Enhancing Predictive Analysis of Vehicle Accident Risk: A Fuzzy-Bayesian Approach

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***Abstract*—Although delivery transport activities aim to ensure excellent customer service, risks such as accidents, property damage, and additional costs occur frequently, necessitating risk control and prevention as critical components of transport supply chain quality. This article analyzes the risk of accidents, a fundamental root cause of critical situations that can have significant economic impacts on transport companies and potentially lead to customer loss if recurring. The case study develops a fuzzy Bayesian approach to anticipate accident risks through predictive analysis by combining Bayesian networks and fuzzy logic. Results reveal a strong correlation between fatal injuries in accidents and factors related to driver and vehicle conditions. The predictive model for accident occurrence is validated through three axioms, offering insights for carriers, transport companies, and governments to minimize accidents, injuries, and costs. Moreover, the developed model provides a foundation for various predictive applications in freight transport and other research fields aiming to identify parameters impacting accident occurrence.**

Keywords—Road traffic injuries; risk management; predictive analysis; Bayesian network; fuzzy logic; accident

I. Introduction

Road traffic injuries (RTIs) are a major cause of death, claiming nearly 1.3 million lives each year. About 90% of these fatalities occur in low- and middle-income countries [source: World Health Organization. Global status report on road safety 2018. WHO, 2018]. The African region had the highest road traffic death rate 26.6 per 100,000 population, while the European region had the lowest 9.3 per 100,000 population [1]. The South-East Asia Region, motorized two- and three-wheelers contribute to a significant 44% of all road traffic deaths [2].

Predicting accidents is inherently complex due to the multitude of contributing factors, including road user behaviors, vehicle conditions, physical road characteristics, and environmental influences [3], [4]. Despite the extensive research on road safety, a significant challenge remains in effectively predicting and mitigating the risk of accidents to enhance overall transport safety.

This paper addresses this gap by developing a predictive model that leverages Bayesian networks (BNs) and fuzzy logic to anticipate accident risks. The fuzzy-Bayesian approach combines the probabilistic reasoning capabilities of BNs with the imprecision handling of fuzzy logic, providing a robust framework for risk prediction and management in transport systems.

The article is organized as follows: Section II provides an overview of the literature on road accidents and the use of Bayesian networks (BNs) in transportation. Section III details the construction and validation of the fuzzy-Bayesian model. Section IV discusses the results obtained. Finally, Section V offers conclusions and suggestions for further research, outlining the practical implications of the findings for carriers, transport companies, and policymakers aiming to reduce road traffic accidents.

By addressing the critical issue of accident prediction and prevention, this study aims to contribute to the broader goal of enhancing road safety and reducing the human and economic toll of RTIs. The proposed fuzzy-Bayesian model not only aids in predicting accidents but also serves as a foundational tool for developing various predictive applications in the field of freight transport and beyond, ultimately striving for safer and more efficient transport systems globally.

II. Related Work

In this section, we briefly present a review of the literature relevant to our study context, which concerns Accident and Bayesian network applications in the transportation field.

A. Risk Road Accidents

In physics, a collision is characterized as a sudden and uncontrolled change in a vehicle's accumulated kinetic energy. Accidentology, the science of studying accidents, focuses particularly on how kinetic energy is dissipated during such events.

In the paper [5], the authors employed image processing methods to identify lane boundary lines, aiming to enhance the development of driver assistance systems for accident prevention. The aim of the study [6] was to detect risk factors related to geometric road design where crashes might happen. As for study [7], they proposed represents an economical accident prevention embedded system based on obstacle detection IR sensor, to Prevent Road Accident by Lane Detection and Controlling. Using a Fuzzy-Bayesian Approach, [8] Predictive Analysis of Delivery Delay Risk including the prediction of the accident’s occurrence. In the same context of Road traffic accidents, [9] offers a comprehensive examination encompassing data sources, analytical methodologies, and influential factors, the authors of [9] has also described different methods utilized for road traffic accident forecasting, that are, Machine Learning [10], Genetic Algorithms [11], [12], [13], Bayesian Networks [14], [15], Support Vector

Machines [16], Convolutional Neural Networks [17], Artificial Neural Network [18], Three Data-Mining Techniques [19].

BNs are considered one of the most powerful prediction methods in a wide range of research fields [20]. This study harnesses the capabilities of Bayesian networks (BN) for risk prediction, aiming to forecast the likelihood of road accidents.

B. Applications of BNs in the Transportation field

Bayesian networks is a powerful Probabilistic Graphical Model for learner modeling under uncertainty. BNs have been used with great success in many systems, with different objectives, from medical diagnostic [21] predicting types of hematological malignancies, to the Water supply field [22] Predicting Rehabilitation of Water Distribution Networks. BNs is employed also in transportation domains for different prevention's categories. In the article [23], authors utilized Bayesian networks (BNs) to quantify accident risks, aiming to identify high-risk areas, in study [24] authors have developed a BNs a BN model to pinpoint factors influencing motor carrier safety. The purpose of two works [25] and [26] was the evaluation of driving behavior, and modeling drivers' vehicle usage patterns based on the time of day. Moreover, the application of BNs extends to various transportation aspects, including traffic congestion prediction [27], freight demand prediction [28], as well as delivery delay risk [8].

III. Modeling the Risk of Accident Using A Fuzzy-Bayesian Approach

A. Definition to Bayesian Network (BN) & Directed Acyclic Graph (DAG)

1) What is Bayesian Network?

A Bayesian network (BN) is a graphical probabilistic model used for acquiring, representing and exploiting knowledge. It is a technique blending artificial intelligence with statistics to depict uncertain information and to draw conclusions from incomplete data.

BN have demonstrated their utility in biomedical research by effectively illustrating intricate relationships between variables, such as diseases and their associated risk factors, in a user-friendly manner [29]. Using a given set of symptoms, BN can compute the likelihood of specific diseases being present.

BN is a type of probabilistic graphical model that utilizes a directed acyclic graph (DAG) to depict variables and the conditional dependencies between them.

2) What is Directed Acyclic Graph (DAG)?

In the fields of graph theory and computer science, a directed acyclic graph (DAG) is a type of directed graph that contains no directed cycles. This means that it consists of vertices connected by edges, where each edge has a direction pointing from one vertex to another, ensuring that no closed loops are formed Fig. 1.

A directed graph maintains consistent edge directions, enabling the vertices to be arranged in a linear order. DAGs find application across diverse scientific and computational domains, such as biological evolution, family trees, epidemiology, and sociology.

