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An analysis of predictive maintenance strategies in supply chain management

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Abstract

The ability to proactively detect equipment problems before they become significant has led many manufacturers to choose predictive maintenance as an area of emphasis within their supply chain management strategies in recent years. An employ of ML methods in predictive maintenance is the focus of this paper's extensive analysis of its application to supply chain management. It defines reverse supply chain processes and their critical importance in maintaining industrial equipment by leveraging timely and systematic reverse logistics operations. The study highlights the economic impact of equipment maintenance, particularly for high-value and complex assets, and underscores the logistical challenges posed by remote and dispersed equipment locations. By advocating for predictive maintenance, the paper discusses how data-driven insights can enhance maintenance schedules, reduce unexpected failures, and extend equipment lifespan. Various ML methods—supervised, unsupervised, and reinforcement learning—are examined for their effectiveness in predicting equipment failures and optimising maintenance processes. The review also provides sector-specific examples, illustrating significant cost savings, improved reliability, and enhanced operational efficiency through predictive maintenance applications across industries such as automotive, aerospace, utilities, logistics, and healthcare.

Keywords: Predictive Maintenance; Supply Chain; Machine Learning; Maintenance Management

1. Introduction

The term "reverse supply chain" describes the procedure by which goods and resources are returned to their original producers for further processing, recycling, repair, or disposal (1). The fundamental reverse SCM activities include equipment maintenance, repair, and replacement services. These pertain to the processes of promptly returning equipment that needs repair or replacement(2). These services are regarded as reverse supply chain activities and are closely linked to the movement of equipment in reverse. These functions are unavailable in the forward supply chain, which is based on the demand for products and materials from customers. On the other side, the demand for returns and repairs dictates the flow in the reverse supply chain. Timely and methodical activities are required for equipment maintenance to be accomplished effectively and efficiently(3). To be more specific, the timeliness of identifying broken or outdated equipment and implementing the corresponding reverse supply chain activities dictates the operational effectiveness of industrial organisations (4)

Many businesses now provide monitoring and maintenance services for the appliances they sell to consumers, including commercial refrigerators, commercial washing machines, catering equipment, information and communication technology, medical, industrial, and other specialised machinery. The upkeep of the equipment these companies sell or lease to their customers accounts for a significant amount of their expenses (either leasing or contracts for equipment

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operation) (5)(6). This is often the case because of the complicated nature, large capital value, and dynamic nature of these assets' operating circumstances. Furthermore, this machinery is often located in inconvenient and far-flung areas, and keeping it in good working order requires intricate planning and substantial financial investments(7).

Conventional techniques of maintenance management should not be replaced by preventive maintenance. However, it is a useful supplement to a comprehensive programme of on-site maintenance. In contrast to traditional maintenance programmes that focus on reactive repairs in the event of a malfunction or breakdown, predictive maintenance systems design specific maintenance tasks in advance, as needed rather than according to a set schedule(8)(9). Machine and plant operations may benefit greatly from improved predictive maintenance systems, even if conventional maintenance procedures will still be necessary. A more dependable maintenance strategy is available with the help of predictive maintenance, which successfully lowers the frequency of unanticipated breakdowns (10).

Predictive maintenance has lately emerged as one of the most significant uses of machine learning across several industries, including SCM. The study's overarching goal is to learn more about supply chain management-based predictive maintenance using ML techniques. The supply chain is often disrupted and inefficient due to traditional maintenance processes that fail to account for unexpected equipment malfunctions. Supply chain operations may be made much more reliable and efficient by using predictive maintenance strategies (11).

