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Chapter 11: AI-Driven Maintenance and Failure Prediction in Smart Connected Systems

11.1. Introduction

The typical introduction opens by placing AI-driven maintenance and failure prediction within smart connected systems (SCSs) in a broad context. It then offers a focused background on definitions, characteristics, and applications of SCSs. For further context, see Enterprise Applications of Smart Connected Systems and Enterprise Applications of Smart Connected Systems, which explore SCSs in greater detail.

Smart connected systems represent a new wave of innovation combining smart machines with advanced data analytics and cloud capabilities, enabled by sensor technology and enhanced computing resources. Consequently, modern smart machines are highly intelligent and capable of communication and task execution in dynamic settings. Beyond sensing and networking, SCSs feature connectivity—encompassing people, processes, data, and things—and the use of big-data analytics and cloud computing for machine monitoring, improved decision-making, increased intelligence, and context-aware behavior. These features collectively constitute a foundational building block of the Fourth Industrial Revolution by enabling the digitization and networking of advanced smart machines with people and business processes.

11.1.1. Overview of Smart Connected Systems

Smart connected systems are characterized by three attributes: the integration of smart components capable of sensing, control, and communication; seamless connection through softwarized networks (e.g., broadband, mobile, satellite); and the ability to advance user experience by providing connected users with access to remote smart resources or by enabling autonomous operation. These features allow smart connected systems to support novel industrial scenarios that utilize automation and data exchange throughout the value chain. In recent years, trends in new production networking have extended the concepts of interconnected enterprises to industrial manufacturing equipment and units, enabling flexible and intelligent business-process control and manufacturing-operation control.

To realize smart connected systems, real-time monitoring and control functions require the support of efficient communication networks, while smart data analytic functions need to be implemented by artificial intelligence (AI) technologies. A dedicated AI research area in this field is AI-for-maintenance, which focuses on the use of AI in maintenance applications in both traditional and smart connected systems. Techniques for AI-for-maintenance promise to meet new challenges created by recently developed smart maintenance strategies and schemes (e.g., data mining, advanced prognostics and health management, smart sensor networks, scanning technologies). Research and development in this area, therefore, integrates AI techniques with applications in real-world industry and maintenance management.

11.2. Overview of Smart Connected Systems

The recent advancements in industrial manufacturing have led to the development of smart components capable of injecting data into the production chain. These novel features can predict breakdowns and suggest preventive maintenance, thus enabling a shift from the traditional reactive maintenance approach to a condition-based maintenance approach [1-3]. This emerging paradigm is known as smart connected systems, or a system-of-systems. Examples of such systems include the Industry 4.0 production line, a power grid, a cascade of hydroelectric power stations, a connected fleet of trucks, and an ecosystem of connected cities.

Failure prediction in smart-connected systems and smart systems is a challenging task. In a smart system, all components practically evolve according to a defined lifetime profile. This property of components is known as degrading states. Degrading states can be explained with an example. In a bag filter system, whenever the differential pressure across the cascade of bag filters goes above the threshold limit, maintenance activity is undertaken. Failure prediction in a smart-connected system encompasses the prediction of the degrading component dynamics. The failure prediction method that considers the degrading states for pinpointing the next or upcoming failing component is referred to as component-level failure prediction.

11.2.1. Definition and Characteristics

The Smart Connected Products concept is still quite novel. However, over the last few years, several aspects have been analyzed that have contributed to the solidification of the features and functionalities that smart connected products are expected to demonstrate. According to Michael Porter [1], Smart Connected Products enable businesses to view, navigate, and create value along every step of the value chain and every phase of the value delivery process, including design, sourcing, manufacturing, logistics, marketing, sales, and service. In transportation, Smart Product Services have a great influence on transportation safety, economic efficiency, and users' convenience. Nowadays, the cargo and fleet operate with progressive control systems that include different smart devices (with fail detection capabilities) that can communicate with external sources.

According to Michael Porter and James Heppelmann [2], a Smart Connected Product must present three important capabilities: Sense, communicate, and control. The Smart Connected Product senses by gathering information about its internal state and the external environment; it typically includes sensors and actuators, which convert physical phenomena into data and electronic signals and vice versa. Smart Connected Products communicate by linking that gathered information to the broader world; they contain embedded processing capability, software, and wireless connections that feed real-time data into enterprise systems and connect them with other products and with people. Smart Connected Products are controlled by directing the product’s operation or altering its physical environment; they integrate processors with software and actuators that increase flexibility and enable products to respond to control signals from external sources.

