Study of Road Traffic Accidents based on Human Factors Analysis and Classification System (HFACS) using Fault Tree Analysis and Machine Learning Models

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(2023)

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A thesis submitted to the in partial fulfilment of the requirements for the degree

of

Master of Science in

Transportation Engineering

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DEDICATION

“To My Inspirational, Caring and Beloved Parents, Without Whom This Wouldn’t be Possible”.

ACKNOWLEDGEMENTS

I would like to express my sincere gratitude to my supervisor, **Dr. Sameer-ud-Din**, for their exceptional guidance, support, encouragement, and motivation throughout the course of this research work. I would also like to thank my G.E.C members, **Dr. Kamran Ahmed** and **Dr. M Usman Hassan**, for their valuable insights and feedback. Finally, I would like to thank my fellow students at the National University of Science and Technology for their constant support and guidance.

ABSTRACT

Globally, approximately 3700 people die daily in RTAs, resulting in 50 million injuries or disabilities, and 1.35 million deaths annually, contributing to 3% of the GDP of most underdeveloped countries in the world. According to the NHTSA, factors related to human contribute approximately 94% of all RTAs. Accident analysis can be approached by two methods, the Person-Based and System-Based approaches. The Person-Based method concentrates on unsafe acts such as errors and violations committed by users due to abnormal processes such as poor motivation, restlessness, forgetfulness, inattention, and negligence. Whilst, the System-Based Approach recognizes that human errors are inevitable, regardless of facility quality, where errors are considered as consequences rather than causes. A lot of work has been done on person-based approach as compared to system-based approach. Our study has focused on System-Based approach by utilizing a holistic approach that combines HFACS, FTA and Machine Learning models to achieve a good understanding of the intricate interplay among human factors that assist in predicting accidents.

Keywords: Traffic Safety, Fuzzy Logic, Machine Learning, ANN, Fault Tree,

System Based Approach.

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LIST OF ABBREVIATIONS AND ACRONYMS

RTA	Road Traffic Accident
WHO	World Health Organization
GDP	Gross Domestic Product
DBQ	Driver Behaviour Questionnaire
HFACS	Human Factors Analysis and Classification System
STAMP	Systems-Theoretic Accident Model and Processes
FT	Fault Tree
FTA	Fault Tree Analysis
ML	Machine Learning
F-AHP	Fuzzy Analytic Hierarchy Process
AHP	Analytic Hierarchy Process
ANN	Artificial Neural Network
DNN	Deep Neural Network
MSE	Mean Squared Error
BE	Basic Event
TE	Top Event
IE	Intermediate Event
LM	Levenberg–Marquardt
ADAM	Adaptive Moment Estimation
DAG	Directed Acyclic Graph
MCS	Minimal Cut Set

CHAPTER 1: INTRODUCTION

Road crashes have resulted in injuries, loss of lives, and damage to properties [1]. Since the first death involving a motor vehicle on August 31, 1869, road traffic accidents (RTAs) have been on the rise [2]. Currently, RTAs are a major cause of death globally, with developing countries being disproportionately affected due to economic constraints as compared to developed nations [2][3]. The estimated cost of a road crash is USD 65 million, and $518 million for middle- and low-income countries [4][5]. This increase in road users over time caused congestion and increment in the occurrence for RTAs. This increment in traffic is mostly related to urban sprawl as the economic activities and development are centered around urban/city units.

Advancements in technology and scientific growth have led to prosperity but have also caused a significant increase in RTAs [6]. In 2008, the World Health Organization (WHO) published a report ranking losses from RTAs as 8th foremost cause of injuries and death [7]. The report predicted that RTAs would be developed as the 5th foremost cause of death in 2030 [8], and traffic injuries would increase to 65% in the following two decades if the current pace continued [9]. The aftermath of RTAs is difficult to estimate due to tangible and intangible costs, including pain and suffering, loss of job opportunities, and the direct and indirect costs of police and court proceedings, insurance, medical rehabilitation, etc. [10]. Globally, approximately 3700 people die daily in RTAs, resulting in 50 million injuries or disabilities, and 1.35 million deaths annually, contributing to 3% of the GDP of most underdeveloped countries in the world [7]. Furthermore, approximately 93% of the fatalities in world are due to RTAs occurring in middle- and low- income countries.

Factor related to human associated with driving include driving style and driving skills [11]. DBQ is widely used to measure driver styles, based on the theoretical classification of errors related to human that categorizes aberrant behavior into violations and errors. The definition of errors is “failure of planned actions to achieve the intended consequence” and are typically due to slips, lapses, or mistakes [12]. Slips refer to memory failures, actions that don’t have their intended consequences, and faults are letdowns in a plan of action, even if implementation is done correctly [13]. Violations, likewise, are “deliberate deviations from those practices believed necessary to maintain the safe operation of a potentially hazardous system” [12][13]. Ordinary violations include acts that are performed against standard operating procedures (SOPs) and are not recognized as safe driving, while aggressive violations contain a violent component while that activity is being performed [14].

Accident Analysis can be approached over two methods, the Person-Based and System-Based approaches. The Person-Based Method concentrates on unsafe acts such as errors and violations committed by users due to abnormal processes such as poor motivation, restlessness, forgetfulness, inattention, and negligence. Countermeasures used aim to reduce unwanted variations in human behavior, such as poster campaigns, disciplinary measures, threats of litigation, blaming, and shaming. On the other hand, the System-Based Approach recognizes that human errors are inevitable, regardless of facility quality. In this method, errors are considered as outcomes rather than causes. Thus, human nature is not deemed the main cause, but rather the recurrent error traps in the workplace and organizational processes that give rise to them. The underlying concept is that the human situation cannot be altered, nevertheless the condition under which humans work can. In case of an unwanted event, the critical issue is not who committed the error but how and why the system failed.

An accident causation model is crucial for investigating and analyzing accidents [15]. Models aid in guideline development, validation, analysis, causality determination, and communication [16]. The systems approach originated in the early 1900s and is a well-established philosophy that emphasizes that safety, as well as accidents in complex sociotechnical systems, results from emergent properties that arise due to nonlinear interactions among the components of such systems [17]. The systems approach is recognized as a suitable means of comprehending and preventing accidents in complex and critical areas such as mining, transport and storage, and railways [18][19]. Nevertheless, systems theory and its application to road protection are often overlooked or neglected in literature reviews. Conventional methods used in road safety have limitations, such as the failure to account for interactions between the road road-user, the vehicle, and the environment [20]. Researchers have acknowledged that systems approaches have the potential to address some of these limitations. Some researchers have employed systems dynamics methodology, AcciMap, STAMP model, cognitive work analysis (CWA), HFACS, CFIM to analyze road safety policies, illustrate the interdependencies involved in road freight accidents, explore beach driving, and analyze road traffic accidents [21][22][23]. Despite the burgeoning number of studies investigating road traffic accidents, a noticeable gap persists in the literature concerning the integration of various analysis methodologies.

Although some studies have employed either the HFACS, FTA, Fuzzy Analytic Hierarchy Process (FAHP), or Machine Learning individually, few have sought to amalgamate all four methods into a comprehensive systems approach to examine the multifaceted factors contributing to accidents. In this research, we endeavor to bridge this gap by utilizing a holistic approach that blends HFACS, FAHP, FT, and ML models to gain a good knowledge of the intricate interplay among human factors that precipitate road accidents. By so doing, our study aims to offer a more comprehensive depiction of the factors involved and uncover novel insights into how to avert accidents and enhance road safety.

1.1 Problem Statement

Current accident analysis methods focus on the person-based approach. This approach is insufficient to identify the root causes of RTAs. Therefore, a holistic system-based approach is needed to understand the complex interaction between different human factors that contribute to accidents.

1.2 Research Objective

There are 3 main research objectives:

1. Identification of key human factors that contribute to the RTAs.
2. Development of FT model for capturing the interaction between human factors that contribute to the RTAs.
3. Prediction of failure occurrence probability of RTAs using ML models.

1.3 Aims and Scope of Study

The focus of the study is to develop a holistic system-based approach to accident analysis using HFACS, FT, Fuzzy Logic and ML models that can be used to identify the root causes of road traffic accidents (RTAs). This approach will focus on the complex interactions between different human factors that contribute to accidents.

1.4 Importance of Research Work

Globally, approximately 3700 people die daily in RTAs, resulting in 50 million injuries or disabilities, and 1.35 million deaths annually, contributing to 3% of the GDP of most underdeveloped countries in the world. According to the NHTSA, factors related to human contribute approximately 94% of all RTAs. This research focuses on developing a comprehensive methodology that integrates HFACS, FT, Fuzzy Logic and ML models to capture complex interactions between different human factors that contribute to accidents. This will help in performing preventive measures for RTAs.

CHAPTER 2: LITERATURE REVIEW

Road transportation is a complicated system comprising roadways, vehicles, individuals, and environment. To successfully manage risks in this system, it is crucial to possess a comprehensive knowledge of the diverse features (e.g., vehicle design, road and traffic system infrastructure, driving regulations, and maintenance protocols for both roads and vehicles) contributing to traffic accidents. Understanding the elements that contribute to traffic accidents is essential for developing effective strategies to minimize their occurrence. Peden et al. [24] identified infrastructure, environmental, vehicular, and human factors as the primary causes of traffic accidents. Addressing these factors can improve road traffic safety and reduce accidents. However, as stated by Stanton and Salmon [44], there is currently a lack of a systematic and reliable approach for assessing the impact of human factors on RTAs. Human error along with driving behavior issues were found to cause around $3/4^{th}$ of traffic accidents. Di Pasquale et al. [26] discovered that 60-90% of RTAs were solely responsible for human error related factors, with technical defects accounting for the remaining incidents. Their study suggests that error caused by human is accountable for approximately 85% of RTAs.

Numerous studies have explored the factors contributing to traffic accidents. Laaraj and Jawab [27] divided research methods into two distinguish groups: traditional and systematic. The former method concentrates on identifying human factor errors (e.g., fatigue-related issues, and aberrations in driving behavior). This has resulted in a disproportionate focus on driver behavior and a lack of attention to other factors [28]. Jiang et al. [29] analyzed 45 severe accidents and identified critical factors (e.g., "speeding," "improper driver operation," "vehicle overload," "fatigue driving," and "poor driving habits.") The conventional approach primarily relies on driver error but may be overly simplistic and/or limited in its ability to comprehend intricate multi-dimensional nature and complexity of systems. It has focused on adapting strategies covering the enforcement, education, and engineering (3E) domain [30], [31]. It is a common belief that traffic-related fatalities and severe injuries were inherited in the transportation system [32]. Efforts were focused on requiring individuals to adjust to the road network, rather than on creating a network that accommodates individuals [33].

Systematic methods (System-Based Approach) consider a broader range of factors, including environmental, human, and machine-related aspects, to comprehend the intricate nature of transportation systems and identify potential areas for improvement. Scandinavian researchers were swayed by the revolutionary work of Gordon and Haddon and began to treat the road and its components as a whole, proposing that multiple stakeholders must collaborate effectively to ensure the overall safety of the transport system of road [33], [34][35]. In 1990s, the concept of a "forgiving" system emerged, where traffic accidents would not necessarily result in fatalities [36]. Originally, Safe System had four mainstays that worked together to create a safe operating system: vehicle, road, speed and people. Later post-crash care, was further added because the event succeeding a crash usually plays a central role in dropping the effect of injury or fatality [37]. Common System-Based Approach includes CREAM [38], Accident Map [39], STAMP [40], HFACS [60], etc. It is evident from both traditional and systematic methods that human behavior, particularly driving habits, is the primary reason for RTAs. Therefore, conducting an inclusive human factor analysis that effect on the system is critical.

Assessing human factors in road traffic accidents is challenging due to the inadequate data, necessitating an analysis that acknowledges the ambiguity and vagueness. Evaluation methodologies can be categorized into expert judgments and experiential techniques. Experiential techniques emphasized data collection on factors related to human, with a huge human reliability catalogue, as established from personal experiences, literature, and interviews [37]. Expert judgment is given increased consideration because of its excellence in handling complexity and vagueness. HFACS is a classification model to investigate human factors, originally used in aviation accidents by the US military [41]. The framework for examining human-caused accidents is based on identifying "active failures" and "latent failures" using Swiss cheese model [42]. This model is categorized into four stages: "unsafe behavior," "preconditions for unsafe behavior," "unsafe supervision," and "organizational influence."

The application of HFACS has been widespread and extensively employed in various fields, such as investigation errors in mining, railways, healthcare, fright in the sea, the construction industry, etc. Due to certain limitations of conventional methods related to human error, HFACS has been often submerged with other hazard examination techniques. For example, Wei et al. [43] employed a blend of HFACS, expert assessment, and Grey System Theory to examine errors related to humans in aviation incidents. [44] employed a “fuzzy TOPSIS” approach in conjunction by HFACS to evaluate various routine preservation tasks in air transportation. Hsieh et al. [45] synergistically integrated TOPSIS, AHP, and HFACS to assess the error related to human in Taiwanese ICUs. In another study, Akyuz [46] effectively employed a combination of the ANP and HFACS to comprehensively investigate and understand the factors contributing to severe incidents of gas leakage caused by liquefied petroleum carriers. Akyuz and Celik [47] successfully combined the CM approach with HFACS, enabling a comprehensive evaluation of marine accidents. Chen et al. [48] conducted a comprehensive study where they successfully integrated Prospect Theory, HFACS and interval type-2 fuzzy numbers to investigate and analyze vessel accidents, enabling a greater knowledge of the underlying issues contributing to such incidents. Furthermore, numerous research investigations have been conducted to validate the dependability of the HFACS, demonstrating its efficacy in scrutinizing factors within an organization or system [49], [50]. Zhang et al. [51][52] utilized the HFACS as a tool to examine the numerous features that impact main RTAs in China. The model is categorized to five stages: "unsafe behavior", "preconditions for unsafe behavior", "unsafe supervision", "organizational influence" and "external factors." However, the inherent vagueness and uncertainty that come with analyzing human factors for road traffic accidents necessitate the integration of Fuzzy Logic, F-AHP, and FT Analysis with HFACS.

CHAPTER 3: THEORETICAL FRAMEWORK

3.1 Fuzzy Logic

There are three methods to address failure probabilities: statistical methods, extrapolation, and expert judgment [53]. The scientific consensus technique of expert judgment is used in this research to assign weights to human factors conducive to RTAs and to evaluate the proficiency of participating experts. Experts provide opinions based on their knowledge, motivations, and cognitive attributes, leading to different analytical models [54]. Various techniques, (e.g., SAM, game theory, max-min Delphi, and fuzzy priority relations), have been developed for aggregating expert opinions [55]. However, experts often provide ambiguous or imprecise expressions in their opinions. To address this issue, AHP and fuzzy set theory are commonly combined to effectively combine ambiguous expert opinions.

According to fuzzy set theory, a fuzzy number [56] $M \in F(R)$ can be defined and called a fuzzy number, if:

$$\left.\begin{array}{ll} \mu_M(x_0) = 1 & x_0 \in R \\ A_\alpha = [x, \mu_{A_\alpha}(x) \geq \alpha] & \alpha \in [0, 1] \end{array}\right\} \quad (1)$$

where:

$F(R)$	represents all fuzzy sets,
R	is the set of real numbers,
μ	is the membership function.

Trapezoidal and triangular and fuzzy numbers can be used instead, and the suitability be contingent on the thorough situation. It is created on the meaning explained earlier that the fuzzy number M on R can be defined as a triangular fuzzy number if its membership function $\mu_M(x) : R$à $[0,1]$ is equal to the following:

$$\mu_M(x) = \begin{Bmatrix} \frac{x}{a_2 - a_1} - \frac{a_1}{a_2 - a_1}, & x \in [a_1, a_2] \\ \frac{a_3}{a_3 - a_2} - \frac{x}{a_3 - a_2}, & x \in [a_2, a_3] \\ 0 & \text{otherwise} \end{Bmatrix} \tag{2}$$

where:

a_1 represents lower value,

a_3 represents the upper value, and

a_2 represents the modal value of M and $(a_1 < a_2 < a_3)$.

So, the triangular fuzzy number can be defined as $M(a_1, a_2, a_3)$. Likewise, for other fuzzy number $N(a_1, a_2, a_3, a_4)$, we can define as follows:

$$\mu_N(x) = \begin{Bmatrix} \frac{x}{a_2 - a_1} - \frac{a_1}{a_2 - a_1}, & x \in [a_1, a_2] \\ 1 & x \in [a_2, a_3] \\ \frac{a_4}{a_4 - a_3} - \frac{x}{a_4 - a_3}, & x \in [a_3, a_4] \\ 0 & \text{otherwise} \end{Bmatrix} \tag{3}$$

For instance, if $N(b_1, b_2, b_3)$ and $M(a_1, a_2, a_3)$ are two different fuzzy numbers, the following operations can be performed:

$$M \oplus N = (a_1, a_2, a_3) \oplus (b_1, b_2, b_3) = (a_1 + b_1, a_2 + b_2, a_3 + b_3) \tag{4}$$

$$M \otimes N = (a_1, a_2, a_3) \otimes (b_1, b_2, b_3) = (a_1 b_1, a_2 b_2, a_3 b_3) \tag{5}$$

$$\gamma \odot N = \gamma \odot (b_1, b_2, b_3) = (\gamma b_1, \gamma b_2, \gamma b_3) \quad \gamma > 0, \gamma \in R \tag{6}$$

$$M^{-1} = (a_1, a_2, a_3)^{-1} = (\frac{1}{a_3}, \frac{1}{a_2}, \frac{1}{a_1}) \tag{7}$$

AHP and fuzzy set theory has been integrated to address the imprecise language used by experts when providing judgments. This integration allows for a more nuanced and flexible interpretation of opinions, resulting in more accurate aggregations. The linguistic expressions of experts are of utmost importance when dealing with complex situations and arriving at meaningful conclusions. The relationship between ambiguous expressions and corresponding fuzzy numbers is essential in complex situations. Numerous tries have been done to transform vague linguistic expressions of experts into their appropriate fuzzy numbers [57][58]. To transform vague expressions into fuzzy numbers, Chen and Hwang's approach, which uses eight scales to represent verbal expressions associated with target events, is widely recognized. These scales range from two to thirteen linguistic terms, and the optimal range for identifying human factors through expert judgment methodology is between five and nine verbal terms [57]. This range is suitable because human memory capacity typically consists of seven terms with a margin of plus or minus two. Therefore, utilizing a range of five to nine verbal terms is believed to be most suitable for accurately and effectively identifying human factors via expert judgment [57][58].

