Condition-Based Asset Monitoring in Logistics Infrastructure: Deep Learning Models for Predictive Failure Analysis in Retail Supply Networks

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1. Introduction

In today's dynamic markets, retail supply chain organizations face multiple challenges to optimize their operations and processes. These challenges may account for up to a third of the costs of final products in markets where margins are particularly tight, reducing the ability to lower customer prices or invest in other initiatives to remain competitive. This paper introduces an innovative solution, predictive maintenance, as a strategic initiative to enhance operational efficiencies and reduce supply chain costs. In this paper, we describe some current retail supply chains and their challenges before discussing the solution, predictive maintenance. A shopping app use case is also introduced that builds a common use predictive maintenance scenario in retail based on historical transactions as well as weather and calendar feeds. Our solutions utilize reinforcement learning-based recommender systems in predictive maintenance applications.

In today's world, organizations across various industries are transforming their traditional supply chains into intelligent, integrated digital supply networks. The retail industry, characterized by intense competition, is embracing emerging technologies to optimize operations, improve customer experiences, and achieve unique industry-wide solutions. The topic of predictive maintenance is especially exciting and relevant in the retail context to drive margins and optimize last-mile delivery of goods. In this paper, we introduce the concept of predictive maintenance in retail and discuss an end-to-end solution that leverages historical transactions, weather data, and calendar data for supermarket shelves and lighting. Our solution can generate store heatmaps that can be an input to fine-tune the replenishment of goods in a supermarket. We also present real-time use cases that sit in an app, providing recommendations on what has the longest shelf life that can be bought now. Our solution has the potential to be a differentiating factor for organizations in the commerce sector.

1.1. Background and Significance of Predictive Maintenance in Retail Supply Chains

Given its relatively new introduction, predictive maintenance is not yet well researched in the retail supply chain context. However, predictive maintenance has been around for many years in manufacturing and other fields. It stems from the evolution of maintenance practices such as reactive and preventive maintenance. Starting from the reactive approach to maintenance, in the form of run-to-failure maintenance, which leads to production stoppage, operational inefficiencies, and high corrective maintenance costs. Predictive maintenance seeks to eliminate these performance obstacles by detecting asset failure with real-time data collection and advanced analytics. The importance of predictive maintenance increases with the complexities of supply chain activities along with different methods of stocking and selling inventory. It is particularly important in the retail supply chain as the competition becomes more intense, and the demand increasingly relies on efficient and effective product delivery. An increasing number of consumers demand faster product fulfillment, further pressuring the use of predictive maintenance for its real-time output in dealing with failures during the product delivery process. In the retail industry, the application of predictive maintenance technologies translates to monitoring shelf inventory and ensuring accurate stock levels on time for consumers.

In predictive maintenance systems, the integration of operational performance metrics derivatives is necessary to maximize their benefits in the retail supply chain. Predictive maintenance's contribution is a course-level activity and an enabler of tracking selected operational performance metrics and, subject to optimal conditions, could significantly impact supply chain performance metrics. The prerequisite for such an impact is the assumption that supply chain operations and the failure conditions are stochastic in nature. Predictive maintenance promises many economic and technical benefits through reduced downtime and eventually decreased future maintenance and operation costs together with smoother operations leading to more production and improving customer satisfaction. Despite these benefits, the applicability of predictive maintenance digital solutions in the retail industry is frequently perceived as a complex model to implement successfully, due to the combination of human and machine interactions. Furthermore, research evidence has demonstrated a lack of training and a shortage of experienced analytics in the retail industry, particularly human skills to deal with predictive maintenance barriers.

2. Overview of Predictive Maintenance

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§ 2 Overview of Predictive Maintenance With the proliferation of data from numerous industrial settings, it has become increasingly affordable and easy to prognose system failures based on data. Predictive maintenance is a related strategy to avoid expensive corrective maintenance, infrequent inspections as in a reactive maintenance setup, and scheduled but perhaps unnecessary or excessive maintenance operations as in preventive maintenance. A predictive maintenance setup aims at forecasting when an item will fail and accordingly performing maintenance operations. Predictive maintenance has further differentiated itself from other types of maintenance, including such options as preventive maintenance (when maintenance is purely scheduled based on time or usage), corrective maintenance (repair performed after a system fault is detected), on-condition maintenance (repair performed after wear is recognized), and their various combinations. Predictive maintenance setups feature data-driven estimation of when equipment might fail and lead time for maintenance, respectively, by leveraging predictive analytics and monitoring of asset states potentially using AI-based learning techniques.

