Machine Learning for Predictive Maintenance in Autonomous Vehicle Fleets

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1. Introduction to Predictive Maintenance in Autonomous Vehicle Fleets

The rapid development of information and communication technology (ICT) combined with the global maintenance management of newer constrained environments like AVFs gather dataset on unprecedented scales. This gives with them possibilities for new innovative solutions for condition monitoring, diagnostic, and prognostic. The approach of intelligent monitoring, and maintenance management strategies would allow to ensure the highest availability, reliability, and mission readiness of AVFs while reducing the overall costs of operation and maintenance from a lifecycle perspective. Such advances like dialectric spectroscopy analysis with the help of Machine Learning algorithms to create a prediction model have been proposed to be applied to predict the Remaining Useful Life (RUL) of mechanical components in vehicles [1].

The deployment of maintenance solutions such as machine learning techniques of predictive and prescriptive maintenance in systems of Autonomous Vehicle Fleets (AVF) is a promising field of research and an important topic in the automotive industry. The use of these techniques alongside intelligent maintenance management systems while enhancing the quality and availability of the maintenance operations, reduces maintenance and operation costs, avoiding unplanned maintenance activities and reducing the overall negative effects of fault occurrences. However, the application domain of machine learning in maintenance is changing quickly along with technological advancements and increasing availability of data. Effective application of these techniques in such dynamic environments requires an overview of the state of these techniques in the domain to guide industrial and academic partners when applying these methods [2].

2. Fundamentals of Machine Learning for Predictive Maintenance

Some industry reports conclude that predictive maintenance is still relatively underutilized. This is predominantly due to challenges in entity recognition, handling high-dimensional sensors, managing class boundaries, and accommodating class imbalance. The theory-driven models that are presented in the literature can also face computational complexity, computation time, risk scores, and physical explanations. The promising results of machine learning are highlighted again in the literature and are expected to reduce environmental waste and support routine actions in predicting the health of a system. This machine learning model is a fusion of multiple algorithms working together, addressing class imbalance and features selection, and using multiple random data samples and cross-validation techniques to stable the results. The method velocity developers of maintenance models, optimally managing positive and negative classes, and extending model performance, are summarized to fill the gap for relieving the open challenges of predictive maintenance [2].

Machine learning is a branch of artificial intelligence, focused on developing algorithms that can learn from and make predictions about large, complex data sets. It has shown great promise in predictive maintenance in autonomous vehicle fleets, supporting the operation and maintenance of these vehicles and minimizing the possibility of unexpected breakdowns [3]. Autonomous vehicle fleets have become an increasingly popular mode of transportation because of their ability to drive efficiently and adaptively. These vehicles support various applications in multiple domains, including smart city, environmental monitoring, agriculture, construction, and surveying. Predictive maintenance is a proactive approach to maintenance operations that involves predicting when a system or component might fail and then performing necessary maintenance work before an unplanned incident occurs. Nonetheless, the spatiotemporal analyses of multi-component and multi-fleet systems and decisions about when and why a maintenance action should be taken, are quite complex. Predictive maintenance therefore remains an open and important challenge.

3. Data Collection and Preprocessing for Autonomous Vehicle Fleets

[4] Autonomous vehicle fleets are characterized by many widely distributed connected assets, which contain more than 100 onboard sensors, onboard sensors onboard gateway in factory, and predictive maintenance. This scenario is also one of the pioneer pilots in the usage of Smart Predictive and To-Do solutions of qualMaaS project. Preventive maintenance schedules

can be overly rigorous and sensitive to the mission profile, leading to unnecessary part replacements, increased logistics costs, power consumption, fuel consumption, and CO2 emissions. In consequence, vehicle component breakdowns, that were not considered in the original preventive schedule, leads to temporary production stops, unproductive downtimes (especially in 24/7 plants, and varying costs to fix supporting infrastructure, for example in medium-voltage installations. Augmented Reality (AR) solutions fail to provide efficient maintenance actions if information about the actual fault, possible root cause and possible other failures is not available. To address this problem, this paper presents a full-fledged system for Predictive Maintenance (PdM) of autonomous vehicle fleets.[1] Our realisitic data collection setup is aimed at gaining insights into the characterization of a pneumatic braking system. We begin by discussing a system to collect real and synthetic data for model development, as well as a method for bringing in new data points. Next, we discuss the specifics of our data collection setup before introducing and dissecting a dataset. It is pertinent to note that all data were collected within the constraints of a university campus, i.e., they are not “roadworthy.” Rather, they are meant to serve as an initial dataset to real-world application of predictive maintenance techniques for a pneumatic braking system. We envision that future work will work towards identifying which patterns can be detected, which part of our predictive model requires improvement, and that similar techniques may be effective in other time-series data prediction problems.

