# Evaluation of the Accidents Risk Caused by Truck Drivers using a Fuzzy Bayesian Approach

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***Abstract*—Road accidents cause hundreds of fatalities and injuries each year; due to their size and operating features, heavy trucks typically experience more severe accidents. Many factors are likely to cause such accidents; however, statistics mainly blame human error. This paper analyses the risk of accidents for heavy vehicles, focusing on driver-related factors contributing to accidents. A model is developed to anticipate the probability of an accident by using Bayesian networks (BNs) and fuzzy logic. Three axioms were verified to validate the developed model, and a sensitivity analysis is performed to identify the factors that have the most significant influence over truck accidents. Subsequently, the result provided by the model was exploited to examine the effects of in-vehicle road safety systems in preventing road accidents via an event tree analysis. The results underlined a strong link between the occurrence of accidents and parameters related to the driver, such as alcohol and substance consumption, his driving style, and his reactivity. Similarly, unfavourable working conditions significantly impact the occurrence of accidents since it contributes to fatigue, one of the leading causes of road accidents. Also, the event tree analysis results have highlighted the importance of equipping trucks with these mechanisms.**

***Keywords*—Heavy truck vehicle; road accident prevention; risk management; bayesian-fuzzy network; analysis tree event**

## I. Introduction

The increase in road crashes is currently a significant concern for health and social policies in countries worldwide. Approximately 1.3 million people worldwide die on the roads yearly, while 20 to 50 million suffer serious injuries, most of which require lengthy and costly treatment [1]. Road crashes result in significant economic losses for victims, their families, and the nation. Most countries spend 1% to 3% of their gross domestic product on road crashes [2].

Collisions with heavy trucks are more critical than other traffic accidents [3]. In 2019, there were 510,000 crashes involving large trucks, of which 4,479 (1 per cent) were fatal [4]. Heavy trucks' large size and operational characteristics make the consequences of large truck crashes catastrophic: injuries are severe to disastrous and property losses are massive [5]. Various factors can contribute to an accident, including road, human, environmental, and vehicle-related factors [5]. However, human error accounts for 90% of fatal accidents [6].

This paper focuses on the driver-related parameters that contribute to accident occurrence. A predictive model incorporating the various causal links between the driver-related variables that influence the probability of an accident is created. Using BNs, the propagation of probabilities on all possible states of each node within the network could be achieved. Also, various scenarios were tested using the configuration of the input nodes in the network. Finally, an event tree analysis was carried out to examine the impact of in-vehicle road safety systems in preventing road accidents.

The model developed will make it possible to estimate a driver's probability of causing an accident in advance, which will help implement preventive measures such as developing targeted awareness programs. These programs will inform high-risk drivers of unsafe behaviors and help them adopt safer driving practices. In addition, financial incentives can encourage drivers to adopt safer behaviors, whether by offering monetary rewards or applying penalties to higher-risk drivers.

The article's body has the following structure: Section II presents the related work. Section III explains the methodology used to build the proposed fuzzy Bayesian model; the results obtained are also discussed in this section. Section IV discusses the likely crisis scenarios relating to a truck accident through the application of event tree analysis. Finally, the conclusion is presented in Section V.

## II. Related Work

Numerous issues about road safety have been investigated in earlier studies. In accident detection, several models based on machine learning and deep learning have been developed to detect road accidents ([7], [8], [9], [10], [11]). Concerning predicting the severity of accidents, neural networks have been used to create models capable of predicting the severity of road accidents [12], [13]. In accident prevention, Kabir et Roy [14] developed an algorithm based on deep learning for real-time collision avoidance. Fan et al. [15] used SVM and deep neural networks to develop an algorithm for identifying and analyzing traffic accident black spots. To predict accidents, neural networks have made it possible to build models capable of predicting the occurrence of road accidents [16], [17]. Sangare et al. [18] combined two approaches: support vector classifier (SVC) and Gaussian mixture model, to give a prediction of traffic accident occurrence.

Regarding BNs, they have been widely used to solve problems related to road safety. Sun et al. [19] used a hybrid method integrating a random parameter logit model and a BN to analyze accidents involving vulnerable road users and motor vehicles in Shenyang, China, focusing on seasonal differences. The study uses three accident datasets: the entire dataset, the "spring and summer" dataset, and the "fall and winter" dataset.

