Proceedings of the 33rd European Safety and Reliability Conference (ESREL 2023)
Edited by Mário P. Brito, Terje Aven, Piero Baraldi, Marko Čepin and Enrico Zio

Published by Research Publishing, Singapore.
doi: 10.3850/978-981-18-8071-1_P398-cd

Components and their failure rates in autonomous driving

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Autonomous driving has been among the most actively researched topics over the past decades. Today, automotive vehicles are already equipped with driving assistance systems with partial autonomous driving capabilities. Thus, the need for quantitative and qualitative assessment of automated driving functions becomes increasingly vital. The used hardware and software must undergo vigorous safety assessments with regard to reliability and safety. This must be done under careful consideration of driving scenarios and environmental conditions. The safety of the intended functionality (SOTIF) standard, which is developed under the corresponding ISO 21448 standard for road vehicles, lies at the center of these considerations. SOTIF deals with the question of how a target function needs to be specified, developed, verified, and validated so that it can be considered sufficiently safe. As a good starting point, we suggest regarding the individual failure probabilities for each of the components comprising the autonomous driving system. Based on the failure probabilities of each component, it is possible to make assumptions about the failure probability of the system as a whole and even identify possible deficiencies.
In this contribution, we aim to identify the typical components needed for an autonomous vehicle (AV) and further provide a comprehensive overview of failure probabilities for said components. Certainly, it would go beyond the scope of this work to create a statistically firm data basis by individually testing all components until failure, especially when taking into consideration that the failure probabilities of each component vary over time and with environmental conditions. Instead, the relevant factors with regard to the typical failure modes are identified and relevant data is accumulated from publications that reflect the current state of the art.

Keywords: Autonomous Driving, Safety of the Intended Functionality (SOTIF), Failure probability, Safety and reliability analysis, Operational Failure, Risk management, Systems risk, Fail-safe, Redundancy

1. Introduction

As autonomous driving technology continues to move forward, one of humanity's goals is slowly creeping into reach. With autonomous driving features hitting the streets, a milestone in urban transportation is reached. The dream of commuting to work in a fully autonomous vehicle (AV) that swiftly navigates through traffic while reading the newspaper and drinking a cup of coffee is closer than ever.

The levels of autonomous driving are classified by the Society of Automotive Engineers (SAE) [1]. The SAE defined six levels of autonomous driving:

- Level 0: No driving automation
- Level 1: Driver assistance
- Level 2: Partial driving automation
- Level 3: Conditional driving automation
- Level 4: High driving automation
- Level 5: Full driving automation

These days, modern vehicles are often equipped with level 2 functionality. They are therefore capable of autonomous steering and accelerating/decelerating, whilst the driver is $100\,\%$ attentive and can take control of the vehicle momentarily if needed.

More recently, Mercedes-Benz is the first company to meet the demanding legal requirements to get level 3 automated driving approved in the United States (USA) and Europe [2]. To engage their "Drive Pilot", drivers must keep their faces visible to the vehicle's in-car cameras at all times, but can also turn their heads to talk to a passenger or play a game on the vehicle's infotainment screen. The SAE level 3 "Drive Pilot" can be activated in heavy traffic on suitable highway sections at speeds of up to $60\,\mathrm{km/h}$ in Germany or $40\,\mathrm{mph}$ in Nevada in the USA.

But it has become clear in recent years, that there is a risk involved when using autonomous driving features. Anyone who has tried the automatic steering feature of a modern car can relate. Everything is working as intended until the requirements for automatic steering are no longer met. In fact, there are reports of deadly accidents that occur while using autonomous driving features. Consequently, an uncomfortable question remains: Is this safe?

Moreover, typical drivers overestimate their own driving abilities and therefore do not accept an autonomous system that performs as well as an average driver. Therefore, AV systems must exceed the safety standards of human drivers to be considered reliable and trustworthy.

The truth of the matter is, that autonomous driving is still under heavy development even though, to this day, it is among the most actively researched topics. Accidents are inevitable and with lives at stake, the need for a quantitative and qualitative assessment of safety-relevant features becomes increasingly vital. The used hardware and software must undergo vigorous safety assessments with regard to reliability and safety. However, due to the complexity of the matter, this must be done under careful consideration of driving scenarios and environmental conditions.

