Device Discovery Techniques for Industrial Internet of Things through Predictive Analytic Mechanism

Santosh Pattar[1], Ritika[1], Darshil Vala[1], Rajkumar Buyya[2], Venugopal K R[3], S S Iyengar[4], and L M Patnaik[5]

[1] IoT Lab, University Visvesvaraya College of Engineering, Bengaluru, India
[2] University of Melbourne, Melbourne, Australia
[3] Bangalore University, Bengaluru, India
[4] Florida International University, Miami, USA
[5] National Institute of Advanced Studies, Bengaluru, India
santoshpattar01@gmail.com

Abstract. Maintenance and management of a manufacturing process involve the collection and processing of the machine data. Integral data from a running machine is to be gathered first to accomplish the effective management of the machine in an industry. This collected data provides the current status of the machine and eventually helps in predicting the machine failures beforehand. These sequences of events are called predictive maintenance of a machine. The approach of device discovery helps to predict the machine failures in a better way by transmitting the machine data to edge devices. In the proposed work, machine failures are predicted with the help of aptly designed detection engines. These engines confirm the machine failures by comparing the current status of the machine data with the set of pre-defined rules. Therefore, a machine is serviced right before any unexpected failure and thereby stops the unusual crash-down of a device.

Keywords: Device discovery · failure detection · ontology · predictive maintenance · industrial internet of things.

1 Introduction

Industrial Internet of Things (IIoT) is an applied domain of Internet of Things (IoT) whose primary purpose is to provide an efficient management system for Industrial applications. It works on the principle of building systems by adopting a network of devices that are embedded with sensors to retrieve necessary data and use the same to monitor the industrial equipment for effective and efficient management. For example an IIoT application designed and implemented for the textile industry, monitors the spindles used for weaving and advice when to change or service them before they breakdown [11].

Predictive maintenance system has to deal with risks and significant challenges (that are explained in subsequent sections) that prevent it from the effective operation. Thus, questions like "What if the service done to any equipment is carried out way too earlier than it is required?" have to be addressed. It is a demanding task for a predictive maintenance system to determine the exact time for replacement or assistance of the devices [22].

Device discovery aims to search for an object that closely matches a given query to complete a required function. Many parameters like the location of the device, network identity document (ID), protocol, *etc*, are required to identify a device [14]. The implementation process of device discovery strategy in industries improves reliability of the devices, communication, time complexity, *etc*, leading to a better outcome in the production process [2]. It is complex task to locate a device due to the presence of a large number of devices and heterogeneity among them. The issue of scalability also arises when a large number of devices are available to perform the same task in different ways and still produce the same output (continuous monitoring of devices and performance analysis is to be cross-checked for every such device in order to select the optimal one). This process consumes a huge amount of time due to the large size of the network and complex relationship among them [21].

1.1 Motivations

Predictive Maintenance is the most recently researched topic which explains how to increase the lifespan of equipment used in any industry. The study of existing work reveals that fault monitoring and condition of the machinery is supervised so that unpredicted breakdown is averted. Device discovery approach enables the detection of physical connections around so that the devices can communicate with each other to build a social relationship. They have a set of rules according to which the devices are standardized [13]. There are multiple drawbacks in the current system of device discovery some of which includes increased power consumption. Moreover, these prevailing criteria of device discovery are not applicable for ultra-dense networks [8].

The proposed predictive maintenance model is based on the set of rules that are already defined and stored in the database. When the sensor gives the surrounding readings, it is mapped with the rules present in the database. These rules define the failure conditions and are defined in simple if-else clauses.

1.2 Contributions

The contributions of this paper are as follows.

- *Ontology Model for PdM*: We have developed an ontological model for PdM. This model is designed based on the generic features of the machine and its failure and helps to monitor the system through semantic technologies. We also demonstrate a use case example and its application.

- *Reference Architecture*: A reference architecture is laid out that depicts the predictive maintenance of each device and these devices are regulated using edgent components.