Let's take a quick look at the fundamental mathematics involved with the Bayesian network.

3) The maths behind the bayesian network: A Bayesian network, a type of probability model, is constructed using a directed acyclic graph. Each variable in the model is factored using a unique conditional probability distribution, which is determined by the variable's parent nodes in the graph. The fundamental concept of probability forms the basis of Bayesian models. To better understand this, we should first define the terms "conditional probability" and "joint probability distribution".

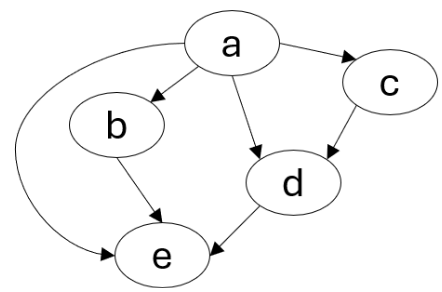

Fig. 1. Example of Directed Acyclic Graph (DAG) (Source: Wikipedia).

Conditional Probability: It is a way to measure the probability of an event (say A) happening, given that another event (say B) has already happened. This is often represented as P(A|B) or sometimes as PB(A), where A is the event we are interested in, and B is the event that is known or assumed to have occurred. This can also be interpreted as the proportion of the probability that event B intersects with event A. Eq. (1) present the formula of the conditional probability that is expressed as a percentage of the likelihood of B crossing with A:

$$P(\text{A}\backslash\text{B}) = \frac{P(A \cap B)}{P(B)} \quad (1)$$

4) Construction of the Bayesian network architecture: There are two approaches to constructing a BN: objective and subjective methods.

Objective methods: It involve using a database to apply structure learning techniques. These methods often involve algorithms that learn the structure of the Bayesian network directly from the data.

Subjective methods: It involve acquiring expertise from field specialists. This may involve written surveys, one-on-one interviews, or collaborative brainstorming sessions. The advantage of this method is that it can incorporate expert knowledge and insights that may not be present in the data.

Both approaches carry their advantages and disadvantages, and the selection between them often depends on the specific context and available resources.

In literature, numerous researchers have leaned on expert insights, as seen in studies [30], [31], [32], [33], [34]. Bearing this in mind, the article opted for the subjective method.

B. Identification of the Parameters that are linked to the Accidents' Occurrence

The subjective method, which relies on the expertise of professionals in the field, was our foundation. As a starting point we conducted an extensive examination of the available literature. After deep research in literature, we noted several parameters that represent the root cause leading to the occurrence of vehicle accidents Table I. The parameters identified are related to, road alignment and grade, traffic controls, weather conditions, driver, stopping distance of vehicle after driver braking, traffic parameters, delivery's planning, and physical condition of the vehicle.

TABLE I. DESCRIPTION OF THE INPUT PARAMETERS OF THE CAUSAL GRAPH

Variable	Description
Traffic way	In annual traffic crash data, released by in 2020 by "U.S. Department of Transportation's National Highway Traffic Safety Administration" (NHTSA) [35], we find that traffic way, is one of the elements registered in all accidents records. In the NHTSA's database [35] the parameter "VTRAFWAY" refer to the traffic way that takes the values: Non-Trafficway or Driveway Access, Two-Way Not Divided, Two-Way Divided by Unprotected Median, Two-Way Divided by Positive Median Barrier, One-Way Trafficway, Two-Way Not Divided with a Continuous Left-Turn Lane, Entrance/Exit Ramp.
Number of travel lanes	Furthermore, a greater number of crashes occur on one-lane roads (1606 times), in which inconsiderate drivers are a major cause of accidents (1910 times) [36].
Road alignment	Most of accident occurred on a straight segment [36].
Road grade	In the NHTSA's database [35] the parameter "VPROFILE" indicate the road grade.
Traffic controls	Traffic control devices like traffic signals, road signs, and road markings provide important information and instructions to road users. If these devices are not properly placed, are malfunctioning, or are difficult to see or understand, they can lead to confusion and accidents [37].
Traffic control device functioning	According to NHTSA's report Revised July 2022 [35], the traffic control is, not functioning, functioning improperly or functioning properly, the variable name was named "VTCONT_F".
Lighting	Lighting conditions have a considerable effect on the occurrence of road accidents, due to the adaptation of speed with visibility conditions [38].
Road Cleaning after accident	If accident locations are not adequately cleaned, the remaining debris, body fluids, and fuel can cause vehicles to skid [8].
Road surface condition	The National Highway Traffic Safety Administration (NHTSA), under the U.S. Department of Transportation, was established by the Highway Safety Act of 1970. NHTSA in his report [35], has considered that the surface's road named on the report "VSURCOND" is one of the parameter affecting the occurrence of the accident.
Weather Condition	In accident prediction process weather condition is one of the parameters to take into consideration. The largest number of accidents occurs in clear weather [36]. Weather conditions impact the effectiveness of traffic controls. Rain or fog can make it difficult for drivers to see traffic signals and road signs, leading to accidents [39]. Adverse weather conditions can negatively impact a driver's ability, the grip of the road, the state of road infrastructure, and the stability and control of the vehicle. This is due to factors such as poor visibility, extreme temperatures, rainfall, strong winds, and lightning [40]. Consequently, these conditions impact traffic demand (as transporters delay or call off scheduled deliveries), traffic safety (due to an increase in accident rates), and the dynamics of traffic flow (alterations in key traffic flow parameters such as volume, speed, and density affect the road system's capacity) [41]. Slippery roads due to rain, snow or ice, as well as the ambient temperature in dry or wet weather, increase stopping distances of vehicles. [42]
Age & Sex of driver	Age and sex are the main factors influencing the driver's driving routine style. According to [43], [44], routine driving style contribute to traffic accidents.
Fatigue	Fatigue and sleepiness, contributes to traffic accidents [43], [44].
Alcohol consumption	The consumption of alcohol while driving is one of the dangerous factor of the driver's conditions, it often leads to fatal accidents [3].
Negative emotions & stress	Negative emotions and stress can lead to increased speed, which is a major factor in accidents. This results in a significant number of injuries and deaths. In fact, one-third of total accidents involving driver speed result in fatalities [36], [45], [46].
Safety distance respect	Driver behavior includes failure to respect safety distance and speed limits, as well as sudden braking and hard acceleration [47].
Hard braking & hard acceleration	According to the article [48] one of the major sources of traffic accidents is who Driver behavior while driving.
Speed limits respect	Passenger vehicle drivers involved in fatal crashes, by speeding involvement, alcohol-impaired driving, and restraint use [49]. According to [49] study, from the 41144 passenger vehicle drivers involved in 2020 in fatal crashes, 2819 were due to speeding, this represent 6.9%. The speed is higher, the stopping distance of vehicle is longer [50].
Occurrence of events that block/slow traffic	Road Traffic can be interrupted by the presence of a number of events, such as festive events (religious, national or international holidays, vacation departure) [8], [51], social events (political demonstrations, diplomatic visits [52], sports events) [8], [51] and unforeseen or occasional events (Vehicle Breakdown, Accident, public works) [8], [52].
Delivery Period	[53].

