Adopting a Deep Learning Split-Protocol Based Predictive Maintenance Management System for Industrial Manufacturing Operations

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January 4, 2023

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Abstract

Abstract— This paper presents the best computational modeling (AI/ML and Quantum Computing) methods to predict the performance optimization of predictive maintenance and management of the shop floor activities in manufacturing sites within the industrial manufacturing facility. For industrial manufacturing sites, shop floor activities play a vital role in the productivity and operational efficiencies of any industrial manufacturing site/facility. In manufacturing units, production planners and supervisors have a critical time to predict the production downtimes and predictive maintenance, and sometimes with the production line, a tiny milling bit breaks, shutting down the line. Some cases of unplanned downtime are not only costly deals but also hamper the unplanned delay and downtime for the supervisors at the production sites/factories in industrial productions. In this paper, we introduce a failure detection system that focuses only most probable failure state at maximum utilization and is delicate in incoming jobs to the backup unit while the overloaded unit will recover and resume in the very fresh state. Our proposed scheme introduces an additional parallel system component with help of split protocol and improves overall systems reliability in case of a component failure.

Keywords: SAP S/4, SAP HANA, Cyber security, AI, ML, IoT

I. Introduction

In a general statement, in the twenty-first century, most of the industrial manufacturing facilities/units along with the operations facilities are still using paper, spreadsheets, excel sheet- based and phone calls to share information on predictive maintenance (PdM) with the plant shop floor from other departments, outside suppliers and customers to fulfill the demand and supply network [7, 8]. Very early digital adder fascinated the scientist and engineers. O. Bedrij described adder system accelerates the addition process by cutting the carry-propagation time to the absolute lowest consistent with a cost-effective circuit design [1]. All these manual activities and work schedules are not easy to maintain, and they are unable to control the operations as per the planned schedule. In industrial manufacturing sites/production units, the downtime of the equipment/machines is the most significant issue, hard to manage, and difficult to predict the downtime and maintenance hours to make them useful. In the manufacturing industry, the failure of the equipment results in downtime, i.e., it remains useless until the maintenance is conducted and it starts functioning again, which may effectively result in a decline in the productivity of the equipment, machines, and shop floor activities [2,3]. According to a recent survey, 10% to 25% of downtime and production losses occur frequently due to predictive maintenance issues (PdM) within heavy industrial manufacturing sites, resulting in large losses and costly deals for the business. This would be important when considering a Make to Order (MTO) and Make to Stock (MTS) scenario [4]. Machine failures can bring production to a screeching halt, and it costs the industry millions of dollars to overcome the sales and operation planning in critical business scenarios [9]. However, traditional ML models need improvement and more thorough tokenization for text pre-processing [6]. A few of the computational models within AI, ML, or IoT can help in improving the overall efficiency of the industry and predict much more accurately the machine/equipment downtimes as per the available datasets [1]. The ML techniques, can assess the historical data of the equipment over a fixed period and develop some patterns of degradation of the component and machine, predicting the potential failure and scheduling the maintenance before the system collapses entirely. Predictive analytics considers both current and historical data patterns of machines/equipment and worksites in industrial plants when making forecasts about future outcomes and performance. It determines whether those patterns are likely to re-emerge, thus allowing manufacturers to adjust their resources to take advantage of probable future events, improve operational efficiencies, and avoid risk. Some industrial manufacturers are also heavily utilizing industrial IoT devices, sensors, and SAP S/4 Manufacturing Execution services, which are built on ML, AI, and Edge Computing features, to calculate PdM Factors and downtimes in work/production sites. Most of these facilities are highly dependent on predictive analytics and smart factories, which drive efficiency on the plant floor and allow companies to convert collected data into tangible, relevant actions [12]. Intelligent predictive maintenance strategies are now being adopted by most production sites to reduce the overall cost and optimize the efficient production score [9]. There are a few key strategies to developing an interactive online application, data collectors to collect the data from machines, humans/operators, and equipment, and reading the machine sensor data as input to predict the possibility of downtime of the machine because of the entire chain of neural constructions in the AI and ML Models. This will be done in a few steps as stated below.

1. Understand the current state, operations, capabilities, technology, and usability of resources and machines. Identify the current or potential gaps, including any existing equipment that does not support activities like automated data capture (ADC).
2. Making the necessary changes at the equipment/machine and factory levels to understand the maturity curve and the potential downtimes and lead times.
3. Data cleansing of the machine/equipment data records, attributes with different parameters of collected data from the devices/sensors of the tubing machine, finds the correlation to identify the pattern concerning downtime of the tubing machine.
4. Collect the datasets from the manufacturing towers to get the actual downtime vs the predictive maintenance downtime (PdM).
5. This step will need to be analyzing the data set, deriving the correlation, and identifying and training the most suitable machine learning model which can predict the system failure well in advance using the live data provided to the corresponding model.
6. The best predictive models with the help of ML, AI, and IoT models are certainly beneficial to the industrial manufacturers (production sites and facilities/supervisors/operators/managers/shop floor managers) who are on the machine and their respective managers and other stakeholders in terms of operations.
7. Predictive analytics assists manufacturers in better understanding, monitoring, and optimizing their plant floor activities by combining historical data with artificial intelligence, machine learning, and the Internet of Things [16].

To maintain a competitive edge, and support the customer/distributor demands, the manufacturers must act now to make strategic investments, and adopt of best computational tools/methods to provide the best potential model to manage the market demands and fulfillment of the customer/distributor demand. With the help of digital twins and shifting from traditional to digital, learning how to manage, and optimize data, information, skilled full resources tools (ERP, Bigdata, Clouds, AI, ML, and MDM) which can run the supply chains, and factory operation. IIoT Devices are deployed on the shop floor, and then it acts on these insights to control the PdM. During the earlier days, there are no certain best practices on PdM and the preventive maintenance of the machine in production units and operational benefits were able to manage [10].

