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Study of Reliability and Availability in Autonomous Electric Vehicles

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Abstract The popularity and development of Autonomous Electric Vehicles (AEVs) bring the need to ensure the safety and reliability of these systems. With the increasing adoption of such vehicles, the promise of reducing human errors and improving transportation efficiency is becoming increasingly attainable. However, failures in autonomous vehicle systems can lead to material damage and loss of human life. Minimizing these failures becomes critical to guarantee the safety of passengers and pedestrians. This work employs Reliability Block Diagram (RBD) and Stochastic Petri Net (SPN) models to evaluate the vehicle safety system of a Level 3 AEV. The proposed approach enables the analysis of availability and reliability metrics, identifying potential improvements in system components. The system's reliability showed a predictable decline over time, allowing for the anticipation of maintenance and necessary enhancements. These results provide valuable insights for AEV developers regarding the optimization of vehicle safety and reliability.

Keywords: Autonomous Electric Vehicles, Reliability Analysis, Stochastic Petri Nets, Reliability Block Diagrams

1 Introduction

The growing demand for safety, the increase in population, the expansion of infrastructure, and the growth of vehicles are driving the adoption of autonomous technologies [Hussain and Zeadally, 2019]. Automated Electric Vehicles (AEVs) have become a benchmark in the field of international automotive engineering and the main competitiveness in the future market [Wang *et al.*, 2023]. The need to minimize human errors and reduce risk situations on the road drives the exploration of these alternative technologies, considering that approximately 94% of accidents are attributed to human errors [Bendiab *et al.*, 2023; Read *et al.*, 2021].

Autonomous Electric Vehicles (AEVs) emerge as a solution, promising not only to improve transportation efficiency but also to redefine road safety standards. The vehicles operate autonomously on a scale ranging from 0 to 5 [Hedel *et al.*, 2023]. Level 0 Autonomous Vehicles are completely controlled by the human driver; Level 1 offers continuous assistance with acceleration, braking, and steering; Level 2 includes an Advanced Driver Assistance System (ADAS); Level 3 performs all driving functions, but the driver must be ready to take control; Level 4 is highly automated, requiring no driver intervention; Level 5 is fully autonomous [Van Brummelen *et al.*, 2018]. Safety issues related to these vehicles present a significant challenge to federal and state authorities, technical companies, software developers, and customers, as they may lead to the imposition of various restrictions on fully autonomous vehicles on the roads [Benarbia *et al.*, 2023].

The growing adoption of AEVs brings concerns about the safety of passengers and pedestrians. Failures in these systems can result in severe consequences, including material damage and loss of human lives. Given this critical scenario, it is crucial that the development and implementation of AEVs consider the reliability and availability of autonomous systems, especially under the possibility of uncertain failures [Bhavsar *et al.*, 2017]. These failures can occur in any component, from sensors and cameras to control and navigation systems. Reliability and availability are essential indicators for assessing AEV safety. Therefore, it is necessary to develop reliability and availability models that quantify the impact of potential failures in autonomous systems.

The literature already presents some works that have evaluated the reliability and availability of AEVs in different areas. The related works have been categorized into four distinct groups according to the focus of each study. The first group consists of research focused on mobility, including strategies to optimize passenger flow and the diffusion of AEVs in urban subsystems [Benarbia *et al.*, 2023; Zhuge and Wang, 2021]. The second group addresses energy, with studies on the reliability of smart grids and automotive traction systems [Hariri *et al.*, 2020; Anand *et al.*, 2022; Shafiq *et al.*, 2020; Hariri *et al.*, 2021]. The third category focuses on optimization, analyzing the reliability of electric powertrain systems and strategies to improve route efficiency [Ebner *et al.*, 2020; Irimia *et al.*, 2022]. Finally, the fourth group focuses on safety, investigating issues related to the reliability engineering of automotive drivetrain architectures and the development of fault-tolerant systems [Schmidta and Zimmermannb, 2022]. Each group contributes with different perspectives for evaluating AEVs, reflecting the complexity and interdisciplinarity of the field.

In this work, we use RBD and SPN models to analyze reliability and availability metrics in vehicle safety systems. We contribute with a simplified and effective approach to evaluate the performance of vehicle systems that make up an AEV and, from their operation, ensure the safety of the AEV and its passengers. The contribution of this article is highlighted in the following aspects:

- Development of Stochastic Petri Nets (SPN) and Reliability Block Diagram (RBD) models that reflect the complex architecture of AEVs, allowing reliability and availability analyses.
- Sensitivity analysis using the Design of Experiments (DoE) technique, identifying critical components and their interactions, which is essential to optimize the design and maintenance of vehicle safety systems.

The remainder of this work is organized as follows: Section 3 presents related works through a comparative table between the studies considered. Section 4 presents the architecture considered in this work. Section 5 presents the proposed SPN and RBD models and the metrics used for availability and reliability evaluation. In Section 6, the sensitivity analysis of the proposed SPN model and the results achieved are presented and detailed, according to its subdivisions. Section 7 presents the conclusions reached and describes future works.

2 Background

This section presents the main concepts and theoretical foundations that support the study, covering aspects related to AEVs, reliability and availability metrics, and analysis models based on RBD and SPN.

2.1 Autonomous Electric Vehicles

AEVs represent one of the most promising innovations in modern mobility, integrating electrification, automation, and connectivity technologies to reduce pollutant emissions and increase transportation efficiency [Grosso *et al.*, 2021]. These vehicles, especially at advanced levels of automation, are capable of performing driving tasks without continuous human intervention, using sensors, actuators, and decision-making systems based on machine learning and sensor fusion [Yeong *et al.*, 2021].

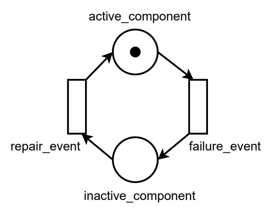
However, the high degree of automation introduces new challenges related to functional and operational safety. A failure in any critical component, such as perception sensors, steering actuators, or power control modules, can compromise the integrity of the system and lead to severe accidents [Wang *et al.*, 2020]. Therefore, the systematic analysis of the reliability and availability of subsystems is essential to ensure the overall dependability of the AEV, guaranteeing that the system operates correctly even in the presence of partial failures or performance degradations.

2.2 Reliability and Availability

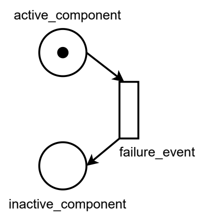
Dependability is defined as the ability of a system to provide a service that can be justifiably trusted, that is, to avoid service failures that occur with unacceptable frequency or severity [Avizienis *et al.*, 2004]. Among its main attributes are reliability and availability, which are fundamental metrics for the evaluation of complex and safety-critical systems. Reliability is the probability that a system continues operating within a time interval $[0, t]$, assuming it was operating at time $t = 0$ [Silva *et al.*, 2022]. Availability, in turn, expresses the readiness of the system to deliver correct service at a given instant [Avizienis *et al.*, 2004]. These two attributes are essential to quantify the temporal behavior of a system, predict downtime periods, and support the planning of preventive maintenance strategies.