	Urban delivery during peak hours is very difficult, as private vehicles and goods vehicles overlap, generating a mixed and dense traffic flow [51]. It is obvious that the congestion observed during the peak hour is related to "home-to-work" trips. Indeed, the BELDAM survey [54] showed that 2/3 of the morning peak trips were related to this reason (65% of the trips between 6am and 9am).There is also a notable difference between school and non-school working days [54]. On school days, the morning peak starts earlier, is higher and therefore concentrates a larger share of trips. On the other hand, on a non-school working day, this morning peak disappears, resulting in a peak of trips around 10:00 am. This means that "home-school" trips also play a role in congestion in Belgium [53], [54], [55], [56]. Delivery period influences traffic, delivery during peak hours can slow down traffic [8].
Physical condition of the Vehicle	A Vehicle having a bad physical condition can be a cause of a dramatic accident [4], [36]. A poor physical condition is often a result of negligence, hence the occurrence of breakdown and delays.
Stopping distance	On the road, assessing the stopping distance is crucial. Braking, under normal or emergency circumstances, takes time and distance. The stopping distance is affected by the driver's reflexes, the vehicle's speed, the weather conditions and the road surface's grip [50]. The stopping distance could be estimated by multiplying the tens figure for the speed of your vehicle by itself. For example, the stopping distance at 120 km/h will be 12 x 12 or 144 m. The values obtained from these calculations are approximate because various factors affect braking. Various factors influence the stopping distance of a vehicle. Some are technical (Road adhesion, Road grade, Vehicle Kinetic energy, Tire State and Condition, Weight of the vehicle), others related to human (Reaction time, Visibility).
Reaction time	Various studies show that reaction time is in the range of 1.8 to 2.5 seconds, in France, it is generally estimated at 2 seconds. The reaction time depends on many factors: fatigue, driving under the influence of alcohol or drugs, as well as activities that reduce the driver's attention, such as talking to passengers or being distracted by their behavior, use of the car radio, GPS, mobile phone or in-car phone [57].
Visibility	Fog, Rain, Snow, Hail, and Night, affect the visibility needed to interpret risks and hazards and influence the reaction time and distance travelled [58].
Road adhesion	Depending on the type of surface of the road, paving stones, sand, earth, draining or non-draining tarmac. All these types of surface have different characteristics that influence the stopping distance. Together with the weather, they constitute what is known as the coefficient of friction between the tires and the road [59].
Road grade	Braking distance is improved on uphill and reduced on downhill. Similarly, steering grip is improved on positive slopes and penalised on negative slopes. [60]
Braking Distance	Braking distance refers to the distance a vehicle travels from the time the driver applies the brakes until the vehicle comes to a complete stop. Accidents often occur when the braking distance is longer than the distance available to stop safely. [61], [62], [63]
Kinetic energy	When a vehicle is in motion, it stores kinetic energy. If you stop the engine, the vehicle will continue to move forward thanks to its momentum. In order to stop it, it is necessary to absorb this energy. The overall function of the braking system is therefore to transform kinetic energy into heat energy [64], [65]. The relationship between kinetic energy and braking distance is such that the higher the kinetic energy, the longer the braking distance, because a higher kinetic energy requires more work to be done by the brakes to bring the vehicle to a stop.
Tire State and Condition	Tire's pressure have a remarkable influence on the braking distance. [66]
State & Condition of braking system	The wear of the brake, as well as the age of the hydraulic fluid, which is sensitive to heat, the temperature of the discs, pads, drums and linings after heavy use, will increase the stopping distance. [67]
Weight of the vehicle	The higher is the weight, the longer the stopping distances [68], [69], [70].

C. *Construction of Bayesian Network Structure*

To build our BN presented in Fig. 2. We have identified in literature the parameters that can cause the occurrence of accidents and the causal relationship among these variables, then the BN was set up in three levels.

The first level, as shown in Table II(a) represents the input nodes, which indirectly influence the occurrence of an accident. This developed level of the BN has 67 nodes. The second level of the BN, detailed in Table II(b) includes the intermediate nodes. These nodes delineate the diverse intermediate causal factors that contribute to the impact factors. The third and ultimate tier of the constructed Bayesian network comprises the final impacts. These factors directly and adversely contribute to accident occurrences. These factors are presented in Table II(c).

After pinpointing the variables Table I which will serve as nodes within the graph, and representing the inputs, intermediate effects, and final impacts detailed in Table II. The structure of the BN is constructed and depicted in Fig. 2.

D. *Generation of Conditional Probabilities (CP) of Intermediate Effects and Final Impacts*

Once the structure of the BN is established, it's crucial to assign conditional probabilities Table (CPT) to the nodes of the graph for effective utilization of the developed BN. These probabilities can be ascertained either through algorithms that are trained on databases or by seeking guidance from experts in the relevant field. However, we encountered a challenge as there was no suitable database for the identified variables in the existing literature. Moreover, the extensive number of conditional probabilities in this developed network that equal to 56.739.144, made it impractical to rely on expert knowledge for an evaluation [71].

