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Public transport risk assessment through fault tree analysis (Baku city example)

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Abstract. Road safety has become an increasingly important issue within urban transportation systems, particularly in developing nations such as Azerbaijan, where traffic accidents continue to be a primary source of injuries and property damage. This purpose of the study was to assess the risks linked to Baku's public transportation network by employing Fault Tree Analysis (FTA) within the Haddon Matrix framework, which organises contributing factors into three categories: vehicle, human, and road environment. The FTA approach facilitated a systematic, deductive examination of potential failure causes that could lead to accidents involving public transport. Significant findings revealed that vehicle-related problems, including malfunctioning braking systems, steering issues, and inadequate maintenance, greatly increase the likelihood of incidents. Human-related risks such as driver behaviour (for instance, speeding and failure to yield), non-compliance with traffic regulations, and unpredictable pedestrian actions also significantly contribute to the problem. Additionally, road-related issues like poor infrastructure, lack of adequate signage, insufficient lighting, and unsafe bus stop designs further heighten the risk. The interplay of these factors indicates that public transport accidents in Baku are multi-faceted and frequently preventable. This study underscored the necessity of systematic safety evaluations, routine vehicle inspections, and improved public awareness initiatives to reduce risks associated with urban transport. The practical implications of this research provide urban transport planners and policymakers with insights into priority risk areas, thereby facilitating more effective strategies to enhance safety within Baku's transit system

Keywords: urban traffic accidents; vehicle, risk analysis; road safety; bus operation risks

Introduction

A study of safety issues in public transport systems has become increasingly important due to the risks posed by rapidly growing urban mobility and rising accident rates. The analysis of road accidents, particularly in bus transport, requires a systematic investigation into technical failures, driver and pedestrian behaviour, and the influence of road infrastructure. Identification of accident causes and modelling their interactions are essential for effective risk management and the improvement of transport safety. In support of this concern, accident statistics from Baku city for the years 2019 to 2024 reveal that the most frequent causes of public transport-related incidents stem from both technical deficiencies and unsafe human behaviours. Statistical data indicate that the main causes of bus accidents in Baku were primarily associated with driver-related behavioural errors. The most common cause was improper manoeuvring, which accounted for 34.0% of all recorded incidents. This was followed by speeding, responsible for 22.4% of accidents. The failure to maintain a safe following distance ranked next, contributing to 5.4% of the cases. In addition, failure to stop at pedestrian crossings (5.4%) and passenger-related violations (4.8%) were also identified as significant contributing factors. Other traffic rule violations accounted for 3.4%, while violations at intersections represent 2.7%. Disregard for road signs and markings accounted for only 0.7% of incidents. Similarly, both driving under the influence and entering the oncoming lane or improper overtaking each represented 0.7% of the recorded accidents. Overall, this distribution illustrates that human factors – particularly driver behaviour – are the leading contributors to accident risk in urban bus operations. While technical malfunctions may occasionally play a role, the findings emphasise the importance of systematically incorporating human behaviour into risk assessments. This underscores the need for comprehensive and integrated

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risk modelling in public transportation systems. (The State Statistical Committee…, 2024).

The risk modelling reveals the necessity of integrating both human and technical factors into analytical models. Consequently, the application of structured methods like Fault Tree Analysis (FTA) becomes critical for systematically identifying and quantifying contributing factors. To support the development of such models, a critical review of the academic literature was presented, focusing on studies that have applied FTA and similar methodologies to transportation safety analysis. Numerous studies have investigated the application of FTA in transport and safety-related systems. However, a closer look reveals a consistent gap in applying these methods specifically to urban public bus systems.

J. Xi *et al.* (2021) applied FTA to model cause-effect relationships within transportation systems, demonstrating its strength in structuring complex risk scenarios. Nevertheless, their analysis lacks attention to the operational context of specific modes like urban buses, including route characteristics and service dynamics, highlighting a need for context-sensitive applications. While the FTA (2021) report primarily categorises risk factors in a descriptive manner, X. Qi *et al.* (2025) employed an entropy-weighted DEMATEL approach to offer a structured quantitative analysis of operational risk in public transportation. They analysed 18 risk variables including safety awareness, human initiative, funding adequacy, and inspection frequency not only ranking them by importance, but also modelling their interdependencies. This provided a stronger empirical foundation for developing prioritised, data-driven risk mitigation strategies, elevating the analysis from mere categorisation to actionable decision-making

A more technical approach was taken by W. Huang *et al.* (2021), who merged Bayesian networks with FTA to analyse failure modes in transit systems. The integration strengthened probabilistic inference capabilities. That said, their scope was confined to hardware and system components, lacking attention to operational practices and human error – factors essential to understanding urban bus vulnerabilities. Taking a broader systems approach, K. Pan *et al.* (2022) combined FTA with system dynamics to study resilience in passenger transport systems through the lens of sustainable mobility. The inclusion of social and ecological perspectives was commendable. Nonetheless, the generality of their model limited its relevance to city bus networks, where specific behaviours, mechanical reliability, and infrastructure constraints were paramount.

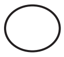
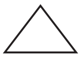
Adding a layer of decision-making under uncertainty, M. Ghadhab *et al.* (2019) integrated fuzzy logic and artificial intelligence into FTA structures. This methodological innovation enhanced adaptability, yet the absence of application to public transport environments – especially interactions between drivers, pedestrians, and urban complexity – diminished its immediate practical value. T.H.A. Nguyen *et al.* (2022) employed Fault Tree Analysis on the Hanoi Urban Mass Rapid Transit system to quantitatively model train collision risk. Their framework constructed a top-level event for collision, incorporated operational data (2018-2021), and validated the model empirically thus establishing a direct link between model outputs and system-specific safety performance.

These studies collectively affirmed the robustness of FTA as a risk analysis tool but revealed underexplored areas in its adaptation to urban public transportation, especially bus operations. Critical variables such as driver behaviour, passenger interaction, technical malfunctions, and infrastructure-related risks were often omitted or insufficiently analysed. Moreover, few studies employed real-world operational data or quantitative modelling software for system-specific evaluations. In response to these gaps, the present study applied the FTA method directly to Baku's public bus network, using incident-based data and software-supported modelling (top event FTA). The purpose of this study was to assess the risks associated with the operation of public transport in Baku by applying the Fault Tree Analysis method within the Haddon Matrix framework, with a focus on identifying and quantitatively classifying the key technical, behavioural, and infrastructural factors that contribute to accidents to develop evidence-based recommendations for improving the safety of urban bus transportation. This approach enabled a hierarchical breakdown of accident scenarios and a quantitative risk classification across key domains technical, behavioural, and environmental. By analysing prevalent accident causes like speeding, violation of traffic rules, technical faults (e.g., brake/steering issues), and pedestrian misbehaviour, the study contributed to data-informed safety intervention planning and prioritised risk management in urban bus transport.

Materials and Methods

Fault Tree Analysis is a structured and deductive technique used to identify cause-effect relationships in hazardous scenarios, especially within complex systems. This top-down method begins with a primary failure – known as the top event – and systematically traces the potential underlying causes contributing to this failure. FTA is particularly valuable for detecting system vulnerabilities, critical risk sources, and interdependencies within operational processes. In this study, the FTA Top Event approach was employed to assess potential accidents in urban public transportation systems in Baku, Azerbaijan. The analysis adhered to the principles outlined in the international standard IEC 61025:2006 (2006), ensuring methodological rigour and comparability with international studies. Reliability analysis is a foundational aspect of risk modelling in technical systems, particularly in transportation. These models allowed for the quantitative assessment of system performance under various failure and recovery conditions (Zio, 2007). To visualise the logical structure of the fault tree, officially recognised symbols (Table 1) were used in accordance with IEC standards, enabling clear interpretation and consistent documentation. The analysis focused on the top event defined as a "public transport accident", and identified key sub-events related to driver error.

Table 1. Symbols used in Fault Tree Analysis

Symbol	Event	Function
	Main event	Event or error that provides the basis for analysis
	Undeveloped event	Event that is not further analysed or has a small impact
	Top or mediator event	Final event arising from more fundamental events
	Situation event	Situation where a special condition exists for the occurrence of an event
	AND gate	Event that results in all inputs to the event occurring simultaneously
	OR gate	Event that results in the occurrence of at least one input event
	Transfer symbol	Symbol referring to another part of the fault tree

Source: F.S. Dashdamirov & A.C. Sharifov (2020)

City-specific data from Baku's public bus network were integrated into the fault tree model. These included traffic density, road infrastructure characteristics, frequency of recorded driver violations, and historical accident reports from the Baku Transport Agency and State Traffic Police Department. The sub-causes associated with driver errors were identified based on observed patterns in Baku's urban traffic and their relevance to accident occurrence:

▷ improper manoeuvring refers to incorrect or hazardous vehicle handling during lane changes, turns, or merging, which can lead to collisions in dense urban traffic;

▷ failure to maintain a safe following distance increases the risk of rear-end collisions, especially in stop-and-go traffic conditions common in urban environments like Baku;

▷ exceeding speed limits reduces a driver's reaction time and control over the vehicle, significantly elevating the likelihood of accidents in areas with high pedestrian activity;

▷ not stopping at pedestrian crossings endangers vulnerable road users and is a major contributing factor in public transport-related pedestrian accidents;

▷ violation of traffic signs and markings indicates non-compliance with road regulations, which can result in confusion, right-of-way conflicts, and intersection-related accident;

▷ driving under the influence of alcohol impairs cognitive and motor functions, making drivers more prone to errors in judgment, delayed reactions, and loss of vehicle control.

