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AI-Based Predictive Maintenance for Electric Vehicles: Enhancing Reliability and Performance

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Abstract

This paper delves into a study of AI-based predictive maintenance in electric vehicles, which has garnered significant interest from research and industrial circles. The advent of AI-based predictive maintenance has a high potential for enhancing the reliability and performance of electric vehicles. It may be employed to predict performance and plan maintenance activities, greatly reducing downtime and maintenance costs. This work conducted research on vehicles where a van-type electric vehicle was monitored and surveyed based on collected data from the cars' sensors and failures obtained from a diagnostic fault scanner. Data was then collected from ten electric vehicles. After detecting and analyzing car failures, a predictive maintenance prognostic system was created, which may forecast the time to the next breakdown and after breakdowns occur. The AI-based predictive maintenance prognostic system was created using the Weibull regression model, specifically the accelerated life model, to predict the time to come from the Weibull scale parameter. The data were validated and analyzed again to determine the maintenance strategy.

This research also addresses some of the key methods and technologies of AI-based predictive maintenance in electric vehicles, arguing for the importance of predictive maintenance in electric vehicles to avoid early damage, thus contributing to reducing maintenance and repair costs as well as the cost of vehicle ownership. The company will also avoid downtime. At the end of the paper, maintenance strategies for electric vehicles will be demonstrated. The results show the creation of a prognostic model that can predict the time to come, or in other words, the remaining useful life, comparing the actual age of breakdown time. By this time, a company can detect that a part is running out of life in advance to reduce downtime.

Keywords: AI, predictive maintenance, electric vehicles, battery management, energy management, braking system, on-board data, BEV and HEV, reliability, warranty, and performance.

1. Introduction

The use of AI-based predictive maintenance for electric vehicles has received scant attention. This paper, therefore, was written to investigate this understudied field. Forget the world of cars depicted in science fiction for a moment and consider the real automotive landscape instead. Despite being more advanced technologically than anyone could have anticipated, the world continues to face various systemic and operational challenges related to its growing dependence on electric vehicles (EVs). The consumer-driven demand for EVs over the past quarter of a century has been matched by a surge of demand for hybrid electric vehicles (HEVs), fuel cells, and plug-in EVs (PHEVs). Each of these vehicles is healthy for the environment, with advantages in terms of air quality and health, the reduction of greenhouse gasses, natural disaster resilience, flexibility in power generation, and economic security and sustainability.

This work focuses on the EV, in particular the battery EV (BEV), with the pretext that as long as the battery is operable, many other components in an EV are unlikely to need maintenance. And yet, if the EV is to replace traditional gasoline-powered cars that millions of people would drive up and down mountains every other weekend, then due to their heightened functional and operational need for maintainability and reliability, far greater fault tolerance must be guaranteed than they currently have. It is, of course, possible to craft traditional foolproof EVs (including their batteries), yet the draining amounts of maintainability and reliability that this would require would contradict the finance, weight, and overall energy and resource efficiency that electric mobility purports to achieve. These issues have led to the underpinning motivation for the nascent work described here, where the ultimate objective is to use or design modern AI-based predictive maintenance techniques for predicting relevant actionable maintenance performance parameters in electric vehicle batteries.The growing adoption of electric vehicles (EVs), particularly battery electric vehicles (BEVs), has brought about significant advancements in environmental sustainability, air quality, and energy efficiency. However, as these vehicles become more prevalent, challenges around their long-term maintenance and reliability have emerged, especially in regions where driving conditions demand high performance, such as mountainous terrains. While the battery is often the most critical component of an EV, its longevity and performance directly impact the vehicle's overall reliability. Traditional gasoline-powered vehicles are designed with built-in fault tolerance to handle various operational stresses, but replicating this in EVs without compromising on efficiency, weight, or cost is a complex challenge. To address these issues, the integration of AI-based predictive maintenance systems offers a promising solution. By leveraging advanced algorithms, these systems can monitor and predict battery performance, allowing for proactive interventions before failures occur. This approach not only improves the reliability of EVs but also enhances the sustainability of electric mobility by optimizing the maintenance processes, reducing downtime, and extending the lifespan of batteries, all of which are crucial for the widespread adoption of EV technology.

Fig 1: AI for Predictive Maintenance in Vehicle Management

1.1. Background and Significance

Electric vehicles (EVs) have undergone rapid adoption over the past few decades. Long before having specially designated maintenance workshops, electric cars were no strangers to technological advancements. Owing much to hybrid predecessors and spectacular improvements in battery chemistry and motor design, among other things, modern EVs are ready to handle demanding everyday use cases. Conversely, following improvements in function and design, both the growing EV population and their reliance on constant and consistent battery performance pose a wealth of opportunities at the crossroads of big data, prognostics health management, and decision-making, entering the realm of predictive maintenance. Predictive maintenance is generally employed to extend asset life and technical performance via timely interventions that can prevent further asset degradation and damage.