TABLE II. PRESENTATION OF INPUTS, INTERMEDIATE EFFECT, AND FINAL IMPACTS OF THE OCCURRENCE OF ACCIDENTS

a) INPUTS		
Negative emotions	Road alignment	Truck fill rate
Accident on the Road	Road Cleaning after accident	Weather Condition
Age	Road grade	Month
Alcohol or drug consumption	Road surface type	Day of week
Anything on road surface?	Safety distance respect	Peak Hours
Children	Sex	School and non-school working day
Education	Speed	International holidays
Fatigue	Vehicle Breakdown history	Vacation departure
Hard acceleration	Speed limit	Religions of National events
Hard braking	Speed limits respect	Social events
Kilometers to be covered	Stability of vehicle while driving	Vehicle Breakdown
Road Lighting	State & Condition of the braking system	Use of accessories (GPS, mobile phone)
Maintenance Planning is respected	Stress	Distracted by passengers
Model year	Tire state & condition	Talking to passengers
Number of exchanges	Traffic control device functioning	Public works on the road
Number of travel lanes	Traffic controls	Vehicle accident history
Professional status	Traffic way	

b) INTERMEDIATE EFFECTS
Kinetic energy
Planning parameters
Road Adhesion
Braking distance
Reaction time
Delivery period
Distracted?
Occurrence of events that block/slow traffic
Visibility
Weight of the vehicle

c) FINAL IMPACTS
Driver Style
Physical Vehicle condition
Road design
Road surface condition
Traffic flow
Driver condition
Stopping distance

Fuzzy logic permits to minimize the number of questions asked to experts while also to reduce the generation of probability tables [72]. Fuzzy logic finds application across diverse domains including control systems, image processing, natural language processing, medical diagnosis, and artificial intelligence:

- Control Systems: Fuzzy logic is often used in control systems for industrial processes, consumer products, and vehicles [73]. It allows for a more flexible and intuitive approach than traditional binary logic, making it ideal for complex, non-linear systems. The article [74] proposes a coordinated control of multiple Photovoltaic Static Compensator systems using fuzzy logic. The results presented by the author validate that the suggested fuzzy controller has the capability to enhance the dynamics of the voltage profile.
- Risk management: In the article [75] Fuzzy VIKOR is used as a part of a three-phase model for managing supply chain sustainability risks.
- Energy consumption: The article [76] compares the energy efficiency of two different approaches to Air Conditioner (AC) usage; the manual method and the fuzzy logic method. The research underscores the efficacy of fuzzy logic in optimizing AC power consumption in response to real-time conditions, resulting in an impressive energy savings of around 41.96%.
- Image Processing: In image processing, fuzzy logic helps with tasks such as edge detection, feature extraction, and image enhancement [77], [78]. It's particularly useful when the image data is imprecise or noisy.
- Natural Language Processing (NLP): Fuzzy logic is used in NLP to understand the meaning of text based on context [79], [80]. This is especially useful in sentiment analysis, where the goal is to determine the emotional tone behind words.
- Medical Diagnosis: Fuzzy logic help doctors and medical professionals make diagnoses based on symptoms and test results [81], [82], [83], [84], [85], [86]. It handles the uncertainty and vagueness often present in the medical field.
- Artificial Intelligence (AI): In AI, fuzzy logic is used to enable machines to reason in a way that is similar to human reasoning [8], [51], [87], [88]. This includes dealing with ambiguous or imprecise information.

Consequently, this paper relied on fuzzy logic approach to initially articulate the experts' evaluations using fuzzy rules, and subsequently created the conditional probability tables through a fuzzy inference mechanism.

Fuzzy Rules, are expressed as IF-THEN statements, capturing the relationship between input variables and output variables in a fuzzy way; for instance: IF "road" is dangerous, "driver's performance" is bad and "Physical Vehicle condition" of is bad, THEN the "occurrence of accident" will have a fatal injury. In a Fuzzy Logic system, the output is represented by a fuzzy set, consisting of membership degrees for every potential output value. Here the degree of "fatal injury" regarding the "occurrence of accident" is depicted qualitatively through a linguistic variable articulated in natural language. Across various rules, the "occurrence of accident" node may be interpreted as one of the following states: No accident, possible injury, fatal injury.

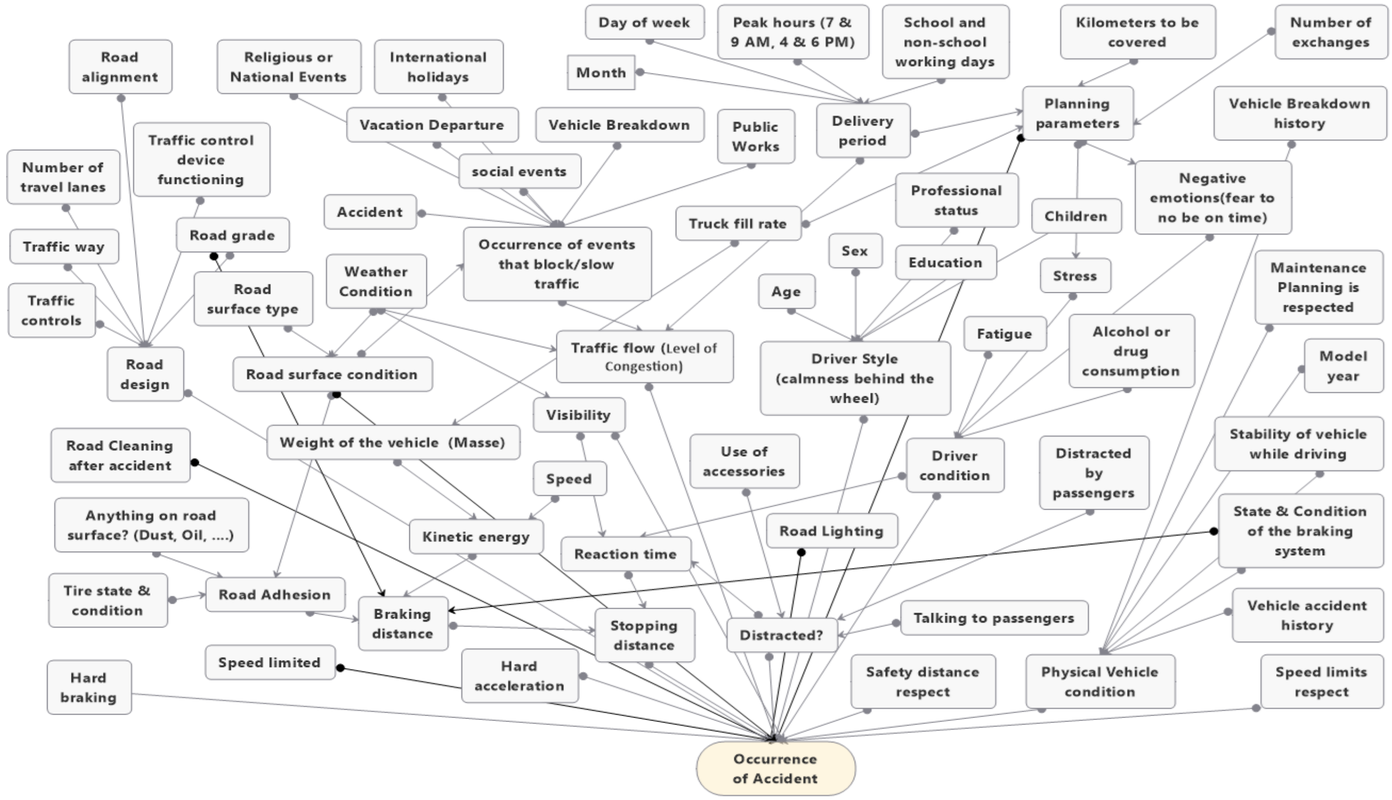

Fig. 2. Structure of the Bayesian network modeling the risk of occurrence of the road accident.

