

# INTRODUCTION TO A DATA-DRIVEN PROGNOSIS APPROACH FOR MULTI-SENSOR DEGRADATION DATA ANALYTICS IN MANUFACTURING INDUSTRY

## Abstract

Recent scientific and technological advancements have led to substantial growth of complex engineering systems that practically changed every aspect of our lives. Even Industrial Systems have become more efficient with the automated complex machinery over traditional ones. As improved automation became popular, unplanned stops had direct implications, including death, environmental damage, and enormous financial expenditures. Unscheduled shutdowns because of machine and subsystem failures pose significant operational and usage challenges over their life cycles. Assuring the safety and performance of complex and safety-critical systems is a significant challenge. Prognostics and Health management (PHM) play a crucial role in increasing safety and facilitating operations planning. However, the growth of data processing and its crucial impact on remaining useful life predictions need continuous development to achieve greater performance levels. Frequently, there is a disconnect between the sufficiency of prognostic pre-processing and the accuracy of prediction methods. One strategy to close this gap is to develop an adaptive data processing system capable of filtering multidimensional condition monitoring data by identifying relevant information from numerous data sources. Due to lack of understanding of multidimensional failure mechanisms and the collaboration between data sources,

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present prognostic approaches are unable to deal effectively with complex interdependence and multidimensional condition monitoring data. This chapter addresses these shortcomings by incorporating a data driven prognosis approach that analyzes the multiple sensor degradation data to forecast the life expectancy of systems using machine learning models for different applications.

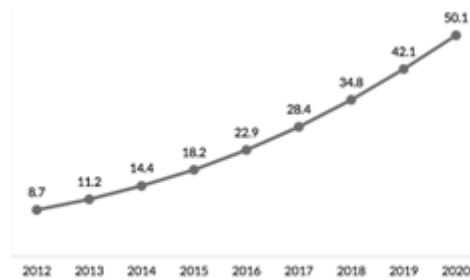
**Keywords:** Prognostics and Health management (PHM), condition monitoring, sensor degradation data, safety-critical systems.

## I. INTRODUCTION

Internet of Things is an Emerging technology with abundant applications in Transportation, Agriculture, and Manufacturing industries. IoT Technology implementation requires selection of technology stacks to stream the data, process the data, build machine learning and deep learning applications. The advancement of technology over the last several years, increased the usage of smart devices and the Internet of things substantially, primarily for the purpose of monitoring the health of industrial machinery. Small embedded electrical or mechanical components with data acquisition, transmission, analysis, or control capabilities are referred to as "smart" devices. They have improved sensor reliability, are smaller in size, have enhanced functionality, are easier to operate, and are more affordable.

**Figure 1:** Increasing Trend of Smart Connected Devices

Smart sensors are one of the most important components of embedded systems, with a market share that is growing at an unprecedented rate.



Industries have benefited from the modern smart device market, including electrical/electronic and industrial control and automation, medical equipment, agricultural equipment, automotive, and consumer and communications equipment. These sensors can measure the intensity of light, pressure, temperature, and vibration.

