accidents. Three of the four criteria considered herein are tire defects: overinflation, non-roundness, and cuts or punctures. The fourth defect is malfunction of the brakes [38]. The correct action must be selected in the event of any of these defects from the following three options: stop the vehicle immediately, stop the vehicle at the nearest repair station, or continue (there is no danger).

The main criteria are measured as follows:

1. Overinflation:

A sensor is used to measure the air temperature and pressure changes inside the tire [39]. If the pressure reaches the critical pressure, the sensor sends warning. The sensor utilizes multiple previously constructed datasets to determine the critical value.

2. Non-roundness:

A sensor is used to detect stretching and changes in the tire radius.

3. Cuts and punctures:

A moving sensor detects any cuts or punctures in the tire.

4. Brakes:

Braking condition is a well-established influential factor that must be constantly examined in IOT environments [40]. A warning is sent to the vehicle if the sensor detects any abnormal conditions.

The steps of the proposed method, as depicted in Figure 2, can be divided into three stages. The first stage is to specify the criteria and actions. In the second stage, the criteria are evaluated using neutrosophic scales to help decision makers determine the optimal action. The third stage applies TOPSIS through the following steps:

5. Normalize the criteria and actions.
6. Find the positive and negative regions.
7. Find the positive and negative Euclidian regions and determine the relative proximity.

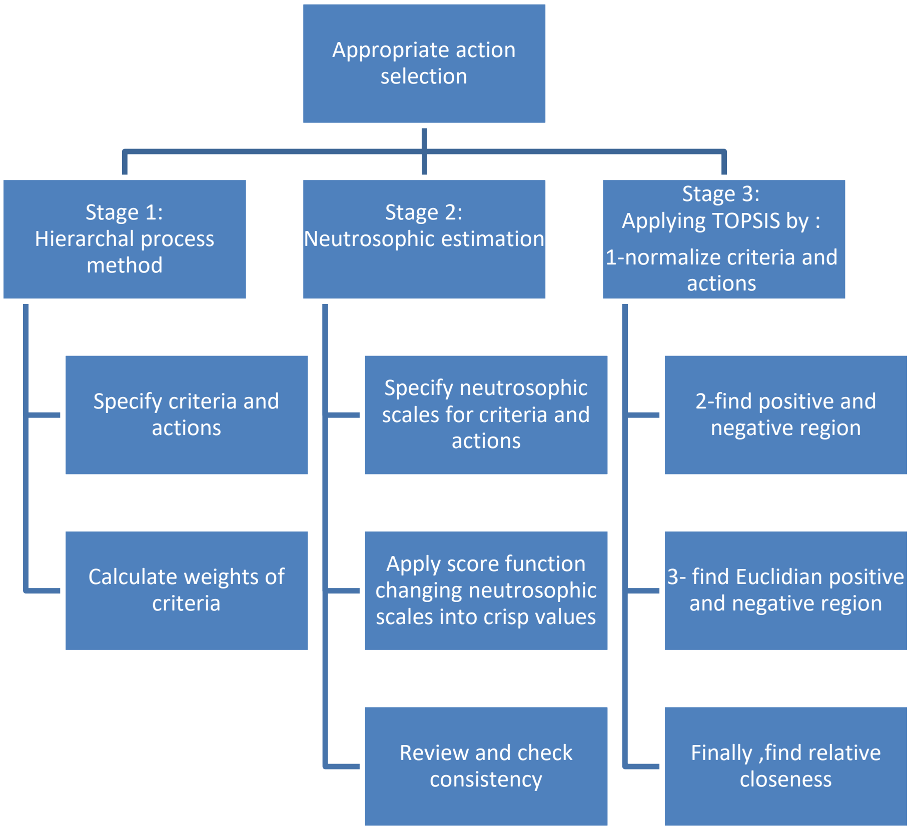

Figure 2. Conceptual steps of the proposed method.