This article employs a fuzzy inference method to derive insights from the given input information and fuzzy rules. The Sugeno inference method is utilized due to its rapid processing speed and effective defuzzification system [89]. The article then chose to express these values in a fuzzy form to associate the degree of membership of each node across all its fuzzy subsets. For instance, within the "occurrence of accident" node, fatal injury is assigned a membership of 92%, potential injury 7%, and no occurrence 1%.

The process of implementing the fuzzy-Bayesian approach, which is used to create conditional probability tables, is carried out in five stages:

Step 1: Initial data collection and variable definition, including the identification of linguistic values and the creation of membership functions [90] [91].

Step 2: Establishment of fuzzy rule sets; constructing a series of "if-then" rules that guide the fuzzy inference system in converting input variables into output[90].

Step 3: Fuzzy conversion; translating input values into fuzzy representations using membership functions, and assessing the membership degree of each fuzzy subset [92].

Step 4: Inference mechanism development; creating a framework to draw conclusions based on the fuzzy rules and input data [93], [94].

Step 5: Defuzzification process; converting the fuzzy system's final output into a numerical format for practical application [95].

Initially, the article establishes the fuzzy variables and their corresponding linguistic values for the implementation of this method. In fact, each variable is represented qualitatively using expressions in natural language, as demonstrated in Table III.

TABLE III. TATE'S OF THE BAYESIAN NETWORK NODES

ID	Nodes	Linguistic values
1	Driver Style	Good, Medium, Bad
2	Kinetic energy	Low, Medium, High
3	Physical Vehicle condition	Good, Medium, Bad
4	Planning parameters	Minimum, Low, Moderate, High, Maximum
5	Road design	Save, Critical, Dangerous
6	Road surface condition	Dry, Dirt, Wet
7	Traffic flow	Smooth, Congested, Stop-and-go
8	Negative emotions	No, Bad, Too-bad
9	Road Adhesion	Good, Medium, Bad
10	Braking distance	Short, Normal, Long
11	Driver condition	Good, Medium, Bad
12	Reaction time	Too Long, Long, Normal
13	Stopping distance	Short, Normal, Long
14	Accident on the Road	No accident, Possible Injury, Fatal Injury
15	Age	Adolescent, Adulthood, Middle-Age
16	Alcohol or drug consumption	Non-Consumption, Negative, Positive

17	Anything on road surface?	Nothing, Dust, Water, Oil
18	Children	No-Child, One-Child, Several-Child
19	Delivery period	Low-traffic, Normal-traffic, High traffic
20	Distracted?	Distracted, Not-distracted
21	Education	Educated, Not-Educated
22	Fatigue	No-Fatigue, Mild-Fatigue, Moderate-Fatigue, Severe-Fatigue, Exhausted
23	Hard acceleration	Low, Normal, Hard
24	Hard braking	Low, Normal, Hard
25	Kilometers to be covered	Long, Normal, Short
26	Road Lighting	Bright, Dim, Low Light, Obscurity
27	Maintenance Planning is respected	Respected, Delays, Frequent-Delays
28	Model year	New, Recent, Mid-Aged, Older, Antique
29	Number of exchanges	No-Exchange, One or Two exchanges, Several-Exchanges
30	Number of travel lanes	One-Lane, Two-Lanes, Three-Lanes, Four-Lanes, More-Lanes
31	Occurrence of events that block/slow traffic	Low, Medium, High
32	Professional status	Junior, Mid-Level, Long-Term
33	Road alignment	Straight, Curve
34	Road Cleaning after accident	Appropriate, Medium, Inappropriate
35	Road grade	Uphill, Level, Downhill
36	Road surface type	Save, Critical, Dangerous
37	Safety distance respect	Respected, Not_Respected
38	Sex	Masculine, Feminine
39	Speed	Low, Medium, High
40	Speed limited	Limited, Not-Limited
41	Vehicle Breakdown	Working, Dysfunctional, Breakdown
42	Use of accessories	No, Rarely, Occasionally, Sometimes, Often, Frequently
43	Speed limits respect	Respected, Not-Respected
44	Stability of vehicle while driving	Stable, Not-Stable
45	State & Condition of the braking system	Good, Medium, Bad
46	Vehicle Breakdown history	No, Rarely, Occasionally, Sometimes, Often, Frequently
47	Vehicle accident history	No, Rarely, Occasionally, Sometimes, Often, Frequently
48	Stress	Stressed, Normal, Relax
49	Tire state & condition	Good, Medium, Bad
50	Traffic control device functioning	Functioning, Not-Functioning
51	Traffic controls	Controls, No-Controls
52	Social events	Major, Significant, Minor
53	Public works	No, Rarely, Occasionally, Sometimes, Often, Frequently
54	Distracted by passengers	No, Rarely, Occasionally, Sometimes, Often, Frequently
55	Traffic way	Two-Way_Not-Divided, Two-Way_Divided, One-Way
56	Truck fill rate	Minimal, Low, Moderate, Full
57	Visibility	Good, Medium, Bad
58	Weather Condition	Clear, Rainy, Foggy, Snowy
59	Weight of the vehicle	Light, Normal, Heavy
60	Month	Winter, Spring, Summer, Autumn
61	Day of week	Beginning, Middle, Weekend
62	Peak Hours	Early Morning, Morning, Midday, Afternoon, Evening
63	School and non-school working day	School, Non-School
64	International holidays	Major, Significant, Minor
65	Vacation departure	Major, Significant, Minor
66	Religions of National events	Major, Significant, Minor
67	Talking to passengers	No, Rarely, Occasionally, Sometimes, Often, Frequently
68	Occurrence of accident	No accident, Possible injury, Fatal injury

The fuzzy system integrated a total of 18,913,048 fuzzy rules, enabling the generation of 56,739,144 conditional probabilities to support the BN. In order to facilitate a deeper understanding of our proposed approach, we elucidate the process of generating CPTs for “Driver reaction time” node. In this instance, the inference mechanism focuses on ascertaining the “Driver reaction time” with respect to the parent nodes states: “Driver Condition”, “Distracted?” and “Visibility”.