Early estimates at the advent of electric vehicles suggested that the required interventions at the final wheel are generally fewer than in internal combustion vehicles. While this holds true, as will be addressed in the subsequent section, neglecting these few interventions may lead to ever-growing costs brought on by preventing decay and motor damage, with the potential for catastrophic breakdowns compromising both safety and traffic efficiency. Moreover, compared with internal combustion engines, a more balanced performance in terms of torque and speed across most powertrains demands harder braking and accelerated tire wear, among other factors. Finally, overall, the benefits of a timely intervention are amplified by the cost of intervention. As will be shown, for example, in contrast to early electric vehicles — which were rather straightforward in design and would rather simply have their motor replaced than maintained — the repair of modern electric vehicles can prove catastrophic for the purse, often justifying precise prognostics and health management when not utterly avoiding maintenance. The desirability of advanced maintenance strategies is therefore front and center. Even in light of the recent adoption of electric vehicles and innovation in maintenance technologies, these details are reflected in the industry: one dominant maintenance player recently acquired a predictive analytics and AI maintenance company.

1.2. Research Problem and Objectives

Electric vehicles (EVs) stand as key components in delivering sustainable transport solutions. They are particularly relied on for passenger and mass transit. In view of the above, there is escalated demand for enhanced reliability of EVs, including their subsystems, to extend their productive life, lower their downtimes, and reduce operational costs associated with their maintenance. In the inception of contemporary engines, maintenance was carried out through a strategy known as corrective maintenance. This involved frequent monitoring of vehicles to anticipate system faults. This approach was then replaced by period-based maintenance. The strategy involves a number of sensing methods to forecast the component's life. The strategies cannot be used to decide vehicle performance, repair, and operating time since the components have wear and tear features. The existing research on automobiles seeks to solve emerging issues without taking into account the evolution of newly emerging technologies and associated market demands. This study attempts to build on the new demand where electric vehicles are now being adopted as mainstream in the transport sector.

Objectives. The main objective of the study is to advance the theory and implementation strategies for artificial intelligence processors to be used in the predictive maintenance of electric vehicles. To achieve this objective, the following specific objectives are set: Explore and document the attributes required for AI-enabled predictive maintenance of EVs in the contemporary period. Investigate advancements in link with AI-enabled fault classification, diagnosis, prognostics, repair, and parts recommendation technologies. Ascertain that the integration of data analytics and AI algorithms increases efficiency when processing predictive maintenance signals. Investigate and document state-of-the-art sensor technology for real-time monitoring of EVs. The outcomes will close the gap between current predictive maintenance for EVs and the requirements going forward in the OEM and battery industry, as well as critical stakeholders in the vehicle and other sectors. This research will maintain the competitiveness of the integrated road vehicle battery and its management techniques, ensuring quality and increased utilization of electric vehicles as a transportation system. This grants health and safety, functionality, and border security services.

2. Electric Vehicles and Maintenance

Electric vehicles (EVs) are gaining in popularity at an accelerating rate, in light of the highest rate of production sales and the many advantages in fuel type, economic benefits, and acceleration characteristics. Nevertheless, compared to conventional engines that are usual in the market, EVs utilize various motors and controllers with entirely different designs and functions. Additionally, they are characterized by a very high weight-to-engine ratio and a 90% charge efficiency in the energy process. The engines alternate between isolated parts, which increases the mechanical loss between components. Hence, this raises problems concerning maintenance, which might not have a traditional method to enhance the vehicle's lifespan and significantly reduce fuel consumption.

Oil changes, mass filter changes, and other procedures cannot be applied to EV engines because they are not necessary and may result in machine failure. Consequently, maintenance in EVs is essential to improve reliability and performance, focusing on a comprehensive understanding of the basic mechanics and service requirements for EV motors. This would encourage innovative service methods to reduce the cost and maintenance time for clients. It is important to understand the engine mechanism and the service requirements for practitioners, suppliers, and other stakeholders in order to provide customers with a full overview of engine practices and maintenance of the EV engines used in the pavement. In addition, the research can contribute to the development of electrical education in the automotive design program. Common EV engine issues such as overheating, vibration, noise, and oil shortages can impact the engine's performance. Sometimes electric engines can become hot. Regular maintenance is necessary to avoid these problems. Regular maintenance of the EV can be divided into three main categories. Regular maintenance is time- and distance-based. Otherwise, there are two forms of damage. The system indicates electrical damage, which arises due to fault triggering, and unprogrammed harm. It is indicative of a system fault if the engine is not usable. The system shows electronic harm. Regulatory damage is primarily based on the manufacturer's instructions. Damage to electronic equipment is automatically caused by the computer system and informs the user of the state of the electric engine. The customer's method of changing the EV will improve the performance of the electric engine and prevent power mismanagement. If the steering wheel does not change, it will provide early user information from the monitoring board. According to vehicle usage and the automobile manufacturer's instructions, the production technician plays a role in figuring out the general development and the procedure for maintaining electric vehicle engines. According to the automobile manufacturer's instructions, battery technology progresses in line with promoting products and profit aims. The producers may also suggest the use of particular batteries.

