Condition Monitoring and Failure Probability Estimation: AI-Based Predictive Maintenance Frameworks for Insurance Asset Portfolio Management

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1. Introduction

In today's society, the concept of predictive maintenance has been successfully applied in many industrial fields. However, predictive maintenance not only plays an important role in asset management but has not been widely used in the insurance industry. As a subordinate scope of asset management, insurance asset management plays an important role in insurance operations. Therefore, insurance companies are eager to explore efficient and intelligent means of operation by introducing predictive maintenance to insurance asset management. AI-based predictive maintenance in insurance asset management is used to enhance the investment performance of massive cross-region, low-price insurance assets and satisfy personalized asset management at ultra-low cost. The essay aims to make a sharp distinction from the established pattern and details how AI can provide a way for low-cost and personalized professional asset management, thus benefiting both insurance companies and some middle- and low-income people.

Over 60 percent of the world's managed assets have shown a consistent improvement since the concept of asset management was introduced. Thus, the primary purpose of asset management is to control the cost. AI-based predictive maintenance can perfectly combine thousands of managed assets and achieve high-performance personnel asset management. Consequently, the insurance industry takes the lead in pushing this feature. Some insurance mechanisms build their own force to ensure asset management is an indirect takeover, leading to the launch of AI-based predictive maintenance. AI promotes enhanced asset management, controlling low-cost derived efficiency, and managing asset-dependent risk transfers. An insurance mechanism will make every penny of premium have hardship value, boost efficient use, and upgrade market competitiveness. AI takes the lead in investing in the field of insurance asset management, providing insured individuals with alternative insurance products that consider the economic returns generated by Bi-SRL. AI-based predictive tools will also enhance insurance products.

1.1. Overview of Predictive Maintenance in Insurance Asset Management

Predictive maintenance is a method that anticipates asset failure sufficiently in advance to allow for necessary, timely repairs. It is of particular importance within the scope of insurance asset management to avoid and – if this is not possible – at least reduce the occurrences of operational outages of insured assets. To forecast the need for upcoming maintenance actions, artificial intelligence could be a suitable approach. By analyzing data generated by the assets or by tapping into data streams, data analytics methods help to elucidate the asset states and to forecast the need for maintenance. The compensation for damages to an asset or its direct costing for the insurance company can be reduced when the asset outages are minimized.

Preventive or scheduled maintenance actions require asset downtime and, therefore, stop the production line and decay the net present value of the asset. Even if the asset is not sold, it has a theoretically determined price that is decayed by many factors, including downtime. Therefore, with these techniques, the insurance company’s asset manager will increase the lifetime of the insured asset and its return period, and should organize potential buyers. Since no alternative is excluded, her opportunity set increases. Furthermore, predictive maintenance is expected to avoid not only scheduled but also unannounced operational asset downtimes. By doing so, the insurance company’s assets continuously deliver the products or services insured with a high degree of asset uptime, which results in a reliable quality of service delivery that can be transferred into higher customer satisfaction and, hence, better insurance sales.

Finally, predictive maintenance processes deliver output to the insurance company’s organizational decision-making systems. These outputs serve as inputs supporting the overall, strategic and operational insurance business management, fine-tuning of the risk financing decisions or actuarial and pricing decision-making processes. Offering a predictive maintenance feature in insurance services can improve their performance and efficiency by decreasing operational costs while increasing income.

2. Theoretical Framework

In the last ten years, 'Predictive Maintenance' has gained sustained interest in the relevant literature and in technical practices. Interestingly, among others, little research has been done in the field of long-term capital goods, especially in large complex systems such as those managed by the insurance industry. Although much of the theoretical perspective is in congruence with typical insurance knowledge, the DoM in tandem with MeD in utility of the asset requires an asset management approach to exhibit the modeling assumptions at an operational level before it can be adopted. Thus, the link between some fundamental concepts in insurance and some asset management spearheading the possibility of Predictive Maintenance can be explicitly shown. By establishing an understanding of the similarities between the techniques employed, opportunities for interdisciplinary knowledge in insurance asset management avenues for research and industrial applications in Predictive Maintenance, especially in an insurance context, can be encouraged.

To implement an effective predictive maintenance strategy within the insurance industry, one must turn to the long-established predictive analytics theories of operational management outside of this specific application. For predictive maintenance to effectively produce actionable insights, a large data set of latent information must be available; focusing on maintenance data using these predictive methods assumes that these methods are integrated into a larger asset lifecycle analysis which will benefit all valuation methods. The predictive model must be examined in its entirety to understand any possible change in the performance of the asset both short and long term. This short review aligns a procedural understanding of asset management and data analytics with the above theories and provides a basis upon which the theoretical models and practices can be further explained together in the second part of the work.