This fault tree framework allowed the systematic identification of high-risk scenarios in Baku's public transport system, supporting the development of targeted risk mitigation strategies. The "Main Events of DDV" programme was used for the analysis, the main event of which is the risk of accidents in public transport. Factors that may be responsible for this risk were identified and a systematic fault tree was created (Fig. 1). The analysis showed that three main groups of factors play a major role in the risk: driver error, pedestrian violations, and technical defects in vehicles. Among the risks associated with pedestrian behaviour, there were incidents of theft, of getting in and out of a bus without waiting for it to stop, of crossing a road without following traffic rules. These behaviours, particularly during rush hours, have a negative impact on the decision-making of drivers and on traffic flow. These include failure to activate the brake system in time, steering system failures, lighting and signalling systems, sudden engine shutdowns, fuel system failures and gearbox failures. These technical failures increase the risk of accidents and prevent uninterrupted and safe operation of the transport system.

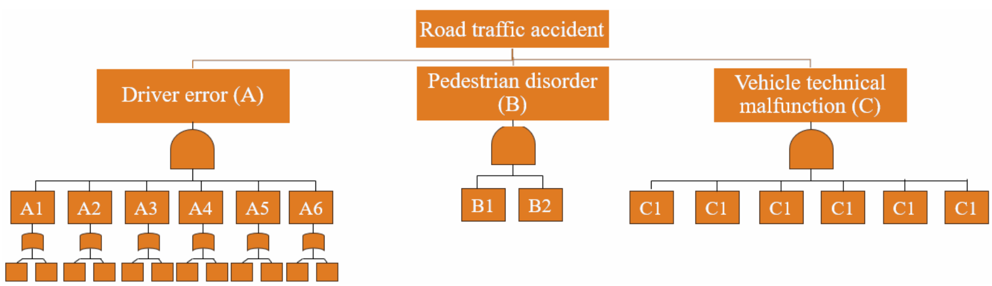


Figure 1. Fault Tree Analysis of accidents on buses in Baku

Source: created by the author

In the FTA analysis, probabilities were calculated for each of these sub-factors, using logical gates (AND, OR). Of these three groups of factors, technical malfunctions and driver errors pose the greatest risk, and targeted interventions are needed to mitigate their impact. The use of the FTA in this study allowed a structured identification of causality relationships, prioritisation of high risk components, and the development of scientifically based public transport safety strategies. Once the risks were identified, they were incorporated into the fault tree structure to examine how individual and combined events contribute to the top event. Following this step, appropriate reliability models were selected within the FTA software to simulate the behaviour and impact of each event. These models included various statistical and probabilistic tools such as constant failure rate, repairable/unrepairable models, and Weibull distributions, which were essential for quantifying failure probabilities and unavailability over time (Fig. 2):

Repairable
Constant
Unrepairable
MTBF
MTTF
Weibull
Dormant

Figure 2. Different reliability models in FTA programme
Source: created by the author based on risk modelling in the FTA software environment

Each was used to describe the failure and recovery characteristics of a different system. The following is an explanation of what they are and when they are used:

1. Repairable model. The system can be restored after failure. The equation for a recoverable system is as follows (Elsayed, 2012):

$$q(t) = qe^{-(\lambda+\mu)t} + \frac{\lambda}{\lambda+\mu}(1-e)^{-(\lambda+\mu)t}. \qquad (1)$$

The reliability models used in FTA required the specification of several key parameters to quantify failure behaviour: λ (failure rate): the rate at which a component or event was expected to fail over time. It was typically measured in failures per unit time (e.g., failures/hour) and was used primarily in models assuming a constant or exponential distribution of failures. μ (repair rate): the rate at which a failed component was restored to operational condition. This parameter was crucial in repairable models and reflects system maintainability. Like λ, it was expressed in events per unit time. q (initial unavailability or probability of failure in the initial state): the probability that a component was already in a failed state at the beginning of the observation or mission time. It was especially relevant in dormant or standby models, where components were not active but still susceptible to hidden failures. t – time elapsed since the start of observation, e – base of the natural logarithm.

$$\omega(t) = \lambda[1 - q(t)], \qquad (2)$$

where ω(t) – failure frequency at time t, indicating how often failures were expected to occur in the system per unit time; λ – failure rate of the system (i.e., the rate at which failures occur in a functioning state); *q(t)* – unavailability function, representing the probability that the system was in a failed state at time t.

2. Constant model. Failure or reliability varied with the severity of the event. For example, some components had a fixed probability of failure over time. Usually modelled by exponential distribution (Elsayed, 2012):

$$q(t) = q. \qquad (3)$$

3. Unrepairable model. After a system failure, it was not restored, it was simply replaced. For example, disposable devices, batteries. Equations (2) and (4) were used.

$$q(t) = (1-q)e^{-\lambda t}. \qquad (4)$$

4. MTBF (Mean Time Between Failures). It showed the average time between failures for systems under repair. Used to measure the time the system was running. Usually modelled by an exponential distribution (Moddares *et al.*, 2016):

$$q(t) = \frac{\lambda}{\lambda+\mu}\, 1 - e^{-(\lambda+\mu)t}, \qquad (5)$$

$$\lambda = \frac{1}{MTBF} \text{ və } \mu = \frac{1}{MTTR}, \qquad (6)$$

where *q(t)* – the probability that the system is in a faulty state at a given time; $\omega(t)$ – fault intensity (the probability of a fault occurring at a given time); λ – failure rate (*MTBF*); μ – recovery speed (related to *MTTR* – mean time to repair).

5. MTTF (Mean Time to Failure). Indicated the availability of systems that were not repaired. 1 –the average time for a component or system to fail (Moddares *et al.*, 2016):

$$q(t) = 1 - e^{-(\lambda+\mu)t}, \qquad (7)$$

$$\lambda = \frac{1}{MTBF}. \qquad (8)$$

6. Weibull. It was used to model different types of failures. The failure rate varied over time (may increase, decrease, or remain constant). For example, in the analysis of fatigue of mechanical components (O'Connor & Kleyner, 2012):

$$q(t) = 1 - \exp\left[-\left(\frac{t-\lambda}{\eta}\right)\right]^{\beta}, \qquad (9)$$

where η – measurement parameter (average value over the life of the system); β – shape parameter (determines the failure rate of the system); γ – start delay time (time after the system was put into operation before the fault starts). The Weibull distribution considered that the failure process changed over time: β > 1 early failure (due to design errors or weak parts); β = 1 constant failure rate (corresponds to an exponential distribution); β < 1 ageing period (failures increase due to wear).

7. Dormant (Passive systems). A system that has not been used for a certain period of time and can only fail when it is active. For example, backup generation systems, fire suppression systems (O'Connor & Kleyner, 2012):

$$q(t) = \frac{\lambda\tau-(1-e^{\lambda\tau})+\lambda MTTR(1-e)^{-\lambda\tau}}{\lambda\tau+\lambda MTTR(1-e)^{-\lambda\tau}}, \tag{10}$$

where τ – specified analysis period. This model described the combination of failure and recovery processes and shows the dynamics of equipment operation and repair.

Repairable and MTBF models were used for systems that can be restored after a failure, allowing for the calculation of both failure and recovery parameters. Unrepairable and MTTF models, on the other hand, were applied to components that are not restored once failed, focusing solely on the expected time to failure. The Constant model assumed a uniform failure rate over time, suitable for components with random, memoryless failures. The Weibull model was ideal for systems subject to mechanical fatigue, where the failure rate varied over time depending on operational stress or ageing. This methodological framework allowed for flexibility in modelling a wide range of system behaviours and supported more accurate risk estimation in Fault Tree Analysis. Selection of the appropriate model depended on the component characteristics and the nature of the risk being assessed.

Results and Discussion

Risks associated with driver behaviour

Distraction (Repairable model). This section presents the results of risk modelling related to driver distraction, interpreted through the repairable model framework. The analysis focuses on the probability of a driver becoming distracted due to factors such as fatigue, stress, or sleeplessness conditions that are typically reversible over time. Since distraction is a temporary and recoverable condition, the repairable model is particularly suitable, as it allows for modelling both the onset of distraction and the probability of attention recovery. Based on assumed working conditions and realistic parameters for an 8-hour urban transit shift, the model supports the assessment of risk dynamics over time and informs effective safety management strategies. The parameters used in this model are detailed in Table 2.

Table 2. Driver distraction risk modelling parameters (Repairable model)

Parameter	Symbol	Value	Disclosure
Failure rate	λ	0.1	Probability of distraction per hour
Recovery speed	μ	0.05	Probability of attention being restored per hour
Value	-	Hour	Calculations are made in units of hours

Source: compiled by the author based on assumed data for the case analysis

The table presents the key parameters for modelling driver distraction using the Repairable model. The failure rate (λ = 0.1) suggests that for every hour of work, there is a 10% probability that the driver may become distracted due to fatigue, stress, or other human factors. This value is particularly critical in long driving shifts common in urban bus operations. The repair rate (μ = 0.05) implies that there is a 5% chance per hour that the driver's attention can be restored through rest, recovery at stops, or other interventions. The values are based on assumed data but align with general fatigue patterns reported in driver performance studies. Using these parameters, further calculations were conducted to simulate how distraction risk evolves during a typical 8-hour workday.

