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Study on State-of-the-Art Preventive Maintenance Techniques for ADS Vehicle Safety

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1. Abstract

Autonomous Driving Systems (ADS) are developing rapidly. As vehicle technology advances to SAE level 3 and above (L4, L5), there is a need to maximize and verify safety and operational benefits. As a result, maintenance of these ADS systems is essential which includes scheduled, condition-based, risk-based, and predictive maintenance. A lot of techniques and methods have been developed and are being used in the maintenance of conventional vehicles as well as other industries, but ADS is new technology and several of these maintenance types are still being developed as well as adapted for ADS. In this work, we are presenting a systematic literature review of the "State of the Art" knowledge for the maintenance of a fleet of ADS which includes fault diagnostics, prognostics, predictive maintenance, and preventive maintenance. We are providing statistical inference of different methodologies, comparison between methodologies, and providing our inference of different techniques that are used in other industries for maintenance that can be utilized for ADS. This paper presents a summary, main result, challenges, and opportunities of these approaches and supports new work for the maintenance of ADS.

2. Introduction

Proper maintenance is a crucial aspect of ensuring the safety and reliability of any vehicle, especially Autonomous Driving Systems (ADS) vehicles. The objective of this study is to conduct a state-of-the-art review of various preventive maintenance techniques that can be employed to enhance the safety of ADS vehicles [1]. Preventative maintenance involves proactively replacing parts that are likely to fail in the near future, based on their expected lifespan and performance and monitored data [1]. This type of maintenance can be based on predetermined schedules or triggered by data from predictive maintenance systems. Definitions and descriptions of the ever-evolving maintenance methodologies which draw from the fields of reliability engineering, prognostics engineering, and risk management as applied in a variety of at-risk industries will be presented and proposed for use by ADS vehicle fleets.

Maintenance can be grouped into several basic concepts and definitions that often overlap, but in general, we can look at it from one of two perspectives proactive v. reactive. Which to apply can involve extensive analysis and introduces two other considerations which are reliability and risk-based. Consider that ADS vehicles are equipped with complex systems and sensors that enable them to navigate and operate without human intervention. These systems include sensors for perception, localization, and mapping, as well as control systems for steering, braking, and acceleration. The reliability of these systems is essential for the safe operation of ADS vehicles and applying the best practice maintenance approach which limits liability and manages the overall program cost is often the ultimate goal.

Preventive maintenance involves identifying and addressing potential issues before they can cause problems, thereby reducing the likelihood of unexpected breakdowns or accidents. There are several preventive maintenance techniques that can be employed for ADS vehicle safety, including prescriptive maintenance, predictive maintenance, and preventative maintenance [36,37].

Regular inspections involve the systematic examination of the vehicle's systems and components to identify any issues that may need to be addressed. These inspections can be performed by trained technicians or automated systems, and they typically involve visual inspections, tests, and measurements of various systems and components.

Predictive maintenance uses data and analytics to anticipate when maintenance may be needed, based on the condition and performance of the vehicle's systems and components [1]. Predictive maintenance relies on sensors and other monitoring devices that collect data on the vehicle's performance, which can then be analyzed to identify potential issues and determine when maintenance is required [1,36].

One of the main benefits of preventive maintenance is that it can help reduce the likelihood of unexpected breakdowns or accidents, which can have serious consequences for ADS vehicles. By identifying and addressing potential issues before they can cause problems, preventive maintenance can help ensure the reliability and safety of ADS vehicles.

However, there are also limitations to preventive maintenance techniques, including the cost and complexity of implementing these techniques, as well as the potential for human error or oversight. Additionally, there may be tradeoffs between the benefits of preventive maintenance and the costs and inconveniences it can impose on the user.

Overall, this study aims to provide a comprehensive overview of the state of the art in preventive maintenance techniques for ADS vehicle safety, highlighting the best practices and strategies that can be employed to ensure the reliability and safety of these vehicles. By examining the various preventive maintenance techniques that are currently available or under development, this study will contribute to the ongoing efforts to enhance the safety and reliability of ADS vehicles.

The rest of the paper is structured as follows: Section 3 describes the development of text analytic tools. This tool is used to segregate the papers into different categories during this study. The background of preventive maintenance and its types has been discussed in Section 4. Section 5 explained the preventive maintenance techniques in different industries. Preventive maintenance in ADS vehicles is explained in Section 6. Identification and evaluation of ADS vehicle failure and safety risks are outlined in Sections 7 and 8. ADS vehicle failure and safety risks are categorized in Section 9 based on components, subsystems, and control interfaces. Today's challenges in preventive maintenance are described in Section 10. Future recommendations for preventive maintenance in ADS vehicle safety are explained in section 11. Concluding remarks are presented in section 12.

3. Development of Text Analytic Tool

Surveying relevant publications, public research libraries, and industry libraries addressing the "state of the art" techniques in preventive maintenance, including potential failures and associated safety risks related to ADS results in more than fifty thousand articles. Filtering such a large volume of literature manually will consume an enormous amount of time, therefore, it is required that a text analytics approach to filter out the relevant literature is used. It improved the quality of the given topic from the database.

With the advancement in data science, there are plenty of tools available that have been developed for text analytics by different companies. These text analytics tool combines a set of machine learning, statistical and linguistic techniques to process large volumes of unstructured text or text that does not have a predefined format, to derive insights and patterns. A few such tools are mentioned in table 1.

TABLE 1 Text analytics tool in the Market

Tool Name	Benefits
MATLAB Text Analytics	Provides algorithms and visualizations for preprocessing, analyzing, and modeling text data
MonkeyLearn	Create a custom text analysis model
Aylien	Powerful API for text analysis
IBM Watson	Advanced text analytics
Thematic	Analyze customer feedback at the scale
Google Cloud NLP	Train your own Machine Learning model
Amazon Comprehend	Pre-trained NLP models
MeaningCloud	Extract insights from unstructured text data
Lexalytics	Text analytics libraries

All the tools mentioned in table 1 utilize some type of machine learning for text analysis and could turn complicated for analyzing text from research papers, articles, and automotive standards. Also, developing text analytics using machine learning could turn out to be a complex and time-consuming task on its own and would require a considerable amount of time which could impact the timeline of the project. Therefore, to analyze text from the research paper and to shortlist relevant papers from the database, a simpler approach for analyzing the text from the research paper and shortlisting the articles into different categories has been developed in this study.

3.1. Text Analytics Tool Development

This study requires authors to survey relevant publications, public research libraries, and industry libraries addressing the "state of the art" techniques in preventive maintenance, and a simple search on google scholar results in more than 50,000 articles. First, all the relevant literature on preventive, predictive, and reactive maintenance techniques in automotive and other sectors from SAE, IEEE, and Elsevier has been downloaded. Similarly, a database has been created and a text analytics tool has been used to read the papers and arrange the papers into different categories.

The tool read each pdf in the directory and extracts all the text from the pdf. Then, we are filtering all the unnecessary words (e.g., the, and, or, then, their, there, etc.) and symbols (e.g., '*', '/', '$', '&', '-' etc.) from the text and then converting all text into the smaller case to make it easy to compare the words with keywords. Then all the words are saved into an array to compare it with keywords specified in table 2 and categorize the research papers into different categories when the number of matches with the word exceeds a certain threshold specified in the program.