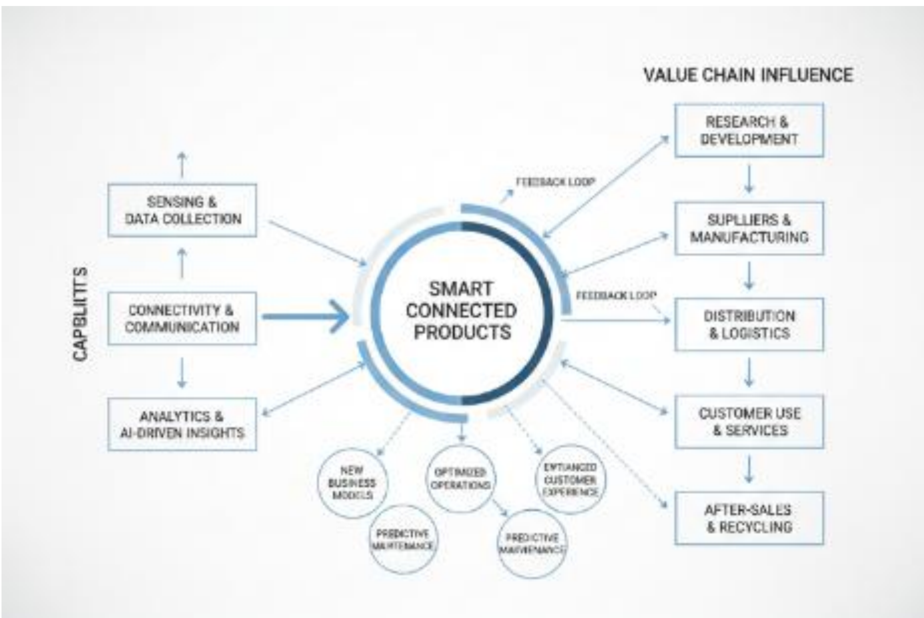

Fig 11 . 1 : Smart Connected Products: Capabilities and Value Chain Influence

11.2.2. Applications in Industry

Industry leaders in various areas promptly recognized the vast potential of deep learning methods. Amazon's extensive use of convolutional neural networks for image pattern recognition and their predictive capabilities for failure rates in Amazon Web Services are key examples. However, the paradigm of being "data rich" but "information poor" is most obvious in the manufacturing industry: data generated by sensors is stored but never leveraged to its full potential. Although never before has so much data been produced and collected, less than 1% of the information is used for analysis, and only 19% is ever inspected microscopically. Still, a handful of manufacturing companies have pioneered the use of sensors, which enable them to collect data related to production quality, equipment status, and worker safety [3-5]. Such data are either processed at the device level or sent to the cloud for further analysis and monitoring of removable hard disk failure using recurrent neural networks and long short-term memory.

The integration of cyber-physical systems and the Internet of Things gives rise to smart connected systems able to monitor each other's state in real time. This capability is critical to the development of advanced, integrated, closed-loop smart manufacturing systems. By implementing integrated monitoring and control functions throughout a plant, smart connected systems can bring risks within the plant under control and make it possible to design and optimize production schedules that are dynamically updated according to each machine's capacity. The intelligence provided by smart connected machinery enables the creation of new business models based on remanufacturing equipment and paying per unit of production, not just the sale of equipment. New intelligence can also help machinery companies improve maintenance activities by performing equipment health monitoring analytics and taking appropriate maintenance actions accordingly.

11.3. Importance of Maintenance in Smart Systems

The field of artificial intelligence holds a profound interest in smart connected systems, which find application in crucial industrial domains such as wind farms, refineries, and warehouses. In these areas, scheduled and unscheduled maintenance play a vital role in minimizing failures. Through the detection, preparation, and prediction of maintenance, it becomes possible to prevent numerous failures and reduce costs.