The random parameter logit model was used to identify significant factors and heterogeneity across the three datasets. The critical factors were then used to build a BN to investigate statistical associations between injury severity and descriptive attributes. Kuang et al. [20] proposed a two-level model, consisting of a cost-sensitive BN and a K-nearest neighbour weighted model, to predict the crash duration. Using the collected data, a cost-sensitive BN can qualitatively indicate whether the accident duration is less than or greater than 30 minutes. Then, the KNN regression model will give the precise duration value for each accident class. Karimnezhad et Moradi [21] considered learning the BN structure from the data collected on the accidents recorded on one of the highways in Iran. They could also calculate the probability of being injured by a driver based on some information about his node. They also examined the effect of seat belt use on the number of fatal accidents. Deublein et al. [22] developed a model to predict the number of injury accidents; this model can give the expected number of road users likely to be slightly, severely, or fatally injured. The model also identifies road sections with a high probability of accidents. The methodology combines three statistical methods: Gamma-updating, multivariate Poisson-lognormal regression analysis and BNs.

Despite the diversity of works that have addressed the road safety problem, the probability of a driver causing an accident has not been addressed in any work. Most of the parameters considered in these studies generally relate to road architecture, vehicle characteristics, and weather conditions. No advantageous interest was given to the human factor.

## III. System Model

The proposed risk assessment model aims to estimate the probability of a driver causing an accident. To achieve this goal, a thorough literature search was conducted and experts were surveyed to discover all the variables that could affect the probability of an accident. These searches allow us to highlight the relationships between these variables and construct the BNs structure. The conditional probability tables were produced using a Sugeno fuzzy inference system in the following phase. Finally, the probability of an accident was calculated by anticipating a few possible scenarios.

### A. Construction of the BN

A BN is a graphical model representing probabilistic relationships between variables; it allows knowledge acquisition, representation, and use [23]. The principle of inference in BNs is based on Bayes' probability theory. The joint probability distribution of a set of nodes N = {$X_1$ , $X_2$ ..., $X_n$ } can be expressed as follows [24] :

$$P(X_1, X_2, \dots, X_n) = \prod_{i=1}^{n} P(X_i|Parents(X_i)) \quad (1)$$

Where Parents($X_i$) represents the set of parent nodes of $X_i$

The availability of values on a child node $X_i$, allows us to express the posterior probability of the parent node $X_j$ as follows [25]:

$$P(X_j|X_i) = \frac{P(X_i,X_j)}{P(X_i)} \quad (2)$$

To build our BN, we conducted an extensive literature review. Also, experts were surveyed to collect their opinions on the factors that can cause an accident and the causal relationships between the different parameters. Thus, a BN was set up in three levels represented in Fig. 1:

- The input nodes are described at the first level; they indirectly impact accident risk. As seen in Table I, they fall into five groups.
- The intermediate nodes (colored in yellow in Fig. 1) lead to the final impacts and make up the second level.
- The third level groups the last effects that directly influence the accident occurrence (colored in gray in Fig. 1).

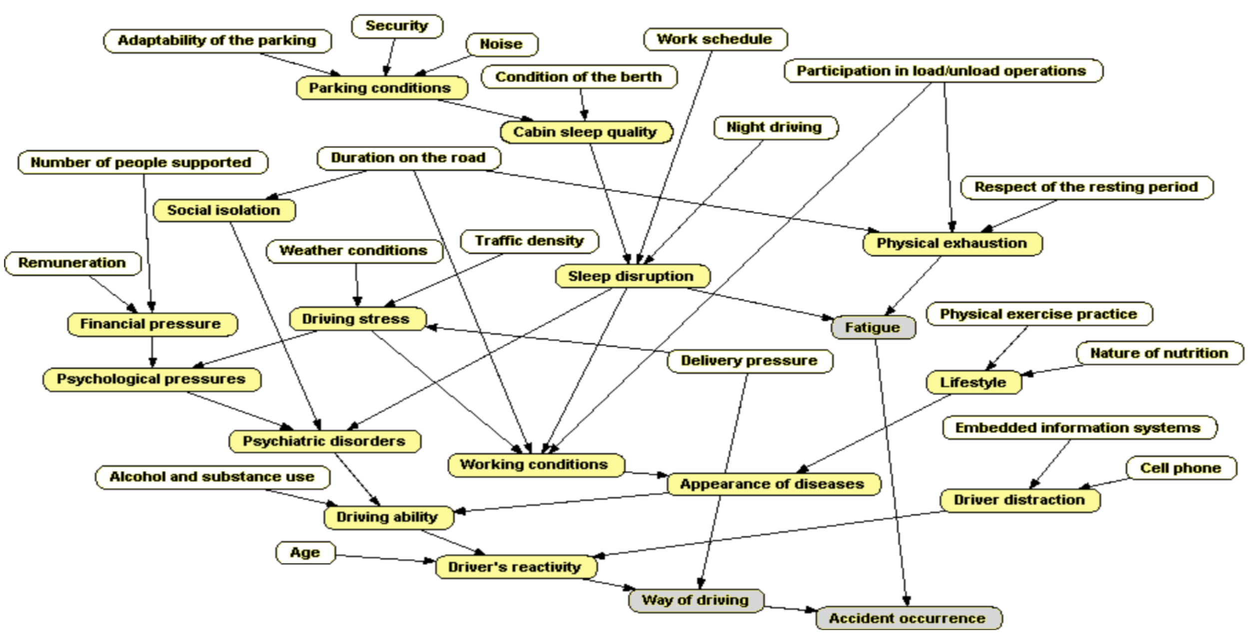


Fig. 1. Driver involvement in an accident model.