Predictive maintenance has likewise been widely used in many application examples, such as the processing industries, automotive, technology industry, pharmaceuticals, aviation, building services, transportation, agriculture, and the energy sector. The appealing advantages of predictive maintenance have contributed to its being commonly used in many industry sectors. The rapid decrease in costs for sensors and digital data storage has also contributed to the strong trend towards predictive maintenance. Demanding maintenance policies and methodologies can aid in optimizing the operations of modern complex production and distribution systems. Retail supply chains are an example of such systems, where large amounts of data are continuously gathered. E-commerce players are also increasingly relying on predictive maintenance along the retail supply chains and have invested in advanced predictive maintenance. In practice, IoT sensors commonly form the core infrastructure of predictive maintenance practices as they are widely used to record various process data including temperature, humidity, pressure, load, flow conditions, and vibrations as part of production units or at the storage and transportation equipment.

2.1. Definition and Concepts

This subsection is dedicated to the definitions and concepts that are considered the frame of reference for predictive maintenance. Predictive maintenance is a proactive maintenance strategy based on data analysis. Predictive maintenance can be defined as the process of monitoring the condition of equipment and using data analysis to predict equipment failures. Predictive maintenance has traditionally focused on two elements: condition monitoring and risk assessment. Condition monitoring is used to collect and observe data about an item—either remotely or locally—in order to determine its health state.

Predictive algorithms and models are used to define the potential failure modes and failure patterns of equipment. These can be simple limits, data processing, pattern recognition, statistics, time and frequency domain analysis, physical models, and hybrid models. Methods should be selected based on the availability of technological data capture options, preferred observation and failure monitoring strategy, ease of implementation and maintenance, and cost. Key to a successful implementation of predictive maintenance is the ability to gather critical and sufficient data in order to progress with a meaningful analysis plan. Equipment health indicators, as the output of the data analysis, are directly related to the decision on the need to carry out maintenance. Data evidence of failure through erroneous maintenance decision-making will either severely increase costs by increasing spare parts inventories or will directly affect the operational schedule. These ever-changing conditions highlight the necessity of a new level of predictive maintenance for the supply chain with the ability to involve a broader base of information in the decision-making process in a collaborative and cross-functional manner.

2.2. Types of Predictive Maintenance

Predictive maintenance is generally categorized into several subtypes. The most prominent distinction is between different types of maintenance, for instance, condition-based maintenance, time-based maintenance, or reliability-centered maintenance. Other distinctions are made according to the parts of the asset being monitored or different levels of predictive maintenance, such as classes of anomalies or machine failure predictions. Although a complex domain, three main predictive maintenance types are identified. The categories of predictive maintenance are likely to coincide with an organization's maintenance management strategy. The key categories for predictive maintenance are as follows: condition-based maintenance, reliability-centered maintenance, and performance-based logistics.

Condition-based maintenance aims at monitoring actual equipment condition and machinery parameters in real-time and taking maintenance decisions based upon acquired diagnostic data. A selection of typical retail supply chain use cases includes the monitoring of the state of equipment and battery-operated machinery or ground power units. Furthermore, transaction logs of mobile base-station failures have been utilized for fault detection and root cause analysis of mobile telecommunications equipment unscheduled maintenance, working with more than 1 terabyte of data. Condition-based maintenance is used in improving retailer uptime reliability and availability of stock. The retailer hardware failure rate has been found to drop by 45% as a result of predictive analytics. RFID located on retail store shelves to monitor stock-level condition and trigger a full vehicle reordering of stock was a novel attempt at supply chain condition-based maintenance. Reliability-centered maintenance operations focus on the performance of actual assets and take decisions considering overall life cycle and scheduling of maintenance procedures. Reliability-centered maintenance is not conducive to retail stores, since the assets managed are generally inexpensive. The choice between the predictive maintenance types requires the supply chain maintainer to consider management and engineering goals and be familiar with risk, cost, and resource availability. For predictive maintenance to be applied cost-effectively and within resource constraints, the business strategy of the enterprise may limit applicability. The following factors can affect such decisions: the degree of partnership between manufacturers and retailers in fostering centralized alliances and B2B systems.