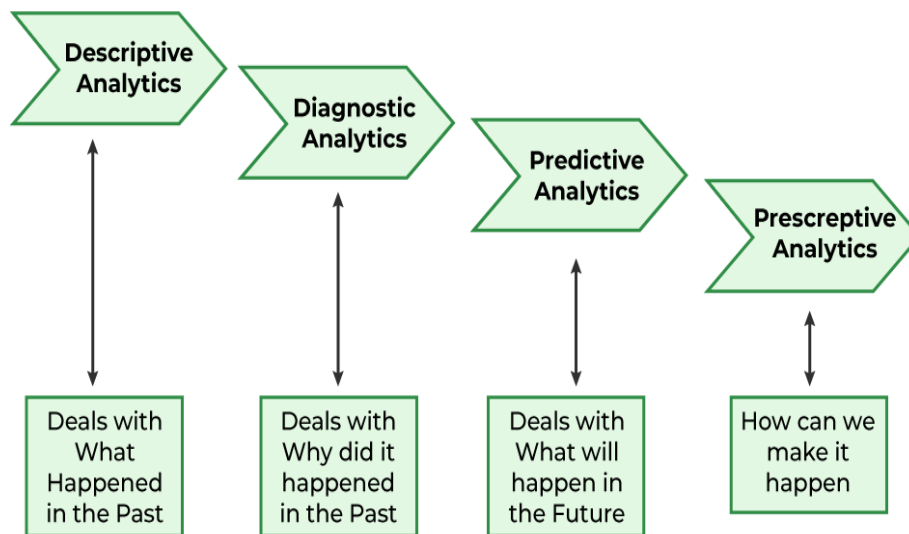
Utilizing smart control devices to manage manual control in diverse industrial equipment results in the creation of multiple sensors in each piece of equipment. However, it has become more difficult to determine the performance of a system while ensuring proper functionality. This type of information gathering results in the study of prognostics, which includes the investigation of failure times and modes, fault states, and the detection of early symptoms of system or component ageing. Predicting the moment of failure has become a primary concern for engineers, whose ultimate aim is to concentrate on the duration of time remaining for the system to work properly. The time to failure is sometimes referred to as the components or system's Remaining Useful life (RUL). RUL estimation has attracted attention in a variety of industries and has developed into a standard challenge for every system or component. This is the critical point at which the component will cease to function properly.

The industrial Internet of Things (IIoT) is the use of Internet of Things (IoT) technologies in manufacturing which tackles smartly the machine data generated by various sensors and applies various analytics on it to gain useful information.

### Types of Data Analytics

There are four major types of data analytics shown in Fig 1.2:

- Predictive (forecasting)
- Descriptive (business intelligence and data mining)
- Prescriptive (optimization and simulation)
- Diagnostic analytics



**Figure 2:** Four Major types of Data analytics

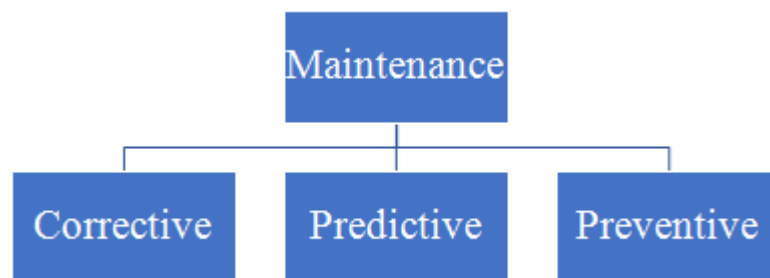
Predictive analytics is helpful when combined with machine data in order to help in tracking and comparing machines' performance and equipment maintenance status and predicting which particular machine will fail.

Predictive analytics is the field that analyzes by examining the status of sensor degradation data, to better comprehend the device's damage propagation. It defines the way damage would progress over time under forthcoming operating conditions and environmental circumstances, and with every other other elements that could affect damage.

An interesting new field of research is analyzing data using the advantages of machine learning algorithms in order to anticipate how long crucial systems will stay operational. To reliably anticipate the remaining useful life, classifiers and prediction algorithms are used. To do this, a variety of machine learning methods are available, which include supervised, unsupervised, semi-supervised, reinforcement, and evolutionary as well as deep learning methods. An important component of smart manufacturing systems is the ability to respond to unplanned and planned changes in performance. The Prognostics Health

Management and Control (PHMC) system provides methodologies, tools, protocols for vigorous sensing, fault prognostics, fault diagnostics, and control that help industrial manufacturers to react to planned and un-planned routine changes thereby increasing the performance of smart manufacturing structures.

