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AI-Driven Predictive Maintenance for Industrial Robots in Automotive Manufacturing: A Case Study

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Abstract

Manual assembly tasks are often labor-intensive and prone to errors. However, with the rise of artificial intelligence technologies, these tasks can be automated with the help of robots. Most automotive manufacturers are implementing the robotization of assembly tasks. However, the type of assembly processes in the automobile manufacturing industry is complex, meaning that maintenance of the robotic arms is exceptionally critical. Scheduled maintenance costs massive downtime of the robotic arm, which concerns both manufacturing throughput and financial losses. On-demand predictive maintenance could optimize repair plans to be performed only when necessary while maintaining a high uptime of the robotic arms.

Therefore, a new framework that learns functional generic product representations and transfers knowledge across different domains is proposed. Then, a case study on on-demand predictive maintenance for industrial robots in the automobile manufacturing industry is presented. The experimental results show that the proposed framework could work in an unseen assembly environment, and knowledge transfer increases predictive maintenance performance. One of the first fully developed robotic arms with torque sensors in the automobile manufacturing industry is used, which is allowed to be studied offline. In contrast to industrial settings, all configurations are controlled directly on the robotic operation script level, making it easy to construct different scenarios of different assembly processes.

Keywords: *Predictive Maintenance, Industry 4.0, Robots, Automotive Manufacturing Artificial Intelligence (AI), Robotics, and the Internet of Things (Iot) are Becoming Integral Components of Manufacturing and Represent the Latest Manufacturing and Industrial Revolution .*

I. INTRODUCTION

Deep learning and domain adaptation approaches for remaining useful life prediction: A review. An overview of neural networks for smart manufacturing: Current status and future trends. Data-driven methods for industrial big-data-enabled smart manufacturing. Big data smart manufacturing: A review. Industry 4.0: The New Industrial Revolution. Towards proactive digital manufacturing. Cyber-physical systems in manufacturing: Services and service-oriented architecture. A system model for cloud manufacturing. Classification of cyber-physical systems: A review of industrial applications in manufacturing. A survey of the applications of AI in cognitive digital twin systems in manufacturing: A state-of-the-art review. A comprehensive review of the applications of AI in the manufacturing sector: Opportunities and challenges. AI-based heuristics for sustainable robotics scheduling in smart manufacturing: A review on recent achievements and future directions. Smart manufacturing: Key characteristics and future directions. Smart manufacturing paradigm: A paradigm shift in a new normal era of manufacturing: Opportunities, challenges, and future directions. A brief literature review of cyber-physical systems in manufacturing. The multifaceted landscape of the smart manufacturing industry in policy, education, standards, technology, and people. The role of big data analytics and smart manufacturing in a circular economy: A systematic review. Embedding the Industry 4.0 strategy in the dust:

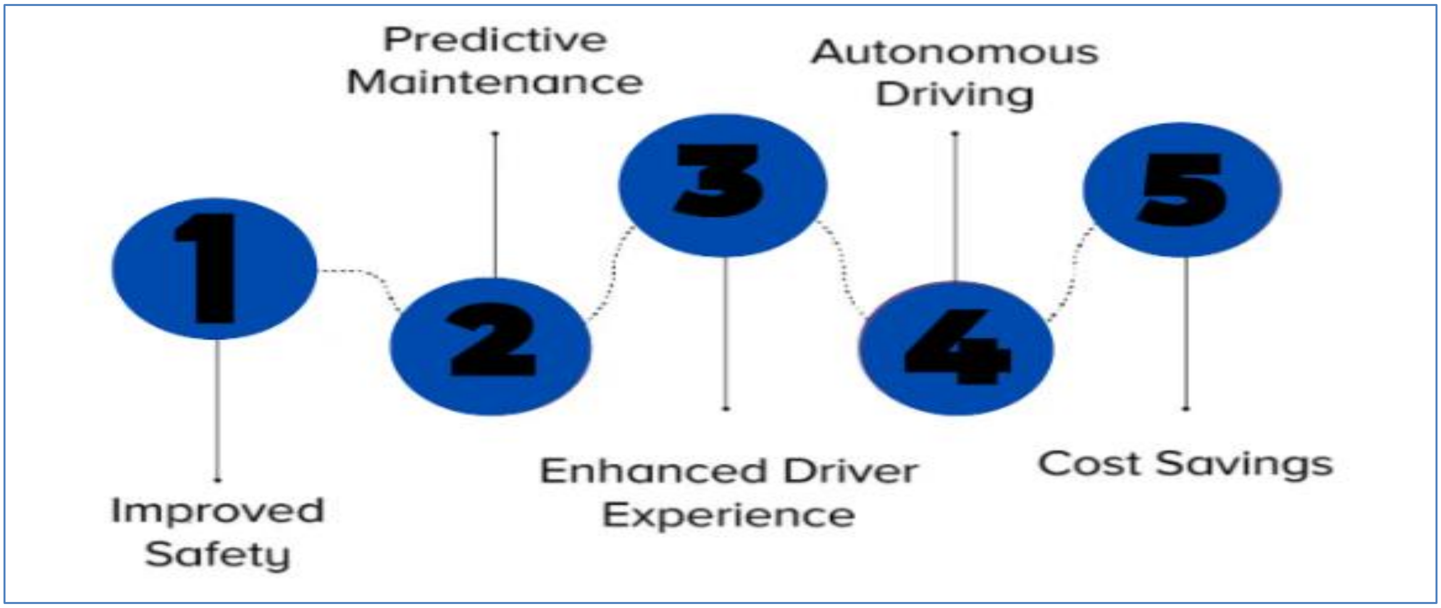

Fig 1 AI-Driven Predictive Maintenance

➢ *Background and Significance*

As a continuous-deployment paradigm that refers to the total lifespan of robot systems, robot lifecycle management provides significant value regarding robotics missions, embedding techniques such as predictive (fault) maintenance for robotic systems . Predictive maintenance operates on the basis of the concept of remaining useful lifetime (RUL); i.e., based on learning from the past, it tries to forecast the future behavior of a robot, to warn its operator of potential failures that are likely to happen (i.e., a threshold drop on the condition of the robot or an increase of faults) over a time horizon. While several approaches exist for robot predictive maintenance covering a wide range of robotic platforms, task types, and techniques, these approaches are often evaluated on isolated case studies, leaving a formulation of the RPD problem at the conceptual level as a research gap.