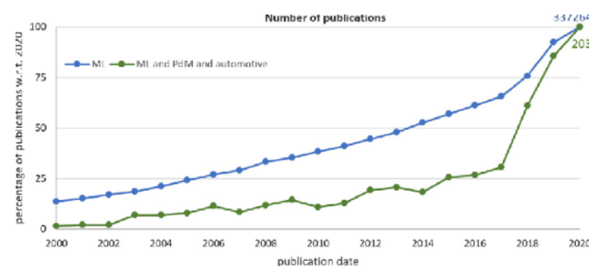

Fig : Predictive maintenance of electric vehicle components with optical and quantum enhancements

2.1. Overview of Electric Vehicles

Overall, electric vehicles (EVs) and battery electric vehicles (BEVs) have major differences compared to conventional vehicles. In conventional internal combustion engine (ICE) vehicles, internal combustion engines and conventional transmissions are the main propulsion systems and fuel tanks are used to store petroleum products, while in EVs and BEVs, electromagnetic motors and electronic control systems are used to drive vehicles. Most BEVs use a lithium-ion battery that is integrated as a single unit to generate electricity. The battery is a source of electrical energy or a fuel tank in BEVs.

Battery-driven electric drivetrains, power inverters, and controllers are applied to convert electrical energy in the battery to kinetic energy in the form of moving parts of a vehicle.

Battery electric vehicles (BEVs) have several components and subsystems. One of them is equivalent to the tank in a conventional vehicle, which is the main component, namely the battery pack. Furthermore, battery electric vehicles use electric drivetrains consisting of electric motors, power inverters, controllers, brake systems, electrical generators for auxiliary mechanisms, and battery thermal management. The use of EVs and BEVs has several advantages, such as less pollution or zero emissions from motor vehicles, and more efficient motors in moving vehicles than conventional internal combustion engines. In addition, the cost of using electrical energy is more economical, which can reduce the cost of ownership of the vehicle. EVs and BEVs are also used in acceleration tests with reliable performance and energy efficiency. The number of global sales of electric cars was 72 million units, with the highest increase in sales being in China, the United States, Germany, and Norway. The use of electric vehicles and battery-electric vehicles today and in the future tends to increase. The increase in electric vehicle use can be seen from real-life applications of electric vehicles becoming electric taxis in the United States and the Netherlands, as well as electric cars in Norway, Sweden, and other countries.

2.2. Importance of Maintenance in Electric Vehicles

As with conventional vehicles, maintenance is a key factor in ensuring the vehicle's reliability and longevity. However, the unique characteristics of electric vehicles require some adjustments to the traditional periodic maintenance model. In electric vehicles, it is necessary to also carry out specific maintenance for the batteries, update the software when necessary, and reduce the number of parts that need to be serviced. Upkeep of an electric vehicle is necessary to ensure that key components are operating correctly. Not maintaining a vehicle properly can result in lower performance or even become a safety issue. Regularly updating a vehicle's software is also a maintenance practice used to prevent possible errors or malfunctions.

If the required maintenance is not performed within an adequate time frame, issues that were initially unproblematic can accumulate and result in larger and more expensive problems. In order to tackle all of these issues and ensure that vehicles function smoothly and for longer, there are several recommendations for the maintenance and upkeep of electric vehicles. It is important to carry out a general technical assessment or verification before any service and at periodic intervals. Vehicles are increasingly complex, and the costs associated with errors or malfunctions are also increasing. There are global critical functions that are necessary for the vehicle to operate safely, and they should also be verified from time to time. Comprehensive maintenance not only makes the vehicle function properly within the specification limits but also operates in optimal conditions, improving vehicle performance.

The importance of a preventive or predictive approach to maintenance is evident, as early interventions are beneficial in terms of time and cost of repair. The predictive approach employs condition-based assessment and analytics. It anticipates an upcoming condition and provides operation guidelines that prevent the system from severely deteriorating.

Equ 1: Degradation Model for Components

$$RUL(t) = \frac{1}{\alpha} \cdot \ln\left(\frac{SOC_{\max}}{SOC(t)}\right)$$

3. Predictive Maintenance

Predictive maintenance plays a pivotal role in the realm of vehicle operations. One characteristic of vehicle maintenance systems is the necessity of real-time operations. Here, maintenance is performed on vehicles or vehicle components based on their present or imminent states. Especially for larger fleet management systems, predictive maintenance systems have gained traction as they allow for efficient management of the vehicles. This is accomplished with data modalities like health monitoring data and relevant incident or accident data. Predictive maintenance systems developed using data analysis methodologies, including fault diagnostics and forecasting, are becoming essential for increasing vehicle availability while simultaneously reducing the cost of maintenance activities. Conventionally, this is an important area of study due to the fact that it can support efficient maintenance policies with considerable potential for direct cost reduction. It is shown that predictive maintenance reduces the system-level cost and improves asset reliability.