TABLE 2 Keywords to categorize local database.

Keyword Class	Keywords
Maintenance	Preventive Maintenance
	Predictive Maintenance
	Condition based Maintenance
	Reactive Maintenance
	Time triggered maintenance
	Maintenance
	Prescriptive Maintenance
	Time based maintenance
Maintenance of Electric/ Electronic System	Electrical System Maintenance
	Electrical System Diagnosis
	Electronic System Diagnostic
	Electronic Fault
	Electrical Diagnostic
	Electronic Maintenance
Vehicle fault	Prognostic
	Diagnostic
	fault
	Fault tolerant
	Fault Diagnostic
	Fault Management
	Fault Prognostic
	Failure Mode
	Failure
	Wear
	Tear
Risk Analysis	Risk Management
	Maintenance optimization
	Potential loss of life (PLL)
	Fatal Accident Rate (FAR)
	Event tree Analysis
	Fault tree analysis
	Failure mode and effect and criticality analysis (FMECA)
	Hazard and operability study (HAZOP)
	FMEA
	Reliability Centered Maintenance (RCM)
	Safety
	FTA
Maintenance for Automotive Industry	Vehicle Health Management
	Vehicle Health
	Vehicle Diagnostic
	Vehicle Prognostics
	Vehicle Fault
	Autonomous System maintenance
	ADS Maintenance
	ADS
	ADAS
	Vehicle Maintenance
	Ground Vehicle Maintenance

(Continued)

TABLE 2 (Continued) Keywords to categorize local database.

Maintenance for Aerospace Industry	IVHM
	Airplane Maintenance
	Airplane Health Management
	Aeroplan Maintenance
	Aeroplan Health Management
	Airplane Fault
	Airplane Prognostic
	Airplane Diagnostic

4. Background-Preventive Maintenance

Preventive maintenance is a type of maintenance that is performed on equipment or machines before they break down or malfunction. The goal of preventive maintenance is to reduce the likelihood of equipment failure and extend the lifespan of the equipment. Preventive maintenance is typically scheduled on a regular basis, such as daily, weekly, monthly, or annually.

Preventive maintenance can take many forms, including inspections, cleaning, lubrication, adjustments, and repairs. The specific preventive maintenance tasks that are performed depend on the type of equipment and the nature of its usage. For example, a manufacturing plant may perform preventive maintenance on its production line by regularly inspecting and cleaning the equipment, lubricating moving parts, and adjusting any components that are out of specification. A hospital may perform preventive maintenance on its medical equipment by calibrating and testing the equipment on a regular basis to ensure that it is operating correctly [18, 51].

Preventive maintenance can be performed by in-house staff or by specialized contractors. In some cases, the equipment manufacturer may provide guidelines for preventive maintenance tasks, as well as recommended frequency and procedures [1, 18]. There are also several software tools and systems that can be used to manage and schedule preventive maintenance tasks, as well as track the history and status of the equipment.

Preventive maintenance has several benefits, including increased equipment reliability, reduced downtime, improved safety, and lower maintenance costs. By catching and addressing problems before they cause equipment failure, preventive maintenance can help organizations avoid costly repairs and lost productivity. Preventive maintenance can also help organizations meet regulatory requirements and improve customer satisfaction. For example, a company that provides critical services, such as electricity or water, may rely on preventive maintenance to ensure that its equipment is reliable and available when needed, to avoid service interruptions and maintain customer satisfaction.

4.1. Types of Maintenance

The automotive industry is witnessing a shift towards the adoption of automated driving systems, as the progress in research has made advanced driver assistance systems (ADAS) features more secure and reliable. The integration of safety features with ADAS is driving this change. For instance, many vehicles now come equipped with pedestrian detection integrated with automatic emergency braking systems. To ensure that ADAS features are always functioning properly, reliable, and safe, robust maintenance of these systems is of utmost importance.

Maintenance techniques play a crucial role in maintaining the proper functioning of ADAS and ADS features, as it acts as a primary defense system to prevent and mitigate safety risks. For example, Lidars, which are commonly used in autonomous and automated vehicles, are responsible for perceiving the vehicle's environment and creating a 3-D image of the surroundings, allowing the vehicle to detect objects. If any system or component associated with the Lidar system experiences an error that is not addressed during maintenance, it could result in a collision, which is a critical safety hazard. There are several other ADS features that require proper maintenance to always function correctly.

At a high level, there are two main categories of maintenance strategies: Preventive Maintenance and Corrective Maintenance. These strategies are further divided into subcategories, as shown in Figure 1.

4.1.1. Corrective Maintenance

Corrective maintenance is a type of maintenance that focuses on fixing a failure or malfunction that has already occurred. This type of maintenance is performed to restore a piece of equipment or a system to its normal operating state, allowing it to perform its intended function as intended. Corrective maintenance can take several forms, including planned maintenance, where the repair is scheduled in advance, or unplanned maintenance, where the repair is necessary for response to a sudden failure [18].

Corrective maintenance is typically performed when a fault is detected during an inspection, when a piece of equipment breaks down, or when a system is behaving abnormally. This type of maintenance is appropriate when the equipment or system can be easily repaired, or when the cost of repairing it is relatively low. In order to ensure that corrective maintenance is effective, it is important to have a well-structured approach to diagnosis, isolation, and repair of the failure.

Overall, corrective maintenance plays a crucial role in maintaining the health of equipment and systems, ensuring that they continue to perform as intended. As such, it is an important aspect of any comprehensive maintenance program [18,19,36].

4.1.2. Preventive Maintenance

This is a maintenance technique that is performed routinely and regularly on a system or any physical asset to minimize unplanned machine downtime and equipment failure that can be very costly for the asset owner [2]. In the case of an autonomous vehicle or a fleet owner, this maintenance technique can help to detect failure and error in the vehicle before it arises. Detected errors can be fixed on time and therefore, makes the vehicle safer to drive on road and reduces the cost of maintenance for the vehicle owner and fleet owner.

Preventive maintenance can be classified into three different strategies depending on what maintenance activity needs to be carried out for the system.

4.1.2.1. Time-Based Maintenance (TBM).

Time-based maintenance (TBM), also referred to as periodic maintenance [33,34] is a traditional technique for the maintenance decision-making process. Maintenance decisions in TBM are carried out based on failure time analysis (FTA), that is, to determine the expected lifetime, T, of any equipment failure time data, and usage-based data is analyzed [35]. For the TBM process to work it is assumed that the characteristic of failure for equipment is predictable.

The bathtub curve is used to analyze the failure trend or hazard trend for the TBM process as shown in figure 2 [36]. The hazard trend is divided into 3 phases: burn-in, useful life, and wear-out which are used to measure the life of equipment [37]. The trend suggests that in the burn-in phase the equipment experience a decreasing failure rate, following that it experiences a constant failure rate that is the useful life of the equipment and at the end of the life cycle the equipment starts to see an increasing failure rate that is the wear-out phase.