Equ 1 Data Preprocessing

$$f_j = \mathrm{FeatureExtract}(x_i(t))$$

Where:

- f_j: Feature extracted from raw signal $x_i(t)$
- Common features: RMS, kurtosis, skewness,

II. BACKGROUND OF PREDICTIVE MAINTENANCE

Predictive maintenance of industrial robots is a well-studied topic that has gained interest owing to the widespread implementation of industrial automation, commonly referred to as Industry 4.0. This industrial paradigm shift necessitates the integration of information and communication technologies in manufacturing production systems. As a result, production and robot data are collected at an unprecedented scale, enabling extensive exploration of production data to derive actionable insights. One of the numerous applications of this data-driven approach is predictive maintenance of industrial robots, which aims to shift maintenance actions from being reactive or time-based to dependent on the health of the equipment and hence on predictive insights. This transition is intended to reduce downtime and maintenance costs. Consumer goods and automotive sectors are one of the earliest adopters of operational AI-driven use cases, especially focusing on the quantitative forecasting of the equipment's condition.

The required expertise and capabilities to describe the current health state and forecast the remaining lifetime of the equipment are implemented using standard machine learning and deep learning techniques. These models are trained on engineering, contextual, and temporal features obtained from different data sources. The validity of these models varies depending on the processes established by subject-matter experts during the equipment design and setup. In the automotive industry, the deployment of industrial robots is complex and time-consuming, leaving little lead time for proper data exploration. In addition, the breakdown of industrial robots demands lead times ranging from three days to one week to source replacement parts and find an alternative work center, which is suboptimal for production efficiency when maintenance is triggered too late.

To address these challenges, an extensible framework for one-shot forecasting of a robot's linear joints error is proposed. The framework consists of CNNs to predict the joint's position, velocity, and torque, as well as the presence of maintenance-sensitive control errors in the future. Extensive experiments are conducted by analyzing different robot models, examining the representation of data used for training, and testing transferability to an unseen work center. Results show not only high accuracy but also early detection of the robot's degradation, enabling condition-based maintenance.

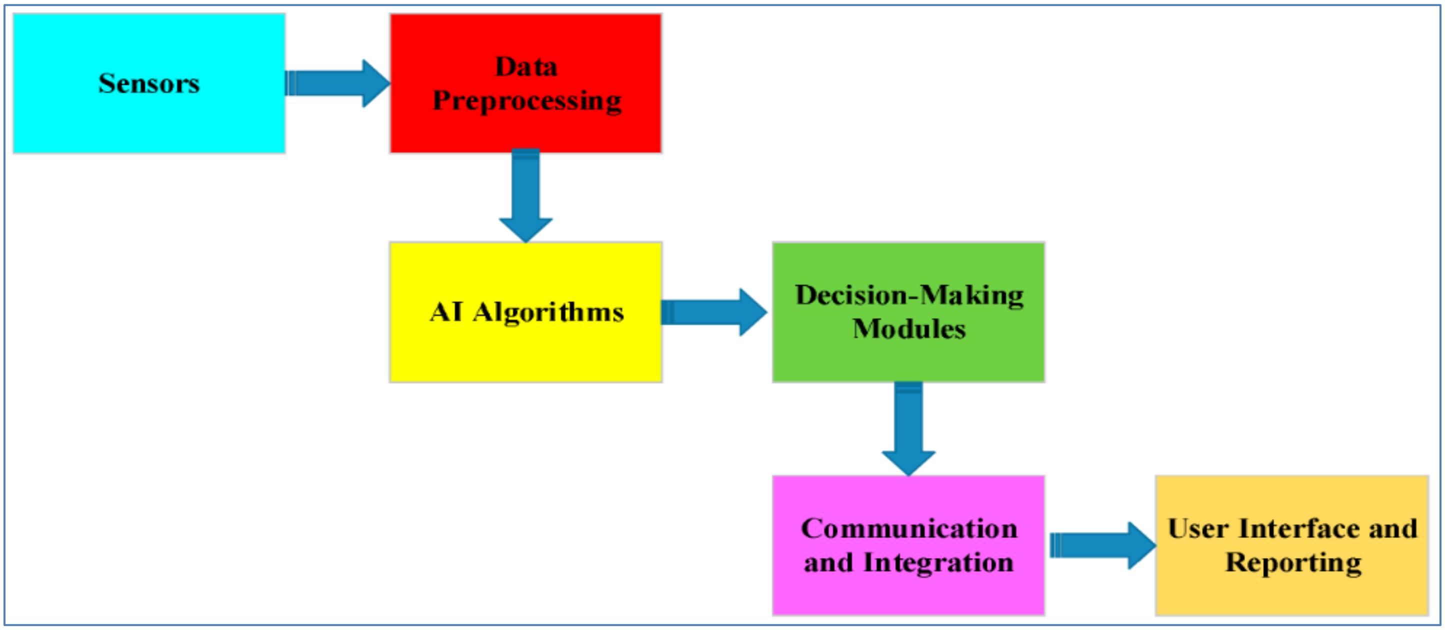

Fig 2 Predictive Maintenance

➢ *Definition and Importance*

The advancement of modern and advanced technology has led to high-quality and competitive automotive products for end users in automotive manufacturing. The challenging task of meeting their demands during production utilizing industrial robots is addressed using Performance Engineering (PE) to find an optimal performance in robotized industrial systems. One of the PE tasks is Predictive Maintenance (PM) of industrial robots and its tools. Traditionally used statistical methods dealing with the certainty of events in a designated time horizon can be improved through data-driven predictions allowing dealing with uncertainty. Such a trend has led to a growing interest of both the scientific community and industry in implementation of Artificial Intelligence (AI) methodologies. An AI-based PM for industrial robots applied in automotive manufacturing using Reliability Function Approximation (RFA) and the Mixed-Integer Nonlinear programming (MINLP) problem of maintenance scheduling was used. A performance measure of a robot tool is mentioned in terms of wear condition describing its output decision variable. An AI surrogate-based RFA model has been proposed based on the draw of experiment scenarios and supervised learning. A case study of an industrial robot tool is presented showing usage in generating an AI-based replacement recommendation. In addition to a performance measure, battery state of charge for AGVs is an input requirement determining replenishment scheduling based on the underlying replacement plan.