Then, the optimal action is determined by the following steps:
Step 1: Specify the criteria using the AHP model according to Table 1.
Step 2: Compare the criteria and actions based on the neutrosophic scale in Table 1.
If criterion 1 is strongly significant than criterion 2, the value of the neutrosophic scale is written as $\langle(4,5,6)0.80, 0.15, 0.20\rangle$; conversely, if criterion 2 is strongly significant than criterion 1, the neutrosophic scale is the inverse of <4,5,6>, which is1/ $\langle(4,5,6)0.80,0.15,0.20\rangle$.
The pairwise comparison matrix between the different criteria is

$$A^k = \begin{bmatrix} x_{11}^k & x_{12}^k & x_{1n}^k \\ - & - & - \\ x_{n1}^k & - & x_{mn}^k \end{bmatrix}, \tag{1}$$

where x_{mn}^k. k represents the decision maker's number depending on the preference of the n^{th} criterion over the m^{th}. For example, in the form of the neutrosophic triangular, the decision maker's sight is presented as <<4, 5, 6>; <0.80, 0.15, 0.20>>, where the neutrosophic triangular scale values are referenced as the lower, median, and upper values.
The decision maker's degree of certainty is represented as <0.80, 0.15, 0,20> truth, indeterminacy, and falsity. Thus, the triangular neutrosophic scale structure is < (L, m, u); T, I, F x_{mn}^k, where l, m, and u refer to the lower, median, and upper neutrosophic triangular scale values. I_{mn}^k , F_{mn}^k T_{mn}^k are the truth, indeterminacy, and falsity, which represent the certainty of the decision maker's perspective.
For example, x_{24}^3 refers to the comparison of criteria 2 and 4 from the perspective of the third decision maker.

Step 3: Aggregate the decision makers' preference relations between the criteria.

To achieve certainty, multiple decision makers evaluate the preference relations between the criteria. The aggregated s_{ij} is

$$s_{ij} = \frac{\sum_{k=1}^{k} \langle (l_{ij}^{k}, m_{ij}^{k}, u_{ij}^{k}); T_{ij}^{k}, I_{ij}^{k}, F_{ij}^{k} \rangle}{k}, \tag{2}$$

and the aggregated pairwise comparison matrix is

$$G = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{mn} \end{bmatrix}. \tag{3}$$

Then, the neutrosophic scales are transformed into crisp values using the score function of (s_{ij}).

$$S\,(s_{ij}) = \left| \left(l_{ij} \times m_{ij} \times u_{ij}\right)^{\frac{T_{ij}+I_{ij}+F_{ij}}{9}} \right|. \tag{4}$$

The scale of the neutrosophic numbers represented by l, m, u and T, I, F symbolize lower, median, upper and truth, indeterminacy, and falsity membership functions of the triangular neutrosophic number.

Step 4: According to the previous matrix, the weights and priorities are calculated.
First, calculate the sum of the average row.

$$w_i = \frac{\sum_{i=1}^{n}(x_{ij})}{n}, \tag{5}$$

where i = 1, 2, 3, 4, …, m and j = 1, 2, 3, 4, …, n.
Second, normalize the crisp value using

$$w_i^{m} = \frac{w_i}{\sum_{i=1}^{m} w_i} \;; i = 1.2.3.4 \ldots \ldots m. \tag{6}$$

Step 5: Verify the decision maker's decision.

$$CR = \frac{CI}{RI}, \tag{7}$$

where CR, CI, and RI denote the consistency rate, consistency index, and random consistency index, respectively. The result achieved an accepted consistency of 1%.

Table 1. Triangular neutrosophic scales corresponding to linguistic phrases.

Score	Linguistic Phrase	Neutrosophic Triangular Scale
1	Equally significant	$1 = \langle\langle 1,1,1\rangle; 0.50, 0.50, 0.50\rangle$
3	Slightly significant	$3 = \langle\langle 2,3,4\rangle; 0.30, 0.75, 0.70\rangle$
5	Strongly significant	$5 = \langle\langle 4,5,6\rangle; \langle 0.80, 0.15, 0.20\rangle$
7	very strongly significant	$7 = \langle\langle 6,7,8\rangle, 0.90, 0.10, 0.10\rangle$
9	Absolutely significant	$9 = \langle\langle 9,9,0\rangle; 1.00, 0.00, 0.00\rangle$
2	Sporadic values between two close scales	$2 = \langle\langle 1,2,3\rangle; 0.40, 0.60, 0.65\rangle$
4		$4 = \langle\langle 3,4,5\rangle; 0.35, 0.60, 0.40\rangle$
6		$6 = \langle\langle 5,6,7\rangle; 0.70, 0.25, 0.30\rangle$
8		$8 = \langle\langle 7,8,9\rangle; 0.85, 0.10, 0.15\rangle$

Step 6: Upgrade the consistency in the neutrosophic AHP by collecting the inconsistent elements in the pairwise comparison matrix using the induced matrix, as mentioned in [38]. Then calculate the normalized decision matrix as follows:

