Social Interaction Enabled Industrial Internet of Things for Predictive Maintenance

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Abstract. As Internet of Things (IoT) advances from interacting objects to smart objects. Further, adopting social networking concepts into IoT leads to social objects. Following this conception, the Social Internet of Things (SIoT) comprising the amalgamation of social aspects into IoT was incised. In the recent past, the use of IoT technologies in the industrial sectors and applications has given birth to a new research area termed as the Industrial Internet of Things (IIoT) has attained notable attention extensively. In machinery based industries, elements such as bearings, axles, brackets, hangers *etc.* are the essential machine element that serves a variety of purposes in the production environment. Thus, any severity related to it causing failure is unfavorable. This paper introduces the SIoT concept into the manufacturing industry for predicting the failure of the machine element before it could occur. This work proposes the construction of the ontological model that assists in the implementation of the Prognostics and health management to predict the Remaining Useful Life (RUL) of machine element, which is essential in minimizing maintenance cost and machine downtime, and further limiting disasters.

Keywords: Bearing Failure, Industrial Internet of Things, Ontological Model, Predictive Maintenance, RUL Prediction, Social Internet of Things.

1 Introduction

The Industrial Internet of Things (IIoT) is an industrial framework where machines or devices are linked and synchronized utilizing software development tools and third platform technologies in a Machine-to-Machine (M2M) and Internet of Things (IoT) context. IIoT applies unified protocols and architectures for the development of devices that has better control, seamless communication, and improved interoperability between the machines. It exhibits quality control, asset tracking, sustainable and green practices, supply chain effectiveness, and supply chain traceability. All this leading to Predictive management in the industrial settings where data from embedded sensors and connected devices are gathered and exchanged intelligently. In industries with a high risk of human error, IIoT comes as a boon, where the precision level that is achieved through IIoT plays a prominent role in Industrial predictive maintenance [1].

Predictive Maintenance (PdM) is a strategy that deals with maintenance issues, given the increasing need to reduce the maintenance cost and machine downtime. Predictive maintenance relies mainly on sensors to monitor the machine and detect when a critical piece of machinery is close to failure. In machinery domain, machine elements plays a crucial role in the production environment, hence predicting its Remaining Useful Life (RUL) to avoid the severity of failure benefits [2]. To predict the RUL of a machine element is still a significant challenge task, as it depends on several factors that cannot be measured and analyzed quantitatively. To enhance the accuracy in the prediction of machine elements RUL and the factors that affect its failures becomes a critical issue and has attracted a large number of prognostic researchers [3].

The Social Internet of Things (SIoT) is a thriving research field that emerged as a result of the integration of social networking concepts with IoT. SIoT is an interaction paradigm where the objects establish social relations with various objects and users to achieve a common goal [4–6]. Integrating SIoT concept into the Industrial Internet of Things advances the machines with the formation of social relationships supporting the human-machine communications and machine-machine interactions. The idea of utilizing SIoT in Industry is named as Social Internet of Industrial Things (SIoIT). SIoIT conceptualizes the application of social behavior to intelligent assets (refers to machines or machine parts, the term asset, machine, and resources are used interchangeably) that are connected with actuators, sensors, or any identification technology [7]. In SIoIT relationships are built among the industrial assets according to the rules set by the asset relationships.

1.1 Motivations:

Predictive Maintenance is the recent research topic that determines the probability of failure of a machine before it could occur and allows industries to progress from a repair and replacement model to a predict and fix maintenance model. For a long time, we have been tending issues in the machinery when they crop up instead of thwarting them, which immensely affects the expenses and endeavors to fix the assets. If the prediction of these issues are made based on the historical data, there can be mitigation in the costs and finer allocation of resources related to the unplanned maintenance. With the introduction of the Industrial Internet of Things (IIoT), it enables us to enhance efficiency and production quality.

The proposed PdM in SIoIT is based on the number of social relationships defined between assets and the actors (human operators). These relationships are used to predict the failure of the machine element and notify the prediction to the maintenance or repair personnel. Meanwhile, the sensor readings are examined over time to learn the relationship of the machine element.