Reliability of machinery, industrial robots inclusive, expressed via probabilistic metrics is a common modeling and monitoring approach to evaluate their working condition. Such a trend has led to a growing interest in data-driven performance queries based on Time-To-Failure (TTF) prediction. With the usage of these confidence intervals of generated predictions, a suitable alarm level for scheduling maintenance actions can be set. Industrial robots are a commonly used solution in the automotive industry due to the reliability and low failure rate of long durability 24/7 continuous working hours.

➢ *Historical Context*

Predictive Maintenance (PM) techniques, which are methods used to forecast the remaining useful life (RUL) of assets in order to determine the best time to conduct maintenance or inspection operations, have seen a significant increase in popularity in recent years. This growing popularity can be attributed to technological advancements and R&D investments that allow for the retrieval and storage of vast amounts of data regarding machinery in any infrastructure, such as manufacturing plants. These techniques, based on machine learning or, more broadly, artificial intelligence (AI), are used to deploy algorithms capable of predicting degradation in almost real-time using only data generated by the industrial processes themselves.

The academic field of PM has grown and developed rapidly over the last two decades. For instance, a search using the keywords "Predictive Maintenance" or

"Remaining Useful Life" shows that there were no journal papers published prior to the year 2000. However, nearly 400 such papers were published in 2020. Machine learning predictive maintenance methods began to be studied in 2010-2015 and gained traction as IoT, Cloud Computing, and Industry 4.0 first entered the production and supply chain domains. Industrial research labs began investing heavily in these technologies. Several companies all have ongoing projects for the deployment of AI-based predictive maintenance in their plants, searching for new partnerships and approaches. One company, for instance, publicly deployed 90 AI use cases in its manufacturing plants in 2020, with seven new use cases added in 2021.

Several AI-based predictive maintenance use cases have also been developed and deployed in large companies' plants. For example, one company implemented AI-based predictive maintenance of servers and disks in its Data Center using machine learning for early warning and key capabilities in modeling the non-linear dependence structure and dimension reduction. Similarly, AI-assisted diagnostics of Advanced Traffic Management Systems was developed at another company using ensemble gradient boosting-based design for data transcription, key capabilities in batch-time analysis of large-time-domain signals, etc. These historical reviews demonstrate the long-standing interest in experimental and proof-of-concept implementations of early-stage smart predictive maintenance technologies. Nonetheless, there are few academic reviews of large-scale implementations of production-ready AI-DRL predictive maintenance technologies across multiple plants at well-known companies.

- *Technological Advances*

Advancements in technology have enabled the implementation of Industry 4.0 predictive maintenance. The manufacturing and automotive industries now use big data, the Industrial Internet of Things (IIoT), and Artificial Intelligence (AI) tools to make their predictive maintenance systems effective. From initial deployment, many intelligent predictive maintenance systems can learn, evolve, and be enhanced with software updates. To retro-fit existing maintenance deployments, AI-driven tools are available now for streamlining data collection, model training, data labelling, and system deployment.

Predictive Maintenance (PdM) has been one of the research foci in the industry for a while. To leverage the benefits of data-driven techniques, knowledge-driven techniques of maintenance personnel have to be included in deploying the framework of PdM in the manufacturing industry. Factor analysis and machine learning techniques have been extensively used to evaluate the influence of a range of attributes on the operational efficiency of machines. Visual analytics should not be only at the exploratory data analysis stage but also at the PdM final stage, where maintenance personnel could provide feedback of equipment to improve the operational efficiency of machines.

Combining the usage of deep learning and transferable features shows a good classification performance under cross-site and cross-domain scenarios, but still requires the identification of health features when monitoring new machines or configurations. Therefore, attention mechanisms and self-supervised learning are extensively used for health feature learning from raw signals. Nonetheless, these fully-data-driven techniques suffer the problem of low interpretability and require a large amount of temporal data. Conversely, the knowledge-driven models are always designed based on mechanics and physical principles of the equipment, but may lack the ability of feature extraction from raw signals. By combination of data-driven and knowledge-driven techniques, explainable PdM techniques can be developed.

III. INDUSTRIAL ROBOTICS IN AUTOMOTIVE MANUFACTURING

The automotive manufacturing industry is one of the most competitive and dynamic industries working towards the optimization of production processes to increase productivity and quality. The innovations in the information technology field like the Internet of Things (IoT) and Machine Learning (ML) Technologies have allowed the evolution into Industry 4.0, comprising smart factories where industrial robots will play a major role. The industrial robots in the automotive manufacturing industry are numerically controlled automatic systems used for the automated manipulation of workpieces. This increases flexibility and productivity as several seconds in a manual operation are reduced to a few milliseconds with the use of industrial robots. These industrial robots in the automotive manufacturing industry execute relatively simple cyclic motions that can wear and partially degrade the actuators over time. In-view of such wear, faults, or degradation, predictive maintenance (PdM) aims to optimize the service of industrial robots by avoiding unplanned breakdowns and fatalities for workers and process losses . The automotive manufacturing industry is one of the most competitive industries working towards the optimization of production processes to increase productivity, flexibility, and quality. A production system failure can lead to production loss costs, quality loss costs, repair costs, etc. Recent innovations in information technology, such as the Internet of Things (IoT), big data, and machine learning (ML) technologies, have allowed the evolution into industry 4.0, comprising smart factories. The IoT technologies provide the ability to collect a huge amount of valuable data. By processing this data, the ML techniques enable creating a knowledge model of the monitored process (e.g., condition monitoring, fault detection and diagnostics, or predictive maintenance). In-view of the century-long evolution of industrial robots, the driving force for the last fifty years has mostly been an increase in their flexibility and productivity by means of faster and larger robots guiding automatic tools with high precision along very complicated trajectories.

- *Overview of Robotics Applications*

Robots have been utilized in the automotive manufacturing industry for more than 50 years. The major types of robots currently utilized in the automotive field are articulated robots, SCARA robots, and gantry and hybrid robots. Applications of robots in the automotive field are varied. The major applications of robots and robotics in the industry are material handling, fabrication operations, welding, painting, assembly, and sealant application.

Material Handling: Material handling is defined as the movement and placement of materials in a work environment for construction, manufacturing, assembly, testing, and maintenance. Application of gantry and articulated robots for material handling has been done extensively in the automotive field. Both multi-axis and single-axis gantry robotics can efficiently and precisely lift loads for many of the material handling applications. Used with end-of-arm tooling, machining arms can be programmed to pick up and place items in a fixed location, and to piece together products on assembly lines. Used together within the same work cell, three-dimensional (3D) scanning and robotic arms can facilitate material dispensing or packing of foam and non-foam components for manufacturing.