4. Supervised Learning Techniques for Predictive Maintenance

The opportunities for cost-savings and increased fleet up-time have sparked interest from autonomous mobility operators in integrating predictive maintenance as part of the fleet management systems [5]. First case discussions for using big data, machine learning and predictive maintenance for automotive electronics go back at least to 2016. Prototypes such as the VW Maintenance App from 2017 have indicated that for the connected car of the future, the vehicle health will be monitored and timely maintenance decisions are being made in cloud based data centers. In addition for electric vehicles (EV’s), operating similar to relatively traditional consumer electronics, predictive maintenance provides a key competitive edge that integrates powertrain and battery health [6].

Machine Learning (ML) techniques are widely used for vehicle health condition monitoring and predictive maintenance [7]. Interrogative and analytical methods can be classified into unsupervised and supervised learning techniques. The unsupervised learning methods already used include k-means (unsupervised clustering algorithm), hierarchical clustering (Agglomerative and Divisive Clustering methods), and anomaly detection. Supervised learning methods like simple linear regression, polynomial regression, multiple regressions, decision trees (CART), and random forests have been used. According to different learning methods, the predictive maintenance has been classified as regression and classification oriented predictive maintenance.

5. Unsupervised Learning Techniques for Anomaly Detection

As mentioned earlier, the main aim of an UNS PN algorithm is to segregate normal operating conditions from potentially anomalous ones. However, two separate approaches can be utilized to solve this general problem; in the first category, we have models that are able to learn efficiently from raw sensor data about the operating conditions, while in the second approach, these models require well-defined features or a set of handcrafted rules that distinguish well between normal operations and anomalies, before further processing can occur. Apart from traditional methods like GMM, Isolation Forest, KDE, etc., PSO has also been efficiently utilized in UDTW E passenger vehicle battery-industrial battery hybrid vehicle [8].

The unsupervised learning process in Predictive Maintenance is generally referred to as anomaly detection, in which time-series data patterns are modelled under normal (non-faulty) situations and any deviation in new data is labelled anomal [9], [10]. Anomaly detection is usually performed using time-series data obtained from various sensors deployed in real-time monitoring systems (TRMS) while the assets are operating under working conditions. Various methods such as Gaussian Mixture Model (GMM) 20, Isolation Forest (IF) 21, Kernel Density Estimation (KDE) 22, among others, have been proposed in the literature to solve the anomaly detection problem. One such common anomaly detection method is one-class SVM, widely used in the domain of PdM to isolate patterns that are vastly different from what the real-world machine data is perceived to be.

6. Reinforcement Learning for Optimal Maintenance Scheduling

We are aware of the potential benefits of clustering-based maintenance strategies, such as avoiding the sudden breakdown of components, minimizing failures, and maintaining a desired level of system reliability and availability. In our study, we consider repairable systems that can resume their tasks after maintenance as well and are subject to stochastic deterioration processes causing the system to perform its held tasks imperfectly with continuous degradation. The semi-Markov decision process model is provided for the dynamic scheduling of tasks in a transportation system. Recurrence intervals for the system intended to complete the task before it turns into a nonfunctional state are investigated. Meanwhile, in addition to the failures, some partial failures are considered in the environment. A simple clustering algorithm is used to cluster partial failures, and the number of required spare parts considered in the simulation is minimized. The different scheduling process based on occurrences of partial failures about single and multiple threshold values observed for the system departure potentiality using wear or failure state, respectively. The effect of system failure potentiality on the number of required spare parts is also discussed.

[11] [4] [1]Maintaining vehicle fleets in an operational state is an enduring challenge. Therefore, predictive maintenance models have gained popularity to predict the condition of the vehicle. Predictive maintenance using deep learning to estimate the remaining useful life (RUL) of vehicle components has become essential for vehicle condition and health status prediction. Despite the emergence of several machine learning models for vehicle health prediction, the importance of effective maintenance scheduling based on the RUL prediction results has insufficiently been addressed. In order to overcome the limitatial drawbacks in traditional models, this work developed two variants of the modular architecture with risk analysis including risk-based predictive maintenance model, LSTM model with risk-based decision model. The proposed RUL models using vehicle sensor data have been validated under an industry-provided dataset, achieving superior results. To take action on time and ensure the longevity of vehicle components, predictive models draw attention to future maintenance tasks, providing an estimate of when a specific inspection, repair, and replacement action should be executed. For electric vehicle fleets, apart from the extended use of different types of eco-friendly vehicles, the need for energy-efficient operation, battery condition monitoring, charging station optimization, etc. are also included in automotive predictive maintenance handling. Here, the maximum profit attainable from the vehicle maintenance should be ensured. In contrast to RL, dynamic and irreversible vehicle operations suggest RMD by maximizing the total reward. For a large group of randomly distributed electric vehicle charging stations (ECS) provisioning more than 1.4 million

charging events of various visit types, including the necessity for vehicle maintenance, the actual sensor data over a specific time interval are inspected.