1.3 Organization

The rest of paper is systematically organised as follows. The background work and literature are surveyed in Section 2. Use case scenario description is specified in the subsequent Section 3. Nextly, in Section 4 with the help of system architecture, our approach of resource discovery for predictive maintenance is explained. Sequentially, the experimental setup is shown along with dataset description and implementations in Section 5. This also includes evaluations, results and discussions. Lastly, we conclude in Section 6.

2 Literature Survey

In this section, we describe some of the most recent works in the IIoT for predictive maintenance and device discovery techniques, in their respective subsections.

2.1 Related Works on IIoT

Rapid advancements in the manufacturing techniques and development have led to the increased use of computational methods to overcome challenges such as productivity, management, and effective resource utilization. A recent paper [1] briefed about the use of IIoT healthcare applications for context-sensitive access to the information. Similarly Liao *et al.* [10] systematically reviewed the insights and literature of IIoT which finds the root cause of product failure along with inclusion-exclusion criteria. Jeschke *et al.* [7] describes the use of IIoT in the manufacturing of cyber systems and other applications. They concluded that an increase in adaptability and robustness plays a major role in the cyber-physical system for smart factories. In the following paragraphs, we review a few recent publications that address the predictive maintenance issue in IIoT.

Huynh *et al.* [5] proposed a parametric predictive maintenance decision-making framework that involves no risks for maintenance. It provides generic and flexible maintenance along with improved performance model. However, the methodology is applicable to a single system only causing sub optimal results with limited resources (that promote in high inspection cost). Likewise, Wang *et al.* [20] implemented a predictive maintenance system based on event-log analysis. The most prominent feature of the selection method used for model construction that can be customized and optimized for any kind of equipment. False alarm rate of the system is not handled efficiently in this work which leads to wastage of human labor and replacement cost without the display of system error log.

Vianna and Yoneyama [19] worked on optimization techniques for redundant systems in aircraft subjected to numerous wear profiles. The operation cost estimates and identification of future degradation (is the most favourable gain whereas the unfavourable opinion is that) the technique does not incorporate troubleshooting tasks while planning.

2.2 Device Discovery Techniques

A device discovery technique aims to locate an appropriate device matching the requirements based on various properties of the devices, relationship with other devices, *etc* [15, 16]. In the following paragraphs, we present a survey on such recent techniques for device discovery in IoT.

Suntholap *et al.* [18] demonstrated the intelligent device discovery in IoT for the domain of robot society. The system is fast, scalable and makes use of a set of criteria for device ranking such that, it measures the device's degree of social relationship, clustering coefficient and betweenness among them. However, concerns like how to standardize the expression of computing requirements are not considered.

Ngu *et al.* [12] surveyed on middle-ware available for the IoT. Their work is broadly focused on enabling technologies using middleware and its related issues. The advantage is that it supports heterogeneity among the IoT devices and is a lightweight platform. But, the system is dependent on the context and forces the users to create their IoT applications according to that context only. Ishino *et al.* [6] discovered relay mobile device with proximity services for user-provided IoT networks. These services are feasible with reduced traffic and improve the existing crowdsourcing based application which can be reused. However, these services are more than the number of user equipment along with their deployment environment and thus the system is not scalable.

Device discovery system proposed by Epstein *et al.* [4] includes a data storage medium that is used for storing clustering data structure. But, the security of this data is not addressed by the proposed work. Although the system includes a processor for device identification helps with decision making, there is an issue of complexity over-heading in hardware system architecture.

Lakshmanan *et al.* [9] worked on the concept of methods and systems for device detection and authorization in IoT framework. The proposed methodology builds a time schedule of proximity events and ranks them according to the assigned weighting factor of every device. However, interrelated proximity events do not consider the dynamic factors where a device's attributes can change abruptly for several devices.