Fabrication Operations: Material shaping, separation, material joinage, and coating removal are examples of fabrication operations that can currently be automated using plain two-finger grippers and machining arms. The targeting of these applications greatly differs between the two aforementioned robot types. Articulated robots have been demonstrated to perform cutting and shot peening. Nevertheless, improvements in sensing and control are still needed, particularly with respect to complying with dynamic environment changes and efficient route planning.

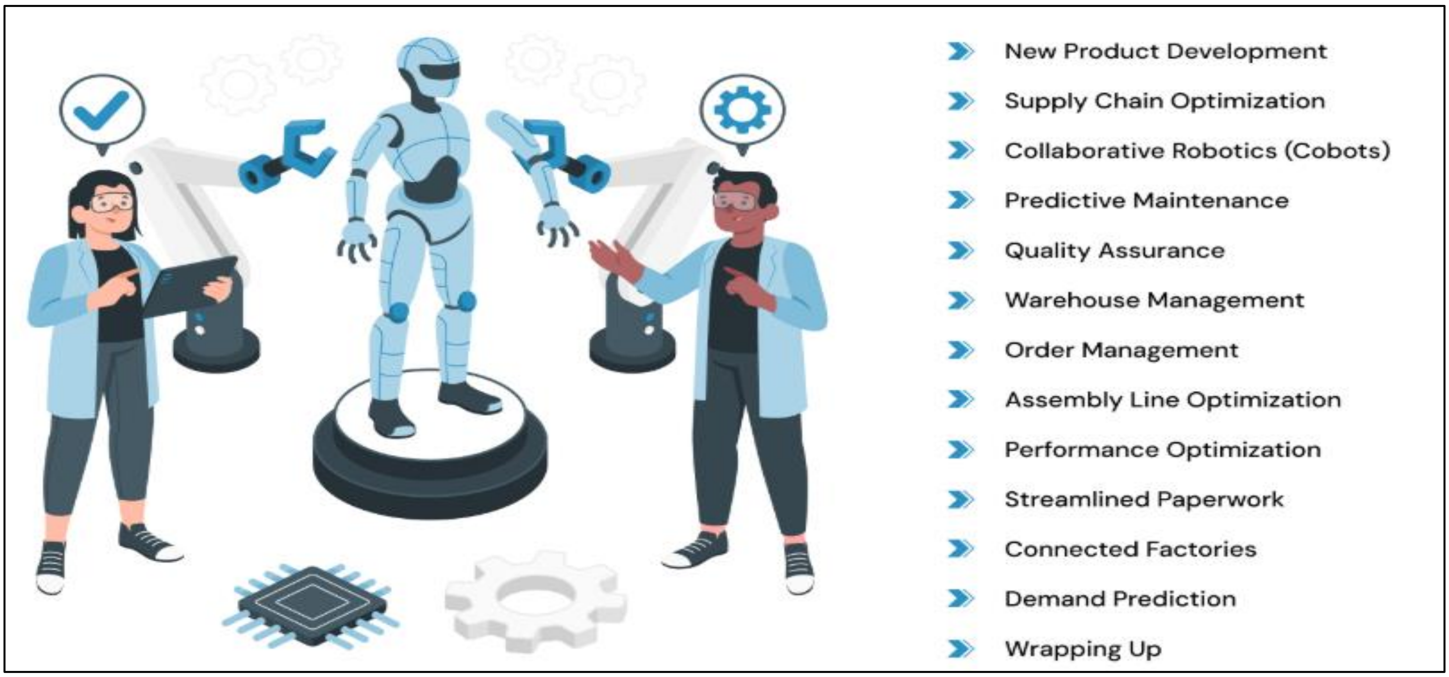

Fig 3 Robotics Applications

- *Key Challenges in Maintena*

Predictive maintenance (PdM) has gained significant attention in recent years, as research addresses some key issues. To facilitate a sound understanding of the challenges of industrial infrastructures, the variety of machine learning methods used in PdM applications and their comparative evaluations in real-world settings are described. The challenges in machine learning and engineering aspects of PdM are identified. Such a systematic review, covering various aspects of PdM, is essential for academia and industry. First, it will improve the understanding of the challenges involved in transitioning from the current state to a PdM system in practical settings. Second, it will highlight available studies and possible future directions, including under-explored topics. It will also help practitioners to gain a broad knowledge on the current development in PdM studies, facilitating a more focused literature search. Automated assembly lines are an essential part of the automotive manufacturing process. By assembly lines are also meant multi-purpose, flexible automated assembly lines where there are both equipment-induced and product-designed specifications. In the automotive business, a component is designed for a specific model, and such a model is required to build a number of similar cars. The assembly equipment attempts to meet the accuracy and manufacturing specifications so that components are fitted into each other ergonomically. During normal operations, some equipment or part of the assembly system might not be able to satisfy the specified manufacturing tolerances. Monitoring equipment, processes, and validating systems to detect equipment failures, setups, and drifts are the goals of condition-based maintenance (CBM) and predictive maintenance (PdM). This paper focuses on the Automated Guided Vehicle(AGV)-based intra-logistics in the automotive manufacturing domain. AGVs are vehicles that transport materials and products in manufacturing and warehousing environments and work under dynamic conditions often as a general purpose material handling system. Work on autonomous Mobile Robots(MR) has been burgeoning and these systems frequently employ a mapping method to create a map representation of a known work environment. Subsequently, an across-gateway confusion detection algorithm is designed in this paper to prevent data loss through gateway-to-gateway handovers and an anti-jamming approach to mitigate front-shot jamming in six-jammer situations is also presented in this paper.

Equ 2 Machine Learning Prediction Model

$$\hat{y}(t) = \mathcal{M}(\mathbf{x}(t - \Delta t), \ldots, \mathbf{x}(t))$$

Where:

- $\hat{y}(t) \in [0, 1]$: Predicted probability of failure
- The model uses time-series data or feature windows

IV. AI TECHNOLOGIES FOR PREDICTIVE MAINTENANCE

Artificial Intelligence has been a rising field for the last few years. Its applications are numerous and some of them revolutionized existing industries. Many methods and approaches that involve deep learning, machine learning, reinforcement learning, and data mining are widely referenced. Of these approaches, Data Science (DS) and Artificial Intelligence (AI) have promised a new way of tackling the most complex problems. Despite that, neither terminology has reached a clear consensus on what should and should not be included. In particular, generality is a core driver for the methods behind the AI terminology. Such flexibility creates intricate circular dependency and ambiguity in definitions.