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

Step 7: Multiply each alternative by its corresponding weight considering its corresponding criterion to obtain an action score using:

$$z_{ij} = w_j \times r_{ij} \tag{9}$$

Step 8: Select the best decision according to the rankings of the alternatives. This process is implemented in several steps:

Step 8.1: Calculate the positive and negative regions using Eqs. (10) and (11), respectively:

$$Q^+ = \left\{ < min\ (y_{ij|i=1,2,\ldots\ldots,m0|} j \in j^- {}^{< max(y_{ij|i=1,2,\ldots\ldots,m)|} j \in j' >,} \right. \tag{10}$$

$$Q^- = \left\{ < max\ (y_{ij} | i = 1,2,3,\ldots.m) | j \in j^- > \quad < min(y_{ij} | i = 1,2,3,,\ldots m) | j \in j^+ >, \right. \tag{11}$$

Step 8.2: Compute the Euclidian distance between the positive (d_i^+) and negative (d_i^-) optimal solutions using Eqs. (12) and (13), respectively:

$$d_i^+ = \sqrt{\sum_{i=1}^{n} (y_{ij} - y_j^+)^2}, i = 1,2,3,4, \ldots.m, \tag{12}$$

$$d_i^- = \sqrt{\sum_{i=1}^{n} (y_{ij} - y\ )^2}, i = 1,2,3,4, \ldots.m. \tag{13}$$

Step 8.3: Compose a final ranking of actions and select the ideal action. For this purpose, calculate the relative closeness as

$$R_j = \frac{d_i^-}{d_i^+ + d_i^-}; \quad 1,2,3,\ldots.,m \tag{14}$$

Step 8.4: Choose the optimal action.

4. Empirical Application

As an empirical application of the neutrosophic model, we consider a vehicle manufacturing company in Egypt. This company hopes to introduce IOT technologies to self-driving vehicles, which will detect vehicle malfunctions during an early stage of driving on the road and make an appropriate decision for accident and disaster avoidance. The company employs an expert panel of four decision makers (Table 2). During a meeting, the expert panel proposed the following four criteria for identifying vehicle malfunctions:

C1: overinflation.
C2: non-roundness.
C3: cuts and punctures.
C4: brake malfunctions.

Decision makers select one of three actions:
1- stop the car immediately.
2- stop the car at the nearest repair station.
3- continue driving (no problem or cause for concern).

The proposed model proceeds through the following steps:

Step1: Select an expert panel of four decision makers. The credentials and demographic information of the experts are listed in Table 2 and the four main criteria and actions related to vehicle malfunctions are proposed in Figure 3.

Table 2. Demographic information of the expert committee.

Demographic information	**Job title**	Qualifications	Age	Gender
First expert	Financial consultant	Master	45	Female
Second expert	Mechatronics engineer	PhD	50	Male
Third expert	Quality and safety manger	Master	35	Female
Fourth expert	Mechanical engineer	Bachelor	40	Male

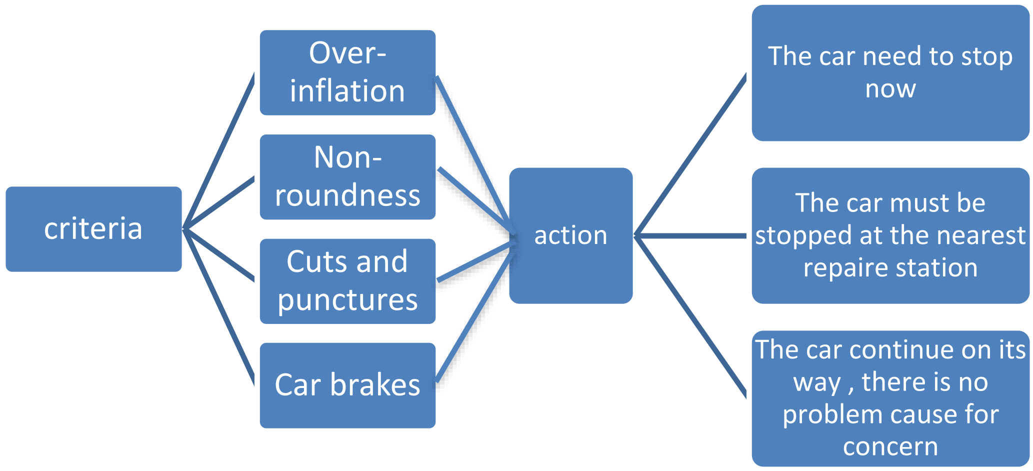

Figure 3. AHP structure of the presented criteria and actions.