The concept of energy efficient device discovery was proposed by Sharma *et al.* [17] for reliable communication in IoT which is based on 5G. The system provides energy, offloading and fault tolerance models. Due to the extra amount of energy that is spent to evaluate percentage packet loss energy expenses increase. Device-to-Device (D2D) communication technologies is explained by Bello *et al.* [3] with a major focus on network layer interoperation in the IoT. Scalable integration and interoperability in D2D technology is an added advanced feature but the TCP/IP protocol stack is limited for future implementations of D2D communication.

3 Use-case Scenario and Predictive Maintenance Ontology

In this section, we outline the research challenges in predictive maintenance of devices in IIoT in detail with the help of relevant use cases and examples. These expected results benefit the stakeholders by improvising the life expectancy of the equipment. For each such failure, we construct a rule and design a Predictive failure Detection Engine (PDE) to analyze the present condition of the machine and thus, aid in its predictive maintenance. The data obtained from the sensors is fed to a processing unit PDE, that identifies the failure condition based on a certain set of rules. The output of the same is further processed by the Predictive maintenance Detection Engine(PmDE) to decide on the failure of the machine.

3.1 Boiler

A boiler is a most commonly used machine to generate steam in industries that manufacture automobiles, locomotives *etc*. These boiler machines play a crucial role in the functioning of the industries and their sudden unexpected failure may lead to heavy financial loss and also pose a threat to the safety of the workers. Figure 1 depicts the boiler's PmDE.

Some of the root causes for failure of a boiler tank are high-temperature creeps, substantial tube well thinning or graphitization of matrix probe. There can be one or more than one such conditions that cause failure. Every condition is sensed and detected by using and processing data gathered from various sensors that are connected to the boiler tank.

We have designed rules for boiler tank failure based on these conditions as follows. We formulate two rules for temperature creep and wall-thinning of the boiler to detect an early failure. Firstly, the boiler failure Rule 1 (R_1) says,

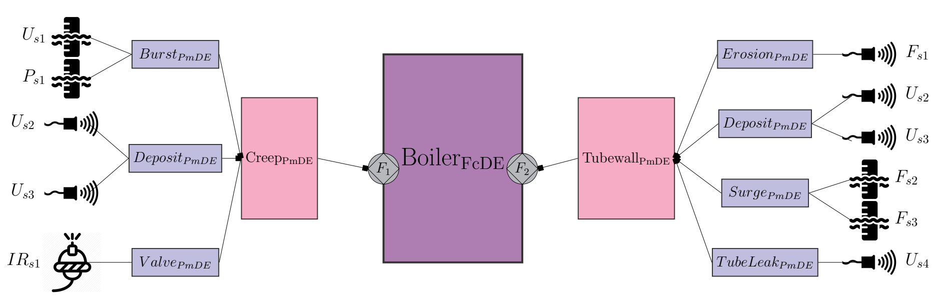

Fig. 1. Boiler Predictive Maintenance Engine

```
IF ((waterLevel > maxWaterLevel) AND (waterPressure < minPressureLevel))
   OR ((sediment > maxSedimentLevel) AND (limescale > maxLimescaleLevel))
   OR (fillValve == broken)
THEN
  tempretureCreep == true
```

When the water level and the water pressure inside the boiler tank exceeds a given threshold value then a boiler can burst. Similarly, another condition like sediment/limescale deposit can be monitored with the help of deposit-sensors. Also if the boiler tank has a broken fill-valve, the possibility of temperature creep is also present. Secondly, the boiler failure Rule 2 (R_2) is expressed as:

```
IF (waterVelocity > maxWaterVelocity)
   OR ((sediment > maxSedimentLevel) AND (limescale > maxLimescaleLevel))
   OR ((steamFlow <= minRate) AND (firingRate >= max ))
   OR (tubeLeak == true)
THEN
  substantialTubeWallThininng == true
```