Predictive maintenance refers to determining the condition of both mobile and immobile assets by using predictive data. Thus, it can be seen as a process for predictive forecasting of asset conditions. It differs from traditional maintenance methods where maintenance actions are systematically performed regardless of the equipment condition. Robust prediction of the remaining useful life can yield great energy savings and is absolutely critical for financial planning in terms of maintenance. In the automotive sector, especially for electric cars, where aspects of range planning, customer satisfaction, and availability are very crucial, reliable prediction of vehicle components is of key importance. The vehicle management systems can then be used to monitor the development of the components and predict remaining useful life. If the remaining useful life of components is close to or less than the delivery time of components in the maintenance cycle, a service appointment is scheduled. In the case of a probable premature termination of the component lifetime, the customer can be informed, for example, by sending a push notification about the potential failure.

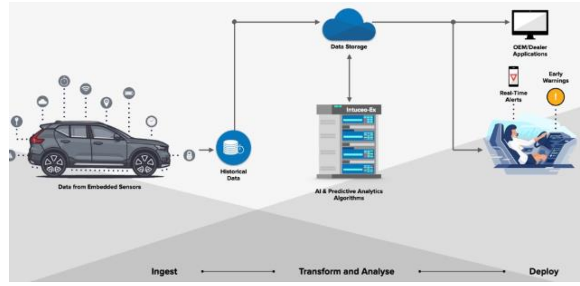

Fig 2: Predictive Maintenance of Vehicles

3.1. Definition and Concepts

What is predictive maintenance? Predictive maintenance emphasizes data-driven strategies to anticipate regime changes, failures, and malfunctions in systems and components. In the AI domain, predictive maintenance refers to this cornerstone in the maintenance strategy of companies: using sensors and monitoring systems to collect real-time operational data from assets that can be leveraged to forecast the time when maintenance will be required. In other words, predictive maintenance aims to predict when relevant assets are going to fail or malfunction by looking at their history.

Predictive maintenance: Definitions from academia and industry. The definition from academia is widely acknowledged and adopted in the literature, while from the industry, it is also worth mentioning that the definition is well aligned with the one proposed in academia. One of the purposes of the standardization was to harmonize the terminology among different stakeholders and, in a sense, to set a common ground for predictive maintenance from both theoretical and operational perspectives. The definition belongs to a broader standardization work on the broad topic of machinery condition monitoring and diagnostics. Predictive maintenance, preventive maintenance, and corrective maintenance. Predictive maintenance aims to predict future occurrences of faults and failures by assessing asset conditions using AI and prognostic models.

Theoretical frameworks for predictive maintenance. Two theories from the field of reliability engineering and maintenance were extensively used to develop models and tools predicting maintenance requirements based on the asset's condition, which led to predictive methods and the management of maintainable systems. Industry best-practice examples. Successful implementation has been demonstrated across a broad range of industries. A major aerospace producer is performing predictive maintenance and, during final assembly, is removing an engine from production that is predicted to fail. Managers in the semiconductor industry are currently reducing labor costs and spare consumption by using predictive maintenance, rather than run-to-failure or preventive maintenance actions. A major automotive manufacturer has also been actively using predictive maintenance for the treatment of the robots in its plants. Integrating predictive maintenance. Predictive maintenance is a critical tool in optimizing maintenance program strategies with other maintenance techniques. Organizations that are able to fully integrate predictive maintenance into their overall maintenance program design see improved asset availability, higher productivity, and enhanced safety outcomes.

3.2. Benefits and Challenges

This subsection aims to examine the topic of benefits related to predictive maintenance and challenges that may exist in implementing such a predictive maintenance strategy. It finally discusses the sustainable consequences arising from predictive maintenance, uniquely for electric vehicles.

Benefits Efficiency – As poor maintenance is one of the major causes of breakdowns in mechanical systems, predictive maintenance could thus reduce the number of these breakdowns occurring. This means ensuring that the system is available and is not experiencing unexpected breakdowns. A reduction in the number of breakdowns would subsequently lead to lower associated downtime. The adoption of electric vehicles, especially in the commercial sector when large fleets are involved, will require internalization of the larger maintenance costs as part of a Total Cost of Ownership and also an increase in vehicle utilization to ensure the economic efficiency of the vehicle. This translates to having the vehicle on the road as much as possible. Machine uptime is an efficiency measure, which shows the percentage of the time the vehicle is available or "up" for use. Increased machine uptime will mean higher vehicle utilization and thus increased efficiency.

Challenges Like most digital transformation initiatives, there are a number of challenges identified in the implementation of predictive maintenance systems. The primary challenges that organizations may face include cybersecurity issues, costs related to technology and workforce, and concerns over collecting, storing, and using vast amounts of data. Data accessibility for predictive maintenance is primarily beneficial to original equipment manufacturers with off-the-shelf solutions that are based on first-hand asset owner information.