3. AI and Machine Learning in Predictive Maintenance

The value of predictive maintenance strategies is greatly increased with the support of artificial intelligence and machine learning. These technologies specialize in data-driven decision-making, used to assess and determine appropriate maintenance actions in conjunction with predictive maintenance. AI encompasses various methods that encourage machines to mimic different human behavioral traits, while ML is the field of AI that allows computer systems to learn from data in order to produce patterns and insights. As the amount of data collected by IoT devices and utilized by predictive maintenance strategies continues to grow, AI and ML are crucial in making sense of the data and ensuring that maintenance decisions are as accurate and opportune as possible.

Applying AI and ML methodologies to predictive maintenance strategies has the potential to improve their accuracy and predictive ability, as they can consider vast amounts of data from various devices. AI methods can bring a new dynamic to predictive maintenance in retail supply chains. AI-based algorithms can utilize the data from IoT devices at a hyper-granular level, allowing them to understand, predict, and optimize the performance of any connected device within an organization. It is a complex platform that analyzes large and complex data sets to reveal patterns and insights in real time. There are two main applications of AI in retail supply chains, namely demand and performance optimization, as well as financial modeling and prediction. Connecting AI with sensor technology enables it to give users more detailed insights faster. However, AI can be complex and is often known for not being compatible with traditional sensor equipment. AI is incredibly effective in this field because it can handle large data volumes and make decisions quickly. Finally, the typical challenge with integrating AI into current systems is the perceived high cost and resistance to change from internal teams. AI can be a decisive factor in organizations moving from a reactive to a preventative predictive maintenance strategy.

3.1. Fundamentals of AI and Machine Learning

Artificial Intelligence (AI) has been around since the mid-20th century and has experienced several hypes, followed by funding booms and winters. Machine Learning (ML) is a subfield of AI, utilizing algorithms for data analysis and decision-making. ML can be divided into three approaches: supervised learning, unsupervised learning, and reinforcement learning. In supervised learning, an AI model is trained using a curated and well-defined dataset, consisting of input/output pairs. The learning algorithm will conduct an optimization process to find model parameters that minimize a predefined cost function. This is done by showing the algorithm the desired result for a given set of inputs. After this training process, the model's performance is tested and validated with a hold-out dataset. If the resulting performance is satisfactory, the model can be applied to new data for which the output target is still unknown.

The model is then updated periodically as more data become available to keep up its generalization capabilities. Applied to big data, these AI technologies lead to innovative business capabilities. In traditional software programming, an engineer follows a list of instructions, telling the machine what to do with input data, and the machine processes it to produce the desired output. However, with the development of AI, the computer can learn how to do this task by itself. State-of-the-art industry applications include superior visual shape recognition, identifying natural language and topics, as well as decision-making. These AI-based software programs are being used in a variety of industries: internet-based services, retailing, banking, and medicine. The quality and quantity of training data are crucial for any machine learning technique to work properly. A model trained on high-quality data will result in higher, more precise outputs. Moreover, additional inputs lead to better, more reliable results for traditional AI models such as linear regression. In the following, we explain some of the main ML paradigms currently studied. For traditional AI models, feature engineering is a crucial step to create a data representation that is intuitive and interpretable for the model. Deep Learning (DL) or neural networks, as a subfield of ML, can learn meaningful features automatically when provided with sufficient data. If the model has the right architecture, it can then extract salient features from high-dimensional data for predictive tasks. Therefore, DL models lend themselves well to large datasets involving complex and high-volume variable interactions. For large input dimensions, a common approach is to use feature extraction models, combined with output layers that are capable of learning the final prediction model. Other ML methodologies for large datasets include tree-based approaches, mainly used for classification or regression problems considering both numerical and categorical predictors. With tree-based models, decision paths are reasoned, revealing high model interpretability. Nonetheless, tree-based models might require special preprocessing for predicting on future datasets.