In the early days, the production units have no interconnected and integration layer due to a lack of sensor data, industrial internet of things devices along with digital twins which were available now in all modern facilities and able to capture a huge amount of data for the future predictions of PdM scores. In smart factories and industries 4.0, the advancement of digital twins and smart equipment like sensors, IIoTs, PLCs, and other machinery could provide the data from across systems and provide the best machine learning models and industrial analytics for the machine and equipment and determine the PdM scores. Industrial manufacturing companies deal with a rising number of product variants as well as aging personnel due to demographic change and customer demand across the globe and outlier detection [28]. Due to these challenges and unprecedented customer demands and unpredictable downtimes, sales and operation planning are key challenges, and optimizations are not up to the mark as per demand vs supply. Industrial manufacturers need to develop their employees' competencies in shop floor activities, skilled development, and adoption of the manufacturing toolset to improve the production lines. In industrial manufacturing and Industries 4.0, the PdM requires data from various sensors, devices, and machines which are connected, monitored, and connected with the equipment to collect the other operational data to complete the production cycles. Mostly all these Predictive maintenance systems are capable to conduct data analysis. Also, stores the results within the production cycles at a low defect. A machine learning tool and a quantum computing tool can certainly help to understand the pattern of predictive maintenance (PdM) and be able to solve real-world problems.

The following is how the rest of the paper is structured: The introduction is covered in section I, and the related work is covered in section II. Then, section III describes predictive maintenance and industry 4.0. Section IV describes the strategy to adopt in predictive maintenance. Section V pillars of the total predictive maintenance in industries 4.0. Section VI describes quantum computing and digital manufacturing 4.0. Section VII talks about reliability- centered maintenance (RCM). Section VIII describes intelligent asset management (IAM) and RCM-controlled predictive maintenance. Sections IX presents system architectures and PDM in Industry 4.0. Section X presents AI-enabled split-migration architecture. The XI talks about the implementation. Finally, section XII concludes the research paper.

II. Literature Reviews:

Here are a few facts and research publications that are evidence and supportive of these publications. Most industrial manufacturers have a strong problem statement concerning the predictive maintenance (PDM) score as per their current business scope. Few of the recent research focused on the various Machine Learning and computational applications for Predictive Maintenance and the most effective way to understand the occurrence of a failure, recurrent events, and any critical breakdown failure as before this happens in the production sites/units. Machine downtime could be analyzed and able to perform predictive maintenance as per the Industrial productions. The computational model and Machine Learning model could help to understand the machine/equipment's/device records and process for the optimized information to predict the better predictive maintenance score in industrial operations. In production and manufacturing operation sites, the industrial information related to production data, device information, production worksheets along with Sensor, IIoT, and PLCs and DCS are stored in a database, and acquires data from plant DCS, registers, associated PLCs, chips, capacitors, and electronic registers around the network [18].

Most of the recent research publication on PdM elaborates on the benefits and utilization of the digital twins and the application of the computational model (AI, ML, QML, QAI, IIoT, and cloud applications) which offer the best way to manage the PdM Capabilities in an industrial manufacturing operation. Most industrial equipment-sensor, electronics batteries, capacitors, and electrical machines degrade with time, load, and use as per the capacity. Ideally each component of the industrial manufacturing equipment's, devices will have a certain deadline and will reach to end f its useful life. Most of these manufacturing sites used to have the schedule-based maintenance planned or time-based maintenance approach to maintaining the equipment across the plant/sites. Some of time, industrial manufacturing sites also adopt the best practices of condition-based maintenance methods which are to maintain or replace equipment/devices/sensors at exactly the right time just before its event/failure, and this is a most tedious job at the site level [11].

III. Overview of predictive maintenance and Industries 4 0

Industrial manufacturing is based on the equipment, machines, devices, and IIoT across the sites, and all these devices need to be zero defect and error-free. Typically, system failures are a common occurrence across all manufacturing industries and within production sites. Predictions of Predictive Maintenance (PdM) scores play a vital role in the fourth industrial revolution and are beneficial for smart factories in Industry 4.0. PdM is the best use case and driver to make a successful critical factor within manufacturing facilities to have smart factories and digital innovations in industrial manufacturing sites [26]. The ML-based predictive approach analyses the live data and tries to find the correlation between certain parameters to predict the system failure or scheduled maintenance of the equipment. ML technology helps identify the fault lines by predicting the failures at the right time and thus utilizing resources effectively. This ensures the establishment of a balance between maintenance needs and resource utilization [11].

Qiushi et all. presented the knowledge-based predictive learning model for predictive maintenance in Industry 4.0 [13]. Deng et all. introduced a low-cost and easy-to-implement solution, with wireless sensors that monitor gradual failures of components [14]. Additionally, with the help of Asset Intelligence Network (AIN) and Artificial Intelligence (AI) computational models, predictive maintenance could be easily managed, and enterprise predictive maintenance scores could be as high as the previously checked in the scoreboard.

Thus, the idea of preventative maintenance (PM), which emphasizes the avoidance of asset breakdowns and the contexts in which they occur, evolved. In contrast to traditional maintenance methods that rely on the life cycle of machine parts, predictive maintenance uses machine learning techniques to identify specific patterns of system failure by learning from data gathered over some time and using live data. [17]. In the real world, most of the PdM and the preventive maintenance could be handled by the application of computational models, and by using the right machine learning tools/methods to predict accurately and understand the key data parameters to train the model in PdM. There are multi dimensions benefits while applying the best machine learning and AI prediction model to understand the real time application in Industrial operations. Below are a few benefits:

- Reduce downtime of the machine/equipment's/devices/IIoT
- Increase productivity/operational effectiveness of machines
- Reduce the TCO and Increase the ROI for the enterprise operations.
- Improve safety and identify the root causes of failures
- Derive the Intelligent assets management by adopting the QML, QAI, ML, and Artificial Intelligence
- Reduced unplanned downtime, and Increase production uptime in industrial manufacturing operation
- Enhance the resource productivity (including human resources and machines) and Improve product quality