Gaussian is the membership function that is utilized for each node in the graph since it produces less inaccuracy than other triangle and trapezoidal functions [96].

In several previous researches, the Gaussian membership function was widely employed [97], [98], [99]. It is identified by two parameters, the mean (m) and the standard deviation (k), as represented by Eq. (2).

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

Fig. 3 illustrates an example of how the Gaussian membership function is used to describe the variable “Driver reaction time”.

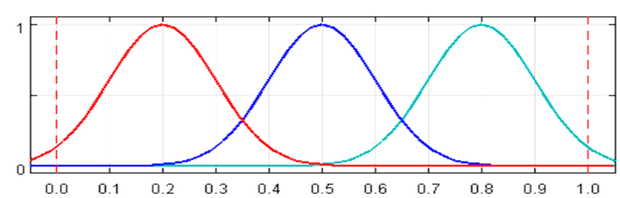

Fig. 3. Membership functions of “Driver reaction time” variable.

Once the membership functions for the “Driver reaction time” nodes and its precursors (Driver Condition, Distraction, Visibility) are established, a fuzzy rule base is then formulated. This set of rules evaluates the variability of the "Driver reaction time" node based on the conditions or factors affecting its parent nodes. The specifics of this fuzzy rule base are outlined in Table IV.

TABLE IV. FUZZY RULES OF THE "DRIVER REACTION-TIME" NODE WITH ITS PARENT NODES

Rule	IF Driver condition	AND Distracted	AND Visibility	THEN Diver Reaction Time
1	Bad	Distracted	Good	0.5
2	Bad	Half-Distracted	Good	0.5
3	Bad	Distracted	Medium	0.2
4	Bad	Half-Distracted	Medium	0.2
5	Bad	Distracted	Bad	0.2
6	Bad	Half-Distracted	Good	0.5
7	Medium	Distracted	Good	0.5
8	Medium	Half-Distracted	Good	0.5
9	Medium	Distracted	Medium	0.2
10	Medium	Half-Distracted	Medium	0.2
11	Medium	Distracted	Bad	0.2
12	Medium	Half-Distracted	Bad	0.2
13	Good	Distracted	Bad	0.2
14	Good	Distracted	Medium	0.5
15	Good	Distracted	Good	0.5
16	Good	Half-Distracted	Bad	0.2
17	Good	Half-Distracted	Medium	0.5
18	Good	Half-Distracted	Good	0.8
19	Bad	Not-Distracted	Good	0.5
20	Bad	Not-Distracted	Medium	0.2
21	Bad	Not-Distracted	Bad	0.2
22	Medium	Not-Distracted	Good	0.5
23	Medium	Not-Distracted	Medium	0.2
24	Medium	Not-Distracted	Bad	0.2
25	Good	Not-Distracted	Bad	0.5
26	Good	Not-Distracted	Medium	0.8
27	Good	Not-Distracted	Good	0.8

Subsequently, input values are used to initialize the fuzzy system at the peaks of Gaussian distributions. Fig. 4 shows the fuzzy inference outcome of the variable "Drivers' Reaction-time" knowing that, "Driver Condition" is medium, Diver is not Distracted and "Visibility" 'is medium.

The conclusions of the 18 activated rules from the total 27 rules are consolidated in Table V.

Subsequently, the various outcomes are combined into an aggregate value for every state. This value is the outcome of adding the various conclusions from the rules that were activated using the max technique. Every single triggered conclusion of the activated rules is subjected to the max technique.

The following has thus been calculated:

Drivrs' Reaction-time (Too Long) = max (0.015,0.015,0.015,0.008,0.015,0.995,0.015) = 0.995

Drivers' Reaction-time (Long) = max (0.008,0.008,0.008,0.008,0.008,0.008,0.008) =0.008

Drivers' Reaction-time (Normal) = max (0.008,0.015,0.008,0.008) =0.015

Thus, the variable "Drivers' Reaction-time" will take the values 0.995, 0.008, and 0.015 for Too Long, Long, Normale, respectively. This is achieved by computing the ratio of each state's probability to the total probabilities of all states, thereby obtaining the conditional probabilities table for the node "Drivers' Reaction-time" is this way be obtained as follows:

P (Drivers' Reaction-time = Too Long | Driver Condition= medium, Driver is not distracted, Visibility = medium) = 0.995/ (0.995+0.008+0.015) = 0.98.

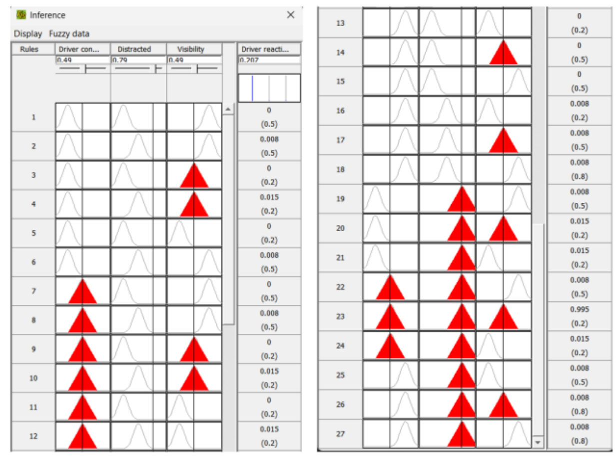

Fig. 4. Fuzzy inference of the variable "Driver Reaction-time".