At the center of these considerations lies the Safety of the Intended Functionality (SOTIF). The SOTIF standard for automotive road vehicles, which is developed under the corresponding ISO 21448 standard for road vehicles, is defined as the absence of unreasonable risk due to a hazard caused by failures and/or functional insufficiencies of the intended functionality [3]. This includes the specification of the intended functionality at the vehicle level as well as the specification and performance of system components. It is stated, that ISO 26262 provides requirements and recommendations to avoid and control random hardware failures as well as systematic failures that could violate safety requirements. Where ISO 26262-1 defines functional safety as the absence of unreasonable risk due to hazards caused by malfunctioning behavior of the electric or electronic system. To identify hazards at the vehicle level, ISO 26262-3 provides guidance on performing a Hazard Analysis and Risk Assessment (HARA).

A possible approach for the assessment is to consider the individual failure probabilities and failure rates for each of the components comprising the autonomous driving system [4]. On the basis of the individual failure probabilities, assumptions with respect to the failure probability of the system as a whole can be made and possible weak points in the system can be identified. Consequently, we provide a derivation from public sources to estimate the failure rates of the individual components that can serve as a starting point for the evaluation of the reliability of the AV.

In Section 2 we will review the state-of-the-art literature on failure probabilities and failure rates. In Section 3 the basic components used in AVs will be discussed, followed by a discussion of how their failure can be modeled in Section 4. This will include analyzes of public data on car deficiencies and autonomous driving disengagements, to estimate accurate failure statistics. Finally, in Section 5 we provide a summary of our findings, limitations, and future directions.

2. Related Work

Several researchers have focused on the safety analysis of AVs, however, concrete data on failure probabilities of individual components or functions is hard to come by since most Original Equipment Manufacturers (OEMs) don't make their testing data public. Bhavsar et al. [5] reviewed the public literature and publicly available data sources to compile a list of failure probabilities that he used to perform a fault tree analysis of the failure of AVs, including external factors like infrastructure and other road users. One has to be very careful when using this data for other purposes since some of the sources are extremely outdated while others are theoretical studies that don't aim to provide accurate failure probabilities. For instance, the failure probability given for the radar in [5] is based on a publication from 1954. Technology has improved considerably since then, thus, this value is not likely to represent the reliability of current radar systems in AVs. Another example is the failure probabilities provided for the lidar and the camera, for which the source publication of the data states that their values are arbitrary and might not represent the real world. An estimation of failure rates computed from those probabilities was performed by Häring et al. [6]. However, since their study was focused on methods for safety assessment of AVs through Markov modeling, they did not need precise and/or accurate values and assumed a time frame of 10 years to convert the probabilities to rates, which may not reflect the experimental conditions of the source publications.

The accuracy and robustness of artificial intelligence (AI) algorithms have also been extensively studied. However, this is a constantly and fast-evolving field. A fatal Tesla accident shows how important the accuracy and robustness of AI algorithms are. Here, an error occurred in the perception module in the form of the misclassification of a white trailer as part of the sky and caused one of the first autonomous driving fatalities [7]. Various real-world datasets for testing the algorithms exist, such as the Audi Autonomous Driving Dataset (A2D2) [8] or the German Traffic Sign Recognition Benchmark (GTSRB) dataset for traffic sign classification [9]. These datasets can be used to evaluate current and new neural networks and deep learning methods in the field of autonomous driving [10].

3. Components of AVs

Ultimately, it should be possible to navigate a car fully autonomously with high-definition cameras only, after all, a taxi driver only has two eyes as well [11]. The more sophisticated the data processing becomes, the less hardware is needed. When selecting sensors many boundary conditions need to be considered and sensors that complement each other can be utilized advantageously. Therefore, in this section, we will examine the hardware used by the most advanced players in the field of autonomous driving.

Tesla has been making progress with its Autopilot system, using a minimalist approach. In a middle-class Tesla Model 3, they use a total number of eight cameras. Tesla began to transition to “Tesla Vision” by relying only on camera vision for autonomous driving [11]. Regrettably, this approach has led to fatalities, but could ultimately result in the most cost-effective solution to autonomous driving.

Nevertheless, developers have different approaches when it comes to picking the necessary hardware for autonomous driving systems. When considering the recently approved level 3 automated driving system of Mercedes, a total of 27 sensors are used as shown in Fig. 1.