Here, λ is the failure rate – the probability of the driver being distracted. The risk event (*q(t)*) is the probability of a distraction occurring within a certain time. μ is the speed at which the driver regains attention by resting. Since the work schedule is 8 hours, the probability of the driver's attention being distracted is assumed to be 10% for each hour. In this case, λ = 0.1. Assuming that the driver's fatigue is relieved by resting and regaining attention is 5% for each hour, then μ = 0.05. In this case, the unavailability graph will be as follows (Fig. 3):

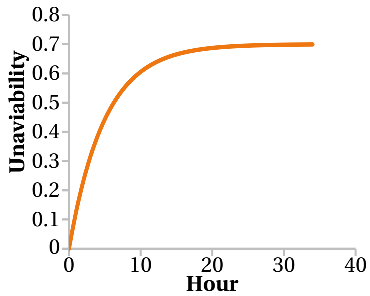


Figure 3. Driver distraction graph based on the Repairable model

Source: created by the author based on risk modelling in the FTA software environment

The distraction risk curve shown in Figure 3 illustrates the probability *q(t)* of a driver being in a distracted state over time, based on the repairable system formulation. Initially, the curve rises steeply, indicating that the risk of distraction increases quickly during the early hours of the shift. For example, by the second hour, the probability of being in a distracted state reaches approximately 16-18%, and by the sixth hour, it exceeds 40%. This trend aligns with known fatigue accumulation patterns, especially when rest breaks are inadequate.

As the shift progresses, the curve gradually flattens, indicating a balance between distraction occurrence and recovery. However, because the recovery rate ($\mu = 0.05$) is lower than the failure rate ($\lambda = 0.1$), the system tends toward higher unavailability – i.e., sustained distraction – unless effective countermeasures (e.g., scheduled breaks or shift rotation) are introduced. This finding highlights the asymmetric nature of fatigue accumulation versus recovery, and it underscores the importance of risk control strategies such as fatigue monitoring systems, micro-breaks, and duty cycle regulation in public transport operations. The simulation confirms that driver distraction is a dynamically evolving risk, which becomes more pronounced over time if not actively managed. The results emphasise the need for real-time monitoring and proactive interventions to prevent human error-related incidents in urban transport systems.

Fatigue (Repairable model). Fatigue is considered a recoverable human factor risk and is therefore modelled using the repairable model, similar to distraction. It represents a temporary decline in alertness and performance due to prolonged working hours or insufficient rest. Since fatigue can be mitigated through sleep, rest breaks, or shift rotation, it fits the logic of a system that can transition from failure to recovery. Continuous fatigue without recovery increases the likelihood of errors in perception, delayed reaction times, and overall driving performance degradation.

Non-conservation of spacing (Weibull model). This risk factor arises when drivers fail to maintain adequate spacing between vehicles, especially under hazardous driving conditions. The likelihood of such behaviour leading to an accident increases significantly when road conditions are poor and tire tread is worn down, both of which affect braking performance and control. Because tread wear is a gradual, time-dependent process, and road conditions dynamically influence accident probability, the Weibull model, which accounts for failure rates that change over time, is considered appropriate for modelling this risk. The parameters used for different road types and corresponding tread wear distances are presented in Table 3.

Table 3. Road conditions and tread wear parameters for Weibull-based spacing risk model

Road conditions	Tread wear distance (km)	β (Shape parameter)
Asphalt	40,000	2.5
Asphalt (rainy)	30,000	2.0
Gravel road	20,000	1.8
Mud road	15,000	1.5

Source: compiled by the author based on assumed data for the case analysis

Since the roads used in the study are asphalted, the shape parameter $\beta = 2.5$ is initially assumed, reflecting a wear-out failure pattern where the risk increases over time. The MTTF of the tires is estimated to be 24 months, and using the Gamma function value $\Gamma(1 + 1 / 2.5) \approx 0.89$. $\Gamma(1 + 1 / 2.5) \approx 0.89$, the corresponding scale parameter (η) can be calculated accordingly. As tread wear is a gradual and cumulative process, the condition of $\beta > 1$ is justified, indicating that failure likelihood grows as the tire ages. Given that asphalt roads dominate in Baku and field observations confirm that tire tread degradation accelerates with use, a more representative shape parameter $\beta = 3$ is adopted for final modelling. Analysis of the table data reveals that the failure probability remains relatively low during the first year but begins to increase significantly after approximately 18-20 months of service. This trend highlights the importance of implementing proactive tire replacement schedules to minimise the risk of blowouts or loss of traction in the later stages of a tire's operational life. The parameters used in modelling tire tread wear risk on asphalt roads using the Weibull distribution are presented in Table 4.

Table 4. Weibull model parameters for tire tread wear risk assessment on asphalt roads

Parameter	Symbol	Value	Disclosure
Characteristic life	Η	26.1 month	Average time for tire tread to wear out completely
Shape parameter	Β	2.5	As wear is accelerating, >1 is taken
Location	Γ	0	Failure can occur from the start
MTTF		24 month	Average service life (time to failure)
$\Gamma(1 + 1 / \beta)$		≈0.92	Gamma function

Source: compiled by the author based on assumed data for the case analysis

Since the roads used by the buses in the study in Baku are asphalted, $\beta = 2.5$. η is calculated as follows (Moddares *et al.*, 2016):

$$\eta = \frac{MTTF}{\Gamma/1 + \frac{1}{\beta}} = \frac{24}{0.92} \approx 26.1$$

The gamma function is taken from the Table 4 (O'Connor & Kleyner. 2012):

$$\Gamma(1 + 1 / 2.5) \approx 0.89$$
$$\Gamma(1 + 1 / 2) \approx 0.89$$
$$\Gamma(1 + 1 / 1.8) \approx 0.87$$
$$\Gamma(1 + 1 / 1.5) \approx 0.83.$$

Notably, the shape parameter ($\beta = 2.5$) confirms that tire wear accelerates over time, and the characteristic life ($\eta = 26.1$ months) indicates the point at which failure becomes most likely. The model shows that while the mean time to failure (MTTF) is 24 months, the system begins entering a high-risk phase slightly before that threshold. The variation of the risk of not maintaining the distance, modelled using the Weibull distribution, illustrates how this probability evolves over time. As shown in Figure 4, the probability of failure interpreted as the risk of not maintaining a safe following distance increases gradually during the initial operational phase, then accelerates as time progresses. This pattern indicates a wear-out behaviour, typical for systems where $\beta > 1$, confirming that the risk becomes increasingly significant with continued exposure, ageing vehicle components, or driver fatigue accumulated over long driving periods.

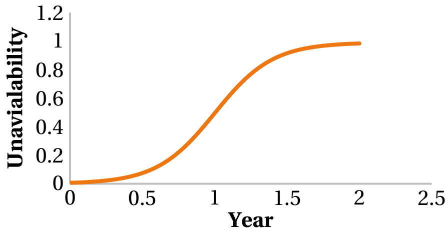


Figure 4. Variation of the risk of not maintaining the distance based on the Weibull model

Source: created by the author based on risk modeling in the FTA software environment

Figure 4 illustrates how the probability of failure due to not maintaining a safe following distance increases over time, as modelled by the Weibull distribution. The curve begins with a gradual slope, indicating lower risk in the early stages, but steepens as time progresses, reflecting the cumulative effect of road wear and driver fatigue. This trend confirms that spacing-related risks exhibit a wear-out pattern, making preventive interventions more critical in the later phases of vehicle or driver service time.

Driver inexperience (Weibull model). It is observed that risks are significantly higher during the initial months of a new driver's career due to factors such as lack of practical experience, unfamiliarity with routes, and limited exposure to real-world traffic conditions. During this early phase, incidents involving traffic violations, slower reaction times, and poor decision-making are more likely to occur, thereby elevating the overall risk level. However, as drivers accumulate experience, they typically demonstrate improved judgment, quicker response, and greater situational awareness, which gradually reduces the probability of errors and accidents. The Weibull distribution was applied to model this phenomenon, as it captures time-dependent variations in failure probability. The parameters used to assess driver inexperience risk are presented in Table 5. Although this type of risk is often associated with a $\beta < 1$ to represent decreasing failure rates, in this case, $\beta = 2.5$ is used to reflect a sharp decline in risk after the first few months of experience (Fig. 5). Figure 5 illustrates the variation in risk associated with driver inexperience over time based on the Weibull model. The curve demonstrates a rapid decline in risk during the first few months, reflecting how the likelihood of errors and unsafe behaviour decreases as drivers gain experience. By around the sixth month, the curve begins to level off, indicating that drivers have acquired essential skills and that further risk reduction becomes marginal.