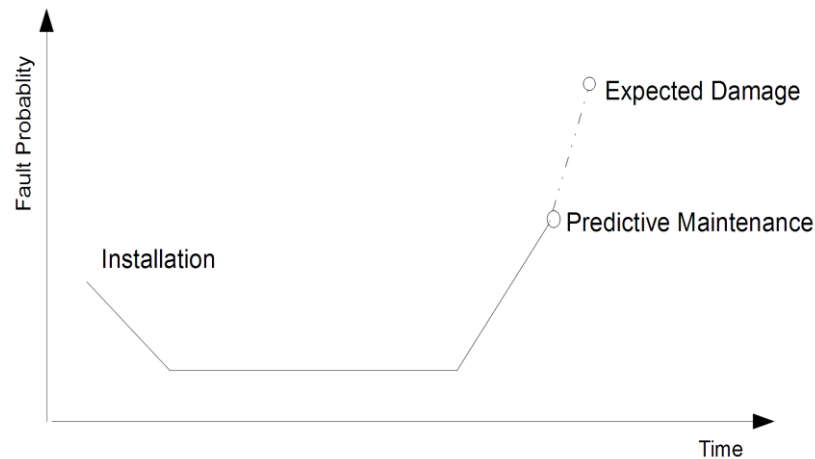
**1. Maintenance and Its Strategies:** The main concern of industry management is growing profitability. In order to achieve this, downtime costs must be reduced, and system quality needs to be improved along with productivity. In order to effectively tackle the challenges of achieving such goals, maintenance strategies need to be effective. Because of this, maintenance has been an important part of modern industrial systems. The U.S. industry spends more than \$300 billion a year on plant operations and maintenance, with 80% of that working to correct chronic machine failures, system failures, and human error. Further, the maintenance group occupies about 5%-10% of the total workforce of an industrial organization. The cost of downtime can be reduced by 40%-60% when the machines are maintained effectively. For safety, reliability, and economy, preventing failures through effective maintenance is crucial. As the importance of maintenance is growing significantly, Prognostics and health management (PHM) research are integrating failure mechanisms, models and decision making procedures with current maintenance approaches. As maintenance tasks become more complex, PHM approaches become more critical. In this chapter, various maintenance methods are briefly introduced that have been evolved over time. Predictive Maintenance techniques are then implemented as part of the regular maintenance procedures. Data processing and data-driven prediction are also discussed in this chapter. To get the most out of a prognostics strategy, it's critical to know exactly how a defect will affect system performance. It is possible to lose revenue and maintenance costs when equipment malfunctions unexpectedly. Typically, the maintenance strategies fall under one of three major categories: Preventive maintenance, Corrective maintenance and Predictive maintenance as shown in Figure 1.3.



**Figure 3:** Maintenance strategies

- **Corrective Maintenance:** Corrective maintenance is called reactive or unplanned maintenance, and it involves troubleshooting equipment under unwanted conditions or when it fails, causing complete loss of operation, which results in equipment downtime. Maintenance that is performed when a failure occurs is known as corrective maintenance. Even though this eliminates needless maintenance, it creates a system where every piece of equipment will fail.

- Preventive Maintenance:** A preventive maintenance schedule involves scheduled maintenance activities designed to prevent failures. It is also called as planned maintenance as it performance maintenance tasks at predefined intervals of time. Even though these activities may reduce operating costs, they tend to be the most expensive to maintain. Planned maintenance is the key to preventive maintenance where the equipment is serviced periodically to detect the onset of failure and therefore rectify it before it occurs.
- Predictive Maintenance:** By monitoring the condition and the performance of equipment during normal operation, predictive maintenance reduces the likelihood of failures. Depending on the condition of the equipment, maintenance is performed at the appropriate time. Maintaining a system after a defect occurs but just prior to its failure is the optimum case for this method in order to avoid unnecessary downtime as shown in the Figure 1.4.



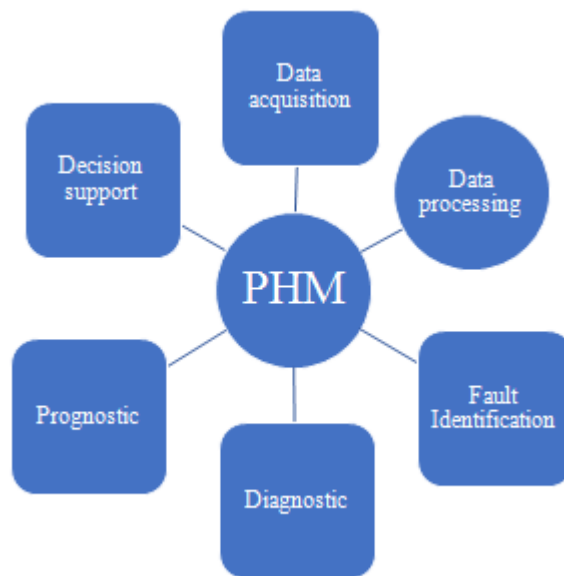
**Figure 4:** The condition of the system over a period of time