Step 2: Map the decision maker's perspectives onto the neutrosophic scale using Eq. (1). The experts' decisions are aggregated using Eq. (2) and are expressed in the format of Eq. (3) in Table 3.

Table 3. Proposed collected perspectives of the decision makers of criteria.

Criterion	C1	C2	C3	C4
C1	<<1,1,1>;0.50,0.50,0.50>	<<4,5,6>;<0.80,0.15,0.20>	1/<<2,3,4>;0.30,0.75,0.70>	<<1,2,3>;0.40,0,60,0.65>
C2	1/<<4,5,6>;<0.80,0.5,0.20 >	<<1,1,1>;<0.50,0.50,0.50>	<<3,4,5>;0.35,0.60,0.40>	<<6,7,8>;0.90,0.10,0.10>
C3	1/<<2,3,4>;0.30,0.75,0.70>	1/<<3,4,5>;0.35,0.60,0.40>	<<1,1,1>;0.50,0.50,0.50>	<<7,8,9>;0.85,0.10,0.15>
C4	1/<<1,2,3>;0.40,0,60,0.65>	1/<<6,7,8>;0.90,0.10,0.10>	1/<<7,8,9>;0.85,0.10,0.15>	<<1,1,1>;0.50,0.50,0.50>

Step 3: For simplicity, convert the neutrosophic aggregated perspectives into crisp values using Eq. (4). The results are shown in Table 4.

Step 4: Compute the weights of the criteria using Eqs. (5) and (6). The results are listed in Table 5 and visualized as a pie chart in Figure 4.

Step 5: Compute the consistency rate using Eq. (7). The consistency was determined as 1%.

Table 4. Crisp values of criteria according to the perspectives of the decision makers.

Criterion	C1	C2	C3	C4
C1	1	1.843	1.855	1.388
C2	0.542	1	1.848	1.450
C3	0.539	0.541	1	2.139
C4	0.720	0.689	0.467	1

Table 5. Criteria weights.

Criteria	Weights
C1	0.377
C2	0.268
C3	0.234
C4	0.159

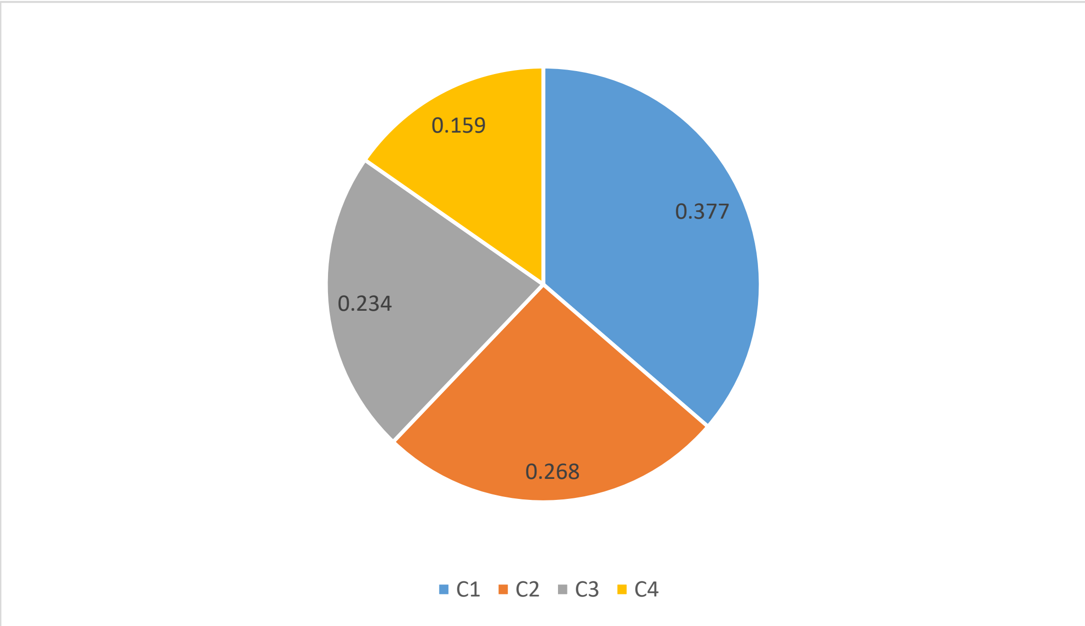

Figure 4. Pie chart of IOVT malfunctions criteria weights.