An introduction to predictive maintenance and its function in SCM is provided at the beginning of this article. Several ML approaches, like as supervised and unsupervised learning as well as reinforced, are examined and debated within the framework of predictive maintenance. In addition, the research also goes further on methods of data acquisition with topics such as sensor data, past records of maintenance, and external conditions that could influence the equipment's status. The study also comprises implementation issues concerning the application of predictive maintenance technologies in supply chain settings. This paper's contributions are discussed below:

- The paper gives a clear and thorough explanation of reverse supply chain management and makes a case for its application in maintaining, repairing, replacing, and disposing of equipment. They help to stress the significance of a timely and systematic management of the reverse supply chain processes' influence on industrial efficiency.
- The review can be summed up by stressing the fact that the maintenance of costly and technologically sophisticated equipment's in various industries, including the healthcare, manufacturing, and ICT, entails high costs. It presents the difficulties arising from the equipment distributed in remote and dispersed locations and the need for effective maintenance coordination.
- The paper advocates for the integration of predictive maintenance systems into traditional maintenance management. It explains how predictive maintenance can reduce unexpected failures, optimise maintenance schedules, and extend the lifespan of equipment through data-driven insights.
- The study explores the application of ML techniques—supervised, unsupervised, and reinforcement learning—in predictive maintenance. It examines how these methods enhance the ability to predict equipment failures and optimise maintenance processes, thereby improving supply chain reliability.
- The review provides detailed examples of successful predictive maintenance applications across various industries, including automotive, aerospace, utilities, logistics, and healthcare. The text effectively highlights the ways in which predictive maintenance may increase operational efficiency, equipment dependability, and cost savings in many industries.

1.1. Organized of this paper

The rest of this paper follows as: Sections II and III provide the overview of predictive maintenance in supply chain management with ML techniques, section IV gives the analysis and discussion of predictive maintenance in machine learning based on SCM then section V provides the literature review based on various research papers along with the research gap, last section provides the conclusion and future work of this work.

2. Predictive Maintenance in Supply Chain Management

Data analysis and ML technologies are used in predictive maintenance, a proactive approach to maintenance management, to assess the likelihood of a piece of machinery or equipment breaking down or requiring repairs. Maintenance that is based on current conditions is called predictive maintenance. This approach is especially useful for SCM, as unplanned equipment failures may negatively impact delivery dates, manufacturing schedules, and overall operational effectiveness.

There are two primary schools of thought when it comes to supply chain management and maintenance strategies: reactive and preventative. Responding to problems as they arise is the goal of reactive maintenance, a method of equipment care. The consequences of this kind of maintenance include supply chain interruptions, higher repair costs, and often unexpected downtime. Rather of relying only on the state of the equipment, preventative maintenance involves doing scheduled maintenance tasks at predetermined intervals. While if done in a too frequent way it may cause operational disturbances, if done in an insufficiently frequent manner it may lead to unanticipated breakdowns and significant maintenance costs. Figure 1 depicts the predictive maintenance-based ML application in the supply chain sector.

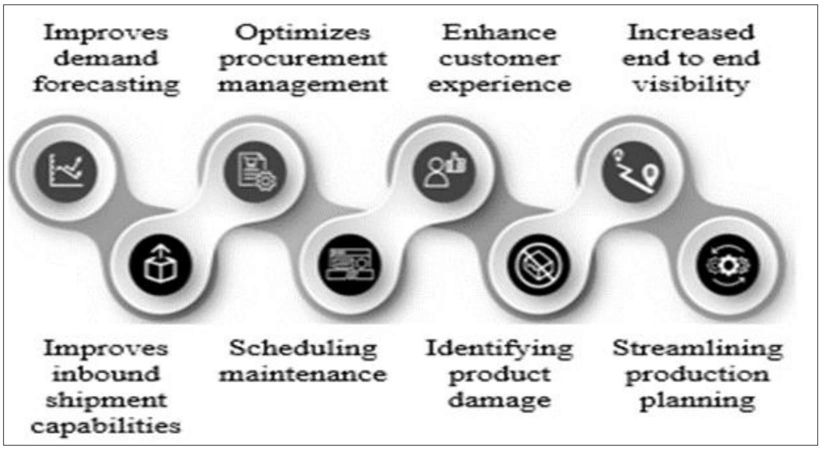

Figure 1 Machine learning in supply chain industry with predictive maintenance(12)

Predictive maintenance makes use of a novel approach. ML algorithms may assess sensor readings, historical data, and other pertinent factors to identify patterns and signs of equipment deterioration or failure. These models then make predictions about the equipment's health and the chance of future failures based on data collected from the device in real-time. Consequently, it is possible to strike the ideal balance between equipment accessibility and maintenance expenses (13).