In quantitative dependability analysis, stochastic models have proven to be effective tools for representing the occurrence of failures and recoveries. Among these, SPNs stand out for enabling the simultaneous modeling of concurrent events, transition times, and dependencies between states. Figure 1a illustrates a generic availability model, in which the active state represents normal component operation and the inactive state represents failure. The transition between these states is governed by parameters associated with the Mean Time To Failure (MTTF) and the Mean Time To Repair (MTTR).

Similarly, Figure 1b presents a generic reliability model, where the system's behavior is evaluated until the first failure occurs, without considering repairs. This approach allows the estimation of the probability of continuous operation of a system and is widely used in critical applications that require high levels of safety and operational continuity.



(a) Generic SPN model for availability.



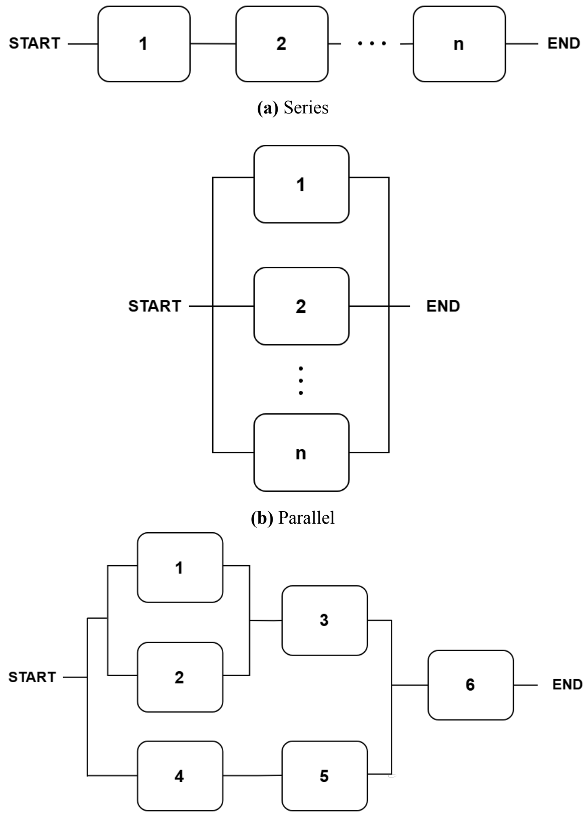
(b) Generic SPN model for reliability.

Figure 1. Generic reliability and availability models based on SPNs.

2.3 Reliability Block Diagrams

RBDs are a classical and widely used technique for modeling and analyzing complex systems. This method graphically represents the logical structure of a system through blocks connected according to their functional dependencies. Each block has an associated probability of success or failure, allowing the evaluation of the impact of each component on the overall system reliability [Hasan *et al.*, 2015].

In an RBD, the configuration of the blocks defines the mode of system operation (Figure 2): *(i)* in a series configuration, the system fails if any component fails; *(ii)* in a parallel configuration, the system continues to operate as long as at least one component remains functional; and *(iii)* in mixed configurations, combinations of these two relationships are used to represent more complex interdependencies [Callou *et al*., 2014; Ebeling, 1997].



(c) Mixed

Figure 2. Examples of RBD configurations: (a) series; (b) parallel; and (c) mixed.

The RBD model allows analytical quantification of reliability and availability metrics, as well as the identification of critical components that impact overall system performance. The total reliability of a system can be generically expressed by Equation 1, where $R(t)$ represents the probability that the system operates correctly up to time t, and $R_i(t)$ represents the individual reliability of each component i [Ebeling, 1997].

$$R(t) = \prod_{i=1}^{n} R_i(t) \tag{1}$$

For independent components, the failure behavior is often modeled by an exponential distribution, given by $R_i(t) = e^{-\lambda_i t}$, where λ_i is the failure rate of the component [Ebeling, 1997]. Thus, the MTTF of a series system can be estimated as:

$$MTTF = \frac{1}{\sum_{i=1}^{n} \lambda_i} \tag{2}$$

2.4 Stochastic Petri Nets

SPNs represent an evolution of classical Petri Nets, developed to model systems that exhibit probabilistic behavior and temporal dependency [Fe *et al*., 2017]. Unlike traditional techniques such as Markov Chains or queuing models, SPNs offer greater expressiveness for describing parallel, concurrent, and interdependent processes, making them particularly suitable for representing systems in which delays, uncertainties, and varying conditions directly influence operational dynamics [Molloy, 1982]. This flexibility enables more realistic modeling, allowing the analysis of not only the logical structure of a system but also performance metrics related to response time and availability [Silva *et al*., 2015].

The main contribution of SPNs lies in their ability to associate probability distributions with transitions, which allows the characterization of events whose occurrence time is not fixed but follows stochastic patterns. In this way, it is possible to rigorously and systematically represent the random behavior of failures, repairs, and recoveries, expanding the applicability of the technique in reliability and performance studies of complex systems, such as communication networks, critical infrastructures, and distributed environments [Silva *et al*., 2015; Molloy, 1982].

3 Related Works

This section presents the related works identified in the literature that have a context or approach related to this project. The articles were selected considering five selection criteria: Focus, Model Type, Reliability, Availability, and Sensitivity Analysis. The detailed description of the articles is based on the classification of the papers. The works were classified into four main groups based on the focus of the study. The focus of the study is relevant when considering in which areas AEV systems are most worked on in the literature. These works were chosen to understand how the modeling evaluation method is used to assess the reliability and availability of electric vehicles and in which areas these research works are developed. The research areas concerning electric vehicles are presented in the table below. Table 1 shows some of the contributions of related works to this study, followed by their selection criteria.

Mobility The first classification deals with studies focusing on the mobility area. The work by Benarbia *et al.* [2023] investigates passenger flow optimization strategies in SEAVM systems. The study covers the integration of communication technologies and geolocation to provide real-time information to users, enhancing service efficiency. Zhuge and Wang [2021] address the diffusion of AEVs and their interactions with six urban subsystems: transportation, land use, environment, energy, economy, and population. The proposed model can help predict future scenarios and optimize policies and investments related to AEVs, contributing to the development of smart cities.

Energy The second classification deals with research focusing on the energy area. The work by Hariri *et al.* [2020]

Table 1. Related works.