As automobiles evolve, companies aggressively develop preventive and predictive maintenance programs, made possible by constant updates from wireless technology onboard the vehicles. Long-term predictive statistics establish the reliability of a system and produce alerts within the maintenance schedule. These recommendations enhance safety and operational reliability, ensuring proper maintenance, reducing unplanned outages, and lowering costs. Predictive maintenance enables efficient monitoring of manufacturing equipment conditions, thereby preventing failures caused by neglect and mechanical wear. It offers numerous benefits, including improved equipment usage, reduced overall risk, increased product quality, enhanced safety, decreased operating costs, accelerated maintenance operations, and greater flexibility in maintenance management.

11.3.1. Traditional Maintenance Strategies

Maintenance strategies played a significant role in the evolution of technology and the context in which preventive maintenance activities were performed. Preventive activities were originally carried out daily until the 1950s. Then, during the 1960s, the experts pointed out the deficiencies of this approach and recommended that preventive maintenance tasks be performed periodically. The next major step was the introduction of predictive maintenance strategies, which focused on the prediction and correction of failures. Predictive maintenance is regarded as one of the most effective approaches in the maintenance process. Since failures often represent an unexpected cost for companies, prediction is crucial to prevent the failure of smart connected systems on time.

The effectiveness of predictive maintenance depends on methods of data analysis and intelligence. Data collected from monitoring processes can be classified into two categories according to the state that they represent or reveal: information about what is going on, or information about what will happen. The data that reveal the current state show the health of the systems at the time of checking, and it enables the system failure probability to be evaluated for the immediate future. Historical data and information over a long period are the basis for prediction [2,4,5]. They make it possible to forecast when the systems will fail and to determine the percentage of reliability, maintenance, and remaining useful life for the systems in various operating conditions.

11.3.2. Challenges in Current Approaches

The prediction of failure in complex systems that have been designed in a way that allows them to communicate information about their real-time status to a Health and Usage Monitoring System (HUMS) forms a major area of application within the implementation of Artificial Intelligence (AI) technologies in smart connected systems. These systems can be thought of as within the Internet of Things (IoT) environment. Failure prediction is primarily used to identify when an asset needs maintenance, thus allowing for maintenance to be planned in the most economical way possible. When this is combined with condition monitoring information, it ultimately enables predictive maintenance, which forms a major enabler for the wider concept of Smart Maintenance.

Several approaches to failure prediction have been proposed for use with smart connected systems, with those currently adopted Linked Health Models being a form of hybrid model, combining physics-based models and data-driven models. While these models combine the strengths of each approach, they also combine many of their weaknesses, such as the requirement for extensive data comprising both measurements and action records, as well as an understanding of the underlying physics. To overcome many of these issues, there has recently been a move toward the use of fully data-driven models for failure prediction. However, due to the rare nature of failures, there is often a lack of failure data available, which presents the well-known issue of imbalance within the training dataset.