1.2 Contributions:

The main contributions of this paper include the following:

1. *PdM-SIoIT Architecture*: An overview of Predictive Maintenance based SIoIT Architecture to detect the failure condition and predict the remaining life of the assets in industries.
2. *Social Relationship Ontology for Predictive Maintenance*: We construct an ontological model to describe various relationships in the prediction of multiple factors that might cause the failure of machine elements based on the obtained data points collected over time through different sensors. The RUL prediction and the health management of machine elements are based on continuous monitoring, and if any discrepancies are observed in the specified threshold, it sends alerts conforming to predefined rules.

1.3 Organization:

The rest of the paper is organized as follows. A brief summary of related works in Industrial IoT, Social IoT, and ontology model is discussed in Section 2. Predictive Maintenance based SIoIT Architecture to detect the failure condition and predict the remaining life of the machine assets is explained in Section 3. The ontology model for predictive maintenance in SIoIT is discussed in Section 4. Section 5, emphasizes on the implementation of the proposed Predictive Maintenance based SIoIT with the aid of a scenario, simulation setup and results. The concluding remarks are presented in Section 6.

2 Literature Survey

In this section, we present the state-of-the-art research works in the field of predictive maintenance in IIoT, SIoT, and ontology-based fault diagnosis methods.

Vianna *et.al.,* [13] have developed a predictive line maintenance optimization strategies subjected to multiple wear conditions in aeronautic systems. It utilizes a Kalman filter technique to calculate trends of degradation and wear values in future. A case study is carried out considering field prognostics data of various hydraulic systems for prediction. The limitation is that the states and variances of the model cannot be combined and shared among different models.

Wu *et al.,* [14] have presented Hidden markov model based on cluster K-PdM for RUL prediction and estimation of machinery deterioration supported by multiple KPIs (Key Performance Indicators). An experimental approach is applied to exhibit its application on the *PHM08* dataset.

Yan *et al.,* [15] have proposed a framework to predict the RUL of Key components in a CNC machine. It exploits single and multiple source data models and employs a vibration signal to estimate the performance and forecast the remaining life. The limitation is deep learning techniques to examine big industrial data were not adopted.

Wang *et al.,* [16] have explored a cloud-based model for predictive maintenance using a mobile agent approach. It enables appropriate information utilization, distribution, and acquisition for improved accuracy and reliability in the prediction of remaining service life, fault diagnosis, and maintenance scheduling of various Induction motors.

Swamy *et al.,* [9] have developed a health-centric tourism recommender system. It is developed on an ontology framework, which can advise the availability of food based on climate attributes using user's personal favourite and nutritive value. Semantic ontologies connect the difference between various user-profile information. The real-time IoT-based healthcare support system is used to evaluate different food recommendations.

Cao *et al.,* [10] have proposed an approach that combines fuzzy clustering and semantic technologies to understand the significance of a machine's failure based on the obtained classical data. A case study on a real-world industrial data set is developed to estimate the suggested method's utility and effectiveness.

Wen *et al.,* [11] have provided an ontology model for fault in the mechanical diagnosis system. It is based on the Resource Space Model(RSM). Protégé 4 is used to make an ontological model for diagnosing AC motor defects. However, for mechanical fault diagnosis, this ontological model cannot be used.

Xu *et al.,* [12] have proposed an ontology-based failure diagnosis technique that overcomes the complexity of learning a sophisticated fault diagnosis information. It additionally provides a comprehensive procedure for fault diagnosis of loaders. The ontology model is highly expansible; because the components of the model like classes, individuals, and properties in the failure diagnosis can be greatly enhanced and updated.

Jung *et al.,* [18] have proposed a model that captures the Spatio-temporal attributes along with assorted co-usage data varieties to predict the relationship between different objects. It explains the entropy and distance-based social strength computations among objects. It portrays the structure of the SIoT model to IoT that offers navigation of networks, which includes adaptation and effective objects discovery and services like human-centric social networks. However, it does not include how it has to deal with the strengthening of social connections as well as time-related deterioration. Further, numerous domains large data sets can also be used.