Step 6: Gain the perspectives of the decision makers on the presented actions and criteria (Table 6), then calculate the crisp neutrosophic values of the decision makers using Eq. (4) (Table 7). Finally, normalize the decision matrix as $r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1} x_{ij}^2}}$. The normalized results are listed in Table 8.

Table 6. Proposed decision matrix of criteria and actions for decision makers.

Criteria	C1	C2	C3	C4
A1	<<6,7,8>;0.90,0.10,0.10>	<<2,3,4>;0.30,0.75,0.70>	<<4,5,6>;0.80,0.15,0.20>	<<1,1,1>;0.50,0.50,0.50>
A2	<<1,1,1>;0.50,0.50,0.50>	<<1,2,3>;0.40,0.60,0.65>	<<2,3,4>;0.30,0.75,0.70>	<<9,9,9>;1.00,0.00,0.00>
A3	<<2,3,4>;0.30,0.75,0.70>	<<4,5,6>;0.80,0.15,0.20>	<<6,7,8>;0.90,0.10,0.10>	<<1,1,1>;0.50,0.50,0.50>

Table 7. Crisp neutrosophic values for decision makers.

Criteria	C1	C2	C3	C4
A1	2.03	1.85	1.84	1
A2	1	1.38	1.85	2.08
A3	1.85	1.84	2.03	1

Table 8. Normalization of decision matrix by applying $r_{ij} = \frac{z_{ij}}{\sqrt{\sum_{i=1} z_{ij}^2}}$.

Criteria	C1	C2	C3	C4
A1	0.415	0.364	0.321	0.245
A2	0.204	0.272	0.323	0.509
A3	0.379	0.362	0.354	0.245

Step 7: To calculate the weighted matrix, multiply the criteria weights obtained from the neutrosophic AHP by the normalized decision matrix [Eq. (9)]. The results are tabulated in Table 9 and presented in Figure 5.

Table 9. Weighted matrix obtained by applying $z_{ij} = w_j \times r_{ij}$ to multiply the criteria weights obtained from the neutrosophic AHP by the normalized decision matrix.

Criteria	C1	C2	C3	C4
A1	0.156	0.097	0.075	0.038
A2	0.076	0.072	0.075	0.080
A3	0.142	0.097	0.082	0.038

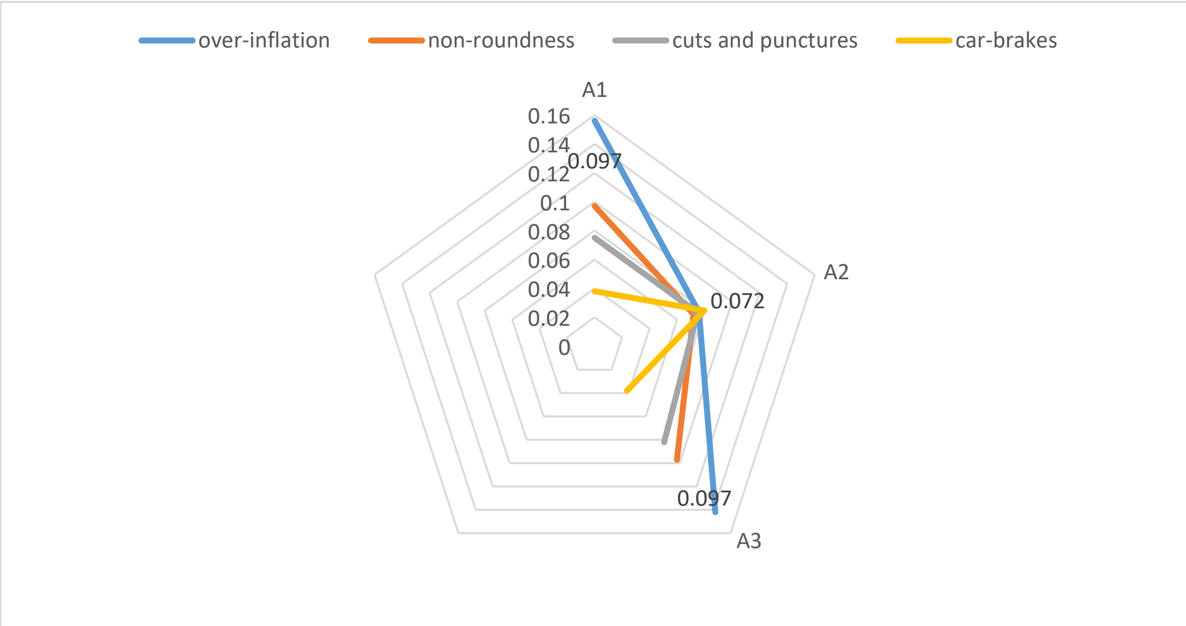

Figure 5. Comparison of the three alternatives based on different criteria Table 9.