TABLE I. THE CAUSAL GRAPH'S INPUT PARAMETERS

| Categories of parameters | Parameters | Description |
|---|---|---|
| Cabin sleep parameters | Adaptability of the parking | It refers to the ability of this space to meet the needs of drivers and carriers for safety, accessibility, and convenience [26]. |
| | Noise | External noises can significantly affect the quality of sleep in the cabin [27]. |
| | Security | It refers to compliance with parking spaces and safety standards concerning lighting, surveillance, and access control. [28]. |
| | Condition of the berth | Creating a comfortable sleep environment depends on the condition of the berth, which significantly impacts drivers' sleep quality and their ability to rest properly. [27]. |
| Personal driver settings | Physical exercise | Regular exercise improves the physical condition of drivers and helps reduce the risk of developing cardiovascular diseases, which are important risk factors for road accidents involving heavy goods vehicles [29]. |
| | Age | Older drivers drive more safely and responsibly and are less likely to drive under the influence of alcohol compared to middle-aged drivers [30]. However, aging can lead to a decline in vision, memory, and coordination, which increases the risk of road accidents [31]. |
| | Nature of nutrition | Poor nutrition leads to a deterioration in the general health of drivers, which can increase the risk of accidents ([32], [29]). |
| | Number of people supported | A significant number of people supported by the driver increases the financial pressures on the driver, which may encourage him to work overtime to support his family. |
| | Alcohol and substance use | Alcohol and substance use can cause reckless behaviour on the road and impair driver faculties [33]. |
| Parameters related to driving conditions | Traffic density | High traffic density can irritate drivers, impairing their concentration and increasing the risk of driving errors and accidents. [34]. |
| | Weather conditions | Weather conditions can disrupt the driver's abilities which can jeopardize their safety [35] |
| | Delivery pressure | Stress at work harms drivers' mental and psychological health [36]; it significantly reduces driving skills and consequently increases the risk of an accident [37]. |
| | Respect of the resting period | Compliance with the rest range is essential to prevent driver fatigue and the resulting risks [38]. |
| | Duration on the road | Increased time spent on the road increases driver fatigue levels, which may influence the probability of an accident [39]. |
| | Night driving | Night driving can disrupt the sleep of truck drivers, which can have dangerous consequences and increase the risk of traffic accidents [40]. |
| Working conditions parameters | Participation in loading and unloading operations | The duties of truck drivers also include non-driving labor. However, non-driver work is not necessarily remunerated [41] |
| | Work schedule | Irregular work schedules of truck drivers can increase fatigue and drowsiness at the wheel, which are vital factors in road accidents [42] |
| | Remuneration | Low pay incentivizes drivers to work overtime, affecting their safety performance [43]. |
| Driver distraction settings | Embedded information systems | Misuse of in-vehicle information systems can distract drivers and thus increase the risk of an accident [44]. |
| | Cell phone | The use of cell phones while driving is one of the critical factors in driver distraction, which can impair concentration and reduce their ability to react quickly to unforeseen events [44]. |

## *B. Generation of Conditional Probabilities*

Assigning conditional probabilities to the graph's nodes is necessary to exploit the developed BN. These probabilities can be determined using algorithms that learn from databases or by consulting subject-matter experts. Unfortunately, no database adapted to the identified variables was found in the literature. In addition, the large number of conditional probabilities in this network hindered the use of expert opinions. Then, fuzzy logic was used to generate conditional probability tables.

Fuzzy Bayesian networks result from the fusion between BNs and fuzzy set theory. This method is widely used to solve problems involving uncertain variables or when it is essential to understand and represent the causal dependencies between these variables [45]. This makes fuzzy BNs a particularly appropriate solution to the problem in question. Nevertheless, inference in fuzzy BNs can be costly in terms of computation time and computational resources, particularly for networks of large size or with a large number of states. This complexity restricts its use for obtaining real-time answers or performing frequent updates.

The implementation of the fuzzy inference system goes through the following steps [46]:

- Fuzzification converts a crisp input value into a fuzzy value via membership functions, determining each fuzzy subset's membership degree [47].
- Inference deduces the result based on fuzzy rules [48].
- The defuzzification transforms the final answer of the fuzzy system into a numerical form [49].