TABLE V. DEGREE OF MEMBERSHIP FOR EACH FUZZY SUBSET OF THE VARIABLE "DRIVER REACTION-TIME"

Rule activated	Language value of the output variable (Driver reaction time)	Degree of membership
R2	Long (0.5)	0.008
R4	Tool long (0.2)	0.015
R6	Long (0.5)	0.008
R8	Long (0.5)	0.008
R10	Tool long (0.2)	0.015
R12	Tool long (0.2)	0.015
R16	Tool long (0.2)	0.008
R17	Long (0.5)	0.008
R18	Normal (0.8)	0.008
R19	Long (0.5)	0.008
R20	Tool long (0.2)	0.015
R21	Tool long (0.2)	0.015
R22	Long (0.5)	0.008
R23	Tool long (0.2)	0.995
R24	Tool long (0.2)	0.015
R25	Long (0.5)	0.008
R26	Normal (0.8)	0.008
R27	Normal (0.8)	0.008

P (Drivers' Fatigue = Long | Driver Condition= medium, Driver is not distracted, Visibility = medium) = 0.008/ (0.995+0.008+0.015) = 0.01

P (Drivers' Fatigue = Normal | Driver Condition= medium, Driver is not distracted, Visibility = medium) = 0.015/ (0.995+0.008+0.015) = 0.01

We acquired the necessary conditional probabilities to supply the BN by generalizing this strategy to all nodes in the causal graph.

E. Anticipation of Scenarios and Interpretation of Results

By the implementation of BN, we were able to investigate how certain nodes' combinations of states affected others within the causal graph. The following sections will assess the probability of an accident by analyzing four distinct scenarios combining different situation of road, traffic, driver, planning and vehicle condition, scenarios are listed below:

- Scenario 1 (S1): Fig. 5, all parameters (road, traffic, driver, planning and vehicle condition) are favourable.
- Scenario 2 (S2): Fig. 6, the parameters related to road & traffic are favourable, the parameters related to the driver and planning are unfavourable and the parameters related to vehicle condition is favourable.
- Scenario 3 (S3): Fig. 7, the parameters related to road & traffic are unfavourable and the parameters related to the driver, planning and to the vehicle condition are favourable.
- Scenario 4 (S4): Fig. 8, the parameters related to road, traffic, driver and planning are favourable and the parameters related to the vehicle condition are unfavourable.

The input parameters associated with road & traffic are those related to road lighting, road cleaning after accident, speed limited, road design, road surface condition and traffic flow.

The input parameters linked with driver are those related to reaction time, driver style, driver condition, hard acceleration, speed limits respects, safety distance respect and hard breaking.

The input parameters associated with delivery planning are those related to kilometers to be covered, number of exchanges, delivery period and truck fill rate.

The input parameters associated with vehicle condition are those related to physical vehicle condition and stopping distance.

Table VI provides details of the four scenarios selected. Each scenario corresponds to a particular arrangement of the input node states.

Once the BN is given the states of each scenario, the inference mechanism facilitates the propagation of probabilities across intermediate effects and final outcomes, ultimately assessing the likelihood of an accident occurrence. The probability distribution for each scenario's likelihood of the occurrence of an accident is shown in Table VII and Fig. 9.

F. Model Validation

The validation of the BN ensures the credibility and accuracy of the outcomes generated by the model. For this reason, an approach based on three axioms was applied to validate the produced BN. The axioms in question were originally proposed by [100] and widely adopted by several researchers such as [8], [88], [101], [102], [103], [104], [105].

The following is the three axioms' guiding principle:

- Axiom 1: a change in the parent node's must also affect the child node's probability.
- Axiom 2: any alteration in the parent node's probability distributions must consistently affect the child node.
- Axiom 3: the combined effect of all parent nodes must be larger than the influence of any one parent.

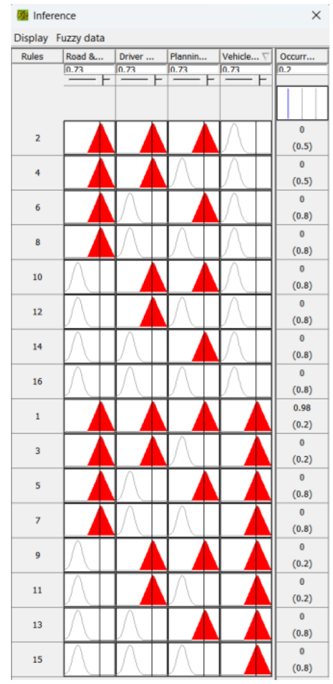

Fig. 5. Fuzzy inference of the variable “Occurrence of Accident” with (S1).

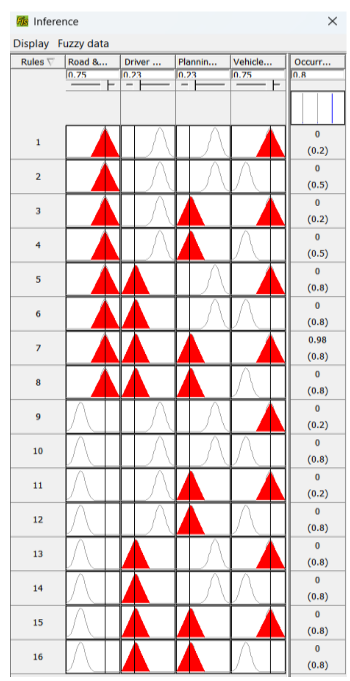

Fig. 6. Fuzzy inference of the variable “Occurrence of Accident” with (S2).

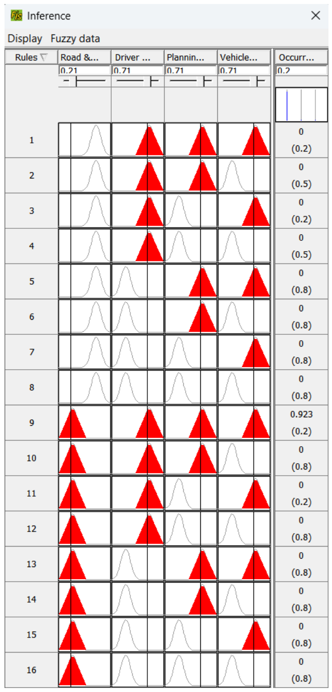

Fig. 7. Fuzzy inference of the variable “Occurrence of Accident” with (S3).

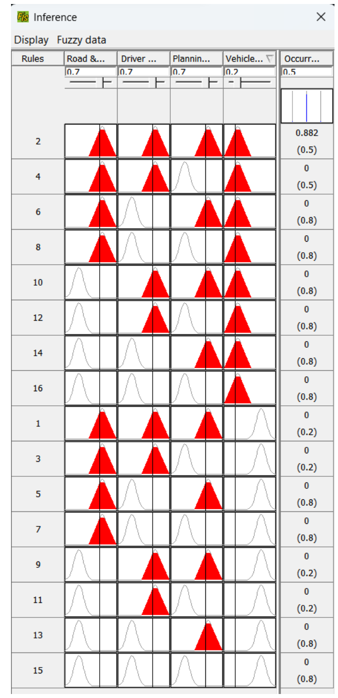

Fig. 8. Fuzzy inference of the variable “Occurrence of Accident” with (S4).