The TBM process can be presented in two simple steps as shown in figure 3 First is failure data analysis and modeling followed by the maintenance decision-making process.

FIGURE 1 Maintenance Types

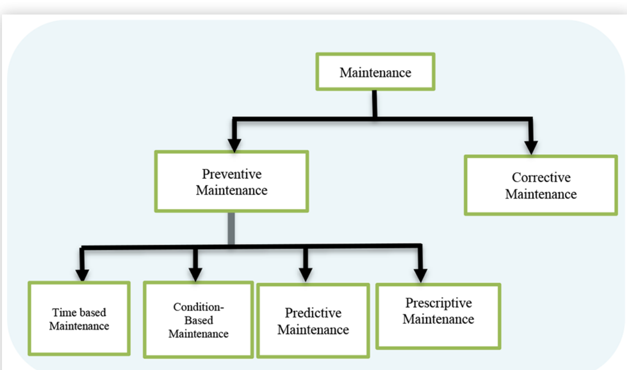


FIGURE 2 Bathtub Curve [37]

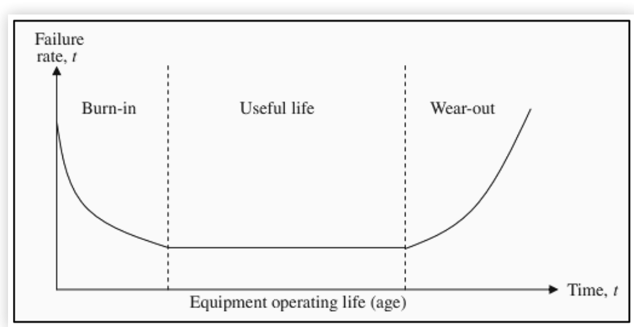
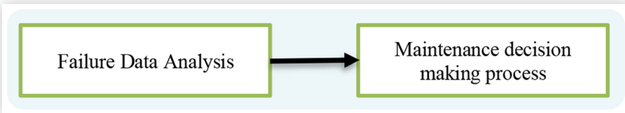


FIGURE 3 TBM Process [36]



During the failure data analysis, characteristics of failure data of equipment based on failure time data gathered are statistically investigated. Figure 4 shows the failure data modeling process for the TBM process.

Failure data modeling uses equipment's failure characteristics such as Mean time to failure (MTTF) and failure trend based on the bathtub curve. Statistical modeling of the gathered data can be carried out using different statistical tools such as the normal distribution model, lognormal distribution model, Weibull distribution model, etc. out of these statistical tools, the Weibull distribution model is widely being used to model failure for many applications due to its ability to model various aging categories of life distribution such as decreasing, stable and increasing failure rates [37,40,41].

When the failure data modeling process suggests that the equipment has an increasing failure rate, then the PM decision-making process becomes effective which aims to provide optimal system availability and safe performance at optimum maintenance cost [42]. Figure 5 shows the maintenance decision-making process.

FIGURE 4 Failure data modeling process [36]

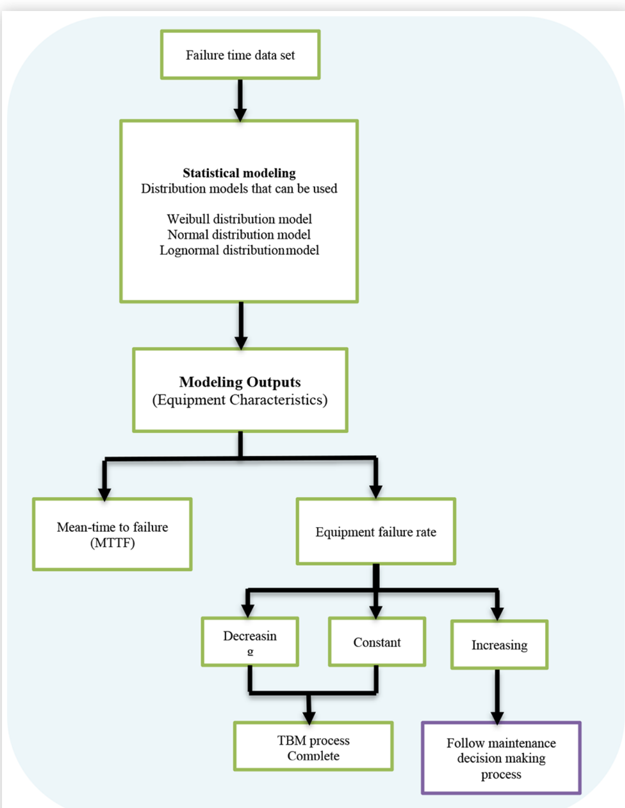
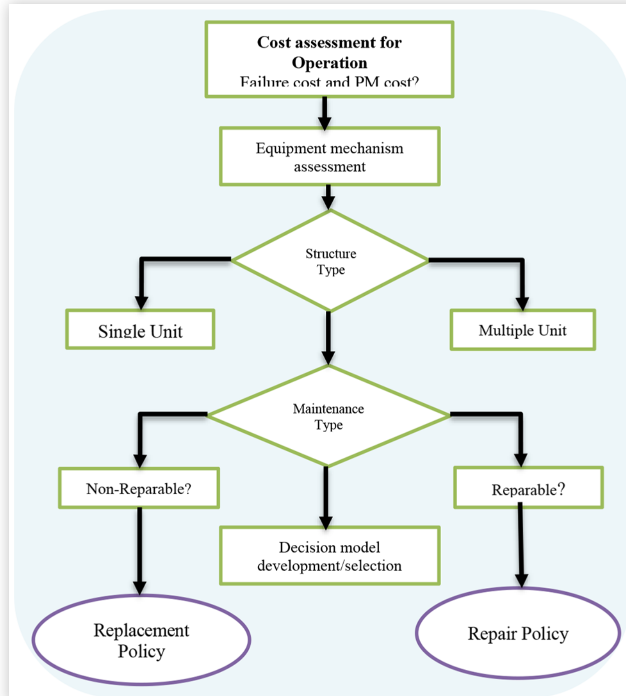


FIGURE 3 TBM decision making process



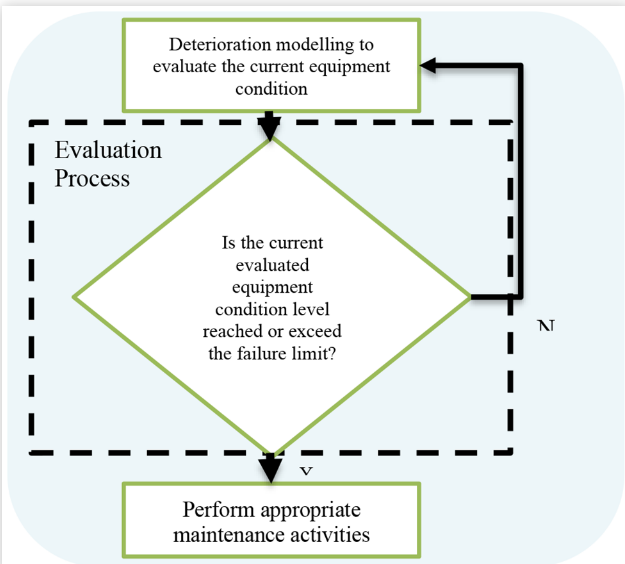
The first step of the maintenance decision-making process is cost assessment which is discussed in section 4 in detail. Then the system's structure type is identified which is then classified into reparable and non-repairable components. Finally, according to the repair and replacement policy, maintenance is performed for the system.