Here, the conditions are erosion, deposit, surge and tube leak that detect the substantial tube wall thinning and boiler tube blocking state. If the water velocity is exceeding the maximum velocity inside the tank, then erosion of the tank occurs. The condition for failure due to deposit is similar to that of previous rule condition *i.e.,* limescale/sediment deposit. Surge refers to the water flow rate inside the boiler tank. When a boiler is started and water begins to rush inside the tank, that flow rate of water is referred to as firing rate. Whereas the tube leak condition can alone determine the wall thinning of a boiler tank. Hence, we can derive to the conclusion that these conditions lead to the boiler tank failure scenario. To detect the malfunctioning or failure of the boiler, we construct a PmDE to process the data obtained from various sensors that are installed at/on the boiler machine.

```
IF (tempCreep == true)
   OR (tubewallThinning == true)
THEN
  boilerFailure == true
```

3.2 Predictive Maintenance Ontology

Predictive Maintenance Ontology (PMO) gives a backbone architecture for the entire model by defining structures. These defined structures assist the PMO to detect machine failures. The conditions that cause a machine to fail are predefined and protocols are set such that the failure can be predicted. PMO ontology is extremely necessary because it builds the system model by taking semantic knowledge as its basic foundation. Semantic knowledge is a domain-oriented language which takes the conceptual ideas and frames a semantic model upon which an ontology can be constructed. PMO not only defines the failure conditions of a machine but also predicts the failure and instructs how to avoid such conditions.

The components of PMO includes machines, failures, failureConditions, predictive Maintenance Detection Engine (PmDE) and Failure Condition Detection Engine (FcDE), as shown in Figure 2. PMO is constructed with respect to Industrial domain, specifically considering the use cases of elevators, turbines, and boilers. The detection engines (DE) utilize the knowledge from other components to derive to a conclusion and thereby deciding the machine failure. For example, the boiler machine FcDE detects the conditions where there are possibilities for a boiler to fail. To detect these failure conditions, the FcDE uses data from failureConditions which is another component of PMO.

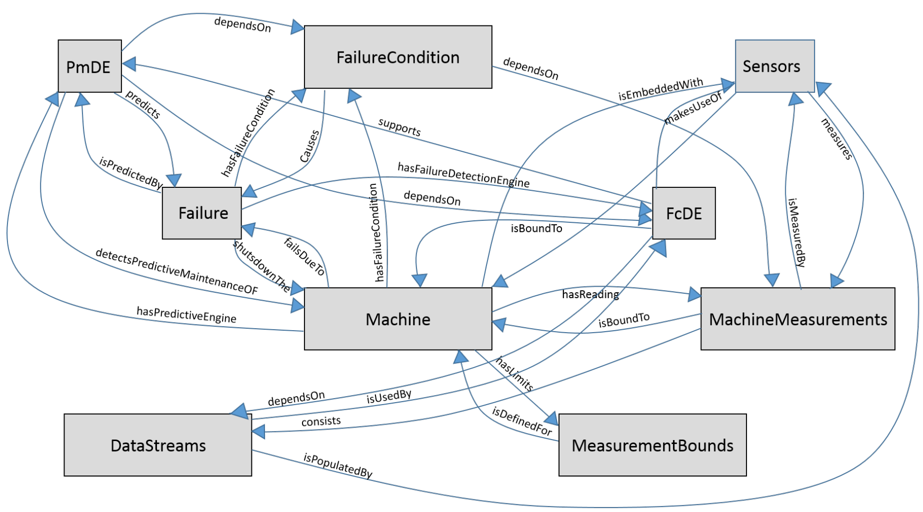

Fig. 2. PMO Architecture

Multiple classes, sub-classes, properties *etc* are defined in the PMO. Classes are related to one another by defining relationship properties between them. Machine class defines the three use cases considered, failure class includes the types of failure for every instance of machine class. Nextly, the failureCondition class holds the scenarios which can cause a breakdown. A sensor class is implemented which has several subclasses. These comprise all the sensors required in PMO to monitor the current condition of a machine. There are two DEs enforced as classes and they're FcDE and PmDE. FcDE detects the failure of a machine due to some context or component failure whereas PmDE predicts the maintenance required by a machine through FcDE. Machine measurements are characterized in another class and their bounds specify the range of machine attribute measurements. Set of data items are captured and are transferred to the users sequentially and continuously at certain intervals of time. These set of data items are illustrated in the data stream class.