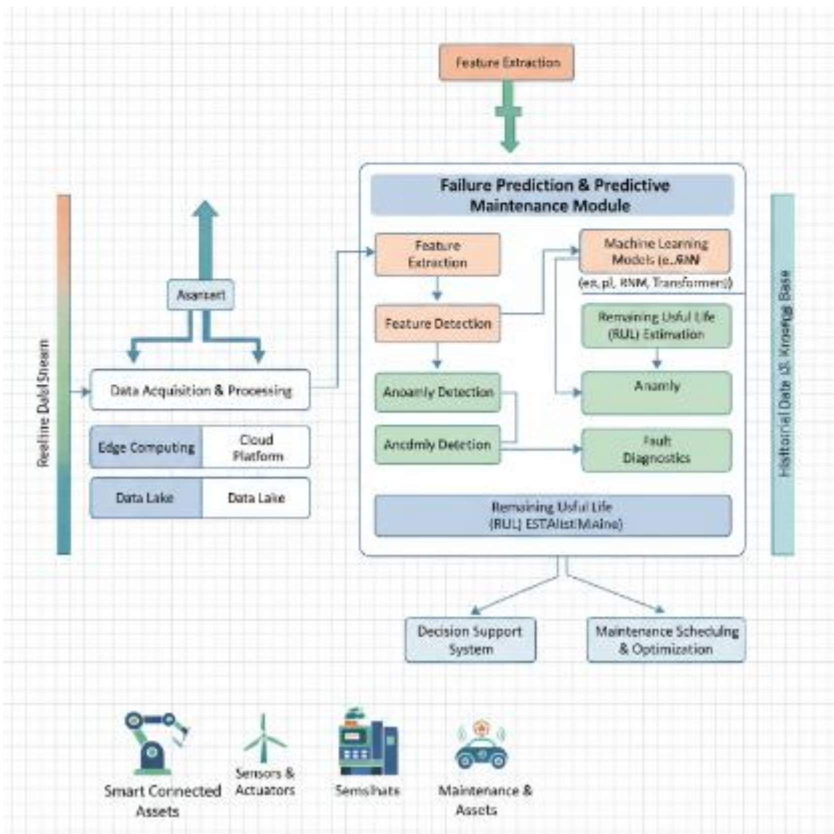

Fig 11 . 2 : Failure Prediction in Smart Connected Systems and Predictive Maintenance

11.4. AI Technologies for Predictive Maintenance

Predictive maintenance (PdM) anticipates failures and diminishes downtime with AI and operational data. It finds faults and gauges the condition of devices, assemblies, and production lines. Maintenance begins precisely when necessary—avoiding futile or late interventions. PdM offers a mindful remedy: instead of maintaining every machine on a schedule, it repairs only in response to equipment condition.

PdM tends to be secondary to condition-based maintenance (CBM), a management method in which asset-condition measurements guide maintenance decisions. CBM relies on AI and Rule-Based systems or on predictive models. In Rule-Based CBM, humans enumerate the signals and declare enumeration criteria that warn about trouble. These explicit commonsense rules minimize false alarms. PdM demands more advanced AI tools, combining operational data and expert opinions to glean continuous insight. Semiconductor, aerospace, rail, and manufacturing outfits are already gathering crucial information from sensors on their equipment. They feed the data to AI, which enunciates rules and models of deteriorating assets, pinpointing the trouble at an early stage.

11.4.1. Machine Learning Algorithms

Today’s smart, connected systems and products integrate sophisticated sensors and CPUs to continually stream data to the cloud. By harnessing the ever-increasing volumes of data generated by these systems, machine-learning algorithms can identify parameters influencing system operation and predict system failure. This analysis enables significant advancements in maintenance optimization through predictive maintenance, condition-based maintenance, and prescriptive maintenance.

Numerous types of machine-learning algorithms—supervised regression and classification algorithms such as Logistic Regression, Support Vector Machines (SVMs), and random forests; and unsupervised algorithms like K-means clustering—have proven effective in the failure-prediction domain. These algorithms generate nuanced insights into system health and remaining life [6-8]. Although deep-learning techniques are currently gaining popularity, deeper networks are not always better; indeed, depending on the use case, traditional supervised algorithms can continue to offer excellent performance.

11.4.2. Data Analytics Techniques

Data Analytics Techniques in AI-Driven Maintenance and Failure Prediction Systems

The heart of the Smart Connected Maintenance and Repair System is the analytics engine. Data is extracted from the components most vulnerable to failure—for example, gas turbines. Specialized AI techniques help determine the likelihood of failure shortly. Scheduling is then performed in an efficient way to satisfy traffic demand and reduce delay, using fuzzy logic and timing-driven genetic algorithms. If the decision is to schedule a maintenance event, suggested tasks and associated logistics are generated and provided to the user. Filtering techniques reduce false alarms, and visualization methods help to communicate alerts and maintenance work—thus reducing costs through more efficient task management and enhanced operational decision support.

Several key building blocks are essential elements for supporting the increasingly important smart maintenance concept. In particular, the quality of the information for predictions and remaining lifetime assessments directly affects the quality of maintenance decisions. Maintenance services today employ a number of fault-detecting techniques: fault detection, fault isolation, fault identification, prognosis, preventive maintenance, and failure mode analysis. For each of these techniques, a different derivation of the fault information is generated based on operational data. The main advantages and disadvantages of some commonly used methods are listed. Those methods that play underpinning roles for actual fault-detecting techniques and are supported by a wide number of publications include classification, similarities, classification and comparison, statistics, regression analysis, pattern recognition, association rules, sequence generation, and clustering. These support methods are particularly useful for establishing an effective maintenance strategy (e.g., predictive maintenance).