We first define the fuzzy variables and their associated linguistic values to implement this method. Indeed, each variable has been qualitatively represented by natural language expressions illustrated in Table II.

TABLE II. LINGUISTIC VALUES OF NODES

| Nodes | Linguistic values |
|---|---|
| Adaptability of the parking | Low, medium, important |
| Noise | Low, medium, important |
| Security | Bad, medium, good |
| Condition of the berth | Bad, medium, good |
| Parking conditions | Bad, medium, good |
| Cabin sleep quality | Bad, medium, good |
| Night driving | Low, medium, important |
| Work schedule | Regular, slightly irregular, irregular |
| Sleep disruption | Low, medium, important |
| Participation in loading and unloading operations | Low, medium, important |
| Driver distraction | Low, medium, high |
| Respect of the resting period | Low, medium, important |
| Social isolation | Low, medium, high |
| Time on the road | Small, medium, important |
| Physical exhaustion | Weak, medium, Strong |
| Fatigue | Light, medium, important |
| Delivery pressure | Low, medium, high |
| Number of people supported | Low, medium, important |
| Age | Young, medium, old |
| Traffic density | Low, medium, high |
| Physical exercise | Low, medium, important |
| Nature of nutrition | Bad, medium, good |
| Weather conditions | Normal, medium, extreme |
| Driving stress | Low, medium, high |
| Remuneration | Low, medium, important |
| Embedded information systems | Absent, light use, extreme use |
| Financial pressure | Low, medium, high |
| Working conditions | Bad, Medium, good |
| Appearance of diseases | Low, medium, high |
| Cell phone | Absent, light use, extreme use |
| Lifestyle | Bad, Medium, good |
| Psychological pressure | Low, medium, high |
| Psychiatric disorders | Low, medium, high |
| Alcohol and substance use | Low, medium, high |
| Driver's reactivity | Bad, Medium, good |
| Driving ability | Bad, Medium, good |
| Way of driving | Bad, Medium, good |
| Accident occurrence | Low, medium, high |

Concerning the membership functions of all the nodes of the BN, the option was made for those of Gaussian type since the errors in the prediction of the data are minimal when compared to other forms, mainly triangular and trapezoidal forms [50]. The Gaussian membership function has been widely used in previous studies ([52] ; [53] ; [54]). It depends on two parameters: the mean m and the standard deviation k; the equation gives it [51] :

$$\mu_A(x) = e^{-\frac{(x-m)^2}{2k^2}} \tag{3}$$

Then, the fuzzy rule base was built based on the experts' judgments. These fuzzy rules are of the "IF-THEN" type; for example: IF ‘Physical exhaustion’ is weak and ‘Sleep disruption’ is medium THEN ‘Fatigue' will be light. Here, linguistic values expressed in natural language represent the variable ‘Fatigue'. It will accept one of the following values for all other rules: light, medium, or important.

As a result, we created a fuzzy inference mechanism that draws conclusions from input data and fuzzy rules. The Sugeno inference method was used because of its fast processing time and efficient defuzzification system [55]. In the Sugeno method, the inputs are linguistic variables.

The output of Sugeno inference $z_i$ of an activated rule i is a linear combination of the input values ($x_i$ and $y_i$). It is written in the following form [55]:

$$z_i = f(x_i, y_i) = a_i x_i + b_i y_i + c_i \tag{4}$$

The final net output Z of Sugeno inference is computed by averaging the outputs of the fuzzy rules weighted with their weights in the following form ([56], [57]):

$$Z = \frac{\sum_r w_r * z_r}{\sum_r w_r} \tag{5}$$

With:

r: the index of activated rules

$w_r$: the implication result (the activation weight) of the rule r

$z_r$: the output of Sugeno inference of an activated rule r

This fuzzy system incorporated 354 fuzzy rules, allowing us to produce 1062 conditional probabilities to feed the BN.

In what follows, the methodology will be explained by calculating the conditional probabilities of the ‘Fatigue’ node.

First, the membership functions and the fuzzy rules for the ‘fatigue' node and its parent (physical exhaustion and sleep disruption) are defined. Then, the fuzzy system is initialized by input values close to the peak of the Gaussian distribution. Fig. 2 presents the inference of the variable ‘Fatigue' knowing that ‘Physical exhaustion’ is weak and ‘Sleep disruption’ is medium.

Next, the max operator is applied to all the triggered conclusions of the activated rules. The following is thus had:

Fatigue (light) = max (0.2, 0.98, 0.008) = 0.98

Fatigue (medium) = max (0.006, 0.008) = 0.008

Fatigue (important) = 0.006

Thus, the variable 'Fatigue' will take the values 0.98, 0.008, and 0.006 for light, medium, and important, respectively. By computing the ratio between the probability of each state and the total probabilities of all states, the conditional probabilities table of the node 'Fatigue' can thus be obtained as follows.:

P (Fatigue = low | Physical exhaustion = weak and Sleep disruption = medium) = 0.98/(0.98+0.008+0.006) = 0,986.