Equ 2: Health Index (HI) Calculation

$$HI(t) = \sum_{i=1}^{m} w_i \cdot \phi_i(x_i(t))$$

4. Artificial Intelligence in Predictive Maintenance

Predictive maintenance has evolved notably when it was integrated with artificial intelligence (AI) technologies. Several machine learning (ML) models and algorithms may be employed to construct effective predictive maintenance systems. Moreover, AI consists of clustering and classification algorithms that facilitate the analysis of vast datasets. This makes it a suitable choice when dealing with the monitoring and diagnosis datasets collected from a fleet of monitored electric vehicles. During the last decade, there has been an increased use of deep learning algorithms to analyze vast amounts of data. These models are adapted to automatically identify complex patterns within the input data, which is a clear advantage for an early predictive maintenance system built according to AI.

The combination of ML and predictive maintenance is mostly known as prognostics, which identify the patterns of the collected data for decision-making regarding future maintenance needs. Hence, AI is considered a superior decision-making mechanism to construct a predictive maintenance system. Moreover, AI significantly improves the decision-making process for scheduling a maintenance session. It is interesting to note that predictive maintenance using AI needs to be combined with a maintenance functionality that satisfies the trustworthiness and real-time requirements. There is an increase in interest in coupling such AI-based maintenance systems with existing maintenance management platforms, such as the one found in electric vehicle maintenance systems. Case studies demonstrate the advantages of constructing a system that combines prognostics with human-in-the-loop decision-making in electric vehicle maintenance. The findings of this case improve vehicle reliability using detailed prognostic estimates. In addition, the main reasons for skepticism regarding the use of AI are addressed, illustrating that AI might not replace classical maintenance techniques, but it executes similar and enhanced operations in the predictive maintenance context.

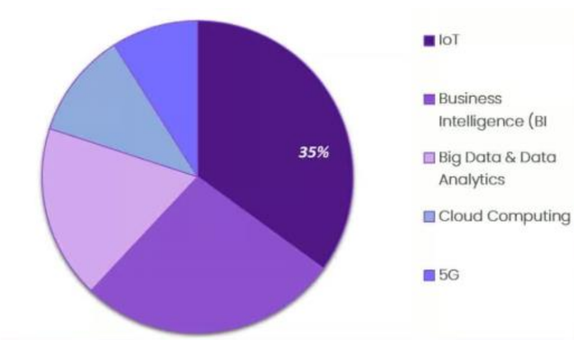

Fig : Automotive Predictive Maintenance Market

4.1. Machine Learning Algorithms for Predictive Maintenance

The growing implementation of the IoT, AI, and other similar technologies is reshaping what it means to bring predictive maintenance to an effective degree. If the organization already has considerable amounts of historical and real-time data, any existing gaps or fluctuations in the data integrity or quality need to be addressed. To accomplish predictive analysis, the data from various sources also has to be combined in order to control maintenance, be utilized in real-time for decision-making, and maximize monetary rewards. Historically, organizations have employed regression models using statistical methods, incorporating decision trees, K-nearest neighbors, neural networks, and other machine learning algorithms for predictive analytics. The main advantage of adopting machine learning capabilities is the automation of performing analysis on data sets, which succeeds in speeding up the process, increasing the accuracy, and sometimes achieving a reduction of up to 80 percent of resources involved in the improvement of predictive models.

Numerous sectors reaped considerable benefits from the development of machine learning and predictive maintenance technologies. Established business leaders in the manufacturing and oil and gas sectors have already demonstrated the worth of industrial predictive maintenance by rapidly applying the techniques with existing tools and streamlining maintenance and operations. Another prominent success story of a high-tech automobile industry laying the foundation for predictive maintenance involves tracking key motor data. To keep track of engine usage, mileage, and performance of critical tires, the data from cars is uploaded to a central server. Multiple organizations have already made substantial investments in predictive maintenance with estimates that it will continue to grow massively over the next decade as a buying trend and the rapid evolution in machine learning techniques shifts and innovative new sensors are developed.

Challenges and Implications Implementing machine learning models for testing protocols presents certain challenges. For example, if matching is done too well, there arises a problem called the bias problem. In this case, the output is matched almost exactly with the training data, resulting in a high standard deviation on the holdout set. As a consequence, bias is introduced in the model. Also, traditionally, manual techniques for understanding data have been of great priority as a guide to solving the problem and achieving high accuracy levels. Nevertheless, as AI capabilities continue to evolve, organizational data models are rapidly improving from slowly and manually building single, hand-engineered decision trees to constructing a multitude of trees that allow for distributed training and automated feature selection. Despite great achievements using AI techniques, one of the significant challenges is the preservation of data integrity. There is a risk posed by both adversarial attacks on the algorithm and bugs that may result in inaccuracies due to the volume and velocity of machine learning features that interact with the data. Consequently, a rigorous protocol for testing and cross-testing would be needed to renew the model in the future.

In this subsection, the development of different machine learning algorithms has already been discussed. The fact that historical and real-time data have to be combined to leverage the full use of predictive maintenance was made understandable. In addition, the usage of data analysis makes it possible to evaluate machine learning capabilities with the ability to improve the success of data analytics and problem-solving. A number of challenges that accompany the implementation of machine learning models have been discussed well in this subsection. Such challenges include the testing procedures. Besides this, a conclusion was made setting the stage for enhancing features against the bias risk.