TABLE VI. INPUT PARAMETER VALUES ACCORDING TO THE SCENARIOS STUDIED

		S1	S2	S3	S4
Road & Traffic parameters	Road lighting	Bright	Bright	Obscurity	Bright
	Road Cleaning after accident	Appropriate	Appropriate	Inappropriate	Appropriate
	Speed limited	Limited	Limited	Not-Limited	Limited
	Road design	Save	Save	Dangerous	Save
	Road surface condition	Dry	Dry	Wet	Dry
	Traffic flow	Smooth	Smooth	Stop-and-go	Smooth
Driver parameters	Reaction time	Normal	Too Long	Normal	Normal
	Driver style	Good	Bad	Good	Good
	Driver condition	Good	Bad	Good	Good
	Hard acceleration	Low	Hard	Low	Low
	Speed limits respects	Respected	Not-Respected	Respected	Respected
	Safety distance respect	Respected	Not-Respected	Respected	Respected
	Hard breaking	Low	Hard	Low	Low
Planning parameters overload		Minimum	Maximum	Minimum	Minimum
Vehicle condition	Physical vehicle condition	Good	Good	Good	Bad
	Stopping distance	Short	Short	Short	Long

TABLE VII. DISTRIBUTION OF PROBABILITIES FOR BN VARIABLES

Variable	Value	S1	S2	S3	S4
Occurrence of accident	No accident,	98%	1%	92.30%	5.90%
	Possible injury	1%	1%	3.85%	88.20%
	Fatal injury	1%	98%	3.85%	5.90%

Validation analyses were performed on every node within the graph to confirm the adherence to the three axioms. The results of verifying axioms 1 and 2 for the "Driver's reaction" node are presented in Table VIII and Table IX To evaluate the influences of the parent nodes "Driver's condition" and "Visibility" on the child node "Driver's reaction," their probabilities were respectively increased by 10% and 20%, then decreased by 5% and 10%. It was observed that when the probability of the "Driver's condition" node was raised by 20%, the probability of the "Driver's reaction" node escalated from 52.3% to 65%. Conversely, when the probability of the "Driver's condition" node was reduced by 10%, the probability of the "Driver's reaction" node increased to 50.1%. The responses of the "Driver's reaction" node to other increments and decrements were consistent, affirming the stability of the developed network.

In relation to the validation of axiom 3, the data in Table X indicates that a more substantial increase results when all parent elements of the 'Driver's reaction' node are elevated to 100%, compared to the increase observed when only a single parent element is separately enhanced. This observation aligns well with the principles of axiom 3.

TABLE VIII. AXIOM 1 VERIFICATION

	Parent node: Driver's condition	Child node: Driver's reaction
20% increase	70 %	65 %
10% increase	60 %	65 %
A priori probability	50 %	52.3 %
5% decrease	45 %	50.5 %
10% decrease	40 %	50.1 %

TABLE IX. AXIOM 2 VERIFICATION

	Parent node: Visibility	Child node: Driver reaction time
20% increase	70 %	80 %
10% increase	60 %	79.9 %
A priori probability	50 %	77.7 %
5% decrease	45 %	72.6 %
10% decrease	40 %	65 %

TABLE X. AXIOM 3 VERIFICATION

Driver condition	Distracted	Visibility	Drivers' Reaction-time	Changes' Percentage
85%	34%	51%	50.5%	
100%	34%	51%	51.3%	0.8%
85%	100%	51%	77.4%	26.9%
85%	34%	100%	65.0%	14.5%
100%	100%	100%	80.0%	29.5%

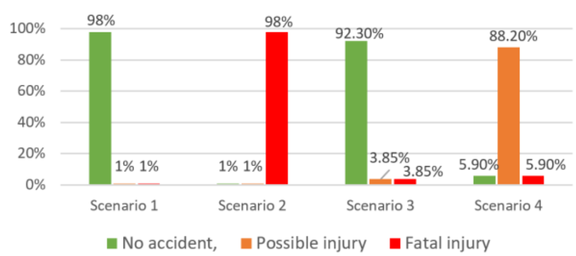

Fig. 9. Probability of accident's occurrence of the different scenarios.

IV. RESULTS

This paper introduces an analysis of potential accidents using a Bayesian fuzzy model, which incorporates numerous internal and external factors contributing to accidents. The interpretation of results from four scenarios reveals that driver behavior and delivery planning (scenario 2) exert a more significant influence on accident occurrences compared to other factors. This indicates that driver behaviors, delivery planning, and vehicle condition have a considerable effect on the occurrence of accidents compared to parameters related to road and traffic conditions.

V. DISCUSSION

The results highlight the importance of monitoring driver behaviors and implementing smart routing planning designs to avoid road accidents. Given that driver behavior and delivery planning have a more significant impact on accident occurrences, transport companies should prioritize these areas in their safety measures. The findings suggest that a focus on driver training, regular vehicle maintenance, and optimized delivery schedules can substantially reduce the risk of accidents.

VI. CONCLUSION

This paper explores the importance of recognizing and preventing risk elements to enhance road safety, with a particular focus on the various factors that increase the likelihood of accidents. According to bibliographical research and expert perspectives, road accidents are not caused by a single factor but by a complex interplay of multiple factors connected by causal interactions. By using the proposed fuzzy Bayesian Network approach, road traffic injuries will decrease, logistics delivery efficiency will increase, and visibility will be at a high level. However, the computational expense of inference in fuzzy Bayesian networks remains a challenge, particularly for large or multistate networks, highlighting the need for further research and optimization in this area.

Future work will focus on optimizing the computational efficiency of the fuzzy Bayesian Network approach to make it more practical for real-time applications. This could involve the development of more efficient algorithms or the use of advanced computational resources. Additionally, further research will be conducted to expand the model to incorporate a broader range of factors and scenarios, enhancing its predictive accuracy and applicability. Collaborations with industry stakeholders and policymakers will also be sought to implement and test the model in real-world settings, providing valuable feedback for continuous improvement. Finally, exploring the integration of this model with other predictive technologies, such as machine learning and big data analytics, will be a key area of investigation to further enhance road safety measures.

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