Step 8: Calculate the positive and negative regions using Eqs. (10) and (11), respectively, then calculate the Euclidian distances between the positive (d_i^+) and negative (d_i^-) optimal solutions to present actions using Eqs. (12) and (13), respectively. Finally, rank the actions using Eq. (14). The ranked results are listed in Table 10.

A^+ = {0.156, 0.097, 0.082, 0.080}

A^- = {0.076, 0.072, 0.075, 0.038}

Table 10. Final ranks of actions.

	d_i^+	d_i^-	c_i	rank
A1	0.042	0.083	0.664	1
A2	0.084	0.042	0.33	3
A3	0.044	0.070	0.614	2

Actions A1 and A2 are considered to be the best and worst choices, respectively, in the opinion of the decision makers. That is, the best action for the driver to take is action A1—stop the car immediately—and the worst action, which the driver must not take, is to stop the car at the nearest repair station, as this action may cause danger or accidents.

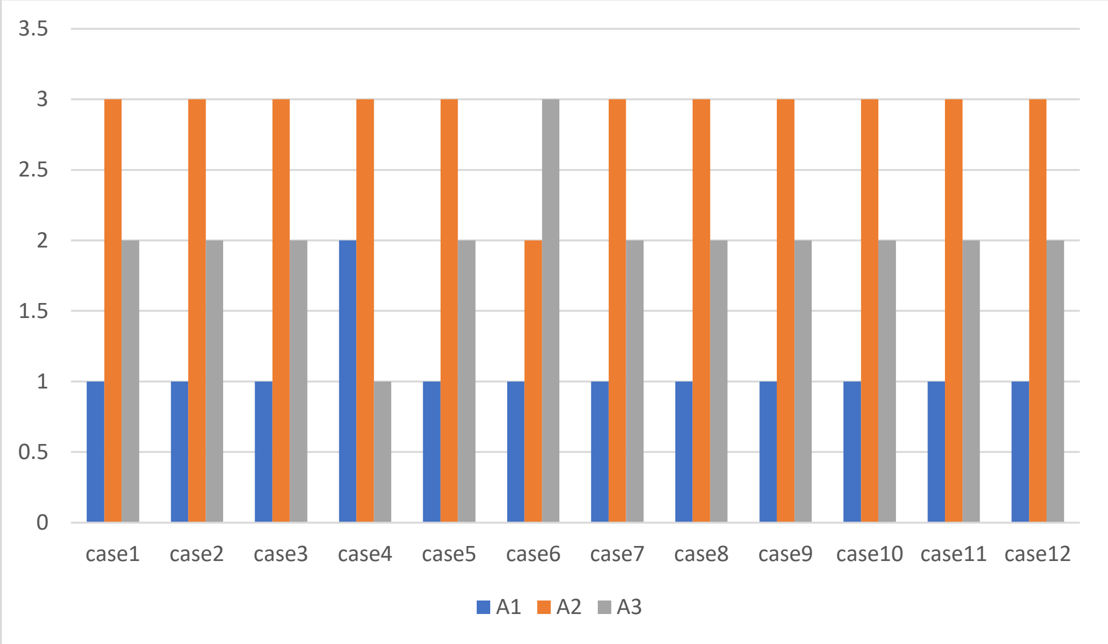

Figure 6. Sensitivity analysis of weights of alternatives depending on various priorities of criteria.

Case#	A1	A2	A3
1	1	3	2
2	1	3	2
3	1	3	2
4	2	3	1
5	1	3	2
6	1	2	3
7	1	3	2
8	1	3	2
9	1	3	2
10	1	3	2
11	1	3	2
12	1	3	2

Table 11. Final ranks of the alternatives for different priorities of criteria A1, A2, and A3

5. Sensitivity analysis

A sensitivity analysis studies the effect of the variance of each input measure on the model output. It is useful for prioritizing the selection of the best alternatives. During a sensitivity analysis, the model is assumed sufficiently precise to reproduce the behavior of the system. The present study conducts a sensitivity analysis on the criteria (attribute) ranking. Specifically, it demonstrates how the prioritization of the criteria affects the final rank of the alternatives. To obtain efficient and accurate results, we selected 12 random cases for the sensitivity analysis (three alternatives and four criteria; see Table (11). Figure 6 illustrates how the final rank of alternatives changes after changing the priority order of the criteria.