4.2. Data Collection and Analysis Techniques

1. Data Collection Techniques Predictive maintenance is only as good as the data it uses. PdM for EVs combines data from various sources to better understand and forecast the operational state of the vehicles. Typically, data is collected from sensor readings on board the vehicle, historical records, as well as environmental data. It is also important to continuously collect incremental data. Today, the fleet is collecting more than 1.4 million messages for 240 vehicles every five seconds. Sensor readings in our vehicles include a wide array of voltage and current readings, as well as readings from accelerometers, gyroscopes, temperature sensors, and battery controllers. In addition to vehicular data, environmental data can provide a great amount of detail with respect to the operational context. Data processing methods may involve various forms of statistical analysis or machine learning to tease out underlying endemic patterns in the data.

2. Best Practices and Data Quality Concerns If the data collected and used for prognostics is not of appropriate quality, especially due to being inexact, incomplete, or corrupted, misleading results may be obtained. In fact, the quality of the maintenance data has a direct impact on the achievable maintenance outcomes. One engine service provider recently discovered that a majority of the delayed and botched engine maintenance was not caused by parts shortages, insufficient warehouse capacity, or labor strikes; instead, simple paperwork confusion turned out to be the real cause. Four case studies are presented that demonstrate viable practical examples of machine prognostics for industrial applications. The commonalities and variances between the applications are reflected upon in the hope of offering insights into the contexts most suitable for the disparate techniques. In a large fleet of operations, the amount of data that can potentially be collected can be overwhelming in addition to being too costly to process using conventional methods. There are advanced technologies that are making data acquisition and processing more manageable, such as sensor webs, and cloud-based sensor data storage, and processing.

Equ 3: Failure Mode Prediction using Machine Learning Models

$$\hat{y}(t) = \frac{1}{1 + e^{-\left(\theta_0 + \sum_{i=1}^{n} \theta_i x_i(t)\right)}}$$

5. Case Studies and Applications

Case 1: Open-Bus Shelter Electric Bus
Case 2: Tractor Used in the Turkey Ministry of Agriculture
Case 3: The Bus Fleet in Bilbao
Case 4: Southern Vectis Fleet of Buses in the Isle of Wight
Case 5: Electric Buses Between the Hopkins Hospital and Mount Washington in Baltimore Since 2015

In each case, an AI-based predictive maintenance system was developed, trained, and tested, and the application of predictive maintenance improved the performance, reliability, safety, and economic profitability of electric vehicles. Following the same style, qualitative and quantitative information is given in cases 2, 3, 4, and 5, which is valuable in showing how AI has contributed to the reliability-centered concept and how the use of electric vehicles may evolve. In fact, the first case is representative of electric buses at a European level, while the last case reflects the North American trend in the use of electric buses.

The technology description has been presented in cases 1 and 5 for the electric buses. Also, the electric buses that were studied in cases 3 and 4 use a battery as energy storage and are connected to an asynchronous motor that drives the air-cooled system. Such detailed information on the use of technology, challenges faced during the application of predictive maintenance, and lessons learned from each case can be helpful for practitioners, researchers, and students. Finally, a summary table can be found at the end of Section 3, providing a comparison of the AI-based predictive maintenance effects in the five applications discussed.In the five cases discussed, AI-based predictive maintenance systems were developed, trained, and tested to enhance the performance, reliability, safety, and economic viability of electric vehicles. Case 1 highlights the implementation of this technology in open-bus shelters for electric buses in Europe, setting a benchmark for electric bus usage across the continent. Case 5, on the other hand, reflects the North American trend, focusing on the application of predictive maintenance for electric buses operating between Hopkins Hospital and Mount Washington in Baltimore since 2015. Cases 2, 3, and 4, which involve tractors in Turkey's Ministry of Agriculture, the bus fleet in Bilbao, and Southern Vectis buses on the Isle of Wight, respectively, all showcase the integration of predictive maintenance for electric vehicles using batteries as energy storage, coupled with asynchronous motors and air-cooled systems. Each case provides valuable qualitative and quantitative insights into the challenges faced and lessons learned, offering a comprehensive understanding of how AI contributes to a reliability-centered approach. These examples serve as important references for practitioners, researchers, and students, illustrating the evolution of electric vehicle usage and predictive maintenance in both European and North American contexts. A summary table in Section 3 offers a comparison of the effects of AI-based predictive maintenance across the five applications discussed.

