# A Review on Machine Learning Techniques for Predictive Maintenance in Industry 4.0

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**Abstract.** Predictive maintenance is the process of continuously monitoring a system to prevent it from breaking down. Along with the traditional equipment maintenance which uses a periodic schedule instead of reacting to equipment failures, predictive maintenance predicts failure of an equipment. Adopting a suitable and reliable predictive maintenance strategy for equipment like automobile part manufacturing machines has remained a difficulty for industry. To minimize the unplanned downtime of a machine caused by its failure in highly automated production line is very challenging piece of predictive maintenance. Recently the Industry 4.0 concept is becoming more widely adopted in manufacturing around the world. The survey emphases on different methods available for predictive maintenance and the various data used in the researches. Machine learning promises the better solutions over the traditional maintenance problem. In this research, intelligent approach is presented which is to be used to design proposed PdM planning model. To predict the failure state with respect to down time a weight optimized GRU model is proposed. And Whale Optimization with Seagull Algorithm has to be used to optimize the weight in GRU based learning. Thus the results are well-suited for PdM planning and capable of accurately predicting future components for Mechanical part making machine.

**Keywords:** Machine learning · predictive maintenance · manufacturing equipment · Industry 4.0 · failure prediction

## 1 Introduction

Experts have termed the current state of industries are evolving as Industry 4.0 (I4.0) I4.0 is the integration of corporal and ordinal systems in development environments [1]. The Industry 4.0 revolution is driven by the Internet of Things (IoT), which improves manufacturing productivity by simplifying connectivity and information exchange between different systems. The components of modern manufacturing processes include highly advanced self-sufficient mechanical equipment that is set in with different software systems which are integrated with different Internet of Things (IoT) devices; thus overall leads the efficiency to be increased in manufacturing [3]. Maintenance is one of the manufacturing areas that Industry 4.0 is introducing the use of computers and digitalization


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in [4, 5] and prognostics and health management (PHM) has become an obvious for smart industrial evolution; moreover, it provides a dependable solution for managing the health state of industrial equipment. Maintenance is vital since it extends the lifetime of an equipment. A system's lifespan can be prolonged by implementing maintenance. Maintenance should be scheduled ahead of time with a precise prediction of the machine failure for avoiding the accidents in production line and to reduce the economic loss. Predictive Maintenance (PdM) is widely employed in a variety of industries, including manufacturing [6, 7], car [8], and aerospace [9]. Engineering tools working well in anticipating the failure time of equipment in advance. Furthermore, PdM is supposed to foresees the failure precisely [10, 11]. Data flexibility is viewed by PdM as a significant concern that could impair algorithm performance for data driven modelling [12]. Processing raw sensor data provides additional problem since sensor data is not labelled. Furthermore, while addressing the problem of data tagging, data sparsity may impair algorithm performance in existing methodologies. Furthermore, it is frequently difficult to discover abnormalities and trends in high-dimensional IoT data [13]. It is considerably more difficult in large data situations because of raw data [14]. However, data-driven AI systems helps in PdM by using the IoT sensor collected data [14–16]. This research is to create a PdM system which uses machine learning practices to generate accurate forecasts of future faults for industrial production lines before they occur. Novel methods were examined using a real-time data collected through sensors for an automobile part making machine to find best model to solve this challenge.

## 2 Related Works

Processing sensor data to enables better decision making is one of the key part of I4.0 [17]. Though, the ambiguity that exists in predictive analytics, as well as in the mortifying process and the time limits that must be met when reaching a choice, offer problems to the use of decision-making algorithms. With the rise of PdM which has shown its effectiveness in recent years, there has been a surge in algorithms which are proved to be better in assisting maintenance choices to extend the lifetime of machine. Ansari et al. [18] has suggested an integrated approach that includes the data-model with the Dynamic Bayesian Network (DBN) in order to learn cause-and-effect relationships, forecast future events, and recommend maintenance planning enhancements. Sarazin et al. [19] proposed a new architecture for a PHM technique that may extract more value from data. There are two levels in this lambda architecture one as a speed layer and another as a storage layer. Maintenance guidelines and the results of machine learning algorithms may be applied on speed layer through the storage layer. Furthermore, the system must deal through diverse data, which necessitates dealing with large data concerns while making the system compatible. Cheng et al. [20] sought to leverage sophisticated technology to create a predictive maintenance plan. An integrated PdM planning structure based on building information modelling and power of IoT for facility maintenance management was created to give a better maintenance strategy for constructing facilities as these BIM and IoT both have the power to improve FMM efficiency. The ANN and SVM machine learning techniques have been used to predict the future status of MEP components. For a big woodworking Italian firm, Calabrese et al. [21] adopted a