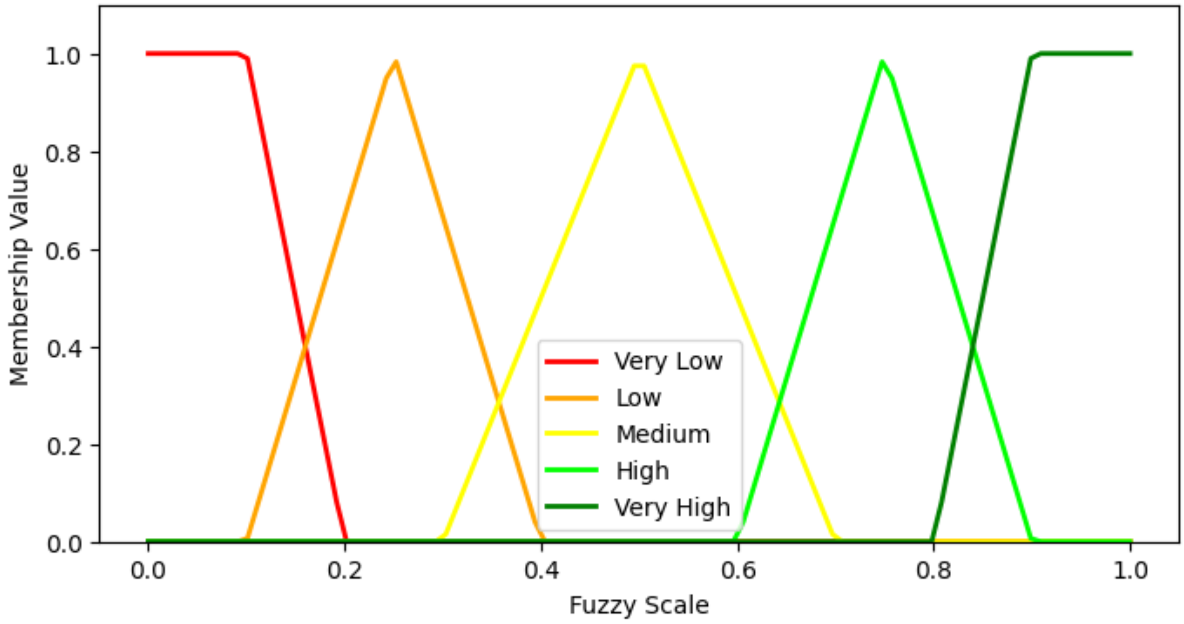

Figure 3-1: Fuzzy scale representation of conversion scale 6

Table 3-1: Verbal Expressions with Corresponding Fuzzy Number [57]

Linguistic expressions	Scale 1	Scale 2	Scale 3	Scale 4	Scale 5	Scale 6	Scale 7	Scale 8
None								(0,0,0.1)
Very Low			(0,0,0.2)		(0,0,0.1,0.2)	(0,0,0.1,0.2)	(0,0,0.2)	(0,0.1,0.2)
Low-very							(0,0,0.1,0.3)	(0.1,0.2,0.3)
Low		(0,0,0.2,0.4)	(0.1,0.2,0.3)	(0,0,0.3)	(0,0.2,0.4)	(0.1,0.25,0.4)	(0,0.2,0.4)	(0.1,0.3,0.5)
Fairly Low				(0,0.25,0.5)	(0.2,0.4,0.6)		(0.2,0.35,0.5)	(0.3,0.4,0.5)
More or Less Low								(0.4,0.45,0.5)
Medium	(0.4,0.6,0.8)	(0.2,0.5,0.8)	(0.3,0.5,0.7)	(0.3,0.5,0.7)		(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.3,0.5,0.7)
More or Less High								(0.5,0.55,0.6)
Fairly High				(0.5,0.75,1)	(0.4,0.6,0.8)		(0.5,0.65,0.8)	(0.5,0.6,0.7)
High	(0.6,0.8,1)	(0.6,0.8,1,1)	(0.6,0.8,1)	(0.7,1,1)	(0.6,0.75,0.9)	(0.6,0.75,0.9)	(0.6,0.8,1)	(0.5,0.7,0.9)
High-very High							(0.7,0.9,1,1)	(0.7,0.8,0.9)
Very High			(0.8,1,1)		(0.8,0.9,1,1)	(0.8,0.9,1,1)	(0.8,1,1)	(0.8,0.9,1)
Excellent								(0.9,1,1)

3.2 HFACS framework

The HFACS is a method of classification that examines human error among accidents through evaluating the human's behavior. The HFACS model [41] is based on the "Swiss cheese model", which highlights the administrative aspect of accident causality [42]. The model consists of four stages: "unsafe behavior", "preconditions for unsafe behavior", "unsafe supervision" and "organizational influence". Each layer of the HFACS model serves as a barrier, with each layer affecting the layer above it. The aim of the model is to lessen the occurrence of accidents and errors at all levels of the system. To enhance the model's effectiveness, a fifth layer of "external factors" was proposed to account for factors such as the economy, law, and policy. The efficiency of the model was analyzed in the setting of accidents in marine by Chauvin C [59]. A five-level framework of HFACS has also been used in HFACS-Grounding [60], HFACS-Coll [80], and HFACS-MAM [62].

HFACS is widely used in various industries (e.g., mining, railways, healthcare, sea freight, construction industry, etc.) to identify human errors, but it has been found to have some limitations when used alone. To overcome these limitations, other methods have been combined with HFACS. For example, a combination of the F-AHP and the HFACS was used to identify acute factors contributing to human-error in the nuclear control room, and a combination of fuzzy TOPSIS, AHP, and HFACS was used to detect and prioritize failure approaches in medical events [63][64]. It is imperative to note that the factors related to human identified within each layer of HFACS are subject to interpretation within the specific situation being investigated. This suggests that the factors identified within each layer may vary as the investigation progresses.

3.3 Analytic Hierarchy Process (AHP)

Saaty proposed AHP [65] as a decision-making tool that has been extensively used by various researchers to evaluate complex multi-criteria alternatives [85][86]. It helps to break down a complicated problem into straightforward criteria which is grounded on three values (i.e., Problem Disintegration, Proportional Assessment, and Relative Importance Amalgamation). The issue is disintegrated into a ordered construction of criteria and sub-criteria, and then pairwise comparisons are made to determine their relative importance. The resulting rankings are calculated using the Eigen vector method, and the reliability of the explanation is verified using the ratio. [68]–[70]

Table 3-2: Scale of Analytic Hierarchy Process (AHP)[66], [67]

Degree of Preference	Definition	Explanation
1	Equally Important	Both criteria are equally important
3	Moderately Important	Experience strongly favors one criterion over another
5	Highly Important	Experience and judgment strongly favor one activity over another
7	Very Highly Important	A criterion is highly dominated over other
9	Extremely Important	The evidence favoring one criterion over another is of the highest possible order of assertion
2,4,6,8	Intermediate Values	If a compromise between two criteria is required, intermediate values can be used

The equation below can be used to assess the reliability of the influences for comparative importance applied throughout the pairwise judgement.

$$Consistency\ Ratio\ (\mathrm{CR}) = \frac{CI}{RI} \tag{8}$$

where:

CI is consistency index,

RI is randomness index.

The Consistency Index (CI) is calculated as follows:

$$Consistency\ Index\ (CI) = \frac{(\lambda_{max} - n)}{n - 1} \tag{9}$$

where:

$\boldsymbol{\lambda_{max}}$ represents major Eigen value,

n is order of matrix.

Randomness index values depend on the value of n. **Table 3-3** shows the randomness index (RI) for different values of n.

Table 3-3: Randomness Index (R.I.) [68]

Number of Criteria	1	2	3	4	5	6	7	8
RI	0.0	0.0	0.58	0.9	1.12	1.24	1.32	1.41
Number of Criteria	9	10	11	12	13	14	15	
RI	1.45	1.49	1.51	1.48	1.56	1.57	1.58	

CR is a metric used to verify the constancy of the solution obtained through pairwise comparisons in AHP. For CR is greater than 10%, indicates that the solution is unreliable, and the weights need to be reallocated. However, pairwise comparison is consistent when CR is below 10%.

Researchers have acknowledged that Saaty's AHP method is valuable, but it has some inherent challenges. One significant limitation is the difficulty in accurately assessing the importance of different criteria, which can be influenced by a decision-makers subjective preferences and judgment. To address such limitations, some researchers have integrated fuzzy set theory with Saaty's AHP. For example, Kordi M [71] and Nabeeh N [72] castoff fuzzy theory to address vagueness and ambiguity in human decision-making. A widely used fuzzy scale that displays the conversion of Saaty's scale is as follows:

Table 3-4: Fuzzy Scale [73]

Definition	Saaty Scale	Fuzzy Scale
Equally Important	1	(1,1,1)
Moderately Important	3	(2,3,4)
Highly Important	5	(4,5,6)
Very Highly Important	7	(6,7,8)
Extremely Important	9	(9,9,9)
Intermediate Values	2	(1,2,3)
	4	(3,4,5)
	6	(5,6,7)
	8	(7,8,9)

3.4 Fault Tree Analysis (FTA)

FTA is an established and structured technique commonly used to measure the reliability and safety of safety-critical systems by assessing the likelihood of an accident follow-on from a sequence of faults and failure events. FTA has been extensively used in numerous research areas [74][75][76]. In FTA, the system's failure probability can be broken down into different failure types and causes while reaching the basic failure causes that cannot be further disintegrated.

A fault tree is a DAG with two types of nodes: gates events. Its components are as follows [77]:

- Gates: Boolean connectors that show how failures in subsystems can conglomerate to cause a system failure. Gates have one output and one or beyond inputs, defining their logical relationship between events. AND and OR are frequently used logical gates in FTA.
- Top Events (TE): The uppermost element of the fault tree, which undergoes decomposition into a series of distinct events.
- Basic Events (BE): The bottom "leaves of the acyclic graph" that can't be further disintegrated.
- Intermediate Events (IE): These are "represented by a combination of Basic Events (BE) or other Intermediate Events (IE)" through the logical gates. Intermediate Events (IE) that decompose into Basic Events (BE) are particularly noteworthy as they provide valuable insight into the progression of system failure.

The probability of the Top Event (TE) failing is calculated by analyzing the probability distribution of the Basic events (BE), considering the rational connections between BE and IE.

The logical associations between events in a FT, represented by OR / AND gates, can be mathematically calculated as follows:

$$\phi(x) = \sum_{i=1}^{n} x_i = \{x_1 + x_2 + x_3 + \cdots + x_n\} \tag{10}$$

$$\psi(x) = \sum_{i=1}^{n} x_i = \{x_1 \times x_2 \times x_3 \times \ldots \times x_n\} \tag{11}$$

where:

$\phi(x)$ and $\psi(x)$	are the Top Events (TEs),
x_i	denotes the i^{th} basic contributing factors (BEs),
$\phi(x)$	is activated when there is at least one input factor, and
$\psi(x)$	that is activated when both input factors are present.

3.4.1 Minimum Cut Set (MCS)

Fault Tree Analysis uses Minimum Cut Set (MCS) to determine the minimum set of events or faults that may lead to system failure, allowing for any assessment of a system's structural vulnerability. The MCS is comprised of a set of basic events where the occurrence of all of them would result in system failure. Conversely, if any of these basic events do not occur, system failure is avoided. The following equation represents the MCS:

$$T = MCS_1 + MCS_2 + MCS_3 + \cdots + MCS_N = \bigcup_{i=1}^{n_c} MCS \tag{12}$$

The exact occurrence probability of the Top Event (TE) can be obtained as follows:

$$P(T) = P(MCS_1 \cup MCS_2 \cup MCS_3 \cup \ldots \cup MCS_N) \tag{13}$$

$$= P(MCS_1 + MCS_2 + MCS_3 + \cdots + MCS_N) - (P(MCS_1 \cap MCS_2))$$
$$+\big(P(MCS_1 \cap MCS_3)\big) + \cdots \big(P\big(MCS_i \cap MCS_j\big) \ldots\big) \ldots$$
$$+(-1)^{N-1} P(MCS_1 \cap MCS_2 \cap \ldots \cap MCS_N) \tag{14}$$

where:

N	denotes the number of MCS, and
$P(MCS_i)$	is the occurrence probability of MCS_i.

For instance, a FT has MCS represented as MCS_i, where $i = 1, 2, \ldots, n_c$. The TE "Z" exists if at least one MCS exists [78].

$$Z = MCS_1 + MCS_2 + MCS_3 + \cdots + MCS_N = \bigcup_{i=1}^{n_c} MCS \tag{15}$$

Figure 3-2: Figurative illustration of ''AND" and ''OR" gates in Fault Tree Analysis

3.4.2 Ranking of Minimum Cut Set (MCS)

Fault Tree Analysis allows for the prioritization of each MCS during risk assessment, enabling a focus on the most critical MCS. Vesely–Fussell Importance Measure ($V-FIM$) helps rank MCS represented by the following equation:

$$I_i^{VF}(t) = \frac{Q_i(t)}{Q_s(t)} \tag{16}$$

Where:

$I_i^{VF}(t)$ denotes importance of MCS_i,

$Q_i(t)$ represents the occurrence probability of MCS_i, and

$Q_s(t)$ represents the occurrence probability of the Top Events (TEs) due to all MCS.

3.5 Artificial Neural Network

Artificial Neural Networks (ANNs) offer distinct advantages over Bayesian Networks (BN) due to their ability to capture correlations among input variables, unlike BN which assumes independence of elementary events [79]. ANNs are well-known for their capability to detect and model complex, nonlinear relationships even in the absence of detailed information or prior knowledge about the underlying physical systems. This makes them particularly useful for handling high levels of uncertainty. ANNs consist of interconnected neurons organized in layers, with each neuron's output serving as an input for the next layer [80]. By applying the transfer function to inputs, neurons process signals. The assessment of an Artificial Neural Network's (ANN) capability relies on two critical factors: meticulous selection of suitable training datasets and thoughtful design of the network architecture. A well-developed ANN can learn from known instances, discern functional relationships, and unveil concealed patterns, even in the presence of unknown underlying associations. This allows for predictions and classifications based on new, unseen data, making ANN highly effective in extracting meaningful insights from complex datasets [81].

3.5.1 Algorithm for Artificial Neural Network (ANN)

ANNs consist of interrelated neurons that are distributed across three primary layers: the input layer, intermediate hidden layers, and the output layer. The neurons in input layers form an input vector (X) comprising of $x_1, x_2, ..., x_i, ..., x_n$. Each neuron in the network is associated with weights, W_j, representing connections from the prior layer to the current layer. The weight vector, W_j, includes w_{ij}, indicating the association weight from the i^{th} node in the prior layer to the j^{th} node in the current layer. A bias vector, θ, is incorporated in the ANN, represented as $\theta = (\theta_0, \theta_1, ..., \theta_j)$. Here, θ_0 represents the bias from the last hidden layer to the output layer, while j denotes the number of hidden layers present in the network. **Figure 3-3** illustrates an illustration of a neuron in a classic ANN configuration.

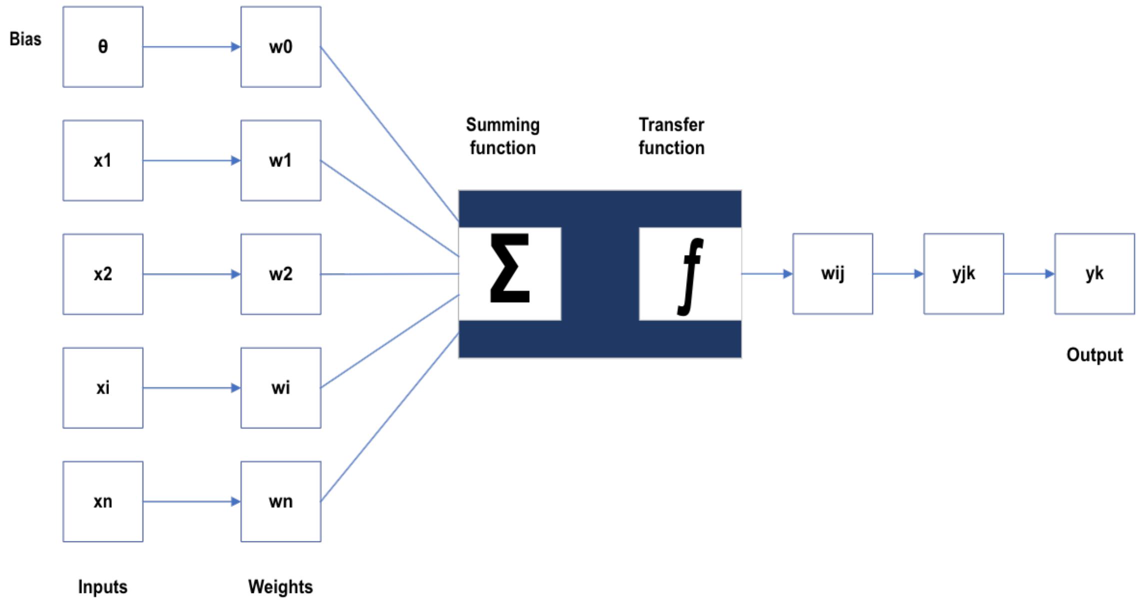

Figure 3-3: Structure of a Neuron in a Classic ANN

The feedforward ANN efficiently processes the provided input vector along with initial weights and bias values to generate accurate prediction values from the output layer. These predictions are obtained through the application of the following equations [82]:

$$Y_{jk} = f_1\left(\theta_j + \sum_i w_{ij}\, I_{ik}\right) \tag{17}$$

$$Y_k = \theta_0 + \sum_j w_j\, Y_{jk} \tag{18}$$

where:

k	is number of neurons at the output layer,
f_1	is transfer function (also known as activation function),
Y_{jk}	is output value of the j^{th} neuron of the hidden layer,
Y_k	represents kth predicted value, and
I_{ik}	is i^{th} input for the k^{th} input vector.

The current study utilizes log sigmoid transfer function, which is the logarithm of the sigmoid function. The sigmoid function is represented as:

$$\text{Sigmoid function} = \frac{1}{1+ e^{-t}} \tag{19}$$

$$\text{log sigmoid} = \log\left(\frac{1}{1+ e^{-t}}\right) \tag{20}$$

The learning process of the network is enhanced by employing the backpropagation algorithm for error calculations and revising biases and weight. The study utilizes the Levenberg-Marquardt (L-M) and Adaptive Moment Estimation (Adams) algorithms to optimize learning performance and minimize errors. Through iterative adjustments of the network's weights and biases, these algorithms contribute to improved accuracy and convergence during the learning phase.

The mathematical expression for Levenberg-Marquardt (L-M) is shown as:

$$x_{(k+1)} = x_{(k)} - [\mathbf{J}^T\mathbf{J} + \mu\mathbf{I}]^{-1}\,\mathbf{J}^T\boldsymbol{e} \tag{21}$$

where:

$\mathbf{J}^T$ is Jacobian of the performance function for weights and biases,

$\boldsymbol{e}$ represents error vector of the proposed network,

$\mathbf{I}$ is identity matrix, and

μ represents the scalar value to ensure a decrease continuously of the value of a performance function.

