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Industry 4.0: AI enabled predictive maintainance strategies

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***Abstract*— Artificial Intelligence revolution is a major breakthrough in achieving intelligent automations in the manufacturing industries. The sensor devices connected to the machines along with the internet of things has enabled the machines to communicate with intelligent control center/hub for receiving proactive instructions to act and correct itself flawlessly. While the underlying technologies are evolving it would take iterative steps to strategies for creating powerful predictive maintenance solutions.**

This paper focuses on how to build an intelligent predictive maintenance system by adopting latest technologies internet of things, 5G, and methodologies such as self-supervised-learning abilities, machine learning, and graph models along with its application, sustainability strategies to deal with various scenarios needed for maintenance.

Keywords—machine learning; predictive maintenance; artificial Intelligence; Internet of things; IIoT; graph models; ontology

I. INTRODUCTION

Emerging technologies have revolutionized the manufacturing industry by adopting key concepts such as automation, IoT, IIoT, cloud computing, cognitive computing and artificial intelligence. These technology drivers are the keys to the success of transforming traditional manufacturing to smart manufacturing system. The benefits out of smart manufacturing is immense as it addresses challenges of adding intelligence to the machinery components through sensor, and analytics on top of it. In an ideal scenario, the machine components can report their status through sensors which contain machine states. The sensors communicate over IoT edge gateway to the analytics hub in the cloud where analytics are applied on the received data to detect anomalies, wear and tear of machinery parts. Based on the inference, maintenance activities are conducted to safe guard the operations from breakdowns to ensure normal operations during the business hours.

Maintenance activities are a must for any manufacturing system. There are scheduled and unscheduled maintenance activities carried out as per the need. Schedule maintenance are pre-defined and planned accordingly. Unscheduled ones are reactive, based on the current situation and are more troublesome than the scheduled ones. Often unscheduled maintenance are carried out because of failure or near failure situations. However, due to lack of predictions or in-accurate predictions, machines fail in most cases resulting into increased down time. Though there are predictive analytics available in some situations, but it becomes ineffective at some point of time, because with time the predictive model is not able to learn the new data patterns, or there is change in business environment, relationship among entities which are not in consideration, or it can be that a new type of algorithm required to achieve better predictions.

The question arises how often the re-train needs to be done? Can the system learn from its environment? What are other factors missing which can also enhance prediction? How those can be enabled?

II. CHALLENGES IN CURRENT PREDICTIVE ANALYTICS SYSTEM

The biggest challenge is how to apply predictive maintenance to deal with unforeseen breakdowns which leads to unplanned downtime. With the proliferation of artificial intelligence to commodity world, technologies are no more a challenge as these are evolving faster than ever before. The question arises though, how these technologies can be applied effectively to predict the unforeseen machine breakdown so that maintenance can be done beforehand to prevent operational outages. Time to critical is very important as there should be sufficient buffer time for repairing or to be ready with parts which can be replaced before system breaks down.

The current predictive maintenance in most of the organizations see a lot of challenges in adopting effective predictive maintenance strategies. Some of the key challenges are highlighted here.

- In-premise predictive maintenance is not feasible as huge volume of data is generated and storing locally and applying analytics would not scale well
- Taking everything to cloud is also not a feasible solution due to
  - limited bandwidth to support huge amount of sensor data
  - latency would limit the purpose of real time predictive maintenance
  - sending data over internet leads to security/privacy concerns

III. AI ENABLED PREDICTIVE MAINTAINANCE

AI enabled predictive maintenance is scalable and can handle complexities. The core of predictive maintenance is based on the artificial intelligence component which takes sensor data as input and senses patterns out of it. Data from sensor devices are captured in the data hub, from there on, it goes through a series of steps such as pre-process, transformations, feature extraction, grouping/sub-grouping, training, evaluation and testing. Each step involved is important for getting the accurate predictions. The AI component is not just a static machine learning model. It has self-learning capabilities. This brings the maturity required for predictive maintenance over time. As the machine components gets older, the sensor data from current state and the past states at various situations are analyzed in the AI system to predict the maintenance needs.

The AI system interacts with the asset database to get the asset history, past maintenances, problem reporting systems to get the history of problems associated with the asset id etc. The AI enabled predictive maintenance system has been depicted in Figure 1.0. It has a number of enablers as discussed in the following sections

A. IoT enablement

IoT enablement would play a key role for remotely analyzing the sensor data. Taking sensor data to cloud has a number of advantages such as scalability and remote analysis. As the sensor data are high in volume and needs to be trained time to time, so it can be stored in the cloud on demand basis. Needless to mention on the remote analysis using cloud, as the Covid-19 has already proven how effective it can be in a situation where manufacturing can be automated with a minimal human intervention.