3 SIoIT Architecture for Predictive Maintenance (PdM-SIoIT)

In this section, we present the SIoIT Architecture for Predictive Maintenance and design an RUL Predictor Engine, which can be applied to a production environment in the industries to examine the assets existing condition and predict its remaining life before entering into practical failure.

The proposed PdM - SIoIT Architecture follows the three-layer system constructed from the base layer, network layer, and application layer, as shown in

Fig. 1. The base layer includes manufacturing assets embedded with identification tags, sensors, and actuators. The second layer is the network layer, which is used for connectivity to cellular networks, GPS, WLANs, or Internet as required. The Application layer consists of two sub-layers: Interface Sub-Layer and SIoIT Component Sub-Layer.

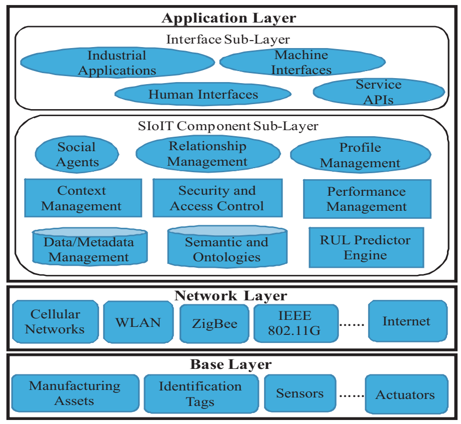

Fig. 1. PdM-SIoIT Architecture

The primary constituents of PdM - SIoIT is positioned in the SIoIT Component sub-layer of the application layer. It includes RUL Predictor Engine, Social Agents, Relationship Management, Profile Management, Security and access control, Performance Management, Semantic Engines, Ontologies, and Data/Metadata Repositories. The Interface Sub-Layer of the application layer consists of Industrial Applications, Machine Interface, Human Interface, and Service APIs to access the IIoT applications using different devices. The RUL Predictor Engine is an essential component of PdM-SIoIT Architecture that predicts the remaining life of the machine assets in industries. The taxonomy of RUL Predictor is illustrated in Fig. 2. The operation of the assets varies for different materials that provide preventive action and its threshold limit to predict the remaining useful life. The predictive methods are applied to collect and analyze the data from sensors embedded on the machine elements. The data is collected based on different parameters such as temperature, vibration, load, lubrication level. When the parameters exceed the specified threshold limit, the machine's failure is predicted in the mere future. Once a prediction is made, the necessary action will be taken to avoid failure in the future. The health management of the assets are performed when a failure is recognized; if the health state indicates a practical failure, then request for an OBM(Operation based maintenance) scheduling. Ultimately, when the maintenance interruption is finished, new data obtained in such interruption is added or updated in the assets data and in the parameters of the predictive techniques to proceed with the Prognostics Health Management cycle.

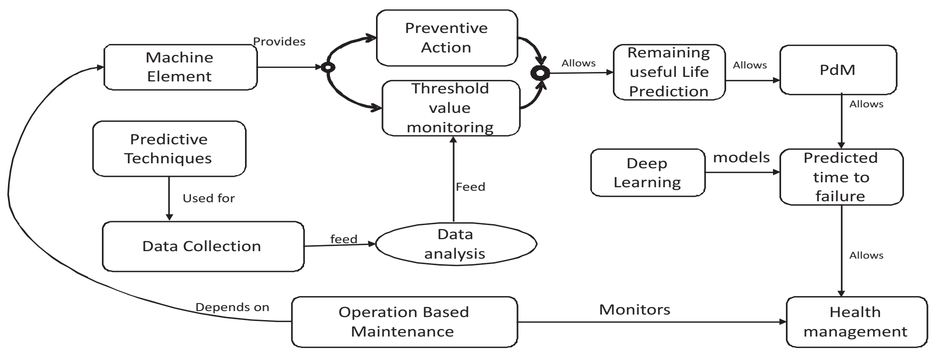

Fig. 2. Taxonomy of Remaining Useful Life (RUL) Predictor

4 Ontology Model for PdM-SIoIT

The ontological model is a structure that defines relationships between classes and subclasses existing in a domain. It analysis data to transfer information for granting decisions regarding the RUL of a mechanical element, before failure occurs. Each asset in the industry is associated with software agents that fulfill several computing essentials of the machine elements, such as managing relationships among the assets and the human operators [8]. We define various relationships that predict the failure of the machine and notify the prediction to the actors like maintenance or repair personnel who interact with the devices. Various relationships can be established among the assets and actors, which are enumerated as follows.