The mathematical expression for Adaptive Moment Estimation (Adams) is shown as [83]:

$$x_{(k+1)} = x_{(k)} - \alpha \times \frac{\acute{m}_k}{\sqrt{\tilde{V}_k + \varepsilon}} \tag{22}$$

where:

α represents a learning rate,

ε represents a small number to prevent any division by zero in the implementation,

$\acute{m}_k$, $\tilde{V}_k$ represent bias-corrected weight parameters.

During the training phase, the process iteratively improves the network's performance. Nevertheless, the training process may terminate under certain conditions, as indicated [84], which are outlined to ensure proper execution. These conditions serve as critical for determining when to conclude the training process and include factors like reaching the highest number of repetitions, exceeding the allotted training time, achieving the target value of the performance function, surpassing the specified maximum magnitude of the adaptive value μ, and consecutively increases in the performance function values on a validation dataset for a specified number of times.

The procedure is continuously iterated to optimize the network's performance till the error was calculated that meets the predefined patience requirement [85]. Various methods are employed to effectively minimize the overall error, including Huber Loss, Mean Squared Error (MSE), and Mean Absolute Error (MAE). MSE calculates the average squared difference between actual and values, while MAE calculates the average absolute change. Huber Loss combines characteristics of MSE and MAE to offer a more robust loss function. These methods enable accurate error minimization and enhance the performance of regression models. MSE is a commonly preferred and widely used method for minimizing overall error [79]. Its' mathematical expression is as follows:

$$\text{MSE} = \frac{1}{n}\sum_{m=1}^{n}(Y_0 - Y_{pre})^2 \tag{23}$$

where:

Y_0 represents observed network error,

Y_{pre} represents predicted output of the network. Top of Form Bottom of Form

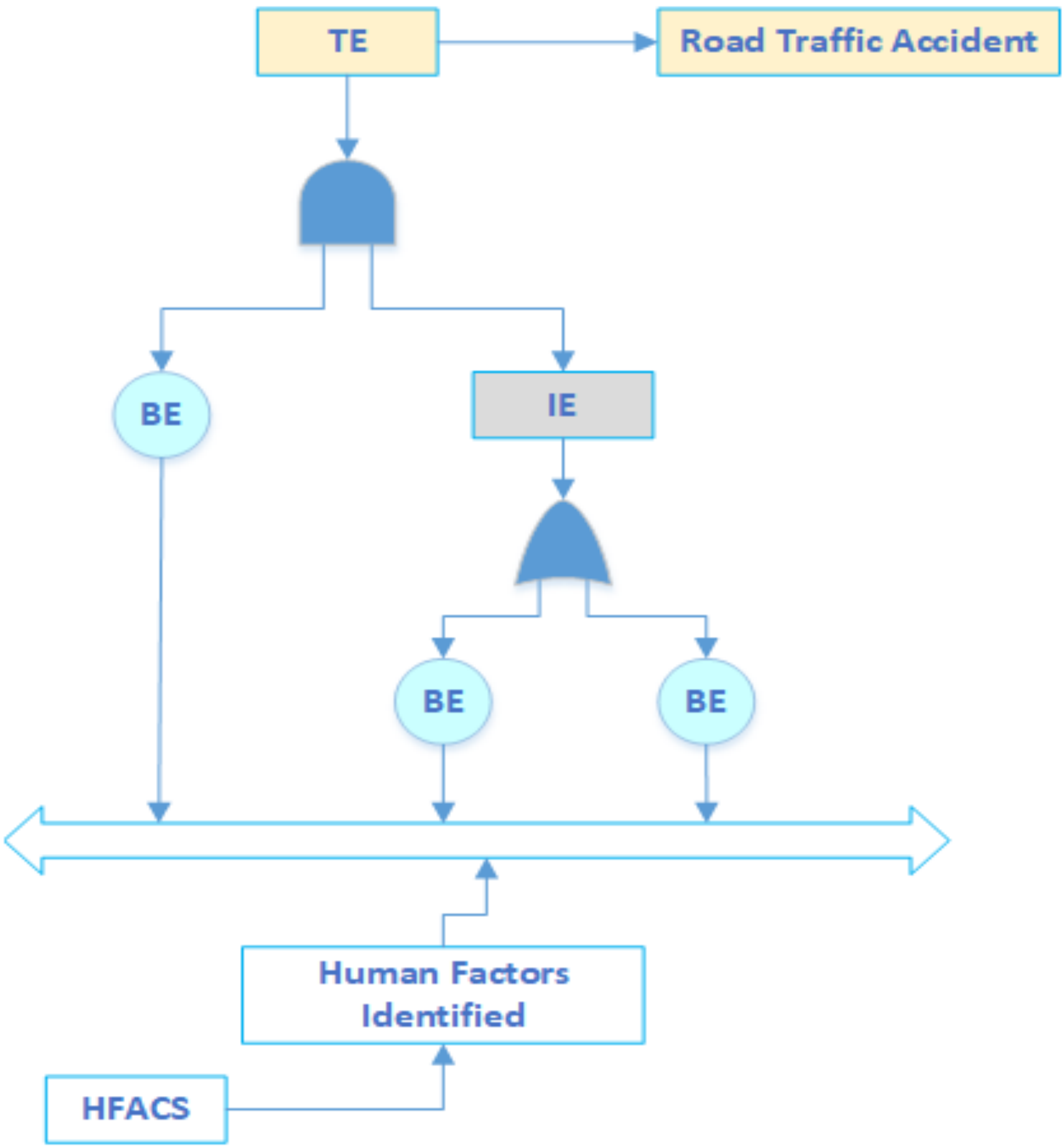

Figure 3-4: *Interplay between FT & HFACS*

3.5.2 *Configuration of ANN Parameters*

Determining the optimal parameters for an ANN is crucial in addressing the challenges of overfitting and underfitting. These parameters encompass many hidden layers and neurons, the choice of learning algorithms, and transfer functions for each layer. Overfitting occurs when there is failure in generalizing the training data due to an excessive information processing capacity, leading to insufficient training for hidden layer neurons. Conversely, underfitting arises when the model lacks enough hidden layer neurons to accurately classify the data.

In practical ANN implementations, a common approach is to use architectures with two hidden layers as it strikes a balance between complexity and performance. Models without hidden layers can only represent linearly separable functions, while networks with three or more hidden layers introduce excessive intricacy and prolong training time exclusive of significant enhancements in productivity [86]. Therefore, careful configuration of the ANN is critical for achieving desirable performance outcomes. By optimizing these parameters, the ANN can effectively process complex datasets while circumventing overfitting and underfitting issues. This meticulous consideration enhances the network's ability to address the specific problem at hand and improves its overall efficiency.

To mitigate the challenges of overfitting and underfitting, several rule-of-thumb approaches have been devised to estimate the ideal hidden layers' number of neurons within an Artificial Neural Network (ANN). These methods aim to strike a delicate balance that avoids both overfitting and underfitting. In current research, a specific rule, proposed in a previous study [87], is adopted. These rules have been selected for their relevance and applicability to the research objectives. Following these rules, the study ensures that the number of neurons for the middle-hidden layers is appropriately determined, enhancing the overall performance of the neural network in achieving its objectives [87]:

1. The number of hidden neurons is recommended to fall within the range bounded by the number of neurons in the output layer and the number of neurons in the input layer.
2. The total number of hidden neurons corresponds to two-thirds of the neurons in the input layer, added to the number of neurons in the output layer.
3. In cases where the feasibility of the former rule is not attainable, it is suggested to set the number of neurons in the first hidden layer to be equal to the count of IEs directly linked to BEs in the FT
4. The number of neurons in the second hidden layer must match the number of IEs directly connected to the TE in the FT. If the second rule cannot be met, it is recommended that the number of neurons in the first hidden layer be equal to the greatest allowable total number of hidden neurons, minus the count of IEs straight linked to the TE in the FT.

CHAPTER 4: METHODOLOGY

To examine the effect of factors related to humans on RTAs, this research proposes an integrated method that combines the HFACS, F-AHP using the Geometric Mean Technique, Fault Tree Analysis (FTA), and Artificial Intelligence (AI). This comprehensive approach aims to effectively address the influence of human factors on RTAs by utilizing multiple methodologies and techniques. Integrating these methods, the research offers a holistic framework for understanding and mitigating the part of human factors in RTAs.

Part 1 applies the HFACS framework to establish specific human factors structure for RTAs, enabling a systematic identification and classification of human-related factors that contribute to accidents. This framework facilitates a comprehensive understanding of the causes of RTAs associated with human elements.

Part 2 concentrates on constructing the Fault Tree structure for RTAs, building on the human factor's framework developed in Part 1. Utilizing the identified human variables, the Fault Tree is visually represented, illustrating the links between various elements and their propensity to cause RTAs. This graphical depiction enhances the examination of the multifaceted interdependencies among factors related to human and their influence on the entire road traffic system.

In Part 3, the failure probability of BE within the FT is computed utilizing the F-AHP and SAM. The inclusion of linguistic factors and expert opinions in fuzzy AHP provides a more accurate assessment of the uncertainty surrounding each event's failure probability. SAM further improves the aggregation of these probabilities by considering similarities between events and incorporating expert judgments.

Part 4 conducts a widespread evaluation and contrast of various machine-learning models to map fault trees. A wide range of ML algorithms, such as Random Forests, SVM, and

Gradient Boosting, are employed to explore their effectiveness in capturing the underlying relationships and patterns in the FT data. Finally, the FT is integrated into an ANN, allowing the logical structure of the FTs to be incorporated into a neural network model. This integration enhances the assessment of system reliability and contributes to improved risk management strategies.

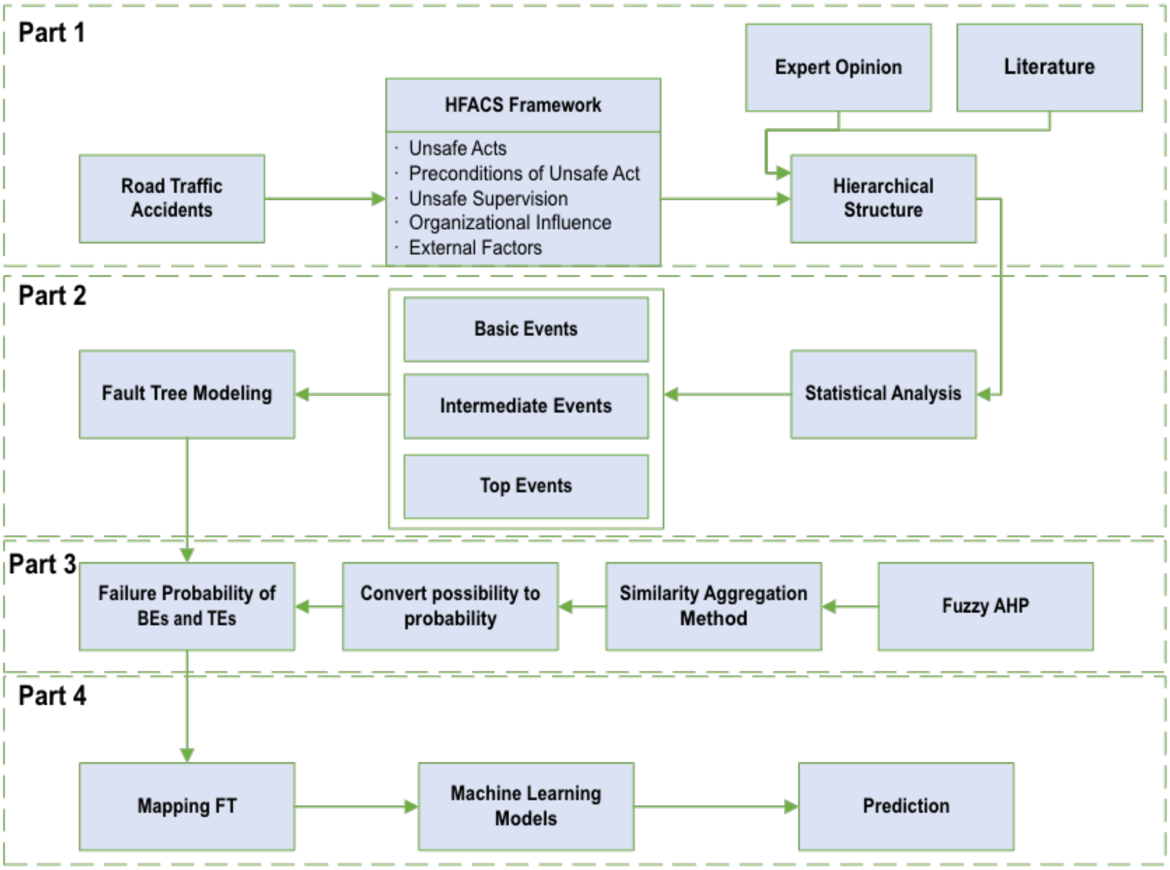

Figure 4-1: Schematic diagram of overall process

4.1 Part 1: The human factors structure is derived using the HFACS framework

4.1.1 Data Collection

To validate the efficacy of the developed methodology, it is essential to establish a comprehensive database of RTAs. In current research, a meticulous selection process was undertaken, focusing on 21,082 road traffic accidents that occurred on arterials in Pakistan between 2012 and 2018

4.1.2 HFACS Framework

The levels and categories of the proposed HFACS are illustrated in **Table 4-1**, which aligns with the five-level framework utilized in previous studies [62][61][88][88][60].

Table 4-1: Description of the levels and categories involved in the proposed HFACS

Level	Failure Mode	Description
External Factors	Regulatory Omissions	1. Laws and regulations need improvement to address prevailing circumstances. 2. Regulations require amendment to align with evolving industry and social demands.
	Administrative Omissions	1. Government department neglecting law implementation and supervision responsibilities. 2. Insufficient safety subsidy policies and policy advocacy leading to safety failures.
Organizational Influence	Human Resources	1. The deficiency of drivers in the workforce has a detrimental effect on the quality and safety of transportation services.
	Financial Resources	1. Limited allocation of funds for the periodic renewal of vehicles and maintenance of equipment.
	Safety Atmosphere	1. Inadequate mutual encouragement for safe driving. 2. Infrequent and passive discussions on safety-related issues.
	Organizational Operation	1. There is no robust system in place for monitoring working hours or recording violations. 2. Safety plans and procedures are not reviewed on a regular basis.
Unsafe Supervision	Insufficient Supervision	1. Irregular safety inspections for drivers and vehicles.

		2. Insufficient on-the-job training and inadequate emphasis on driving safety education.
	Incompletely Planned Operating Mechanism	1. Non-standardized work procedures and risk assessment mechanisms.
	Failure To Correct Known Errors	1. Neglecting known system defects and avoiding necessary improvements by the authorities responsible for road supervision.
Pre-conditions for Unsafe Act	Personal Readiness	1. Inadequate rest periods between shifts for drivers. 2. Inadequate familiarity of drivers with road conditions.
	Poor Mental State	1. Behavioral or personality issues, such as carelessness or impatience, leading to unsafe driving practices. 2. Inattention caused by fatigue or exhaustion, compromising driving safety.
	Poor Physical State	1. Impaired driving due to illness, medication, physical discomfort, or dizziness.
	Environment Factor	1. Adverse weather conditions and environmental factors, such as prolonged periods of darkness or light, can contribute to unsafe driving behavior.
Unsafe Act	Driver Decision-Making Error	1. Failure to accurately assess the driving status of other vehicles and respond to emergencies. 2. Failure to accurately assess road conditions.
	Driver Operating Error	1. Inappropriate driving conduct, such as reckless lane changing, lane deviation, and failure to maintain a safe driving distance.
	Driver Violations	1. Repetitive disregard for rules by drivers despite awareness of potential hazards and legal repercussions.

4.1.3 Hierarchical Structure of Human Risk Factors Involved

This segment analyses and classifies risk factors related to humans that contribute to RTAs. These risk factors are structured hierarchically based on expert knowledge and integrated into the Fault Tree (FT) model. Expert elicitation is a widely accepted method employed in various fields, such as accident examination and risk examination, as it relies on the expertise of professionals to derive accurate scientific conclusions [89]. It is beneficial to have a diverse group of experts with varied backgrounds and experiences rather than a homogeneous group, as it permits a further wide-ranging examination of the subject matter. A diverse group can provide a deeper and more multifaceted understanding by bringing together experts with different areas of expertise and perspective [89]. In this study, four experts were consulted assessing human factors, and their credentials were evaluated based on job experience, age, and educational level [90][91][92][93]. **Table 4-2** presents the score rankings for the various pointers used to evaluate the capabilities of the experts.

Table 4-2: Scoring Ratings for Capability Assessment Indicators

Indicator	Classification	Score	Indicator	Classification	Score
Age	≥ 50	4	Experience	6 – 9	2
	40 – 49	3		≤ 5	1
	30 – 39	2	Education level	Ph.D.	5
	≤ 30	1		Masters	4
Experience	≥ 30 years	5		B.E or B. S	3
	20 – 29	4		Junior College	2
	10 – 19	3		School Level	1

Accident descriptions are critical for conducting comprehensive factor analyses as they provide detailed information about the incident [62]. However, these reports usually focus solely on driver-related factors, necessitating the inclusion of additional sources such as literature reviews and interviews to recognize a broader choice of risk factors related to RTAs.

Table 4-3 provides a summary of the overall factors highlighted in this research through accident reports, literature reviews, and interviews.