Table 5. Weibull model parameters for driver inexperience risk assessment

Parameter	Symbol	Value	Disclosure
Characteristic life	η	6 months	Time it takes for a driver to learn the basic rules and gain experience
Shape parameter	β	2.5	Shows that errors decrease as experience increases ($\beta > 1$)
Location	γ	0	Risk starts from the first day of work
Value	-	Month	Analysis is performed with a monthly unit of measurement

Source: compiled by the author based on assumed data for the case analysis

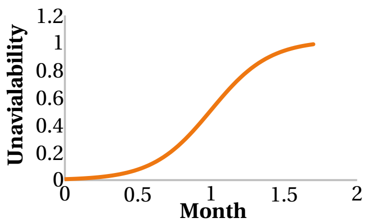


Figure 5. Risk effect of driver inexperience – variation according to the Weibull model

Source: created by the author based on risk modelling in the FTA software environment

Graphics delay (Dormant model). Schedule delays occur when drivers fail to depart or arrive on time according to the planned timetable. In an effort to compensate for lost time, drivers may increase their speed or bypass standard safety procedures, which elevates the risk of accidents. Since this risk typically remains inactive (dormant) during normal operations and only becomes active when a delay occurs, the Dormant model is considered appropriate for its analysis. This model helps to assess the transition from a low-risk to a high-risk state, triggered by schedule disruptions and unsafe compensatory behaviour. The parameters used for modelling this risk are presented in Table 6. The risk becomes active only under certain conditions (such as when a delay occurs) and remains active for a limited time. In such cases, the "dormant" model is ideal for representing the passive nature of the risk before activation and its rapid transition afterward. This model is particularly useful for capturing conditional failures that depend on triggers like inspection intervals, external disruptions, or timing mismatches. It allows for better modelling of latent risks that are not continuously present but can lead to significant disruptions if activated. This factor represents risks that are conditional, time-bound, and event-triggered requiring specialised modelling to reflect their dynamic behaviour (Fig. 6):

Table 6. Dormant model parameters for graphics delay risk assessment

Parameter	Symbol	Value	Disclosure
Failure rate	λ	0.05	Daily delay probability (5%)
MTTR	-	10 min	Driver speed recovery time
Inspection interval	τ	1 day	Daily schedule control
Value	-	Hour	Calculations are made hourly

Source: compiled by the author based on assumed data for the case analysis

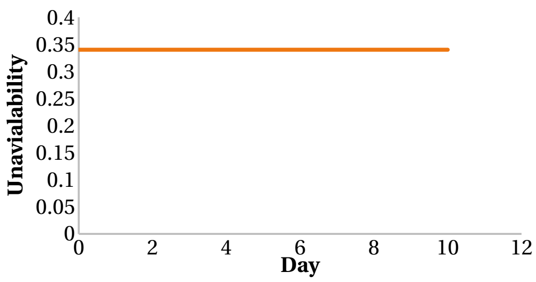


Figure 6. Change in risk due to schedule delay under the Dormant model

Source: created by the author based on risk modelling in the FTA software environment

Figure 6 shows how the risk level changes under the Dormant model when a schedule delay activates a previously passive hazard. Initially, the risk remains low or inactive, reflecting normal operating conditions where the driver adheres to the schedule. However, once a delay occurs, the risk increases sharply, demonstrating how the driver's compensatory behaviour such as speeding or skipping safety checks transforms the situation into a high-risk scenario.

Incitement by other vehicles (Constant model). In some accidents, buses are placed in a dangerous position due to the pressure or unpredictable actions of surrounding vehicles, such as sudden lane changes, tailgating, or aggressive overtaking. These incidents typically occur without prior indication and can happen at any moment during operation, making the Constant model appropriate due to its assumption of a uniform failure probability over time. This model enables the quantification of a persistent, background risk that is posed by external traffic behaviours beyond the bus driver's control. The parameters used to model this type of risk are provided in Table 7 and form the basis for calculating both the frequency and duration of risk exposure.

Table 7. Constant model parameters for risk of provocation by other vehicles

Parameter	Symbol	Value	Disclosure
Failure frequency	*W*	0.005	Provocations per hour
MTTR	-	1 hour	Time to eliminate the threat caused by the provocation
Value	-	Hour	Calculations are made hourly

Source: compiled by the author based on assumed data for the case analysis

The parameters required for modelling the risk of a bus being forced into danger by another vehicle include unavailability (q) and failure frequency (w). Unavailability refers to the probability that the bus is in an unsafe state due to external provocation, while failure frequency indicates how often such events are expected to occur. Failure frequency is calculated by considering how often provocation events occur and how long their effects persist, providing a measure of the system's exposure to repeated external threats. Failure frequency is calculated using the following equation:

$$w = \frac{q}{MTTR} = \frac{0.005}{1} = 0.005\ event/hour.$$

MTTR: 1 hour (average time to eliminate the threat posed by a provocation event).

Daily failure frequency:

$$0.005 \text{ x } 24 = 0.12 \text{ event/day}.$$

$$\text{q} = \frac{\lambda\ x\ MTTR}{1+(\lambda\ x\ MTTR)} = \frac{0.005\ x\ 1}{1+(0.005\ x\ 1\ )} = 0.00498 \approx 0.005.$$

In that case, the graph illustrates how the probability of being hit by another vehicle remains constant over time, assuming a fixed failure rate. This reflects the continuous and random nature of external provocation, where the risk does not increase or decrease with the vehicle's operational duration but instead persists uniformly throughout the entire period. Such a modelling approach is especially relevant for urban traffic environments where unpredictable driver behaviour – such as sudden overtaking or lane changes creates a steady-state background risk that must be considered in safety planning. This scenario is effectively visualised in Figure 7. The Weibull model effectively captures the non-constant nature of risk associated with drunk driving, allowing for a time-dependent failure rate that mirrors real-world conditions. This model is particularly valuable for assessing how the likelihood of incidents escalates during high-risk periods, such as evenings, weekends, or holidays, when alcohol-related behaviours are more prevalent. It also supports the development of targeted safety interventions based on temporal trends, including time-of-day or day-of-week patterns. The parameters used to model this risk are summarised in Table 8.

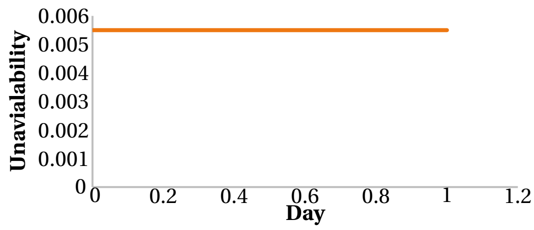


Figure 7. Probability of being hit by another vehicle – variation on the Constant model
Source: created by the author based on risk modelling in the FTA software environment

Table 8. Weibull model parameters for drunk driving risk assessment

Parameter	Symbol	Value	Disclosure
Characteristic life	Η	1 month	Average time for drunk driving incidents to reach dangerous levels
Shape parametric	Β	1.8	Indicates that risk increases over time (evenings and weekends)
Location	Γ	0	Risk starting point – incident can occur at any time
Value	-	Month	Monthly unit of measure

Source: compiled by the author based on assumed data for the case analysis

This expression represents the unavailability function for a repairable system, where λ denotes the failure rate and μ represents the repair (recovery) rate. The function calculates the probability that the system is in a failed state at any given time *t*, incorporating both failure occurrence and recovery over time. The accompanying table provides specific parameter values used to estimate time-dependent risk in systems that undergo random failures followed by maintenance-based recovery. This model is particularly valuable for evaluating technical components in public transportation, where maintenance actions can restore functionality after a breakdown. A similar time-based risk variation is illustrated in Figure 8, which shows how the probability of drunk driving incidents changes over time using the Weibull model.

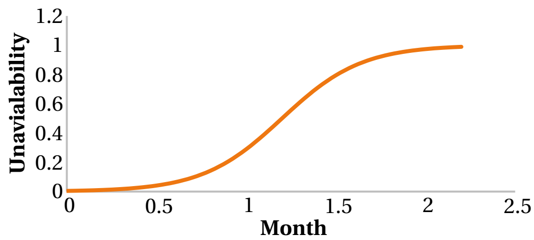


Figure 8. Risk of drunk driving – variation according to the Weibull model
Source: created by the author based on risk modelling in the FTA software environment

Pedestrian disorderly behaviour (Weibull model). This risk factor is another important cause of accidents involving public transport. The erratic behaviour of passengers and pedestrians especially boarding or alighting before the bus fully stops, or crossing the road inattentively frequently leads to accidents. These behaviours are not constant but vary over time and are influenced by behavioural patterns and situational habits. As such, they are best evaluated using the Weibull model, which accommodates time-dependent increases in risk. The parameters used for this modelling are summarised in Table 9, which outlines the characteristic life, shape, and location factors for estimating the risk of pedestrian disorderly behaviour.

Table 9. Weibull model parameters for risk of pedestrian disorderly behaviour

Parameter	Symbol	Value	Disclosure
Characteristic life	η	1 month	Average time for this type of behaviour to reach a dangerous level
Shape parametric	β	1.8	Indicates that the risk increases over time
Location	γ	0	Risk starting point – the event can occur at any time
Value	-	Month	Calculations are made monthly

Source: compiled by the author based on assumed data for the case analysis

Table 9 presents the parameters used in the Weibull model to evaluate the risk associated with disorderly pedestrian behavior, such as boarding or alighting from a bus before it stops and crossing without observing traffic. The characteristic life (η = 1 month) indicates the average time for such risky behavior to reach a critical threshold. The shape parameter (β = 1.8) shows that the risk increases over time, reflecting the cumulative effect of habitual unsafe actions. The location parameter (γ=0) assumes that the risk can arise at any moment, without an initial delay. The evolution of this risk over time is illustrated in Figure 9, which shows how the probability of accidents grows as unsafe behaviors persist.