11.4.3. Sensor Technologies

Smart Connected Systems, particularly those targeting smart manufacturing, require sensing capabilities to gather information about the environment and status of assets at the edge levels. Although human operators perform the maintenance process, the entire production line maintenance needs to be systematized, automated, and, indeed, expedited. Systems alert personnel on the status of individual machines during the operation and provide them with the required data to perform effective predictive maintenance and failure prediction assessment.

An effective Human–Machine Interface applies diverse acoustic and vibration sensor technologies together with advanced AI applications running deeply trained algorithms at the edge, ready to answer queries at different levels of the maintenance process. Acoustic and vibration technologies, supported by modern sensors and signal processing, reveal aspects of asset operation and condition maintenance analysis that were formerly difficult to identify with the traditional assistance of the human ear.

11.5. Failure Prediction Models

The two main sets of models based on the presented data are models of component failure prediction and models of maintenance impact assessment. The purpose of component failure prediction models is to forecast the health state of particular components at a system level, in order to schedule their replacement, rather than perform an unplanned and potentially costly repair.

Maintenance impact models aim to optimize the sequence of maintenance actions by inspecting components in a chain or circuit and focusing attention on the components with the highest failure impact. These models are needed to reduce energy consumption in component maintenance and repair activities. Maintenance impact models highlight the need to consider the impact of failure on other components, and not just the failure itself.

Both failure dependency and maintenance impact models require open fault data from the test bed and detailed component interconnectivity [5,7,9]. Present analyses consider only automated fault injection analyses of components connected to the main board of the test bed, as these provide useful air links for model training. A semi-Markov fault injection process with adjustable sojourn times and run sequences simulates a dynamic fault environment and generates the necessary information on component failure dependencies and maintenance impact.

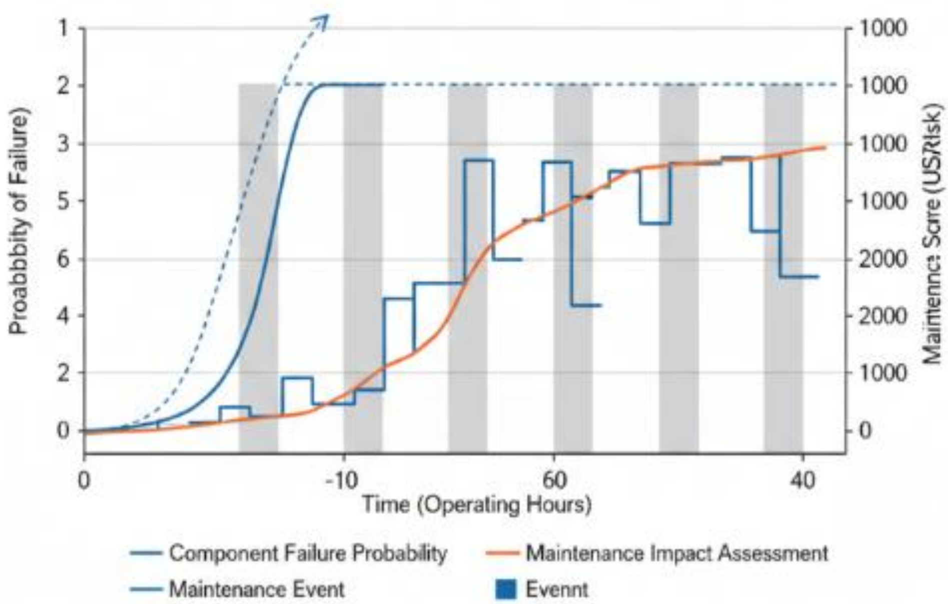

Fig 11 . 3 : Component Failure Prediction and Maintenance Impact Assessment

11.5.1. Statistical Models

Statistical models used as a function of time for the analysis of maintenance and failure prediction in Smart Connected Products (SCP) are introduced in the following. The preference is for parametric models based on probability functions whose shape is determined by various parameters. Nonparametric models also exist and serve to determine trends in the failure rate as a function of time without assuming any probability distribution.

Among the parametric models, the model based on the exponential function assumes that the reliability evolves exponentially as a function of the time until failure. This implies that the subsequent failure rate is constant over time. This assumption appears to be a fairly imprecise model of reality, where one usually expects either an increasing failure rate or a decreasing failure rate; hence, the Weibull model makes it possible to represent these situations through a change in the shape parameter.