4.1.2.2. Condition-Based Maintenance (CBM). This maintenance strategy involves monitoring the normal behavior of the system and suggesting maintenance in case of deviation from normal behavior or degradation in the asset [3]. The abnormality in the system is detected using condition monitoring technology such as cloud computing and IoT [1]. Using new technologies such as Artificial Intelligence and Machine Learning condition monitoring can be improved further to perform maintenance more optimally [5]. Since condition-based maintenance focuses majorly on the diagnostic of the system it is also referred to as Diagnosis-based maintenance [1].

Under CBM, maintenance decision-making can be classified into two types: Diagnostic and Prognostic [36]. Diagnostic of equipment helps to find the source of fault whereas prognostic of the system helps to estimate or predict the occurrence of failure [43, 44]. Prognostics aims to provide the engineers with early signs when monitoring the condition of the equipment that is showing abnormality. Abnormal behavior of the system does not mean that the equipment has failed and cannot be used further. This is where prognostic is done to estimate the time when a failure might occur. This can help to maximize the equipment use and schedule maintenance right before failure and thus save time and unplanned maintenance costs.

Equipment deterioration modeling can be used to make maintenance decisions, particularly towards the prognostic process. There are two methods to make decisions: Current condition evaluation-based (CCEB) and Future condition prediction-based (FCPB) [36]. In the CCEB method, the current equipment condition is first evaluated based on which appropriate maintenance steps are taken. Monitoring data is collected to evaluate the condition of equipment at present which is then compared to the predetermined failure limit. If the limit is exceeded, then the maintenance is performed under the CCEB process. Generally, this process is performed by inspection monitoring of the current condition of the system. Figure 6 illustrates the decision-making process under the CCEB process.

FIGURE 4 CCEB Decision Process [36]



The second method is FCPB which is used for making CBM decisions based on the analysis of the future trend of assets condition. Depending on the predictive modeling process if the system reaches or exceeds the predetermined failure threshold then maintenance is planned accordingly, otherwise, the system is in a good state and can further be operated. The monitoring of asset condition is done by using sensors and condition monitoring technology to continuously monitor the state of the asset condition. Figure 7 shows the FCPB process.

4.1.2.3. Predictive Maintenance. It is also referred to as prognostic maintenance as this maintenance type involves gathering data from different parts that compose and surround the asset [6]. The information is then used to predict the remaining life of the asset. There are four phases in this maintenance strategy [7]:

1. Monitoring and collecting data from different sensors of the asset.
2. Processing the gathered data
3. Diagnosing faults in the system
4. Making the decision for maintenance strategy

FIGURE 5 FCPB decision-making process [36]

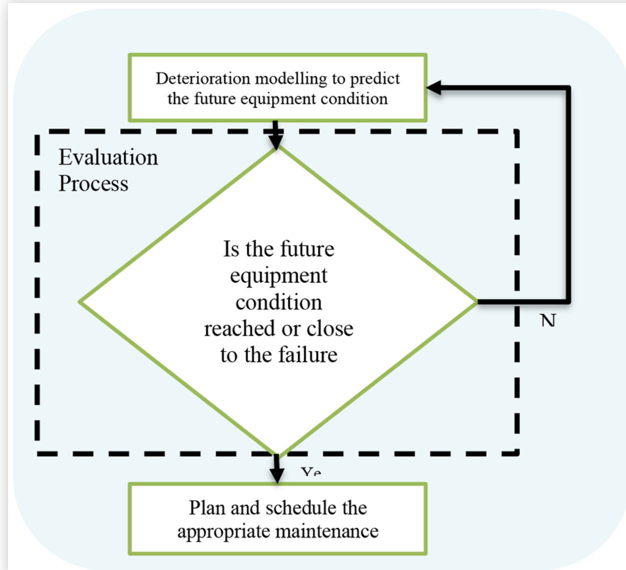


FIGURE 6 Predictive maintenance decision-making process [1]

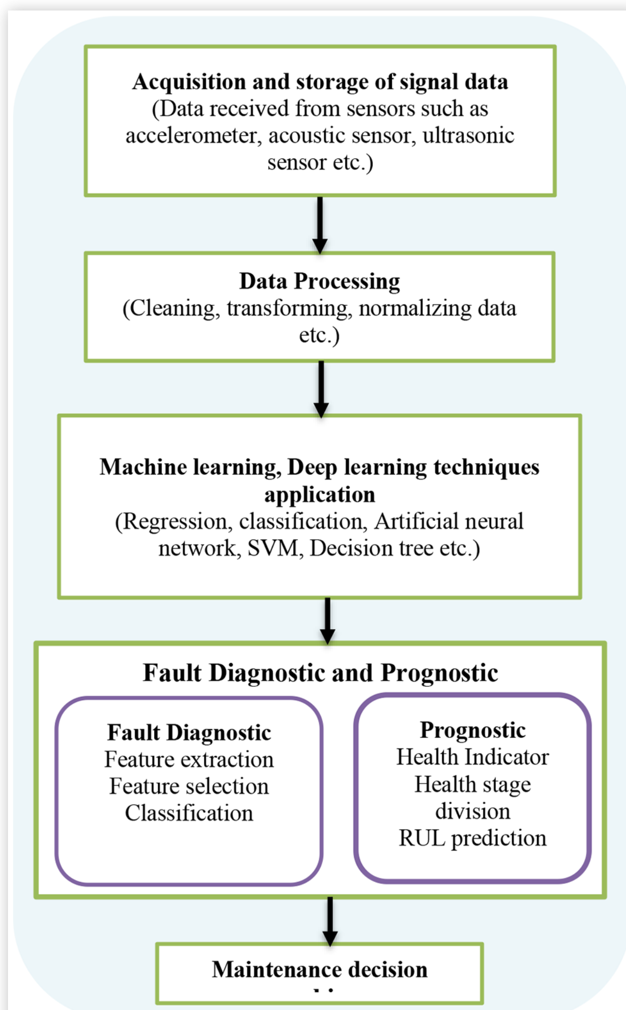
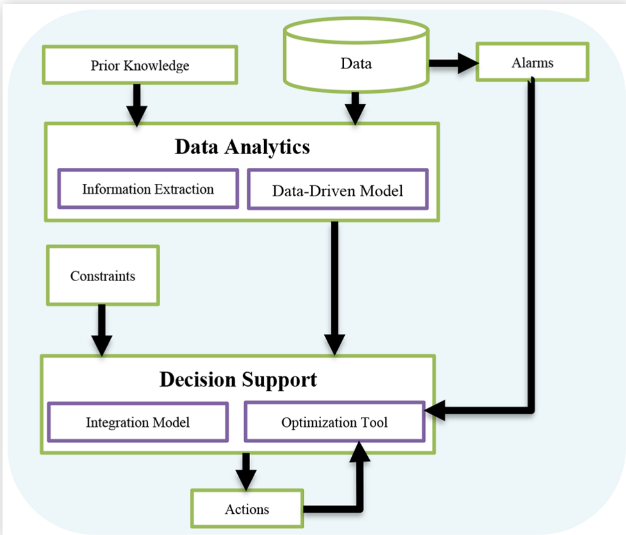


FIGURE 7 Prescriptive Maintenance Framework [50]



Furthermore, to process the data gathered from the sensors surrounding the system, Artificial Intelligence (AI) and Machine Learning (ML) techniques are used [8,9]. Predictive maintenance can be performed in several ways [10],

- Physical model approach

This uses underlying physics and mathematics to evaluate the degradation of assets. The accuracy of this modeling technique depends on the accuracy of the model as well as the statistical method used to process and validate the data [45].

