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AI-Driven Predictive Maintenance Using IoT in Automotive Manufacturing

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Abstract

Artificial Intelligence (AI) in conjunction with the Internet of Things (IoT) provides new possibilities for predictive maintenance in automotive manufacturing. An AI based predictive maintenance systems collects real-time data using IoT-enabled sensors, applies algorithms that have an artificial intelligence/machine learning component to predict equipment failures, new down time, and enables equipment sustainability through optimal operating efficiency. This review article provides an examination of the technical structures, methodologies, and applications of AI based predictive maintenance in automotive production systems with priority of focus on electric vehicle (EV) manufacturing and in-operations case examples of AI based predictive maintenance. The paper describes the processing of sensor data for machine learning modeling, integration of machine learning models into organizational decision-support systems, and layers of a predictive maintenance framework. The paper critically analyzes current limitations in predictive maintenance frameworks, ranging from data quality, update requirements, data design and analysis, explainability, enforceability and continued workforce modernization and development. The paper also identifies the future of predictive maintenance, including federated learning, digital twin technology, edge computing, and sustainable enhancement of operations. By evaluating the current state of research and industrial implementation of AI based predictive maintenance this paper shows how predictive maintenance represents a strategic component for efficiency, competitiveness, and sustainability, as a foundational component of next generation automotive manufacturing systems.

Keywords: Predictive Maintenance; Artificial Intelligence; Internet of Things; Automotive Manufacturing

1. Introduction

The automotive manufacturing industry is changing due to the advent of artificial intelligence (AI) and the Internet of Things (IoT). These technologies have enabled predictive maintenance (PdM) systems that intervene to correct faults and degradation of machinery instead of waiting for failures to occur. Predictive maintenance harnesses real-time sensor data, analytics, and machine learning algorithms to improve operational efficiency and increase equipment lifespan while decreasing downtime.

In an age of increasingly advanced automotive systems utilizing electric vehicles (EVs), the requirement for intelligent maintenance solutions is increasing exponentially. Movement away from reactive and scheduled maintenance methods to predictive systems that could be more cost-effective and compatible with Industry 4.0 is set to increase. AI-based PdM relies on machine learning based on historical and real-time data from IoT devices to recognize faults and predict failures - allowing a data-driven decision-making method for vehicle production environments [1].

The IoT sensors that are embedded in the production lines are constantly, or always, collecting data such as vibration, pressure, temperature, and other important operational indicators. These streams of data from the IoT-enabled sensors will be utilized for AI deep learning algorithms, which can predict breakdown failure. These real-time predictive

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analytics systems will enable a just-in-time maintenance approach, which will reduce unplanned outages and maximize yearly uptime for equipment [2].

2. Role of AI and IoT in Predictive Maintenance

In this way, Artificial Intelligence, of which deep learning (DL), machine learning (ML), and neural networks are its respective components, will be instrumental in the predictive-maintenance process by utilizing complex data to help determine hidden relationships between failure points, and the remaining useful life (RUL) of automotive components. The IoT sensors are the backbone of these systems, providing data from a continuum of sensors throughout the machinery and vehicles [3].

In the automotive manufacturing process, predictive maintenance (PdM) systems are found in robotic arms, conveyor belts, CNC machines, and autonomous guided vehicles (AGVs). The predictive maintenance framework incorporates many steps, including data creation, preprocessing, anomaly detection, and failure detection. Various deep learning models, which include convolutional neural networks (CNNs) and recurrent neural networks (RNNs) can be used to detect behavior and temporal anomalies from time series IoT sensor data [4].

The conjunction of IoT sensors and cloud-based systems allows for real-time monitoring and decision-making. These systems can increase Overall Equipment Effectiveness (OEE) by increasing machine availability, performance, and quality [1]. AI-powered models can adapt to changes in machine behavior over time, becoming more accurate for predictions, while also reducing the false-positive rate [2].

3. Implementation in Electric Vehicle (EV) Manufacturing

The deployment of AI-enabled PdM systems in electric vehicle (EV) manufacturing plants is of particular significance because of the complex battery systems that are highly automated. Predictive maintenance in EV production involves PdM for mechanical systems and battery health monitoring. Machine learning models can be trained on earlier failures datasets, so models trained on historical failures and real-time diagnostics can predict failures, especially in battery cell welding machines and electrode coating systems [6].