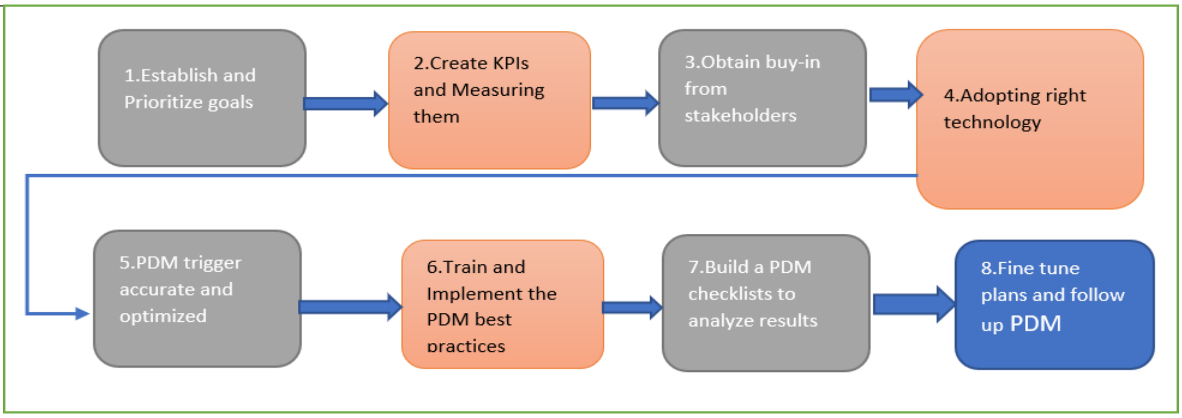

FIGURE 1. Steps in Predictive Maintenance (PdM)

IV. Strategy to adopt in Predictive maintenance

The recent study on the manufacturing and production operations, and per the industry 4.0 best practices recommends a few key critical strategies, steps, and processes to be adopted while considering a better predictive maintenance score (PdM) Scores for the industrial manufacturing automation and optimization as part of digital twins. A few of the key critical steps which need to be followed to obtain the PdM are listed below [14].

- Identify and prioritize goals.
- Create, track, and monitor the KPIs.
- Update the stakeholder buy-in
- Adoption of the right technology or software and Set up PdM mechanism update
- Training on the best implementation methods for preventive maintenance plans in Industrial sites.
- Develop the preventive maintenance checklist.
- Fine-tune plan based on results in Production sites.
- Smart Manufacturing Sites and Automation
- IIoT, sensors, and smart factories.

A. Application of Machine Learning methods to predict Predictive Maintenance (PdM):

Abidi et all., used various machine learning and computational model (AI, ML, QML, QAI) are used to understand the reality in accuracy while considering the predictive maintenance in the industrial operations and useful for the manufacturing facilities to get the most accurate and updated PdM score [5]. In our case, we have been using the Decision tree, based on the available data sets and data parameters, and trained the model to get the most updated score of prediction and optimized them as per our case. The decision Trees are extremely useful for the decision-making process and help to consider a decision in a complex mathematical calculation process. Computational models require collecting massive amounts of data on the failure Vector Space Model (VSM), LR, DT, and RF [5]. The below Fig 2&3 represents the various machine learning models with the most accuracy in the prediction factors in PDM score for the predictive maintenance in large industrial manufacturing facilities in the USA.

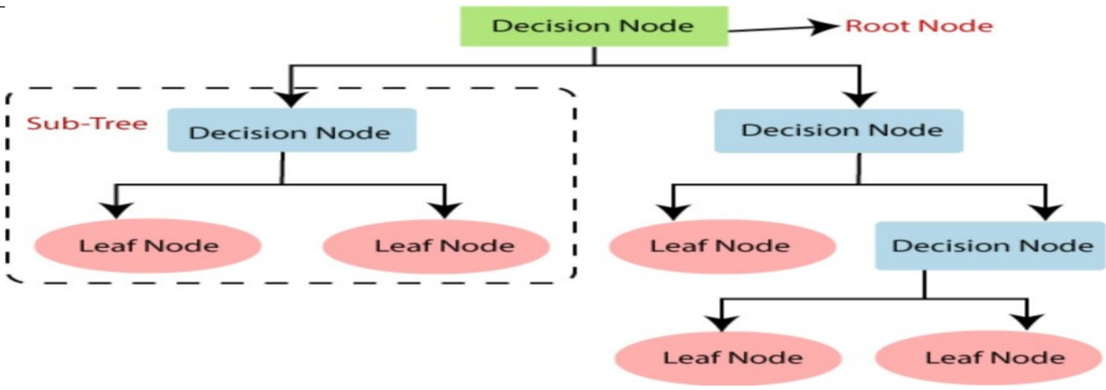

FIGURE 2

Overview of Decision Trees (DT)