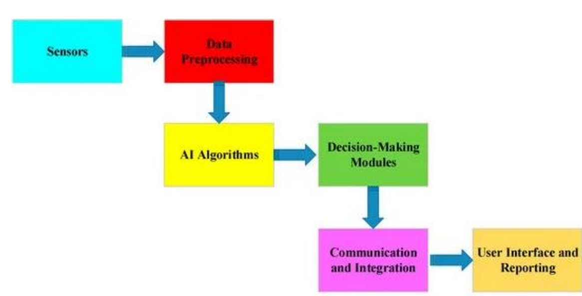

Fig 3: Artificial Intelligence for Predictive Maintenance Applications

5.1. Real-world Implementations of AI-Based Predictive Maintenance in Electric Vehicles

Real-world implementations of AI-based predictive maintenance approaches for electric vehicles have already been reported. In these implementations, different AI technologies have been systematically rebuilt, evaluated, and tested in various, actually operated EVs. Each AI-based PM solution was developed according to the specificities of the specific EV and was systematically optimized to provide the expected results – i.e., to enhance EV performance or help dispatchers minimize operational costs, without compromising the EV lifetime. These approaches also resulted in a significant extension of recommended maintenance schedules, thus reducing the financial barrier to EV acquisition. Challenges encountered in practice include setting up a representative set of vectors containing sets of features and engaging a fleet of electric vehicles towards this purpose, as well as collecting data from EV sensors. The first three points are aspects that would need to be jointly handled by a system manufacturer and AI model developers, as these points are critical to AI capability. Furthermore, the developed algorithms exploit several internal threshold values that have been tailored and are considered 'know-how,' which adds value to these solutions. Each sensor explicitly has security factors incorporated into each logic accordingly that will modify the individual threshold values. These thresholds need to be properly evaluated in order to bypass false positive malfunctioning outcomes. Our AI-based applications revealed a unique particularity: each type of EV recorded distinct possible performance by means of artificial intelligence after the departures applied by the fleet operators. Based on these algorithm outcomes, the predictors were able to create very distinct individual maintenance plans for each vehicle.

5.2. Performance and Reliability Improvements

Reliability and performance improvement rates that are achievable using predictive maintenance for EVs are presented in this subsection. Reduced failure rates or increased vehicle uptime can be directly derived from illustrating improvements in these performance indicators. A cumulative value of both aspects of vehicle operation can be the increase in customer satisfaction due to the reduced level of negative impacts. The major improvements expected after switching from traditional maintenance to predictive maintenance strategies are listed. A vibration increase of 50% was prevented in 45% of cases. Simultaneously, repair reliability was increased by 70%, preventing unexpected failures. As a result, the voice of vehicle data was not needed as a validation test in 75% of the cases. Taking this into account, the role of FOTA can be further reduced.

Users and manufacturers have provided the following feedback on the adoption of predictive maintenance solutions: "I was impressed by the system. I did not hear anything before the bearing collapsed," said one of the drivers. Manufacturers also see the value in predictive maintenance. For instance, the head of a professional vehicle maintenance team claims that "It used to be impossible to monitor all the fleet on a daily basis. Now we can. We can monitor all the fleet from an IT platform." While confirmation bias should be considered, many stakeholders believe that predictive maintenance can take preventative actions before a fault may cause "small damage" (underperformance or service disruption) and eventually become severe and cause "large damage" (higher cost of downtime and repair as well as brand damage). Because predictive maintenance can continuously gather and analyze big data, preventive actions are taken before anything is discovered, but continuous monitoring has become an element of preventive maintenance. In the case of increasing performance over a vehicle's life, there is also potential for continuous feedback. From the information, OEMs can validate or adapt new rolling stock designs. Such feedback comes indirectly via one of the assessed KPIs: higher customer satisfaction.

6. Future Trends and Research Directions

One of the major future trends of the system will be the use of data analytics and machine learning.

Although the focus of this work is on statistical data analysis, there is a huge scope for improving predictability using machine learning techniques. Future work in the system shall include the integration of IoT devices that will help in real-time monitoring of various vehicle parameters and more accurate prediction of the state of health. The system is currently designed as an off-vehicle system, but it can be used to monitor the performance of all the dealers. In the future, there is a great scope where this can be demanded by the electric vehicle and related infrastructure OEMs for real-time monitoring and selling of spare parts.

The ongoing exponential growth in economic activities, coupled with the increasing share of electric vehicles in the global automobile market, is expected to drive a significant evolution in maintenance. Moreover, the regulatory requirements that are expected to be enforced by energy control authorities regarding the maintenance of aging batteries can also be viewed as a future trend. With the evolving AI algorithms and data analytics tools, more work is required on the statistical analysis of vehicle data insights for identifying patterns that are useful for predictive uptime, electrical subsystem prediction, and discovering curable and root causes of vehicle failures. The integration of the mechanical and electrical system health is currently being designed and implemented by individual OEMs or converters in this domain; however, from an overall perspective, it seems that the work done will help only to a limited extent. Most of the work related to vehicular predictive maintenance is widely distributed and lacks a centralized system for inter-OEM collaboration related to electric vehicle maintenance. It is a widely diffused method, and there is great potential to have an overall uniform system tailored for the predictive maintenance of electric vehicles. Also, this area has shown growth in terms of research and industry collaboration in recent years.