Especially in the last years, there has been increased interest in predictive maintenance approaches for machinery and operations models . These methods utilize the technological developments in the information era, where the Internet of Things (IoT) has distributed sensors attached to any operation or machine, and these sensors can gather data at unprecedented scales. Predictive maintenance tries to use this data to prevent unexpected breakdown of machines, in order to save costs of lost production and spare parts.

This case study focuses on industrial robots in the automotive field, looking at one robot in a paint hall of a car body plant. The behaviour of this robot is monitored by a set of camera systems. With the help of AI, this behaviour will be classified and key performance indicators (KPIs) extracted from this classification that quantifies the robot's behaviour quantitatively but also qualitatively. Then, these KPIs can be read into a predictive maintenance model that enables the maintenance managers to see estimates of degradation or wear of hard- and software. Following the approach of predictive maintenance, this degradation can be checked against thresholds derived from historical breakdowns. If this threshold is hit, or is hit with high certainty, that a maintenance action needs to take place.

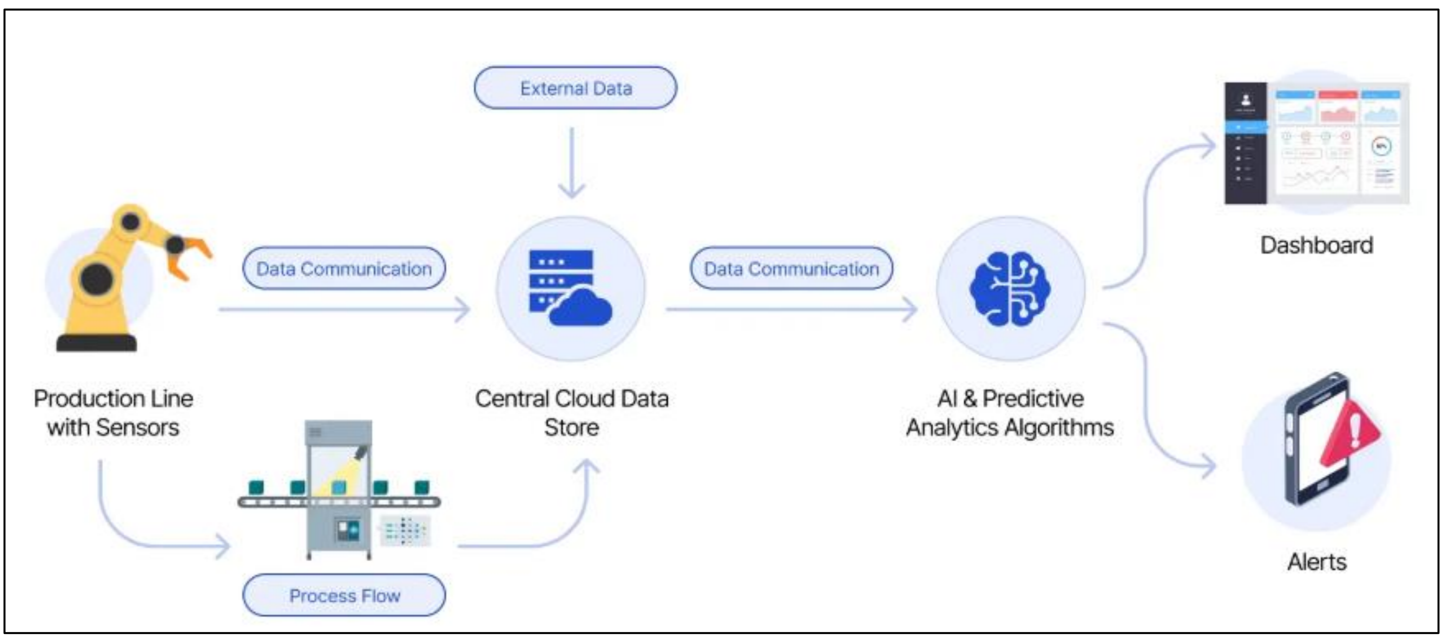

Fig 4 AI Technologies for Predictive Maintenance

- *Machine Learning Algorithms*

Predictive maintenance (PdM) is a strategy that aims at reducing equipment degradation and thus reducing the likelihood of failures by forecasting their time of occurrence. In an industrial scenario, data to be monitored can be generated through different protocols and strategies by considering different variables over time, producing one or more time series. The ability to analyze multivariate time series to forecast machine malfunctions depends on the adopted types of models and on the availability of available data, which often cannot be acquired at a constant frequency and at the same sampling rate. In addition, training a model foreseeing predicted values in a large future horizon requires a huge quantity of disaggregated data over time, that is needed for overfitting prevention and model generalization. To cope with these issues, computer-aided methods can be taken into consideration to favor maintenance operations providing support to improve the machinery performance and reliability and limiting the fault propagation.

Detecting machine failures ahead of time offers many advantages such as limited downtime, enhanced asset performance, and the ability to anticipate failures while they emerge. As a direct consequence, the condition monitoring (CM) of machines is a growing challenge in the industry. Knowing how well a machinery is behaving is critical in manufacturing systems where intelligent control is required. This study aims at predicting machine failures from multivariate time series representing data recorded historically by a monitoring system installed on a hot stamping press. Recently, machine learning (ML) and deep learning (DL) paradigms have been demonstrated to produce robust and generalizable models that can reduce the effort of manual feature engineering with respect to classic statistical multivariate methods.

Machine learning can play a key role in manufacturing by analyzing processes and asset states from small fragments of time series, being able to provide forecasts and insights afterwards. An industrial data-driven case study representing predictive maintenance is proposed. In more detail, faulty and healthy production campaigns of a hot stamping press are considered, and an aspect of monitoring the production cycles over time to detect the forced machine stops is presented. Data has been recorded over a long time horizon by a monitoring system reproducing multivariate time series. Different approaches are tested to predict faulty campaigns as a function of the length of the input time-series fragment and of the sampling frequency for predictions being trained with the correct amount of information.

Relevant works on predictive maintenance, its evolution, and paradigms are discussed in this section. These blocks have been designed during the training process to analyze three different active learning strategies to generate synthetic data in the presence of different conditional independence levels.