3.2. Applications in Predictive Maintenance

Predictive maintenance, a highly anticipated application domain of AI, is already utilized by companies all over the globe. It addresses the issue of timely maintenance planning, going beyond rule-based classifications and attaching more intelligent insights. Modern toolsets used by data-driven companies can explore historical data on machine maintenance, assess the average time between repairs or component replacements, and identify the timing for preventive actions. By monitoring conditions, an AI algorithm can determine whether a sudden failure may occur or if component wear has already exceeded acceptable levels.

In heavy industry, AI pays off in condition monitoring. If an algorithm notices that a particular machine part has begun to overheat, it can signal the need for human maintenance. Similar issues have been successfully addressed in the automotive industry, mining, and companies operating large distribution centers for consumer goods. Here, retailers utilize AI for predictive maintenance, not just on a machine level, but also to improve supply chain operations. Maintenance of conveyor belts, for instance, plays a significant role in ensuring timely deliveries in the environment of smart logistics. An elongation of just a fraction of an inch is predictive of a potential breakdown, and intelligent algorithms know that, enabling those big companies to act in advance. In doing so, they can prevent their conveyor belts—in sum spanning hundreds or thousands of miles—from seizing function. Different nodes of a retail supply chain also rely on predictive maintenance techniques, especially in the realm of smart inventory and warehouse management. Retail shelves resupplied only when needed can be of a fragile nature. Optimal inventory is thus an outcome of predictive analytics and machine learning-based predictions. Thanks to accurate forecasts, employees no longer waste time on unnecessary shelf refills, and the publicly demanded item is always in stock.

Getting maintenance policy right is crucial, both on the machine level and for the supply chain as a whole. AI can make logistics more efficient by optimizing the scheduling of maintenance interventions. Operations restart on time after slight equipment errors prompted by preventive fixes. By incorporating fleet management into the game, joint maintenance policy-making can even reduce immediate maintenance costs while adjusting the system to overall requirements. This way, AI does not only increase engineering reliability; it also reduces storage costs and ensures inventory can always be replenished as scheduled. Additionally, predictive algorithms support the management of backup fleets and inventories in the case of unexpected interferences, saving costs for safety measures. AI helps predict the timing of interventions in products and machines, but also moods: supermarkets are aware that consumers tend to restock fridges and cellars of their homes with water and food if a heatwave is in the air. Supply solutions can be sketched for hot spells and cold spells way in advance with predictive analytics—this also is a predictive maintenance application.

4. Implementing Predictive Maintenance in Retail Supply Chains

Many steps are necessary to create predictive maintenance for the retail supply chain based on AI. It is advisable to approach this development in a structured manner because each step, from data collection to software integration, forms a promise for success. A successful implementation of predictive maintenance has to start with systematically asking the question of what the business need for predictive maintenance is in order to drive the process. Once the question is answered sufficiently, the data collection and data preparation process can be started. This step creates the foundations for any subsequent work, as it dictates the ensuing outcomes for our predictive maintenance.

The first organizational phase concerns the collection and storage of the necessary data, which has to be channeled into data pipelines, streams, and storage systems. The second phase focuses on data and the corresponding data cleansing. If no proper data cleansing strategy is implemented, the subsequent model training will be affected if, for example, too many outliers need to be cut from the model as they have not been imputed. The next step comprises the development of the predictive maintenance model and the collection and furnishing of sufficient high-quality data that may include failing parts and the corresponding onset of specific system conditions, as well as a clean database to train on. After model development and extensive validation and testing, the last phase entails the integration of predictive maintenance, leveraging existing software and workflows to apply exactly the model that has been developed in day-to-day operations. This always represents a challenge, especially in well-established organizations, as the reliance on manually executed inspections by expert users may be great and the acceptance of new systems critical. This requires time and a change in mindset, which can often stand in the way of predictive maintenance.

4.1. Data Collection and Preparation

Combining predictive analytics and maintenance in retail supply chains empowers organizations to operate an even more cost-efficient and responsive supply chain.

Nevertheless, these advantages can only be gained if the organization is able to gather, store, and prepare the necessary data accordingly. First, data of the corresponding equipment needs to be collected. Second, data of older equipment needs to be provided. In particular, maintenance and repair work carried out in the past are required. Third, configuration-relevant parameters were gathered. These data sources can typically be found in sensor datasets, historical records, and more advanced maintenance logs. Data should be accurate, reliable, comprehensive, continuous, and of high frequency. Before the collected data can be analyzed, it has to be cleansed, transformed, and validated to guarantee that the data used for training models actually represents reality. The automated acquisition of the necessary data can serve as a motivation to implement predictive maintenance in retail stores.

