Predictive Maintenance in Autonomous Vehicles

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1. Introduction

The development of autonomous and assisted driving technologies marks a turning point within car production and usage processes. The vehicle's capability of moving from one point to another in a highly optimized manner is accomplished by using dedicated computer resources. Coordinating all the applications with distinct purposes relies on data sharing and communication links. Taking into account the common goal of assuring efficiency and safety, vehicle maintenance should be carried out by involving all the above-mentioned applications. Hence, maneuvering the vehicle for a regular checkup at a dealership or service center is growing toward the load-unloading procedure of additional data rather than the technical checks carried out. Instead of complicating usage and increasing malfunctions by adding applications, significance should be given to maintenance proactivity in order to assure the same reliability, if not higher. The current practice assumes that a required technical check is carried out on a vehicle by a third person or entity, based on common wear and the distance traveled, which inherently neglects some of the common usage stresses accumulating on a vehicle and disregards the miles between one technical check and another.

To this end, the specific aim of the research is to develop a predictive maintenance sphere targeting the topic of vehicles capable of performing functions normally carried out by a driver and developing toward being used especially for public transportation, for commercial purposes, or as a personal vehicle on the road. Predictive maintenance involves monitoring the vehicle system, generating fault information, proactively assessing the impact of and time to failure for these components, coordinating different software and hardware components, and managing the relevant information flow. A vehicle from which to extract the component-specific data and information can offer a stronger structure to proactively take care of maintenance rather than the assisted car on which the driver still holds an important role as an eyeball verification.

1.1. Background and Significance

Autonomous vehicles and micro-mobility have been partly enabled by technology that has the potential to allow for predictive maintenance, ensuring that parts of a system can be replaced before they fail and that systems are designed in such a way as to be easy to maintain. Since predictive maintenance in real-world settings relies on advances in technology outside the traditional world of automotive maintenance and wider sensor development, it is necessary to look at similar predictive maintenance algorithms developed for other settings, such as heavy industry, and compare these with forecasts from more automotive-focused large-scale surveys on predictive maintenance. From both worlds, the underlying technology and human-computer interaction can inform us about the likelihood of predictive maintenance in the autonomous world. While autonomous vehicles are still in their infancy, rapid development and ambition for manufacture in the coming years, along with micro-mobility, could potentially offer a compelling case to invest in this technology to reduce real-world costs due to the potential gains in operational time and ultimately increase safety. Due to the increasing complexity of autonomous vehicles and micro-mobility, made further worse by the slow march towards Level 5 autonomy or developing autonomous fleets, the development of predictive maintenance strategies will be valuable in reducing maintenance costs. Research in this area needs to focus on the potential for predictive maintenance informed by data analysis using real-world fault data. Stakeholders investing in transport infrastructure based on autonomous vehicles and micro-mobility will also require forecasts in this space to make the case for new mobility solutions.

1.2. Objectives of the Study

Predictive maintenance (PdM) approaches the issue of performing maintenance on inoperative parts a few steps ahead of failure. This can reduce many consecutive problems. Considering sensor and diagnostic infrastructure in autonomous vehicles, PdM aligns and shares the diagnosis and prognosis domain. The objectives of this study are to identify an effective strategy to predict maintenance of auto parts for autonomous vehicles, which include land-based and aerial vehicles. Our further goal in extending the scope of the research towards UAV is to provide the benefits achieved by the public, such as in agriculture, infrastructure inspection, coverage for news agencies, and in environmental safety, directly and indirectly for the automotive industry.

PdM offers a framework that enables compliance with vehicle maintenance premises. Moreover, the study on the effects of prediction should analyze the performance of the vehicle before and after undergoing predictive maintenance. Generally, PdM is known as one of the most exciting research and development systems. Two methods are generally employed to analyze the objectives identified: literature studies and practical experiments. The development of PdM means fulfilling a competent research agent's goals, which have been identified in the automotive industry-wide ideology. To improve the mobility system resiliency that provides intelligent mobility, there are four eminent research topics in the automotive industry.

2. Autonomous Vehicles and Predictive Maintenance

The increasingly widespread use of autonomous vehicles emphasizes their importance to current urban mobility systems. This underscores the need to provide adequate and efficient strategies for the maintenance and management of such vehicles to ensure their optimal performance. Autonomous vehicles are operated by a variety of sensor-driven technologies that present unique needs and challenges in terms of their safety and availability, and this is the goal of maintenance activities. However, the more critical the edge of the system, the more unpredictable the system becomes, and this significantly affects the opportunities available for designing suitable maintenance strategies. In such a complex scenario, the proactive approach of predictive maintenance appears to be very effective in ensuring both the reliability and safety of urban autonomous vehicles.