strategy using machine learning applied to woodworking industrial equipment. Using tree-based categorization models, predicted failure probabilities are derived from time series event data. Researchers trained a group of classification algorithms and applied temporal feature engineering techniques to forecast the remaining useful lifetime (RUL) of equipment used in wood industry. The effectiveness of the recommended technique is demonstrated by checking a self-regulating sample of machines without turn-off the display machine. To explore and visualize offline information from diverse sources, an approach based on machine learning models was presented in [22]. Data from three sensors were used to detect clusters in this case. They displayed three faulty circumstances as well as standard machine tool operations. Additionally, these findings were used to construct a condition-screening model, which aided in the development of machine tools for PdM solutions. To lower the complexity of a recurrent neural network algorithms firmness, Markiewicz et al. [23] proposed a novel structure where sensors are handling the processing. Based on the likelihood that the machine was working incorrectly, the data analysis was performed by a sensor, and at that time just a single packet was delivered. This structure makes use of ultra-low-power circuitry, allowing sensors to be powered by gathered energy. This arrangement dramatically increased processing power while consuming very little energy. Zenisek et al. [24] suggested a random forest (RF)-based machine learning strategy to identify the behavior of putative idea drifts in continuous flow of data. The purpose of this idea was to monitor a particular condition of equipment data supplied by sensor-equipped equipment in order to detect deterioration along with future failure. By eliminating failures and improving performance, these advancements proved the prospect of lowering material and time costs. However, in order to create computational models, it was necessary to screen high quality data. Also a novel technique was developed to identify the implication of data as a possible symptom of unusual performance of a system; the technique was based on previous synthetic dataset trials. Traini et al. [25] described the use of PdM for a milling cutting-tool, which was validated using actual datasets. This model, in general, offered a fundamental model for generating a device to analyze the wear level, a basic engineering tool, and failure avoidance to boost productivity along with human machine collaboration. 3 The Cox proportional hazard deep learning (CoxPHDL) approach was established by Chen et al. [26] to address the issue with limited and cleaned data concerns in while performing maintenance. The main purpose is to take into account the advantages of improved dependability and deep learning in order headed for providing a useful outcome. To begin with, a valid representation of nominal data was created using an auto encoder. The time-between-failures (TBF) of the censored data was then determined using the CoxPHM. Cheng et al. [27] presented a model for FMM that used BIM and IoT approaches. To provide the optimum maintenance performance, this paradigm incorporated application and information layers. To estimate the likely condition of the mechanical, electrical, and piping components, SVM and ANN machine learning techniques were applied. A machine learning technique was developed to execute PdM on nuclear infrastructure in [28]. A logistic regression (LR) and a SVM were used to compare and navigate through unusual occurrences that might occur in a nuclear structure. The SVM yielded the most accurate assessment results. In addition, both the LR and SVM algorithms had their parameters optimized. The previous research used a lot of data, but a new model with a much lower probability density was