The sensitivity analysis clarified that in all cases except Case 6, A1 is the best alternative and A2 is the worst alternative. A3 ranked medium in most cases.

6. Comparative analysis

This part of the study compares the results of our suggested approach that integrates AHP, neutrosophic theory, and topsis with those of another approach that assumes a fuzzy environment [41],[42],[43]. Applying the fuzzy approach to select the best action of an autonomous vehicle in our case study, the alternatives are ranked as follows: A3> A1>A2 (Figure 7).

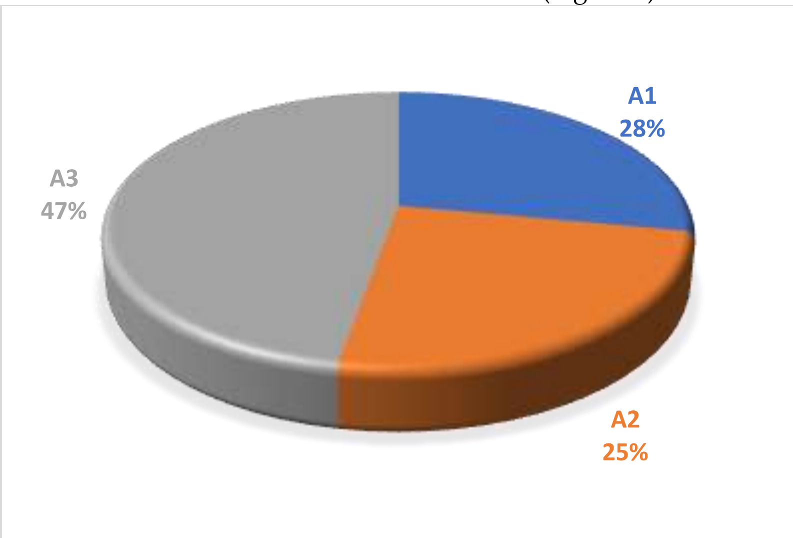

Figure 7. Alternative ranking based on the fuzzy approach.

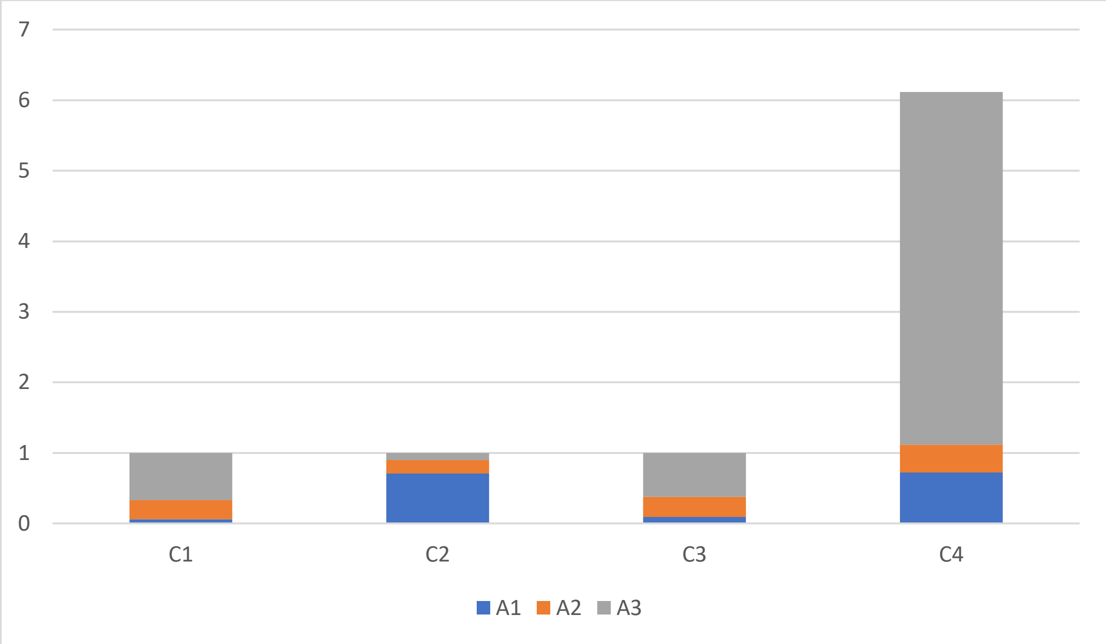

Figure 8. Aggregated results for each alternative according to each criteria.