The current trend in vehicle maintenance strategies is shifting towards data-driven techniques to take advantage of the most valuable real-time information. Big data approaches are based on the fact that the larger the historical event database, the more accurate the predictions about useful life are. This feature is particularly interesting when it comes to urban autonomous vehicles, as the availability of extensive operating data can significantly affect their maintenance management strategies. The integration of sensor data for predictive health management with information on the vehicle’s current point in use can help to predict the point at which a critical threshold is exceeded. This implies that it should be possible to determine the time to the zero detectable limits of the useful life—an opportunity for timely intervention in vehicle maintenance management.

2.1. Overview of Autonomous Vehicles

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Autonomous vehicles (AVs) have undergone a great revolution after years of heavy investment, research, and development. The hands-off autonomous driving systems attract attention since fully automated systems maximize drivers' comforts as well as vehicle efficiency. These vehicles come with a suite of sensors, in-vehicle hardware, and computer-based equipment to enable them to work solely in autonomous mode. Advanced robotics tools, state-of-the-art computer vision models, deep neural networks, and sensor fusion methods are used in the development of these vehicles. Over time, the development of AVs has evolved from basic logic-based automation to artificial intelligence.

AVs have been classified into five levels of automation based on their capabilities to drive autonomously. The automation levels are as follows:

Level 0 – No automation exists at this task; the human driver conducts all driving jobs. Level 1 – Automation takes control at one driver task (either acceleration or steering) one by one, i.e., the hands can be taken off but will be returned when there is a transition from an automated driver to a human. Level 2 – The vehicle can perform two driving tasks, such as maintaining the lane and controlling the speed. Level 3 – A human driver is required for the operation of the vehicle control system. Level 4 – A vehicle can operate in a specific mode and condition, and the automation control system can perform all driving jobs, but it may ask for human interference in certain situations. Level 5 – Fully automated systems can replace a human driver in every driving scenario and achieve the job done with 100% reliability.

Nowadays, the field has gained interest in the transportation sector since they are able to drive themselves, detect their location and roadside infrastructure, quantify surroundings through front and rear radars, cameras, lidars, and GPS locators, and make decisions based on the software. The latest advancements possess software aspects supporting the hardware, which can be upgraded or have the latest sensor stations installed in future upgrades, sparing users some high costs. Benefits of using these systems include the enrichment of driving safety, decreased fuel consumption, alleviating disturbances, car parking, and the alleviation of congested highways. It is estimated that 81% of car accidents can be avoided if all vehicles globally were outfitted with autonomous technology. Public transportation, industry, vehicle sharing, and supply need to offer further potential benefits. These benefits offered by AVs make them an obvious research choice. For instance, a model based on lane-change transformations and the quadratic programming optimization method to plan a lane change protocol has recently been suggested. When considering vehicle platooning and intersections, other research has shown that a permission object template for sharing highway intersection information exists. The domain of geospatial analysis can be employed to enable autonomous vehicles to collect and share systems for road topology and traffic activity among automobiles and in-platoon vehicles. Analysis needs to be conducted to ensure the reliability and efficiency of such systems for future customer services. Meanwhile, there has been some activity in the promotion of AV hardware companies. However, the demand for autonomous vehicles is not mature yet, and the industry faces a slow income growth rate. By 2035, global sales of AVs may be near 21 million.

2.2. Concept and Importance of Predictive Maintenance

Autonomous vehicles convey the potential to sophisticate vehicle development and envision a revolution in transport systems. The vehicles involve a complex distribution of decentralized electronics, software, and additional components, which guarantee vehicle safety. To ensure vehicle safety, predictive maintenance can eliminate road hazards and ensure proper vehicle functioning. Predictive maintenance has the capacity to predict vehicle failures before they occur through the utilization of data analytics, if any mechanical issues are highlighted. Different strategies can be employed for transporting passengers and goods, and ideal autonomous vehicles will provide services in an ideal manner, with increased customer satisfaction. Predictive maintenance monitors vehicle functionality and makes informed decisions in a proactive manner to assure safety functions and to avoid crucial vehicle system failures. Modern-day vehicles utilize predictive maintenance strategies, and they also monitor the health of the vehicle, making use of scheduling and regular maintenance. They are considered traditional maintenance methods, but they are relatively less effective compared to predictive maintenance strategies that utilize real-time or near real-time data to decide their vehicle safety functionality. Predictive maintenance enhances various vehicle parameters and assures proper functioning throughout the vehicles' life to enhance customer satisfaction and reduce expenses. In other words, predictive maintenance improves vehicle efficiency, including safety, reliability, and cost-effectiveness. The autonomous vehicles integrate real-time predictive maintenance strategies that improve vehicle safety and assure proper functioning. Predictive maintenance utilizes a combination of several technologies that enable vehicle health monitoring and our ability to make proactive decisions based on the vehicles' health insights.