11.5.2. Machine Learning Models

A failure prediction in smart connected microgrids demands domain knowledge for feature engineering, labels for sample data, and a baseline predictive model. No standard dataset exists for microgrid failure at present. To overcome this absence, a hybrid simulation approach can be used. One option involves managing failure events randomly generated by controllable Mittag–Leffler clocks applied to loads and feeders of the microgrid simulator, then sending the failure messages and the operational conditions to the cloud, where storage and prediction processes are defined. Another possibility consists of designing a failure model with random failure and repair rates for each device based on either a Markovian or a semi-Markovian model. The failure model and the operational data are then fed into the microgrid simulator, and the failures are recorded as events and sent to the cloud for prediction and storage. In both cases, it is important to select relevant operational features for prediction and to keep in mind the real causes of failures in the considered domain.

The application of AI methods in distribution networks allows efficient service for customers. The smart distribution network simulator generates both operational features and failures over time. The information is passed by the virtual environment to a database in the cloud, imitating the maintenance domain and fulfilling all the prerequisites of a failure prediction. The database mimics a certificate of execution of the failures by maintenance managers. The suppliers of distributors, agencies, and the maintenance managers who make the decisions about the execution priority deserve dedicated software tools. Agents driven by learning models, along with a ranking system, are included to provide a prioritized order for the execution of corrective maintenance, considering the severity level of the failures and the level of risk of the network in the failure zone. Monitoring the status and evolution of failures and the operational conditions of feeders supports the detection of dependencies between failures. Knowledge discovery provided by ML models indicates which failure types produce further failures and what is needed to prevent them.

11.5.3. Hybrid Approaches

Hybrid approaches constitute a major category of machine learning (ML) techniques that combine models of diverse analysis types and input data modalities, usually incorporating some form of physical models. Domain-knowledge-guided data generation is an example, where large quantities of labeled data required to train supervised-modeling prognostics and health management (PHM) applications can be synthesized using physics-based models [1]. Here, the physical modeling workflow is illustrated using a model that simulates the dynamics of an aircraft, whose sensor data are employed to train an ML-based autopilot capable of flying an aircraft model. Transfer learning is then applied to retrain the model using real flight data, yielding a real-time classifier of stability in flight. Domain knowledge can also be integrated into ML-based anomaly detection directly through constraint optimization; for instance, in known-operation-conditioned anomaly solicitation (NOSA), known contexts help define the range of anticipated operational quantities [2]. ML models are trained on labeled data generated by a physical-modeling workflow and subsequently applied to data collected from attaching inertial measurement unit (IMU) sensors to a bicycle's frame. Anomalous events identified by the models are isolated, while non-anomalous events—bounded by contextually defined acceptance functions—are discarded as overly sensitive, thereby increasing confidence that identified anomalies reflect true malfunctions.

3D heat-conduction analyses can provide thermal damage maps for nowcasting and predicting turbine-blade fatigue service life [3]. Scans of an actively cooled blade, acquired through infrared thermography at various blade-tip conditions, are fed into a 3D-heat-conduction simulation, the results of which estimate the thermal loading endured by the material at specific points in time. Combining these thermal-damage estimates with the time of occurrence supports a fatigue-service-life prediction model. Then, record heat loads can be detected and used to estimate blade service life, characterize when damage occurred, and flag blades requiring additional inspections or special attention before or during operations.

11.6. Data Collection and Management

Central to the execution of an AI-driven predictive maintenance strategy is the repeated failure of components with similar root causes. Data on these failures can be collected from proper maintenance procedures and stored in a failure knowledge base/database. Additional information about the system is needed, such as its operational states and updating mechanism. Typically, the failure knowledge base includes data on the failure list and classification, failure description, number of trials or performed tests before the failure occurrence, failure frequency, failure probability, the shortest period between failures, failure effects and consequences, suggested actions for error detection and recovery, and source of failure data. Collecting, processing, and analyzing this information expediently can assist in forecasting future failures.