created to correlate data from the nuclear infrastructure. Abidi et al. [29] proposed a five-stage intelligent PdM planning model that includes data correction, normalization of data, optimum choice of features, accurate decision-making, and estimate. Manufacturing sustainability is improved by predictive maintenance since there are fewer breaks, failures, and material waste. An effective PdM aids in the reduction of both material and time waste. Mishra K. and Manjhi S. [30] have presented a failure prediction model for preventive maintenance. The Proposed ML model uses several inputs for the prediction of future break down time of an ATM machine at a component level. Rahhal J. S. and Dia A. [31] have presented PdM model using NN estimator, where the large amount of database has been formed by using collected data through different IOT sensors. And the collected data used for prediction that has shown the promising result. Two different types of NN has been applied as Vanilla-RNN and LSTM-RNN, where these two have presented better predictions for light bulbs. M. Paolanti et al. [32] have also been worked on PdM and presented a Random Forest ML approach. A real time industrial data is collected through various sensors and communication protocols, then analyzed on the Azure Cloud architecture, and then the ML approach has been applied. Finally, the results have also compared using the simulation tool analysis. Three types of historical data have been used. Zhang D. et al., [33] proposed a two stage approach to foresee production-line breakdown. PCA and clustering methods have been used. Also the final model is deployed using Random forest with better performance. A new model that performs better than earlier attempts must be created in order to get over the limitations of present research works such as longer training times, high computer complexity, and the time-information dependency when employing statistical analysis methods. Industrial equipment failure causes the industry with lot of production and quality degradation, and unplanned downtime till that machine get back to its expected work. So PdM is expected to reduce unplanned downtime of equipment production line. PdM also helps to minimize the time and money spent on repair cost spent after machine stops working and maintenance without requirement. Thus PdM ensures the proper utilization of assets in optimal way. Thus PdM can be performed by using acoustic monitoring, electromagnetic thermography, analyzing the vibrations of an equipment, lubricant analysis and mechanical analysis. Among different equipment's used in manufacturing industries the automobile part making machine is monitored for further research to fulfill the research objectives. The PdM system development is good for time saving, cost saving and also prevent the complete breakdown of the whole production line. The article by Li et al., divided the possible system failures into four categories as element letdown, atmospheric influence, man made errors and wrong method treatment. The basic approach for the PdM model development using ML will have to follow the specific approach. Table 1 shows the study on PdM using different techniques of ML and has used the real time data collected through monitoring the device and also some systems have used the historical data of machine failure.

**Table 1.** Applications of ML in PDM

| Sr. No | Technique used | Equipment Used | Dataset Description | Application | Ref. |
|---|---|---|---|---|---|
| 1 | RF | Electric motor | Data from Sensors, Plc's and Comm. Protocols | Condition monitoring | [33] |
| 2 | SAFE | Semiconductor Manufacturing | Maintenance cycle data | Exploit Time series data | [36] |
| 3 | DTMM | Complex component | fatigue crack data-set and laser dataset | system reliability assessment | [37] |
| 4 | RNN, LSTM | Light bulbs | Data from sensors connected to CPU | RUL calculation | [32] |
| 5 | ARIMA-LSTM | bearing production line | data from the PLC | predicts the state | [35] |
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| 8 | RF | Supermarket Refrigeration System | Data for Defrost state and Temperature sensor data | Time series based classification | [39] |
| 9 | Bayesian DL | turbo fan engines | C-MAPSS data | RUL estimation | [40] |
| 10 | Weibull proportional hazards model | lead-acid batteries | dataset from accelerated battery aging test in SAE J2801 | RUL distribution | [41] |

## 3 Motivation

With the emergence of the fourth industrial revolution, the use of artificial intelligence in the manufacturing realm is becoming more common. Maintenance is a vital activity in the production process, and it demands careful attention. Predictive Maintenance (PdM) has become crucial in industries in order to reduce maintenance costs and achieve sustainable operational management. The PdM idea is to foresee the next failure; consequently, maintenance is scheduled before the expected failure happens. Facility managers often use reactive or preventative maintenance mechanisms in the development of maintenance management. However, reactive maintenance cannot avoid failure, and preventive maintenance cannot anticipate the future state of mechanical, electrical, or hydraulic components. As a result, such components are fixed ahead of time to extend the life of the facilities. In this research, intelligent approaches are used to design a PdM planning model.