Work	Focus	Type of Model	Reliability	Availability	Sensitivity Analysis
Benarbia *et al*. [2023]	Mobility	SPN	✗	✓	✗
Schmidta and Zimmermannb [2022]	Safety	SPN	✓	✗	✗
Hariri *et al*. [2020]	Energy	Generalized Analytical Method	✓	✗	✓
Anand *et al*. [2022]	Energy	Markov Chain	✓	✗	✓
Ebner *et al*. [2020]	Optimization	SPN	✓	✓	✗
Shafiq *et al*. [2020]	Energy	Probabilistic Modeling	✓	✗	✓
Hariri *et al*. [2021]	Energy	Analytical Model	✓	✗	✓
Zhuge and Wang [2021]	Mobility	Agent-Based Modeling	✗	✗	✗
Irimia *et al*. [2022]	Optimization	Mathematical Model	✗	✓	✓
This work	Safety	SPN and RBD	✓	✓	✓

addresses the evaluation of the reliability of smart grids, including renewable and non-renewable distributed generations and plug-in hybrid electric vehicles (PHEVs). The authors propose a new generalized analytical method for evaluating reliability, highlighting the introduction of a new state matrix (S-matrix) model that considers the operational modes of the smart grid using concepts of segmentation and graph theory. The study by Anand *et al*. [2022] focuses on reliability engineering in automotive traction system architectures, with emphasis on simulating multiple trajectories to evaluate the reliability of fault-tolerant traction system architectures in AEVs. The work emphasizes the importance of considering rare events in reliability simulations, showing how the multiple trajectory simulation technique can overcome the limitations of traditional numerical analysis and simulation approaches. Shafiq *et al*. [2020] evaluate the reliability of energy systems, considering the impact of full electric vehicles (FEVs) and PHEVs. The authors propose a probabilistic model to integrate FEVs and PHEVs into existing power grids, taking into account important vehicle characteristics such as battery capacity, discharge distance, and charging rates. The work by Hariri *et al*. [2021] addresses the reliability and adequacy evaluation of smart electric grids, considering the analytical modeling of PHEVs. The authors develop an analytical model that considers the stochastic characteristics of PHEVs, such as arrival time, departure time, and distance traveled, under different charging scenarios.

Optimization The third classification presents works that focus on the optimization area. The study by Ebner *et al*. [2020] analyzes the reliability of electric powertrain systems in automated vehicles, such as robotaxi, which do not have a driver to ensure passenger safety. The work presents a model-based approach using SPN to evaluate the reliability and availability of different configurations of electric traction systems, considering powertrain degradation. The results demonstrated the influence of configuration parameters on reliability measures, which can be used to optimize the vehicle's overall design. The study proposes a methodology to build simulation models that evaluate the reliability of electric traction systems, aiming to optimize the design space. The research by Irimia *et al*. [2022] focuses on the optimization of transportation systems and vehicles. The authors explore strategies to improve route efficiency, minimize fuel consumption, and reduce environmental impact. They propose a model based on Integer Linear Programming (ILP) to optimize the planning of delivery vehicle routes, considering capacity constraints, time windows, and operational costs. Additionally, the study addresses the application of genetic algorithms to optimize vehicle allocation in public transport fleets.

Safety The final classification includes the mapped research that focused on the safety area. The study by Schmidta and Zimmermannb [2022] investigated the reliability of automotive drivetrain architectures using a model-based engineering approach. The researchers employed SPN and multi-trajectory simulation to evaluate how component failures impact the system's operational safety. Additionally, the study emphasizes the importance of fault-tolerant designs, providing a methodology to analyze performance and dependability metrics that directly supports the development of more reliable autonomous systems.

Contributions of this Work This work aims to evaluate SPN models to analyze reliability and availability metrics of a vehicle safety system. The analysis is conducted by modeling a vehicle safety system, consisting of powertrain, automation, and steering systems to be active. The analysis of reliability and availability metrics allows for a better understanding and identification of requirements and issues. The mentioned factors assist in system modeling, simplify planning, and allow the evaluation of alternatives while reducing risks, resulting in more efficient implementations that provide greater safety. The evaluation of the proposed SPN model considers the availability and reliability analysis of the system. Unlike other works that performed sensitivity analysis using techniques such as Monte Carlo, parametric variations, and FEA/FEM, our study adopts the DoE technique. This approach allows verifying how the system behaves when changes are made to the resources of some specific system components. The analysis pointed out the systems with the greatest impact on system availability. The model is designed for designers to adjust the structure parameters and the number of components as needed.

4 Architecture

This section describes the proposed architecture. Figure 3 presents the architecture used for this study. The architecture is composed of three vehicle systems that integrate the Level 3 AEVs: the powertrain system, the automation system, and the steering system. These systems were considered vital to ensure the safety of the vehicle and its passengers.

The safety of the autonomous vehicle is a central aspect of the proposed architecture. The automation system, in particular, uses data from multiple sensors to ensure accurate environmental perception, which is crucial for making safe decisions. Additionally, considering that we are evaluating a Level 3 AEV, the presence of a driver in the vehicle is mandatory. This driver must be prepared to take control of the vehicle whenever the autonomous system requests or in case of emergencies. This additional layer of safety ensures that, even in the event of a failure in the autonomous system, the vehicle can be manually operated to prevent accidents.

The powertrain system is responsible for providing the necessary energy for the vehicle's movement. It integrates components such as the battery system and the power distribution unit. These components work together to ensure that the vehicle has the necessary power to move efficiently and safely. The availability and reliability of these components are vital because any failure can compromise the vehicle's ability to move properly, directly impacting safety.

The automation system, in turn, is the brain of the AEV. It is composed of an integration platform and various automation components, including GPS, cameras, and parking sensors. These devices enable the vehicle to perceive its surrounding environment, make decisions, and navigate autonomously. Accuracy and robustness are important to avoid accidents, recognize obstacles, and react to unforeseen situations, ensuring safety during operation. At Level 3 of automation, the system is capable of performing most driving tasks, but still requires the driver to be present and ready to intervene.

The steering system is responsible for controlling the directional movement of the vehicle. It includes steering sensors, an electronic control unit, and an electric steering motor. These components ensure that the vehicle can maneuver according to the decisions made by the automation system, maintaining the desired trajectory and reacting appropriately to road conditions. Safety in this system is crucial to ensure that the vehicle responds correctly to changes in direction and adverse driving conditions.

5 Proposed Models

This section presents the proposed models following the architecture described in the previous section. The configurations adopted for the models are based on the characteristics highlighted in the architecture. The proposed models help evaluate the system's availability and reliability. The models and simulations were built using the Mercury tool [Maciel *et al.*, 2017; Bashir and Luštrek, 2021].

5.1 RBD Models

This subsection presents the RBD models designed to compute the MTTF and MTTR for the main subsystems, powertrain, automation, and steering, which were later integrated into the SPN model. The RBD models were designed according to the failure tree described by Hedel *et al.* [2023], providing the fundamental reliability parameters for each subsystem. Figure 4 illustrates the RBD representations developed for the AEV vehicle safety system.

The powertrain system (PS) is composed of the battery system (BS), ignition motor (DM), power distribution unit (PDU), and motor controller (MC). Each of these subsystems was further divided into their internal components, such as battery modules, control units, sensors, and power electronics, to obtain more accurate reliability metrics. Similarly, the automation system (AS) includes the integration platform (P) and automation components (AC), subdivided into sensors and perception devices such as LiDAR, radar, GPS, cameras, wheel encoders, and parking sensors. The steering system (SS) comprises the steering sensors (SSen), electronic control unit (ECU), and electric steering motor (SEM), which were also decomposed into subcomponents, including torque and angle sensors.

All RBDs were modeled in series configuration, meaning that the failure of any component leads to the failure of its subsystem. For simplification, the MTTR value for all components was fixed at 1 hour. The MTTF values were obtained from Hedel *et al.* [2023], converted from failure rates (λ) expressed in failures per million hours, using the equation $MTTF = 1/\lambda$. The adoption of a uniform MTTR represents a plausible and analytically convenient baseline for comparative evaluation across subsystems. Since reliable empirical MTTR data for all considered components were not consistently available in the literature, this assumption allows controlled sensitivity analysis without introducing heterogeneous repair-time bias. It is important to emphasize that the proposed modeling framework is fully parametric, enabling practitioners to adjust MTTR values according to specific operational contexts, maintenance policies, or organizational data. Table 2 summarizes the MTTF values for all components across the three subsystems.