Executing an AI-driven predictive maintenance policy comprises four steps: failure classification, data collection, takeover, and data updating. The failure classification stage involves grouping collected failure data into main and subcategories based on the root cause. Fault types may vary from system to system, but the main categories generally include external, systemic, and internal risks. External failures are usually linked to environmental risks and factors such as temperature, humidity, vibration, and dust. Systemic failures also relate to external factors and frequently predict the occurrence of another failure. Internal failures pertain to inherent system problems, such as damaged components or poor design. Failure classification in such a manner allows evaluation of the most affected sources. Though all conditions are important and suitable for predictive maintenance, each has varying applicability and relevance for different systems [8-10].

11.6.1. Data Sources

Before designing a data analytics AI system for failure prediction, the data sources used need to be understood. Internet systems generate massive amounts of data every minute, including Social Media Data, Weather Data, Sensor Data, Video Monitoring Data, Documents Data, Emails Data, Stock Data, Surveillance Data, etc. For failure prediction, maintenance data or integrated datasets, including maintenance data and other datasets, are used.

For short-term maintenance predictions, recent operational data is used. However, for long-term predictions, only component health data is used. The latter type is more robust in real-life situations, since current operations can be random while actual health changes take longer and provide a better picture of the condition of the system. Therefore, sensor data for component health monitoring is used. Conditions must be defined for each component, categorizing their status as Very Bad, Bad, Medium, Good, or Excellent.

Various types of weather, sensor, temperature, and other relevant data can be integrated to create a feature-rich dataset.

11.6.2. Data Quality and Preprocessing

Connected systems subject to analysis generate increasing amounts of data and are usually instrumented with sensors. These sensors identify present conditions and achieved performances. Specific configurations of sensors permit feature extraction that can feed dynamics models. Such models ideally cruise at high performance for long periods before showing signs of degradation, which eventually, in the last phases, deteriorate rapidly until system failure. Startup of a system is typically said to not be in the "normal" operating regime because of the type and indeed the magnitude of the transients related to the start-up of the system. There are different types of failures, and their prediction takes into account their distinctive traits, not all being of sudden onset. Machine learning's ability to detect patterns cannot be questioned when, in its complement with physical models, it is the key element to fully exploit the potential in big data and big computing power over vast periods of their life cycles. Models of different natures, DM for the normal regime, and ML for the irregular periods, are worked out for the failure prediction of a ground vibration test rig, with emphasis on the loss of resilience of the system.

Data quality is one of the most important issues for effective analysis with ML. Although more data is often considered better in ML, the quality of the data should be the focus when performing ML. Many assumptions are applied to data, especially for data-driven models such as ML. Poor data quality can lead to violations of these assumptions, resulting in inapplicable model predictions and interpretations. Ensuring data quality before implementing ML can reduce the risk of violating assumptions. Model predictions depend heavily on the data, and the "garbage in, garbage out" principle applies. Poor data quality used for model development can have serious impacts on prediction quality and subsequent decisions. Proper preprocessing is essential to transform data into useful model inputs or meaningful frameworks for analysis. Data preprocessing involves transforming raw data into data of acceptable quality through data cleansing, normalization, feature extraction, data transformation, and other necessary steps. It is a preliminary step in data mining processes to achieve good quality data for effective and quality mining results.

11.6.3. Data Storage Solutions

Having identified, transferred, and transformed data, the final step of the data pipeline is data storage. Sources for storage include conventional data centres, data lakes in the cloud, and modern distributed database systems. Data lakes store data, enabling mining for knowledge extraction and decision-making. However, these data lakes typically lack ongoing intelligence services and may not be designed to support declining performance trends or early warning indicators, as required in a PHM system. Beyond storage, the pipeline must also provide computational resources to execute intelligent algorithms that create the desired intelligence.

Furthermore, the intelligent algorithms locating destructive trends or incipient activities often require additional data attributes to give confidence in their outcome. These attributes may be manually or automatically entered as software updates and can include operator key performance indicators, additional environmental or energy data, and model-based asset profiles. The software updates are then used to append the storage structures to maintain the integrity of the data as it evolves.

Currently, no existing, publicly available, end-to-end cybersecurity asset management framework that incorporates smart, cyber-physical intrusion detection of ICS and SCADA systems exists. Modern connected systems incorporate a variety of domain specializations, including operational technology (OT), quality assurance (QA), natural language processing (NLP), business intelligence, and machine learning. These applications involve unique data sources with different levels of sensitivity, each of which requires executive attention. Because of the heterogeneity of these environments, layering the OT with QA, NLP, and other applications can expose these asset management systems to novel attack vectors, including supply chain risk, social engineering, asymmetric attack surfaces, and insider threat.