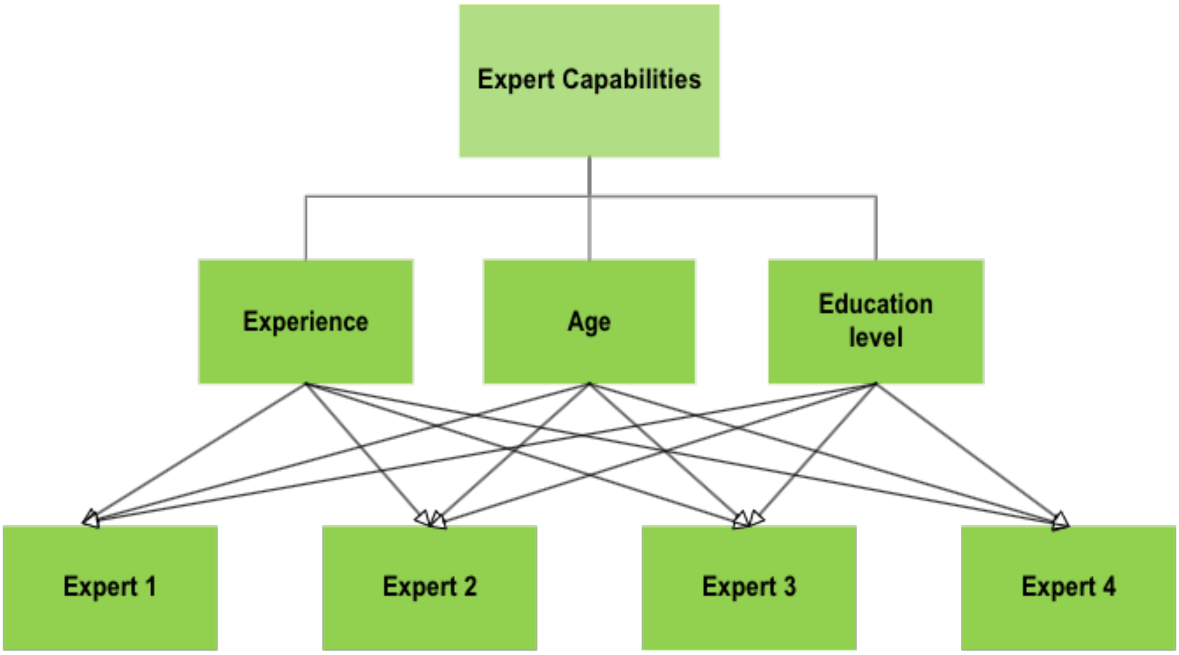

Figure 4-2: Analytic hierarchical process for the evaluation of expert capability

Table 4-3: Description of the risk factors related to RTAs on Arterials

Item	Risk Factors	Description
1	Axle Broken	Inadequate vehicle maintenance, overloading, and reckless driving can cause axle failure and lead to road accidents.
2	Brake Failure	Poor brake maintenance practices and overloading of vehicles can result in brake failure, increasing the risk of road accidents.
3	CNG Cylinder Burst	Insufficient training or guidelines for installation, maintenance, and inspection of CNG cylinders, as well as inadequate safety regulations and the use of uncertified or improperly filled cylinders, can increase the likelihood of cylinder bursts and lead to road accidents.

4	Steering Failure	Poor maintenance practices, ignoring warning signs of steering problems, and driving on rough or uneven terrain can contribute to steering failure and increase the risk of road accidents.
5	Tyre Burst	Inadequate maintenance practices, such as failure to check tyre pressure or neglecting to replace worn-out tyres, combined with excessive speed or overloading of vehicles, can cause tyre bursts and pose a serious threat to road safety.
6	Strong Wind	Driving in strong wind conditions without adjusting the speed or vehicle handling techniques, accordingly, can increase the risk of losing vehicle control and pose a significant threat to road safety.
7	Dense Fog	Driving in dense fog without adjusting speed, using appropriate headlights or fog lights, and maintaining a safe distance from other vehicles can greatly increase the risk of collision and pose a serious threat to road safety.
8	Slippery Road Due to Rain	Driving on a slippery road due to rain without reducing speed, ensuring adequate tire traction and visibility, and maintaining a safe distance from other vehicles can increase the risk of losing vehicle control.
9	Driver’s Fatigue	Driving while fatigued, without taking proper rest breaks or adhering to regulated working hours, can damage the driver's response time, decision-making ability, and focus, increasing the risk of accidents.
10	Driver Under Effect of Alcohol/Drugs	Driving under the effect of alcohol or drugs impairs a driver's judgment, reaction time, and vehicle control, significantly increasing the risk of accidents and posing a serious threat to road safety.
11	Mental and Physiological Pressure	Driving while experiencing mental or physiological pressure, such as stress, anxiety, or illness, can impair a driver's cognitive function and ability to react to potential hazards on the road.
12	Absence of Work Zone Signage	The absence of work zone signage can occur due to lapses in planning or execution of a road construction project. This can

		cause confusion among drivers, leading to errors in judgment and an increased risk of accidents.
13	Absence of Wildlife Crossing Signage	The absence of wildlife crossing signage can increase the risk of accidents between vehicles and animals, which can be attributed to inadequate consideration of ecological factors during road planning and design.
14	Poor Road Conditions	Roads with poor conditions, such as potholes, cracks, or insufficient lighting, can increase the risk of accidents for drivers. These conditions can result from inadequate maintenance, insufficient funding, or limited planning and design considerations.
15	Monotonous road conditions	Monotonous road conditions can cause drivers to become fatigued or distracted, leading to an increased risk of accidents due to human factors. This can be addressed through measures such as rest breaks, stimulating environments, or advanced driver assistance technologies.
16	Excessive Load for Trucks	Excessive load for trucks can lead to accidents caused by factors such as poor judgement and inadequate training of drivers, as well as pressure to meet delivery deadlines.
17	Dangerous Overtaking	Overtaking can be a contributing factor to road traffic accidents due to human factors such as misjudgement, lack of attention, distraction, fatigue, and noncompliance with traffic laws and safety guidelines.
18	Driving at Night Exclusive of Proper Lights	Driving at night without proper lights can be hazardous due to factors such as reduced visibility, impaired judgment, increased risk of collision, and inadequate reaction time.
19	Failure to Apply Brakes in a Timely Manner	Distraction, impaired judgment, fatigue, inexperience, inadequate training, or overconfidence can lead to delayed response time and reduced vehicle control, which can expand the risk of a RTA.

20	Improper U-turns	Misjudgement, inattention, impatience, poor decision-making, and lack of knowledge or skills can lead to risky manoeuvres that rise the risk of a RTA.
21	Reckless Driving	Careless driving can result from factors such as lack of attention, impaired judgment, distraction, overconfidence, disregard for traffic rules and safety measures, and fatigue.
22	Not Maintaining a Safe Distance (Tailgating)	Tailgating can increase the risk of RTAs by reducing the time available for a driver to react to sudden changes in traffic conditions, such as sudden braking or obstacles on the road.
23	Over Speeding	Over Speeding can be caused by various factors, such as impatience, overconfidence, peer pressure, and lack of awareness or regard for traffic rules and safety guidelines. These factors can lead to risky driving performances that increase the risk of collisions and endanger the safety of all road users.
24	Illegal Parking	Impatience, lack of consideration for others, lack of awareness or regard for traffic rules and signage, and the belief that the driver won't be caught can contribute to dangerous parking behaviors that increase the risk of collisions and traffic congestion.
25	Pedestrian Fault	Distraction, overconfidence, impairment, and disregard for traffic rules can contribute to pedestrian fault in road traffic accidents, leading to risky behaviors and increased collision risk that endangers pedestrians and other road users.
26	Age Factor	Age is a contributing factor to road traffic accidents, with younger and older drivers beyond expected to be involved in accidents due to factors such as inexperience, overconfidence, physical or cognitive decline, and reduced ability to respond to hazards on the road.
27	One Way Violation	Violating one-way rules is often due to distraction, unfamiliarity with the road, impatience, or recklessness, leading to collisions and putting other road users at risk.

28	Failure to Conduct Regular Safety Inspections of Vehicles	The absence of regular safety inspections for vehicles can prime to an increased risk of RTAs, particularly in countries where such inspections are not mandatory. In developed countries, periodic inspections are required either annually or during the transfer of vehicle ownership. For instance, the Ministry of Transport test in the UK is a mandatory annual assessment of a vehicle's safety, roadworthiness, and exhaust emissions for vehicles over three years old.
29	Failure to Conduct on-the-job Training for Drivers and Strengthen Driving Safety Education and Training	Lack of attention to the potential risks and consequences of insufficient training can lead to inadequate preparation and poor decision-making, which can ultimately result in accidents on the road.
30	Absence of Road Safety Manuals	The rise in the risk of road traffic accidents due to the lack of standardized guidelines and procedures for ensuring safe road conditions.
31	Failure to Conduct Road Safety Audits	The failure to conduct road safety audits can increase the likelihood of road traffic accidents by allowing hazardous conditions to go undetected. Moreover, it hinders the implementation of effective safety measures to mitigate identified risks, potentially resulting in more severe and frequent accidents.
32	Insufficient Accident Record-Keeping System	An insufficient accident record-keeping system can contribute to road traffic accidents by limiting the ability to identify and analyze trends in accident data, leading to delayed or inadequate implementation of appropriate safety measures.
33	Safety-Related Issues are not	Absence of open discussion and active communication on safety-related issues among stakeholders and decision-makers

	Frequently or Actively Discussed	can contribute to a lack of awareness and prioritization of road safety, leading to increased risks of traffic accidents.
34	Outdated Road Safety Legislation	The NHSO of 2000 controls road safety on national highways. However, it needs updating to reflect new innovations and best practices. The Motor Vehicle Ordinance (MVO) of 1965 and Motor Vehicle Regulation (MVR) of 1969 controls road user safety on provincial roads but are almost few decades old and don't reflect evidence-based best practices. Penalties must be reviewed to effectively deter drivers and other road users from upsetting. None of the ordinances deal with seat belt wearing. For instance, in 2018, the Indian government amended the Motor Vehicles Act of 1988 to include stricter penalties for traffic violations, such as an increase in fines for not wearing a helmet, driving under the influence of alcohol, and not wearing a seat belt. The amendment also included provisions for improving road safety infrastructure and emergency services. As a result of these amendments, India saw a 20% reduction in road fatalities in 2019 compared to the previous year.
35	Insufficient Safety Subsidy Policies	Road crashes in many developing countries result in significant economic and social costs, including loss of life, disability, and damage to infrastructure and vehicles. However, despite these consequences, there is often limited government subsidy allocated to road safety issues. For instance, in Pakistan, road crashes cost nearly 3% of the GDP, yet there is a lack of government funding towards road safety initiatives.
36	Outdated / Inappropriate Licensing Mechanism	Outdated or inappropriate licensing mechanisms can lead to unsafe drivers on the road, which can increase the likelihood of accidents. According to a study by the WHO, inadequate driver training and licensing practices contribute to up to 30% of road deaths middle- and low- income countries [94].
37	No Rigorous Working Hour	When drivers are overworked or fatigued, their driving ability can become impaired, leading to an increased risk of accidents.

	Rules or Violation Record System	The absence of working hour rules can result in fatal public transport accidents. The lack of strict regulations and monitoring systems for working hours can result in drivers being pushed to work longer hours, leading to increased risk of accidents due to fatigue.

Table 4-4 presents the hierarchical structure of risk factors based on the classification within the HFACS framework.

Table 4-4: Hierarchical structure of risk factors

HFACS Classification	**Risk Factor**	**Assigned Code**
Unsafe Act	Excessive Load for Trucks	L1 – 1
	Brake Failure	L1 – 2
	Reckless Driving	L1 – 3
	Dangerous Overtaking	L1 – 4
	Driving at Night Without Proper Lights	L1 – 5
	Failure to Apply Brakes in a Timely Manner	L1 – 6
	Improper U-turn	L1 – 7
	Not Maintaining a Safe Distance (Tailgating)	L1 – 8
	One Way Violation	L1 – 9
	Over Speeding	L1 – 10
	Illegal Parking	L1 – 11
Pre-conditions for Unsafe Act	Axle Broken	L2 – 1
	Strong Wind	L2 – 2
	CNG Cylinder Burst	L2 – 3
	Dense Fog	L2 – 4
	Driver’s Fatigue	L2 – 5
	Driver Under Influence of Drugs/Alcohol	L2 – 6
	Pedestrian Fault	L2 – 7
	Poor Road Conditions	L2 – 8

	Slippery Road Due to Rain	L2 – 9
	Steering Failure	L2 – 10
	Tyre Burst	L2 – 11
	Mental and Physiological Pressure	L2 – 12
	Monotonous Road Conditions	L2 – 13
	Age Factor	L2 – 14
Unsafe Supervision	Absence of Work Zone Signage	L3 – 1
	Absence of Wildlife Crossing Signage	L3 – 2
	Failure to Conduct Regular Safety Inspections of Vehicles	L3 – 3
	Failure to Conduct on-the-job Training for Drivers and Strengthen Driving Safety Education and Training	L3 – 4
Organizational Influence	Absence of Road Safety Manuals	L4 – 1
	Failure to Conduct Road Safety Audits	L4 – 2
	No Rigorous Working Hour Rules	L4 – 3
	Outdated / Inappropriate Licencing Mechanism	L4 – 4
	Insufficient Accident Record-Keeping System	L4 – 5
	Safety-Related Issues are not Frequently or Actively Discussed	L4 – 6
External Factors	Outdated Road Safety Legislation	L5 – 1
	Insufficient Safety Subsidy Policies	L5 – 2

4.2 Part 2: The Fault Tree structure is developed according to the part 1

4.2.1 Statistical Analysis

Performing Occurrence Frequency Analysis is a crucial step in conducting a risk analysis, as accidents are inclined by numerous risk factors and the causes of each accident can vary [95]

4.2.2 Occurrence Frequency Analysis

The analysis of each risk factor is conducted individually, and the findings are presented in **Figure 4-3**.

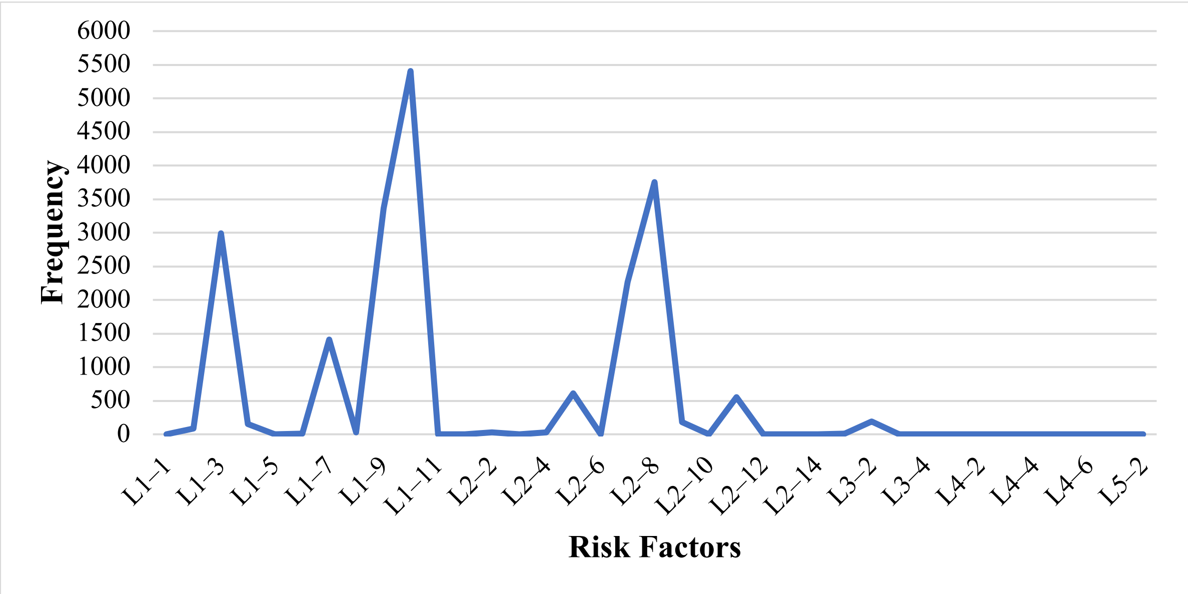

Figure 4-3: Occurrence frequency of risk factors

From **Figure 4-3**, it is evident that several significant risk factors, including over speeding (L1 – 10), one-way violation (L1 – 9), poor road conditions (L2 – 8), and reckless driving (L1 – 3), collectively contribute for approximately 74% of all traffic accidents. However, certain non-reported risk factors in accident descriptions are still reflected critical relying on literature reviews and expert judgments, despite having a frequency of 0.

Table 4-5: Intermediate events

Grouping	Description	Assigned Code	Description	Assigned Code
Primary Intermediate Events	Unexpected Conditions	J2	Organization Fault	J7
	Supervision Failure	J3	Error	J8
	Road Condition	J4	Violation	J9
	Mechanical Fault	J5	External Fault	J10
	Health Condition	J6-1	Poor Visibility	J1-1
	Wrong Practices	J6-2		
Secondary Intermediate Events	Adverse Circumstances	S1	Policy and Administrative Management	S5
	Deficiencies in Operation	S2	Unfavourable Environmental Situations	J1
	Resource Management	S3	Health Factors	J6
	Operation Fault	S4		

4.2.3 Fault Tree Modelling

In the development of the FT model, each risk factor is treated as a BE in the FT, as shown in **Table 4-3**. Intermediate events are identified and incorporated in the fault tree through casual consequence analysis, which is shown in **Table 4-5**. The ultimate event within the constructed FT is classified as the "road traffic accident" representing the top-level event.

4.3 Part 3: Failure Probabilities of basic events in fault tree are calculated using Fuzzy AHP and Similarity Aggregation Method (SAM)

4.3.1 Expert Rating

To address the potential cognitive biases of individual experts, it is essential to incorporate the thoughts of numerous experts. This can be achieved by objectively assessing the capabilities of each expert through a weighted scoring system. It should be recognized that the criteria for evaluating these capabilities may differ depending on features such as experience, age, and education. Prior to the evaluation, a rating score is established, and pairwise comparison matrices are created to consider the indicators of each expert's capabilities. The weight assigned to each expert is then calculated using the following steps [96]:

⇒ A pairwise synthetic comparison matrices $\tilde{B} = [\widetilde{b_{ij}}]$ using the geometric mean technique is used to handle fuzzy as follows:

$$\widetilde{b_{ij}} = (\widetilde{a^{(1)}_{ij}} \otimes \widetilde{a^{(2)}_{ij}} \otimes \dots \otimes \widetilde{a^{(k)}_{ij}})^{\frac{1}{4}} \tag{24}$$

where:

$\widetilde{A^{(k)}} = [\widetilde{a^{(k)}_{ij}}]$ k^{th} indicator represents expert capability evaluation in pairwise comparison matrix

⇒ The fuzzy weights standards for each SME can be estimated using succeeding equation:

$$\widetilde{r_i} = (\widetilde{b_{i1}} \otimes \widetilde{b_{i2}} \otimes \dots \otimes \widetilde{b_{in}})^{\frac{1}{n}} \tag{25}$$

where:

$\widetilde{r_i}$ represent the fuzzy weight of the i^{th} expert.

The fuzzy weights of each criterion are defined as follows:

$$\widetilde{w_i} = \widetilde{r_i} \otimes (\widetilde{r_i} \otimes \widetilde{r_2} \otimes \ldots \otimes \widetilde{r_n})^{-1} \tag{26}$$

where:

$\widetilde{w_i}(lw_i, mw_i, uw_i)$ implies the fuzzy weights of i^{th} criterion.

lw_i, mw_i, uw_i indicates lower, middle, and upper values of the fuzzy weights of i^{th} criterion.