It is worth noting that some components present MTTF values that differ by orders of magnitude. Under the adopted exponential assumption and the series RBD configuration, the equivalent subsystem failure rate is dominated by components with higher individual failure rates (i.e., lower MTTF values), while extremely high-MTTF components contribute negligibly to the aggregated subsystem metrics. The RBD simulations produced total subsystem MTTF values of approximately 62.08 hours for the powertrain, 405.32 hours for the automation system, and 62.79 hours for the steering system. These results were later integrated into the SPN model to analyze overall system dependability and perform sensitivity analyses.

5.2 Availability Model

This section presents the model used to calculate the system's availability. Figure 5 shows the model with the following

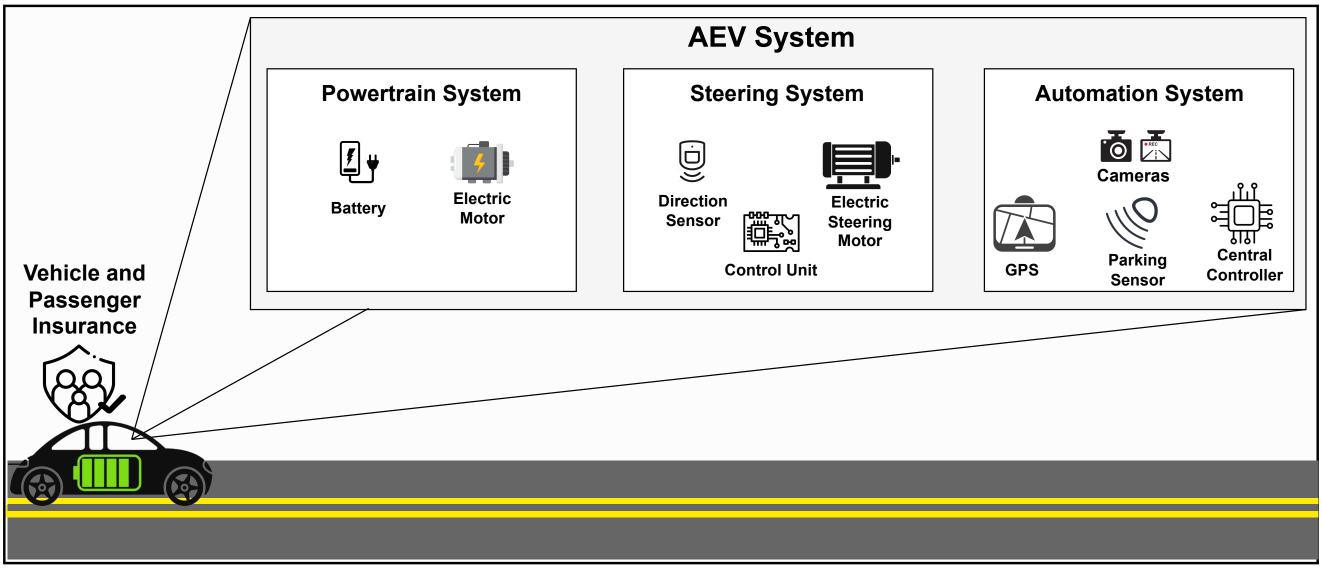
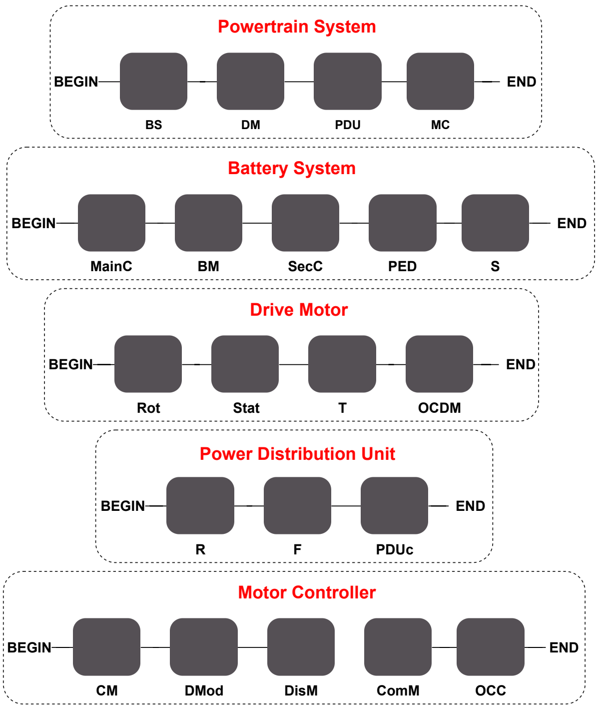
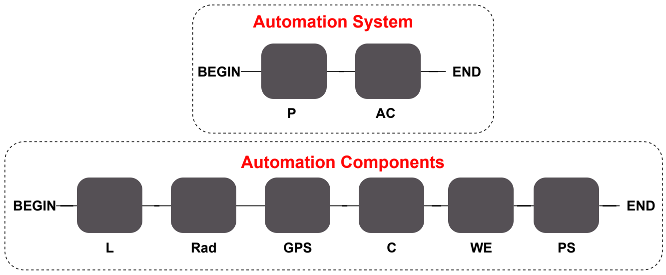


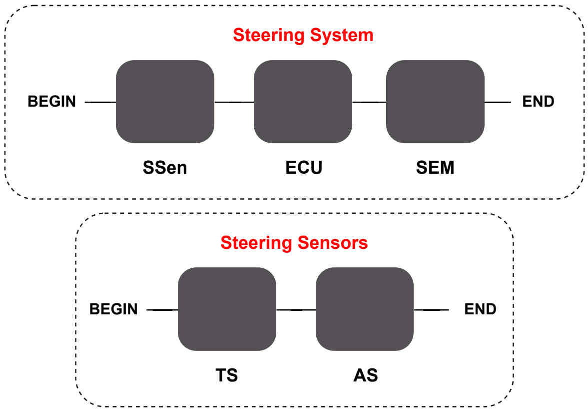
Figure 3. Vehicle system architecture of an AEV.



(a) RBD model of the Powertrain System.



(b) RBD model of the Automation System.



(c) RBD model of the Steering System.

Figure 4. RBD models for the AEV vehicle safety system.

systems: (i) vehicle safety system; (ii) powertrain system; (iii) automation system; and (iv) steering system.

The vehicle safety system depends on the simultaneous operational condition of the three subsystems. Thus, the failure of any subsystem triggers the transition of the vehicle safety system to the unavailable state. This dependency is implemented through the guarded transitions FAIL and RECOVER, controlled by expressions EG1 and EG2 (Table 3). The FAIL transition is enabled when at least one subsystem is inactive, whereas the RECOVER transition is enabled only when all subsystems are operational.

Table 3. Guard expressions for the model.