- Knowledge-based approach

This modeling approach depends on some prior knowledge and expertise which is used to reduce the complexity of the system. The knowledge of the system can be reproduced to apply automatically by using some inference mechanism to emulate thought to provide practical solutions for instance fuzzy logic and expert systems [46].

- Data-driven approach

This method uses data collected from the system to evaluate health using computation and statistics. This model is further classified into the following categories: Statistical models, stochastic models, and machine learning models [47,48]

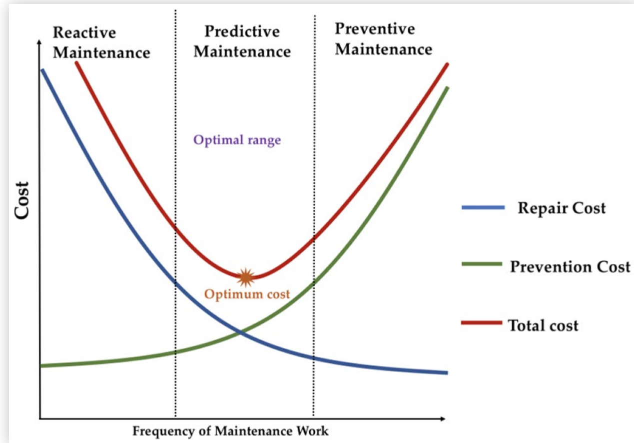
- Digital twin approach

This method uses the modeling of physical systems to create a virtual replica which is linked together to monitor the health of the system. Data from both physical and real-world systems is evaluated along with virtual twins to analyze and evaluate the system [49].

Figure 8 illustrates the predictive maintenance decision-making process.

4.1.2.4. Prescriptive maintenance. Prescriptive maintenance uses advanced ML techniques, AI techniques, and analytics similar to predictive maintenance but it optimizes maintenance based on prediction [1]. It prescribes an action plan for maintenance in addition to using historical and real-time data to predict the status of the system [11]. The framework presented in figure 9 shows the working of a predictive maintenance strategy.

FIGURE 8 Cost graph [14]



One key aspect of prescriptive maintenance in the automotive industry is the use of data and analytics to identify potential issues and determine the appropriate maintenance actions. For example, sensors and other diagnostic tools can be used to monitor the performance of a vehicle and send data back to a central system, which can then analyze the data to identify patterns and predict when maintenance is needed.

In addition to using data and analytics, prescriptive maintenance in the automotive industry often involves following a predetermined maintenance schedule based on factors such as the age of the vehicle, the number of miles driven, and the type of driving conditions it has been exposed to. This can involve tasks such as replacing oil and filters, checking and replacing brakes and tires, and performing general inspections to identify any potential issues. By following a prescriptive maintenance schedule, automotive companies can help ensure that their vehicles are operating at optimal levels and minimize the risk of unexpected failures or downtime.

4.2. Cost Analysis for Maintenance Strategies

For every maintenance strategy there is a cost associated with it and choosing the right maintenance model for a component is necessary to be cost-efficient. Not all maintenance strategies cost the same, for example, an asset or component which is cheap to replace must follow a corrective or reactive maintenance strategy whereas a complex system can use predictive, preventive, and reactive maintenance strategies based on the requirement and budget to increase the productivity at an optimum cost. All costs need to be accounted for while deciding which maintenance strategy is best. For the corrective maintenance strategy, maintenance is performed when the equipment fails or stops working therefore the cost involved accounts for only corrective maintenance cost (Cc), whereas for preventive maintenance since it requires sequential maintenance actions, the cost involved accounts for cost related to inspection (Ci), the cost for preventive maintenance (Cp), cost related to downtime (Cd) as well as cost for corrective maintenance (Cc) as some equipment could have stopped working [14].

In [13], Grall et al., has presented a cost model in their paper continuous time predictive maintenance that aims to find an optimal prevention threshold for the maintenance of a system. The cumulative cost of maintenance is represented in Eq.1

$$C(t)=C_i \cdot N_i(t)+C_p \cdot N_p(t)+C_C \cdot N_c(t)+C_r \cdot d(t) \qquad \text{Eq. 1}$$

Where $N_i(t)$ represents the number of inspections, $N_p(t)$ represents the number of preventive repairs, $N_c(t)$ represents the number of corrective repairs and d(t) represents the duration for which equipment is not operating all of them in the time interval [0, t].

The objective function to be minimized given in Eq. 2 represents the cumulative expected cost for long-term maintenance of the asset.

$$EC_\infty = \lim_{t \to \infty} \frac{E[C(t)]}{t} \qquad \text{Eq. 2}$$

Where, $E[C(t)]$ is the expected value of long-term maintenance.

In [16], Mobley has pointed out that the corrective maintenance type has the lowest prevention cost, whereas the repair cost associated with preventive maintenance is the lowest because of well-scheduled and planned downtime for the system. As pointed out by Ran et al., in [15], failure predictions are used to take maintenance actions for predictive and prescriptive maintenance, therefore, the cost model for prediction is associated with the remaining useful life of the asset or equipment. Figure 10 suggests that predictive maintenance presents the optimal compromise between maintenance cost and prevention cost.

5. Preventive Maintenance Techniques in Different Industries

Preventive maintenance techniques are used in many industries to ensure the smooth and safe operation of equipment. These techniques can include regular inspections, cleaning, and lubrication, replacing worn parts, testing and calibration, and predictive maintenance. By identifying and correcting potential problems before they cause equipment failures or other issues, preventive maintenance can help to reduce downtime, increase productivity, and extend the lifespan of the equipment. The specific techniques used will depend on the types of equipment being used, the operating conditions, and the maintenance goals of the organization. For example, a preventive maintenance program for a wind turbine might include weekly inspections to check for cracks or other damage to the blades, as well as regular measurements of vibration and lubricant levels, while a program for a food processing facility might include daily cleaning of production equipment and weekly lubrication of bearings and other moving parts.