Predictive maintenance offers a plethora of significant benefits when applied to supply chain management, such as:

- A more consistent flow of business operations across the supply chain is achieved by predicting and preventing equipment breakdowns, which helps reduce unplanned downtime to a minimum.
- Proactive maintenance may help reduce need for costly emergency repairs and number of pointless preventive maintenance tasks. Costs are saved as a consequence of this.
- Maintenance personnel may make greater use of their resources if they concentrate their attention on the parts of the equipment that really need attention.
- Improved Supply Chain's Ability to Handle Uncertainty. Preventing disruptions will make the supply chain more robust and capable of handling unforeseen circumstances or shifts in customer demand.
- Extended Period of Equipment Service Life. If regular maintenance is done on time and in accordance with predicted insights, it would be feasible to increase the lifespan of machinery and equipment.
- Data-informed decision-making Predictive maintenance reveals priceless information about equipment health, consumption trends, and potential process improvement opportunities (14).

Predictive maintenance, at its core, is a method that allows traditional maintenance procedures to go from being time-based and reactive to data-driven and proactive. In the long run, this leads to stronger, more dependable, more effective supply chain operations (15)(16).

2.1. Predictive Maintenance Is Effective in Many Supply Chain Applications

A number of studies have shown that predictive maintenance, when used across many industries and supply chains, may improve equipment dependability, decrease downtime, and maximise overall maintenance efficiency(17). Following are a few instances where predictive maintenance has been successfully used in supply chains (18):

2.1.1. The Industrial and Manufacturing Sector:

- Manufacturing Automobiles: This is a tool used by the automobile industry to monitor machines and robots that work on assembly line. By spotting problems early, they are able to keep production lines running smoothly and save money.
- Aerospace Industry: Aeroplane makers and airlines use predictive maintenance to monitor the planes' engines and other components. Ensuring safe and punctual flights is facilitated by this measure, which also helps to prevent issues during flight.

2.1.2. The Provision of Power and Utilities

- Predictive maintenance is performed by utility companies as part of their power-generating operations on turbines, generators, and transformers. When maintenance is done on schedule, power plants operate more efficiently and unscheduled interruptions are reduced.
- Predictive maintenance is used in an oil and gas sector to keep an eye on the machinery in oil refineries, including the pipelines, pumps, and compressors. As a result, leaks are less likely to occur, downtime is minimised, and worker safety is ensured.

2.1.3. Transport and Logistical Considerations

- Fleet Management: Predictive maintenance is used by logistics companies to keep an eye on the condition of their cars, which reduces the number of breakdowns and increases delivery reliability(19).
- To ensure the safety of all train components, including tracks, signals, and more, operators use a method called predictive maintenance. Because of this, service delays are less likely and passenger safety is more likely.

2.1.4. The Construction Industry and Mining

- Heavy equipment: Mining companies and construction sites utilise predictive maintenance to monitor the condition of their heavy equipment, including haul trucks and excavators. This lowers the cost of equipment maintenance while extending the equipment's operating life.

2.1.5. Medical care

- Medical Equipment: Essential medical equipment, such as MRI scanners and ventilators, is monitored by hospitals using a technique known as predictive maintenance. That way, people may be certain that lifesaving equipment is always in good functioning condition.

2.1.6. Commerce in stores and online

- Distribution Centers: Predictive maintenance is a technique used by e-commerce companies to monitor their automated sorting systems and conveyor belts. This guarantees that there will be no delays in order processing or delivery (20).

2.1.7. The field of telecommunications:

- Predictive maintenance is a crucial component of network architecture that telecom operators utilise to keep an eye on network equipment and cell towers. By doing this, the possibility of service disruptions and network failures is decreased.