- *Data Analytics Techniques*

Machine-level data is typically raw and unprocessed data captured by manufacturers' equipment. The collected data must be pre-processed before being fed to algorithms such as the converting of timestamps to numeric formats, and dealing with missing values or outliers. In this research, a windowing technique is employed to convert raw data into meaningful features. In the windowing approach, the pre-collected continuous time series data is split into non-overlapping windows that a specific set of algorithms can be applied for interpretation.

Raw data is nevertheless time-stamped, this timestamping can be converted directly into numeric values, windows can be refined by avoiding too-short windows that would miss information. In the case of missing values, the set of replacement values can either be the mean or median of the windows or previous or next values based on the assumption that they are robust against harsh changes. In the case of outliers or extreme values, applying a threshold or a box-plot-based filter would be a common approach.

The specific types of sensors that are chosen from industrial robots are shown in table format. Three temperature values: motor, driver, and controller, and four flags: servo motor error, servo driver error, connector attention, and servo driver attention are included in the analysis. The attention and error flags are binary whereas temperature values are continuous between −6 and 1000 in Celsius.

- *Sensor Technologies*

Most of the robotic arms used in an automotive manufacturing company are old, and some of them do not have any sensors or data recording functionalities on board. As a consequence, many robots rely on momentary sensors to fuse the status. In some cases, only a few sensors are monitored out of the tens that produce different control values, and they can get stuck in a false-positive status, which may lead to expensive downtime motions of a robot that is fulfilling its task. As the automotive manufacturing company relies on such robots for high-volume production of hundreds of cars per hour, implementing additional sensors or updating highly demanded data fetching capacity may greatly increase productivity because the majority of robots are wasting valuable working time due to such malfunction. In the future, the company plans to implement more advanced maintenance monitoring solutions to partially alleviate some of the problems that arise from limited sensor implementations. However, the approach is based on state-of-the-art solutions capable of predicting such drift defaults using reconstructed output signals from a trained neural network model. Unfortunately, the re-engineering of the robotic arms, or any device in such an environment, is very limited. The majority of these robots are decades old, and new units are very expensive. As a consequence, adding additional sensors is limited, as well as adapting a hidden layer on an existing solution. The developed solution can easily estimate the default of older types of robots with not so complex structures and limited data recording possibilities before an expensive downtime. Developing a similar solution can add more input data from already available controllers or low-cost sensor equipment. The data from the company's six MG960 robots were selected to extend the possibilities with two-dimensional data from a relevant research project. The robots were built in 1990 with C-structure, and they serve in an assembly station where the previously manufactured parts are glued together, sometimes with short-acting adhesive. If the A-PFA is reaching expired time for the storage of opened adhesive, misalignment is produced actively accelerating the malposition of manufactured parts, as well as A-PFA wear. Both accelerated wear and misalignment may lead to longer cycle times due to misaligned vision unit perspectives and production stops due to erroneous A-PFA that mistakenly releases adhesive on the inactive part of the assembly area.

V. CASE STUDY OVERVIEW

Electronic Manufacturing Services (EMS) is a rapidly growing area in the electronic industry. The demand for EMS is growing due to small batch production and customized production in the electronic market, as well as increasing working hours and demand for higher speed from machines. However, this also leads to more machine malfunctions, which can cause high economic and non-economic costs. Shift settings are inconvenient and force operators to stay for long hours. The working conditions for these operators can be poor and lead to non-economic costs such as health concerns.

Predictive maintenance of machines is a new field that aims to prevent or reduce machine failures/malfunctions and their consequences. EMS companies mainly use machine operating condition monitoring data and previous machine historical data from two sources in a semi-supervised manner to build predictive maintenance models. Many factors can lead to machine failures. Using temperature data alone does not provide satisfactory results. The absence of high-quality and reliable data, especially under a cold start setting, makes training deep learning models very difficult.

This research presents a case study with an auto manufacturer working with many machine vendors for assembly robots in a wait and go mode. The auto manufacturer has one-sixth of a monthly budget allocated to maintenance, which leads to possible machine malfunctions/failures. There is little time to sell, and most robot maintenance data are available for the vendors only. The maintenance platform is based on concepts and cannot provide an entire ecosystem due to limited computational resources. In addition, these robots are too costly and used sparsely, and the average time to failure for them is longer than the average time between cold starts. Most data are either from vendor-made dataset representing failed states or normal historical data that need to be cleaned, and a portion of the time series is noisy.

This research thus explores an eco-system-free AI platform without the need for a cloud or external resource to monitor robot states and detect possible malfunctions/failures or require unnecessary maintenance. The research involves feasible transparent and interpretable algorithms with lack of computational resources in the platform's environment, and analysis of generalizability across machines with different vendors, modalities, and designs. At last, this research proposes an unsupervised transfer learning-based method that can detect possible malfunctions/failures without prior knowledge for machine settings. A case with five real-life robots of different vendors and designs is presented.