1. *Coercion object relationship (COR)*: enables machines to intimate the maintenance personnel that machine element has crossed its specified fatigue limit, which might cause fatigue failure.
2. *Torrid Object Relationship (TOR)*: is established between a temperature sensor and the maintenance team to take immediate action when the temperature exceeds its maximum limit, to avoid overheating of machine elements.
3. *Corrosion Object Relationship (CROR)*: When the machine elements are exposed to corrosive fluids or corrosive atmosphere, it forms a CROR with Saddle type eddy current sensor, and then the information is transferred to the technician.
4. *False Brinell Object relationship (FBOR)*: When excessive external vibration occurs, a False Brinell Object relationship is established between the vibration sensor and the maintenance team to avoid false brinelling on the machine elements.

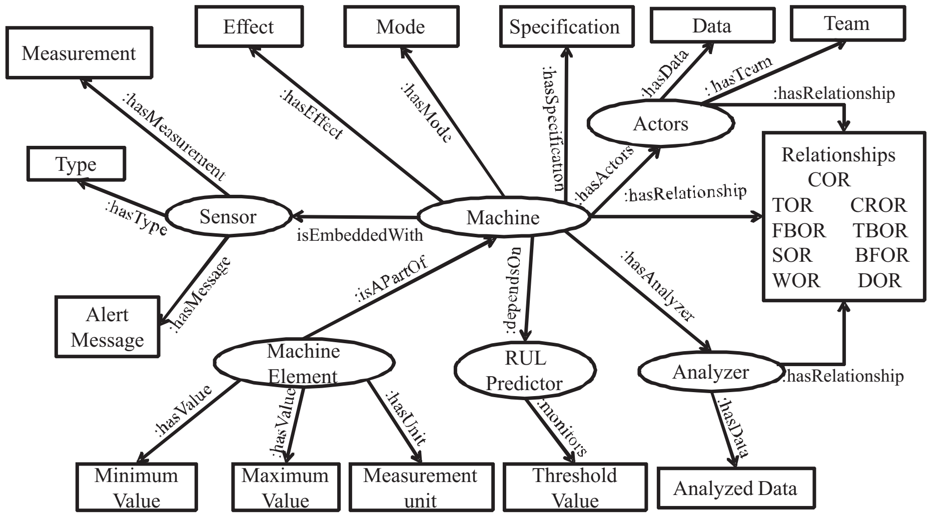

Fig. 3. Ontology Model for Predictive Maintenance

5. *True Brinell Object relationship (TBOR)*: When the load exceeds the elastic limit of the ring material, a True Brinell Object relationship is established between the vibration sensor and the maintenance team to avoid true brinelling on the machine elements.
6. *Spalling Object Relationship (SOR)*: is formed between the UV sensor and technician when there is a marked increase in the vibrations generated by the machine elements.
7. *Back Freight Object Relationship (BFOR)* : When the load is induced in the opposite direction, a BFOR is established between an Infrared sensor and maintenance personnel to avoid early failure of machine elements.
8. *Withered Object Relationship (WOR)* is established between smart oil sensors and lubrication experts when the required lubrication is not supplied to the machine element, which might cause excessive wear of balls and cages.
9. *Defile Object Relationship (DOR)*: When there is contamination in the operating area, a DOR is Formed between the RPM (Revolutions Per Minute) sensor and the maintenance team to avoid machine element dents.

The ontological model for predictive maintenance and its components is as shown in Fig. 3. The components of the model includes machines, sensors, machine element, actors, analyzer, and RUL Predictor. The model is constructed in the Industrial domain, studying machine elements such as bearings, brackets, axles, hangers *etc.* The RUL Predictor utilizes the information from other components and thereby predicts the Remaining life of Key machine element much ahead the actual failure occurs. In the ontology model, the object properties represent the links between components; and the data properties describe the values of the components. The ontology elements such as object and data properties for predictive maintenance is detailed in Table 1.