	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	TT (Sec)
xgboost	Extreme Gradient Boosting	0.9959	0.7732	0.8095	0.9951	0.9953	0.9385	0.9388	0.6180
lightgbm	Light Gradient Boosting Machine	0.9956	0.7711	0.7976	0.9950	0.9951	0.9342	0.9346	0.8470
catboost	CatBoost Classifier	0.9956	0.7776	0.8097	0.9949	0.9951	0.9342	0.9344	5.3500
rf	Random Forest Classifier	0.9953	0.7805	0.8049	0.9945	0.9948	0.9297	0.9299	0.1260
et	Extra Trees Classifier	0.9949	0.7809	0.7965	0.9942	0.9943	0.9232	0.9234	0.0920
lda	Linear Discriminant Analysis	0.9940	0.7804	0.7818	0.9939	0.9934	0.9094	0.9097	0.0100
gbc	Gradient Boosting Classifier	0.9932	0.7741	0.7620	0.9936	0.9932	0.9002	0.9009	1.5040
nb	Naive Bayes	0.9931	0.7827	0.7516	0.9927	0.9925	0.8961	0.8964	0.0080
dt	Decision Tree Classifier	0.9913	0.7771	0.7378	0.9922	0.9914	0.8714	0.8717	0.0210
ridge	Ridge Classifier	0.9836	0.0000	0.4907	0.9780	0.9795	0.7529	0.7547	0.0840
knn	K Neighbors Classifier	0.9720	0.6008	0.3143	0.9563	0.9621	0.3719	0.4340	0.0440
svm	SVM - Linear Kernel	0.9651	0.0000	0.1865	0.9365	0.9502	0.0530	0.0940	0.0680
ada	Ada Boost Classifier	0.9486	0.7532	0.5671	0.9812	0.9595	0.6820	0.6956	0.0910
qda	Quadratic Discriminant Analysis	0.0107	0.0000	0.1733	0.0001	0.0002	0.0000	0.0000	0.0480
lr	Logistic Regression	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.8840

FIGURE 3. Various Machine Learning models with % prediction rates in PdM

In this paper, we have analyzed the collected data, understood the data from various equipment, prepared the model, and finally trained the model to get the ultimate prediction factors for the machine/device and the equipment. In our data model, we used more variables to get the most accurate predictions, which was an iterative process.

V. Pillars of the Total Predictive Maintenance in Industries 4 0

In a broader sense, total predictive maintenance (PdM) is the state of optimizing maintenance scores, records, and productibilities and reaching the maximum state of optimized predictive maintenance (PdM) which is the most efficient in any production site for the operations.

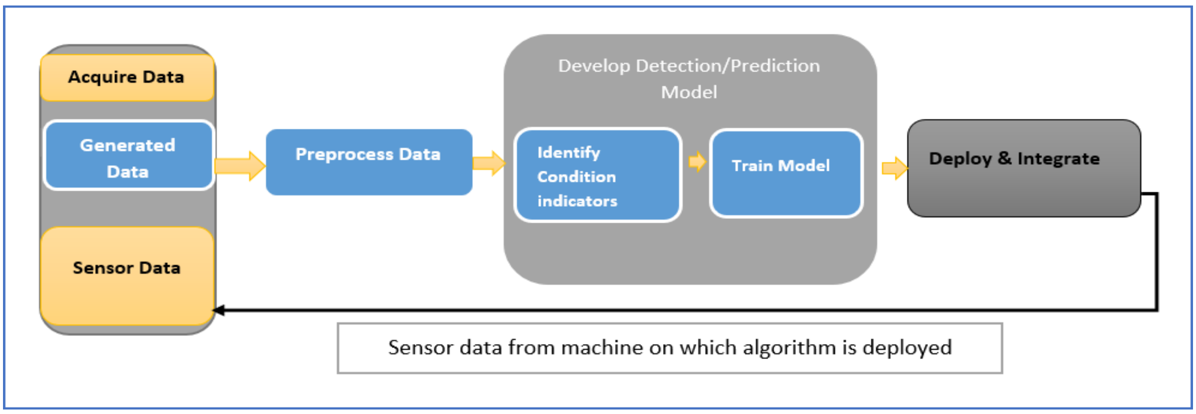

FIGURE 4. Implementing the predictive algorithm model in PdM

PdM is the focus of predictive maintenance and events which can be managed through various machines, devices, and IIoT devices within the industrial operations. The ideal goal of predictive maintenance is to achieve the overall efficiency of predictive maintenance score in PdM, and it is based on the below factors.

- Non-stoppages or suboptimal production rates.
- No defects and zero defects.
- Managed unplanned downtime or reactive time losses.
- No accidents occur around the production units

The below Picture shows the most sought pillars of Total productive maintenance (TPM) in a holistic approach within the industrial manufacturing space. It also emphasizes proactive and preventative maintenance to maximize the operational efficiency of equipment/machines and devices within the production factory/units [15].

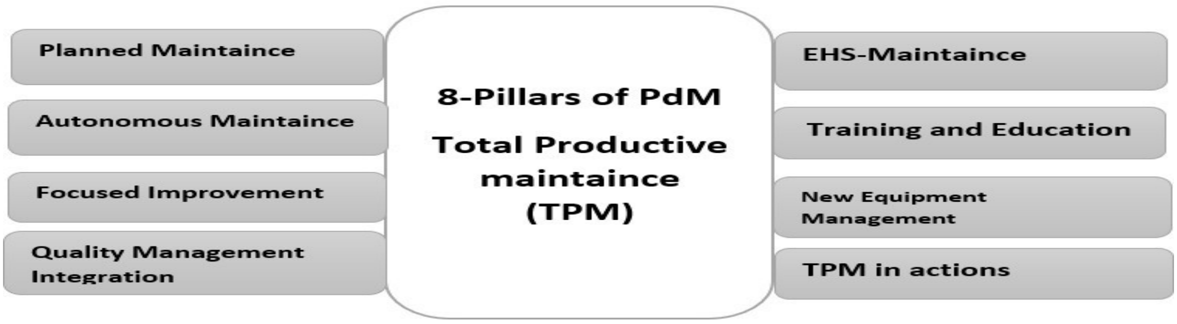

FIGURE 5.Steps in Predictive Maintenance (PdM)

Within the machine learning tools, XG Boost classifier, we could be able to predict the most ROC curve along with the True positive and false negative ratios. The below graphs explain the most accurate prediction of the machine and equipment's database and the ROC of the class.