Advanced analytics tools aggregate sensor data from machinery used in electrode drying, electrolyte filling, and pack assembly to detect anomalies and generate maintenance alerts. Predictive models also monitoring cooling systems and environmental controls; these systems are vital to safety and battery integrity while under manufacturing conditions. Additionally, AI can detect deviations from the electrochemical performance model for batteries. With an understanding of these deviations, an early intervention in calibration or component replacement can be suggested to maintain the integrity of the battery [7].

4. Technical Framework and Architecture

The technical architecture for implementing AI-based predictive maintenance in automotive manufacturing has four layers: sensor layer, data aggregation layer, analytics layer, and decision layer. The sensor layer comprises IoT devices and embedded systems that provide metrics such as torque, vibration, humidity, and electrical resistance. The data aggregation layer communicates this data via industrial data communication protocols (for example, OPC UA or MQTT), from the sensor layer to data lakes or computed in edge devices.

Table 1 Key Components of AI-Driven Predictive Maintenance Framework

Component	Description	Technology Used
Sensor Layer	Captures machine health parameters	IoT Sensors, MEMS
Data Aggregation	Collects and transmits sensor data	Edge Gateways, Cloud APIs
Analytics Layer	Analyzes data for fault detection and RUL estimation	ML, Deep Learning
Decision Layer	Provides actionable insights	Dashboards, Alerts

Adapted from [8]

The analytics layer includes AI models that derive meaningful insights. The analytics layer also includes fault detection algorithms, prognostics, and scheduled maintenance modules. The decision layer displays the insights generated in dashboards or alerts for visibility to operators and maintenance engineers that need to act swiftly [8].

5. Benefits and Efficiency Improvements

There are significant benefits for implementing predictive maintenance in automotive manufacturing. First, predictive maintenance provides manufacturers with greater asset utilization by reducing unplanned downtimes. Second, predictive maintenance enhances safety by identifying any dangerous operating conditions prior to a catastrophic event to avoid injuries. Third, predictive maintenance reduces the total cost of ownership of parts since replacements can be planned based on actual wear and tear instead of planned uses [9].

One key measure to assess the performance of PdM is Overall Equipment Effectiveness (OEE), which is the metric of availability, performance, and quality. Research indicates that the OEE of facilities incorporating AI-PdM systems directly improves. Some facilities report equipment uptime increases up to 20%. In terms of inventory management, predictive analytics supports just-in-time spare part ordering and can also reduce warehousing costs.

redictive maintenance also supports sustainability goals by reducing energy. Equipment that is not operating correctly will typically consume energy less efficiently and consequently operate with greater levels of emissions. When equipment is maintained to operate correctly, AI-PdM adds to green manufacturing and carbon footprint reduction goals [10].

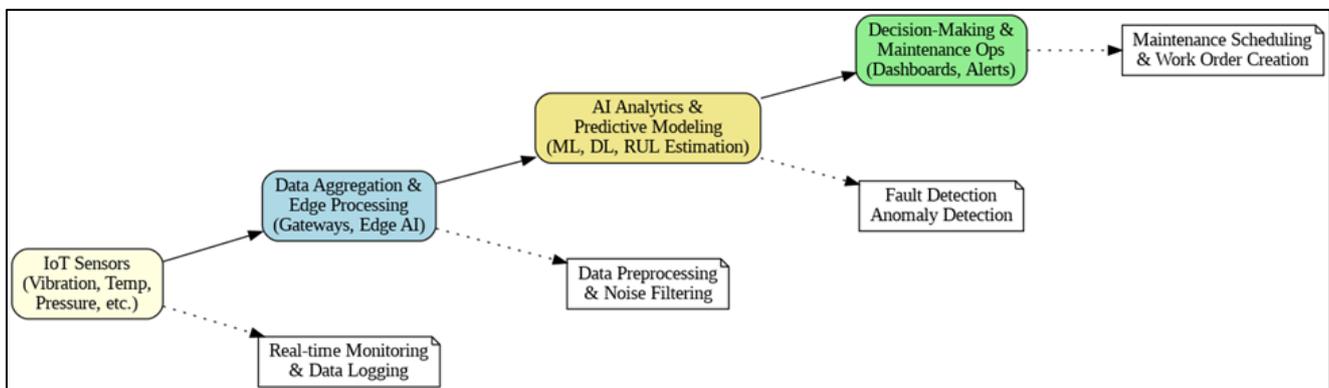


Figure 1 General Architecture of AI-Based Predictive Maintenance in Automotive Manufacturing. *Figure Source: Adapted from [8]*