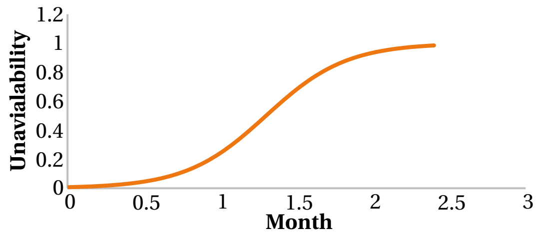


Figure 9. Risk of hop-on/hop-off behaviour without stopping the bus – variation according to the Weibull model
Source: created by the author based on risk modelling in the FTA software environment

The parameters in Table 10 reflect the modelling of behavioural risks that escalate quickly over time, such as aggressive or reckless driving. A shape parameter of β = 2.5 indicates that the risk does not remain constant but grows at an accelerating rate as the behaviour continues unchecked. The characteristic life η = 2 months suggests that, on average, such risky behaviour may reach a critical threshold within a relatively short period if no corrective action is taken. This modelling approach helps quantify how quickly certain behaviours can transition from moderate to high-risk, underscoring the need for early interventions such as monitoring, driver retraining, or enforcement strategies (Fig. 10).

Table 10. Weibull model parameters for rapidly increasing behavioural risks

Parameter	Symbol	Value	Disclosure
Characteristic life	η	2 months	Average time for risky behaviour to reach a dangerous level
Shape parameter	β	2.5	Higher β is assumed because risk increases more rapidly
Location	γ	0	Risk starting point – event can occur at any time
Value	-	Month	Used for monthly analysis

Source: compiled by the author based on assumed data for the case analysis

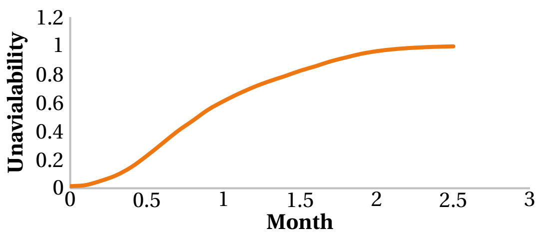


Figure 10. Pedestrian crossing the road without considering vehicles – variation according to the Weibull model
Source: compiled by the author based on assumed data for the case analysis

Figure 10 shows the variation of risk over time associated with pedestrians crossing the road without considering vehicle traffic. The curve, based on the Weibull distribution with a high shape parameter (β = 2.5), reflects a rapidly increasing risk, emphasising that repeated exposure to such behaviour intensifies the likelihood of accidents. This model captures the escalating nature of behavioural risks that emerge quickly and intensify without immediate corrective measures. Pedestrians crossing the road without considering vehicle traffic significantly increases the risk of accidents. This behaviour, especially prevalent during peak hours or in areas with inadequate pedestrian infrastructure, tends to escalate over time due to habitual negligence or lack of enforcement. The fact that this risk increases more rapidly over time makes the Weibull model more appropriate for this case.

Risks associated with technical failures

Technical failures are a significant contributor to accidents in public bus transportation, often resulting from the malfunction of critical components such as brakes, steering, or electrical systems. These failures tend to follow specific wear-out patterns over time, making them suitable for time-dependent risk modelling. The Weibull model is particularly effective in capturing the increasing likelihood of failure as components age or wear. In the following section, each major technical risk is analysed individually using the Weibull model to better understand its behaviour and inform preventive maintenance strategies.

Steering system failure (Weibull model). Steering system failure poses a serious safety hazard because it directly affects the driver's ability to control the vehicle. Over time, wear and tear, inadequate maintenance, or mechanical fatigue can increase the likelihood of such failures. Table 11 presents the Weibull model parameters used to evaluate the risk of steering system failure, highlighting the time-dependent nature of this risk through the shape and characteristic life parameters.

Table 11. Weibull model parameters for steering system failure risk assessment

Parameter	Symbol	Value	Disclosure
Characteristic life	η	3 months	Average time to failure of the steering system
Shape parameter	β	2.2	As the risk of failure increases over time, β > 1 is taken
Location	γ	0	The failure can start at any time
Value	-	Month	Calculations are performed monthly

Source: compiled by the author based on assumed data for the case analysis

Table 11 presents the Weibull model parameters used to assess the risk of steering system failure in buses. The characteristic life η = 3 months indicates that, on average, significant failures in the steering system are expected to emerge within this time frame under regular operating conditions. With a shape parameter β = 2.2, the model reflects a wear-out failure pattern, meaning the likelihood of failure increases as the component ages, reinforcing the need for periodic inspections and timely maintenance.

Figure 11 illustrates how the probability of steering system failure evolves over time according to the Weibull model. As seen in the graph, the failure probability increases progressively, reflecting the mechanical fatigue and degradation common in steering components. This trend emphasises the need for regular inspection and timely maintenance to prevent accidents caused by loss of control. Figure 11 shows the dynamic variation of steering system failure risk modelled using the Weibull distribution in the FTA software environment.

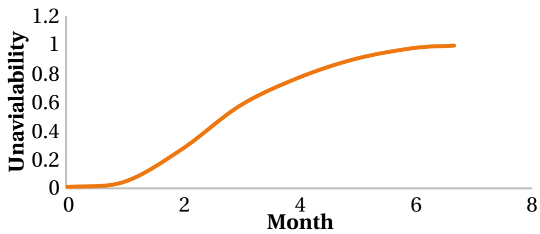


Figure 11. Risk of steering system failure – variation according to the Weibull model
Source: created by the author based on risk modelling in the FTA software environment

Figure 11 illustrates the variation in the risk of steering system failure over time based on the Weibull model. The graph shows a gradual increase in failure probability during the initial months, followed by a sharper rise as the system approaches its characteristic life (3 months). This pattern highlights the importance of proactive maintenance, as the risk becomes significantly higher if the steering system is not serviced within the expected operational period.

Malfunction of lighting and signal systems (Dormant model). Malfunctions in lighting and signalling systems can go unnoticed during normal operation but become critical when these systems are suddenly needed, such as during night driving or adverse weather conditions. These failures may remain undetected for a long time, which increases the danger when they are eventually triggered. Table 12 presents the parameters of the dormant model used to assess the risk associated with potential failures in lighting and signalling systems.

Table 12. Dormant model parameters for risk of lighting and signal system failures

Parameter	Symbol	Value	Disclosure
Failure rate	λ	0.0003 hours	Probability of system failure
MTTR	-	0.002 hours	Time required to eliminate the failure
Inspection interval	τ	720 hours	30-day maintenance period
Value	-	Month	Calculations are made monthly

Source: compiled by the author based on assumed data for the case analysis

Lighting and signal systems play a vital role in ensuring visibility and communication between road users, especially in low-visibility conditions. The failure of these systems may not pose an immediate risk but becomes highly critical when activated during specific situations such as night time or foggy weather. The Dormant model captures this behaviour by modelling the risk as passive until triggered, highlighting the importance of regular inspections. Figure 12 illustrates how the risk of lighting and signal system failure evolves over time according to the Dormant model, emphasising the sudden activation of risk under specific conditions. Figure 12 shows the variation in the risk of lighting and signal system failure using the Dormant model. The graph indicates that the risk remains inactive or minimal under normal conditions but rises sharply once the system is activated or needed such as during night driving or in poor visibility. This emphasises the critical importance of regular inspections, as failures in these systems may remain undetected until the moment they are urgently required, posing immediate safety hazards.

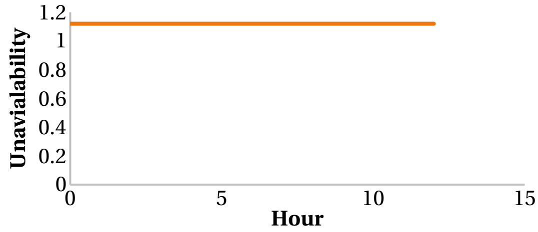


Figure 12. Risk of lighting and signal system failure – variation on the Dormant model

Source: created by the author based on risk modelling in the FTA software environment

Sudden engine stop (Unrepairable model). A sudden engine stop can lead to the complete loss of control over the vehicle, especially in high-density traffic areas, making it one of the most dangerous technical failures in public transport. Since such failures often require total replacement rather than repair, they are best analysed using the Unrepairable model, which assumes that once a failure occurs, the component remains non-functional. Table 13 presents the parameters used in the Unrepairable model for assessing the risk of sudden engine failure, including the failure rate and the unit of time for calculations. Figure 13 illustrates the variation in risk associated with sudden engine stoppage as modelled by the Unrepairable model, which assumes the system remains non-functional after failure.

Table 13. Unrepairable model parameters for sudden engine stop risk assessment

Parameter	Symbol	Value	Disclosure
Failure rate	λ	0.0003 hours	Engine failure probability
Value	-	Month	Calculations are made monthly

Source: compiled by the author based on assumed data for the case analysis

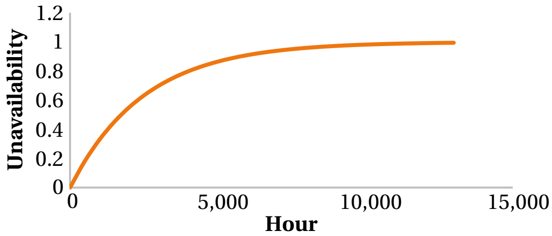


Figure 13. Risk of sudden engine stoppage – variation on the Unrepairable model

Source: created by the author based on risk modelling in the FTA software environment

The graph demonstrates a steady increase in failure probability over time, reflecting the cumulative nature of this critical technical risk. Table 13 presents the parameters used to model the risk of a sudden engine stop using the Unrepairable model. The failure rate $\lambda = 0.0003/$hour indicates a low but persistent probability of engine failure that accumulates over time, and the analysis is conducted on a monthly basis to capture long-term risk trends. Figure 13 shows how the probability of engine failure increases steadily, with no possibility of recovery once the failure occurs characteristic of unrepairable events. This highlights the critical importance of early diagnostics and replacement strategies, as a single engine failure can lead to severe safety consequences, particularly in urban traffic conditions.