VI. Quantum Computing and Digital Manufacturing 4 0:

In production sites, most of them are adopting the best modern control processes, equipment, IIoT devices, Sensors, and advanced analytics along with the machine learning and automation in place to optimize their production growths and satisfy their make to order and make to stock capacity. In the digital era, Quantum computing and quantum machine learning play a vital role over the classical computers as Quantum computers run the principle of Qubits over the bytes, which is a supernatural, entanglement and optimized the most successful in the predictions of the success rates. Most of the manufacturing operational planning and executions could be much more accurate and optimized through the industrial applications of quantum computing, quantum machine learning, and quantum AI. Industries leaders are focusing on the user benefits and application benefits of quantum computing, smart factories, and the optimized prediction factors in any of the given datasets. Com- pared to classical computers and machine learning, quantum machine learning, and quantum AI would be in much demand and have a significant benefit to the industrial and operation applications in production sites. Quantum computing and applications could reduce shop floor pain, and Predictive maintenance issues, and in the event of failure of productions sites, it may also help to increase significantly industrial manufacturing and critical business operational planning in productions, capacity, business continuity, production flows, and robotics scheduling for complex products, such as industrial automobiles, are highly complex, and their simulation and optimization are very computed intensive.

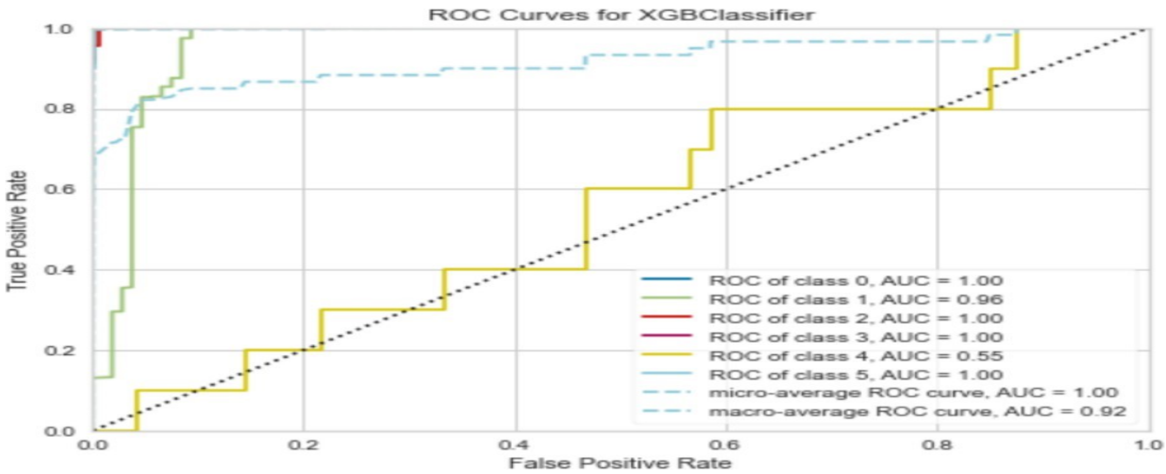

FIGURE 6.ROC Curves for XGB Classifier

The quantum simulation model could help industrial manufacturers to design the productions, new features and add the new BOMs into the sopping floor capacity, and optimize the most complex industrial sensors, machines, and IIoT devices across the business units [20].

VII. Reliability-Centered Maintenance (RCM)

In the industrial manufacturing space, reliability-centered maintenance (RCM) offers a wide range of service-based maintenance and ensures that all systems can run at optimal efficiency and accuracy as per the business needs. It offers best practices and adaptive models to save money, improve safety, and enhance machine performance and reliability in industrial manufacturing sites.

A. Benefits of the RCM approach:

The RCM-guided program to the sites provides numerous benefits to industrial manufacturers, including the prevention of machinery failures and shutdowns.

- Cost efficiency
- Improved performance:
- Enhanced safety
- Equipment longevity
- Production predictability.

The RCM-based predictive maintenance could be assessed and achieved with the following steps, and it should be applied to the Industrial applications and production units.

B. Key Principles of Reliability-Centered Maintenance (RCM)

Reliability centered maintenance (RCM) is to manage the electrical power distribution, the most effective way to manage the power equipment, sensors, and devices within the industrial manufacturing sites. Essentially, RCM helps to understand the best cost-effective way of managing the industrial Predictive maintenance (PdM) and the time-based maintenance (TBM) method, to use the effectiveness of industrial power distributions [21].

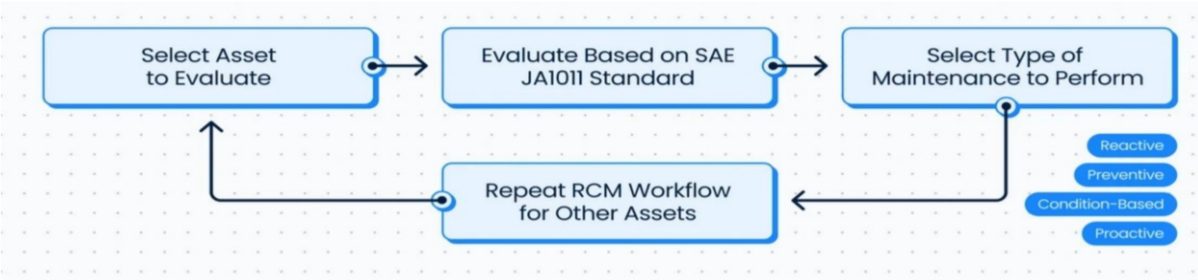

FIGURE 7. Flow chart of RCM Approach

	UDI	Type	Air temperature [K]	Process temperature [K]	Rotational speed [rpm]	Torque [Nm]	Tool wear [min]	Target	Failure Type	Label	Score
0	6	M	298.1	308.6	1425	41.9	11	0	No Failure	No Failure	1.0000
1	19	H	298.8	309.2	1306	54.5	50	0	No Failure	No Failure	0.9999
2	38	L	298.8	309.1	1439	39.2	104	0	No Failure	No Failure	1.0000
3	40	L	298.8	309.1	1350	52.5	111	0	No Failure	No Failure	0.9999
4	58	L	298.8	309.1	1513	40.3	160	0	No Failure	No Failure	0.9999

FIGURE 8. Overview of RCM Approach

There are a few best practices and steps that need to be followed while adopting RCM (reliability-centered maintenance) in industrial production sites:

- Accept the failure events
- Failures are not the final number as it is the way to manage the rest of equipment life
- Learn to recognize the failure (type of failure and impact of the failure as per their risk parameters)
- Identify the breakdown facts on equipment's
- Identification of possible hidden failures.
- Possible Maintenance plan for the equipment and devices.