Table 1. Object and Data Properties for Ontology Model

	Properties	Domain	Description
Object Properties	hasMode	Machine	Represents the mode of machinery operation.
	hasEffect	Machine	Identifies the effect of failure.
	hasMeasurement	Sensor	Measures the threshold values.
	hasCause	MachineElement failure	Determines the cause of an element failure.
	hasType	sensor	Represents different types of sensors used.
	isPartOf	Machine/Machine Element	Identifies the part that might get affected.
	isIdentifiedWith	Symptoms/effects	Rectifies the variations in normal routine operations of a machine.
	hasSpecification	Machine	Provides the machine specifications.
	hasAnalyzedData	Analyzer	Analyzes the data obtained from sensor.
	hasData	Actor	Represents the available predicted data.
	hasTeam	Actor	Represents the different types of actors.
	isEmbeddedWith	Machine	Represents that the machines are embedded with different types of sensors.
	hasRelationship	Machine,Actors and Analyzer	Represents the relationships between actors and machine elements.
	dependsOn	Machine	Machine depends on predictor for RUL prediction.
	monitors	RUL Predictor	Monitors the threshold value for RUL prediction.
Data Properties	Minimalvalue	MachineElement	The minimum value under which an element can operate normally.
	MaximumValue	MachineElement	Represents the maximum value which causes failure of a machine element.
	MeasurementUnit	Machine Element	Every measurement has different units.
	AlertMessage	Sensor	Alerts when specific threshold is reached.
	FatigueLimit	Machine Element	The load an element can accept.
	MaximumTemperature	Machine Element	Maximum temperature condition an element can reach.
	VibrationValue	Machine Element	The speed at which a an element can operate.
	ContaminationLevel	Machine Element	The limit of contamination which does not affect an element operation.
	LubricationLevel	Machine Element	The minimum lubrication level an element should maintain.
	Loadtype	Machine Element	The type of load on machine element.
	BrinellEffect	Machine Element	The effect of different loads on an element is measured.
	Threshold Value	RUL Predictor	Life Span of a machine element.

5 Implementation of PdM-SIoIT

In this section, we present an overview of the feasible implementation of the designed PdM-SIoIT architecture by an illustration under multiple wear conditions of assets and the simulation setup.

5.1 A Scenario:

A bearing is a machine component that minimizes friction among moving parts, forcing relative motion to merely the desired motion. Bearing facilitates free rotation around the fixed axis of the moving parts or a free linear movement. The bearing usually does a pretty excellent job of managing the moving parts; however, when a bearing fails, the outcomes can be catastrophic [21]. Bearing fail unexpectedly and untimely, despite planning and maintenance. The primary reasons of damage and unexpected bearing failure for all bearing types are overheating, overloading, improper lubrication, excessive external vibration, contamination *etc.* [17], they are discussed as follows:

1. *Overloading*: When the bearing is at a speed of 2200 rpm, the maximum load it can accept is approximately 47620 Newton; if the load exceeds, there will be the formation of irregular spiderweb-like cracks and craters in the overlay surface which causes bearing failure.
2. *Excessive External Vibration*: When Bearings in a machine experiences vibration above 3200 rpm, the bearing might face true and false brinel, which might cause bearing failure due to excessive vibrations.
3. *Contamination*: A bearing that is typically contaminated beyond 1141 Megapascal causes denting of the bearing, and balls emerged from high vibration and wore, leading to bearing damage.
4. *Overheating*: Temperature above 400 °F anneals the ring and ball materials of bearings. Excessive heat can cause serious problems, resulting in machine failure and hours of downtime.
5. *Improper Lubrication*: Minimum Lubrication level of a must be maintained at 1.97 Micrometer, the bearing is serviced either according to a schedule or when the lubricant goes below the specified minimum level.
6. *Life Span*: The life of a bearing depends on the load and the speed at which it operates. Most of the bearings last approximately 8 to 12 years.