Fuel system problem (Repairable model). Fuel system failures, such as pump malfunctions, can temporarily disrupt the engine's operation but are often addressed through standard maintenance procedures. The repairability of this type of failure makes it suitable for modelling with the repairable model, which accounts for both failure and recovery rates. Table 14 outlines the parameters used in the Repairable model for evaluating fuel system failure risk, including the failure rate, repair rate, and calculation timeframe.

Table 14. Repairable model parameters for fuel system failure risk assessment

Parameter	Symbol	Value	Disclosure
Failure rate	λ	0.0008 hour	Probability of fuel pump failure
Repair rate	μ	0.003 hour	Probability of recovery to eliminate the malfunction
Value	-	Month	Calculations are made monthly

Source: compiled by the author based on assumed data for the case analysis

As Table 14 demonstrated, a failure rate $\lambda = 0.0008/$hour and a repair rate $\mu = 0.003/$hour. These values suggest that while failures occur at a low frequency, the relatively higher repair rate enables effective restoration of the system, minimising long-term unavailability. Fuel system failures may not lead to immediate accidents, but they significantly compromise vehicle reliability and operational continuity, especially during peak service hours. Timely repair of such failures can mitigate prolonged downtime and reduce service disruption risks in public transport (Fig. 14).

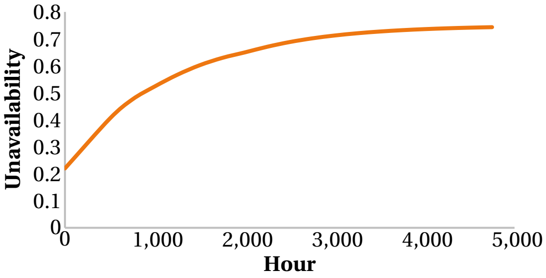


Figure 14. Risk of fuel system failure – variation on the Repairable model

Source: created by the author based on risk modelling in the FTA software environment

Figure 14 shows the change in the risk of fuel system failure over time, modelled using a maintainability model based on both the failure rate and the repair rate. As can be seen, the probability of fuel system failure varies over time, initially increasing but stabilising due to ongoing repair work. This balance between failure and repair reflects the nature of fuel system problems, where timely maintenance can effectively control operational risk and prevent disruptions to business continuity.

Steering system failure (Repairable model). Steering system failures are among the most critical technical malfunctions that directly affect vehicle control and safety. The ability to repair these faults within a reasonable time frame allows for operational risk mitigation and continuity of service. Table 15 presents the key parameters used in modelling the risk of steering system failure under the repairable model, including failure and repair rates.

Table 15. Repairable model parameters for steering system failure risk assessment

Parameter	Symbol	Value	Disclosure
Failure rate	λ	0.0005 hours	Probability of steering failure
Repair rate	μ	0.005 hours	Recovery speed
Value	-	Hour	Calculations are made hourly

Source: compiled by the author based on assumed data for the case analysis

Table 15 provides the failure and repair rates used to model steering system failure under the repairable model, with a failure rate $\lambda = 0.0005$/hour and a repair rate $\mu = 0.005$/hour. The significantly higher repair rate suggests that, despite the critical nature of such failures, they can be addressed quickly, reducing long-term system unavailability and improving operational safety. Figure 15 illustrates the variation in the probability of steering system failure over time, based on the repairable model. This model assumes that although steering system failures occur, they can be mitigated through timely repairs.

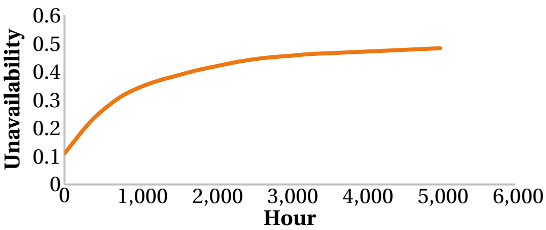


Figure 15. Risk of steering system failure – variation on the Repairable model

Source: created by the author based on risk modelling in the FTA software environment

Figure 15 shows the modelled risk trajectory of steering system failure using repairable parameters in the FTA software environment. The risk of steering system failure initially grows but gradually stabilises as the repair process becomes effective over time. This trend emphasises the importance of routine maintenance and rapid response protocols, which help contain failure risks and maintain control system integrity in public transport vehicles.

Gearbox failure (Repairable model). Gearbox failure can lead to a complete breakdown in vehicle operation, especially in heavy urban traffic conditions where frequent gear shifts are required. Timely repairs are usually feasible for this type of failure, making the Repairable model a suitable approach for risk evaluation. Table 16 presents the parameters used for modelling the risk of gearbox failure, including the failure rate and the rate of repair, both assessed on an hourly basis and Figure 16 illustrates how the probability of gearbox failure changes over time using the Repairable model. As shown in the figure, the failure probability initially increases but then stabilises due to the system's ability to be repaired after malfunction. This model highlights the importance of regular maintenance and timely interventions in minimising long-term risks. It shows the variation of gearbox failure risk over time, modelled using Repairable system parameters. This pattern highlights how effective maintenance strategies can significantly limit the long-term risk associated with mechanical component failures.

Table 16. Repairable model parameters for gearbox failure risk assessment

Parameter	Symbol	Value	Disclosure
Failure rate	λ	0.0006 hour	Probability of gearbox failure
Repair rate	μ	0.004 hour	Probability of recovery to eliminate the fault
Value	-	Hour	Calculations are made hourly

Source: compiled by the author based on assumed data for the case analysis

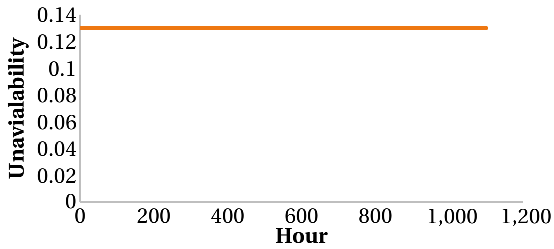


Figure 16. Risk of gearbox failure – variation on the Repairable model

Source: created by the author based on risk modelling in the FTA software environment

Table 17 presents the Minimal Cut Sets for traffic accidents identified through FTA. Each cut set represents a unique combination of basic events that can lead to the top event (a road traffic accident). The "Unreliability" column indicates the probability that a specific minimal cut set causes a system failure, while the "Importance" column shows the relative contribution of each cut set to the overall system failure. The first few cut sets (e.g., rows 1 to 4) have significantly higher importance values. indicating that they are critical contributors to the overall accident risk. In contrast, the remaining cut sets, although numerous, have negligible individual contributions, reflecting a long tail of low-probability failure paths. This analysis helps to prioritise which combinations of faults need the most attention to improve system reliability and reduce accident risk.

Table 17. Risk analysis of road traffic accidents by Minimal Cut Sets

No	Minimal Cut Set	Unreliability	Importance
1	Event2.Event3.Event4.Event8.Event11.P	1.40729E-27	0.394
2	Event2.Event3.Event4.Event8.12.P	8.6884E-28	0.243
3	Event2.Event3.Event4.Event8.P	6.72518E-28	0.184
4	Event2.Event3.Event4.Event8.10.P	6.04234E-28	0.169
5	Event2.Event3.Event4.Event8	5.34502E-28	0.0015
6	Event2.Event3.Event4.Event7.Event8	4.49273E-30	0.00013
7	Event2.Event3.Event4.Event7.Event8.12.P	2.77374E-30	0.00078
8	Event2.Event3.Event4.Event6.Event7.Event8	2.14699E-30	0.00060
9	Event2.Event3.Event4.Event8.7.Event8	1.929E-30	0.00054
10	Event2.Event3.Event4.Event6.Event7	1.70638E-32	0.0000048
11	Event2.Event3.Event4.Event5.Event8	1.14729E-32	0.00000032
12	Event1.Event2.Event3.Event4.Event8	7.08322E-34	0.00000020
13	Event1.Event2.Event3.Event4.Event6.Event8	5.4872E-34	0.00000015
14	Event1.Event2.Event3.Event4.Event5.Event8	4.92602E-34	0.00000014
15	Event2.Event3.Event4.Event6.Event8	3.08455E-34	0.000000086
16	Event2.Event3.Event4.Event7.Event8.11.P	2.18985E-34	0.000000061
17	Event1.Event2.Event3.Event4.Event7.Event8	1.53198E-34	0.000000039
18	Event3.Event4.Event7.Event8.12.P	1.04649E-34	0.000000029
19	Event3.Event4.Event6.Event7.Event8	9.40233E-35	0.000000026
20	Event3.Event4.Event7.Event8.11.P	5.94325E-35	0.000000017
21	Event1.Event2.Event3.Event4.Event5.Event7.Event8	4.35753E-36	0.0000000012
22	Event3.Event4.Event8.Event12.P	3.66927E-36	0.000000001
23	Event3.Event4.Event8.Event7.Event8.11.P	3.66269E-36	0.0000000010
24	Event3.Event4.Event6.Event8.Event8.12.P	2.84016E-36	7.96E-10
25	Event2.Event3.Event4.Event8.Event8.10.P	2.55179E-36	7.15E-10
26	Event2.Event3.Event4.Event8.Event8.9.P	2.26129E-36	6.33E-10
27	Event2.Event3.Event4.Event8.Event8.12.P	1.75033E-36	4.90E-10
28	Event2.Event3.Event4.Event7.Event8.12.P	1.57261E-36	4.40E-10
29	Event3.Event4.Event8.Event7.Event8.11.P	9.84732E-37	2.76E-10
30	Event3.Event4.Event8.Event10.P	8.31725E-37	2.33E-10
31	Event3.Event4.Event7.Event8.11.P	6.89172E-37	1.96E-10
32	Event2.Event3.Event4.Event7.Event8.Event8	4.31615E-37	1.21E-10
33	Event1.Event2.Event3.Event4.Event7.Event8.8.P	3.34088E-37	9.36E-11
34	Event3.Event4.Event8.Event7.Event8.12.P	3.00166E-37	8.41E-11
35	Event3.Event4.Event7.Event8.11.P	2.25732E-37	6.32E-11
36	Event3.Event4.Event8.Event7.Event8.Event8	1.89736E-38	5.31E-12
37	Event1.Event2.Event3.Event4.Event7.Event8.10.P	1.39138E-38	3.89E-12