Regular inspections: Inspections can be performed on a regular basis, such as daily, weekly, or monthly, depending on the equipment and the operating conditions. During an inspection, an operator or maintenance technician may look for visual signs of wear or damage, such as cracks, corrosion, or leaks. They may also use specialized tools to measure things like temperature, vibration, or pressure, to ensure that the equipment is operating within normal parameters. A wind turbine's preventive maintenance schedule could include weekly inspections of its blades for cracks or other damage and regular monitoring of vibration and lubricant levels.

Cleaning and lubrication: Proper cleaning and lubrication of equipment can help to prevent wear and tear and can extend the lifespan of the equipment. Cleaning may involve removing dust, dirt, or other contaminants from the equipment, while lubrication involves applying lubricants to moving parts to reduce friction and wear. For example, a preventive maintenance schedule for a food processing facility might include daily cleaning of production equipment, as well as weekly lubrication of bearings and other moving parts.

Replacing worn parts: As the equipment is used over time, certain parts may become worn or damaged and will need to be replaced to keep the equipment functioning properly. These parts may include things like bearings, seals, belts, and other worn items. For example, a preventive maintenance schedule for an aircraft might include replacing the tires, brakes, and other worn items on a regular basis to ensure that the aircraft is safe to fly.

Testing and calibration: Equipment may need to be tested and calibrated to ensure that it is operating within its specified tolerances. Testing may involve running the equipment through a series of tests to ensure that it is functioning properly, while calibration involves adjusting the equipment to ensure that it is measuring or performing within specified limits. For example, a preventive maintenance schedule for a power plant might include testing and calibrating the control systems and sensors on a regular basis to ensure that the plant is operating safely and efficiently.

Predictive maintenance: Predictive maintenance involves using sensors and other monitoring devices to predict when equipment is likely to fail so that preventative action can be taken. By collecting data on things like vibration, temperature, and other parameters, it is possible to predict when equipment is likely to fail and take action to prevent it. For example, a predictive maintenance program for a factory might involve using vibration sensors on its production machinery to monitor for abnormal vibrations that could indicate an impending failure, and scheduling maintenance to fix the problem before the equipment fails.

6. Preventive Maintenance in ADS Vehicles Safety

As autonomous vehicles (AVs) continue to gain popularity, it's crucial to consider the safety risks involved. These advanced vehicles rely on complex software systems and a variety of sensors to navigate and make decisions on the road, but there are several potential hazards that must be addressed.

One significant risk is the possibility of a cyber-attack. AVs are vulnerable to hackers who could potentially take control of the vehicle or manipulate its sensor data, leading to dangerous or malicious behavior. To protect against this threat, AV manufacturers must implement strong cybersecurity measures, such as secure communication protocols and frequent software updates.

Sensor malfunctions can also pose a risk to AVs. These vehicles rely on sensors like cameras, radar, and lidar to gather information about their environment, but if any of these sensors fail or produce incorrect data, the AV could make incorrect decisions and potentially cause an accident. To reduce this risk, AV manufacturers should use redundant sensors and have robust error-checking systems in place.

Incorrect software behavior is another potential hazard for AVs. The software that controls these vehicles is complex and can be difficult to test thoroughly, so there is a risk that it may behave unexpectedly in certain situations. To minimize this risk, AV manufacturers must implement thorough testing and validation processes to ensure the safety and reliability of the software.

While these vehicles are designed to operate without human intervention, there are still situations where a human operator must take control. If the operator is not paying attention or is not properly trained, they may not be able to react in time to prevent an accident. To reduce the risk of human error, AV manufacturers should design vehicles with appropriate safeguards and ensure that operators are well-trained and prepared for emergency situations.

Finally, the limitations of infrastructure can also pose a risk to AVs. These vehicles rely on GPS, mapping systems, and other infrastructure to navigate and make decisions, but if these systems are inaccurate or unavailable in certain areas, the AV could become lost or make incorrect decisions. To address this risk, AV manufacturers should ensure that their vehicles can operate safely in a variety of environments and work with relevant authorities to improve infrastructure as needed.

7. Identification and Evaluation of ADS Failures and Safety Risks

Autonomous vehicles (AVs) have garnered a lot of attention in recent years due to their potential to improve road traffic safety by replacing human drivers and using better recognition, decision-making, and driving skills. However, AVs also have inherent safety and security challenges that must be addressed before they can be widely adopted.

Cui et al., in [57] present an in-depth analysis of research on AV safety failures and security attacks, as well as the available safety and security countermeasures.

Safety failures in AVs can be classified into failures related to AV components (VF) and failures related to infrastructure (IF). VFs include hardware system failures, software failures, vehicle mechanical failures, communication system failures, and interaction platform failures. IFs include failures of other road users, weather, construction zones, road conditions, and traffic signals and signs. To address these failures, safety countermeasures (CMs) can be applied. CMs can be classified into active CMs and passive CMs. Active CMs provide active safety features that aim to prevent the vehicle from crashing, while passive CMs serve to protect vehicle users during a crash. Active CMs include several driving assistance methods and AV-specific countermeasures. Passive CMs consist of crash-worthy systems or devices and the conspicuity of the vehicle.

In addition to safety failures, AVs are also vulnerable to security attacks. These attacks can be classified into three categories: attacks on the communication system, attacks on the on-board computer and in-vehicle network, and attacks on the vehicle itself. To mitigate these attacks, several security countermeasures (SCMs) have been proposed. These include secure communication protocols, intrusion detection, and prevention systems, and secure software development practices.

There are also open issues and challenges in the field of AV safety and security that need to be addressed. These include the need for robust and reliable sensors and communication systems, the need for effective sensor data fusion and decision-making algorithms, and the need for effective testing and validation methods for AVs. In addition, there is a need for standardization and regulation in the field of AV safety and security.

Overall, ensuring the safety and security of AVs is a complex and multifaceted challenge that requires the integration of various technologies and practices. Further research is needed to address the open issues and challenges in this field to enable the widespread deployment of AVs.

There are several approaches that have been used in the literature to quantify the safety of AVs. These approaches include target crash population studies, road test data analysis, driving simulators, system failure risk assessment, and AV safety effectiveness.

One approach to evaluating AV safety is target crash population studies, which estimate the number of preventable crashes in each population. This approach involves analyzing crash datasets to extract crash characteristics and quantifying the safety benefits of AVs in terms of the number of preventable crashes or the reduced cost of crashes. AV safety is often attributed to advanced driver assistance systems (ADASs) and autonomous driving systems (ADSs).

Another approach to evaluating AV safety is road test data analysis, which involves analyzing data from AV road tests to investigate the characteristics of AV crashes and compare them to conventional vehicle crashes. This approach is often used to compare the incident rate of AVs to that of conventional vehicles, using metrics such as the number of crashes per vehicle miles traveled (VMT) or the number of disengagements per VMT.

8. ADS Failures and Associated Risks

Autonomous driving systems have the potential to revolutionize transportation and improve safety on the roads. However, as with any complex system, there is a risk of failure that can occur during the operation of autonomous vehicles. This section of the research paper will focus on the various types of failures that can occur in autonomous driving systems and the associated risks that these failures pose to the vehicle's passengers, other road users, and the overall operation of the vehicle. The purpose of this section is to understand the types of failures that can occur in autonomous driving systems and the associated risks, as well as to identify potential solutions to mitigate these risks and improve the overall safety and reliability of autonomous vehicles.