⇒ The center of area technique is employed to weight each SME expressed as:

$$P(E_i) = \left(\frac{1}{3}\right)[uw_i + mw_i + lw_i] \tag{27}$$

4.3.2 Aggregation of Data

The SAM is employed for combining the viewpoints of SMEs and determining the failure probabilities associated with each risk factor. Each SME denoted as $E_i(i = 1,2,3,\ldots,n)$, expresses their perspective on specific risk factors using a set of linguistic variables as aforementioned. The crisp values, obtained by defuzzifying fuzzy numbers after converting from triangular or trapezoidal numbers based on the linguistic variables, are calculated using the following method [91]:

1) Calculation of Degree of Similarity.

$S_{uv}(\widetilde{E_u}, \widetilde{E_v})$ is the degree of agreement for various opinions between each group of SMEs. Let's assume two triangular fuzzy numbers are represented by $\widetilde{E_u}(a_1, a_2, a_3)$ and $\widetilde{E_v}(b_1, b_2, b_3)$ such that $(u \neq v)$. The degree of agreement between $\widetilde{E_u}$ and $\widetilde{E_v}$ is gained by using the succeeding equation:

$$S_{uv}\left(\widetilde{E_u}, \widetilde{E_v}\right) = 1 - \frac{1}{j}\sum_{i=1}^{j}|a_i - b_i| \qquad i = 1, 2, 3 \tag{28}$$

where:

j number of fuzzy set members, (e.g., $j = 4$ for trapezoidal and $j = 3$ for triangular fuzzy number)

2) Calculation for the Average of Agreement (AA) degree for each expert viewpoint.

$$AA(E_u) = \frac{1}{U-1} \sum_{u \neq v,\ v=1}^{U} S_{uv}\left(\widetilde{E_u}, \widetilde{E_v}\right) \tag{29}$$

where:

U overall number of SMEs.

3) Calculation for the Relative Agreement (RA) degree between two types of experts.

The value of $RA(E_u)$ for the u^{th} expert is obtained by the following:

$$RA(E_u) = \frac{AA(E_u)}{\sum_{u=1}^{U} AA(E_u)} \tag{30}$$

4) Estimation of the Consensus Coefficient (CC) for each expert.

The value of $CC(E_u)$ for the u^{th} expert is estimated using the following:

$$CC(E_u) = [\beta \times P(E_u)] + [(1-\beta) \times RA(E_u)] \tag{31}$$

where:

$\beta (0 \leq \beta \leq 1)$ coefficient initiated to represent prominence of $P(E_u)$ over $RA(E_u)$

The greater the value of β is, the greater the importance of $P(E_u)$.

5) Calculation for the aggregated results of the experts' viewpoints.

The aggregated results denoted by $\widetilde{R_A}$ is computed by following:

$$\widetilde{R_A} = CC(E_1) \otimes \widetilde{E_1} \oplus CC(E_2) \otimes \widetilde{E_2} \oplus \ldots \oplus CC(E_u) \otimes \widetilde{E_u} \tag{32}$$

6) Defuzzification of the aggregated results.

The Center of Area Method is widely used for the defuzzification of the aggregated results, which is expressed as follows:

$$X = \frac{\int \mu_M(x) x dx}{\int \mu_M(x) dx} \tag{33}$$

where:

X represents the defuzzification result and $\mu_M(x)$ indicates the accumulated membership functions.

The fuzzy number of combined results is denoted as $\widetilde{R_A}(c_1 , c_2 , c_3)$ and $\widetilde{R_A}(c_1 , c_2 , c_3 , c_4)$, for fuzzy triangular and trapezoidal numbers is defuzzified as eq (34) and (35) respectively

$$R_A = \frac{\int_{c_1}^{c_2} \frac{(x - c_2)}{(c_2 - c_1)} x dx + \int_{c_2}^{c_3} \frac{(c_3 - x)}{(c_3 - c_2)} x dx}{\int_{c_1}^{c_2} \frac{(x - c_2)}{(c_2 - c_1)} dx + \int_{c_2}^{c_3} \frac{(c_3 - x)}{(c_3 - c_2)} dx} = \frac{c_1 + c_2 + c_3}{3} \tag{34}$$

$$R_A = \frac{\int_{c_1}^{c_2} \frac{(x - c_1)}{(c_2 - c_1)} x dx + \int_{c_2}^{c_3} x dx + \int_{c_3}^{c_4} \frac{(c_4 - x)}{(c_4 - c_3)} x dx}{\int_{c_1}^{c_2} \frac{(x - c_1)}{(c_2 - c_1)} dx + \int_{c_2}^{c_3} dx + \int_{c_3}^{c_4} \frac{(c_4 - x)}{(c_4 - c_3)} dx} \tag{35}$$

$$= \frac{1}{3} \frac{(c_4 + c_3)^2 - (c_2 + c_1)^2 - c_4 c_3 - c_1 c_2}{c_4 + c_3 - c_2 - c_1} \tag{36}$$

4.3.3 Transforming Crisp Failure Possibility (CFP) of BEs into failure probability

To transform the possibility of risk factors, obtained from expert judgments, into failure probability, a function [97] is applied. This function considers the proportion between human impression and the logarithmic worth of a physical quantity. The rate of probability can be derived from the possibility rate using the following equation [97][98][99][100]:

$$FP = \begin{cases} \dfrac{1}{10^k}, CFP \neq 0 \\ 0 , CFP = 0 \end{cases} \quad k = [(\frac{1 - CFP}{CFP})]^{\frac{1}{3}} \times 2.301 \tag{37}$$

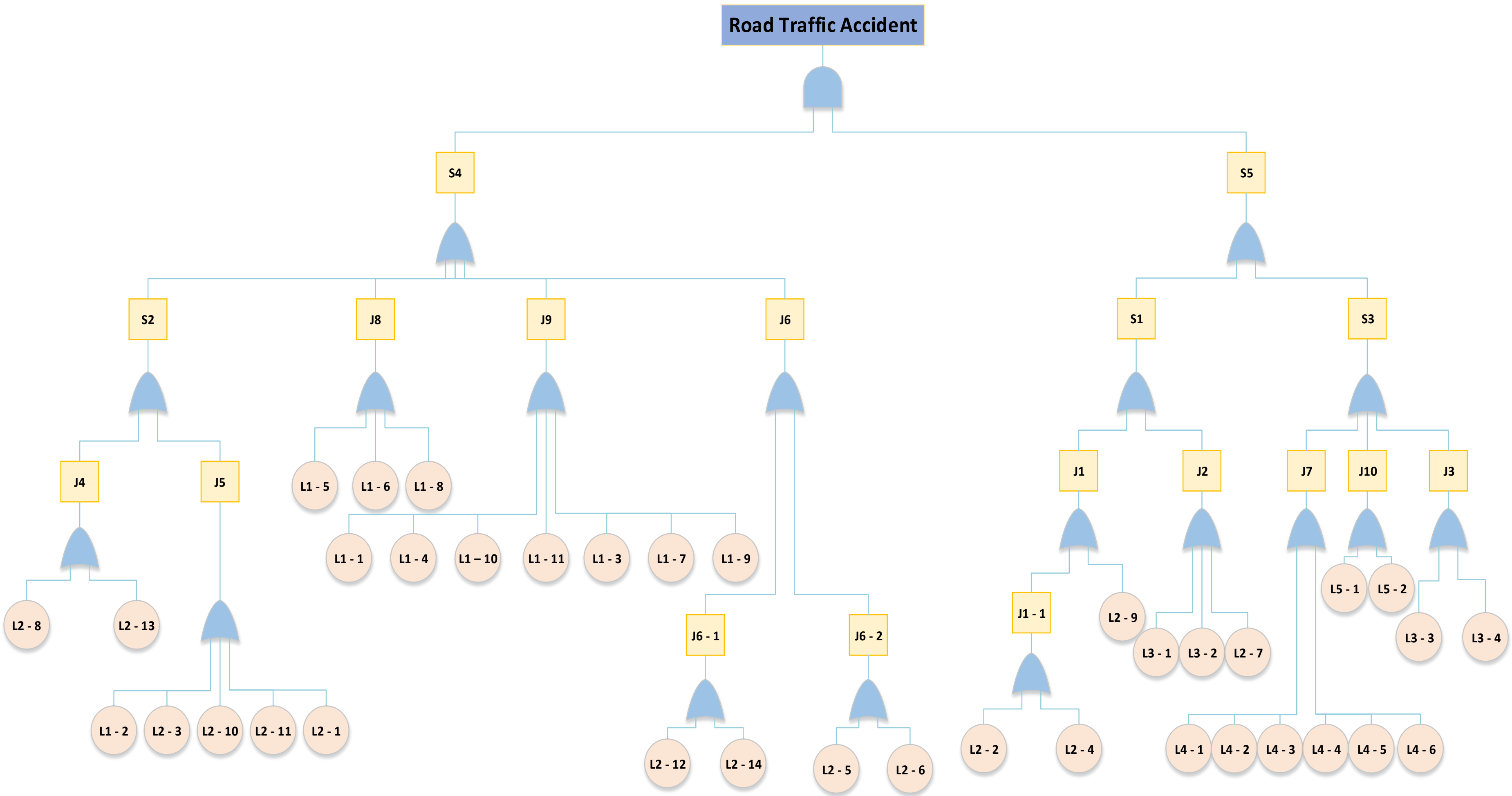

Figure 4-4: Developed FT model for the RTAs

4.4 Part 4: Mapping of FT using Various Machine Learning Models

4.4.1 Failure Probability for Basic Events

The failure probability of BEs is calculated through expert judgment using the Similarity Aggregation Method (SAM). Using the capability criteria based on F-AHP, as discussed in above **Table 4-2**, the outcomes are shown in **Table 4-6**.

Table 4-6: Evaluation results of subject matter experts

SME	Experience	Age	Education Level	Weight
Expert 1	10 to 19	40 to 49	PhD	0.27947854
Expert 2	<= 5	30 to 39	PhD	0.19589687
Expert 3	10 to 19	40 to 49	PhD	0.27947854
Expert 4	10 to 19	30 to 39	PhD	0.24514605

Information about expert opinion for the failure rate of linguistic expression is given in **Table 4-7**.

Table 4-7: Expert views on human factors

Items	Expert 1	Expert 2	Expert 3	Expert 4
L2 – 1	L	VH	H	M
L1 – 2	L	H	VH	H
L2 – 3	M	H	M	H
L2 – 10	L	M	L	M
L2 – 11	H	VH	VH	VH

L2 – 2	M	M	VL	H
L2 – 4	L	H	H	M
L2 – 9	VH	H	M	H
L2 – 5	L	M	H	L
L2 – 6	M	H	L	H
L2 – 12	H	H	L	VH
L3 – 1	H	M	H	H
L3 – 2	L	H	VL	H
L2 – 8	M	M	M	H
L2 – 13	M	M	L	H
L1 – 1	M	H	H	M
L1 – 4	H	VH	L	VH
L1 – 5	H	H	L	VH
L1 – 6	L	H	L	H
L1 – 7	VH	H	M	H
L1 – 3	H	VH	H	VH
L1 – 8	L	M	M	H
L1 – 10	VH	VH	VH	VH
L1 – 11	L	M	L	M
L2 – 7	H	VH	M	L
L2 – 14	M	H	M	H
L1 – 9	H	M	M	M
L3 – 3	VH	H	H	H
L3 – 4	H	H	L	M

L4 – 1	M	M	M	H
L4 – 2	H	M	H	VH
L4 – 5	VH	H	VH	VH
L4 – 6	M	L	VL	M
L5 – 1	H	H	L	H
L5 – 2	M	M	VL	H
L4 – 4	H	M	L	M
L4 – 3	M	H	L	H

Table 4-7, indicating the significance of the SMEs, gives an appropriate value of β which indicates their importance [101]. Previous research has shown that variations in the value of β do not affect fuzzy multiple attributes assisted in decision-making [102]. Through sensitivity analysis, it was determined that choosing β = 0.5 was the best choice for this system [102]. We have used 0.5 as a value of β. Applying the equations from (38) to (39), each factor related to human can be aggregated as a trapezoidal fuzzy number, which is subsequently defuzzified to obtain a crisp failure probability. The crisp failure probability is then converted into failure probability using equation (40). The overall outcomes are presented in **Table 4-8**.

Table 4-8: Aggregation result of each of human factors

Items	Expert 1	Expert 2	Expert 3	Expert 4	Probability
L2 – 1	(0.1,0.25,0.4)	(0.8,0.9,1,1)	(0.6,0.75,0.9)	(0.3,0.5,0.7)	0.008911131
L1 – 2	(0.1,0.25,0.4)	(0.6,0.75,0.9)	(0.8,0.9,1,1)	(0.6,0.75,0.9)	0.012766002

L2 – 3	(0.3,0.5,0.7)	(0.6,0.75,0.9)	(0.3,0.5,0.7)	(0.6,0.75,0.9)	0.01093684
L2 – 10	(0.1,0.25,0.4)	(0.3,0.5,0.7)	(0.1,0.25,0.4)	(0.3,0.5,0.7)	0.001749854
L2 – 11	(0.6,0.75,0.9)	(0.8,0.9,1,1)	(0.6,0.75,0.9)	(0.8,0.9,1,1)	0.043906011
L2 – 2	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0,0,0.1,0.2)	(0.6,0.75,0.9)	0.003219277
L2 – 4	(0.1,0.25,0.4)	(0.6,0.75,0.9)	(0.6,0.75,0.9)	(0.3,0.5,0.7)	0.007948953
L2 – 9	(0.8,0.9,1,1)	(0.6,0.75,0.9)	(0.3,0.5,0.7)	(0.6,0.75,0.9)	0.021411993
L2 – 5	(0.1,0.25,0.4)	(0.3,0.5,0.7)	(0.6,0.75,0.9)	(0.1,0.25,0.4)	0.002865316
L2 – 6	(0.3,0.5,0.7)	(0.6,0.75,0.9)	(0.1,0.25,0.4)	(0.6,0.75,0.9)	0.007727623
L2 – 12	(0.6,0.75,0.9)	(0.6,0.75,0.9)	(0.1,0.25,0.4)	(0.8,0.9,1,1)	0.012533582
L3 – 1	(0.6,0.75,0.9)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.6,0.75,0.9)	0.011688341
L3 – 2	(0.1,0.25,0.4)	(0.6,0.75,0.9)	(0,0,0.1,0.2)	(0.6,0.75,0.9)	0.004278214
L2 – 8	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.6,0.75,0.9)	0.007623697

L2 – 13	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.1,0.25,0.4)	(0.6,0.75,0.9)	0.0048506
L1 – 1	(0.3,0.5,0.7)	(0.6,0.75,0.9)	(0.6,0.75,0.9)	(0.3,0.5,0.7)	0.011239855
L1 – 4	(0.6,0.75,0.9)	(0.8,0.9,1,1)	(0.1,0.25,0.4)	(0.8,0.9,1,1)	0.017164839
L1 – 5	(0.6,0.75,0.9)	(0.6,0.75,0.9)	(0.1,0.25,0.4)	(0.8,0.9,1,1)	0.012533582
L1 – 6	(0.1,0.25,0.4)	(0.6,0.75,0.9)	(0.1,0.25,0.4)	(0.6,0.75,0.9)	0.004501106
L1 – 7	(0.8,0.9,1,1)	(0.6,0.75,0.9)	(0.3,0.5,0.7)	(0.6,0.75,0.9)	0.021411993
L1 – 3	(0.6,0.75,0.9)	(0.8,0.9,1,1)	(0.6,0.75,0.9)	(0.8,0.9,1,1)	0.043906011
L1 – 8	(0.1,0.25,0.4)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.6,0.75,0.9)	0.0048506
L1 – 10	(0.6,0.75,0.9)	(0.8,0.9,1,1)	(0.8,0.9,1,1)	(0.8,0.9,1,1)	0.06297101
L1 – 11	(0.1,0.25,0.4)	(0.3,0.5,0.7)	(0.1,0.25,0.4)	(0.3,0.5,0.7)	0.001749854
L2 – 7	(0.6,0.75,0.9)	(0.8,0.9,1,1)	(0.3,0.5,0.7)	(0.1,0.25,0.4)	0.009162154
L2 – 14	(0.3,0.5,0.7)	(0.6,0.75,0.9)	(0.3,0.5,0.7)	(0.6,0.75,0.9)	0.01093684

L1 – 9	(0.6,0.75,0.9)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	0.007842427
L3 – 3	(0.8,0.9,1,1)	(0.6,0.75,0.9)	(0.6,0.75,0.9)	(0.6,0.75,0.9)	0.034195074
L3 – 4	(0.6,0.75,0.9)	(0.6,0.75,0.9)	(0.1,0.25,0.4)	(0.3,0.5,0.7)	0.007948953
L4 – 1	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.6,0.75,0.9)	0.007623697
L4 – 2	(0.6,0.75,0.9)	(0.3,0.5,0.7)	(0.6,0.75,0.9)	(0.8,0.9,1,1)	0.022475359
L4 – 5	(0.8,0.9,1,1)	(0.6,0.75,0.9)	(0.8,0.9,1,1)	(0.8,0.9,1,1)	0.067051585
L4 – 6	(0.3,0.5,0.7)	(0.1,0.25,0.4)	(0.1,0.25,0.4)	(0.3,0.5,0.7)	0.001922031
L5 – 1	(0.6,0.75,0.9)	(0.6,0.75,0.9)	(0.1,0.25,0.4)	(0.6,0.75,0.9)	0.01093684
L5 – 2	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0,0,0.1,0.2)	(0.6,0.75,0.9)	0.003219277
L4 – 4	(0.6,0.75,0.9)	(0.3,0.5,0.7)	(0.1,0.25,0.4)	(0.3,0.5,0.7)	0.005000345
L4 – 3	(0.3,0.5,0.7)	(0.6,0.75,0.9)	(0.1,0.25,0.4)	(0.6,0.75,0.9)	0.007727623

4.4.2 Data Generation

Due to the limited database of traffic accidents available for this study, which does not match the requirements for developing an ideal machine learning (ML) model, a random probability generation function is employed [103]. For each basic event (BE), 50,000 random probabilities are produced while assuming a normal distribution. The means of these normal distributions correspond to the probabilities listed in **Table 4-8**, with a standard deviation of 15%. The FT architecture is implemented in Python, and TE for each BE is calculated using this architecture. This data generation process provides data for the training, validation, and testing of the ML models. In the established ML models, all the generated 50,000 data points are divided into three parts: 30,000 (60%) for training, 10,000 (20%) for validation, and 10,000 (20%) for testing.