The art of estimating equipment life expectancy is known as prognostics, and it is considered the "holy grail" of condition-based maintenance. Prognostics may play a critical role in enhancing safety, reducing downtime, and strengthening the bottom line by assisting operations planning. In the industrial sector, Predictive Maintenance (PM) has emerged into a specialized area of Prognostics and Health Management (PHM) that provides a wide range of capabilities. The primary role of PHM include fault detection and isolation, as well as failure prognostics, which allows for the prediction of RUL and, ultimately, making appropriate management decisions. When it comes to the PHM method, predicting the RUL with extreme accuracy is critical because its incorrect estimation can lead to unexpected catastrophic outcomes.

- Prognostics and Health Management:** PHM is a branch of engineering that strives to sustain system behavior and function by assuring operational capability, safety, and efficiency. Manufacturers require standards and guidelines for designing, deploying, verifying, and validating, the technologies of monitoring, diagnostic, and prognostic equipment in order to improve decision-making. The technical focus is to enhance

decision-making assistance by advancing the state-of-the-art in PHM monitoring and control.

In the context of Condition Based Maintenance (CBM), PHM can be characterized as the research and engineering disciplines that provide the necessary foundations. It makes use of data gathered through monitoring and maintenance engineers to discover the health state of monitored system's remaining life expectancy, and use that information to schedule any necessary maintenance action(s). Figure 1.5 shows the six primary responsibilities that make up PHM.



**Figure 5:** Major responsibilities of PHM

- **Data Acquisition:** It can be defined as a technique of collecting signals from the base of measurements, like sensors hooked up to crucial subsystems, and digitizing those sensor signals for storing, analyzing, and presenting it on autonomous systems. This is an important stage in developing PHM algorithms as it can have an impact on the quality of the ultimate decision making process. The two kinds of data collected from essential components are condition monitoring data and event data.
  - **Condition Monitoring Data:** Data from condition monitoring refers to measurements of the physical asset linked to the asset's health or state. The conditions in which data is being sought are quite versatile. This kind of information gives the health state in the form of Vibration data, fan speed data, oil inspection data, temperatures, pressure, acoustic material, humidity, and about climate or environment.
  - **Event data:** It contains descriptive data about the monitored system such as recordings of Installation setup, failure, examination of the system thoroughly and the causes of repair. The explanation of the action that was taken to restore failure and the severity of failure that was reinstated are also recorded.

- **Data Processing:** Data processing provides a reliable solid foundation to data-driven techniques. Preprocessing the gathered data before modeling can improve the model's performance. This phase intends to draw usable information from raw sensor records by applying transformations. In general, raw sensor facts are commonly quite complex, processing such sensor data is thus essential prior to developing degradation models. Data processing methods are categorized into two major tasks: pre-processing and data analysis. The primary objectives are described as below:
  - Enhancing the quality of raw noisy sensor data.
  - Producing more information by understanding the underlying process of generating the data.
  - Improve the performance of degradation models by using the dimensionality reduction
  - Produce computationally efficient models by reducing the size of measurements
- **Fault Identification:** This is the task of identifying whether a fault occurred with the equipment under investigation or not. The observed change from the monitored equipments' normal state to a new abnormal state may be considered as a concern. If the system's behavior falls inside the nominal zone, the system is deemed to be normal. If the sensor data falls outside of the typical range, it is considered to be faulty.
- **Diagnostics:** Analyzing data in order to identify fault location, its type, size, and cause is known as diagnostics. Faults have an effect on both the associated event and the output signal they correlate to. The diagnostic procedure begins by examining the incoming signals. Fault categories that have been previously identified are used in the final diagnostic conclusion.
- **Prognostics:** The process of determining how long a system or a component will last before it fails is known as prognostics. Risks associated with unexpected equipment failure are managed via the use of prognostics. Some prognostic systems are still based on the skill and knowledge of maintenance engineers. Human decision-making, on the other hand, is not always as trustworthy, when working with sophisticated machinery. So, in the last several years, there has been a lot of effort put into developing models that may be utilized to reduce the need of manual intervention in controlling devices. An estimate of RUL and health status evaluation may be used to schedule the necessary maintenance measures before they are needed.
- **Decision Support:** Data received by monitoring the system's health status is used to determine which maintenance procedures are the most effective. Maintenance tasks can be better planned with the use of scheduling policies. In order to make maintenance decisions, outcomes of the previous operations cannot be used directly. Prioritizing maintenance tasks is essential to cutdown on the amount of time and money spend on maintenance. The findings obtained by this approach are being used as a source of input for maintenance decision making. An automated decision-making