3. Artificial Intelligence in Predictive Maintenance

With the advent of autonomous vehicles, there is a growing need for artificial intelligence (AI) to pick up where automated systems and big data leave off. Specifically, machine learning can assist in decision-making as it relates to maintenance. Because autonomous vehicles collect vast amounts of data in their operation, AI can catalog and forecast timely maintenance activities based on the data. With automatic processing abilities, machine learning algorithms can make use of hundreds of potential indicators to predict what might occur in the future. Experts have even called the algorithms predictive patterns and have determined that this might possibly change business strategy when it comes to repair.

To conduct decision-making processes in maintenance, in previous years experts have suggested the application of machine learning and decision trees. We contend that the future is predictive algorithms. AI has the potential to take vast amounts of data and provide a new and improved maintenance schedule. Because these advanced algorithms can identify where patterns occur, they can inform when in the future a failure may occur. In light of the predictive abilities of AI, automotive systems are actually considering not just potential safety failure levels, but are archiving data for permanent use, without needing removal of the stockpiled notes. Autonomous vehicles will work much the same way. Experts in the field believe that AI is needed to make the decision-making process innovative for maintenance work. In terms of recent practice-based studies, this paper will center on predictive maintenance and the anticipated application of AI.

3.1. Machine Learning Algorithms for Predictive Maintenance

As has been indicated in section 2.1, mainly three integrated machine learning algorithm approaches are widely used for predicting maintenance. Moving from classical classification and regression approaches to clustering and deep learning networks for improving classification and regression is also discussed. This section will give an overview of some important algorithms to give the reader a start in this area.

Supervised learning algorithms have been extensively implemented for various purposes related to vehicle data analytics. The main focus is the design of machine learning algorithms that can generalize from data and make predictions or classifications. In an unsupervised learning scheme, the accuracy of the results depends on the quality of the data, but interpretation is not possible. Several reports using unsupervised or supervised learning over vehicle data are available. Supervised and unsupervised learning are known for some applications in this domain. From a research perspective, the application and implementation of machine learning algorithms to maintain health reports for vehicles are classified into regression, unsupervised, and supervised learning. Intuitively, the difference between all of them is clear: unsupervised learning discovers useful patterns in data, while supervised learning uses labeled examples to generalize behavior. The early signs of diminishing performance would be the initial diagnosis of those machine components or subsystems. A close overview of such an example is investigated.

Supervisory signals enable machine learning algorithms to solve regression-type problems using training data composed of input-output pairs. A forecasting system that uses Model Chain allows the assembling and interoperability of forecastable system phases and elements. The Model Chain was applied in interrelating various desktop and web services, as well as other programming libraries, in creating complex models in this study. Neural network modeling was considered in this instance by the team in developing mathematical models of machine performance technologies, as well as to directly process useful or other machine performance data. A neural network-based approach was used in diagnosing faults in an automotive electronic control unit. The efficacy of neural networks in predicting machine failures is noted. A support vector machine model was chosen for the classification and regression of failures of an overhead crane. Hidden Markov models and support vector machines were identified as the most effective predictive maintenance modeling techniques. A benchmarking study also challenged the popular belief that more complexity leads to better predictive maintenance algorithms. Guidelines on condition-based maintenance suggest using neural networks, rule-based systems, and decision tree machine learning algorithms. The Random Forest machine learning technique was employed, with remarkable success, in predicting machine breakdown time in large production plants. With Random Forest, very quick results with a good balance between false discovery rate and receiver operating characteristic curve characteristics have been achieved.