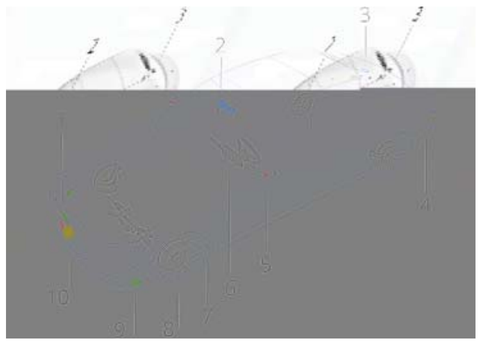

Fig. 1. Sensor setup of the Mercedes S-Class with the “Drive Pilot” [12]. The numbers are labeled as follows: 1) front long-range radar: opening angle 90° / 9°, 2) stereo multi-purpose camera: opening angle 70°, 3) rear multi-purpose camera: opening angle 50°, 4) ultrasonic sensors: 12x opening angle 120°, 5) 360°-camera: 4x single cameras with opening angle 180°, 6) driver camera, 7) moisture sensor, 8) redundant electrical brake and steering system, 9) multi-mode radar: 4x opening angle 130°, and 10) lidar: opening angle 120°.

When considering a third big player, namely Audi, commonalities become visible. In their 2018 Model Audi A8, the list of sensors is similar to the one from Mercedes. Multiple cameras are used to achieve a 360° vision, multiple front-facing cameras with different opening angles are used to enable near and far field vision as well as stereo vision depth sensing, ultrasonic sensors are used to detect approaching objects during parking maneuvers, and multi-mode radar or laser scanners are used for reliable depth sensing to cross-reference the collected camera-based depth information.

It is crucial to consider the different sensor types and also their fusion when determining the failure probability of an AV. In principle, sensor redundancy is important and can prevent catastrophic failure.

4. Failure Modes/Metrics

4.1. *Modeling failure*

Two commonly used approaches for modeling component failure are the bathtub curve and the Weibull hazard function. The former is a theoretical curve that represents the likelihood of failure over time and is characterized by three phases: Early failure, random failure, and wear-out failure [13]. The first phase is usually related to manufacturing flaws. The components that survive this phase enter the next stage in which random failures predominate, these are assumed to be stress-related. Finally, the wear-out failures gain relevance as the components get older. A schematic of the bathtub curve can be seen in Fig. 2.

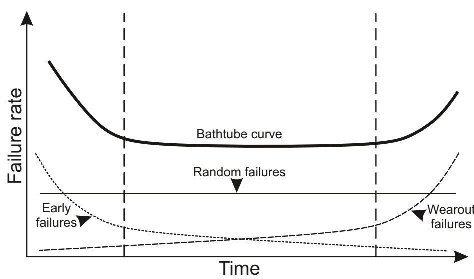

Fig. 2. Depicts a typical Bathtub curve with early, random, and wear-out failure.

The Weibull hazard function $h(t)$, on the other hand, is a mathematical function that can be used to model the failure rate of a component over time [14] and has different shapes depending on the chosen parameters. The general expression can be written as follows.

$$h(t) = \alpha\lambda(\lambda t)^{\alpha-1} \tag{1}$$

Where α is the shape parameter and λ is the scale parameter. These two parameters define the failure rate behavior. Considering $\alpha < 1$ will result in a decreasing failure rate over time. A constant failure rate could be modeled by choosing $\alpha = 1$, while $\alpha > 1$ will represent an increasing failure rate. It is possible then to reproduce the bathtub curve by using different Weibull hazard functions with different shape and scale parameters at different times. However, analytical expressions of the bathtub curve can also be found in the work of Suhir et al. [15].

Regardless of the failure model used, the main problem that remains is choosing the correct parameters. To do so one needs access to reliable experimental data, which is scarce in most cases, as discussed in Section 2. In the following sections, we will dive into the sources of AV failures and present some approaches to estimate failure rates and probabilities from public data of yearly inspections and AV disengagement reports.

4.2. *Failure sources in AVs*

On one hand, traditional failure sources of non-autonomous cars remain possible points of failure. These would include failures in the braking system (e.g., brake pedal, vacuum pump or compressor, electronic braking system), steering system (e.g., electronic power steering, steering gear, steering alignment, hydraulic system), or lighting equipment (e.g., headlight source, projection system, electronics) among others. A detailed study on these traditional sources can be found in Section 4.3.