5.2 Simulation Setup and Results:

As IoT enabled Industrial setting has not been extensively implemented to date, the experiment of such an ecosystem is deployed on Node-RED [19], an open-source simulation and modeling tool. Table 2 presents the complete information of the varieties of sensors deployed along with the threshold limit exerted for each of the bearing failure types. The performance of the bearing is monitored continuously and if any discrepancy is observed in the specified threshold the

Table 2. Sensor Description for Bearing Threshold Monitoring

Sensor	Description	Unit	Threshold Limit
Temperature Sensor	Temperature Value	Fahrenheit (°F)	400
Pressure Senors	Fatigue limit	Newton (N)	47620
Smart oil Sensor	Lubrication level	Micrometer (μm)	1.97(min)
Vibration sensor	External Vibration	Revolutions per minute (rpm)	3600
RPM Sensor	Contamination	MegaPascal (MPa)	1141

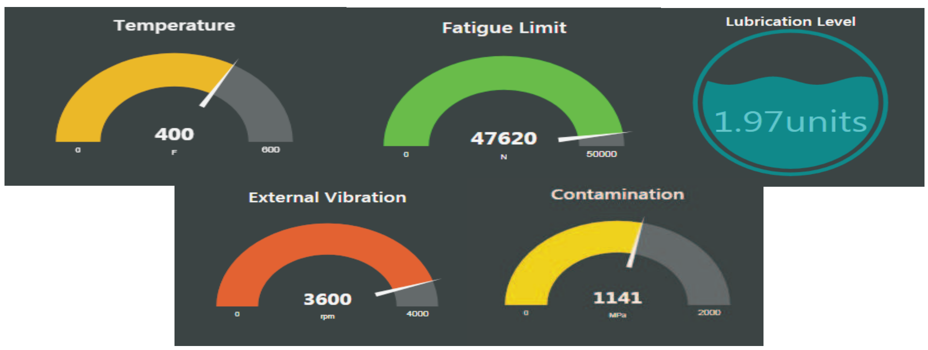

Fig. 4. Alerts Generated using NodeRED Simulation Tool

system sends alerts to the dedicated maintenance personnel regarding the fundamental specification of action. Fig. 4 depicts the example of alerts generated in the event of any exceptional behavior with the help of NodeRED simulator.

Simultaneously besides creating alerts the system also regularly predicts the RUL of the bearing, so that the maintenance can be planned in advance. The dataset used in this Experiment is from Prognostics and Health Management (PHM08) [20], which includes time series data. The dataset is separated into training and test datasets. It comprises twenty-one sensor measurements and three operational settings of an engine with varying degrees of initial wear and manufacturing variation. We develop a data-driven method to predict the RUL of a machine that deteriorates from an unknown primary state to failure. The proposed method uses the data from the training set, then the performance of the RUL prediction using testing data is evaluated. The solution employs an advanced, recurrent neural network to improve the prediction accuracy of the bearings remaining life. To reliably evaluate the fault diagnosis of a bearing, along with accuracy we compare the other metrics such as, preision, recall and F1-Score as shown in Table 3.

We see that the deep learning model results are better than the template when analyzing the above test results in the predictive maintenance template. It should be noted that the dataset used here is minimal, and deep learning models

Table 3. Results

Model	Precision	Recall	F1-Score	Accuracy
Deep Learning Model	0.960000	0.96	0.960000	0.978495
Template Model	0.952381	0.80	0.869565	0.940000

are known to offer excellent results with large datasets, so more massive datasets should be used for a more fair comparison.

6 Conclusions

In this paper, the inclusion of Social interactions into the industry settings for predictive maintenance is envisioned. A novel architecture for Predictive Maintenance in SIoIT systems is introduced to monitor future failure by keeping the companies prepared and allows them to plan even before the failure occurs. An ontological model is constructed to describe various relationships in the prediction of multiple factors that might cause an asset failure. To implement the proposed PdM-SIoIT architecture, the failure condition of an essential machine element, *i.e.* a bearing is discussed as an example. The simulation model is developed to detect the failure condition and predict the remaining life of a bearing. Further, we intend to implement the recommended scheme in the actual manufacturing settings and exploit the other deep learning techniques to improve prediction accuracy.

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