P (Fatigue = medium | Physical exhaustion = weak and Sleep disruption = medium) = 0.008/(0.98+0.008+0.006) = 0,008.

P (Fatigue = high | Physical exhaustion = weak and Sleep disruption = medium) = 0.006/(0.98+0.008+0.006) = 0,006.

The generalization of this approach for all the nodes of the causal graph allowed us to obtain the conditional probabilities necessary to feed the BN.

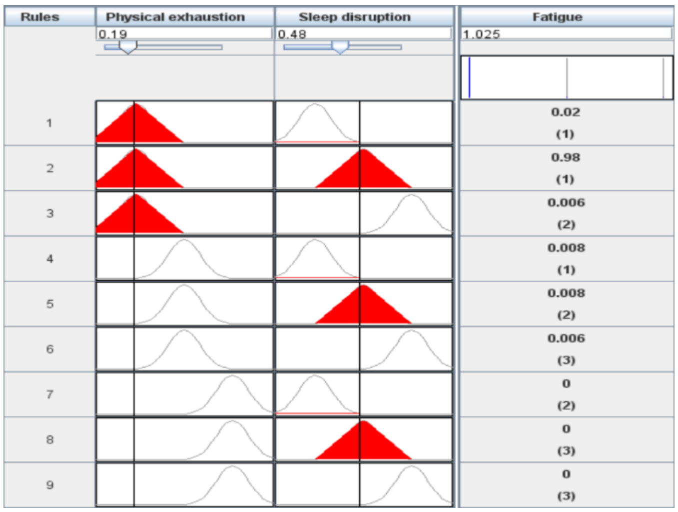


Fig. 2. Result of the inference mechanism.

### C. Anticipation of Scenarios

Implementing the BN allowed us to examine the effect of the distribution of states for some nodes on the other nodes of the causal graph. In what follows, the probability of a driver causing an accident will be anticipated through the study of four scenarios listed below:

- Scenario 1 (S1): the parameters related to the driver are favourable and the parameters related to the work environment are favourable.
- Scenario 2 (S2): the parameters related to the driver are favourable and the work environment's parameters are unfavourable.
- Scenario 3 (S3): the driver parameters are unfavourable, and the work environment parameters are favourable.
- Scenario 4 (S4): the driver parameters are unfavourable, and the work environment parameters are unfavourable.

The driver-related parameters concern the driver's parameters and those that contribute to his distraction. On the other hand, the work environment parameters refer to the set of parameters related to the driving and working conditions and those related to sleep in the cab. Table III provides the configuration of the network input parameters according to the studied scenarios. The probabilities associated with the nodes were obtained using the inference of the fuzzy-Bayesian model. Since the network has many nodes (38), the probability of occurrence of some nodes has been presented in Table IV.

TABLE III. THE INPUT PARAMETER VALUES ACCORDING TO THE SCENARIOS STUDIED

| | S1 | S2 | S3 | S4 |
|---|---|---|---|---|
| **Driver settings** | | | | |
| Embedded information systems | Light use | Light use | Extreme use | Extreme use |
| Cell phone | Light use | Light use | Extreme use | Extreme use |
| Physical exercise | Important | Important | Low | Low |
| Age | Medium | Medium | Old | Old |
| Nature of nutrition | Good | Good | Bad | Bad |
| Number of people supported | Low | Low | Important | Important |
| Alcohol and substance use | Low | Low | High | High |
| **Work environment settings** | | | | |
| Traffic density | Low | High | Low | High |
| Weather conditions | Normal | Extreme | Normal | Extreme |
| Delivery pressure | Low | High | Low | High |
| Respect of the resting period | Important | Low | Important | Low |
| Time on the road | Small | Important | Small | Important |
| Night driving | Low | Important | Low | Important |
| Participation in loading and unloading operations | Low | Important | Low | Important |
| Work schedule | Regular | Irregular | Regular | Irregular |
| Remuneration | Important | Low | Important | Low |
| Adaptability of the parking | Important | Low | Important | Low |
| Noise | Low | Important | Low | Important |
| Security | Good | Bad | Good | Bad |
| Condition of the berth | Good | Bad | Good | Bad |