Table 17. Continued

No	Minimal Cut Set	Unreliability	Importance
38	Event1.Event2.Event3.Event4.Event7.Event8.12.P	1.1714E-38	3.28E-12
39	Event3.Event4.Event6.Event7.Event8.Event8	9.06712E-39	2.54E-12
40	Event3.Event4.Event7.Event8.Event8.Event8	8.1465E-39	2.28E-12
41	Event3.Event4.Event8.Event10.P	2.65525E-39	7.44E-13
42	Event2.Event3.Event4.Event8.10.P	2.51468E-40	7.04E-14
43	Event1.Event2.Event3.Event4.Event8.Event8	1.78527E-40	5.00E-14
44	Event3.Event4.Event8.Event8.11.P	1.1022E-40	3.09E-14
45	Event2.Event3.Event4.Event8.Event8.12.P	8.53148E-41	2.39E-14
46	Event2.Event3.Event4.Event7.Event8.10.P	7.66524E-41	2.15E-14
47	Event1.Event2.Event3.Event4.Event8.Event8.9.P	7.26035E-41	2.02E-14
48	Event2.Event3.Event4.Event8.Event8.9.P	4.79978E-41	1.34E-14
49	Event3.Event4.Event8.Event10.P	4.84522E-42	1.36E-15
50	Event3.Event4.Event8.Event8.10.P	2.99137E-42	8.38E-16
51	Event3.Event4.Event7.Event8.9.P	2.31544E-42	6.49E-16
52	Event3.Event4.Event7.Event8.8.P	2.08034E-42	5.83E-16
53	Event3.Event4.Event8.Event7.Event8.12.P	1.30266E-42	3.65E-16
54	Event3.Event4.Event8.Event7.Event8.11.P	9.24811E-43	2.59E-16
55	Event3.Event4.Event7.Event8.10.P	8.02802E-43	2.25E-16
56	Event3.Event4.Event8.Event9.P	6.78036E-43	1.90E-16
57	Event2.Event3.Event4.Event8.Event8.8.P	5.70965E-43	1.60E-16
58	Event2.Event3.Event4.Event7.Event8.9.P	5.69942E-43	1.60E-16
59	Event3.Event4.Event8.Event10.P	4.35753E-43	1.22E-16
60	Event3.Event4.Event8.Event8.10.P	3.66927E-43	1.03E-16
61	Event3.Event4.Event7.Event8.11.P	3.66269E-43	1.03E-16
62	Event2.Event3.Event4.Event8.Event8.10.P	2.84016E-43	7.96E-17
63	Event2.Event3.Event4.Event8.Event8.9.P	2.55179E-43	7.15E-17
64	Event2.Event3.Event4.Event8.Event8.12.P	2.26129E-43	6.33E-17
65	Event2.Event3.Event4.Event7.Event8.12.P	1.75033E-43	4.90E-17
66	Event3.Event4.Event8.Event7.Event8.11.P	1.57261E-43	4.40E-17
67	Event3.Event4.Event8.Event10.P	9.84732E-44	2.76E-17
68	Event3.Event4.Event7.Event8.11.P	8.31725E-44	2.33E-17
69	Event2.Event3.Event4.Event7.Event8.Event8	6.89172E-44	1.96E-17
70	Event1.Event2.Event3.Event4.Event7.Event8.8.P	4.31615E-44	1.21E-17
71	Event3.Event4.Event8.Event7.Event8.12.P	3.34088E-44	9.36E-18
72	Event3.Event4.Event7.Event8.11.P	3.00166E-44	8.41E-18
73	Event3.Event4.Event8.Event7.Event8.Event8	2.25732E-44	6.32E-18
74	Event1.Event2.Event3.Event4.Event7.Event8.10.P	1.89736E-45	5.31E-19
75	Event1.Event2.Event3.Event4.Event7.Event8.12.P	1.39138E-45	3.89E-19
76	Event3.Event4.Event6.Event7.Event8.Event8	1.1714E-45	3.28E-19
77	Event3.Event4.Event7.Event8.Event8.Event8	9.06712E-46	2.54E-19
78	Event3.Event4.Event7.Event8.8.P	8.1465E-46	2.28E-19
79	Event3.Event4.Event8.Event7.Event8.12.P	2.65525E-46	7.44E-20
80	Event3.Event4.Event8.Event7.Event8.11.P	2.51468E-47	7.04E-21
81	Event3.Event4.Event6.Event7.Event8.Event8	1.78527E-47	5.00E-21
82	Event3.Event4.Event8.Event8.11.P	1.1022E-47	3.09E-21
83	Event2.Event3.Event4.Event8.Event8.12.P	8.53148E-48	2.39E-21
84	Event2.Event3.Event4.Event7.Event8.10.P	7.66524E-48	2.15E-21
85	Event1.Event2.Event3.Event4.Event8.Event8.9.P	7.26035E-48	2.02E-21
86	Event2.Event3.Event4.Event8.Event8.9.P	4.79978E-48	1.34E-21
87	Event3.Event4.Event8.Event10.P	4.84522E-49	1.36E-22
88	Event3.Event4.Event8.Event8.10.P	2.99137E-49	8.38E-23
89	Event3.Event4.Event7.Event8.9.P	2.31544E-49	6.49E-23
90	Event3.Event4.Event7.Event8.8.P	2.08034E-49	5.83E-23
91	Event3.Event4.Event8.Event7.Event8.12.P	1.30266E-49	3.65E-23
92	Event3.Event4.Event8.Event7.Event8.11.P	9.24811E-50	2.59E-23
93	Event3.Event4.Event7.Event8.10.P	8.02802E-50	2.25E-23
94	Event3.Event4.Event8.Event9.P	6.78036E-50	1.90E-23
95	Event3.Event4.Event8.Event8.8.P	5.70965E-50	1.60E-23

Source: compiled by the author based on assumed data for the case analysis

One of the key outcomes of the FTA conducted in this study is the identification of Minimal Cut Sets (MCS) – the smallest combinations of basic events that, if they occur simultaneously, inevitably lead to the Top Event, i.e., a road traffic accident involving a public bus. Each minimal cut set represents a unique combination of technical, human, and environmental factors, and provides valuable insight into the most critical risk pathways within the system. For example, the first minimal cut set (Event2.Event3.Event4. Event8.Event11.P) includes the following high-risk events:

- Event2 – steering system failure;
- Event3 – brake system failure;
- Event4 – driver error;
- Event8 – heavy traffic conditions;
- Event11 – provocation by other vehicles.

Although the combined probability of occurrence for this set is very low (1.40729E-27), the importance factor (0.394) signifies that this combination makes a significant contribution to overall system risk. In total, Table 17 presents 95 such minimal cut sets, each quantifying the contribution of different combinations of failures and unsafe behaviours to the top event. This analysis forms the foundation for prioritising safety interventions by ranking which combinations of risk factors require immediate attention.

These findings align with similar applications in international research. For instance, A.A. Baig *et al.* (2020) conducted an FTA study on urban bus safety in Delhi and identified driver error and brake system failures as primary causes of accidents. The present study confirmed this through the high-priority cut sets that combine steering and braking failures with human error. The convergence of findings underscores the synergistic effect of technical and behavioural failures on urban transport safety.

Furthermore, the application of the Weibull model to represent time-dependent risks, such as mechanical degradation and behavioural shifts, is supported by studies such as L. Chen & Y. Wang (2021). Their research in China confirmed that technical components like gearboxes and steering systems exhibit increasing failure probabilities over time, particularly when operating under intensive service conditions. The use of $\beta > 1$ in current study, consistent with their findings, reflects the accelerating nature of wear-related risks in urban public transport systems.