Table 12 lists the final ranks of the alternatives using the fuzzy approach presented in [41] and [42] and our suggested neutrosophic topsis approach.

Table 12. Final rankings of alternatives based on our proposed approach and a fuzzy approach.

Alternatives	AHP neutrosophic topsis approach	Fuzzy approach
A1	1	2
A2	3	3
A3	2	1

To compare the ranks of the neutrosophic topsis approach and fuzzy approach, we applied Spearman's correlation method [44], which estimates whether two continuous variables are correlated or uncorrelated:

$$S_m = 1- \left[\frac{6.\sum_{r=1}^{t}(d_r)^2}{t.(t^2-1)}\right] \tag{15}$$

In this formula, t denotes the number of alternatives and d_r is the difference between two ranks of alternatives. If Sm is +1 or -1, the correlation is strong and if S_m is 0, the variables are uncorrelated. The Pearson's correlation indicates the degree of linear correlation between two variables. It ranges from -1 (completely negatively correlated) through 0 (completely uncorrelated) to +1 (completely positively correlated). The Pearson correlation is calculated as

$$P_{(a,b)} = \frac{cov(a,b)}{\sigma_a \sigma_b}, \tag{16}$$

where cov (a, b) denotes the covariance of a and b, and σ_a and σ_b denote the standard deviations of a and b, respectively. The Spearman's correlation coefficient was computed as 0.5, indicating a strong correlation between our proposed approach and the fuzzy approach. The Pearson's correlation coefficient between the two approaches was also 0.5. By ranking the weights of the criteria and alternatives and comparing the results of our proposed and fuzzy approaches, we find that our proposed approach simplifies the application as follows:

1. As the fuzzy approach requires more equations than our approach, it is necessarily more complex, time-consuming, and storage-demanding than the AHP neutrosophic–topsis approach.
2. Our proposed approach depends on the truth degree, falsity degree, and indeterminacy degree whereas the fuzzy approach depends only on the truth and falsity degrees. Therefore, our proposed approach can handle ambiguous and conflicting information which cannot be efficiently handled by the fuzzy approach. Moreover, the neutrosophic–topsis approach can simulate natural human thinking.
3. The fuzzy approach depends on linguistic variables, so is restricted in scale and cannot provide a logical confirmation degree. In contrast, our proposed approach allows decision makers to use suitable linguistic variables and confirmation degree.

7. Applications

The study proposes an intelligent hybrid model that merges AHP, neutrosophic theory, and topsis. The model handles MCDM problems and optimizes decision making to overcome the problems introduced by uncertainties and incomplete information. Although IOVT is being rapidly developed, its many advantages are partly offset by the increased risk of accidents caused by vehicle malfunctions that are undetected and not corrected by an appropriate action in a timely manner. The objective of this study was to ensure safety and security on the roads by discovering malfunctions in self-driving vehicles and quickly implementing the optimal action. Factories, companies, manufacturers and developers of self-driving vehicles will benefit from this model because it identifies and prioritizes the proper attributes and actions in the event of any problem or danger.

8. Conclusions and Future Work

The study proposes an intelligent hybrid model that merges AHP, neutrosophic, and TOPSIS techniques to solve MCDM problems and help decision makers overcome the problems of uncertainty and incomplete information. Many countries are witnessing significant developments in IOVT, which has some disadvantages and risks that arise from undetected vehicular malfunctions. These risks can be mitigated by taking the appropriate action in a timely manner. The objective of this study was to achieve safety and security on the roads by discovering malfunctions in self-driving vehicles in a timely manner and implementing the optimal action.

Comparing our proposed approach with the fuzzy approach, we concluded that our neutrosophic topsis approach is more effective and simpler to implement than the fuzzy approach; moreover, it simulates natural human thinking.

In the future, we will update this technique to predict more vehicular defects using diverse multicriteria decision-analysis methods. Further, we will improve this method by applying evolutionary algorithms to determine the most effective criteria. we will apply many methods such as VIKOR, ENTROPY, and DEMATEL method in the future to this problem.

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