2.1.8. A Look at the Food and Drink Industry

- Equipment for Processing: Predictive maintenance is a technique used by many food-related organisations to monitor the equipment used in the production and packaging operations. As a result, production downtime is decreased and product quality is preserved.

2.1.9. The pharmaceutical industry:

- A Tools and Equipment Used in Manufacturing Businesses in a pharmaceutical sector often employ predictive maintenance, a method, to keep an eye on the machinery involved in producing drugs. This gives comfort in knowing that strict regulatory requirements are fulfilled exactly.

2.2. Predictive maintenance strategies in SCM

Predictive maintenance solutions in supply chain management rely on data analytics, ML, and IoT (Internet of Things) technology to forecast when equipment or machinery may break, allowing for preemptive repair(21)(22). This approach aims to reduce downtime, improve operational efficiency, and lower maintenance costs. Key elements include:

- Data Collection: Sensors and IoT devices gather real-time data on equipment performance.
- Data Analysis: Algorithms for machine learning examine both current and past data to find trends and forecast failures.
- Proactive Maintenance: Maintenance is scheduled based on predictions, preventing unexpected breakdowns.
- Integration with SCM: Predictive maintenance is integrated into supply chain management systems to optimise inventory levels, production schedules, and logistics.

Benefits include increased equipment lifespan, reduced operational disruptions, and more efficient resource allocation.

3. Machine Learning

ML is a branch of AI that enables computers to gradually improve their performance on new tasks without any human input or explicit programming. It is the goal of machine learning researchers to create software that can autonomously learn from data. The field of computer science known as machine learning (ML) studies statistical models and techniques that computers may use to learn and execute tasks more efficiently and accurately when given only implicit(23)(24)(25), pattern-based information rather than direct, human-level instructions. This is considered a subfield of AI. Machine learning algorithms learn to make predictions or judgements automatically by constructing a mathematical model using training data, which consists of sample data. Machine learning methods find widespread usage in domains where it would be impractical to create a custom algorithm with instructions for doing the task, such as computer vision and email filtering. A subfield of computational statistics, ML is concerned with the use of computers to make predictions. Mathematics of optimisation provides ML with theory, methodologies, and domains for applications(26).

3.1. Supervised Learning

An algorithm creates a mathematical model for supervised learning by using a collection of data that includes both the input and the intended outputs. Labelled instances, or those where the input and intended outputs are known, are used to train these algorithms. The learning process involves feeding an algorithm a collection of data points and expecting it to provide the right results. An algorithm may improve its performance by inspecting its outputs for mistakes and comparing them to the right ones. Model is thereafter adjusted appropriately. Supervised learning is used for tasks like classification and regression. Random forest(27), Naïve Bayes, Decision Tree, Regression Tree, Nearest Neighbour, and other similar methods are instances of supervised ML.

3.2. Unsupervised learning

The goal of unsupervised learning is to construct a mathematical model using a dataset consisting only of inputs(28)(29). Optimal output labels are absent from this learning method. When dealing with data that does not have a history classification, unsupervised learning is used. Such algorithms include K-means and Association Rules.

3.3. Reinforcement learning

This category of learning pertains to the manner in which software agents implement actions in an environment to optimise the cumulative reward. This kind of education calls for the use of both positive and negative reinforcement in an ever-changing environment(30). Typically, they find their way into autonomous vehicles or into the process of learning to beat human opponents in games(31). One application of reinforcement learning is Q-learning.

4. Analysis and Discussion

The lecture provides case studies and real-world examples to demonstrate how ML may be effectively used in supply chain management for predictive maintenance. The possibilities for improved supply chain resilience, lower maintenance costs, more efficient management of spare parts stocks, and longer equipment uptime are all shown by these instances of predictive maintenance in action. Future prospects and possible breakthroughs in the subject are discussed in the concluding portion of the study. The creation of hybrid models that integrate various ML techniques, the integration of explainable AI to make predictive maintenance recommendations more understandable, and the integration of predictive maintenance with other strategies for optimising the supply chain are all examples of such developments. This research set out to demonstrate how predictive maintenance may completely alter the face of SCM. Supply chain management stands to gain a great deal from predictive maintenance's ability to reduce interruptions and downtime via the use of ML algorithms, which in turn may lead to an overall more efficient and dependable ecosystem.