Health Monitoring of ADS and Automated Vehicle

Jeong et al. [58] developed a self-diagnosis system for autonomous vehicles that utilize an Internet of Things (IoT) infrastructure and deep learning models. The system includes a detailed communication network to read data from the vehicle and transfer it to a cloud-based backend. A multilayer perceptron (MLP), which is a type of artificial neural network (ANN), is used in a supervised learning scenario with dynamically adapted nodes and layers. The condition of vehicle components is then classified as "normality," "inspection," or "danger," and the driver is warned in case of risk.

Van Wyk et al. [59] combined a convolutional neural network (CNN) with well-established anomaly detection methods to detect and identify anomalous behavior in connected and automated vehicles. Using real data, they showed that a combined approach of feature extraction and classification outperforms the use of either method alone. The proposed system can be applied to any motor data.

Failure in Generators, Electric Motors, and Starter

An adaptive neuro-fuzzy inference system (ANFIS), which combines an artificial neural network with fuzzy logic, was used by Wu and Kuo to classify faults in automotive generators. To gather the data for their study, they set up an experimental system featuring an engine and a generator as the primary components. Synthetic failures were then induced in the generator, and the output voltage signal was analyzed using a discrete wavelet transformation (DWT). The DWT coefficients were extracted as features, and the ANFIS was trained to recognize various fault classes at different engine speeds. This approach resulted in a classification accuracy of 98.8% [60].

Seera et al. [61] developed a hybrid condition monitoring model for electric vehicles, which use induction motors extensively. The model consists of a fuzzy min-max artificial neural network (ANN) and a random forest. The researchers tested the effectiveness of their model in monitoring multiple incipient faults in induction motors using only stator current data in both noise-free and noisy environments. They also considered the interpretability of the model and extracted a decision tree to explain the model's predictions to domain experts. An experiment was conducted to monitor and predict three different induction motor conditions: normal operation, stator winding faults, and eccentricity issues.

Simsir et al. [62] developed a real-time monitoring and diagnosis system for faults in a hub motor. They gathered data on key system parameters and trained an artificial neural network (ANN) to detect a range of faults, including an open circuit in a coil, a short circuit in a coil, a problem with a hall effect sensor, a short circuit between coils, and damaged bearing faults. To enable mobile, real-time monitoring, and fault diagnosis, the model was integrated into an Arduino Due microcontroller card.

Vehicle Fault Detection

Fault detection in autonomous and automated vehicles has been a topic of interest in several research studies. One approach, proposed by Theissler, [63] involves using an ensemble of one-class and two-class classifiers to detect faults in data collected from road trials using the in-vehicle network. The one-class classifiers are trained on recordings of normal vehicle operation, while the two-class classifiers are trained on both normal and faulty data. This semi-supervised approach allows for the detection of both known and unknown fault types, while a standard classification approach would only be able to detect known faults. Theissler used and enhanced the support vector data description (SVDD) as a base classifier and evaluated the approach using data from multiple vehicles.

Tagawa et al. [65] proposed the use of structured denoising autoencoders, a variant of denoising autoencoders, for fault detection in driving scenarios. This method allows for the incorporation of partial knowledge about the relationships between variables and faults. The authors demonstrated that their approach outperformed other methods such as one-class support vector machines, vanilla denoising autoencoders, and the local outlier factor. However, their study did not use real faults, but rather recorded different driving scenarios and assumed one of them to represent the normal condition while others simulated faults such as going down a slope.

On the other hand, Shafi et al. [64] developed a system for fault detection in a fleet of vehicles. They collected data from the on-board diagnostic (OBD) interface of the vehicles and transferred it to a common backend, where a knowledge base for the entire fleet was created. Decision trees, support vector machines, k-nearest neighbors, and random forests were used for fault detection in different vehicle subsystems. The approach was evaluated using data from 70 vehicles, and the authors stated that faults identified in one vehicle would also be used to warn drivers of vehicles with similar conditions.

Failure in the Brake System

Jegadeeshwaran and Sugumaran [66] propose an approach for the detection of faults in the brake system. Vibration signals are acquired from a brake test rig with an additional accelerometer. From these signals, statistical features are extracted, and a subset is algorithmically selected. Classification is then conducted with a clonal selection classification algorithm.

In [67], the research group around Jegadeeshwaran preprocessed the vibration data from the brake test rig via wavelet analysis. Based on that they evaluated a set of classification approaches, namely best first trees, Hoeffding trees, SVMs, and an ANN, to detect and classify ten different hydraulic brake states, ranging from "Good" over "Drum Brake Pad Wear", "Air in Brake Fluid", up to failure states like "Brake Oil Spill" and "Reservoir Leak". The best classification results were achieved with the Hoeffding trees.

Failure in the Electric Power Steering

Ghimire et al. [68] developed a physics-based model of an electric power steering system. Through a series of fault injection experiments, they were able to derive fault-sensor measurement dependencies to isolate the faults. They used support vector regression (SVR) to estimate the severity of faults. In the later work of Ghimire et al. [69], the same main author enhanced the previous work. In the first step, a physical model was built, and simulations were conducted under different fault conditions. In addition to physical models, the authors evaluated data-driven approaches, namely k-NN, a probabilistic ANN, SVM, decision trees as well as rough set theory. According to the authors, the rough set theory method performed superior on sparse data compared to the other methods.

9. Categorization Based on ADS Component, Subsystem, and Control Interfaces

Durability-related safety risks are risks that are related to the ability of an autonomous vehicle (AV) or its components to withstand the stresses and strains of normal operation over an extended period. These risks can have serious consequences, including accidents or injuries, and it is important for AV developers to carefully consider and address them to ensure the long-term safety and reliability of AVs.