process takes into account the prediction of RUL, the health status, and the accompanying uncertain system structure, as well as machine degradation statistics, to help the plant manager establish an optimal maintenance plan. In order to facilitate communication between the PHM system and its users, an interface known as a human machine interface (HMI) is employed.

**3. Rul Prediction Methods:** Since the introduction of RUL prediction techniques in recent years, there have been three basic methods [3]:

- Physics model based
- Data-driven based
- Hybrid based

➤ **Physics model-based:** In the physics based approach, a series of differential or algebraic equations, is utilized to anticipate RUL in circumstances when the failure data provided is inadequate. This method requires a broad physical foundation and expertise.

➤ **Data-driven based:** With adequate failure data, the data-driven technique is utilized to model the deterioration and estimate the RUL for the equipment. The ease with which many industrial systems' monitoring data may be collected has prompted numerous academics to utilize data-driven models to estimate the RUL.

➤ **Hybrid based:** To estimate its RUL, the hybrid technique combines physics model-based and data-driven approaches.

Extraction of performance deterioration signals from multisensory data is a crucial technological challenge for complex systems as data becomes more multidimensional, affecting prediction performance dramatically. When generating features manually for complex domains, there are two drawbacks. First, a large amount of human effort is required, and information might be lost. Secondly, speed cannot be assured.

Industrial IoT, a developing technology that has the potential to considerably improve the safe and intelligent functioning of many equipment. Predicting the remaining usable life allows Original Equipment Manufacturers (OEM) to evaluate the asset's health status as well as the status of its connected components on a continual basis. The ability to forecast the remaining useful life of critical equipment in industrial systems increases operating efficiency and minimizes component and vehicle subsystem failure rates. OEMs may add value to their goods by boosting their dependability and durability. Aviation, communication, electrical generation and distribution, railways, defence, and numerous energy industries are the domains which use multiple sensors that are miniature and self powered need integration with artificial intelligent systems for timely action by optimizing the resources. Other domains with which this research is associated include machine learning and data dimensionality reduction. All these major domains are currently the broad areas with good scope of research in terms of predictive maintenance.

## II. IMPORTANCE OF DATA – DRIVEN BASED PROGNOSIS APPROACH IN RUL PREDICTION

Integrated Systems Health Management includes fault detection, fault diagnosis (or fault isolation), and fault prognosis. Prognosis is the art of detecting the precursors of a failure, and predicting how much time remains before a likely failure. Algorithms that use the data -driven approach to prognosis learn models directly from the data, rather than using a hand -built model based on human expertise.

## III. APPLICATIONS OF DATA – DRIVEN BASED PROGNOSIS APPROACH

- **Sensor-Data-Driven Prognosis Approach of Liquefied Natural Gas Satellite Plant:** In this application, a sensor-data-driven prediction approach is proposed for the proactive maintenance of a satellite Liquefied Natural Gas LNG plant. The remaining time needed to refuel the remote plants can be predicted using data analytics from sensors installed in the satellite plants. Satellite terminals send their collected data to a central server located far away, where it is stored. For remote meter reading, consumption tracking, and control, these data are helpful. Unfortunately, the stored data have issues including duplicate records and missing and erroneous values. The monitoring technique is an event- and time-based method (with a sample time of 1 h), resulting in asynchronous and non-uniform sampled signals, with the goal of reducing the amount of delivered data. It is essential to guarantee data quality before to use. Our approach utilizes offline data processing and, like the approach suggested in, integrates signal processing methods with spatial models to validate and rebuild missing and erroneous data.