Object property characteristics show the attributes of a particular object. There are several functions available that give a better framework for the defined object properties like functional, transitive, reflexive, etc. The object properties denote a connotation between two classes. For example, failure conditions cause failure. Here, failure conditions and Failure are two different classes and causes is the object property defined with failure condition as domain and failure as a range. There can be one/more object properties between any two classes, hence to distinguish uniquely, the functional characteristics are provided. Every object property in the PMO is defined with a specific domain and range (which happens to be class again).

Data properties are the attributes that define a class. For example, sensor attributes in a data property that defines the sensor class and the information like sensitivity, linearity, accuracy, range *etc* can be derived for a particular sensor instance. These are listed in Table 1.

Table 1. PMO Ontology Details

Domain	**Object Property**	**Range**	**Description**
– PmDE – FcDE	dependsOn	– FcDE – Failure Condition	Failure depends on failure condition.
Machine Failure	hasFC	Failure Condition	Machine fails on meeting one of its failure condition.
Failure	hasFDE	– Failure Condition – FcDE	Failures are detected using detecting engines.
Measurement Bounds	isDefinedFor	– Machine Measurements – Machine	Limiting bounds are defined for measuring every parameter of machine.
Machine Measurements	isUsedBy	FcDE	Failure condition detection engine uses machine measurements.

4 PdM Architecture

In this section, we discuss the architecture designed for the discovery techniques of devices for industrial internet using predictive analytic mechanism.

4.1 Overview of Architecture

The PM architecture can be explicitly explained based on a layered architecture as shown in Figure 3. This architecture comprises four layers, each with specific functionality. Here, the layered architecture focuses on the processing of edgent components. The PM architecture includes four layers: Sensor Layer (SL), Topology Layer (TL), Provider Layer (PL), Application Layer (AL). The sensor layer lies at the bottom part of the architecture. It holds the collection of sensors that are embedded on the machine to monitor its working condition. These sensors collect the information about its surrounding environment and a set of data is taken for consideration. These data collected from the sensor layer is given to the second layer in architecture *i.e.*, topology layer that creates a specific data stream out of the data collected from the sensor layer based on the failure conditions that are to be monitored by the experts. These data streams are fed above by the provider layer which is responsible for handling the execution of failure prediction and failure detection of the machine.

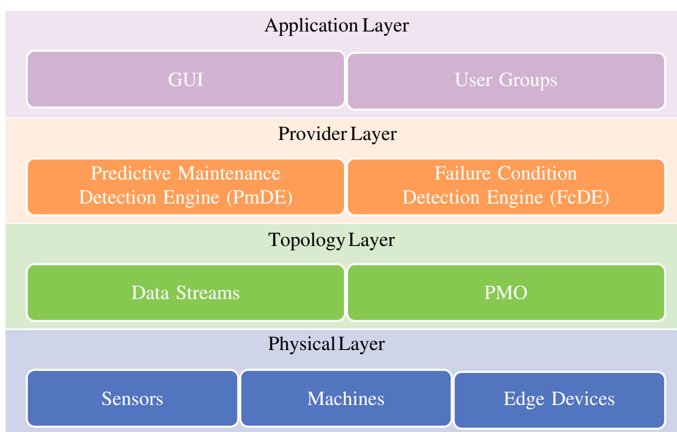

Fig. 3. PdM Component Architecture

Firstly, the *physical layer* consists of a hub, a machine and a group of edge devices. These three components are embedded and interconnected to one another in the physical layer itself. The machine components are further embedded with respective sensors to read the machine environment conditions. Secondly, the *topology layer* includes a set of databases that stores the data stream values and a PMO database that backlogs the populated datastreams. Thirdly, the *provider* *layer* frames four different data containers namely FcDE database (FcDE-DB), PmDE database (PmDE-DB), Rule-Set database (RS-DB) and Processed Data Stream (PDS-DB) database. The FcDE-DB holds the prediction results, RS-DB comprises of well-defined rules that determine machine failure, the PDS-DB incorporates the processed data stream from the previous layer. Finally, the components of *application layer* are the more relevant real world. The three main components of the application layer are users group, enterprises that use our application and lastly the repair consultant/handyman.