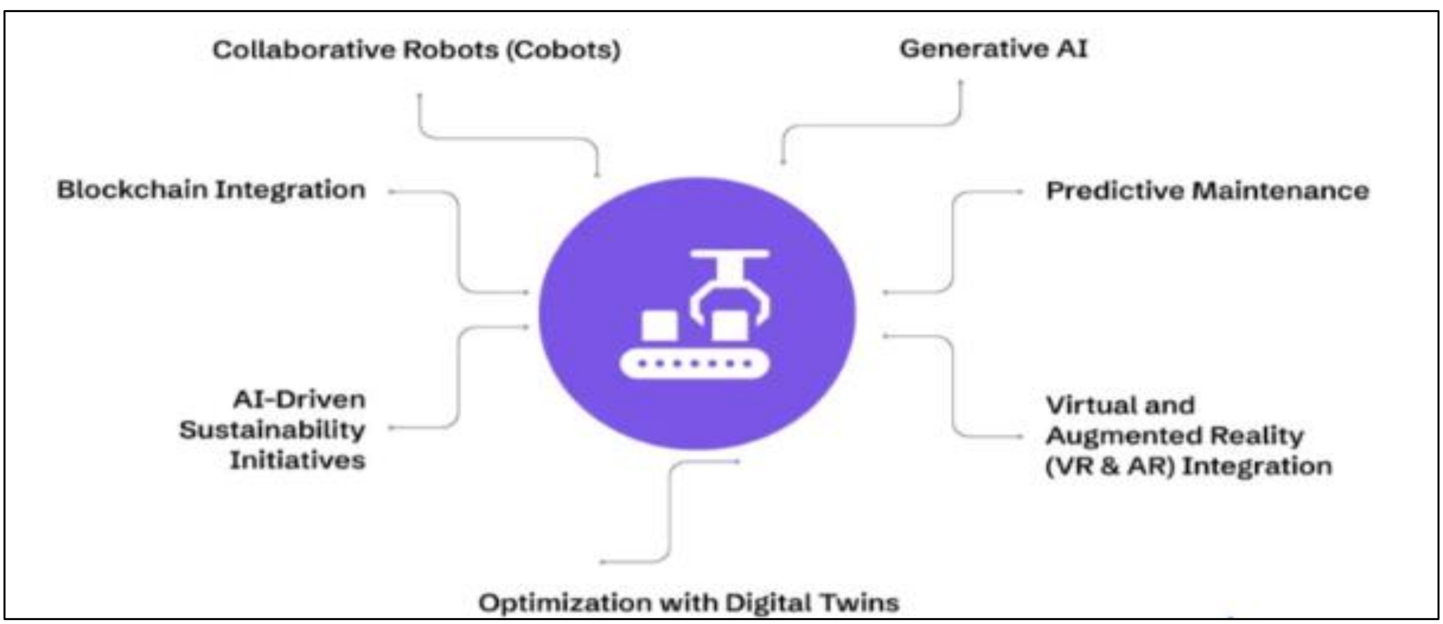

Fig 5 AI in Manufacturing Use Cases and Examples

➢ *Selected Automotive Manufacturer*

In the field of automotive manufacture, one of the largest producers in the world was selected. The selected automotive manufacturer has been in operation for over 50 years and primarily manufactures passenger cars for the SUVs, Sedan, and Luxury classes. The selected manufacturing facility has over 400 industrial robots. In addition to the configurations that are not publicly available, a general overview of how the selected robotic manufacturing cells work is provided. It will include a brief introduction to the robotic cells in terms of functions and processes, and a list of the robot model types. As a large automotive producer, the selected manufacturer builds several different models in a single manufacturing facility. The high-level operations of the robotic manufacturing process are: robot processing handling parts, finished manufacturing parts for diversion to staging, cosmetic inspection scanning the external part of a chassis and performing a quality check of the 3D CAD model and the manufactured part. These operations are accomplished through several robotic manufacturing cells that are provided by deburring, polishing, and inspection robots.

In the highly automated automotive industry, robotic manufacturing cells are intensively integrated with human effort. The robotic systems of these cells suffer from material fatigue, static degradation, and varying operating conditions. Due to safety concerns for humans working in collision with moving robots, end-effector failure for the expensive robots, and stoppage overheads between robotic processes, the top goal of designing the advanced robotic manufacturing systems is to enhance reliability and maintainability almost an order of magnitude over human effort. However, to allow low-cost sensing, many of the crucial disturbances for the robotic cells are usually unmeasured. Additionally, the time publication is assessed based on a small number of independent simulations that do not consider variations in disturbance and process conditions. Leading automotive manufacturers must develop robust diagnostic algorithms. This requires accurate behavior models, but the input uncertainties, random measurements, and high-dimensional nonlinearity of hybrid systems present enormous challenges. In this particular field, intensive research efforts on advanced analytics, such as first-principle or data-driven approaches, have been dedicated, but these efforts have not yet had a major impact on the industrial practice.

For better and broader adoption of advanced analytic technologies in the automotive industry, a comprehensive and industry-grade case study is presented. This study firstly analyzes a latent failure in smart automotive manufacturing and synthesizes large-scale simulation data sets by leveraging a discretization approach. Based on the data generated, a data-driven hybrid fault class-on classification and reconstruction method is developed and successfully tested on the dataset. It is concluded with a large number of targets for future improvements.

➢ *Objectives of the Case Study*

The automotive industry is in the midst of the connected car revolution, wherein both infrastructure and vehicles start becoming aware of each other in order to provide services that previously would have not been possible. Hence, transforming factories into smart manufacturing facilities entails many key aspects, such as leveraging industrial Internet-of-Things (IIoT), utilizing big data techniques, managing information security and privacy, improving data governance, creating and capturing value, and implementing management and business models. Most of these aspects have a technical nature, but it often results in overlooking the human-centered ones [6]. The automotive industry is at the forefront of automation, deploying next-generation industrial robots such as welding robots for body-in-white fabrication, palletizing robots for component assembly and sealing robots for cooling system assembly. However, the observed productivity gains attained so far by industrial robot deployments is often exhausted within a few years, when robots are entrapped in vicious cycles of production stability and reliability degradation. At this juncture, the absence of timely machine health information impedes comprehension of the observed degradation phenomenon. Furthermore, the lack of practical predictive maintenance methods thwarts leveraging historical robot usage data to evaluate remaining service lifetime. To address these challenges, the aim of the presented novel technology is to enable AI-driven predictive maintenance for industrial robots in automotive manufacturing (AAM) in order to facilitate timely machine health information delivery, effective duration forecast of remaining service lifetime, and optimized maintenance planning of human intervention against potential robot faults.

This technology features a cloud-edge hybrid architecture composed of a cloud-based simulation platform and a server–client architecture deployed in local edge devices, such as industrial gateways, IIoT sensing nodes and PCs. The inclusion of edge computing environment and IIoT devices allows the implementation of a cloud-edge hybrid architecture that not only collocates AI algorithms on local edge devices to enable (1) offline AI modelling of robot health and remaining service lifetime, (2) online monitoring of robot health under data drift and anomaly detection and (3) service lifetime evaluation under robot life deterioration but also uses data filtering techniques and on-demand modelling to reduced the computing burden on cloud server. In addition, the configuration of multi-thread and signal processing devices enables parallel execution of service lifetime deteriorating processes and simulation-based algorithm evaluation on multiple instances of the algorithm. The AI-driven maintenance scheduling model can also be visualized as parallel branches, each evaluated independently with internal control commands independently deciding for each sub-process the next time point whether to call a cloud-edge AI model for health evaluation or a server-edge estimation model for remaining service lifetime evaluation.