It entails the following actions:

- **Step 0 (obtain variable values):** Each text line contains metadata, such as the date and time of the event, the name and value of the variable, and the satellite plant's identifier. Getting the variables' values and converting date-time data to ISO format is the first step. A different file is used to store each variable.
- **Step 1 (detection of duplicate records):** Using time information, duplicate records are located and eliminated.
- **Step 2 (physical-range restrictions and equipment status):** In this step, you'll check to see if the data fall within the parameters of the sensor's physical range before taking the relevant measurement. Sensor specs or past data records can be used to determine the measurements' anticipated range. It also enables checking.
- **Step 3 (Resampling data):** It enables the construction of a periodic sequence of fresh samples based on the first dataset since data are asymmetric. By utilizing linear interpolation between nearest-neighbor data, resampling is carried out. The minimum amount of time between two consecutive events is used to determine the sampling time.
- **Step 4 (trend level):** determines whether the data are derivative by

determining whether the size of change over successive sample times is within the range of the predicted rate. This enables the detection of rapid, unforeseen, and potentially undesirable changes in the data.

- **Step 5 (spatial model):** Verifies the correlation between data from sensors that are spatially connected and the spatial model that was used to acquire the data for that sensor. This geographical model was created using the physical connections between the plant variables.
- **Data – Driven Based Prognosis Approach for Aircraft Turbofan Engine Data:** The science of prognostics has substantially grown during the last ten years, and general intuition of the system health prognosis problem and its implications has grown significantly. The remaining usable life (RUL) is the amount of time an asset has left to be used. Its estimation is crucial for prognostics, condition-specific care, and health management. The estimation of remaining usable life (RUL) approaches is crucial for condition-based maintenance and system safety. Since RUL tends to be random and unknown, it must be inferred from information that is currently available, such as data from status and health monitoring. Due to the rapid improvements in condition monitoring techniques, there has been an increase in interest in the research on how to most accurately assess the RUL. In recent times, the systems are integrated as a combination of data-driven, physics-based and hybrid systems. It has been demonstrated that both physics-based and data-driven techniques have distinctive advantages that are particular to application scenarios. There is no one optimal method that can be applied universally to provide the most accurate estimation approach due to its complex relationship with visible health information. Computational intelligence's primary objective is to offer solutions to challenging real-world issues. However, the lack of run-to-failure data sets was a major hurdle in the development of data-driven approaches. Real-world data typically provide fault signs for a growing problem at different severity levels, but little to no data typically record fault evolution through failure. To address this issue, prognostics data repository was created in 2007 by the Prognostics Center of Excellence (PCoE) at NASA's Ames Research Center. Since then, several datasets have been released and used by scholars all over the world. Five datasets from the commercial modular aero-propulsion system simulation model C-MAPSS, which simulates turbofan engines, are included in the list. Datasets for prognostics development were produced by modeling a range of operational circumstances and inserting defects of varied degrees of degradation. At the PHM'08 conference, a prognostics data challenge was conducted using one of the earliest datasets. Later, a different set with differing degrees of complexity was released. Since then, these datasets have been extensively utilized in publications for comparing prognostication algorithms.

In recent years many of the researchers have designed hybrid classifier technique with feature selection methods. These methods attained higher accuracy compared with single classifiers. On the other hand small amount of work is done on automatic feature extraction.