7. Deep Learning for Predictive Maintenance in Autonomous Vehicles

In the paper referred to, authors propose an application of Long Short Term Memory (LSTM) deep learning models in order to predict the Remaining Useful Life (RUL) of lithium-ion LiFePO4 batteries. Thanks to the layered structure, LSTMs can model long spatio-temporal dependencies and are very suited for time series forecasting [12]. They have nowadays gained significant attention from the machine learning community and have been applied to several forecasting problems, like financial time series prediction, speech recognition, signal processing etc. However, to the best of our knowledge reasons that motivate the use of LSTMs in the context of predictive maintenance have never been exhaustively discussed in the literature. For the reasons above, in this paper, in Section 3 LSTMs are studied for predictive maintenance in the domain of batteries prognostics. The architecture, the parameters and hyper-parameters that are specific to this type of models are discussed here [7].

It is well-known in the literature that Deep Learning methods are particularly suitable for solving predictive maintenance problems in case of large amount of signals and data [1]. Another considerable advantage of this classes of models is that they are able to find patterns in time series without any a priori knowledge about the underlying physical phenomena that occur in the system being considered. For these reasons Deep Learning has become one of the mainstream techniques for predictive maintenance in the research area. Furthermore, in the last years, neural network architectures of several types have been proposed and tested and results have been updated in terms of features that characterize these innovative architectures. Deep learning models can be applied in supervised or unsupervised mode. In the first case the model is trained on labeled data which map the input variables into class labels in the context of classification problems. On the other hand, unlabeled data are adopted to train the model in unsupervised mode.

8. Integration of Predictive Maintenance Systems in Fleet Management Platforms

In the modern era, not only diagnostics but also several other maintenance strategies evolved to anticipate and mitigate potential failures. Vehicle diagnostics are part of system-level predictive maintenance (PdM). Though there are many reviews on fault diagnosis, a small number of reviews focus on different architectures and architecture elements required to integrate diagnostics functionalities in fleet management platforms as needed for the Industry 4.0 [10]. We discuss those elements which are relevant to fleet management. The present study takes into account external and internal vehicles' data at the base of multi-layer heterogeneous data fusion. To manage those data streams we consider two tasks: load and initiate the PdM operator's elements such as the PdM agent and manage heterogeneous data sources fields present in the fleet management platform.

Although a recent survey has recognized predictive maintenance (PdM) as a critical feature in a fleet management platform, how to develop and deploy intelligent software applications to benefit from PdM features in an autonomous vehicle fleet, remains an open research issue. The present work presents a PdM-based system designed to tackle faults and associated health degradation in an autonomous vehicle fleet. The closed-loop solution integrates heterogeneous technologies as different kind of classified learning strategies, data-drive maintenance solutions based on statistical learning methods and proven, currently adopted methods to evaluate detect and classify faults in fleets of autonomous vehicles in industrial settings [2]. As machine learning applications to extract useful knowledge from raw data, we consider support vector machines, extreme gradient boosting and neural networks.

9. Case Studies and Real-World Applications

A critical component of autonomous vehicle fleets is predictive maintenance. Importantly, fleets are designed to operate for extended durations, such as 24 h each day. Maintenance is needed to replace safetycritical components when necessary. Scheduled maintenances (e.g., daily inspections) are performed to prevent operational issues that can occur due to damaged components. Scheduled maintenance may be avoided if we can predict component failures. Additionally, predicting component failures will greatly reduce unscheduled maintenance. A fleet of autonomous vehicles present an array of design challenges distinct to autonomous rather than human-operated vehicles, such challenges arise due to the complexity of the environment: potholes, speed-bumps, traffic lights, heavy goods vehicles. Lower marginal costs of operation enable autonomous vehicles to be utilized more extensively. Predicting component failures will consequently reduce the operational costs of self-driving cars. In the long-run, fleet-wide predictive maintenance will scale infrastructure costs down, potentially steering down vehicle fares, enabling progressive electrification of more populous geographic environs. Predictive maintenance models will be vital for achieving and maintaining an effective fleet-wide maintenance strategy—optimally sacrificing vehicle utilization as briefly as possible to conduct replacements. This is an engineering challenge distinct to transitioning from centralized, human-operated motor fleets to decentralized, computer-controlled counterparts. This complex problem represents a significant new opportunity for academia and industry: Predictive maintenance for fleets typically consists of three essential problems: Detecting need for repair from sensor data about vehicle trajectories, identifying the nature of the repair from available vehicle and factory histories, and determining when each vehicle should be scheduled to undergo maintenance. All three problems can be solved using various machine learning methods. Consequently, it is anticipated that predictive maintenance will be an active area of research activity and a core concern for start-ups developing autonomous vehicle fleets in the next decade. [1]