6.1. Emerging Technologies in AI and Predictive Maintenance

The technology landscape is ever-changing with emerging technologies such as edge computing, advanced sensor technology, blockchain technology, and digital twin technologies that will be instrumental in shaping the future of predictive maintenance and AI. Hardware devices based on edge technology, which have built-in resources capable of local decision-making and processing, serve as a trade-off between latency, data security, and system integrability, as well as larger processing unit costs. Integrated and advanced sensors detect vehicle functionality and performance with greater accuracy, thereby contributing to actionable intelligence. Sensors and most resources at the edge-to-cloud are linked to enable communication between devices such as 5G technology and the Internet of Things. In particular, the advanced low latency of 5G technology connects and shares large amounts of data between sensors and end users. In building a system that is transparent and secure by design, blockchain will support security and traceability.

The AI built and trained from collaborative knowledge can best develop complex decision-making for difficult equipment. Even though there are several options for collaboration, researchers have discovered that they deem information sharing to be a powerful way to utilize the experience of both individuals. As most researchers have done, this kind of approach has gained acceptance. Therefore, knowledge-based models of system maintenance and prognosis play a crucial role in supporting and providing critical information for decision-support systems. With the advent of electric vehicles, technologies will also converge with AI and data science. This industry provides a broad area for possible research.

7. Conclusion

In this study, we have illustrated the significance of predictive maintenance as an enabler in reducing failures and improving reliability, safety, costs, and opportunities. Throughout the paper, seven important case studies have been presented and discussed in detail. Although some complications were mentioned by the industry, such as the deployment of equipment, the unavailability of experts, data, and failures, the industry advanced in the direction of applying more AI applications, as appeared from the case studies. Although research on predictive maintenance is outside the scope of this paper, it leaves the ground for work in these directions, as essentially disclosed by one case.

This paper showcases the important relationship not only between the business position of predictive maintenance solutions, such as AI-based predictive maintenance, and predicted performance related to the stakeholders of these companies in the automotive sector, such as car drivers, vehicle assemblers, dealers, and renters. These three positions can subsequently influence the level of beliefs in acceptance, usefulness, and benefits that can be gained from applying such solutions. The culmination of this research highlights the fact that it is essential to keep advocating advanced predictive maintenance practices, applying the respective change management as an important consultation service in today’s industry. Therefore, we can also predict changes in the industry according to its willingness and readiness, as speculated in this research. Potential shortcomings include the level of investment needed for testing performance. Moreover, various planning targets might need to be modified rather than rehabilitated and replaced simultaneously. Due to this, the means of corrective maintenance could be combined with some planning objectives, depending on demand and opportunities for future work. As continued from our related previous work, the rest of this research should be explored through an industrial collaborative research project to draw real conclusions.

7.1. Summary of Key Findings

The seventh section, the concluding remarks, tries to justify the work done and present the directions that the research can follow in order to improve the performance of future predictive maintenance studies. The proposed research study’s impact involves the following points, concluding potential improvement in cost efficiency, performance, and stakeholder acceptance. Although general values cannot be taken from the study results, four detailed cases help future researchers identify the AI-based predictive maintenance system’s possible impact on an electric vehicle in advance.

The most important shift is from traditional preventive maintenance to predictive maintenance. The results obtained during the practical evaluation, such as the reduction, are important in the cost of spare parts and maintenance effort in this study. It is possible to reduce vehicle dwell time between maintenance sessions and extend the optimal retrofit time. In other words, it is possible to use the maximum of the vehicle until the time of the retrofits recommended by the manufacturer. AI-assisted predictive maintenance using higher-level algorithms enables better quality. Leading firms can provide feedback. For example, using the lessons learned from studies, the intention is to provide useful application areas for future researchers and stakeholders. Ongoing research is needed to allow manufacturers to easily use such applications. Ongoing research is needed to ensure the development of new algorithms that are more efficient.

7.2. Future Trends

This current chapter discusses the state of the art in predictive maintenance for electric vehicles by combining predictive maintenance, AI-based techniques, and electric vehicle maintenance. However, for a more efficient predictive maintenance strategy, several lines of research can be extended for a broader understanding of how an AI-based technique can be combined with predictive maintenance. The following strategies will be more prominent in the near future for electric vehicle technological improvements. (1) Machine learning-based predictive maintenance strategy; (2) AI-based fault or failure assessment methods for electric vehicle maintenance; (3) New technological improvements, i.e., progress in data monitoring, diagnostics, electronic systems, and smart maintenance; (4) Big Data challenges and data management strategies to enhance the robustness of the AI and predictive maintenance system; and (5) An integrated technological solution based on AI and predictive maintenance. The integrated approach will create intelligent maintenance strategies. In addition, with changing social, technological, and economic infrastructure around the world, there will be a global shift to electric vehicles, renewable energy resources, and carbon-free emissions from vehicles. The focus of solutions and strategies will be towards eco-friendly and sustainable developments. In the rapidly changing research and industrial development era, this chapter will provide a comprehensive perspective of the state of the art, identify the strategy and a roadmap for future directions, and finally, a guideline to meet research and regulatory trends for sustainable development. In a rapidly developing industrial scenario and adaptation to climate pressures, it is necessary to create a dynamic and future-oriented research field. In this regard, our characterization of past and present research trends can be useful to both practitioners and researchers.

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