On the other hand, software is a centerpiece in AV functions. As AVs include more and more functionalities and sensors, the source of possible failures grows exponentially. Autonomous driving is based in large part on AI such as machine learning and neural networks [16]. Driving is an action that requires a high level of awareness of the surroundings (e.g., traffic lights, road lanes, traffic signs) as well as a capacity to predict the behavior of other road users. Of course, AI algorithms that make all this possible are not exempt from malfunctions. While detection algorithms have improved dramatically in the last years, one has to take into account that the algorithms needed in the automotive industry are required to be real-time (such as You Only Look Once (YOLO) algorithms) and need to be optimized for the hardware present in the AV. Accurate and standardized data to quantify the failure rates of such algorithms are hard to come by as their intricate details are mostly kept secret by the Original Equipment Manufacturers (OEMs). Nevertheless, in Section 4.4 we will analyze available public data from AV testing in California, to get an idea of the magnitude and sources of the malfunctions.

Last but not least, external factors will also influence the AV function. Bad weather like fog can severely impact the visibility conditions, affecting the object recognition algorithms based on camera imaging. Snowfall or rain will influence the lidar's ability to accurately measure object distances [17]. Redundant sensing systems based on different technologies can aid to overcome some of these issues [18]. For LiDAR and camera, Wu et al. [19] propose a LiDAR/camera sensor fusion system for pedestrian detection in various environments. A Vedolyne VLP-16 lidar and Logitech C920 cameras (30 FPS) were used as input sensors, resulting in an accuracy of $99.16\,\%$ for 8,000 frames, which is equivalent to $267\,\mathrm{s}$. From these values, we can compute the failure rates per hour with Eq. (2), obtaining $1.14\mathrm{E}{-1}\,\mathrm{h}^{-1}$.

$$\lambda = \frac{-ln(1-F(t))}{t} = \frac{-ln(A(t))}{t} \tag{2}$$

where $F(t)$ is the failure probability at time t and $A(t)$ is the complementary accuracy. These data are representative (upper bound) as they satisfy an error rate that would be lower with professional equipment.

The road condition, construction sites, and unexpected behavior of other road users will also play a major role in the correct functioning of the AV. For instance, we can estimate the frequency of accidents with cyclists from the New York State Department of Motor Vehicles crashes report from 2020 [20], in which 938 bicyclist deaths and 38,886 bicyclist injuries in traffic crashes were reported in the USA. When taking the average speed of $\overline{v} = 97\,\mathrm{km/h}$ of a passenger car [21], and the total distance of $5.28\mathrm{E}12\,\mathrm{km}$ driven by vehicles in 2020 [22], we can determine a failure rate of $7.32\mathrm{E}{-7}\,\mathrm{h}^{-1}$ according to Eq. (3).

$$\lambda = \frac{N \cdot \overline{v}}{D} \tag{3}$$

Where N is the number of accidents and D is the total vehicle kilometers traveled during the studied time period.

Similarly, we can calculate a rate for pedestrian-involved accidents. According to an National Highway Traffic Safety Administration (NHTSA) report [20], in 2014 there were 6,516 pedestrian deaths and an estimated 54,769 pedestrian injuries in traffic crashes in the USA. Following Eq. (3) the resulting rate is $1.13\mathrm{E}{-6}\,\mathrm{h}^{-1}$.

Regarding external factors like construction sites, according to the Traffic Safety Evaluation of Nighttime and Daytime Work Zones in the USA [23], the crash rates in work zones are generally higher than those in non-work zones. Based on the published table, we can derive the average crashes per hour in the USA which is $9.32\mathrm{E}{-7}\,\mathrm{h}^{-1}$, by multiplying the total number of accidents 267.40 at construction sites with the average traveled speed at construction sites $72.42\,\mathrm{km/h}$, divided by the total length of construction sites $20.79\mathrm{E}9\,\mathrm{km}$.