## 4 Proposed Methodology

The PdM technique is used to optimize asset maintenance plans by forecasting asset failures using data-driven models. PdM implementation reduces downtime and improves product quality. PdM is also known as condition-based maintenance, and it seeks to identify failures and eventual deterioration by recognizing trends in component conditions using past data; consequently, rapid actions must be included. However, PdM has various difficult tasks in terms of forecasting system failures and fixing components to increase service lifespan. The proposed PdM planning model makes use of datasets

collected by using different types of sensors in butt weld machine to provide the best prediction details. The proposed Predictive Maintenance Planning Model Based On Optimized Machine Learning Approach is divided into four stages: data pre-processing, optimum feature extraction, prediction network decision-making, and 5 prediction. First, the datasets are cleaned by detecting outliers and filling in missing values. Following pre-processing, feature extraction is carried, with redundant data eliminated. The feature extraction phase in a complex manufacturing environment, where PdM models must be re-trained every time new relevant data is recorded, must be an automatic procedure; in this regard, a standard framework for time series feature extraction is to partition the input time series into a number of intervals and compute statistical moments for each interval; however, the previous approach has a major drawback, in that the statistical moments do not account for dependency between information and time. Thus Supervised Aggregative Feature Extraction with, a supervised regression approach must be employed that uses a functional learning paradigm to represent learning problems with time-series type inputs and scalar outputs. Because prediction value fluctuates the given range of temperature which attempts to accurately predict a target variable by combining the estimates of a set of simpler, weaker models. In addition, to predict the failure state with respect to down time, the existing works they utilized LSTM based model which creates the long dependency problems. To overcome the above problems in this research a weight optimized GRU model is used which incorporates the two gate operating mechanisms and Whale Optimization with Seagull Algorithm used to optimizes the weight in GRU-based learning. As a result, the proposed framework will show to be well-suited for PdM planning and capable of accurately predicting future component condition for maintenance planning. To solve the global optimization problem a novel hybrid algorithm, called whale optimization with seagull algorithm (WSOA), is being used. The primary explanation is that the spiral attack prey of seagulls and whale bubble net predation behavior are highly similar, and the WOA has powerful global search capabilities. From the studies of performance of the WSOA with the performances of seven famous metaheuristic algorithms, the results shown its strong competitiveness and proven its effectiveness [37].

Figure 1 represents the architecture of proposed model for PdM with having 5 different stages, starting from data collected for butt weld machine, data processing, feature extraction, and XGBoosting the decision of prediction.

## 5 Conclusion

The amalgamation of Industry 4.0 and ML has increased the possibilities in evolving the quality of manufacturing industries throughout the supply chain. The most evolving field in the industries is the earlier detection and prevention of failure along with all the pre-processing and effective utilization of diverse sensor data. The motive behind predictive approach is to effectively analyse and use the collected data along with the historical data if any so that the current state of machine is predicted in addition to avoid the future failure of that equipment. To develop the model a Supervised Aggregative Feature Extraction is employed with, a supervised regression approach to represent learning problems with time-series type inputs and scalar outputs. In this research a weight optimized GRU model

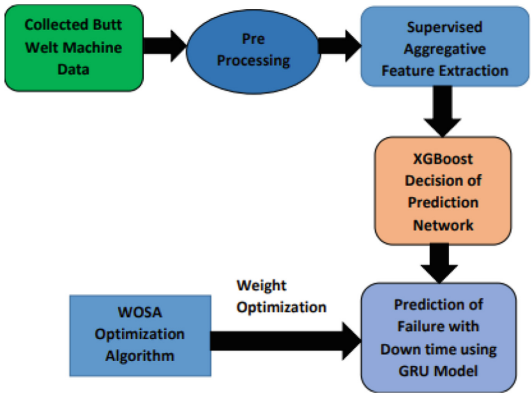


**Fig. 1.** Architecture of Proposed Predictive Maintenance Planning Model

is used which incorporates the two gate operating mechanisms and Whale Optimization with Seagull Algorithm is being used to optimizes the weight in GRU-based learning to predict the failure state with respect to down time as it solves the global optimization problems. In future proposed framework will be showing to be well-suited for Predictive Maintenance planning and capable of accurately predicting future component condition for maintenance planning for Automobile part making machine with proven results and to understand the critical parameters in failure using Machine Learning.

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