VIII. Intelligent Asset Management (IAM and RCM-controlled predictive maintenance)

In industrial manufacturing and Industries 4.0, asset management plays a vital role and substantial demands for better outcomes, which may reduce and helps to manage the predictive maintenance at the production sites/factory locations. In the digital journey, most of the production sites, and factories are using heavily "digital devices, sensors, IIoT's and enterprise asset managers" to manage the production sites in a better way. As per the industrial manufacturing scenario, the Asset Intelligence Network (AIN) would help to manage the predictive maintenance (PdM) score and the degree of efficiency in the production sites. The strain on operators to enter equipment information decreases as this asset information grows, data quality improves, and both parties can communicate information about the asset's performance over its lifetime [22].

The AIM is the combination of the registered industrial/manufacturing devices/sensors/IIoT devices in industrial units. All this equipment's registered with the OEMs- original equipment manufacturers' calendrer and within the production site supervisors. Organizations can achieve operational excellence by using cloud-based solutions that foresee issues with operations before they arise[23]. Most of the industrial operations and maintenance are based on the equipment, components, and equipment models, associated with any of the factory's warranties and any predictive maintenance or preventive maintenance plan for the whole industrial assets. In production sites, the

Industrial IoT (IIoT) offers a wide range of activities and tasks which could be the most important for any manufacturing operations. Tasks are listed below.

- Data collection on industrial manufacturing readings
- Vibrations and frequency, TPM
- Motor current, device temperature, and IAM

The predictive asset insights (PIA) within the SAP-IAM offers the assets health indicators, connectivity, and monitoring scores of any industrial manufacturing assets in the industrial manufacturing units, moreover it is built on "in-memory computing" and with the help of most computational models-AI, ML, Quantum AI, Quantum ML, and Qubits, in the Business Technology Platform (BTP) to update the best prediction and computational model to provide the best accurate and suitable Predictive maintenance management(PdM). It also offers alerts when problems are detected enabling maintenance to occur when truly needed at the factory sites and production units for any failure of the predictive maintenance suitable to industrial manufacturing applications to reduce the cost, and risks and avoid downtime compared to other maintenance strategies, like run-to-failure and preventive maintenance [25]. On the other hand, the IAM (Intelligent asset management) could be of significant use to manage the predictive maintenance and score in any of the production sites/user plants. IAM is a combination of the digital twin, Internet of Things, machine learning, and data analytics applications that are used to solve real-world problems in industrial manufacturing facilities. The potential takeaways within the IAM solutions are:

- Enterprise Asset Management (EAM): can effectively manage the life cycle of physical assets in production sites/factory areas.
- Organizations can achieve operational excellence by using cloud-based solutions that fore- see possible operational issues before they arise.
- Cost management effectively within the production sites.

A. Wings within the IAM:

- *Asset Intelligence Network (AIN)*
- *PDMSMS- stands for Predictive Maintenance Service.*
- *Asset Strategy and Performance Management (ASPM)*

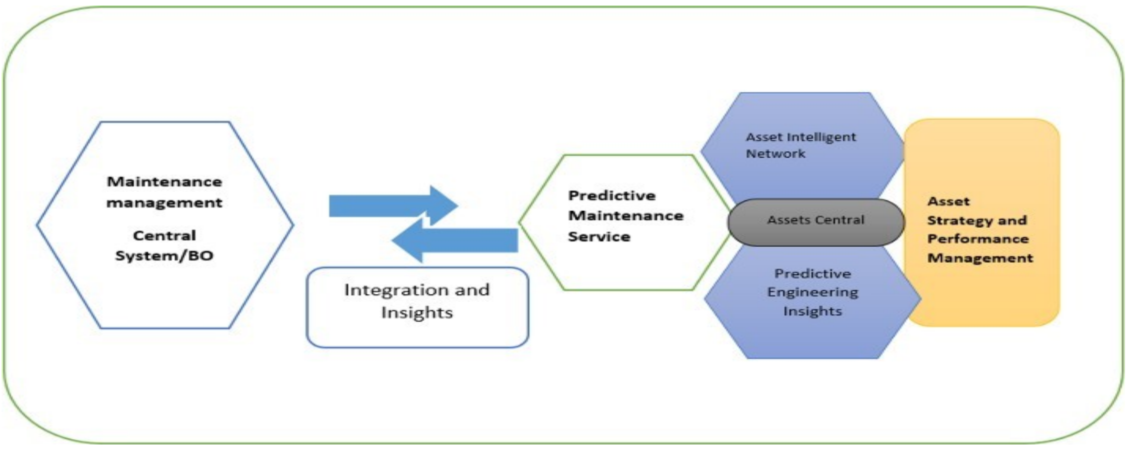

FIGURE 9.IAM and digital manufacturing In Industry 4.0

B. Benefits that could be achieved from AIN:

In the paradigm of predictive maintenance (PdM), intelligent asset management (IAM), asset intelligence network (AIN), AI, ML, and quantum AI play vital roles to optimize the most valuable predictive maintenance score of the assets, machinery, and equipment's in industrial manufacturing. Most asset intelligence applications are the combination of IIoT, AI, and the digital twins which focused on the digital business transformation of any manufacturing business. Some of the key pillars within AIM are listed below:

- Connected with Products – end-to-end visibility into product-centric operations in manufacturing operations.
- Connected with Assets – an enabler to linking the production system and s, assets with manufacturing industrial operation and reduce costs and increase asset uptime.
- Connected the Fleets – the ability to offer the tracking, monitoring, analyzing, and maintaining all the moving assets wherever they are in a production site.
- Connected Infrastructure – ability to offer digital operational intelligence for better performance and capabilities.