4.2 Workflow

The real-time sensors planted within the machine environment, reads the values to fetch its surrounding area conditions. Every stream is stored, pre-processed and populated into the PMO-DB. It encompasses all of the processed data stream values and sends the same to the provider layer. The FcDE-DB excavates the failure condition of a machine and compares the data with the input data streams whereas the PmDE-DB detects a fault in a machine by correlating the processed input data stream with pre-defined set of rules from RS-DB. The result of PmDE is given to the enterprise via the user interface in the application layer.

4.3 Example

Fault Detection in Boiler Machine is describes as example. There are two main conditions for a boiler machine to fail. It can fail either if there is creep in temperature of boiler machine or due to the substantial wall thinning. The circumstances that lead to temperature creep of a boiler machine are tank-burst, tank-deposit or broken-fill-valve. On the other hand, we have the boiler machine failure due to substantial wall thinning condition. There are four cases that margin the wall thinning conditions *i.e.,* tank-erosion, tank-deposit, tank-surge, and tank-tube-leak. Correspondingly, the erosion-FcDE, deposit-FcDE, surge-FcDE and leak-FcDE are devoted failure condition detection engines.

As mentioned earlier the sensors nested within a boiler machine are ultrasonic sensors, pressure sensors, infra-red sensors, and flow sensors. These dedicated FcDEs are fed with the corresponding data streams like the tempCreepDS (temperature creep data stream) and thinWallDS(wall thinning data stream). The tempCreepDS is further populated with burstDS, depositDS, and valveDS. Likewise, the thinWallDS is colonized with erosionDS, depositDS, surgeDS, and leakDS. The respective sensors for these, collect the datasets and send the data to PMO-DB. In turn, the PMO-DB compiles the rules set and analyzes the machine condition measurements, measurement bounds and hence PmDE gives the output in terms of fault detection.

5 Experiments and Results

5.1 Dataset Description

For the use-case boiler machine, we have taken nine sensors into consideration which measures required environmental parameters. We collected the sensor data from internet. These data sets are fed into the PdM machines in the form of input data.

5.2 Implementation and Experimental Setup

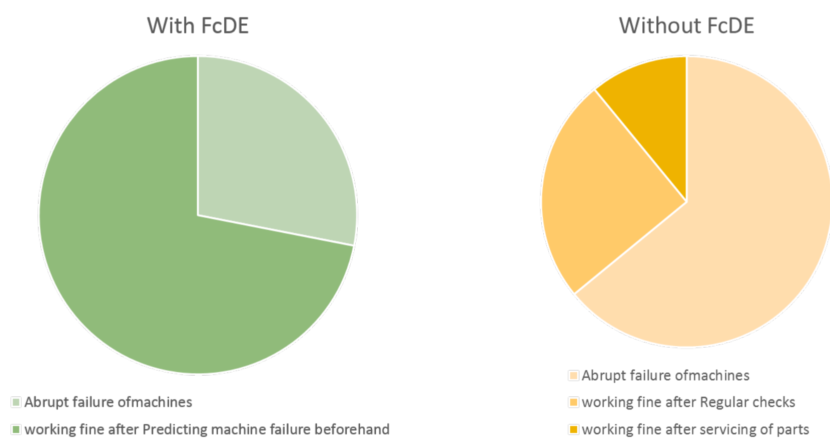

Fig. 4. Result Evaluations

we analyzed the proposed failure detection engines and compared the observations with old result statistics. Firstly, we created detection engines for every use case as shown in Figure 4 and made use of reference PMO architecture . In order to detect the failure we require the sensor readings that are fit into the use case machines. Using edgent technology we get specific data streams from every sensor for *e.g.*, Temperature sensor gives temperature reading of boiler every 1 to 2 ms in the form of data streams. Similarly all the sensors that are involved in the process of failure detection of boiler, are activated and data streams are collected and then fed into detection engines.