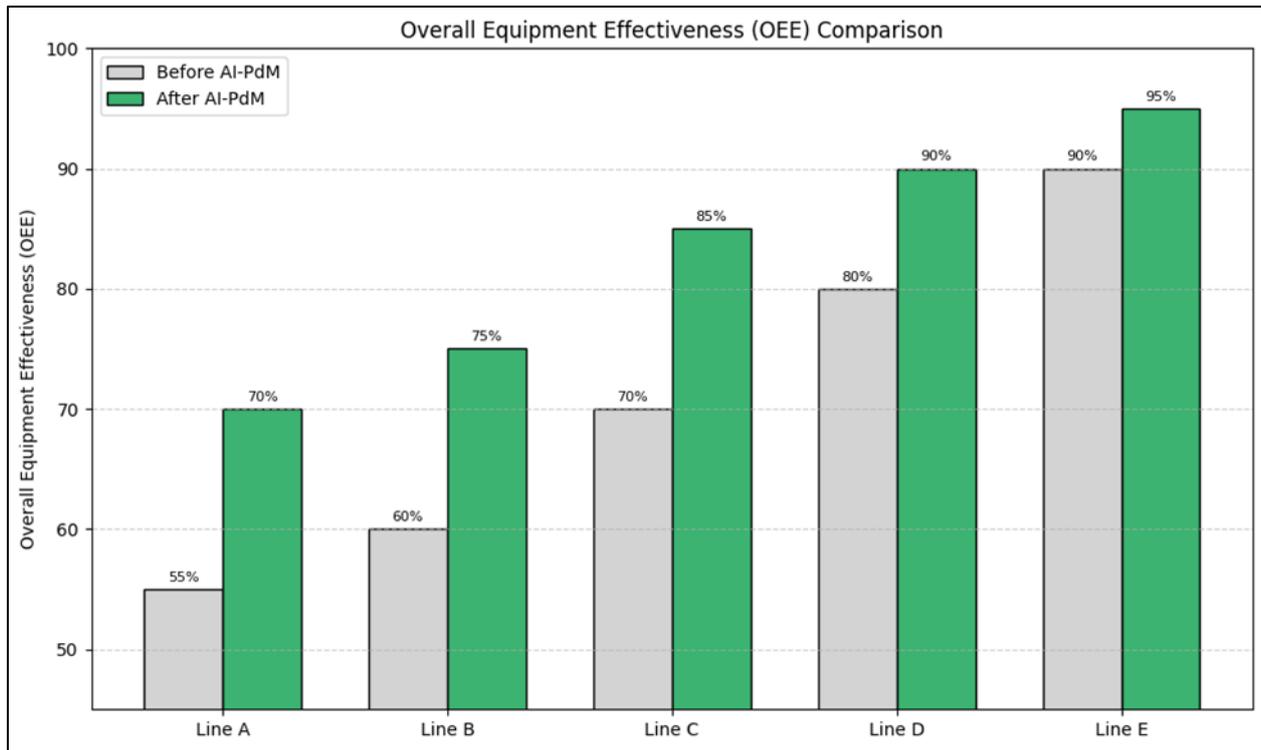


Figure 2 OEE Improvement Before and After AI-PdM Integration. *Graph Source: Adapted from [9]*

6. Challenges and Limitations in AI-Driven Predictive Maintenance

Although AI-PdM will bring transformative benefits to the automotive manufacturing industry, there are technical, operational, and organizational challenges in the implementation of AI-PdM. The first challenge is data quality and integrity. Predictive models require substantial amounts of clean, well labelled, high quality historical data and real-time data. Inaccuracies because of inconsistent patterns of data collection, missing values, noise from sensors and data latency can significantly impact the performance of the model and ultimately the predictive outcome [1].