TABLE IV. DISTRIBUTION OF PROBABILITIES FOR BN VARIABLES

| Variable | Value | S1 | S2 | S3 | S4 |
|---|---|---|---|---|---|
| **Working conditions** | Bad | 0,0010 | 0,9908 | 0,0010 | 0,9908 |
| | Average | 0,0365 | 0,0082 | 0,0365 | 0,0082 |
| | Good | 0,9625 | 0,0010 | 0,9625 | 0,0010 |
| **Psychiatric disorders** | Low | 0,9837 | 0,0026 | 0,9712 | 0,0012 |
| | Medium | 0,0083 | 0,0111 | 0,0208 | 0,0115 |
| | High | 0,0080 | 0,9863 | 0,0080 | 0,9873 |
| **Way of driving** | Bad | 0,0110 | 0,9669 | 0,9799 | 0,9917 |
| | Average | 0,0526 | 0,0318 | 0,0121 | 0,0072 |
| | Good | 0,9364 | 0,0013 | 0,0080 | 0,0011 |
| **Fatigue** | Light | 0,9889 | 0,0011 | 0,9889 | 0,0011 |
| | Average | 0,0100 | 0,0086 | 0,0100 | 0,0086 |
| | Important | 0,0011 | 0,9903 | 0,0011 | 0,9903 |
| **Accident occurrence** | Low | 0,9357 | 0,0014 | 0,0083 | 0,0012 |
| | Average | 0,0523 | 0,0107 | 0,0391 | 0,0093 |
| | High | 0,0121 | 0,9879 | 0,9526 | 0,9896 |

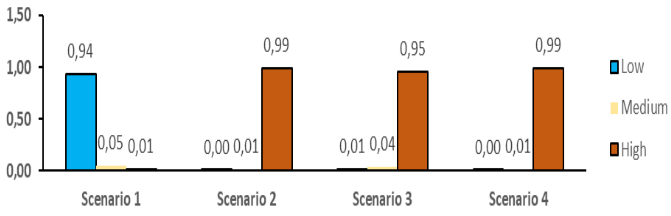


Fig. 3. The probability of occurrence in the different scenarios.

The probability distribution for the occurrence of an accident for each scenario is displayed in Fig. 3.

## *D. Result Discussion*

In the first scenario, the probability of fatigue and psychiatric disorders is low, with a probability of 98.89% and 98.37%, respectively. Also, the way of driving and the working conditions are good, with 93.64% and 96.25%, respectively. Therefore, the probability of an accident is low, with a value of 93.57%.

Regarding the second scenario, there is a 99.03% chance that the driver will become fatigued; the working conditions and the way of driving are bad, with 99.08% and 96.69%, respectively. In addition, a high probability of psychiatric disorders with 98.63% is observed, which leads to a high risk of accident occurrence of 98.79%.

For the third scenario, the probability of fatigue is low, with 98.89%. In addition, the working conditions are good at 96.25%, and the probability of psychiatric disorders is low at 97.12%. On the other hand, the way of driving is bad, with a probability of 97.99%. Therefore, the probability of an accident is high at 95.26%.

In the fourth scenario, we have a high probability of fatigue and the appearance of psychiatric disorders, with 99.03% and 98.73%, respectively. Regarding the way of driving, the working conditions are bad with 99.17% and 99.08%, hence a high probability of accident occurrence is with 98.96%.

According to the findings of the inference of the first and third scenarios, the probability of an accident increases if the driver's parameters are unfavorable. Additionally, unpleasant working conditions significantly influence the probability of accidents.

## *E. Sensitivity Analysis*

Sensitivity analysis makes it possible to find the most dominant factors in the occurrence of a particular event [58]. This analysis would allow us to make the necessary prevention adjustments and reallocate resources more efficiently.

The results of the sensitivity analysis of the 'Accident occurrence' node are shown in Fig. 4. According to this figure, we can estimate that the preponderant factors in accidents are: alcohol and substance consumption, poor driving, fatigue, and distraction caused mainly by cell phones and embedded information systems. These results highlight the crucial role of the human factor in the occurrence of accidents.

## *F. Model Validation*

The validation of the BN guarantees the reliability of the results provided by the model. In order to validate the developed BN, a method based on three axioms was used. This method was proposed by [59] and widely used by several researchers such as: [60], [61] and [62]. The principle of the three axioms is as follows [63]:

- Axiom 1: the increase or decrease in the probability of the parent node must result in a change in the probability of the child node.
- Axiom 2: The occurrence of a change in the probability distributions of the parent node must have a consistent impact on the child node.
- Axiom 3: The total effect of all parent nodes must be greater than either parent's effect.

Validation analyses were conducted on all nodes in the graph to confirm the verification of the three axioms. Tables V and VI show the verification results for axioms 1 and 2 for the 'Lifestyle' node. The impacts of the parent nodes 'Exercise Practice' and 'Nature of Nutrition' on the child node 'Lifestyle' were evaluated by increasing them by 10% and 20%, respectively, and then decreasing them by 5% and 10%. We found that the probability of the 'Lifestyle' node increased from 64.82% to 82.06% when the probability of the 'Exercise' node was increased by 20%. However, the probability of the 'Lifestyle' node increased to 56.20% when the probability of the 'Exercise' node was reduced by 10%. The 'Lifestyle' node replies for the other increments and decrements were consistent, supporting the developed network's stability.