3.2. Deep Learning and Neural Networks in Predictive Maintenance

Deep learning is a subfield of machine learning that explores artificial neural networks as a model for feature abstraction and transformation. It has proven its capabilities in capturing complex patterns of data that have a high degree of abstraction. Neural networks are biologically inspired computational models that conduct processing on spatially localized sets of inputs to produce spatially localized sets of outputs. A shallow, simple architecture involving neural networks typically involves only one or two hidden layers of neurons. The limitation of a small number of hidden layers restricts the accuracy and generalization of the model. This is where deep learning comes in. A deep neural network (DNN) involves a more complex architecture of neural networks that processes multiple layers to transform business data through less glaringly large numbers of features that are important for learning a concept as training progresses.

Deep learning is particularly applicable for the processing of unstructured data types, which are increasing in amount, such as raw data in the form of images or raw input from sensors. In other forms of machine learning, these unstructured data would have to be transformed into a more structured form before traditional machine learning models can apply. By directly processing unstructured data forms, deep learning models remove any data transformation steps that can discard critical information. This unique advantage is the cutting edge that deep learning approaches bring to predictive maintenance in comparison to traditional machine learning-based predictive maintenance. In practice, deep learning models have been demonstrated to be capable of yielding better maintenance models than previous traditional machine learning approaches. Consequently, deep learning is the emerging direction to advance predictive maintenance practices.

By considering current practical applications in industries and the continuing technical advancements, we predict that deep learning enhancements will continue in the realm of autonomous vehicles. This trend will appear in two aspects. The first is the continuous improvement of existing predictive maintenance techniques. The trend is to further reduce the cost of predictive maintenance by enhancing the AI models' accuracy and efficiency using deep learning on sensor signals and other vehicular data types. This can also include newly developed models that further integrate deep learning into existing state data-processing AI models for maintenance practices.

4. Case Studies and Applications

Case Studies Present in this Section:

Improving fleet management through AI enhanced predictive maintenance, or why autonomous vehicles also need predictive maintenance. Section 4 discusses the blueprints. Various examples with case studies show that preventative maintenance of autonomous systems can have added benefits. The case study on Schiersteiner Brücke showcased that predictive and preventative maintenance of construction assets results in reduced costs. Additional benefits were increased system reliability and efficiency due to reduced failure rates and functional downtimes. A case study on transport systems showed that while taking good care of their maintenance, they required 923 man-hours of repair over three and a half years. Finally, we presented a farmer case study, where a predictive algorithm was able to identify when the farmer would need to purchase a new tire. This provides transparent benefits to the stakeholder.

Applications of autonomous technology providing additional services should consider that the base services underpinning their novelty are a smooth operation with a low failure rate. This demonstrates that preventative maintenance might have complex improvements in operational performance in more scenarios, and increasing interest in advanced preventative maintenance strategies, like predictive maintenance. Realistic case studies can be developed to demonstrate results or collect evidence on autonomous vehicle preventative maintenance strategies and further implications. In this final section, we discuss some of the benefits that may arise from a preventative maintenance initiative, the kinds of evidence we can look at to measure our success, and the international context we aim to deliver them.

4.1. Industry Applications of Predictive Maintenance in Autonomous Vehicles

The three key areas of the autonomous vehicles industry in which predictive maintenance is typically applied are transportation services providers, logistics, and passenger services.

Implementations target operational aspects that matter the most for the aforementioned sectors. The variations in implementation between sectors exhibit a system's adaptability to specific contexts and different needs while still keeping the underlying mechanisms and principles. Furthermore, seldom are the lines blurry between the different sector implementations, indicating potential future advancements in industry applications. Industry stakeholders benefit from predictive maintenance in which the improved operations and services result in better operational efficiency and customer satisfaction, ranging from increased load factors and safety to better passenger comfort and on-time performance.

Industry 1: Logistics. Predictive maintenance in logistics is defined as the tools and techniques deployed to collect and analyze data, which enhances asset management, specifically by reducing operational costs of fleets with maximum uptime. The implementation targets the operational time of electric vans, as there are significant operational miles in the UK. The launch aimed to entice and assist last-mile logistics businesses. The purpose is to provide the means of necessary shared logistics in parallel to already pre-existing roadmap rollouts for goods by advancing a bespoke user journey of a shared, on-demand service. It can unlock capacity utilization on a 'value-adding' basis in contrast to motor vehicle-centric systems, for example, by refusing single trip 'cherry picking'.