Machine learning methods have become a game-changer in engineering applications. These methods are capable of adapting with the trajectory of time, provide general solution, overcome uncertainty and thus makes us less dependent on the assumptions and no need to develop complex mathematical models [12]. Machine learning methods have been embedded in wide disciplines of applications, to mention such as diagnostic, health monitoring, quality control, financial market prediction, D2D communication systems, pattern recognition and fault prediction models. The awareness and use of time series data has also grown in the recent few years and machine learning by taking time series data inside system improves response, accuracy and dependability of the system. In Tab.1, machine learning category, capabilities and applications of focal area is plotted.

10. Challenges and Future Directions in Predictive Maintenance for Autonomous Vehicle Fleets

The proposal for fleet management systems to be looking for the IoT technology available more broadly. The usage of IoT in vehicles will allow vehicle components to have different sensing functionalities. The predictive maintenance based on IoT data will allow access to the data diagnosis and prognosis methods for vehicles. The data prediction is updated each time new data become available, giving to fleet managers the confidence to predict failures in real scenarios. This opportunity makes IoT a suitable technology for recording necessary information for autonomous vehicle`s maintenance. In this way, the maintenance data would be useful if used within a broader decision-making framework, encompassing simultaneously multiple vehicles including predictive maintenance for hybrid electric vehicles, plug-in hybrid electric vehicle and fuel cell electric vehicle. In short, the most suitable strategy to ensure uninterrupted transport operations is to develop a battery degradation model for hybrid and fully electric vehicles, and evaluate different SOC-based battery management strategies for each vehicle type in different working conditions. This paper presented an intelligent and automated repair strategy for heterogeneous EVs, where they are placed in a dynamic and unpredictable environment, to ensure that they can always be repaired and synchronized in the most suitable time window to ensure the quality of service without interruption. Concluding, the proposed predictive maintenance policy represents a compact framework encompassing the services to be planned and coordinated in a team of multiple vehicles taking intelligent autonomous vehicle fleets into account [13].

The lack of manpower and the highlight of the problem of vehicle overheating in hot weather has to be taken into consideration. Equipment failures and overheating of vehicles is common in extreme environmental conditions. The evaluation of extreme environmental conditions such as extremely hot, extremely cold and rainy will continue to be investigated in our future work for all electric vehicle platforms and fuels including hybrid electric vehicles and their internal combustion engine. Autonomous vehicles are equipped with more sensors to improve security, and their large amount of data would incorporate richer information related to system performances, which provides the chance to collectively analyze the sensor data to deliver servi [...] [1]

11. Conclusion

In this work, we provided a predictive maintenance model for a production industry applying machine learning algorithms on an Italian company of metal manufacturing. In this case, vehicles and engines are crucial devices that can make the business model sink if a breakdown occurs. In particular, the automotive company considered in this work, are characterized by Non-periodic Production Phenomena (NPP) events: these are to be inefficiently handled using traditional maintenance strategies. MLDPM approach, implemented as a general model guiding by the factors of demand and MVLs provided by the company, showed to be a solution that warranties high performance in terms of reducing downtime and increasing safety. The research considered and analyzed so many different bi-objective optimizations by handling many factors and choosing the most relevant ML algorithms for providing predictive maintenance solution at a single asset basis too. The conducted case study managed to provide the offers and limitations provided by such a predictive maintenance general approach in a unique production sector. The selected maintenance strategies capture all the possible repair solutions which are feasible in the resolution of an anticipated failure and allow us to reduce the cumulative financial burden due to future maintenance actions [8].

In the last few decades, machine learning (ML) algorithms started playing a crucial role in the field of predictive maintenance (PdM) [5]. PdM helps to overcome the traditional maintenance strategies, such as regular diagnostic inspections and preventive maintenance. These traditional approaches are often inefficient, costly, and lead to unexpected failures and unplanned maintenance. In this work, we presented a predictive maintenance (PdM) model for a deployment of vehicle fleets using ML algorithms, applied on a European Aerospace company with worldwide recognition. The explore the deployment of vehicle fleets from a genuine automotive company with worldwide recognition. We believe that PdM approaches will address the issues involving irregular usage of vehicles in a proper manner and hence will improve the correlation between criticality and demand. Results also have indicated the significance of exploring optimally all the parameter's sets and selecting the most significant parameters and algorithms in order to build a predictive model will bring. The following contributions are the key success factors of this work [4].

12. References

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