Expression Index	Guard Expression
EG1	$((PS\_U > 0)$ AND $(AS\_U > 0)$ AND $(SS\_U > 0))$
EG2	$((PS\_U < 1)$ OR $(AS\_U < 1)$ OR $(SS\_U < 1))$

Each subsystem is modeled using a two-state structure composed of an operational place (U) and a failed place (D). A subsystem remains operational only if all its internal components are active. Failure events are governed by timed

Table 2. MTTF values for components of the powertrain, automation, and steering systems.

System	Component	MTTF (Hours)
Automation	Integration Platform (P)	4336.3
	Automation Components (AC)	447.12
	LiDAR (L)	831.45
	Radar (Rad)	4336.30
	GPS	9433.96
	Cameras (C)	1,725,190.00
	Wheel Encoder (WE)	2145.92
	Parking Sensor (PS)	4336.30
Steering	Steering Sensors (SSen)	105.26
	Electronic Control Unit (ECU)	41420.12
	Electric Steering Motor (SEM)	156.25
	Torque Sensor (TS)	222.22
	Angle Sensor (AS)	200.00
Powertrain	Battery System (BS)	108.10
	Ignition Motor (DM)	725.69
	Power Distribution Unit (PDU)	1048.00
	Motor Controller (MC)	221.04
	Battery Module (BM)	289.63
	Master BMS Controller (MCBMS)	587.89
	Slave BMS Controller (SCBMS)	612.75
	Power Electronic Devices (PED)	1085.38
	Sensors (S)	647.67
	Rotor (Rot)	3333.33
	Stator (Stat)	3968.25
	Transducer (T)	3875.97
	Other Ignition Motor Components (OCDM)	1760.56
	Relay (R)	5347.59
	Fuse (F)	1333.33
	Power Distribution Connector (PDUc)	58139.53
	Control Module (CM)	529.10
	Drive Module (DMod)	668.90
	Discharge Module (DisM)	3546.10
	Communication Module (ComM)	2932.20
	Other Controller Components (OCC)	1937.98

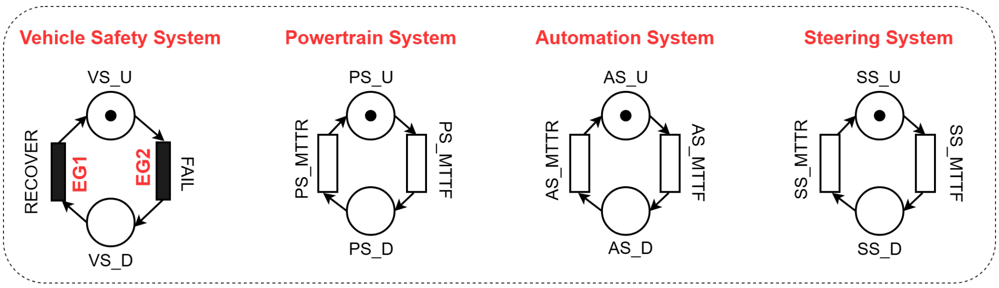


Figure 5. AEV Model for Avaibility Analysis.

transitions parameterized by the subsystem MTTF, while recovery events are governed by transitions parameterized by the MTTR. Component failures propagate to their respective subsystems, and subsystem failures immediately impact the vehicle safety system according to the defined guard conditions. This structure enables the evaluation of the system's overall availability based on the operational state of the vehicle safety system.

The main component, the vehicle safety system, is controlled by the activity status of the other three systems. System availability is defined as the probability that place VS_U contains at least one token, representing the operational condition of the vehicle safety system, as expressed in Equation 3.

$$P(\#VS\_U > 0) \tag{3}$$

When evaluating the system's availability, it is also important to calculate its downtime (D). Downtime can be obtained by Equation 4. A represents the system's availability, and 8760 is the number of hours in a year.

$$(1 - P(\#VS\_U > 0)) \times 8760 \tag{4}$$

5.3 Reliability Model

Figure 6 presents the reliability model, which is structurally similar to the availability model. The model operates in the same way as the availability model and the same component parameters and failure rates are adopted. The difference with the availability model is that the components do not have elements that allow recovery from an inactive to an active state [Lima *et al.*, 2024]. These components are removed to assist in calculating the system's reliability, which focuses strictly on the time until the first failure occurrence.

Equation 5 is used to perform the reliability calculation in the model. P indicates the probability that the system becomes inactive in the sector it represents. This equation generates a graph that demonstrates how reliability decreases over time.

$$1 - P(\#VS\_U > 0) \tag{5}$$

6 Results Analysis

In this section, we discuss the main results of the sensitivity analyses, highlighting their relevance for the implementation of the systems that compose an AEV, with emphasis on vehicle and passenger safety. The analyses focused on the most critical components of the vehicle infrastructure and on evaluating system availability, downtime, and reliability metrics. The models were parameterized using the reference values reported by Hedel *et al.* [2023]: the powertrain system has an MTTF of 62.08 hours, the automation system 405.32 hours, and the steering system 62.79 hours. A uniform MTTR of 1.0 hour was adopted for all systems to standardize the simulations, ensuring consistency and accuracy throughout the sensitivity analyses.

6.1 Design of Experiments

For this study, the DoE technique was used to analyze the system's sensitivity. DoE tools are statistical methods that help to understand how the input factors (both isolated and combined) affect the output (responses) [Luiz *et al.*, 2021]. In this analysis, simulations were conducted by varying the input factors to understand their impact on the output.

Figure 7 presents the effect plot of the factors, showing the impact of the factors on the analyzed measure through bars in descending order. The higher the bar, the greater the influence of the corresponding factor. This graph helps to identify and classify the critical factors of the system. Figure 8 shows interaction plots, using lines to demonstrate how the factors relate. Parallel lines indicate no interaction between the factors; however, if the lines are not parallel, this indicates that the factors interact with each other.

For the experiment conducted, we will present only the factors that interact, as interaction is verified based on the impact of the combination of factors on the availability metric. The factors adopted for the study were (i) PS_MTTR, (ii) AS_MTTR, (iii) SS_MTTR, (iv) PS_MTTF, (v) AS_MTTF, (vi) SS_MTTF. Both factors have two levels: low and high configurations. Table 4 shows all the factors and levels analyzed.

Table 4. Factors and settings used in the simulation.

Factor Name	Low Setting	High Setting
PS_MTTR	0.5	1.5
AS_MTTR	0.5	1.5
SS_MTTR	0.5	1.5
PS_MTTF	31.04	93.12
AS_MTTF	202.66	607.98
SS_MTTF	31.395	94.185

The analysis of Figure 7 reveals that *PS_MTTF*, *SS_MTTF*, and *SS_MTTR* are the dominant parameters, showing the strongest correlation with system availability. This behavior highlights that failures and repairs of the steering and powertrain subsystems have a greater influence on overall performance than the automation modules. The smaller effect observed for *AS_MTTR* and *AS_MTTF* indicates that automation failures have a lower impact on steady-state availability compared to the other systems, due to less time-sensitive operations.

Figure 8a illustrates the interaction between PS_MTTR and PS_MTTF. The nearly parallel lines indicate a weak interaction between the factors. Availability varies modestly across configurations, remaining between 93% and 97%. Although increasing PS_MTTF improves availability, the slope suggests that repair time remains the dominant factor. Therefore, reducing recovery time provides a more effective improvement strategy than extending component lifetime for the powertrain subsystem.