Machine learning's predictive maintenance applications in SCM show substantial improvements in operational efficiency, cost savings, and supply chain resilience as a whole. Utilisation of predictive maintenance yields these advantages. No less than three categories may be applied to these results. Predictive maintenance models provide the ability to anticipate when certain equipment may cease to operate effectively by using past data and real-time monitoring. This makes it possible for quick repairs to be completed. This is often observed to have the following immediate effects, which may be interpreted as follows:

- Predictive maintenance techniques result in a noticeable decrease in the amount of unplanned downtime caused by particular equipment malfunctions. This immediately leads to better production schedules, higher customer satisfaction ratings, and on-time delivery.
- An implementation of predictive maintenance enhances maintenance operations, thereby reducing the number of essential repairs and eliminating the necessity for extraneous scheduled maintenance, thereby generating cost savings. The concept of predictive maintenance can be characterised as a hybrid of predictive analytics and preventative maintenance. This results in an enhancement in the allocation of resources and a decrease in the costs associated with maintenance (32).
- Maintenance teams are able to plan actions exactly when equipment health indicators show that they are necessary as a consequence of optimised maintenance scheduling. Consequently, the utilisation of resources and labour is more efficient.
- The longevity of apparatus and equipment is enhanced by implementing preventative measures to resolve potential issues before they escalate. As a result, the return on investment will increase, and the total quantity spent on capital expenditures will decrease.
- A crucial element of inventory optimisation is the effective management of spare parts inventory via the use of predictive maintenance. Companies are able to reduce the costs related to excess inventory while still guaranteeing availability when needed by storing the right components in the right quantities.
- One way in which predictive maintenance improves supply chain resilience is by reducing the frequency of disruptions caused by the breakdown of particular equipment components. It is imperative to prioritise this in order to maintain the efficiency of operations in the presence of unforeseen events or fluctuations in demand(13).

5. Literature Work

Predictive maintenance solutions in SCM are a topic that is addressed by previous work in this field using statistical techniques and basic ML models.

To understand Business Analytics and Finance (33), one must first understand time series data, how to extract patterns from it, and how the data is affected by the seasons. Business Analytics can be conducted with efficiency and Supply Chain Management can be enhanced through the application of these concepts. This journal addresses these concepts and specifically discusses the utilisation of Predictive Analytics to forecast the inventory sets that should be retained for sale. This method enables the firm to generate revenue from its goods and services that generate high-quality profits while incurring minimal losses. The algorithm that underpins Predictive Production is the subject of this discussion, as well as the potential for its integration with Inventory Precision to generate profit from the revenue generated.

In particular, Fischer, Iskandar et a, (2015) the widespread availability of data by APC systems about an execution of maintenance presents an opportunity for semiconductor makers. The majority of research on PdM deployment has been conducted at the technical level, with little consideration given to the potential operational and economic impacts on supply chains, as shown by the reviewed literature. Therefore, using discrete-event modelling, the study being presented attempts to examine the operational and financial effects of PdM for semiconductor production on the related supply chain (34).

This study, Hamilton-Basich, (2020) seeks to provide an exhaustive analysis of predictive maintenance strategies used by systems that deal with medical devices. It addresses challenges related to circularity and proposes a novel conceptual framework that utilises historical machine data to predict Remaining Useful Life (RUL) and evaluate the feasibility of circulation. Furthermore, this paper explores potential gaps and identifies various areas for future research (35).

In, Yadav and Gurjar (2019) the primary research poles' study shows that interactive and observational techniques are opening up new research avenues, while learning approaches are gradually gaining ground. they conclude by offering a research roadmap for further studies on AI applications in SCM. The significance of behavioural factors in future studies is emphasised by our findings (36).