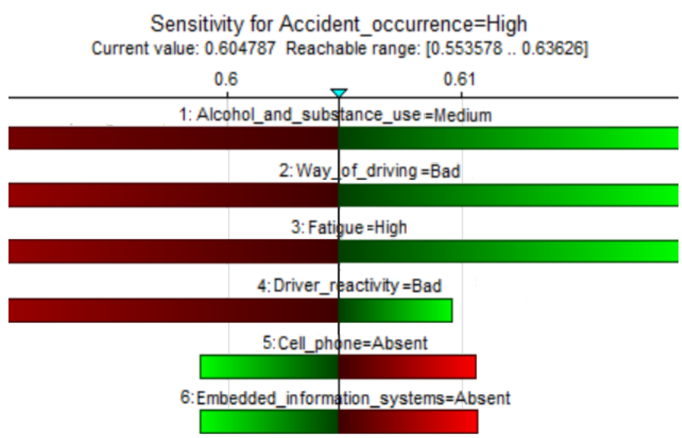


Fig. 4. Sensitivity analysis for accident occurrence.

TABLE V. AXIOM 1 VERIFICATION

| | Parent node: Physical exercise | | Child node: Lifestyle | |
|---|---|---|---|---|
| 20% increase | Low | 95% | Bad | 82,06% |
| 10% increase | | 85% | | 73,44% |
| A priori probability | | 75% | | 64,82% |
| 5% decrease | | 70% | | 60,51% |
| 10% decrease | | 65% | | 56,20% |

TABLE VI. AXIOM 2 VERIFICATION

| | Parent node: Nature of nutrition | | Child node: Lifestyle | |
|---|---|---|---|---|
| 20% increase | Bad | 97% | Bad | 83,32% |
| 10% increase | | 87% | | 75,06% |
| A priori probability | | 77% | | 66,80% |
| 5% decrease | | 72% | | 62,67% |
| 10% decrease | | 67% | | 58,54% |

TABLE VII. AXIOM 3 VERIFICATION FOR THE 'LIFESTYLE' NODE

| Nature of nutrition | | Physical exercise | | Lifestyle | | Percentage change |
|---|---|---|---|---|---|---|
| Bad | 90% | Weak | 84% | Bad | 77,53% | |
| | 100% | | 84% | | 83,33% | 7,48% |
| | 90% | | 100% | | 92,20% | 18,92% |
| | 100% | | 100% | | 100% | 28,98% |

Regarding the verification of axiom 3, from the results presented in Table VII, we can say that the total effect of increasing all parents of the ‘Lifestyle’ node to 100% resulted in a more significant increase than when only one parent is increased separately, which is well in line with axiom 3.

### G. Result Discussion

This article examines the importance of identifying and preventing risk factors in improving road safety. It focuses specifically on driver-related parameters that increase the risk of accidents. Based on bibliographical research and experts' opinions, road accidents cannot be attributed to a single type of cause but to a panoply of parameters linked together by causal relationships that ultimately give rise to a road accident. In order to prevent accidents, this article has developed an approach based on fuzzy BNs so that carriers can take the necessary precautions to avoid catastrophe. Adopting this model will ensure a high level of visibility and improve the efficiency of logistics deliveries. In addition, validating the proposed BN further guarantees the reliability of the results provided by the model. The scenarios studied highlighted the impact of working conditions on the occurrence of accidents. The sensitivity analysis results confirm that the most critical factors in accidents are: alcohol and substance abuse, poor driving style, fatigue, and driver distraction. These results underline the crucial role of the human factor in accident occurrence. This model has also created a synthetic database that can be used by learning models to predict the risks associated with road accidents.

The following section focuses on integrating in-vehicle safety devices to improve road safety. This aspect is explored through analysis of the proposed event tree.

## IV. PREDICTIVE MANAGEMENT OF HEAVY VEHICLE ACCIDENTS BY APPLICATION OF EVENT TREE TECHNOLOGY

### A. Event Tree Analysis

Event tree analysis uses a tree structure of events to provide potential probabilities of the outcomes of events that contribute to the success or failure of a management. The tree is constructed chronologically by predicting, in the first place, the probability of an initiating event. Then, a sequence of intermediate events occurs to prevent additional risk [64].