Data collection must align with the organization's objectives and strategy. Especially, the question of what information is required to solve the organizational matter in the context of maintenance-related problems should be addressed. Subsequently, there may be organizational matters that the organization is not willing to address but that might be best tackled with predictive maintenance. In such cases, the results of predictive maintenance might not be guaranteed to create value for the organization. Data acquisition also plays a crucial role when it comes to compliance enforcement, especially when data from external sources is taken into consideration. The organization should investigate all involved parties that can guarantee data compliance. In addition to one-off data acquisition, ensuring privacy through, for example, obfuscation or anonymization is just as important, especially in edge case scenarios.

4.2. Model Development and Training

The repetitive construction of a model, training, validation, and evaluation are significant parts of developing predictive maintenance models. There are many different useful algorithms for constructing this type of model. When selecting an algorithm, it is crucial to consider some background requirements such as large datasets with different components of variance. Even if some of the available predictive algorithms should be used carefully, they provide powerful tools for predictive maintenance of systems and supply chains. The choice of model development techniques is heavily affected by the training dataset's size and diversity. Validation of the model is an extensive process that highly depends on the training data used and the performance metrics to ascertain.

Model evaluation and performance metrics. There are many different ways to determine if a model is effective at identifying and predicting different machinery and system failures. In the predictive maintenance literature, there are various performance metrics used to assess model performance, but the most common metrics are precision and recall. When the model is validated, it is crucial to observe the sensitivity or recall of the models. Predictive maintenance is an iterative process, so the model is trained on historical data, but as we collect new data, the models will be improved in order to respond to the changing equipment or system conditions more effectively. Building models in supply chains and retail will involve system information from the people who operate the system and the data generated from this system. This means cross-functional teams need to be set up to consider the built models overall and provide a complete system overview. Scoping of the project will, therefore, involve multiple domains including data science, retail, and operations in the development and training of predictive maintenance models to ensure the sustainability of the models post-project.

4.3. Integration with Existing Systems

Predictive maintenance is currently being adopted by some retail supply chain companies, often through partnering with specialist AI value providers or technology experts. Critical to this is the need to be compatible with service providers, retail and other proprietary source control solutions, and enterprise resource platforms. Given the increasing investment in such systems, it is essential for predictive maintenance tools to be able to operate within these systems for a secure and efficient operation. Furthermore, only by being embedded within these tools can the full value of predictive maintenance —particularly interoperability with parallel digital technologies—be fully leveraged.

Wariness surrounding dismantling or replacing large, difficult-to-deploy systems arises as an organizational challenge. Users are also resistant to employing systems that require them to change their established practices. Mitigating such concerns takes a concerted change management strategy. Furthermore, a system's seamless integration potential must also be factored into the choice. The development of AI tools that can operate both within proprietary supply chain and operating systems and potentially as independent systems can thus warrant the highest level of potential users. The addition of middleware can also render the flow of predictive maintenance platform data unobtrusive to existing operating systems. They also do single system may prevent the segregation of proprietary and retail-controlled information.

Gradual integration is often considered a low-risk strategy since it can be rolled out with little disruption and allows for increasing value realization. A real-time, single-database solution sees a company waiting for an enterprise to integrate predictive maintenance into their system. The advantage of this approach is that it allows highly effective predictive actions to be taken. This is in contrast to integration across multiple systems—a costly, slow, but flexible approach—or as an add-on, which is low-cost and can offer quick wins, but can be organizationally more disruptive. Techniques for such integration and value analysis incorporate a live case study demonstrating the successful implementation of predictive maintenance into a complex retail supply chain industry. In this way, strategic integration of predictive maintenance with existing retail supply chain systems is a crucial aspect to ensure the full range of benefits from predictive maintenance is experienced.

5. Case Studies and Success Stories

In this section, we want to provide a collection of case studies and success stories where predictive maintenance has illustrated spectacular applications at the operational level. We aim to present a variety of use cases from various industries and visions, aiming to show how predictive maintenance can be applied.