According to the NHTSA [24], there were a total of 5,376,000 crashes in 2015, of which $22\,\%$ were weather-related (i.e. weather was a contributing factor in the crash). The total number of driven kilometers in the USA in 2015 is $4.89\mathrm{E}12\,\mathrm{km}$ [22]. According to Eq. (3), the weather-related failure rate is $2.35\mathrm{E}{-5}\,\mathrm{h}^{-1}$.

The summarized values for failure rates calculated in this section can be found in Table 1.

4.3. *Yearly car inspections (Germany)*

One approach to estimate failure rates over time is to analyze public data on yearly car inspections. Regular vehicle inspections are required to ensure that vehicles on the road are safe and meet certain standards in Germany, which are monitored by the Kraftfahrt-Bundesamt (KBA), the federal agency responsible for vehicle safety. The inspections are conducted by authorized inspection centers, which are certified by the KBA. The KBA is responsible for the statistical processing of the yearly reports from the inspection centers.

The age range of the car studied in the KBA report [26] is: up to 3 years, over 3 to 5 years, over 5 to 7 years, over 7 to 9 years, and over 9 years. Based on a study from Weimar et al. [27], the expected lifespan of passenger cars is 16 years and

Table 1. Overview of factors which can contribute to failures in AVs.

Factors	Failure Modes	Failure rate (1/h)
LiDAR & Camera	Overlapping, connecting objects and segmentation algorithm [19]	1.14E-1
Cyclists	Yearly 110.9 million bike trips were made, where 39,824 accidents involve cyclists. [20]	7.32E-7
Pedestrians	61,285 crashes happened where pedestrians were at fault among the annually 42 billion walking trips. [20]	1.13E-6
Construction zones	Maintenance of traffic control devices, driver behavior, and weather around the construction zones. [23]	9.32E-7
Weather	Adverse weather conditions like fog, mist, rain, severe crosswind, sleet, snow, dust/ smoke. [25]	2.35E-5

was considered in determining the failure rates presented in this study.

The data contained in the report pertains to all automobiles throughout their existence, categorized by the age of said vehicles. However, it is imperative to transform the data into failure rates per car and per hour with respect to the cars' lifetime and according to the deficiencies of the components and functions as per the following equation.

$$h^{\mathrm{def}}_{[t_1,t_2]} = \frac{N^{\mathrm{def}}_{[t_1,t_2]}}{N_{[t_1,t_2]}(t_2 - t_1)} \tag{4}$$

Where $h^{\mathrm{def}}_{[t_1,t_2]}$ is the average failure rate for the time interval $[t_1, t_2]$, $N^{\mathrm{def}}_{[t_1,t_2]}$ is the number of a particular defect in that time interval, and $N_{[t_1,t_2]}$ is the total number of inspected cars.

The resulting failure rates per component and vehicle's age have been computed and listed in Table 2. The particular details of the listed subsystems can be found on the KBA website [28]. We can observe a clear pattern of increasing failure rates over time due to aging effects. The data does not show the triphasic behavior characteristic of a bathtub curve. This could be due to good quality control by manufacturers and/or due to the data averaging over the first three years, which could factor in the low rate of random failures where we would expect early failures.

4.4. *AV disengagement vs driver disengagement*

The California Department of Motor Vehicles (DMV) publishes an annual disengagement report, which includes data from companies that have been licensed to test autonomous cars on public roads in California. [29] The report of 2021 outlines various types of disengagements from the different companies that occurred during the testing of AVs between December 2020 to November 2021. These disengagements have been meticulously categorized based on their initiation, which could be either by the autonomous system or the test driver, and their underlying causes. The disengagement rates per kilometer are derived by dividing $6.59\mathrm{E}6\,\mathrm{km}$, the number of kilometers driven, by the total number of AVs. Assuming that the number of disengagements of an autonomous system correlates with its failure rate, the data can be contrasted as shown in table Table 3.