Sensor deployment and calibration create more hurdles to be overcome. While IoT sensors are critical for capturing machinery's operational parameters, keeping them adequately accurate and reliable over time requires regular calibration and maintenance. A single malfunctioning or inaccurate sensor can mislead the AI algorithm, bringing about false alarms or missed fault and degradation detections. Moreover, the integration of these sensors into legacy manufacturing systems, many of which were not designed for network connectivity in practical terms, amplifies the cost [2].

Another limitation is the model explainability of AI frameworks, especially in the case of deep learning-based systems. No user will accept the advice of a black-box model if it cannot provide a clear explanation of its prediction. In high-stakes manufacturing environments where safety and cost are critical, and especially if there are health concerns, being asked to follow insights without any understanding can be difficult to accept. As a result, there is less trust in such solutions and lower adoption rates for AI solutions in operational environments, were given the option of verifying the soundness of the insights provided [3].

A final significant limitation would be scalability of systems, predictive maintenance systems for example. Small pilot projects may yield promising results and much excitement, however, the real challenge arises in scaling this experience across multi-site, multi-machine, or multi-geographic locations which involve standardizations, cybersecurity, and the appropriate infrastructure. Realistically, generating data at scale can exceed the capacity of cloud or edge infrastructures, which would then require investment in bandwidth, storage, and processing power for the data being generated at scale [4].

Organizational resistance to change is another complex obstacle. A large portion of manufacturing organizations have been structured in a traditional "top down" manner, as the transition from using a traditional approach to one based on data and analytics is no simple feat, and will typically require not just technological change but cultural change as well.

Training and reskilling the entire workforce will be essential to ensure that operators and maintenance personnel can understand and interpret the information produced by AI and embed its use into the everyday operational processes [5].

A further complication with AI implementations may relate to data privacy and compliance issues. Several AI systems or predictive analytics solutions involve cross-national solutions, or third-party clouds. Manufacturers may have to navigate a variety of data governance frameworks, and ensure that their sensitive operational data is spared from unauthorized third-party access or breaches [6].

Price continues to put a strain on AI, particularly for small and medium-sized automotive manufacturers. For larger manufacturing companies who can afford to invest in sensors, associated AI technology and infrastructure, the initial capital investment is often less of a challenge than if its impacts are not felt in the shorter-term, or a limited return on investment (ROI) is possible - smaller manufacturers may not be able to afford upfront costs just 'to wait and see' how they later fare in the longer term. This represents a digital divide in which a very small part of the automotive manufacturing sector can take advantage of its predictive maintenance technologies [7].

Further, algorithmic limitations exist. Predictive models, such as supervised learning which prevails predictive maintenance, typically require retraining and recent calibration to convey predictive model configuration to another machine or under different conditions of operation and production. In addition, false positives (or false alarms) and false negatives (or real failures missed) create challenges that can detract from the credibility of the system and cause non-value added upon either preventative maintenance [8] or unexpected failures.

Finally, the amount of labor involved in data labelling and model training cannot be underestimated. Supervised learning predictive maintenance (the most common application of Predictive maintenance), requires large labelled datasets to train the model, which poses a serious challenge to operating well-maintained environments as failure events are rare. One possible solution, far from ideal, is generating synthetic data to train or simulating the use of a predictive model. However, each of these approaches can introduce longer term issues in model credibility (realism) and generalization [9].

A comprehensive response to these challenges should include a combined effort to improve technical and organizational practice. In the automotive manufacturing context, providing greater transparency into the AI models used, investing in the development and upskilling of all labour (workforce), and implementing a hybrid edge-cloud systems, can all work together to improve the limitations and benefits AI approaches to predictive maintenance [10].

7. Future Research Directions and Innovations

As AI-powered predictive maintenance continues to mature, the future use of predictive maintenance in automotive manufacturing will have several improvements. One possible pathway is through the application of federated learning in PdM systems. Federated learning allows AI models to be trained on decentralized devices or systems without having to transfer the raw data, so the training is collaborative while the data remains private across two separate plants or companies [1].

Federated learning allows manufacturers to train their algorithms or methodologies without sharing their details such as raw data and the relationships within the data. If a car manufacturer shares their raw PdM data with other manufacturers, then each plant can build a better-trained model from the raw data without losing its data confidentiality.