CHAPTER 5: RESULTS AND DISCUSSIONS

5.1 Evaluation of Performance of Various Machine Learning Models

In the current research, multiple ML models were employed to map the fault tree process for system-based road traffic accident analysis. The performance of these modes was assessed by comparing their results with those obtained from Fault Tree Analysis (FTA). A set of sixty data samples generated using Python was used for testing and evaluation. Firstly, the probabilities of a TE in the FT were computed using the FTA technique on these generated data samples. Then, each machine learning model was individually fed with the same data samples, treating each one as a distinct Basic Event (BE). The computational code was executed, and the ML models predicted the associated probability of the TE. The performance evaluation of twelve machine learning models is given in **Table 5-1**, which includes the maximum difference between the results and mean of ML models and FTA.

Table 5-1: Performance evaluation for ML models

ML Models	Mean Difference	Maximum Difference	Mean Squared Error (MSE)
Linear Regression	0.0001	0.000509	1.68e-08
Principal Component Regression (PCR)	0.0018	0.006622	5.5594e-06
Decision Tree	0.0019	0.006603	4.9597e-06
Random Forest	0.0011	0.003533	1.8674e-06
XG Boost	0.0004	0.001199	2.556e-07
Support Vector Machine (SVM)	0.0022	0.007924	7.3433e-06
K-Nearest Neighbours (KNN)	0.001	0.003758	1.3948e-06

The use of Fault Tree (FT) analysis in risk assessment for road traffic accidents is accompanied by several flaws, which are illustrated as follows:

I. FT is static and lacks the ability to simulate the dynamic developments of failures [104]. It fails to account for the mutable type of events and their effect on the system.

II. FT does not consider interactions and interdependencies among system components. It treats all basic events as independent events, disregarding the potential cascading effects and dependencies [105], [106].

III. The expertise and evaluations of experts in the field may have limitations and biases. FT analysis may not encompass all potential modes of system failure [107], leaving room for oversight and incomplete risk assessments.

IV. Handling a complex accident with various scenarios having thousands of events and subsequent gates would be challenging in developing FT. Analyzing and interpreting a large amount of data becomes cumbersome and may hinder effective decision-making.

These flaws highlight the need for alternative approaches and methodologies that address the limitations of FT analysis and provide a more comprehensive and dynamic assessment of risk in RTAs.

5.2 ANN Establishment

This ANN based on FT structure is illustrated in **Figure 5-2**. It incorporates the algorithm depicted in **Figure 3-4,** the computation process outlines in **Figure 5-1**, and the mapping rules outlined in 3.4. Combining these components, the ANN model successfully integrates the FT structure, enabling a comprehensive and accurate analysis of road traffic accidents.

In the ANN architecture, all 37 BE (from BE1 to BE37) were treated as input neurons, representing the input features. The TE was treated as a neuron in the output layer, representing the output target of the ANN. The ANN utilized a feedforward backpropagation type, consisting of two-hidden layers. In the production of the proposed ANN model, the following parameters and configurations were proposed and used:

I. Eleven neurons were considered in first hidden layer, while the second hidden layer consisted of seven neurons.

II. The input layer of the ANN included all 37 BEs obtained from the FTA. These BEs served as input features, and the corresponding failure probabilities formed the input vector for the network.

III. The Xavier initialization method was used to generate commencement values for the weights and biases of the ANN.

IV. The activation functions of the logarithmic sigmoid for both hidden layers were employed in the ANN model. Whilst the linear function for the output layer.

V. Two different training functions were examined in the study: Levenberg-Marquardt backpropagation and Adaptive Moment Estimation (Adam).

VI. The MSE was chosen as the error metric for assessing the functioning of the said ANN model.

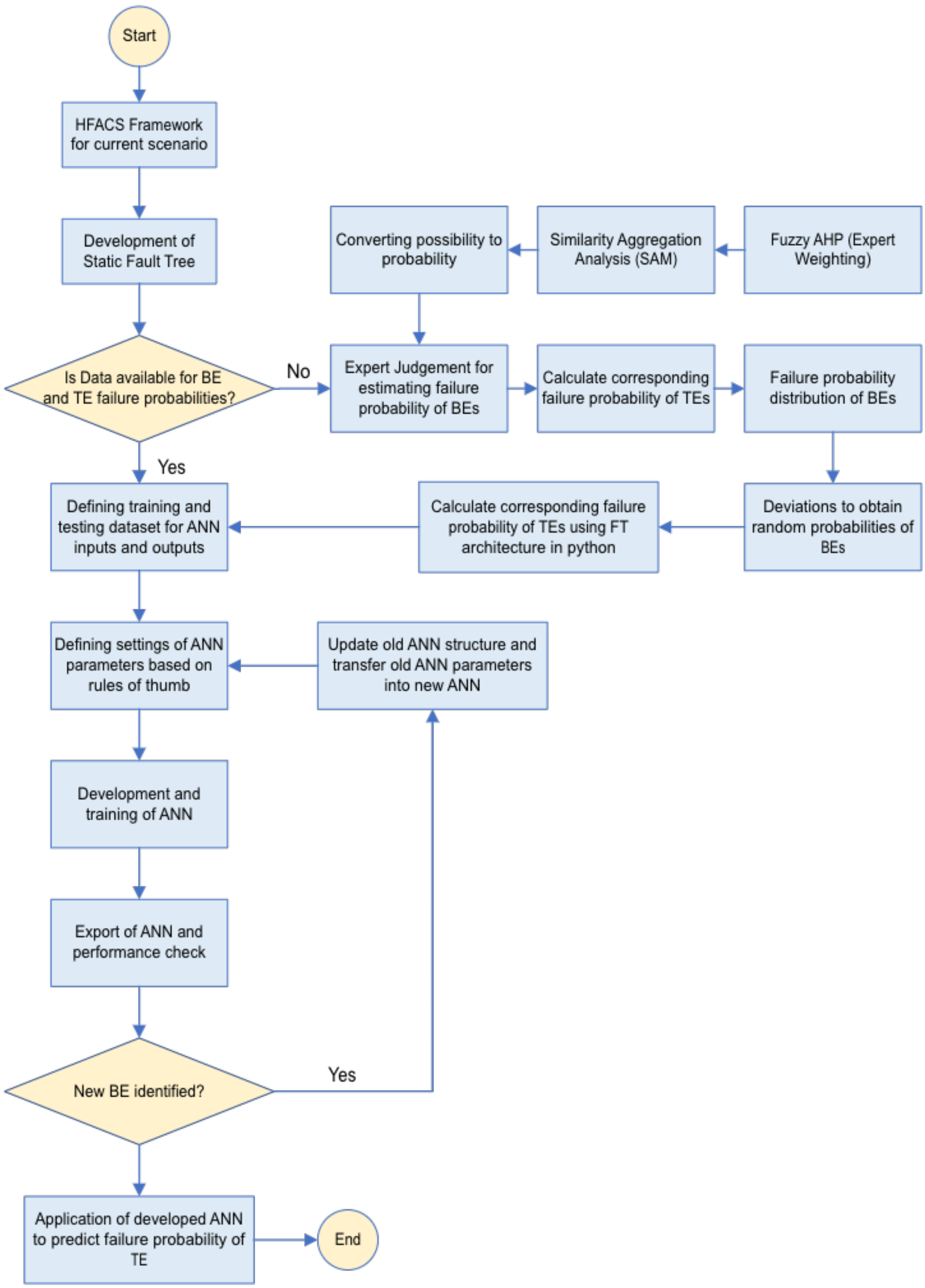

Figure 5-1: Implementation process of the proposed method

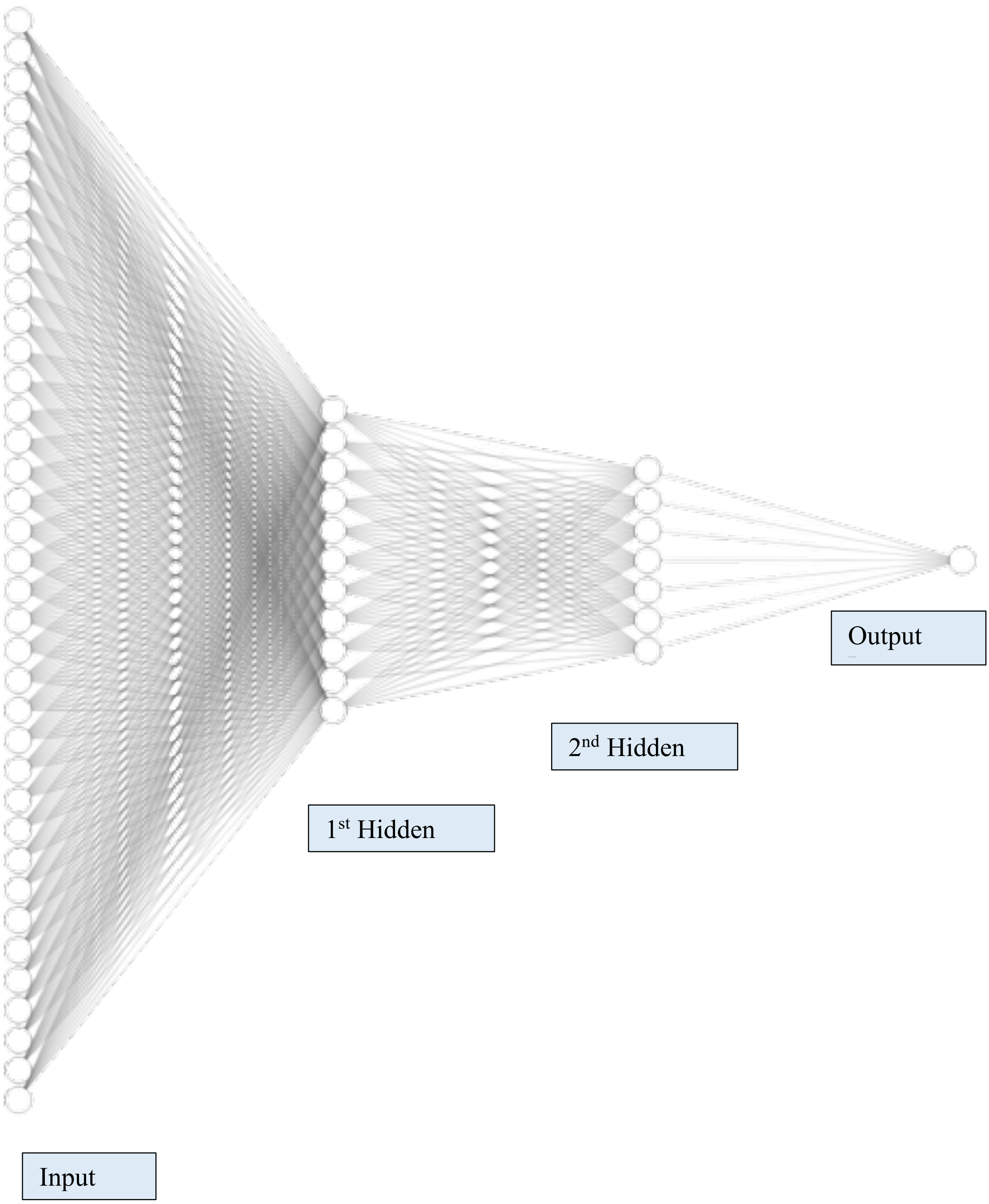

Figure 5-2: Architecture of the developed ANN

5.3 Evaluation of the Proposed ANN's Performance

For the performance evaluation of the Artificial Neural Networks (ANN), the same set of sixty data samples generated in the evaluation of ML models was used for testing. For the case of training with the Adaptive Moment Estimation (Adam) algorithm, the outcomes gained from the ANN were associated with those from the FTA. The comparison results were displayed in **Figure 5-3** and **Figure 5-4.** The mean value of the difference between the ANN and FT results was calculated to be 0.0048, including a relatively small average deviation between the two models. The extreme value of the difference between the FT and ANN results was found to be 0.0126, which represents the highest deviation observed between the models. Additionally, the difference's MSE was computed to be 3.11648e-05, suggesting a relatively low overall error between the predictions of the FTA and the ANN, including that the ANN model is qualified of accurately forecasting and analyzing road traffic accidents in a manner comparable to the FT methods.

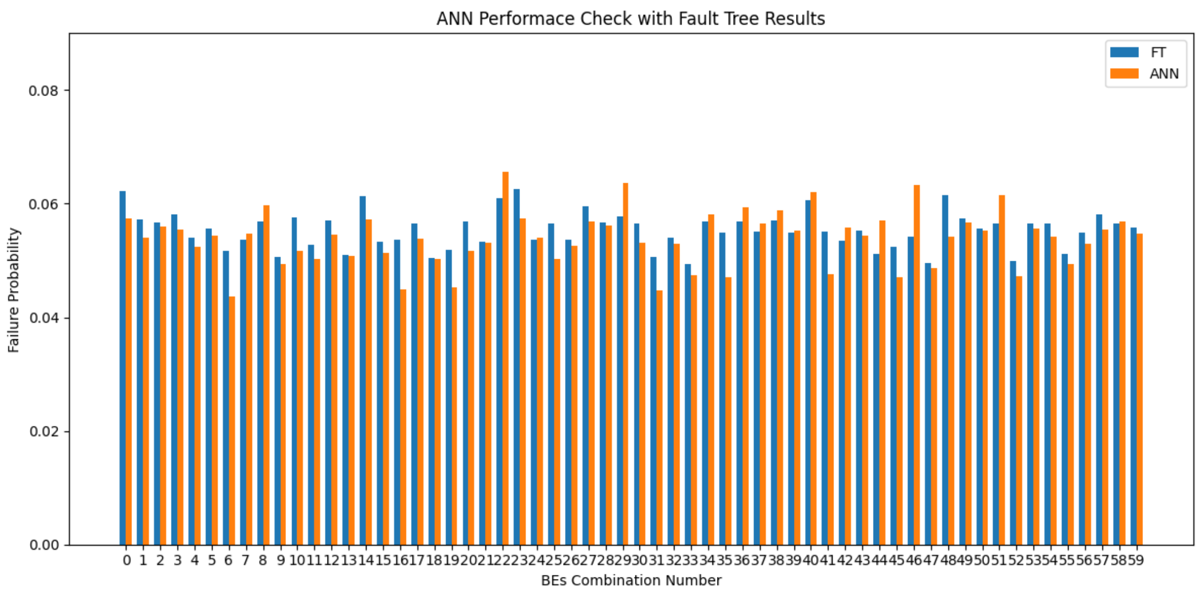

Figure 5-3: Comparison between the result of FTA and ANN (Adam)

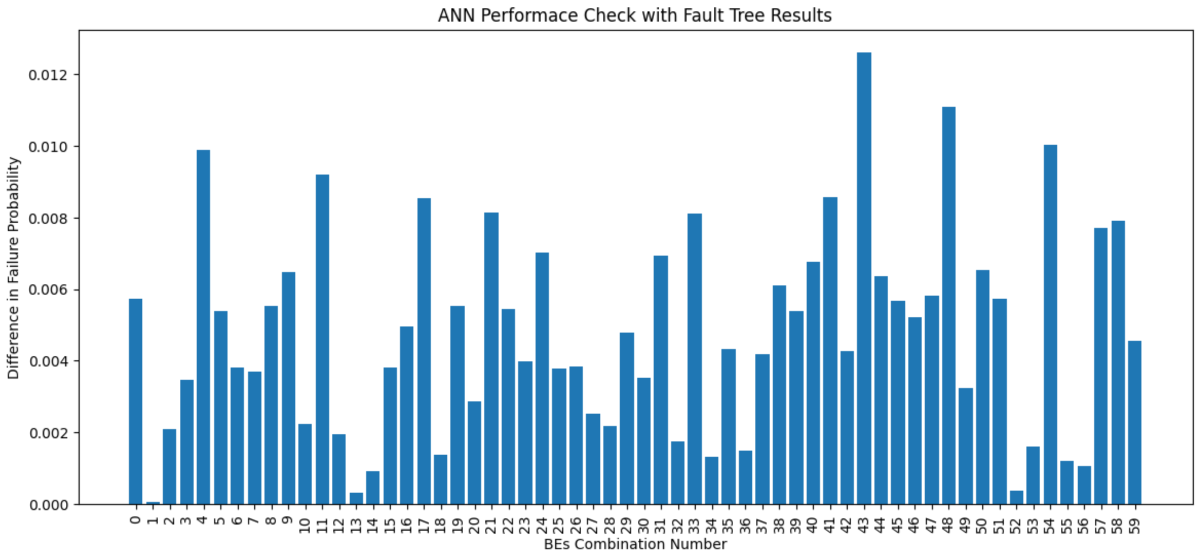

Figure 5-4: Differences between the result of ANN and FTA (Adam)

In In the case of training with the Levenberg-Marquardt backpropagation algorithm, the results gained from the ANN model were associated to individuals from the FTA. The comparison results were visualized in **Figure 5-5** and **Figure 5-6**. The mean value of the difference between the ANN and FT results was found to be 0.0043, indicating a relativity small average deviation between the two models. The extreme value of the difference between the ANN and FT results was determined to be 0.0101, representing the highest observed deviation between the models. Furthermore, the difference's MSE was calculated to be 2.4685e-05, which signifies a relatively low overall error between the predictions of the ANN and the FT. These figures, inducting the mean value, maximum value, and MSE, further demonstrate a good match between both models, reaffirming the capability of the ANN model to accurately predict and analyze road traffic accidents in a manner consistent with the FT method.