1.1 Overview In this section, we present three case studies as a perspective to show that predictive maintenance and predictive asset strategies, more generally, are widely applicable across asset portfolios. They can provide value in various industries, from utility-scale assets to small engineering systems like manufacturing and retail. Herein, we demonstrate how, in an emerging predictive maintenance application, physical principles and stakeholders' knowledge can be used to create domain knowledge-based models that underpin AI, thereby providing significantly enhanced predictive value. Lastly, we discuss how one customer is successfully operationalizing insights derived from machine operational data collected via a live operational platform, initially focusing on pump systems and compressor engines that they deploy in the field.

2. First Solar Case Study First Solar is a leading manufacturer and provider of solar energy solutions. In this use case, data from four years of performance and revenue data

for over a dozen utility-scale solar farms was anonymized and aggregated to produce machine-learning algorithms to predict the total revenue of the asset over the preceding year. The revenue data was not directly used for training; only data that the owner or operator has immediate access to, such as weather data, was used. The models, including random forests, gradient-boosted machines, and artificial neural networks, were trained on the Coefficient of Determination and explained feature variance, which was the maximum combined score of a validation set of half-hourly data.

3. Cetin Case Study Cetin engaged our services in the design and development phase of creating an AI-based product forecast tool. As Circuit Breaker Specialists in EMT, they aimed to model the 'healthy' and 'off-health' regimes of their circuit breakers in order to enable 'condition-based maintenance' for end-users. This could materialize as the sale or rental of their electrical assets, with a subscription-based service. This EMT expertise was used in feature engineering for their AI algorithms. The company has a prototype ready and is currently traversing the anatomy of their economic model. Analysis of this case yields detailed requirements of what data, how, and why it needs to be processed, noting the data stream through the system and how AI has been trained. A variety of actionable outcomes are also presented for implementation, including best practices. Insights into how the project was operationalized illuminate readiness considerations for capacity, IT systems, and communications ahead of a full-scale project. This work presents an increased understanding of where data is collected 'in the wild,' revealing issues with the capture of data and allowing meaningful discussions with software providers to address such limitations. Full practical implementation of the AI tool is being planned for June 2021. The pilot project relates to pump systems, including electric motors, and is expanding the scope to include compressor engines, which are also undergoing installation for testing and further AI learning.

5.1. Real-world Examples of Predictive Maintenance in Retail Supply Chains

Several examples demonstrate the reference to real-world examples of predictive maintenance in retail supply chains. Each use case has been described in detail, focusing on the main challenges of the company, the implemented solution, and the achieved results. One notable challenge in retail supply chains is the fluctuation in demand. A real-time inventory management platform was developed to operationalize predictive maintenance at a retail company. It improves the hardware operational uptime of the robot picking system and adds customer value by enabling fully automated replenishment. The operational uptime of the stacker is also improved. More importantly, the platform enforces the synchronization of essential data that provides input to batch allocation, optimizing travel paths in the supply chain. An indispensable side effect of this optimization is a significant improvement in the streamlined use of space in the warehouse.

A European clothing retailer aimed to respond to these challenges by optimizing a distribution center equipped with automated tilt tray and conveyor sortation. The center is responsible for handling both incoming goods and outbound garment orders for assignments to various retail stores. The retailer analyzed the constraints of the equipment, which were broken down into the three primary failure states and the individual distributions associated with each failure state. In collaboration with the remaining life distribution, a quantitative risk calculation and the remaining lifetime prediction model were developed. The remaining life expectancy of the two service paths in the sorter was continuously updated. Concerning a lot acceptance strategy, the perishability of the assignment was taken into account. The results have shown a total cost reduction resulting in substantial profit increase due to predictive maintenance implementation. Furthermore, the results are discussed in the context of the operational impact and risks arising from the penetration of predictive maintenance decisions at the business and tactical level. In summary, the clothing retailer is now functional as desired, which enables the steering of the business and tactical goals. The most important benefits derived in this case from risk reduction included the prediction of the percentage out of service of the system supplying the clothing retailer, reduction of the utilization time of the out-of-service system that also guarantees the availability of the system supply, and the prediction of the remaining useful life of the split-tray and pusher system. These predictions impact the overall performance of the clothing retailer and assure a smooth operation within the operational domain. A main obstacle was overcome in the shape of the convergence of the maximum likelihood estimation method. The financial and operational drivers for predictive maintenance strategy specifications are taken into account. In this work, it is shown that one can use a model to optimize the maximum average revenue over time for different maintenance strategies. Based on that, production is now proactively put out of service and maintained, working towards an operational cost reduction and life cycle cost reduction over four years.