In order to develop the scenarios of probable crises related to a truck accident, different road safety devices installed were taken into account, such as:

- Adaptive cruise control: This system uses sensors to monitor the distance between the truck and other vehicles on the road and automatically regulates the speed to maintain a sufficiently safe distance.
- Driver Fatigue Monitoring System: This system uses sensors to monitor eye movements and the driver's head position. If the system detects the driver is tired or distracted, it can warn them to take a break.
- Automatic Emergency Braking System: This system uses sensors to detect objects near the truck and can automatically initiate emergency braking if the driver does not react quickly enough.

Then, the steps prescribed below were followed:

- Initiator event gave rise to the system's critical state; in our case, it is a road accident.
- Intermediate events aim to detect or prevent the initiating event or reduce its consequences as much as possible. The intermediate events that have been chosen are: adaptive cruise control system activated, driver fatigue monitoring system activated and automatic emergency braking system activated
- Identification of consequences specifies the expected outcomes of each series of events.
- Quantization of the tree assigns probabilities for each branch in order to calculate the probability of each sequence in the following form:

$$P(R) = \prod_1^n P(B_i) \qquad (6)$$

With $B_i$: Set of branches that make up the path to the result R.

Fig. 5 illustrates the event tree developed to study the probability of successful accident prevention based on the safety systems installed.

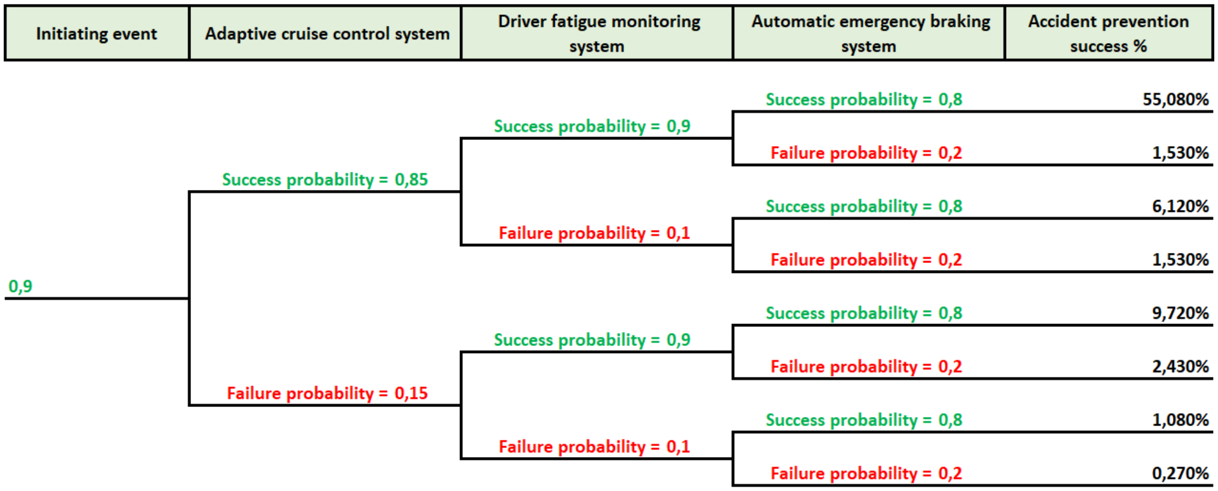


Fig. 5. Event tree showing the probability of success in preventing an accident based on the success rate or failure of the various safety systems installed.

### B. *Analysis of Results*

The quantification of our event tree allowed us to predict the probability of success of road accident prevention efforts according to the different operating rates of the safety systems installed. We found that the success rate is highest (55.08%) if all installed systems are working correctly and minimal (0.27%) for the opposite case. These results highlight the importance of equipping heavy goods vehicles with systems monitoring driver behavior to improve road safety.

## V. Conclusion

Road accidents involving heavy goods vehicles attract particular interest because of their devastating consequences of loss of life and property damage. In this article, the focus was placed on the prediction of heavy vehicle accidents in order to improve road safety and adequately manage this problem. To this end, BNs and fuzzy logic were combined to develop a model capable of scrutinizing the possibility of an accident.

The simulation of several scenarios allowed us to value the impact of the factors identified on the occurrence of accidents. In addition, the results deduced from the application of event trees allowed us to shed light on the importance of road safety mechanisms in preventing road accidents.

The developed system takes advantage of BNs and the strength of the fuzzy set theory, making it a robust and efficient model capable of providing reliable predictions. Similarly, this work may promote the development of new systems operating in research fields other than transport.

The limitations of the model developed lie in the complexity of road accident scenarios; the plurality of factors that can influence the occurrence of accidents makes it inappropriate to take them all into consideration, which could impact the accuracy of the predictions provided by the model.

One of the potential perspectives at work presented is the model's generalization to all occupational risks relating to truck drivers, such as work accidents the appearance aggravation of certain diseases; and we also intend to use deep learning methods in our future work to push back the prediction of the risks mentioned above and manage the resulting crises appropriately.

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