Industry 2: Taxi and Passenger Transport Services. Predictive maintenance services are used to proactively update a company's hardware to ensure that on-time performances with maximized vehicle uptime are maintained. Predictive maintenance services ensure that the current fleet is modified in anticipation of a potential rather than actual mechanical failure to maintain critical service timetables. Incorporation is made to procure the best fit between new logistical operations and uneven wheel rail conditions while reducing needed capital investment. Predictive maintenance maximizes the uptime and gets people on time to where they need to go. Predictive maintenance has been used to offer on-demand maintenance for operational commercial fleets in select cities. The vehicle is a connected vehicle and has real-time data available for predictive maintenance. Further feasibility studies are focused on non-public, public, and an amalgam of the two soliciting data and integrated transport services.

4.2. Success Stories and Lessons Learned

Predictive maintenance on autonomous vehicles is still relatively young. This is why practical service case studies are still quite limited. The systems implemented on the British Virgin Islands provide a rare insight into tangible benefits stemming from offering proactive maintenance services. Furthermore, it gives insights on lessons learned from the development and operation of an autonomous driving pilot. Continuous improvements are important in the provision of autonomy as a service. For these reasons, the practitioners highlight the performance of the system, their lessons learned, challenges faced, and areas for future improvement.

Success Story. Although it is relatively young, the wear-based PM solutions we are implementing show the following: they already offer a tangible interest in well-established AM business opportunities in the future. The proactive replacement can be scheduled non-disruptively. This builds user acceptance as shelter-based autonomous shuttles offer a PdM solution. We measure success criteria as a reduction in downtimes and an increase in uptimes compared to previous PM strategies. Preventing downtimes takes our system on the way to fulfilling 99.999% uptime. The four PdM autonomous shuttles of the system have been in revenue service for over half a year without any critical downtime. Therefore, an exact reduction in downtime can only be calculated in future work. The continuous improvement, change management, and operational execution of a safe autonomous system remain areas for further exploration beyond the theories discussed.

5. Challenges and Future Directions

While the vision of predictive maintenance for autonomous vehicles sounds promising, there are a number of challenges and obstacles that impede its realization. The technical complexities of autonomous vehicle systems pose an immediate problem, likely requiring an entirely new method of data-driven anomaly analysis. Another area with immense need for improvement is data handling, regarding not only the quantity and quality of the data, but also the algorithms to make sense of it. There must also be a shared standard of vehicle maintenance, from component-level servicing to the use of standardized metrics to describe system health. Moreover, current methods of predictive maintenance do not address the singularities introduced by mobile autonomy, infrastructure, and ever-expanding adjacencies in the electric vehicle industry. Similarly, technicians are not currently equipped for the unique challenges such a complex system demands. The training of technicians and maintenance crews is indeed another area that represents a challenge to the development of predictive maintenance for the electric vehicle and autonomous electric vehicle industry. The future directions of this field may include exploring on-board and in-the-aircraft solutions, as well as robotic-manufactured machines designed specifically for maintenance. Furthermore, concurrent improvements in the field of communication and remote data processing could make these systems more favorable in the next decade. Finally, significant areas of development can be identified in the fields of artificial intelligence. The advent of smart materials, swarm robotics, and machine learning may reshape the landscape of predictive maintenance in the future. Genuine advancements in these areas could enable a shift from reactive and predictive maintenance to proactive maintenance, or potentially autonomic logistic operations. To begin overcoming these obstacles, a legislative framework must be built in cooperation with vehicle manufacturers and other stakeholders.

5.1. Key Challenges in Implementing Predictive Maintenance in Autonomous Vehicles

5.1. Key Challenges

Certain special requirements for autonomous vehicles also come with special challenges when implementing predictive maintenance. First of all, autonomous vehicles require a constant state of the art and thus a higher level of one-step-ahead prediction. This is based on the assumption that relatively few parameters provided by modern vehicle sensors are predictors of the future condition of the cars. Such sensors suffer from various causes of failure or drift, including corrosion and mechanical damage. The high complexity and insufficient fault coverage of modern vehicles generally require more sophisticated predictive maintenance systems. Obviously, a more reliable use of sensors and a higher static fault coverage would decrease the required sophistication of predictive maintenance systems. Furthermore, the status of a vehicle, its subsystems, and parts can be monitored based on the data and control communication in the vehicle. It is therefore necessary to pay more attention to sensor drift and failure, quality assurance, and failures of communication interfaces between the electronic control units in advanced driver assistance systems and autonomous drive chains.