11.7. Conclusion

Estimation systems for assets such as machines and equipment, as well as for car operation status and remaining mileage, have been conventionally explained mainly using models that analyze operational state data. Recent developments integrating information from social networking services (SNSs) enable associations with event information gathered from social big data. Failure estimation systems that link the operation status of various cars with failure case information from SNSs allow for more convenient estimation of warning and failure time information based on changes in operation status data, such as abnormal or noticeable changes.

A person’s life involves dreams and desires that motivate their behavior, but also insecurities and anxieties about the future that are influenced by social circumstances. Nevertheless, individuals can take control and proactively shape their behavior, often unconsciously influencing the future and the world around them. Social events are the cumulative result of such individual behaviors. Therefore, social events are factors that make the future uncertain; it is necessary to actively strive for the future to become predictable. Social prediction attempts to forecast aspects of the future in a way that reduces uncertainties about social events.

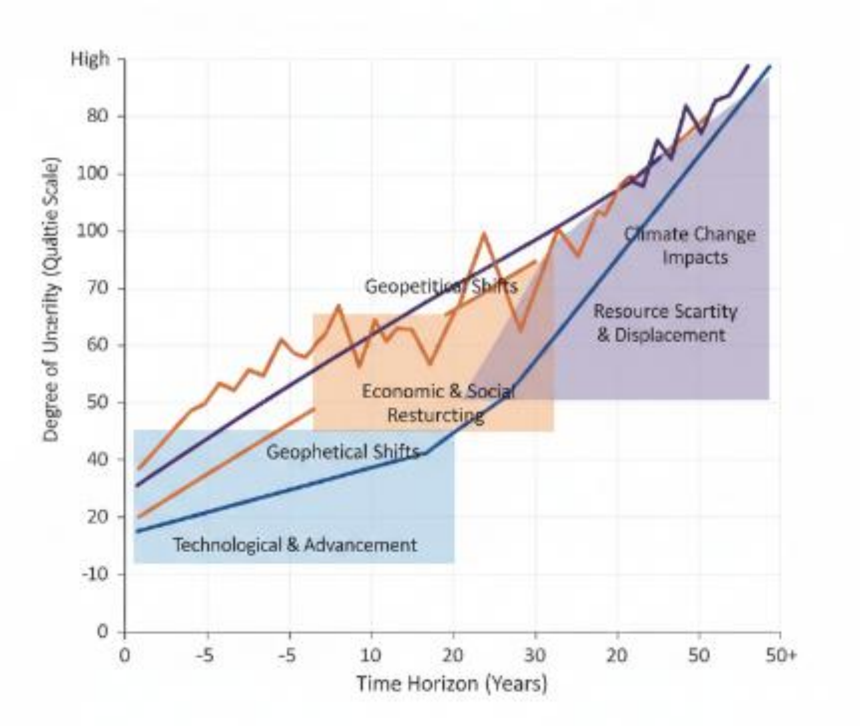

Fig 11 . 4 : Fundamental Drivers of Future Uncertainty

11.7.1. Final Thoughts and Future Directions

Data-driven failure prediction has garnered significant interest in the literature due to its ability to intelligently direct maintenance activities and enhance derivative services. While traditional condition-based maintenance relies on continuously collecting system condition data and conducting complex analyses or using model-based and physics-based approaches, these methods require an intimate understanding of component degradation and the underlying physics. They also demand accurate models that reflect the operating degradation process. Supervised machine learning techniques, such as classification and regression models, depend on labeled failure data to extract degradation signatures.

However, supervised methods inherently overlook data not associated with failures, and the scarcity of labeled failure data severely limits the performance of these approaches. In response, recent efforts have shifted toward using only normal operation data to model system degradation. Accurately identifying and classifying anomalous states within the incoming stream of sensor data from products in operation remains a complex challenge. The myriad of possible failure modes, their influence on operational behavior, and how these relationships are affected by current operating conditions and product variant characteristics present significant difficulties that open exciting research avenues.

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