6. Future Direction

The latest up-and-coming item within the retail supply chain configuration is edge AI, data analytics, and smart systems designed to enhance predictive capability and facilitate better decision-making. Moving forward, it is pivotal to develop systems that integrate machine learning and AI to carry out predictive maintenance. Such a system has yet to be developed to its full potential, leaving a lurking possibility of innovation. The use of powerful forecasting can help in predicting shop sales, buyer trends, and transportation requirements that are suitable for reducing delivery irregularities and improving the overall experience of the customer. IoT and technology that is edge-based to handle data analytics will monitor all necessary components for organizational maintenance purposes within the supply chain. Technological improvements in the utilization of IoT are predicted to provide a better understanding of the connected supply chain, as it is of growing interest to practitioners in the field for understanding connections. Predictive maintenance in retail supply chains is a significant emerging field, and all forecasts strong growth in this area with no saturation point in sight. This is because predictive maintenance in retail supply chains is at the cutting edge and will develop further as both IoT technology develops, AI, and big data analytics. Although it is anticipated that there will be little human involvement in maintenance roles as automation grows, it could be that technology becomes a challenge and makes digital systems at risk from hacking; thus, security and data privacy may be a future consideration subject to further testing. The adaptive maintenance system and increased trust in AI systems will see mass adoption across the sector and specific industries in years to come.

7. Conclusion

This paper has explored predictive maintenance in retail supply chains in order to improve the availability of systems, processes, and machinery. The integration of predictive maintenance with the retail environment bears tangible benefits, such as an improved EBITDA due to a higher operational efficiency with considerable cost savings and strategic advantages. The application of machine learning technologies and Artificial Intelligence has considerable potential in boosting the performance of predictive maintenance. More specifically, physics-based simulation and knowledge management contribute to higher predictive accuracies. Nonetheless, a number of potential factors might restrain the adoption of predictive maintenance in retail supply chains.

Predictive maintenance is often based on mathematical modelling and, in particular, machine learning techniques. The most challenging element of machine learning-based predictive maintenance is that these are, to a certain degree, evolved. Hence, maintenance practitioners should perform a recalibration and fine-tuning of predictive maintenance systems on a regular basis. A number of oil companies that contemplated adopting predictive maintenance explored these as well. There, respondents who were sceptical of machine learning-based predictive maintenance highlighted the diverse data quality and the unavailability of data for scenario-driven analysis. Showcasing similar complexity, a successful business model, and algorithmic agnostic mathematical frameworks and simulation approaches from physics and chemistry contribute to value creation. When monitoring, maintaining, diagnosing, and correcting damage to industrial assets in complex systems, a-priori knowledge has been shown to yield significant progress in predictive accuracy. Initial efforts are being made to adapt fishbone diagrams in the realm of AI and physics. Bringing these frameworks together is not only facilitating ways to add value, but also has sustainable value to businesses by reducing their costs and increasing their profitability. These new maintenance strategies, most notably predictive, are revolutionizing the maintenance arena, forcing businesses to develop in order to gain a competitive edge.

We note that the retail industry and its supply chain management efforts must adapt continually to customer, organisational developments, and technological advancements. These adaptations expose the retail sector as they increase the history of technical failures and hinder the development of maintenance predictions frequently in their systems. Therefore, we call for the development of predictive maintenance initiatives in the retail sector, which should be adjusted every five years and accompanied by a masterclass day for all stakeholders providing further guidance and experimental results. Retail supply chains can benefit substantially from the development of predictive maintenance. For software solutions, a first case study demonstrated that predictive maintenance brought substantial operational efficiencies and reported reduction in several types of operational costs. The increased consistency and cost-effectiveness of predictive maintenance when executed on-site need further examination. However, when applied to hardware and on-site, these tools can extend the definition of predictive maintenance, reaching features such as predictive stock management.