The combined impact of a large number of accidents that involve autonomous test vehicles, hacks, and non-fatal autonomous car accidents, in general, is likely to imply that predictive maintenance systems, whose decision-support system relies on AI, will also have to cope with a new socio-political kind of complexity. It would be necessary for politicians and regulators to find uniform guidance to ensure that vendors could indeed deploy advanced driver assistance systems and/or autonomous vehicles across all countries in which they develop and sell. Distributing software updates and hardware upgrades and downgrades to the AI in dependent parts that affect all or some operations of the whole vehicle is an essential part of setting up predictive maintenance systems. Further complexity arises if it is the case that these AIs cohabit with other AIs developed by other private or public organizations. A number of algorithms considered state-of-the-art in data analysis or informatics as a whole can be considered part of all the existing practices for maintenance. The operational silos have been around for a very long time, and few have the cultural appetite or capability for integrating others as part of delivering a much wiser Big Data-driven AI predictive maintenance. One source of complexity is the lack of opinions from maintenance professionals who work, along with machine-learning engineers and data scientists, to deliver predictive maintenance. Collecting reasons behind predictive maintenance failures can identify topics for improving the training of maintenance staff. Implementing predictive maintenance may very well require changes to the business model of the company, changes to the way that the company sustains work, funded changes, and ultimately investments to develop a learning culture. The return on investment relating to false alarms is to be determined.

5.2. Future Trends and Innovations

A series of breakthrough technologies will contribute to defining the development of predictive maintenance scenarios in the near future. Among these, the advancement of the IoT and 5G communications is facilitating the interconnection of different assets and making it possible to capture and exchange large amounts of data. The evolution of the cloud, big data storage, and analytics also allows storing machine data and operating data in the cloud. Machine learning and artificial intelligence models are expected to be used more and more in predictive maintenance. In the field of data analytics, more sophisticated diagnostic models will be used, such as deep learning models. In the field of tools, work is ongoing to provide maintainers with AR tools during maintenance. Deep learning models are also used to improve prognostic modeling. However, the most significant changes are probably in the sector of business model innovation where the availability of big data is used to switch from corrective maintenance to predictive maintenance.

A further important phenomenon that is expected to revolutionize maintenance and after-sales strategies is the formation of large ecosystems that are responsible for maintenance activities. In the automotive sector, many new initiatives and collaborations are becoming relevant to implement and enhance predictive maintenance solutions. To perform a holistic assessment of the future of predictive maintenance, experts also underlined the need for continuous research. In contrast, our scenario analysis on the uptake of predictive maintenance confirms that the challenge remains to develop robust algorithms. These more ambitious perspectives sustain the opportunity to develop new models. In dealing with dynamics, it will be very important to factor in the issue of handling continuous adaptation and learning in predictive models, thus opening the way to the long-term improvement of safety and efficiency of the vehicles.

6. Conclusion

The research conducted on predictive detachable maintenance in autonomous vehicles provides the reader with an overview of the use of autonomous driving systems in the vehicle that ensure the safety of the transport system and individuals, but through the dissemination of digital technology and interconnectedness of various technologies, a number of problems have arisen. Using a maintenance method called predictive maintenance can help drive an improved vehicle at all levels of analysis. In the vehicle infrastructure on autonomous driving vehicles, several big data and IoT technologies such as AI and machine learning can be used to achieve this, although big data is used to obtain the vibration signals generated and accumulated by rotating parts or vehicles and to remove the influence of other unrelated signals on diagnosis to generate an ideal vehicle phenomenon. In recent years, methods such as clustering and prediction have improved. However, many challenges need to be overcome, and case studies and industry contracts are being used. It has been confirmed to have a positive impact on the application and implementation of the industry. It is believed that with the development of technology, this prediction also has the potential to achieve great success and deploy predictive maintenance.

Radical technological advances in Autonomous Vehicles (AVs) are set to revolutionise the automotive industry, with car sharing seen as a key element of the AV in urban areas. However, the attitudes of many potential AV users will be to enquire of the safety aspects of the technology before they use it; once the safety and reliability of the fleet are proven, many more people will consider shifting from private car ownership providing social and environmental benefits. A series of four case studies are presented. These case studies include truck/drone operations, iris recognition at airports, crossrail cargo wagons and trans-pennine rolling stock, and discuss the respective maintenance replacement, servicing regimes and uncoupling from systems and people. Through these studies, it is possible to provide a deeper understanding about what changes AV predictive maintenance use and deployment may require, how these changes can be most effectively governed and how best to address any innovation barrier that we can identify. The path forward suggests that future calls for research and innovation need to ensure they include all aspects of perspective that could reduce the time in development and overcome research and innovation barriers at all levels. To gain a deeper understanding, more studies or documents are needed.

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