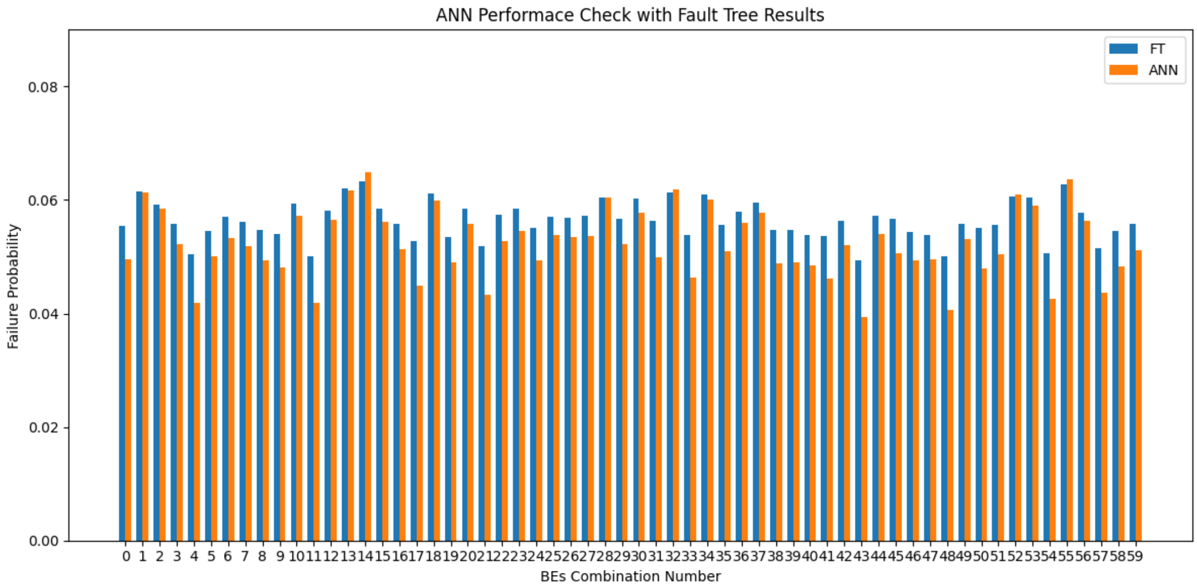

Figure 5-5: Comparison between the result of FTA and the ANN (LM)

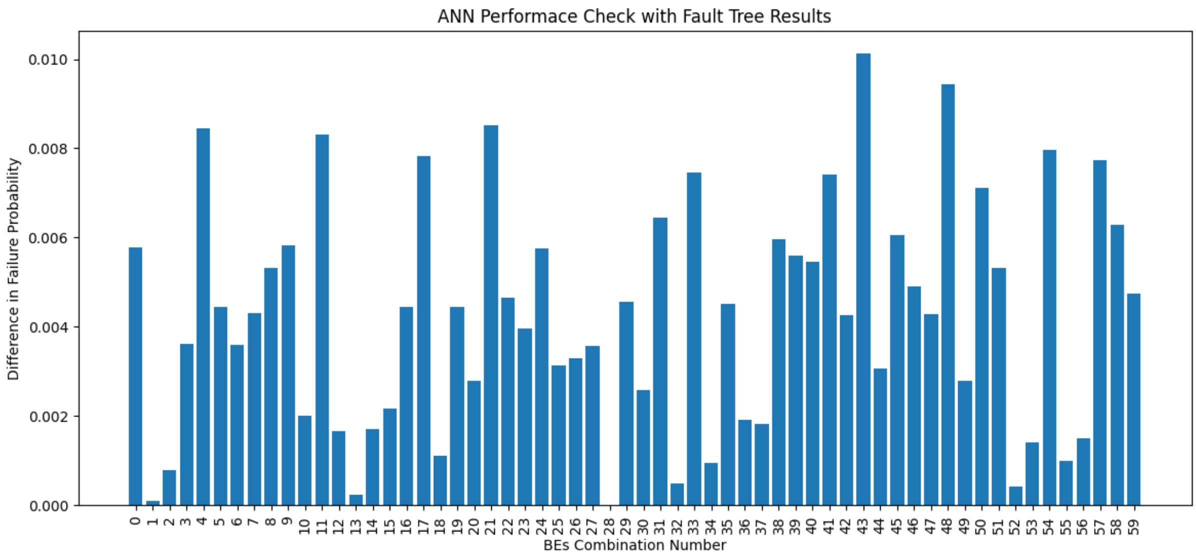

Figure 5-6: Differences between the result of the ANN and FTA (LM)

By associating the performances of the two training algorithms, it can be concluded that training with the Levenberg-Marquardt backpropagation resulted in a better match between the FT and ANN model.

The mean value of the difference between the ANN and FT results was slightly lower when using the Levenberg-Marquardt backpropagation algorithm compared to the Adaptive

Moment Estimation (Adam) algorithm (0.0043 vs. 0.0048). Similarly, the maximum value of the difference was also lower (0.0101 vs. 0.0126). These values indicate that the Levenberg-Marquardt backpropagation algorithm achieved a closer alignment between the predictions of the ANN and the results obtained from the FT analysis.

Moreover, the difference's MSE was smaller for the Levenberg-Marquardt backpropagation algorithm (2.4685e-05) compared to the Adam algorithm (3.11648e-05). A lower MSE suggests that the predictions of the ANN model using the LM are closer to the FT results on average.

Therefore, based on these performance metrics, it can be concluded that training with the LM provided a enhanced match between the ANN model and the FT analysis in terms of accurately predicting and analyzing road traffic accidents.

5.4 The Advantage of the ANN with FT as the Base

ANN model could learn and capture the underlying mathematical relationships between input and output variables by modifying internal parameters, such as synaptic weights and biases, during the training process using relevant datasets. Although the use of FTA is not mandatory for developing ANN models, incorporating FT as a foundation can offer considerable advantages, particularly in the context of complex system risk assessments. Integrating FT into the development of the ANN modes, we gain access to a powerful framework that aids in identifying causal links within the system. This framework assesses choosing appropriate inputs and outputs for the ANN models, ensuring that they accurately represent the key variables that influence the system's behavior. The insights derived from the FT guide the systematic and informed construction of ANN models, improving their accuracy and relevance in the analysis of complex systems.

5.5 The Impact of Increased Data Availability on Developed Artificial Neural Networks

The incorporation of new data offers an opportunity to enhance the effectiveness of current Artificial Neural Network (ANN) models for failure analysis. Augmenting the current data resources, a carefully selected set of 20,000 new samples was systematically constructed. The dataset included failure probabilities for both BE and TE. The newly collected dataset was then utilized to train the constructed ANN model, enabling adjustments to the network's connection biases and weights. The empirical outcomes of the training process revealed significant improvements in the functioning of the ANN model. For the ANN trained with the Adaptive Moment Estimation (Adam) algorithm, the mean difference between the ANN predictions and the actual values decreased to 0.0011, and the maximum difference was reduced to 0.0048. Similarly, for the ANN trained with the LM, the mean difference decreased to 0.0028, and the maximum difference was reduced to 0.00183.

These remarkable results indicate that the addition of new data can have a substantial impact on the precision and effectiveness of ANN-based models for failure investigation. The incorporation of this supplementary data allows the ANN model to better capture the underlying patterns and relationships within the system, resulting in more accurate predictions and improved performance.

5.6 Impact of Varying Numbers of Hidden Neurons on Network Performance

The projected ANN-based model was trained using the same dataset created for Basic Events (BEs) and Top Events (TE), employing various configurations of hidden neurons. The findings, shown in Error! Not a valid bookmark self-reference. and **Table 5-3**, provide insights into the mean and maximum difference between the ANN-based model outputs and the testing values of TE failure probabilities for each configuration.

Table 5-2: Results of ANN (Adam) models with varying numbers of hidden neurons

Training Data	**Number of Neurons in hidden layer 1**	**18**	**15**	**12**	**10**
	Number of Neurons in hidden layer 2	**12**	**10**	**8**	**6**
60	Mean difference (%)	23.45	5.94	22.75	4.56
	Maximum difference (%)	25.75	14.1	24.56	8.59
300	Mean difference (%)	1.18	1.84	0.93	1.26
	Maximum difference (%)	2.57	6.38	1.96	3.73
600	Mean difference (%)	0.47	1.03	0.7	1.29
	Maximum difference (%)	1.98	2.46	2.29	2.81
12000	Mean difference (%)	0.73	0.3	0.55	0.53
	Maximum difference (%)	1.87	0.7	1.88	1.59

Table 5-3: Results of ANN (LM) models with varying numbers of hidden neurons

Training Data	Number of Neurons in hidden layer 1	18	15	12	10
	Number of Neurons in hidden layer 2	**12**	**10**	**8**	**6**
60	Mean difference (%)	12.88	41.7	31.68	69.62
	Maximum difference (%)	15.03	44.5	34.71	72.57
300	Mean difference (%)	30.16	15.24	4.7	23.59
	Maximum difference (%)	32.78	17.81	6.98	25.33
600	Mean difference (%)	1.05	11.07	15.55	5.7
	Maximum difference (%)	2.39	11.9	17.46	7.42
12000	Mean difference (%)	0.58	0.67	0.95	0.6
	Maximum difference (%)	2.17	2.66	3.96	2.05

These results reinforce the notion that the volume of the training data and the selection of an appropriate ANN design significantly impact the performance of the model. It is important to highlight that an expanded and refined training dataset holds the potential to facilitate the development of an alternative ANN architecture that surpasses current performance benchmarks. By incorporating more diverse and comprehensive data, it becomes possible to uncover additional patterns and relationships within the system, leading to improved accuracy and predictive capabilities.

Therefore, the continuous enhancement and augmentation of the training dataset, along with careful consideration of the ANN architecture, are vital for achieving superior performance in failure analysis. These factors contribute to the development of an ANN model that better captures the complexity of the system and produces more reliable results.

5.7 Impact of Decreasing Input Features based on Correlation

The impact of reducing input features based on correlation has also been investigated in the study. Having many input features in an ANN can lead to computational complexity, increasing overfitting risks, higher data requirements, and challenges in feature redundancy and interpretability. To resolve these issues, the study focuses on mitigating feature redundancy by removing highly correlated features, specifically BE13 and BE32. As a result, the ANN model is trained with 35 input features instead of the original 37. Trained using the Adaptive Moment Estimation (Adam) algorithm, the ANN yields a mean difference of 0.0031 and a maximum difference of 0.0139 between its outputs and the testing values of TE failure probabilities. Alternatively, the LM achieves a mean difference of 0.0061 and a maximum difference of 0.0444.

These findings indicate that reducing input features based on correlation can help mitigate computational complexity and improve model performance by addressing feature redundancy. However, it is imperative to note that the choice of training procedure also plays a role in the model's performance. Both algorithms show reasonable results, but the Adam algorithm appears to achieve slightly better accuracy with lower mean and maximum differences compared to the Levenberg-Marquardt backpropagation algorithm.

Overall, the study highlights the importance of feature selection and the impact it can have on the performance of ANN models. By carefully considering feature correlations and removing redundant features, it is possible to enhance the efficacy, interpretability, and precision of the model.

CHAPTER 6: CONCLUSION

The research presented a comprehensive and systematic methodology for analyzing road traffic accidents, with a specific focus on human factors. By integrating fuzzy logic, fault tree analysis (FTA), and machine learning (ML) models, the methodology offers an effective approach to understanding and predicting failure occurrence probability of risk factors associated with RTAs. The research acknowledges the limitations of the fault tree analysis, such as its static nature and inability to capture interdependency among basic events. To overcome these limitations, the research incorporates machine learning models, particularly ANNs, which can understand the intricate non-linear associations among variables.

A significant dataset comprising 21,082 road traffic accidents is utilized, and the HFACS framework is utilized to detect and categorize risk factors associated with the accidents. Fuzzy logic is applied to find the failure probability, and the developed fault tree structure serves as an informative foundation for the ANN-based model. The research investigates the impact of varying numbers of neurons on the functioning of the ANN model. It is found that aligning the number of hidden layers and neurons with the intermediate events in the fault tree leads to optimal performance. Additionally, the study demonstrates that utilizing newly available data and optimizing the ANN architecture based on the study findings further enhances the model's performance.

RECOMMENDATIONS AND LIMITATIONS

In future work, the focus will be on integrating additional data to improve the methodology's performance and refine the parameters within the artificial neural networks. Further exploration of key human factors in road traffic accidents is also prioritized to enhance the accuracy and predictiveness of data-driven models. Moreover, the research aims to standardize the evaluation process and develop practical applications that can be effectively utilized in real-world settings. Ongoing efforts are dedicated to addressing these concerns and advancing the work in this part. Overall, the proposed methodology offers a deeper understanding of road traffic accidents and offers enhanced predictive capabilities regarding the associated factors.

The study acknowledges that only 4 experts were considered, which could be considered a limitation. The study suggests that more experts should be employed in future studies to improve the validity of the findings.

REFERENCES

[1] O. Osabuohien-Irabor, “Empirical analysis of road traffic accidents: A case study of Kogi State, North-Central Nigeria,” *International Journal of Physical Sciences*, vol. 8, Oct. 2013, doi: 10.5897/IJPS2013.3978.

[2] M. Khasawneh, A. Alomari, and B. Gannam, “Forecasting Traffic Accidents in Jordan Using Regression Techniques,” *Jordan Journal of Civil Engineering*, vol. 12, Feb. 2018.

[3] T. Anjuman, S. Hasanat-E-Rabbi, C. Siddiqui, and M. Hoque, “ROAD TRAFFIC ACCIDENT: A LEADING CAUSE OF THE GLOBAL BURDEN OF PUBLIC HEALTH INJURIES AND FATALITIES,” 2007.

[4] “World report on road traffic injury prevention.”

[5] “16156532”.

[6] S. Li, Z. Zhang, Y. Liu, and Z. Qin, “A Short-Term Traffic Flow Reliability Prediction Method considering Traffic Safety,” *Math Probl Eng*, vol. 2020, p. 6682216, 2020, doi: 10.1155/2020/6682216.

[7] WHO, “Road traffic injuries,” Jun. 20, 2022.

[8] W. H. Organization, *Global status report on road safety 2018*. World Health Organization, 2018.

[9] “World report on road traffic injury prevention.”

[10] “Traffic Safety Facts (2016 Data).”

[11] J Elander, R West, and D French, “Behavioral correlates of individual differences in road-traffic crash risk: an examination method and findings”.

[12] J Reason, A Manstead, S Stradling, J Baxter, and K Campbell, “Errors and violations on the roads: a real distinction?”.

[13] P. C. Cacciabue, *Modelling Driver Behaviour in Automotive Environments: Critical Issues in Driver Interactions with Intelligent Transport Systems*. 2007. doi: 10.1007/978-1-84628-618-6.

[14] J. C. F. de Winter and D. Dodou, "The Driver Behaviour Questionnaire as a predictor of accidents: A meta-analysis," *J Safety Res*, vol. 41, no. 6, pp. 463–470, 2010, doi: https://doi.org/10.1016/j.jsr.2010.10.007.

[15] M. Ouyang, L. Hong, M.-H. Yu, and Q. Fei, "STAMP-based analysis on the railway accident and accident spreading: Taking the China–Jiaoji railway accident for example," *Saf Sci*, vol. 48, no. 5, pp. 544–555, 2010, doi: https://doi.org/10.1016/j.ssci.2010.01.002.

[16] B. P. Hughes, S. Newstead, A. Anund, C. C. Shu, and T. Falkmer, "A review of models relevant to road safety," *Accid Anal Prev*, vol. 74, pp. 250–270, 2015, doi: https://doi.org/10.1016/j.aap.2014.06.003.

[17] H. W. Heinrich, *Industrial Accident Prevention. A Scientific Approach.*

[18] B. Scott-Parker, N. Goode, and P. Salmon, "The driver, the road, the rules … and the rest? A systems-based approach to young driver road safety," *Accid Anal Prev*, vol. 74, pp. 297–305, 2015, doi: https://doi.org/10.1016/j.aap.2014.01.027.

[19] M. G. Lenné, P. M. Salmon, C. C. Liu, and M. Trotter, "A systems approach to accident causation in mining: An application of the HFACS method," *Accid Anal Prev*, vol. 48, pp. 111–117, 2012, doi: https://doi.org/10.1016/j.aap.2011.05.026.

[20] P. Larsson, S. W. A. Dekker, and C. Tingvall, "The need for a systems theory approach to road safety," *Saf Sci*, vol. 48, no. 9, pp. 1167–1174, 2010, doi: https://doi.org/10.1016/j.ssci.2009.10.006.

[21] Y. M. Goh and P. E. D. Love, “Methodological application of system dynamics for evaluating traffic safety policy,” *Saf Sci*, vol. 50, no. 7, pp. 1594–1605, 2012, doi: https://doi.org/10.1016/j.ssci.2012.03.002.

[22] S. Newnam and N. Goode, “Do not blame the driver: A systems analysis of the causes of road freight crashes,” *Accid Anal Prev*, vol. 76, pp. 141–151, 2015, doi: https://doi.org/10.1016/j.aap.2015.01.016.

[23] N. J. Stevens and P. M. Salmon, “Sand, surf and sideways: A systems analysis of beaches as complex roadway environments,” *Saf Sci*, vol. 85, pp. 152–162, 2016, doi: https://doi.org/10.1016/j.ssci.2016.01.009.

[24] Peden M *et al.*, “World report on road traffic injury prevention,” 2004.

[25] N. A. Stanton and P. M. Salmon, “Human error taxonomies applied to driving: A generic driver error taxonomy and its implications for intelligent transport systems,” *Saf Sci*, vol. 47, no. 2, pp. 227–237, 2009, doi: https://doi.org/10.1016/j.ssci.2008.03.006.

[26] V. Di Pasquale, S. Miranda, R. Iannone, and S. Riemma, “A Simulator for Human Error Probability Analysis (SHERPA),” *Reliab Eng Syst Saf*, vol. 139, pp. 17–32, 2015, doi: https://doi.org/10.1016/j.ress.2015.02.003.

[27] N. LAARAJ and F. JAWAB, “Road accident modeling approaches: literature review,” in *2018 International Colloquium on Logistics and Supply Chain Management (LOGISTIQUA)*, 2018, pp. 188–193. doi: 10.1109/LOGISTIQUA.2018.8428276.

[28] Johnston, Ian Ronald and Muir, Carlyn and Howard, and Eric William, *Eliminating serious injury and death from road transport: a crisis of complacency*. CRC press, 2013.

[29] W. Jiang, Z. Zhang, and X. Deng, "A Novel Failure Mode and Effects Analysis Method Based on Fuzzy Evidential Reasoning Rules," *IEEE Access*, vol. 7, pp. 113605–113615, 2019, doi: 10.1109/ACCESS.2019.2934495.

[30] B. P. Hughes, A. Anund, and T. Falkmer, "A comprehensive conceptual framework for road safety strategies," *Accid Anal Prev*, vol. 90, pp. 13–28, 2016, doi: https://doi.org/10.1016/j.aap.2016.01.017.

[31] A. Shalom Hakkert and V. Gitelman, "Thinking about the history of road safety research: Past achievements and future challenges," *Transp Res Part F Traffic Psychol Behav*, vol. 25, pp. 137–149, 2014, doi: https://doi.org/10.1016/j.trf.2014.02.005.

[32] D. Mohan, "Traffic safety: Rights and obligations," *Accid Anal Prev*, vol. 128, pp. 159–163, 2019, doi: https://doi.org/10.1016/j.aap.2019.04.010.

[33] M.-Å. Belin, P. Tillgren, and E. Vedung, "Vision Zero – a road safety policy innovation," *Int J Inj Contr Saf Promot*, vol. 19, no. 2, pp. 171–179, Jun. 2012, doi: 10.1080/17457300.2011.635213.

[34] B. P. Hughes, S. Newstead, A. Anund, C. C. Shu, and T. Falkmer, "A review of models relevant to road safety," *Accid Anal Prev*, vol. 74, pp. 250–270, 2015, doi: https://doi.org/10.1016/j.aap.2014.06.003.