5. Conclusion

In this work, we have identified the typical components needed for an AV by examining the state of the art. Car manufacturers and their developers demonstrate best practices and thus provide a good foundation for our analysis. Unfortunately, it is difficult to find reliable failure rates for some components, in which case publicly accessible statistics, such as the "Fahrzeuguntersuchungen" from the KBA and the autonomous driving disengagement reports by the DMV, can be used to estimate the failure rates. By assessing individual components of the AV, while taking into account the car's architecture, a prediction can be made about the safety of the vehicle. Thus we have provided a starting point for the safety assessment of an AV and a possible way to identify hardware deficiencies. In the future, additional work in this field could be done by generating synthetic data of

Table 2. Average failure rate of subsystems of passenger cars for time intervals corresponding to main inspection intervals (per car per hour) according to Eq. (4) and using data of the years 2018-2022. [26]

Subsystems	< 3 years	3 - 5 years	5 - 7 years	7 - 9 years	over 9 years
Braking system	6.23E-07	7.26E-07	1.09E-06	1.32E-06	1.91E-06
Steering system	2.15E-08	2.45E-08	6.33E-08	1.30E-07	2.95E-07
Visibility conditions	2.92E-07	2.98E-07	2.93E-07	2.77E-07	3.06E-07
Lighting equipment and other parts of the electrical system	1.16E-06	1.15E-06	1.59E-06	2.09E-06	2.71E-06
Axles, wheels, tires, suspension	8.11E-07	8.83E-07	1.12E-06	1.32E-06	1.68E-06
Chassis, frame, body, attached parts	1.14E-07	1.11E-07	2.13E-07	3.26E-07	1.21E-06
Other equipment	2.23E-07	2.08E-07	2.67E-07	2.65E-07	2.54E-07
Noise development	8.09E-09	9.15E-09	2.33E-08	5.18E-08	1.10E-07
Engine exhaust	1.15E-07	1.20E-07	1.77E-07	2.38E-07	4.63E-07
Other environmentally relevant items	1.61E-07	1.82E-07	3.49E-07	5.97E-07	1.46E-06

Table 3. Autonomous vehicles disengagements initiated by driver or autonomous system with mean failure rates for different functionalities and components. [29]

Functionality or Components	No. of Disengagements			Failure rates [1/h]
	Driver	AV	Total	
Perception	1138	91	1229	3.73E-03
Camera	6	0	6	1.82E-05
Database	0	3	3	9.10E-06
Environment	4	11	15	4.55E-05
GPS	1	0	1	3.03E-06
Lane detection	157	0	157	4.76E-04
Localization	290	4	294	8.92E-04
Map	1	0	1	3.03E-06
Object detection	645	63	708	2.15E-03
Positioning	33	0	33	1.00E-04
Sensor failure	1	0	1	3.03E-06
Sensor fusion	0	10	10	3.03E-05
Decision & Control	948	100	1048	3.18E-03
Control	15	1	16	4.86E-05
Other vehicles	69	0	69	2.09E-04
Path planning	619	50	669	2.03E-03
Prediction	30	0	30	9.10E-05
Software error	7	3	10	3.03E-05
Trajectory planning	208	46	254	7.71E-04
Vehicle Platform Manipulation	105	247	352	1.07E-03
Actuation	72	65	137	4.16E-04
Gears	0	1	1	3.03E-06
General system	22	0	22	6.68E-05
Hardware issue	5	48	53	1.61E-04
Software component	2	133	135	4.10E-04
System error	4	0	4	1.21E-05

failure scenarios using simulation software such as Carla.

Acknowledgement

The presented work is funded by the German joint BMWE project on Real Driving Validation (RDV). [Grant number 19A21051D, 2022-2025]