The below diagram represents the Intelligent asset management and the best practices of the portfolio for predictive maintenance and services in industrial manufacturing operations. SAP IAM offers asset performance, reduces maintenance across the production units, and performs the dynamic asset performance and service management of the associated assets and devices, real prediction of asset maintenance could be easily possible to manage through the SAP IAM Applications in any industrial production sites.

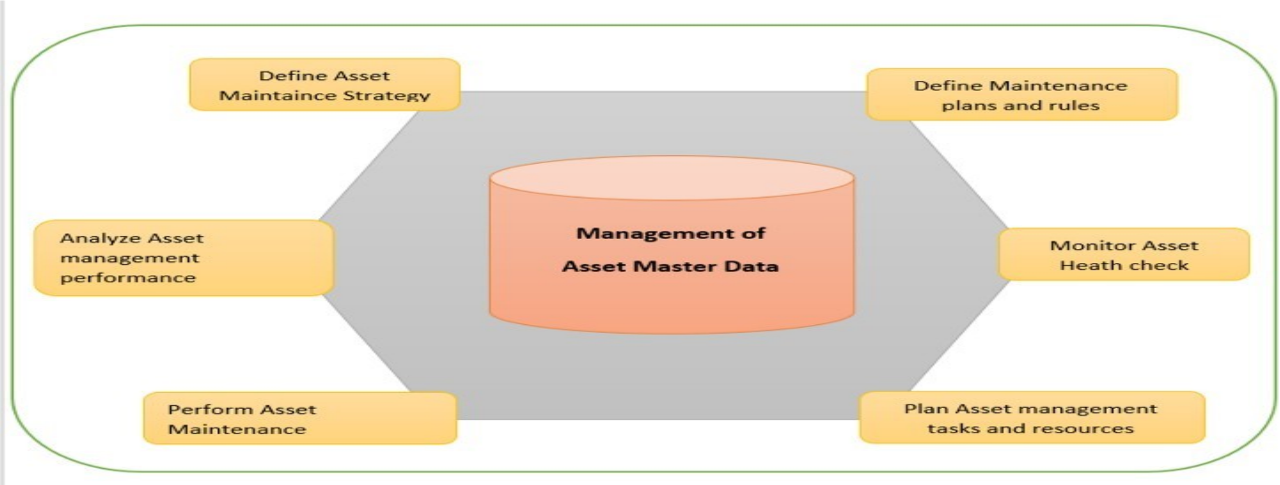

FIGURE 10. SAP IAM portfolio for PdM Management

IX. System Architectures and PDM in Industries 4 0

In a holistic approach within the Predictive maintenance management (PdM), a system architecture and database system play important roles and interconnective with the machinery, equipment, sensors, IIoTs, and Devices and understand the up-to-date data, conditions of machinery health checks and determine any specific conditions when the machine is going to fail or need some attention to gain the maintenance capacity to have long run operations. There are several methods, industrial practices, and technologies trends that are accelerating or KPIs to update the predictive maintenance (PdM). There are many of these critical system nodes, a few of them are listed below and updated in this paper.

Server: In industrial manufacturing, the data from various sensors, IIoTs, devices, and machines of the tubing machine is fetched continuously and stored on the company server (back offices) or any of the ERP applications for further use. Most enterprises use SQL or MongoDB databases since the volume of data generated is large in nature. This data is then later used for maintenance of the manufacturing unit. Because this project deals with a small amount of data, it makes use of the MySQL database and uploads the data to the server. Few modern industrial shop floors use digital twins (including Big Data- data warehouses, cloud computing, quantum machine learning (QML), edge computing, Internet of things (IoT), and most supercomputers like Quantum computers in place, which will be the key enabler within the system architecture and part of integration architecture of the PdM landscape.

Client: The operator at a particular manufacturing plant can get updates on the manufacturing unit, and they would get to know the sensor readings at a particular timestamp from the server, which would help to know if the unit is functioning properly or not, Hence, they can conduct the maintenance of the machine, accordingly, thus preventing the complete machine failure in any given instance.

Backend System/Office: The data fetched from the sensors are cleaned and preprocessed to extract prominent features for data analysis and finding patterns and correlations among the parameters. The cleaned data is then used to train a machine learning model, which would predict the parameter values over a period. Different models were trained on the parameters and their accuracy was calculated. The models were trained using classification and regression algorithms. An LSTM model of deep learning was also implemented to make the predictions. Most of cases, any ERP, Large data processing system could offer a wide range of back office and operational benefits to manage the predictive maintenance (PdM) in industrial manufacturing sites.

X. AI-enabled Split-Migration Architecture

Failure categories

A. Sudden Failure State (000): A sudden (but noticeable) breakdown occurs while the production line is running well. This includes things like broken tools, snapped bands, melted wire, etc.