Equ 3 Reliability and Failure Rate Functions

$$R(t) = e^{-\left(\frac{t}{\eta}\right)^{\beta}}, \quad \lambda(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1}$$

Where:

- β: Shape parameter (wear-out if $\beta > 1$)
- η: Scale parameter (characteristic life)

VI. CONCLUSION

The proposed AI-based predictive maintenance system was successfully developed and validated within a simulated automotive manufacturing environment. A custom-built Asset Simulation Generator produced a realistic simulated environment comprising robot assets, component models, and asset loads. The Time Series Generator created asset condition data to replicate existing sound data and serve as a feed to the Predicting Maintenance Unit. The unit employed classical forecasting and machine learning methods to generate condition forecasts. A built-in explainability module explained forecast results using Shapley Value, facilitating the analysis of real-condition sub-optimizations.

The simulation explored predictions of a multidimensional series of assets and insights-guidance actions to optimize total failure costs. Scenario analysis indicated that asset replacement decisions are clear-cut, delaying failure predictions negatively influenced maintenance scheduling, and that the forecast horizon significantly affects the amount and intensity of texts. A range of objectives, including company-wide robustness and flexibility prospects, were assessed.

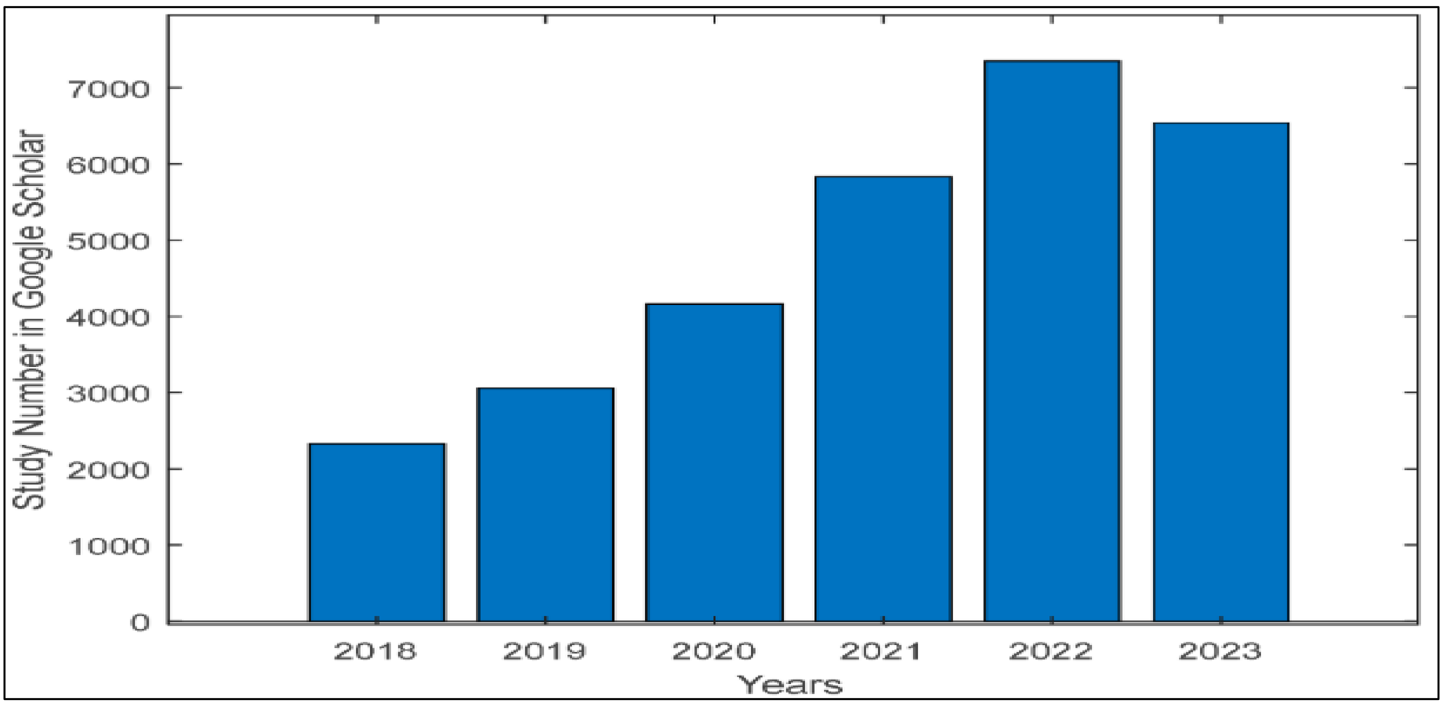

Fig 6 Artificial Intelligence for Predictive Maintenance

➢ *Emerging Technologies*

Some specific emerging technologies in the field of data science and Artificial Intelligence that have the potential to significantly aid predictive maintenance in automotive manufacturing include:

- Predictive Maintenance as a Cyber-Physical System: Predictive maintenance is defined as a cyber-physical system that uses data from connected machines to intelligently predict maintenance needs and recommend or automatically initiate maintenance actions. This requires skills across the boundaries of knowledge domains.
- Predictive Maintenance: Bridging Artificial Intelligence and IoT: Predictive Maintenance utilizes data from IoT and machine learning to build predictive analytics, aiming to minimize unplanned breakdowns and maintenance costs. While early implementations were strongly based on physics-based models and did not use IoT, with the introduction of novel technologies, data-driven techniques have gained a large share in PdM applications.
- Predictive Maintenance in Manufacturing: Sleep Mode Considerations: Predictive Maintenance aims to estimate the Remaining Useful Life of manufacturing equipment to prevent costly failures while taking action to avoid

unnecessary costly maintenance. PdM was often conducted based on historical data and simplified operational settings, focusing on the asset under normal operations.

- The Future of Automation: Machine Learning in Manufacturing: The fast-paced advancement of machine learning where data has been stored on customer sites, volume, and complexity has aggravated the surrounding environment, even creating new business value. The advanced technologies that the automation/discrete industries should employ include 5/6G, IoT/Edge/Cloud Computing, MLOps, and simulation models.
- AI for Predictive Maintenance in the Cloud: A cloud-based solution for Predictive Maintenance is proposed by leveraging the capabilities of Artificial Intelligence, the Internet of Things, and the Cloud. IoT is used to monitor machinery condition via sensors. The Cloud is used to continuously assess condition data against failure conditions. Advanced Machine Learning is strategically placed on the Cloud to build and deploy AI models. This architecture enables organizations to avoid costly failures and standstill.

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