Figure 8b depicts the interaction between SS_MTTR and SS_MTTF. The non-parallel and crossing profiles indicate a clear interaction effect, meaning that the impact of repair time depends on the failure rate level (and vice versa). When SS_MTTF is lower, increasing SS_MTTR produces a pronounced decrease in availability, whereas this decrease is less steep when SS_MTTF is higher. Moreover, the relative ranking of SS_MTTF levels changes across SS_MTTR, reinforcing that improvements in component lifetime alone may not translate into higher availability if recovery processes are slow.

Figure 8c indicates a mild interaction effect, as evidenced by the crossing of the response lines. However, the magnitude of this interaction is small. While increasing AS_MTTR significantly reduces availability, variations in AS_MTTF produce comparatively minor changes. This behavior indicates that the main effect of AS_MTTR is substantially stronger than that of AS_MTTF, suggesting that improvements in repair processes yield greater gains in availability than equivalent proportional increases in component lifetime.

6.2 Availability and Reliability Analysis

In this study, we employed approaches to analyze the system's dependability to understand how failure and recovery dynamics affect its operation. Figure 9 presents the availability results of the model, highlighting the influence of the powertrain subsystem parameters on the availability metric. Although the interaction analysis indicated a stronger interaction for the steering subsystem, the case study focuses on

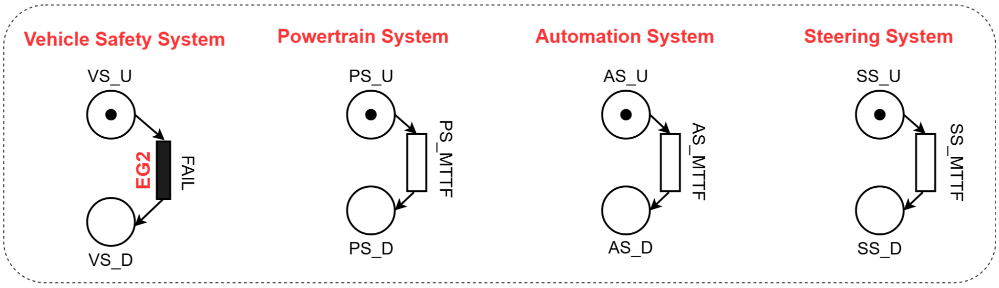


Figure 6. AEV Model for Reliability Analysis.

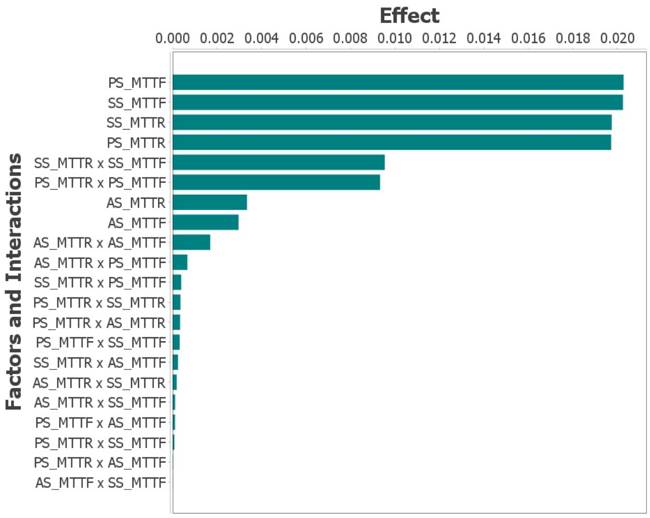


Figure 7. Impact of different factors on system availability.

the powertrain subsystem due to its comparable aggregated MTTF value and its higher structural complexity, making it a representative scenario for evaluating the isolated impact of failure and recovery parameters.

Figure 9a shows that availability decreases monotonically as PS_MTTR increases. This behavior is consistent with availability theory, since longer repair times extend the duration of inactive states after failures. For higher PS_MTTF values (e.g., 93.12 h), the system maintains higher availability levels even when recovery times increase. In contrast, when PS_MTTF is lower (31.04 h), availability drops more sharply as PS_MTTR grows. This indicates that longer intervals between failures mitigate the negative impact of increased repair times.

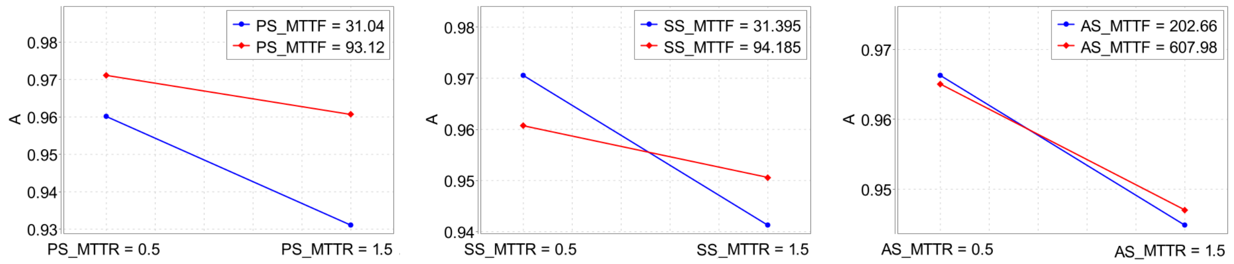
The same tendency is reflected in Figure 9b, which illustrates system downtime. Downtime increases proportionally with PS_MTTR for all PS_MTTF configurations, confirming that repair duration is a dominant factor in system unavailability. However, higher PS_MTTF values consistently result in lower downtime levels. For instance, at $PS\_MTTR = 1.6$ h, the configuration with $PS\_MTTF = 93.12$ h presents substantially less downtime than the configuration with $PS\_MTTF = 31.04$ h. This occurs because higher PS_MTTF values correspond to less frequent failures, reducing the overall number of recovery cycles over time.

Figure 10 shows how the system's reliability is affected by the variation in the time-to-failure of the powertrain system. The trend indicates that higher PS_MTTF values lead to higher overall system reliability. For all configurations, reliability decreases gradually over time, as expected in models without recovery processes. However, when PS_MTTF is 93.12 h, reliability remains at higher levels for longer periods, whereas with PS_MTTF of 31.04 h, the decline is more pronounced over shorter time intervals. This relationship between the lifespan of the powertrain system and overall reliability is evident in the simulations, highlighting the strategic importance of improving component lifetime.