- The feature selection techniques Principle Component Analysis (PCA) and Correlation Feature Selection (CFS) etc. used to extract the feature selection in machine learning and some of researchers used autonomic feature selection to extract the features and produced higher performance.
  - Majority of the techniques used benchmark datasets such as datasets from a turbofan engine simulation model - C-MAPSS (Commercial Modular Aero-Propulsion System Simulation) dataset. Approximation of the actual performance of the RUL prediction in real time data is difficult to evaluate.
  - Recent researchers have been applied data mining and machine learning techniques. Most of these techniques were built on shallow learning architectures. These architectures are still somewhat unsatisfying for RUL prediction.
  - The classical machine learning algorithms are inefficient to predict the upcoming failure of a critical component with minimum error and due to insufficient quantity of labelled training data.
  - Deep learning algorithms are suitable for feature learning and classification with huge amount of datasets.
- **An Rul Prediction Approach for Lithium-Ion Battery:** Rechargeable batteries with lithium ions as their main component are known as lithium-ion batteries. They are crucial components of many applications, such as electronic equipment, renewable energy systems, and electric vehicles (EVs) with outstanding characteristics like quick charging, affordable maintenance, and environmental sustainable. Although they have a long lifespan that enables them to be recharged and used several times prior to the need of replacement. Lithium-ion batteries age over a period of time , resulting in a degradation of their performance. A lithium-ion battery experiences some wear and tear with each charge and discharge cycle. These cycles also have the potential to permanently harm the battery's internal components, which reduces the battery's capacity and longevity. When a lithium-ion battery's optimal discharge capacity drops to 70% to 80% of its specified capacity, it is commonly considered to have reached its final stage of life called End of Life (EOL) and needs to be recycled. The remaining usable life (RUL) of a battery is the number of battery cycles between the current and the EOL. If the battery is used after failing, there is even a chance that it could overheat, which could lead to a fire or explosion if not handled carefully. In many applications and industrial sectors, being able to forecast the capability and RUL of batteries powered by lithium-ion is essential. It can provide the maintenance and care required to help reduce potential dangers and ensure the safe and efficient use of lithium-ion batteries. The RUL and capacity of the battery must be predicted, just like in the case of EVs, to ensure consistent and safe operation. Additionally, charging and discharging procedures must be optimized to increase the performance and lifespan of battery. Therefore, for technology to evolve and be widely used, accurate and reliable ways to estimate battery capacity and RUL must be developed. A key source of energy in new energy vehicles, cell phones, etc. is the lithium battery. Its RUL is dependent on how well its equipment system is functioning. The remaining useful life (RUL) of lithium batteries has been predicted using a variety of model-based techniques, and some studies have started to employ lithium battery monitoring data to do so. he widespread use of data-driven residual life prediction in the field of equipment is encouraged by the continual improvement in the equipment's ability to

continuously detect and monitor itself throughout its life cycle. Currently, the lithium batteries' RUL data-driven prediction approach mostly uses a single time-series forecasting model. The prediction method's robustness and generalizability are insufficient. To increase the predictability's robustness and accuracy, it has to be further enhanced. According to the predictions' outcomes, immediate preventive maintenance steps must be implemented to guarantee a reliable supply of energy at all times. Relevance vector machine (RVM), random forest (RF), elastic net (EN), autoregressive model (AR), and long short-term memory (LSTM) Network are the five fundamental learners that make up the ensemble learning approach, which aims to improve prediction performance. In the ensemble learning approach, the genetic algorithm (GA) is utilized to locate and establish the ideal basic learner weights and to get the lithium battery prediction outcome. The CS2\_35 lithium battery data set is then used to run the simulation.

#### IV. BENEFITS OF PREDICTIVE MAINTENANCE:

Predictive maintenance programs optimize performance by detecting equipment inefficiencies, allowing targeted maintenance, reducing inspections and repairs, and enabling early intervention to prevent serious problems. The benefits include Reduction or near elimination of unscheduled equipment downtime caused by equipment or system failure; Increased labor utilization; Increased production capacity; Reduced maintenance costs; Increased equipment lifespan.