The following are some of the durability-related safety risks for AVs,

1. Sensor degradation: AVs rely on sensors to gather information about their surroundings, including cameras, lidar, radar, and ultrasonic sensors. These sensors can degrade over time due to a variety of factors, including exposure to the elements, physical wear, and tear, and electrical or electronic issues. If sensors degrade, it can lead to reduced accuracy and reliability, which could impact the performance and safety of the AV.
2. Actuator failure: Actuators are components that move or control other parts of the AV, such as steering, braking, and acceleration. If an actuator fails, it could result in the loss of control of the AV, potentially leading to accidents or injuries.
3. Software degradation: AVs rely on complex software systems to process sensor data and make decisions. Over time, the software may become outdated or may develop errors that could impact the performance and safety of the AV. This could be due to issues with the software itself, or due to changes in the operating environment that the software was not designed to handle.
4. Structural failure: AVs are subjected to a variety of loads and stresses during normal operation, including impacts from other vehicles or objects, and the weight of passengers and cargo. If structural components of the AV become damaged or weakened, it could lead to the failure of the AV. Structural failures could occur due to physical damage, corrosion, or other factors.
5. Wear and tear on components: AVs have many moving parts that are subjected to wear and tear during normal operation. This can lead to component failures and reduce the reliability of the AV. Wear and tear can be caused by a variety of factors, including friction, impact, and corrosion.
6. Accumulation of damage: AVs may be subjected to impacts or other forms of damage during normal operation, which can accumulate over time and lead to failures. This could include damage to sensors, actuators, or other components.
7. Corrosion: AVs may be exposed to corrosive elements such as salt, water, or chemicals, which can cause corrosion and weaken components. This can lead to component failures and reduced reliability of the AV.
8. Electrical or electronic issues: AVs rely on electrical and electronic systems to function, and these systems can experience issues over time that could impact the performance and safety of the AV. These issues could include electrical shorts, power surges, or other problems.
9. Human error: Human error in the maintenance or operation of an AV can lead to durability-related safety risks. For example, if an AV is not properly maintained, it could result in component failures or other issues. Similarly, if an AV is operated in a manner that is not in accordance with its intended use or capabilities, it could increase the risk of durability-related safety issues.
10. Poor quality components: Using low-quality components in the construction of an AV can increase the risk of component failures and other durability-related safety issues. Poor-quality components may be more prone to failures or may not be able to withstand the stresses and strains of normal operation.
11. Misuse of the AV: Using an AV in a manner that is not in accordance with its intended use or capabilities can increase the risk of durability-related safety issues. For example, using an AV to transport heavy

loads beyond its rated capacity could lead to structural failures or other issues.

12. Operating outside of design limits: Operating an AV outside of its design limits, such as by exceeding its maximum speed or carrying more weight than it is designed for, can increase the risk of durability-related safety issues.

Different frameworks have been developed by the industry to deal with durability-related safety risks for example., Waymo's Fatigue Risk Management Framework is a set of guidelines for preventing, monitoring, and mitigating fatigue-induced risks during the testing of autonomous driving systems. The framework is informed by practices from a variety of industries, including transportation, aviation, and nuclear and chemical sectors, and follows the principles of a Safety Management System, in which specific hazards are identified and risk is managed systematically. The framework consists of three main components: fatigue prevention, fatigue monitoring, and fatigue mitigation, which work together to form a cycle. The fatigue prevention component includes measures such as work-rest scheduling, training, and fatigue awareness, while the fatigue monitoring component involves the use of tools such as questionnaires, wearables, and other sensors. The fatigue mitigation component includes strategies such as emergency procedures, shift adjustments, and contingency plans. Overall, Waymo's Fatigue Risk Management Framework aims to ensure the safe testing and development of autonomous driving systems.

10. Challenges Today

Preventive maintenance for autonomous driving systems is crucial for ensuring the safe and reliable operation of these vehicles. However, as the technology behind autonomous vehicles is still relatively new and rapidly evolving, there are several challenges that engineers and technicians must face to effectively maintain these vehicles. There are several challenges to the preventive maintenance of autonomous driving systems,

Complexity: Autonomous driving systems are highly complex and consist of multiple subsystems and components, making it difficult to identify and diagnose potential issues.

Safety: Ensuring the safety of passengers and other road users is a top priority, which can make it difficult to perform maintenance without disrupting the system's functionality.

Cost: Autonomous driving systems are expensive to develop and maintain, and preventive maintenance can add significant costs to the overall operation of the system.

Data management: Autonomous driving systems generate large amounts of data, which must be effectively managed and analyzed to identify potential issues and plan maintenance.

Software updates: Autonomous driving systems rely on sophisticated software, which must be regularly updated to address security vulnerabilities and improve performance.

Regulation: Governments and industry organizations have not yet developed a clear regulatory framework for the maintenance of autonomous driving systems, which can make it difficult for manufacturers and operators to know how to maintain and service their systems.

Scalability: Autonomous driving systems need to be able to operate in a wide range of environments and conditions, making it difficult to develop a one-size-fits-all maintenance strategy.

Remote monitoring: Autonomous driving systems need to be monitored in real-time to identify potential issues before they become critical, but this can be difficult and costly to implement, especially in remote locations.

Cybersecurity: Autonomous driving systems are vulnerable to cyber-attacks, and preventive maintenance must include measures to protect the system from potential threats and breaches.

11. Future Recommendations

To effectively maintain autonomous driving systems, it is crucial to develop advanced diagnostic systems that can detect and diagnose potential issues with the vehicle's sensors, software, and other components in real-time. These systems should be based on the latest technologies such as artificial intelligence and machine learning, which would enable the ability to analyze large amounts of data quickly and accurately, and alert maintenance personnel to any potential problems. Furthermore, it is recommended to have a centralized monitoring system that can track the vehicle's performance and report any issues to the maintenance team.

Cybersecurity is another important aspect that should be considered when it comes to the preventive maintenance of autonomous driving systems. It is recommended to implement advanced security measures to protect the vehicle's systems from cyber-attacks, such as encryption of sensitive data, secure communication protocols, and regular security updates. Additionally, it is essential to conduct regular penetration testing to identify and address any vulnerabilities in the system. Furthermore, it is recommended to have a dedicated cyber security team that can monitor the systems and take proactive measures to prevent any cyber-attacks.

In addition to the aforementioned recommendations, it is important for maintenance personnel to stay up to date with the latest advancements in autonomous vehicle technology. This can be achieved by attending training and education programs, participating in industry conferences and workshops, and staying informed about the latest research in the field. Furthermore, it is recommended to have a dedicated team that can conduct research and development to develop new and advanced maintenance techniques.

A comprehensive and proactive maintenance strategy should be developed that considers the unique characteristics and requirements of autonomous vehicles. This strategy should include regular inspections and testing of the vehicle's sensors, software, and other components, as well as regular updates and upgrades to keep the vehicle's technology current. Furthermore, it is recommended to have a clear communication channel between the vehicle manufacturers and the maintenance providers to ensure that they are aware of the latest updates and can conduct the necessary maintenance accordingly.

It is also recommended that vehicle manufacturers and maintenance providers collaborate with government agencies and other organizations to establish industry standards and guidelines for autonomous vehicle maintenance. This will help to ensure that all autonomous vehicles are maintained to the same high standards and will help to promote the safe and reliable operation of these vehicles on the road.

Finally, it is important for vehicle manufacturers and maintenance providers to invest in new technologies, such as artificial intelligence, machine learning, and other advanced analytics tools, that can help to improve the efficiency and accuracy of preventive maintenance for autonomous vehicles.

12. Concluding Remarks

Preventive maintenance for autonomous driving systems is critical for ensuring the safe and reliable operation of these vehicles. As the technology behind autonomous vehicles is still relatively new and rapidly evolving, there are several challenges that engineers and technicians must face to effectively maintain these vehicles. These challenges include ensuring the accuracy and safety of the vehicle's navigation, dealing with the large amount of data generated by the vehicle, ensuring the security of the vehicle against cyber-attacks, and staying up to date with the latest developments in autonomous vehicle technology. Despite these challenges, research and development in this field are ongoing, and new solutions and approaches are being developed to address these challenges. With continued advancements in autonomous vehicle technology, it is likely that the challenges associated with preventive maintenance for these vehicles will be overcome and autonomous vehicles will become a safe and reliable mode of transportation for all.

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