6.3 Discussion of Results

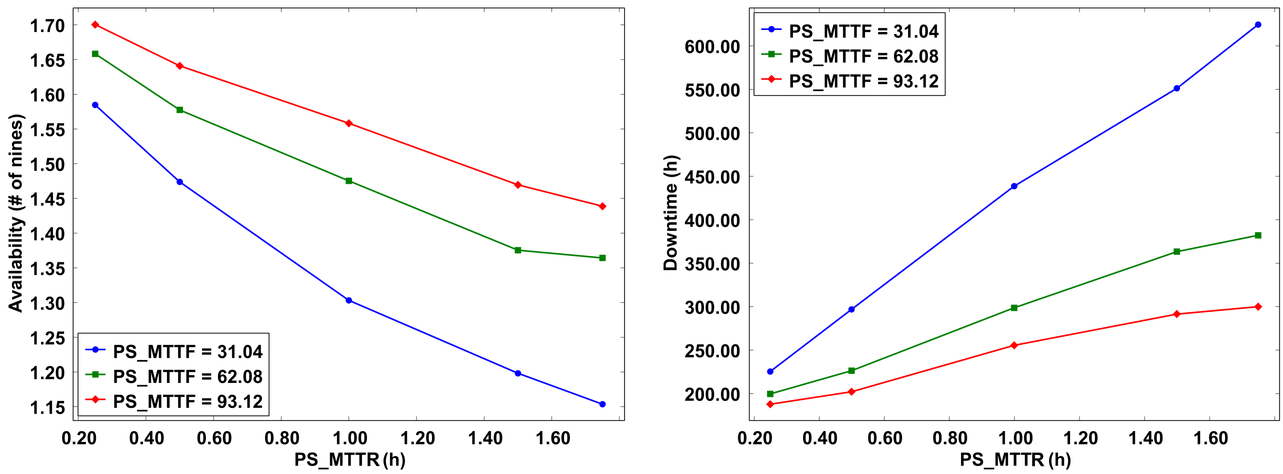
The results provide important insights into the design and quality of the AEV components. Through SPN modeling, the system's availability and reliability were evaluated considering variations in the powertrain, steering, and automation subsystems. The analysis demonstrated that both failure frequency and repair duration influence system-level dependability, with their relative impact varying across subsystems. In practical terms, improving component lifetime contributes to higher reliability, while reducing repair time tends to produce more immediate gains in availability. Therefore, effective dependability enhancement requires a balanced strategy combining increased time to failure and optimized recovery processes.

However, it is important to recognize the limitations of the study: (i) Although the analyzed configuration corresponds to Level 3 autonomy, the present analysis focuses exclusively on the intrinsic technical dependability of the considered subsystems. In Level 3 systems, human takeover performance and environmental conditions may influence operational continuity following subsystem failures. However, these aspects were not explicitly modeled. Consequently, the presented results represent the reliability and availability of the vehicle architecture under purely technical failure conditions, without incorporating driver response dynamics. (ii) The exponential failure distribution was adopted for all components due to its analytical simplicity. This assumption implies a constant failure rate over time and may not fully represent early-life failures or wear-out phases typically observed in electronic units and sensors; (iii) The mentioned specifications increase the complexity and size of the proposed architecture. To overcome this issue, RBD models were used to obtain the MTTF and MTTR values of each component and simplify the SPN model.



(a) MTTR of the powertrain system * MTTF of the powertrain system. **(b)** MTTR of the steering system * MTTF of the steering system. **(c)** MTTR of the automation system * MTTF of the automation system.

Figure 8. Interaction between factors and their impact on the MRT metric.



(a) Comparison of system availability over different MTTF. **(b)** Comparison of system downtime over different MTTF.

Figure 9. Availability results for the vehicle safety system.

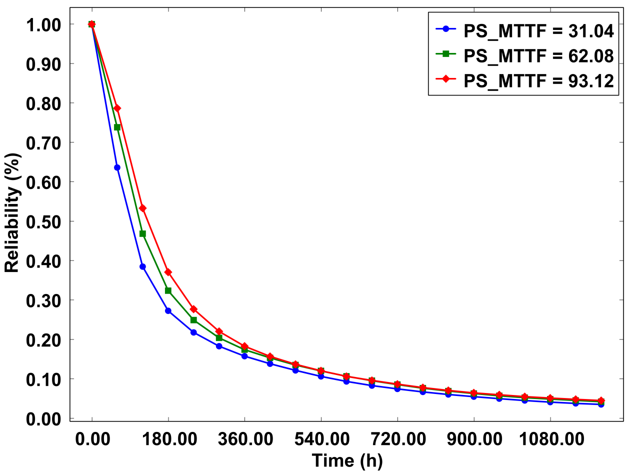


Figure 10. Comparison of the system's reliability over different PS_MTTF.

7 Conclusion

This work proposed RBD and SPN models to evaluate the dependability of the vehicle safety system in a Level 3 AEV. The goal is to assist AEV developers in identifying improvements in components to enhance the safety of AEVs. The models enables the quantitative estimation of availability, downtime, and reliability based on subsystem failure and recovery parameters. The results indicate that MTTF and MTTR affect system behavior differently. Sensitivity analysis showed that steering parameters have a strong impact on availability, particularly through repair time variations, while powertrain MTTF significantly influences reliability degradation over time. These findings reinforce the importance of jointly considering maintenance efficiency and component lifetime in safety-critical vehicle design. As for future research directions, the proposed models could be expanded to include more granular details of subsystems and the impact of external conditions. Furthermore, there is an opportunity to integrate these quantitative dependability metrics with international safety standards to evaluate how technical availability aligns with the regulatory requirements.

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Declarations

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Authors' Contributions

All authors contributed equally to the work.

Competing interests

The authors have no relevant financial or non-financial interests to disclose.

Availability of data and materials

Data sharing is not applicable.

References

Anand, M., Bagen, B., and Rajapakse, A. (2022). Reliability oriented distribution system analysis considering electric vehicles and hybrid energy resources. *International Journal of Electrical Power & Energy Systems*, 137:107500. DOI: 10.1016/j.ijepes.2021.107500.

Avizienis, A., Laprie, J.-C., Randell, B., and Landwehr, C. (2004). Basic concepts and taxonomy of dependable and secure computing. *IEEE Transactions on Dependable and Secure Computing*, 1(1):11–33. DOI: 10.1109/TDSC.2004.2.

Bashir, E. and Luštrek, M. (2021). The mercury environment: a modeling tool for performance and dependability evaluation. In *Intelligent Environments 2021: Workshop Proceedings of the 17th International Conference on Intelligent Environments*, volume 29, page 16. IOS Press. Available at:`https://ebooks.iospress.nl/volume/intelligent-environments-2021-workshop-proceedings-of-the-17th-international-conference-on-intelligent-environments`.

Benarbia, T., Kyamakya, K., Al Machot, F., and Kambale, W. V. (2023). Modeling and simulation of shared electric automated and connected mobility systems with autonomous repositioning: Performance evaluation and deployment. *Sustainability*, 15(1):881. DOI: 10.3390/su15010881.

Bendiab, G., Hameurlaine, A., Germanos, G., Kolokotronis, N., and Shiaeles, S. (2023). Autonomous vehicles security: Challenges and solutions using blockchain and artificial intelligence. *IEEE Transactions on Intelligent Transportation Systems*, 24(4):3614–3637. DOI: 10.1109/TITS.2023.3236274.

Bhavsar, P., Dey, K., Chowdhury, M., and Das, P. (2017). Risk analysis of autonomous vehicles in mixed traffic streams. *University Transportation Research Center - Region 2*. Project No: UTRC/RF Grant No: 49198-28-27. DOI: 10.3141/2625-06.