In contrast, R. Joomjee *et al.* (2024) applied the constant model to assess the impact of unpredictable external risks – such as road congestion and aggressive behaviour by surrounding vehicles in highway scenarios. A similar approach was adopted in this study to model provocation by other vehicles, particularly in dense urban traffic in Baku, where such threats are stochastic and environment-driven, validating the robustness of the constant model structure for external, uncontrollable variables.

From a behavioural risk standpoint, risks such as lighting or signal system failure or improper passenger boarding were analysed using the Dormant model, which remains inactive until triggered by specific conditions. This modelling strategy is consistent with the work of M. Li *et al.* (2022), who used a similar approach to evaluate latent risks in tram systems. Their study affirmed the importance of dormant risks, which, although infrequent, have severe consequences when activated-especially in unpredictable urban traffic scenarios.

The concept and application of Minimal Cut Sets, as utilised in this study, are rooted in the foundational methodology developed by W.E. Vesely *et al.* (1981) for aerospace safety. The current adaptation of this method to public transport risk management allows for quantitative prioritisation of risk pathways, guiding resource allocation and intervention strategies more effectively. This approach also complements advanced reliability modelling by integrating technical failures with human and contextual factors within a comprehensive fault-tree framework.

Moreover, the classification of failures into repairable and unrepairable categories, following the rationale K. Kaur (2023), helps to improve maintenance planning. In this case, components like the fuel system and gearbox were modelled as repairable, allowing for service restoration through timely intervention, while engine failure was modelled as unrepairable, where full replacement was more realistic. This differentiation supports a cost-effective maintenance strategy, avoiding overinvestment in systems where repair is not viable. The integration of time-loss and reliability concerns into fault-tree modelling reflects insights from V. Dixit *et al.* (2019), who studied the perception of travel time risk. In this study, these disruptions – whether from technical failures or driver-related issues – feed into broader system inefficiencies, such as delays, increased congestion, and reduced public trust in transportation services. By embedding these concepts into the FTA framework, a holistic understanding of both accident causality and operational risk is achieved.

Several recent studies have examined the strengths and limitations of classical Fault Tree Analysis and its alternatives in safety-critical systems. For instance, N. Khakzad *et al.* (2011) conducted a comparative analysis of FTA and Bayesian Networks (BNs) within the context of process safety. Their findings underscore that while FTA relies on a static, deductive structure, and assumes event independence, it lacks the capability to model uncertainty, temporal progression, and complex interdependencies. In contrast, BN offers greater modelling flexibility, incorporating conditional relationships, expert judgments, and probabilistic updates. Although their study demonstrates a transition mechanism from FTA to BN and applies both methods to an accident scenario, it does not consider applications in public transportation systems, particularly in bus operations. Critical factors such as route structure, driver and passenger behaviour, environmental dynamics, and cost-risk implications are omitted, indicating a gap in contextual adaptation of these methods to urban transit safety.

In a related contribution, W. Wang *et al.* (2010) proposed the Incident Tree Analysis (ITA) approach, which extends FTA by introducing temporal event evolution and tracking the flow of information during incident development.

This dynamic structure provides a more comprehensive view of accident progression, particularly in complex systems with feedback loops. While ITA introduces a valuable framework for modelling real-world accident sequences, the study lacks specificity to public transport systems such as buses or metros and does not incorporate weather conditions, infrastructure characteristics, or socio-economic consequences, all of which are highly relevant to urban mobility planning.

Similarly, O. Derse & E. Göçmen (2019) explored the integration of FTA with mathematical optimisation methods to support risk-informed transport mode selection. Their model successfully incorporates uncertainty and user discomfort into the decision-making framework, positioning FTA as a strategic planning tool. However, the study remains largely theoretical and scenario-based, without calibration using real-world data. More importantly, it fails to engage with urban bus systems, dynamic passenger flow patterns, or context-specific environmental risk indicators. In contrast, the present study applies FTA directly to urban bus networks in Baku, integrating technical (e.g., gearbox, steering), behavioural (e.g., fatigue, distraction), and environmental (e.g. road congestion. weather conditions) risk factors. It further utilises actual incident data and FTA software (Top Event) to derive minimal cut sets and assign priority to critical event combinations, thereby transforming conceptual models into operationally relevant safety assessments.

Beyond identifying methodological gaps, this study also aimed to propose actionable measures for enhancing safety in public transport systems. Based on the modelling outputs and comparative analyses, several policy and operational recommendations can be made here. Driver-focused safety programmes should include fatigue detection systems, cognitive-behavioural training, and targeted monitoring during the first six months of employment, where risk is highest. Predictive maintenance schedules should be developed based on failure probability modelling (e.g., Weibull analysis), particularly for components with accelerating wear-out behaviour such as gearboxes, fuel systems, and steering mechanisms. Advanced monitoring systems (e.g., telematics, GPS-based diagnostics, lane departure warnings) should be deployed to capture real-time risk signals related to technical failures or aggressive surrounding vehicle behaviour. Integrated data platforms should be established to link operational, behavioural, and environmental data for system-wide risk surveillance and dynamic decision-making. Institutional capacity-building is required to embed fault-tree logic and quantitative risk modelling into transport safety audits, ensuring that risk prioritisation guides both investments and daily operations.

Conclusions

The purpose of this study was to evaluate key risk factors in public bus transportation systems by applying Fault Tree Analysis in combination with various reliability models. The main objective was to assess the failure probability of different technical and behavioural factors under varying traffic and operational conditions, and to determine their criticality in road traffic accidents. The results of the analysis confirmed that the selected methodological approach effectively identified and quantified significant risk contributors, thus achieving the primary research goal.

The research began with the classification of risk sources into three broad categories: technical failures (e.g., steering, braking, engine), behavioural errors (e.g., pedestrian misbehaviour, driver faults), and environmental triggers (e.g., traffic density, influence of other vehicles). Each risk was analysed using a reliability model appropriate to its failure nature – such as the Weibull model for time-dependent failures and the Constant or Dormant models for continuous or passive risks. Quantitative parameters like failure rate (λ), repair rate (μ), characteristic life (η), and shape factor (β) were used to simulate system behaviour over time. Based on these parameters, risk curves, and probability distributions were generated for each scenario. Additionally, the study employed a Minimal Cut Set analysis to rank the most critical event combinations that could lead to accidents.

The findings underscored that driver error and pedestrian behaviour were among the most significant contributors to bus-related accidents, particularly when combined with mechanical failures under high-traffic conditions. The combination of FTA and reliability modelling not only allowed for detailed risk decomposition but also helped to trace the pathway of accident causation in a structured and quantifiable manner. The analysis also demonstrated that some failures, despite having low probability, pose high criticality due to their involvement in key failure pathways.

Overall, the integration of probabilistic models into FTA-based transport safety assessments contributes to a more comprehensive understanding of urban mobility risks. These results provide a robust foundation for developing predictive models and proactive safety interventions tailored to public transportation systems. The findings of this research may serve as a foundation for improving transport safety strategies and can be applied to reduce accident rates and enhance urban mobility resilience in similar metropolitan settings. Future research should explore the integration of real-time telematics and machine learning algorithms to dynamically update fault trees based on actual vehicle performance and behavioural data. Additionally, socio-demographic and route-specific variations in risk exposure require further empirical investigation to tailor safety measures with greater precision.

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Conflict of Interest

None.

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Оцінка ризиків для громадського транспорту за допомогою аналізу дерева відмов (приклад міста Баку)

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Анотація. Безпека дорожнього руху стає дедалі важливішим питанням у міських транспортних системах, особливо в країнах, що розвиваються, таких як Азербайджан, де дорожньо-транспортні пригоди продовжують бути основним джерелом травм та пошкодження майна. Це дослідження мало на меті оцінити ризики, пов'язані з мережею громадського транспорту Баку, за допомогою аналізу дерева відмов у рамках матриці Хаддона, яка розподіляє фактори, що сприяють цьому, на три категорії: транспортні засоби, люди та дорожнє середовище. Підхід аналізу дерева відмов сприяв систематичному, дедуктивному дослідженню потенційних причин відмов, які можуть призвести до аварій за участю громадського транспорту. Результати дослідження показали, що проблеми, пов'язані з транспортними засобами, серед них несправність гальмівних систем, проблеми з кермовим керуванням та неналежне технічне обслуговування, значно збільшують ймовірність виникнення аварій. Ризики, спричинені людиною, такі як поведінка водія (наприклад, перевищення швидкості та ненадання належної дорожньої допомоги), недотримання правил дорожнього руху та непередбачувані дії пішоходів, також значною мірою сприяють цій проблемі. Крім того, стан доріг, погана інфраструктура, відсутність належних знаків, недостатнє освітлення та небезпечна конструкція автобусних зупинок, ще більше підвищують ризик. Взаємодія цих факторів вказує на те, що аварії на громадському транспорті в Баку є багатогранними та часто їм можна запобігти. Це дослідження підтвердило необхідність систематичного оцінювання стану безпеки, проведення планових оглядів транспортних засобів та покращення ініціатив з підвищення обізнаності громадськості для зменшення ризиків дорожніх аварій, пов'язаних з міським транспортом. Результати цього дослідження висвітлили найсерйозніші зони ризику, що може надати керівникам міського транспорту сприяння при розробці більш ефективних стратегій для підвищення безпеки в транспортній системі Баку

Ключові слова: міські дорожньо-транспортні пригоди; транспортний засіб, аналіз ризиків; безпека дорожнього руху; ризики експлуатації автобусів