References

1. On-Road Automated Driving (ORAD) Committee, *Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles*, Apr. 2021.
2. Mercedes-Benz AG, "Mercedes-benz world's first automotive company to certify sae level 3 system for u.s. market," 2023.
3. I. O. for Standardization, "Road vehicles - Safety of the intended functionality," June 2022.
4. J. Menčík, "Reliability of systems," in *Concise Reliability for Engineers* (J. Mencik, ed.), IntechOpen, 2016.
5. P. Bhavsar, P. Das, M. Paugh, K. Dey, and M. Chowdhury, "Risk analysis of autonomous vehicles in mixed traffic streams," *Transportation Research Record*, vol. 2625, no. 1, pp. 51–61, 2017.
6. I. Häring, Y. Satsrisakul, J. Finger, G. Vogelbacher, C. Köpke, and F. Höflinger, "Advanced markov modeling and simulation for safety analysis of autonomous driving functions up to sae 5 for development, approval and main inspection," *Proceedings of the 32nd European Safety and Reliability Conference*, pp. 104–111, 8 2022.
7. Y. Tian, K. Pei, S. Jana, and B. Ray, "Deeptest: Automated testing of deep-neural-network-driven autonomous cars," in *Proceedings of the 40th international conference on software engineering*, pp. 303–314, 2018.
8. J. Geyer, Y. Kassahun, M. Mahmudi, X. Ricou, R. Durgesh, A. S. Chung, L. Hauswald, V. H. Pham, M. Mühlegg, S. Dorn, T. Fernandez, M. Jänicke, S. Mirashi, C. Savani, M. Sturm, O. Vorobiov, M. Oelker, S. Garreis, and P. Schuberth, "A2d2: Audi autonomous driving dataset," 2020.
9. J. Stallkamp, M. Schlipsing, J. Salmen, and C. Igel, "Man vs. computer: Benchmarking machine learning algorithms for traffic sign recognition," *Neural Networks*, vol. 32, pp. 323–332, 8 2012.
10. J. Zhang, J. R. Taylor, I. Kozin, and J. Li, "Analyzing influence of robustness of neural networks on the safety of autonomous vehicles," 2021.
11. Tesla, "Tesla vision update: Replacing ultrasonic sensors with tesla vision."
12. G. M. Mercedes-Benz, "Drive pilot in the s-class: Sensor technology and redundancy," Dec 2021.
13. D. D. J. Smith, *Reliability, Maintainability and Risk (Tenth Edition)*. Butterworth-Heinemann, tenth edition ed., 2022.
14. D. Prabhakar Murthy, M. Bulmer, and J. A. Eccleston, "Weibull model selection for reliability modelling," *Reliability Engineering & System Safety*, vol. 86, no. 3, pp. 257–267, 2004.
15. E. Suhir, "Analytical bathtub curve with application to electron device reliability," *Journal of Materials Science: Materials in Electronics*, vol. 26, 2015.
16. K. Muhammad, A. Ullah, J. Lloret, J. D. Ser, and V. H. C. de Albuquerque, "Deep learning for safe autonomous driving: Current challenges and future directions," *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 7, pp. 4316–4336, 2021.
17. A. D. Abu-Shaqra, N. J. Abu-Alrub, and N. A. Rawashdeh, "Object detection in degraded lidar signals by synthetic snowfall noise for autonomous driving," in *Autonomous Systems: Sensors, Processing and Security for Ground, Air, Sea and Space Vehicles and Infrastructure*, International Society for Optics and Photonics, SPIE, 2022.
18. D. J. Yeong, G. Velasco-Hernandez, J. Barry, and J. Walsh, "Sensor and sensor fusion technology in autonomous vehicles: A review," *Sensors*, vol. 21, no. 6, 2021.
19. T.-E. Wu, C.-C. Tsai, and J.-I. Guo, "Lidar/camera sensor fusion technology for pedestrian detection," in *2017 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC)*, pp. 1675–1678, 2017.
20. U. D. of Transportation, "Dot hs 813 266," Mar 2022.
21. N. H. T. S. Administration, "National traffic speeds survey iii: 2015," Mar 2018.
22. F. H. Administration, "Annual vehicle miles traveled in the u.s.," 1971-2022.
23. Transportation Research Board and National Academies of Sciences, Engineering, and Medicine, *Traffic Safety Evaluation of Nighttime and Daytime Work Zones*. Washington, DC: National Academies Press, 2008.
24. N. H. T. S. Administration, "Traffic safety facts 2016," May 2016.
25. N. H. T. S. Administration, "Traffic safety facts 2014 data," May 2016.
26. Kraftfahrt-Bundesamt, "Fahrzeuguntersuchungen (fu) - hauptuntersuchungen und einzelabnahmennach Überwachungsinstitutionen," 2018-2021.
27. E. Weymar and M. Finkbeiner, "Statistical analysis of empirical lifetime mileage data for automotive lca," *International Journal of Life Cycle Assessment*, vol. 21, pp. 215–223, 2 2016.
28. Bundesministerium für Verkehr und digitale Infrastruktur, *Verkehrsblatt. Amtsblatt des Bundesministeriums für Verkehr und digitale Infrastruktur der Bundesrepublik Deutschland*, vol. 23. Bundesministerium für Verkehr und digitale Infrastruktur, 12 2017.
29. Department of Motor Vehicles California, "Autonomous vehicle disengagement reports," 2021.