Callou, G., Ferreira, J., Maciel, P., Tutsch, D., and Souza, R. (2014). An integrated modeling approach to evaluate and optimize data center sustainability, dependability and cost. *Energies*, 7:238–277. DOI: 10.3390/en7010238.

Ebeling, C. E. (1997). *An Introduction to Reliability and Maintainability Engineering*. Waveland Press, Long Grove, IL, USA. Book.

Ebner, C., Gorelik, K., and Zimmermann, A. (2020). Model-based dependability analysis of fail-operational electric drivetrains. In *2020 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM)*, pages 256–263. IEEE. DOI: 10.1109/aim43001.2020.9158882.

Fe, I., da Silva, F. A., Maciel, P., and Callou, G. (2017). Stochastic model of performance and cost for auto-scaling planning in public cloud. In *Proceedings of the 2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, pages 2081–2086, Banff, AB, Canada. DOI: 10.1109/SMC.2017.8122926.

Grosso, M., Raileanu, I. C., Krause, J., Alonso Raposo, M., Duboz, A., Garus, A., Mourtzouchou, A., and Ciuffo, B. (2021). How will vehicle automation and electrification affect the automotive maintenance, repair sector? *Transportation Research Interdisciplinary Perspectives*, 12:100495. DOI: 10.1016/j.trip.2021.100495.

Hariri, A.-M., Hashemi-Dezaki, H., and Hejazi, M. A. (2020). A novel generalized analytical reliability assessment method of smart grids including renewable and non-renewable distributed generations and plug-in hybrid electric vehicles. *Reliability Engineering & System Safety*, 196:106746. DOI: 10.1016/j.ress.2019.106746.

Hariri, A.-M., Hejazi, M. A., and Hashemi-Dezaki, H. (2021). Investigation of impacts of plug-in hybrid electric vehicles' stochastic characteristics modeling on smart grid reliability under different charging scenarios. *Journal of Cleaner Production*, 287:125500. DOI: 10.1016/j.jclepro.2020.125500.

Hasan, O., Ahmed, W., Tahar, S., and Hamdi, M. (2015). Reliability block diagrams based analysis: A survey. *AIP Conference Proceedings*, 1648. DOI: 10.1063/1.4913184.

Hedel, J., Nguyen, N., and Abuelrub, A. (2023). Reliability evaluation of autonomous electric vehicles using fault tree method. In *2023 North American Power Symposium (NAPS)*, pages 1–6. IEEE. DOI: 10.1109/naps58826.2023.10318670.

Hussain, R. and Zeadally, S. (2019). Autonomous cars: Research results, issues, and future challenges. *IEEE Communications Surveys & Tutorials*, 21(2):1275–1313. DOI: 10.1109/COMST.2018.2869360.

Irimia, N. D., Luchian, M., Lazar, F. I., and Ipatiov, A. (2022). Performant fault tolerant control by using space vector modulation (svm) technique of a five phases bldc motor for autonomous driving applications. In *2022 10th International Conference on Systems and Control (ICSC)*, pages 317–322. DOI: 10.1109/ICSC57768.2022.9993892.

Lima, L. N., Sabino, A., Barbosa, V., Feitosa, L., Brito, C., Araujo, J., and Silva, F. A. (2024). Dependability analysis and disaster recovery measures in smart hospital systems. *Journal of Reliable Intelligent Environments*, pages 1–17. DOI: 10.1007/s40860-024-00222-2.

Luiz, M. T., Viegas, J. S. R., Abriata, J. P., Viegas, F., de Carvalho Vicentini, F. T. M., Bentley, M. V. L. B., Chorilli, M., Marchetti, J. M., and Tapia-Blacido, D. R. (2021). Design of experiments (doe) to develop and to optimize nanoparticles as drug delivery systems. *European Journal of Pharmaceutics and Biopharmaceutics*, 165:127–148. DOI: 10.1016/j.ejpb.2021.05.011.

Maciel, P., Matos, R., Silva, B., Figueiredo, J., Oliveira, D., Fé, I., Maciel, R., and Dantas, J. (2017). Mercury: Performance and dependability evaluation of systems with exponential, expolynomial, and general distributions. In *2017*

IEEE 22nd Pacific Rim international symposium on dependable computing (PRDC), pages 50–57. IEEE. DOI: 10.1109/prdc.2017.16.

Molloy, M. K. (1982). Performance analysis using stochastic petri nets. *IEEE Transactions on Computers*, 31(9):913–917. DOI: 10.1109/TC.1982.1676110.

Read, G., Shorrock, S., Walker, G., and Salmon, P. (2021). State of science: Evolving perspectives on ‘human error’. *Ergonomics*, 64:1–46. DOI: 10.1080/00140139.2021.1953615.

Schmidta, S. and Zimmermannb, A. (2022). Model-based reliability engineering of automotive drivetrain architectures with multi-trajectory simulation. Avaialble at:`https://www.iapsam.org/PSAM16/papers/AR216-PSAM16.pdf`.

Shafiq, S., Irshad, U. B., Al-Muhaini, M., Djokic, S. Z., and Akram, U. (2020). Reliability evaluation of composite power systems: Evaluating the impact of full and plug-in hybrid electric vehicles. *IEEE access*, 8:114305–114314. DOI: 10.1109/access.2020.3003369.

Silva, F. A., Brito, C., Araújo, G., Fé, I., Tyan, M., Lee, J.-W., Nguyen, T. A., and Maciel, P. R. M. (2022). Model-driven impact quantification of energy resource redundancy and server rejuvenation on the dependability of medical sensor networks in smart hospitals. *Sensors*, 22(4):1595. DOI: 10.3390/s22041595.

Silva, F. A., Fe, I., Callou, G., and Maciel, P. (2015). Planning mobile cloud infrastructures using stochastic petri nets and graphic processing units. In *Proceedings of the 2015 IEEE 7th International Conference on Cloud Computing Technology and Science (CloudCom)*, pages 471–474, Vancouver, BC, Canada. DOI: 10.1109/CloudCom.2015.46.

Van Brummelen, J., O’brien, M., Gruyer, D., and Najjaran, H. (2018). Autonomous vehicle perception: The technology of today and tomorrow. *Transportation research part C: emerging technologies*, 89:384–406. DOI: 10.1016/j.trc.2018.02.012.

Wang, D., Cao, Y., and Ahmad, N. (2023). Security and privacy-preserving for automated electric vehicle. In *Communication, Computation and Perception Technologies for Internet of Vehicles*, pages 275–292. Springer. DOI: 10.1007/978-981-99-5439-$1_1 5$.

Wang, J., Zhang, L., Huang, Y., and Zhao, J. (2020). Safety of autonomous vehicles. *Journal of Advanced Transportation*, 2020(1):8867757. DOI: 10.1155/2020/8867757.

Yeong, D. J., Velasco-Hernandez, G., Barry, J., and Walsh, J. (2021). Sensor and sensor fusion technology in autonomous vehicles: A review. *Sensors*, 21(6). DOI: 10.3390/s21062140.

Zhuge, C. and Wang, C. (2021). Integrated modelling of autonomous electric vehicle diffusion: From review to conceptual design. *Transportation Research Part D: Transport and Environment*, 91:102679. DOI: 10.1016/j.trd.2020.102679.