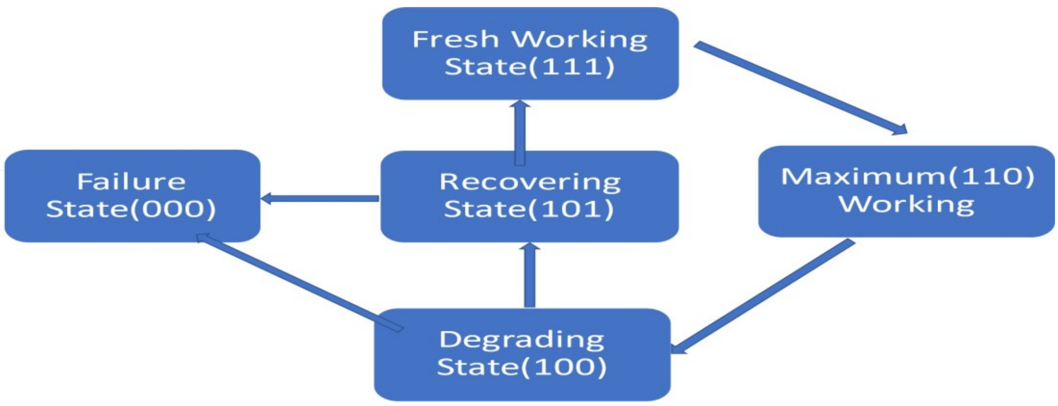

FIGURE 11. Component failure state diagram

A. Sudden Failure State (000): A sudden (but noticeable) breakdown occurs while the production line is running well. This includes things like broken tools, snapped bands, melted wire, etc.

B. Intermittent Failure State (010); The "complete" machine failure is typically on the path to intermittent failures, which come and go. By their very nature, these intermittent or random failures might be challenging to pinpoint. Regular maintenance can frequently stop intermittent breakdowns.

C. Gradual Failure State (100); These are the malfunctions that become apparent over time as a machine's usefulness gradually deteriorates. Regular maintenance can frequently stop Gradual breakdowns. For this work, we assume an intermittent failure state and a gradual failure state as a degrading state (100). As shown in Figs 11 &12., AI will predict a maximum working state i.e., a state in which a component is heavily stressed-out state adding more loads will go into a degrading state or a failed state. As soon as AI detects or predicts an MWS (110) state it will migrate new tasks to the backup unit FSW (111) using a split-migration technique [32]. The split components [29, 30, 31, 32, 33, 34], are considered parallel components so each additional component will improve the reliability of the system.

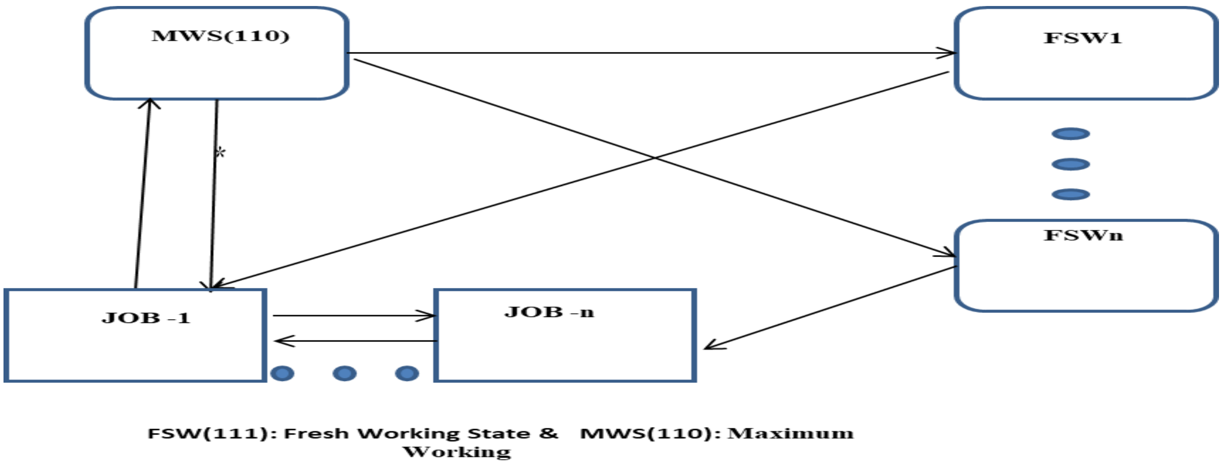

FIGURE 12. Task Delegation with Split-Protocol

XI. Implementation details:

A large amount of data must be collected, stored, and processed in the predictive maintenance prediction within large industrial manufacturing sites and plants to get a better prediction of upcoming downtimes and predictive maintenance in the sites and plants. Data has been collected from the condition of the equipment; vibration; acoustic; ultrasonic; temperature; power consumption. Dataset The dataset used comprises the sensor data of the machine MNL15, of which the main factors thought are stated below [26].

- EJECTION-PCT: Excess material ejected from the machine during production.
- Error history: can be collected from the factory and plant sites from machine and equipment sites.
- EXTRUDER PRESSURE: Pressure sensor value from the extruder of the machine.
- Maintenance/repair history/Speed: Speed of the machine while manufacturing and under- standing its repair history.
- Machine operating conditions and actual values-inputs: input of raw material given to the machine.
- Equipment metadata and Heating Zone: Temperature reading of each section and equipment metadata.
- Standard feed-forward neural networks, such as CNN and RNN, do not have feedback connections. LSTMs have an advantage in this aspect over simple neural networks.
- The fields of Deep Learning and Natural Language Processing use the artificial recurrent neural network (RNN) architecture known as LSTM (Long Short-Term Memory) [24].

XII. Conclusion:

This model proposes a system that will predict the failure of the manufacturing unit based on parameters like temperature, and pressure and the machine parameters like speed, revolutions per min, ams/ccm input, etc. These parameters are recorded by the sensors of the tubing machine over a period, even the IIOT devices and automated sensors are capable enough to read the data from the machines, and devices from the various production units/units, and hence maintenance can be scheduled as per the requirements. This model will prove to be extremely useful in maintaining productivity and minimizing the cost of maintenance. This will reduce the time for which the unit remains idle for maintenance. The model was highly effective in predicting the time when the machine would be down based on the previous historical sensor data that it received. In our AI-enabled failure prediction model, the AI will forecast a maximum operating state or a state in which a component is severely stressed-out and will enter a degraded state or a failed state when further loads are applied.

When AI recognizes or anticipates that a component is stressed, it will shift the new task to the backup unit. This will even result in a minizine system failure. Each new component will increase the system's reliability because the split protocol components are thought of as parallel components.

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