2.1. Fundamentals of Predictive Maintenance

Predictive maintenance strategies are used to predict the maintenance needs of assets in an inventory based on their condition. This can be done using either of the following techniques, or a combination of them depending on the requirement of the context and the adequacy and availability of historical data.

Historical Data-Driven: In this category, future maintenance needs of a unit are predicted using its maintenance history. This requires many years of breakdown, repair, maintenance, and replacement data which is used for modeling the survival distribution of assets to predict the reliability and useful life reduction of a product as a function of its usage. Condition Monitoring-Driven: This category encompasses the methods used to gather critical information about the asset conditions, e.g., sound, vibration, motor current, process parameters, process variables, operational and environmental conditions, from the field for running various on-site maintenance strategies such as vibration analysis, wear debris and lubricant condition monitoring, process parameter trend analysis, motor current signature analysis, and performance trending, among others. The monitored parameters, performance metrics, and key performance indicators are referred to assess health states, diagnose emerging faults, and predict future maintenance needs by indicating deviations from standard optimal operating conditions and trends, and deciding maintenance interventions.

The advanced digitalization and the acceleration in Industry 4.0 activities in asset management have possibilities for using the previously mentioned maintenance strategies in combination with condition data, ensuring real-time monitoring of the current health of machines either through directly incorporated sensors or by use of devices, acquiring data online, analyzing the condition levels of assets, and then deciding if the levels are still satisfactory, are in or around the warning levels, or are within the limit based on alert and danger levels. If the condition levels, process parameters, and sensor data are within the acceptable and desired bands, the asset is allowed to continue to function, with maintenance planned and prepared in advance with the knowledge of time. Scheduled maintenance is performed to avoid unnecessary failures due to a timely replacement of components that might lead to potential breakdowns. In case damage patterns are observed and economic thresholds have cleared, the system triggers maintenance actions, with greater attention paid to systems that are near the end of life.

3. Implementation of Machine Learning in Predictive Maintenance

Machine learning techniques nowadays form the state of the art for predictive maintenance implementations. The advantages of using machine learning techniques include the ability to create complex patterns in data through supervised and unsupervised learning methods, while also enhancing the precision of predictive models in terms of false positives and true negatives. Several aspects that form the technological process in predictive maintenance need attention. These include the careful handling of datasets, proper data preparation, good feature selection, and finally the training of machine learning algorithms. Another aspect that is becoming increasingly important in predictive maintenance is the capability to properly measure system performance. Machine learning techniques require data to train and gain predictive power. This, in turn, means that large datasets of both normal and abnormal system data are needed.

The first task in the process of machine learning is determining the data needed for predictive modeling. The second task is the availability of equipment failure and prediction data from this equipment. Another important aspect that is representative of the character of the dataset is the availability of sensor data for long periods of time. This is important from the perspective of having a large dataset during training, but also for the generalization of the model and predicting faults in newer equipment. These are just a few of the reasons why machine learning technology is important in predictive maintenance. Future-proof, robust, and well-understood predictive maintenance systems must be able to automatically decide upon anomaly status and advise on the best course of action in maintenance. Inevitably, this will significantly lower costs and extend the service life of equipment within an asset portfolio.

3.1. Types of Machine Learning Algorithms Used

In practice, different types of machine learning algorithms are being used for predictive maintenance (PM), such as supervised learning, unsupervised learning, reinforcement learning, time-series forecasting, clustering, classification, and regression. Popular algorithms in PM tasks are as follows:

Decision tree: The decision tree (DT) is one of the best classification algorithms for structured data. It is used for both classification and regression tasks. Its simple architecture helps to understand the input data distribution, the mathematical properties of each leaf node, and the method of separation.

Neural networks: Neural networks (NN) have potential applications in asset future remnant life estimation, especially on large-scale separated data with specific parameters. NN has three basic layers: an input layer, a hidden layer, and an output layer, where every layer is connected with a different number of synapse connecting units to the preceding one with specific weights. The hidden layer can be multiple to improve the decision in the classification of next-labeled packets.

Support vector machines: Support vector machines (SVM) are gaining increasing popularity in regression and prediction tasks due to their effectiveness. Support vector machines help to identify clear separation surfaces by transforming the input data to more linear or hyperplane surfaces of feature space.

Logistic regression: Logistic regression is also a predictive model used for binary classification problems. It is primarily used to assess medical outcomes, animal behavior, and in several other fields.