In, Kanawaday and Sane, (2017) the goal of this research is to improve the manufacturing process by predicting potential failures and quality problems using ARIMA forecasting using time series data obtained by many sensors on a Slitting Machine. With applications in quality control and management, maintenance cost reduction, and overall manufacturing process enhancement, ML is therefore proving to be an essential part of the IIoT(37).

In this paper Kaparthi et al., (2020) provide an example of how machine learning is being used in a factory management scenario for predictive maintenance. By using diverse methods including GB, RF, and DL, they demonstrate how ML may provide significant improvements in the precision of equipment failure prediction. In addition to increasing the overall efficiency of manufacturing processes, our study's findings show that predictive maintenance utilising ML may decrease maintenance expenditures and downtime (38).

Current research on predictive maintenance (PdM) in supply chain management predominantly focuses on technical implementations using statistical methods and shallow machine learning models, yet it often neglects the broader operational and economic impacts. There is a need for more comprehensive studies integrating advanced ML techniques, real-time data processing, and time series analysis to enhance predictive accuracy and efficiency. Additionally, the economic benefits, industry-specific case studies, and the role of behavioural and organisational factors in PdM adoption remain underexplored. Furthermore, the potential for PdM to contribute to sustainability and circular economy principles, as well as the development of holistic frameworks combining PdM with inventory precision and overall supply chain optimisation, presents significant research gaps.

This table 1 summarises the methodologies, results, limitations, and suggested future work for various studies related to predictive maintenance, machine learning, supply chain management, and business analytics.

Table 1 Related work summary for predictive maintenance in SCM based on ML techniques

Reference	Methodology	Results	Limitations	Future Work
(33)	Time series analysis, trend detection, seasonality analysis	Efficient Business Analytics, improved Supply Chain Management, prediction of inventory needs	Focus on shallow models, limited to basic statistical methods	Integration with advanced machine learning models for better predictive analytics
(34)	Discrete-event simulation, Advanced Process Control (APC) systems	Examination of the financial and operational effects of PdM on the semiconductor supply chain	Lacks consideration of broader supply chain impacts, focuses on technical implementation	Broader evaluation of PdM's economic and operational impacts across different industries
(35)	Review of predictive maintenance applications, conceptual framework for RUL prediction	Framework for predicting Remaining Useful Life (RUL) and evaluating feasibility of circularity in medical devices	Conceptual framework not empirically validated, specific to medical device systems	Empirical validation of the framework, exploration of predictive maintenance in other sectors
(36)	Observational and interactive learning methods	Identification of emerging research areas in AI applications in SCM, importance of behavioural considerations	Early stages of adoption, limited practical applications	Detailed study of behavioural impacts, advanced AI integrations in SCM
(37)	ARIMA forecasting, time series data analysis from sensors	Prediction of machine failures and quality	Limited to ARIMA, lacks exploration of more complex models	Exploration of advanced machine learning techniques for better

		defects, improved manufacturing process		predictions and process improvements
(38)	ML algorithms (RF, GB, DL)	Reduced maintenance expenses, downtime, and improved accuracy in anticipating equipment failures	Case study-specific, limited generalizability	Application in different manufacturing settings, comparison with other predictive maintenance strategies

6. Conclusion and Future Work

In conclusion, predictive maintenance stands as a transformative approach in the realm of supply chain management, offering substantial improvements in equipment reliability, cost savings, and overall operational resilience. An integration of ML algorithms into maintenance strategies facilitates data-driven decision-making, minimising unexpected downtimes and optimising maintenance schedules. However, the current research predominantly focuses on technical implementations, often neglecting broader supply chain impacts. Future work should aim to empirically validate conceptual frameworks across various industries, explore the behavioural implications of AI applications, and integrate more complex machine learning models to enhance predictive accuracy. Additionally, developing hybrid models that combine multiple ML techniques and incorporating explainable AI could further refine predictive maintenance systems, ensuring their applicability and reliability across different supply chain contexts. By addressing these gaps, predictive maintenance can continue to evolve, driving significant advancements in SCM and industrial operations.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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