Another proposed improvement is digital twins. Digital twins can be referred to as virtual twins of a physical manufacturing systems that simulate and processes data in near-real time of how a manufacturing system behaves based using sensor's data and input from machine-learning models. When linked to predictive maintenance, a digital twin can aid automotive manufacturers with scenario analysis, failure simulations and proactive decision-making interventions with precision [2].

Finally, edge AI is increasing in applications in predictive maintenance. Edge AI can make real-time judgment on the equipment on the manufacturing floor without the reliance of a cloud connection. Edge computing means there is a reduced latency which increases system reliability and autonomous maintenance decisions even when a plant is in isolation or bandwidth constraints exist. Edge AI with real-time monitoring will further reduce safety risks and increase responsiveness of production lines [3].

In addition, explainable AI (XAI) is currently receiving considerable attention to alleviate the issue of model interpretability in black-box models. Methods such as SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) are being applied to maintenance models to aid the interpretation of predictions to human users. This increases trust and encourages uptake by non-technical stakeholders [4].

Regarding algorithms, unsupervised and semi-supervised learning methods may allow for the use of lower amounts of labelled failure data. These methods can identify anomalies, without requiring multiple labelled data to learn the model, and can be useful for use with new machinery or in environments where failure data is limited. Reinforcement learning is being considered to dynamically optimise maintenance schedules on user operational feedback, assessments of costs, and benefits [5].

Standardization of IoT architectures and communication protocols will also be significant. Maintaining interoperability across multiple component types (sensors), data storage formats (types of data), and AI induced decision-making will be an important aspect for successful scalability of PdM solutions across global manufacturing supply chains. In industry-wide frameworks, the use of standardized APIs will allow for a more rapid deployment time of PdM software and correspondingly less integration costs [6].

Sustainability considerations will probably also shape future research. AI-supportive maintenance systems can be optimized for performance, but there is also the opportunity to optimize for energy use or loss, materials waste, and environmental impacts. Predictive analytics may even extend to tracking carbon footprints, optimizing energy use in production equipment, and recycling or reusing components [7].

Another frontiers include the integration with blockchain. By integrating blockchain technologies, such systems can preserve the integrity and security of the maintenance record, and create an auditable trail of interventions, part replacements, and outputs of predictive analytics processes. This is particularly beneficial in regulated environments where traceability and compliance are critical [8].

Human-centered design will also gain prominence in future PdM systems. By incorporating intuitive user interfaces, AR/VR for training, and voice-based interaction systems, AI-driven maintenance can become more accessible and actionable for frontline workers, bridging the gap between digital intelligence and human expertise [9].

Finally, interdisciplinary collaborations between AI experts, mechanical engineers, and industrial psychologists will be essential to refine the technical, human, and ethical dimensions of AI-PdM. With continued investment in research and cross-functional innovation, predictive maintenance is expected to evolve from a reactive support function to a strategic enabler of competitiveness and sustainability in automotive manufacturing [10].

8. Conclusion

AI-Predictive Maintenance enabled by IoT technologies, is altering the operational environment of automotive manufacturing from a reactive, and preventive, strategy to a data driven, predictive maintenance model. This shift allows for reduced downtime, improved equipment lifespan, enhanced safety, and maximized production schedule efficiency. Analyzing sensor data in real time with advanced machine learning technology allows for early fault detection, and failure rate predictions, and enables better allocation of resources.

Predictive maintenance is becoming increasingly essential for battery system integrity, and overall production quality, within electric vehicle manufacturing, where precision and reliability are critical. The reviewed research shows that AI-Predictive maintenance frameworks are not only viable, but also advantageous in enhancing overall equipment effectiveness (OEE), and generating cost savings.

However, while the benefits are considerable, AI-PdM systems do have limitations related to unstructured data, incomplete sensor information, features of model interpretability, and the inertia of the organization. Solutions to these limitations would require a multidisciplinary focus incorporating technology, patterns of workforce learning, and transparent and scalable outcomes located within organization values.

Future research and industry development shall be directed toward improving model explainability, more fully exploring federated learning, more digital twin usage, and sustainability with active or passive energy-efficient maintenance actions. Predictive maintenance as I expect the growth of AI and IoT solutions, will be an aspect of intelligent, efficient, and resilient automotive manufacturing systems development.

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