[35] A. E. Mendoza, C. A. Wybourn, M. A. Mendoza, M. J. Cruz, C. J. Juillard, and R. A. Dicker, "The Worldwide Approach to Vision Zero: Implementing Road Safety Strategies to Eliminate Traffic-Related Fatalities," *Curr Trauma Rep*, vol. 3, no. 2, pp. 104–110, 2017, doi: 10.1007/s40719-017-0085-z.

[36] B. Elvebakk, "Vision Zero: Remaking Road Safety," *Mobilities*, vol. 2, no. 3, pp. 425–441, Nov. 2007, doi: 10.1080/17450100701597426.

[37] "Global Plan for the Decade of Action for Road Safety 2011–2020," 2011.

[38] Hollnagel and Erik, *Cognitive reliability and error analysis method (CREAM)*. Elsevier, 1998.

[39] J. Rasmussen, “Risk management in a dynamic society: a modelling problem,” *Saf Sci*, vol. 27, no. 2, pp. 183–213, 1997, doi: https://doi.org/10.1016/S0925-7535(97)00052-0.

[40] N. Leveson, “A new accident model for engineering safer systems,” *Saf Sci*, vol. 42, no. 4, pp. 237–270, 2004, doi: https://doi.org/10.1016/S0925-7535(03)00047-X.

[41] Scott A. Shappell, “The Human Factors Analysis and Classification System–HFACS,” Feb. 2000.

[42] Reason and James, *Human error*. Cambridge university press, 1990.

[43] Wei S-X, Sui Y-C, and Chen Y-C, “Research into the human errors evaluation method of flight accidents based on HFACS,” *Aeronaut Comput Tech*, 2014.

[44] M.-C. Chiu and M.-C. Hsieh, “Latent human error analysis and efficient improvement strategies by fuzzy TOPSIS in aviation maintenance tasks,” *Appl Ergon*, vol. 54, pp. 136–147, 2016, doi: https://doi.org/10.1016/j.apergo.2015.11.017.

[45] M. Hsieh *et al.*, “Application of HFACS, fuzzy TOPSIS, and AHP for identifying important human error factors in emergency departments in Taiwan,” *Int J Ind Ergon*, vol. 67, pp. 171–179, 2018, doi: https://doi.org/10.1016/j.ergon.2018.05.004.

[46] E. Akyuz, “A marine accident analysing model to evaluate potential operational causes in cargo ships,” *Saf Sci*, vol. 92, pp. 17–25, 2017, doi: https://doi.org/10.1016/j.ssci.2016.09.010.

[47] E. Akyuz and M. Celik, “Utilisation of cognitive map in modelling human error in marine accident analysis and prevention,” *Saf Sci*, vol. 70, pp. 19–28, 2014, doi: https://doi.org/10.1016/j.ssci.2014.05.004.

[48] X. Chen, X. Liu, and Y. Qin, "An extended HFACS based risk analysis approach for human error accident with interval type-2 fuzzy sets and prospect theory," *Journal of Intelligent & Fuzzy Systems*, vol. 37, pp. 8381–8395, 2019, doi: 10.3233/JIFS-190929.

[49] N. S. Olsen, "Coding ATC incident data using HFACS: Inter-coder consensus," *Saf Sci*, vol. 49, no. 10, pp. 1365–1370, 2011, doi: https://doi.org/10.1016/j.ssci.2011.05.007.

[50] W.-C. Li, D. Harris, and C.-S. Yu, "Routes to failure: Analysis of 41 civil aviation accidents from the Republic of China using the human factors analysis and classification system," *Accid Anal Prev*, vol. 40, no. 2, pp. 426–434, 2008, doi: https://doi.org/10.1016/j.aap.2007.07.011.

[51] Y. Zhang, T. Liu, Q. Bai, W. Shao, and Q. Wang, "New systems-based method to conduct analysis of road traffic accidents," *Transp Res Part F Traffic Psychol Behav*, vol. 54, pp. 96–109, 2018, doi: https://doi.org/10.1016/j.trf.2018.01.019.

[52] Y. Zhang, L. Jing, C. Sun, J. Fang, and Y. Feng, "Human factors related to major road traffic accidents in China," *Traffic Inj Prev*, vol. 20, no. 8, pp. 796–800, Nov. 2019, doi: 10.1080/15389588.2019.1670817.

[53] C. Preyssl, "Safety risk assessment and management—the ESA approach," *Reliab Eng Syst Saf*, vol. 49, no. 3, pp. 303–309, 1995, doi: https://doi.org/10.1016/0951-8320(95)00047-6.

[54] D. N. Ford and J. D. Sterman, "Dynamic modeling of product development processes," *Syst Dyn Rev*, vol. 14, no. 1, pp. 31 – 68, 1998, doi: 10.1002/(SICI)1099-1727(199821)14:1<31::AID-SDR141>3.0.CO;2-5.

[55] Y. Liu, Z.-P. Fan, Y. Yuan, and H. Li, "A FTA-based method for risk decision-making in emergency response," *Comput Oper Res*, vol. 42, pp. 49–57, 2014, doi: https://doi.org/10.1016/j.cor.2012.08.015.

[56] D.-Y. Chang, “Applications of the extent analysis method on fuzzy AHP,” *Eur J Oper Res*, vol. 95, no. 3, pp. 649–655, 1996, doi: https://doi.org/10.1016/0377-2217(95)00300-2.

[57] J. S. Nicolis and I. Tsuda, “Chaotic dynamics of information processing: The ‘magic number seven plus-minus two’ revisited,” *Bull Math Biol*, vol. 47, no. 3, pp. 343–365, 1985, doi: https://doi.org/10.1016/S0092-8240(85)90031-X.

[58] C.-L. Chen Shu-Jen and Hwang, “Fuzzy Multiple Attribute Decision Making Methods,” in *Fuzzy Multiple Attribute Decision Making: Methods and Applications*, Berlin, Heidelberg: Springer Berlin Heidelberg, 1992, pp. 289–486. doi: 10.1007/978-3-642-46768-4_5.

[59] C. Chauvin, S. Lardjane, G. Morel, J.-P. Clostermann, and B. Langard, “Human and organisational factors in maritime accidents: Analysis of collisions at sea using the HFACS,” *Accid Anal Prev*, vol. 59, pp. 26–37, 2013, doi: https://doi.org/10.1016/j.aap.2013.05.006.

[60] S.-T. Chen, A. Wall, P. Davies, Z. Yang, J. Wang, and Y.-H. Chou, “A Human and Organisational Factors (HOFs) analysis method for marine casualties using HFACS-Maritime Accidents (HFACS-MA),” *Saf Sci*, vol. 60, pp. 105–114, 2013, doi: https://doi.org/10.1016/j.ssci.2013.06.009.

[61] C. Chauvin, S. Lardjane, G. Morel, J.-P. Clostermann, and B. Langard, “Human and organisational factors in maritime accidents: Analysis of collisions at sea using the HFACS,” *Accid Anal Prev*, vol. 59, pp. 26–37, 2013, doi: https://doi.org/10.1016/j.aap.2013.05.006.

[62] A. Mazaheri, J. Montewka, J. Nisula, and P. Kujala, “Usability of accident and incident reports for evidence-based risk modeling – A case study on ship grounding

reports," *Saf Sci*, vol. 76, pp. 202–214, 2015, doi: https://doi.org/10.1016/j.ssci.2015.02.019.

[63] M. Karthick, T. P. Robert, and C. S. Kumar, "HFACS-based FAHP implementation to identify critical factors influencing human error occurrence in nuclear plant control room," *Soft comput*, vol. 24, no. 21, pp. 16577–16591, 2020, doi: 10.1007/s00500-020-04961-1.

[64] M.-C. Hsieh *et al.*, "An Investigation of Human Errors in Medication Adverse Event Improvement Priority Using a Hybrid Approach," *Healthcare*, vol. 9, no. 4, 2021, doi: 10.3390/healthcare9040442.

[65] T. L. Saaty, *The analytic hierarchy process : planning, priority setting, resource allocation*, 2nd ed. RWS, 1990. [Online]. Available: https://cir.nii.ac.jp/crid/1130000793905690240

[66] N. Subramanian and R. Ramanathan, "A review of applications of Analytic Hierarchy Process in operations management," *Int J Prod Econ*, vol. 138, no. 2, pp. 215–241, 2012, doi: https://doi.org/10.1016/j.ijpe.2012.03.036.

[67] A. Emrouznejad and M. Marra, "The state of the art development of AHP (1979–2017): a literature review with a social network analysis," *Int J Prod Res*, vol. 55, no. 22, pp. 6653–6675, Nov. 2017, doi: 10.1080/00207543.2017.1334976.

[68] T. L. Saaty, "What is the Analytic Hierarchy Process?," in *Mathematical Models for Decision Support*, G. Mitra, H. J. Greenberg, F. A. Lootsma, M. J. Rijkaert, and H. J. Zimmermann, Eds., Berlin, Heidelberg: Springer Berlin Heidelberg, 1988, pp. 109–121.

[69] R. W. Saaty, "The analytic hierarchy process—what it is and how it is used," *Mathematical Modelling*, vol. 9, no. 3, pp. 161–176, 1987, doi: https://doi.org/10.1016/0270-0255(87)90473-8.

[70] K. Ransikarbum and S. J. Mason, “Goal programming-based post-disaster decision making for integrated relief distribution and early-stage network restoration,” *Int J Prod Econ*, vol. 182, pp. 324–341, 2016, doi: https://doi.org/10.1016/j.ijpe.2016.08.030.

[71] M. Kordi, “Comparison of fuzzy and crisp analytic hierarchy process (AHP) methods for spatial multicriteria decision analysis in GIS,” 2008.

[72] N. Nabeeh, M. Abdel-Basset, H. El-Ghareeb, and A. Aboelfetouh, “Neutrosophic Multi-Criteria Decision Making Approach for IoT-Based Enterprises,” *IEEE Access*, vol. PP, p. 1, Apr. 2019, doi: 10.1109/ACCESS.2019.2908919.

[73] D. PFATB, “Fuzzy Analytical Hierarchy Process (FAHP) using geometric mean method to select best processing framework adequate to big data,” *J Theor Appl Inf Technol*, vol. 99, no. 1, pp. 207–226, 2021.

[74] T. Zhou, C. Wu, J. Zhang, and D. Zhang, “Incorporating CREAM and MCS into fault tree analysis of LNG carrier spill accidents,” *Saf Sci*, vol. 96, pp. 183–191, 2017, doi: https://doi.org/10.1016/j.ssci.2017.03.015.

[75] S. Kum and B. Sahin, “A root cause analysis for Arctic Marine accidents from 1993 to 2011,” *Saf Sci*, vol. 74, pp. 206–220, 2015, doi: https://doi.org/10.1016/j.ssci.2014.12.010.

[76] D. Wang, P. Zhang, and L. Chen, “Fuzzy fault tree analysis for fire and explosion of crude oil tanks,” *J Loss Prev Process Ind*, vol. 26, no. 6, pp. 1390–1398, 2013, doi: https://doi.org/10.1016/j.jlp.2013.08.022.

[77] E. Ruijters and M. Stoelinga, “Fault tree analysis: A survey of the state-of-the-art in modeling, analysis and tools,” *Comput Sci Rev*, vol. 15–16, pp. 29–62, 2015, doi: https://doi.org/10.1016/j.cosrev.2015.03.001.

[78] J. D. Andrews and T. R. Moss, "Reliability and risk assessment," Professional Engineering Pub., 2002.

[79] M. Sarbayev, M. Yang, and H. Wang, "Risk assessment of process systems by mapping fault tree into artificial neural network," *J Loss Prev Process Ind*, vol. 60, pp. 203–212, May 2019, doi: 10.1016/j.jlp.2019.05.006.

[80] H. A. Illias, X. R. Chai, A. H. A. Bakar, and H. Mokhlis, "Transformer Incipient Fault Prediction Using Combined Artificial Neural Network and Various Particle Swarm Optimisation Techniques," *PLoS One*, vol. 10, 2015.

[81] H. R. R. Ashtiani and P. Shahsavari, "A comparative study on the phenomenological and artificial neural network models to predict hot deformation behavior of AlCuMgPb alloy," *J Alloys Compd*, vol. 687, pp. 263–273, 2016, doi: https://doi.org/10.1016/j.jallcom.2016.04.300.

[82] N. Chitsazan, A. A. Nadiri, and F. T.-C. Tsai, "Prediction and structural uncertainty analyses of artificial neural networks using hierarchical Bayesian model averaging," *J Hydrol (Amst)*, vol. 528, pp. 52–62, 2015, doi: https://doi.org/10.1016/j.jhydrol.2015.06.007.

[83] R. N. Singarimbun, E. B. Nababan, and O. S. Sitompul, "Adaptive Moment Estimation To Minimize Square Error In Backpropagation Algorithm," in *2019 International Conference of Computer Science and Information Technology (ICoSNIKOM)*, 2019, pp. 1–7. doi: 10.1109/ICoSNIKOM48755.2019.9111563.

[84] "Multilayer Shallow Neural Network Architecture."

[85] I. A. Basheer and M. Hajmeer, "Artificial neural networks: fundamentals, computing, design, and application," *J Microbiol Methods*, vol. 43, no. 1, pp. 3–31, 2000, doi: https://doi.org/10.1016/S0167-7012(00)00201-3.

[86] S. Karsoliya and M. A. K. Azad, “Approximating Number of Hidden layer neurons in Multiple Hidden Layer BPNN Architecture,” 2012.

[87] F. S. Panchal and M. Panchal, “Review on Methods of Selecting Number of Hidden Nodes in Artificial Neural Network,” 2014.

[88] J. J. H. Liou, P. C. Y. Liu, S.-S. Luo, H.-W. Lo, and Y.-Z. Wu, “A hybrid model integrating FMEA and HFACS to assess the risk of inter-city bus accidents,” *Complex & Intelligent Systems*, vol. 8, no. 3, pp. 2451–2470, 2022, doi: 10.1007/s40747-022-00657-1.

[89] M. Yazdi, S. Daneshvar, and H. Setareh, “An extension to Fuzzy Developed Failure Mode and Effects Analysis (FDFMEA) application for aircraft landing system,” *Saf Sci*, vol. 98, pp. 113–123, 2017, doi: https://doi.org/10.1016/j.ssci.2017.06.009.

[90] L. M. R. MIRI, J. Wang, Z. Yang, and J. Finlay, “Application of fuzzy fault tree analysis on oil and gas offshore pipelines,” 2011.

[91] M. Celik, S. M. Lavasani, and J. Wang, “A risk-based modelling approach to enhance shipping accident investigation,” *Saf Sci*, vol. 48, no. 1, pp. 18–27, 2010, doi: https://doi.org/10.1016/j.ssci.2009.04.007.

[92] M. Omidvari, S. M. R. Lavasani, and S. Mirza, “Presenting of failure probability assessment pattern by FTA in Fuzzy logic (case study: Distillation tower unit of oil refinery process),” *J Chem Health Saf*, vol. 21, no. 6, pp. 14–22, Nov. 2014, doi: 10.1016/j.jchas.2014.06.003.

[93] S. M. Lavasani, A. Zendegani, and M. Celik, “An extension to Fuzzy Fault Tree Analysis (FFTA) application in petrochemical process industry,” *Process Safety and Environmental Protection*, vol. 93, pp. 75–88, 2015, doi: https://doi.org/10.1016/j.psep.2014.05.001.

[94] “GLOBAL STATUS REPORT ON ROAD SAFETY 2018,” 2018.

[95] M. Zhang, D. Zhang, F. Goerlandt, X. Yan, and P. Kujala, "Use of HFACS and fault tree model for collision risk factors analysis of icebreaker assistance in ice-covered waters," *Saf Sci*, vol. 111, pp. 128–143, 2019, doi: https://doi.org/10.1016/j.ssci.2018.07.002.

[96] J. J. Buckley, "Fuzzy hierarchical analysis," *Fuzzy Sets Syst*, vol. 17, no. 3, pp. 233–247, 1985, doi: https://doi.org/10.1016/0165-0114(85)90090-9.

[97] T. Onisawa, "An approach to human reliability in man-machine systems using error possibility," *Fuzzy Sets Syst*, vol. 27, no. 2, pp. 87–103, 1988, doi: https://doi.org/10.1016/0165-0114(88)90140-6.

[98] T. Onisawa and Y. Nishiwaki, "Fuzzy human reliability analysis on the Chernobyl accident," *Fuzzy Sets Syst*, vol. 28, no. 2, pp. 115–127, 1988, doi: https://doi.org/10.1016/0165-0114(88)90194-7.

[99] T. Onisawa, "An application of fuzzy concepts to modelling of reliability analysis," *Fuzzy Sets Syst*, vol. 37, pp. 267–286, 1990.

[100] T. Onisawa, "Subjective analysis of system reliability and its analyzer," *Fuzzy Sets Syst*, vol. 83, no. 2, pp. 249–269, 1996, doi: https://doi.org/10.1016/0165-0114(95)00381-9.

[101] Hsi-Mei Hsu and Chen-Tung Chen, "Aggregation of fuzzy opinions under group decision making," *Fuzzy Sets Syst*, vol. 79, no. 3, pp. 279–285, 1996, doi: https://doi.org/10.1016/0165-0114(95)00185-9.

[102] M. Yazdi, S. Daneshvar, and H. Setareh, "An extension to Fuzzy Developed Failure Mode and Effects Analysis (FDFMEA) application for aircraft landing system," *Saf Sci*, vol. 98, pp. 113–123, 2017, doi: https://doi.org/10.1016/j.ssci.2017.06.009.

[103] M. Sarbayev, M. Yang, and H. Wang, "Risk assessment of process systems by mapping fault tree into artificial neural network," *J Loss Prev Process Ind*, vol. 60, pp. 203–212, 2019, doi: https://doi.org/10.1016/j.jlp.2019.05.006.

[104] N. Khakzad, F. Khan, and P. Amyotte, "Dynamic safety analysis of process systems by mapping bow-tie into Bayesian network," *Process Safety and Environmental Protection*, vol. 91, no. 1, pp. 46–53, 2013, doi: https://doi.org/10.1016/j.psep.2012.01.005.

[105] A. Bobbio, L. Portinale, M. Minichino, and E. Ciancamerla, "Improving the analysis of dependable systems by mapping fault trees into Bayesian networks," *Reliab Eng Syst Saf*, vol. 71, no. 3, pp. 249–260, 2001, doi: https://doi.org/10.1016/S0951-8320(00)00077-6.

[106] N. Khakzad, F. Khan, and P. Amyotte, "Safety analysis in process facilities: Comparison of fault tree and Bayesian network approaches," *Reliab Eng Syst Saf*, vol. 96, no. 8, pp. 925–932, 2011, doi: https://doi.org/10.1016/j.ress.2011.03.012.

[107] D. A. Crowl and J. F. Louvar, *Chemical process safety: fundamentals with applications*. Pearson Education, 2001.