- **Longer Lifespan of Equipment:** Maintenance-assisted equipment performs better and lasts longer. Data-driven predictive maintenance reduces wear and tear, eliminates failures, and allows maintenance teams to react quickly to anomalies. Machine learning (ML) algorithms are used in predictive maintenance to examine a set of related data points received by building systems in order to identify potential issues that may impact equipment operation in the future. As a result, your equipment will last longer, you'll get the most use out of it, and you'll spend less money on it as often. Hence, Data-driven predictive maintenance improves equipment performance and longevity by reducing malfunctions, and detecting anomalies. Utilizing machine learning algorithms, it extends equipment life, maximizes value, and reduces capital expenses.
- **Lower Maintenance Costs:** Reactive service calls following equipment malfunctions are, on average, three times more expensive than proactive calls, according to the PRSM 2012 HVAC Benchmarking Report. That amounts to about \$400 extra per call on average. These savings are much greater when using a predictive maintenance plan because it helps to optimize the frequency of maintenance. When used properly, predictive maintenance can almost completely eliminate unforeseen reactive repair while also lowering the price of preventative maintenance
- **Less Downtime:** Predictive maintenance helps engineering teams avoid unplanned downtime and reduce planned downtime by shortening equipment downtime and planning usage-based downtimes to minimize disruptions.

- **Enhanced Routine Maintenance Activities:** The machine learning (ML) technology behind predictive maintenance can improve normal maintenance tasks when given real-time data. This is accomplished by offering data-driven fault detection and diagnostics capabilities along with a sophisticated and precise evaluation of equipment performance. By revealing the problem's fundamental causes, this reduces the amount of time professionals and contractors need to find and evaluate problems.
- **Budget Control:** The ability to schedule repairs and maintenance prior is due to real estate operations teams who have better control over maintenance expenditures. To maximize cost savings, equipment service requests can be planned at opportune periods.

## V. CHALLENGES OF RUL PREDICTION AND PREDICTIVE MAINTENANCE:

Challenges and limitations to predictive maintenance found in scientific literature, are explained considering the following list of challenges: Financial and organizational obstacles, data source limitations, limits of machine repair activities and optimization narrowness.

- **Financial and Organizational Obstacles:** Profit-seeking companies must consider expected costs associated with PdM investments, such as sensor installation, information extraction, and model preparation and maintenance. These costs may vary based on factors like asset complexity, consulting costs, and knowledge extraction. To evaluate the benefits of PdM, a projected Return on Investment (ROI) is created, considering the value of results, amortization time, and costs. The financial reasoning of PdM usage and applicability depends on the company's size and type, with larger companies being less vulnerable to financial risks. Technology providers must adapt to customer preferences and market needs.
- **Data Source Limitations:** Data is crucial for creating a PdM model, but companies often lack all necessary data at the start. To overcome gaps, companies must specify and solve them. The quality of existing sources of information may not meet the required needs, but data preparation can overcome this. PdM methods may face challenges if data sources deliver imprecise or incorrect measurements, leading to incorrect predictions or false alarms. Sensor technology also faces challenges, such as offline operation and asset interruptions. Improving stability, precision, and integrity of source data is essential for PdM prediction models. PdM prediction models can deteriorate over time if not retrained or automatically updated with new data. Newer data is more relevant for machine prediction and should be added flexibly.
- **Limits Of Machine Repair Activities:** Assets currently rely on human interactions for control and maintenance, with effectiveness relying on human management and skills. Intelligent assets can propose or autonomously start beneficial actions for system health, asset throughput, or product quality. Self-aware assets can evaluate conditions based on data stored in a PdM system, recognizing critical conditions and autonomously making maintenance decisions. However, assets lack self-awareness and self-maintenance, making it difficult for machines to plan maintenance schedules for themselves or groups of assets.

- **Optimization Narrowness:** The optimal maintenance time for an asset depends on its goals and optimization figures. Factors such as energy consumption, raw material use, and scrap production quality are crucial for an asset's health. Environmental impact is not considered in PdM decisions, but illustrations of environmental footprint in production can be useful. Environmental success often has an indirect economic influence, but the link depends on factors like regulations, customer consciousness, and willingness to accept higher costs for environmentally friendly products. Companies must find their own importance of environmental success, which is a prerequisite for incorporating it into the PdM model.