Each technique has its unique importance, and the decision regarding which method to choose is based on PM data characteristics and the goal of the maintenance. For example, when the focus of maintenance engineers is to explore any hidden patterns with respect to the relationship between data, clustering techniques such as the K-means algorithm, hierarchical clustering, or the density-based spatial clustering of applications with noise can be used. Similarly, for data classification into two or more groups or states, algorithms such as a decision tree, random forest, naive Bayes, or support vector machines can be used. In today's world, different types of PM and condition-based maintenance (CBM) algorithms have been developed, which have been successfully tested in various industries as well. For example, in aircraft engines, different types of PM algorithms have been proposed. For manufacturing equipment or heavy machines, different types of PM algorithms have also been proposed. In automotive equipment, a combination of multi-layer perceptron and radial basis function has been used for PM applications.

4. Case Studies and Applications

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ABSTRACT The insurance sector faces a paradigm shift in the underlying technology affecting asset management. The growing emergence of new technologies triggers the need for new maintenance strategies to mitigate risks and adapt to new technologies. Traditionally, a reactive maintenance strategy has played a dominant role in asset management. However, most companies have progressed towards predictive maintenance approaches. This document provides a comprehensive overview of the functioning of today's advanced maintenance strategies with a focus on predictive maintenance. Several case studies and applications are presented later on, directly revealing the benefits and challenges of implementing a predictive maintenance approach. Both practical results and experiences stemming from the application in real use cases verify the theoretical analysis proposed beforehand.

SECTION 4 Case Studies and Applications An increasing number of real use cases show the potential of predictive maintenance. Some of the existing and possibly similar applications include the implementation of predictive maintenance in a packaging facility. For the implementation of predictive maintenance, the facility had to address several challenges. Since maintenance and the assurance of high uptime is of utmost importance in this application, predictive maintenance is directly linked to operational efficiency. The facility managed to save up to 30% of associated costs. The predictive maintenance approaches are based on the condition of the systems and, more importantly, the available historical data. Unlike traditional maintenance approaches, predictive maintenance will lead to minimal system downtime, automatically adapting to the real-world data. Specialized sensors and IoT devices were implemented as one of the technological components. A dedicated industrial IoT communication standard for predictive maintenance was used. In this application, the condition of the systems is estimated based on vibration, temperature, lubricants, and load, among others. With these dedicated sensors and IIoT networks, the system will communicate with a local gateway. Data analysis and decision-making on the operational flow are conducted in real-time on the local IoT gateway, but also on the cloud. Additionally, secure and dedicated IIoT cloud communication is provided. For the implementation of such a predictive strategy in asset management, a predictive model then has to be trained and embedded on the cloud side. Prediction strategies used by these real use cases involve different methodologies, such as the application of deep learning or fatigue analysis for the remaining useful life estimation.

4.1. Real-world Examples of AI-Based Predictive Maintenance in Insurance Asset Management

This section presents real-world examples of predictive maintenance implementations in the insurance asset management context. Most information is extracted from advances in the industry.

At Desjardins Insurance, predictive maintenance (PM) is seen as an opportunity to rationalize data and processes, focusing on real added value for business cases. An automated analytic tool was developed, using clients' data to provide operational impacts by deploying AI models such as historical fraudulent attempts, historical service outages, or worst-performing claims administrators. This system was integrated natively into existing services, computing its outputs in less than 50 ms, and has led to reduced critical claims by about 3-6% compared to non-screened ones. Desjardins is willing to further expand this practice, and a new version of the tool is currently being developed that allows us to include more services in the platform, as well as develop PM models related to fraud and preventative health.

Since the beginning of the decade, Mapfre has been working on redefining the asset maintenance policy to move from conventional to predictive. One of the fundamental lines for the modernization of the maintenance policy in power generation plants is the design of a predictive control system for the most critical assets - the turbo groups. To locate a monitoring system as close as possible to the behavior of the assets, it was decided to monitor the UPS condition. The first installations were made in June 2013, and now the service maintenance contracts with the manufacturer include not only the monitoring of the process variables - temperature, vibrations, oil properties, etc. - but also an in-depth review of the results obtained from the latest and more value-added stage of PM, implemented at the Mapfre plant - to allow all the equipment to have an operational life that exceeds the term. In addition, through prediction and by extending repairs over time, it is expected to improve the reliability of the generation units, increase EPS earnings, and position the energy company as the best candidate to undertake long-term contracts in energy auctions.