As shown in Figure 5 the number of failures grows when the machine is used for a longer period of time. Here, the proposed model of predictive maintenance is not being implemented. Therefore, the boiler machine failures are increasing linearly. In similar conditions when the proposed model of PdM is implemented, the results are shown in Figure 6. Here, the number of failures are relatively less when compared.

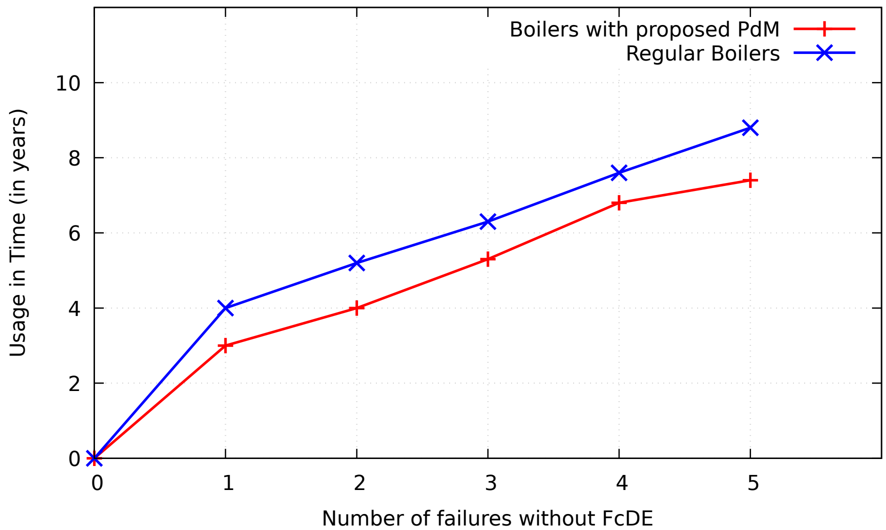

Fig. 5. Without FcDE

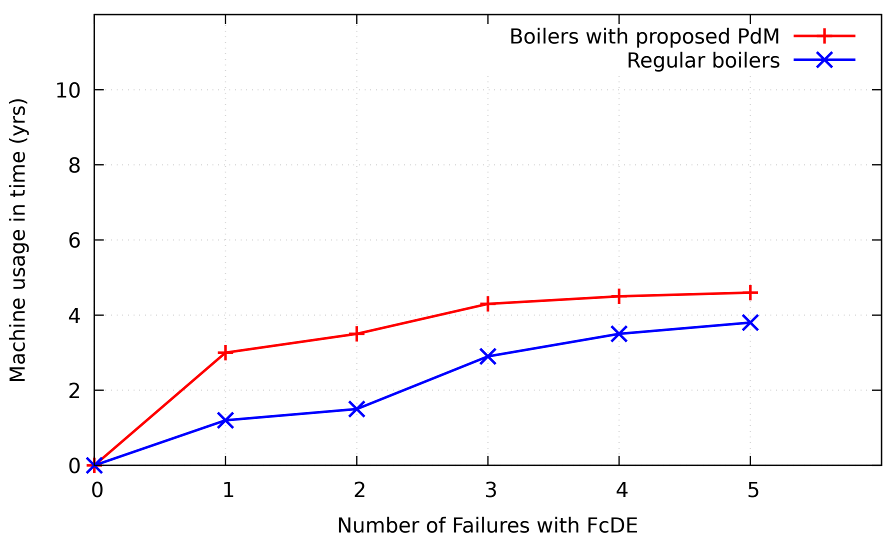

Fig. 6. With FcDE

6 Conclusions

This paper proposes a novel and efficient yet simple way of predicting a machine's failure beforehand. The set of rules are to standardize the conditions of machine parts. If the machine parts performance does not match the rule standards, the probability of machine failing is discovered. Apparently, these predictive maintenance engines are set up exclusive to a machine and hence is effective as there's no redundancy of data.

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