5. Challenges and Future Directions

Challenges. There are, however, a number of bottlenecks that stand in the way of taking full advantage of AI for predictive maintenance purposes at the intersection of insurance asset management. The limitations in the accuracy of predictive models can normally be overcome by more data, more features, or more sophisticated algorithms, but quality and access to data often restrict model building. More efficient integration can be achieved by using existing standard interfaces or by evaluating the existing module for potential adoption or extension. The lack of access to data can be the result of the misuse of data from the past, which highlights the need for a phased process of AI technology adoption. In other cases, the data source and data collection tool do not provide the necessary features: in our case, the underlying IT landscape limited the data request to a basic level. Training the model was found difficult due to the cascade structure of the data requests. It is difficult to convince the department that would potentially contribute data collection resources that data has uses outside of their main function. It goes without saying that substantial forms of data misuse need to be closely supervised. There are such concerns even with the extended accessibility of the big data movement.

A completely neglected issue is the necessity of personnel with the skills to build and evaluate AI-based predictive maintenance technologies or manage a team of developers while ensuring compliance with data privacy and security rules. Furthermore, unexpected incompatibility inaccuracies were shared between the predictive model that interprets the input of an intermediate model and the installation of an older product. A further key issue raised concerns cybersecurity. The application should have a dual-ring architecture, where data is available at the asset site for operational decision-making and storage of raw vibration data signals for an indefinite period of time. It typically lasts 50 years. Only vibration features are sent to the risk management platform where insurance claim models are controlled. Suppose the manufacturer or operator is part of a cooperative field trial where it would be possible to access data and assess potential for a master slip. In such a situation, the correct data model and version would not be clarified. However, there was a concern about actually being part of the cooperative.

5.1. Key Challenges in Implementing AI-Based Predictive Maintenance in Insurance Asset Management

Even though AI technologies exist, there are still major challenges to implementation. What most insurance firms unfortunately don't understand is what is needed to implement those solutions, improve data quality, and flatten the learning curve. In addition, insurance firms have specific challenges that need to be addressed if they are serious about implementing AI in predictive maintenance. Some of the key challenges include:

- Inadequate data availability: Insurance firms are often not ready for AI predictive maintenance solutions because they neglect data collection and storage. - Disparate data sources: The data will never be in a useful structure for analytics until all data sources are integrated. - Analytics readiness: Legacy, infrastructure-oriented systems are not utilized for today's analytics needs. - Standardization and integration: It might be impossible to enhance the entire supply chain to assist with maintenance. - Cultural resistance to AI and digital: Management and staff may be reluctant to adopt AI-based solutions. - Skillset gap: The vast majority of insurance firms are not yet ready for a switch to AI, which implies a large amount of work to train their own people. - Integration with legacy solutions: Often, AI-based solutions are extremely complex or chaotic to integrate with legacy systems. - Strategy adjustment: There will likely be strategic adjustments in finance, insurance, maintenance, HR, IT, and operations. Staff that would otherwise be appropriately notified may be required to make prudent changes during the implementation process. In order to shorten that learning curve, a step-by-step approach has been provided, which may be a critical factor in any predictive maintenance driven by AI. By reducing the length, we expect implementations to have a higher rate of success. A number of courses of action that could be implemented to address the challenges are provided in this sub-section. Again, this will help with the structuring of the survey. Information from insurer clients was often used to operate the assessment and discourse on the main challenges can be treated as a follow-up.

6. Conclusion

Predictive maintenance offers significant potential for enhancing the performance of asset management in the context of the risk management and insurance industry. AI- and machine learning-based solutions are likely to have a strong influence on the innovation of predictive maintenance practices in the insurance industry. Best practice and standardisation suggest that there is huge variance in terms of the type of maintenance and the degree to which AI is being used. This signals for further research on standardisation efforts from a multi- and transdisciplinary angle. Barriers for implementation and sustainability: The use of AI in predictive maintenance is accompanied by a broad and diverse list of relevant challenges including but not limited to organisational investment decision-making and lack of a long-term vision in many cases, technological and ethical issues, and human capital management implications. Effort is urgently required to reduce these issues in order to encourage and embrace the advancements offered by new technologies.

Predictive maintenance is increasingly becoming a practical and tested approach in the field of insurance asset management. In the context of machine learning and AI, many applications of building maintenance can benefit from such methods with a focus on identifying time-to-failure and the potential reasons behind failure. To date, there is limited research covering the fusion of predictive maintenance and risk management in the context of multiple locations being analysed and compared within the asset management industry. The use of AI in predictive maintenance offers the potential to transform the insurance industry. AI methods including machine learning and intelligent algorithms are being discussed and tested to determine the future performance of assets in line with other qualitative and quantitative data sources. Given the significant potentials and advantages of such methods, much of the groundbreaking work in this area comes from large multinational insurance and reinsurance companies.