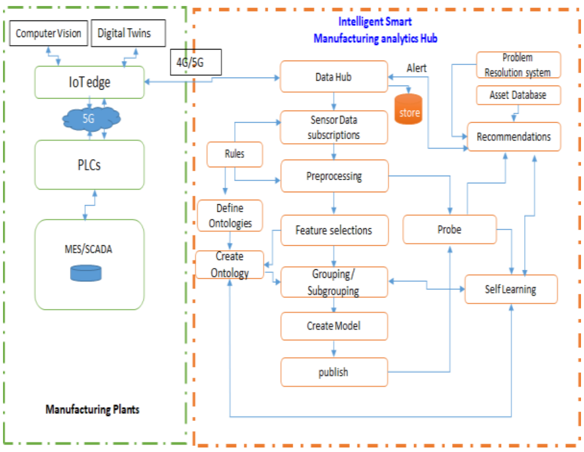

Fig. 1. Intelligent Smart Manufacturing Analytics Hub

Fig 1 depicts how sensor send data to IoT edge where computer vision and digital twin applications receives the data to apply analytics for quickly identifying defects on real-time. The sensors can use a 5G network to send high resolution images for immediate defect detections. The edge keeps sending data to analytics hub for maintaining the history which can be used for training and predictions to derive insights on remaining useful life, future maintenance predictions, and recommendations using prescriptive analytics. Intelligent hub acts as a central control system where powerful analytics are applied using artificial intelligence and machine learning to derive insights. At the hub rules can be defined to filter out data, transform, and apply condition monitoring, feature selections, machine learning model development, training, model evaluations, testing etc.

B. 5G @ Edge

5G would bring high bandwidth for data transfer with low latency and high availability. It can support a large number of devices, machines, objects. 5G would enable the edge cluster/gateway to receive data reliably with high speed. The edge with high computing power can consume the data quick and apply predictive models to get instant predictions on device states.

C. Digital twin at IoT edge

IoT edge is the first level where predictive maintenance analytics can be applied. Instead of sending sensor data to the cloud data hub and applying analytics on top of it, can be time consuming to understand when the system requires quick maintenance. Manufacturing industries are exploring to deploy digital twin [1] solutions at the edge. There are successful case studies shared by industry leaders. Using digital twin solution, the state changes of the machines can be captured to detect the anomalies, and forecast models can be used to predict when a component is going to fail. This strategy is useful for quick detection of machine failures.

D. Self-Supervised-Learing capabilities

Self-supervised learning capabilities can be enabled at the edge and in the cloud where AI is being deployed. The models and analytics used in predictive maintenance would fail in future if models are not re-trained. Deciding when to re-train is not easy. So using self-supervised-learning abilities prediction models can continuously learn automatically to improve the accuracy of predictions.

E. Computer Vision

The components such as conveyor belt, deep cracks on metallic surfaces, paints etc. requires visual inspection. For example, if a conveyor belt is decaying, the images can be quickly analyzed by the computer vision [2] component at the edge to prevent damaging the belt.

F. Intelligent smart manufacturing analytics hub

The intelligent smart manufacturing analytics hub is the extended part of the predictive maintenance. It has various sub-components starting from data acquire at the data hub till creating models and publish. Predictive models are created using deep learning abilities. It has the self-learning capabilities to learn from the learnings for better predictions. The intelligence smart hub is comprised of the following components

a) Graph Models to create Ontology: The power of graph models are lesser known as the industry is heavily investing in machine learning models. However, machine learning models have its own strength but lacks in establishing entity relationships with respect to dependencies. For example, an engine exhausts through an exhaust component which has a sensors to measure temperature and pressure and can be related to fuel intake pressure to determine if excess fuel is being injected. The exhaust component itself has a number of exhaust units, so grouping these and defining the ontology helps in establishing relationships. This relationship helps in faster diagnostic of the root cause of the issue and impacted components rather than trial and error methods.

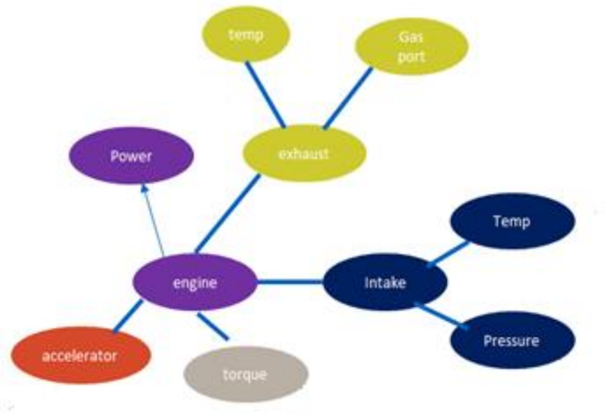

Fig. 2. Graph Model

b) Recommendation Engine: The recommendation engine brings the prescriptive analysis on the prediction results. The recommendation engine gets input from a number of sources such as problem reporting system, asset registry, warranties, agreements, self-learning system, graph models and history of sensor data to arrive at the final decision. It also forms the basis for the subsequent predictions on similar assets.

c) Alert Management System: The alert management system deals with the output of recommendation system. Alerts are sent to the data hub from where it can be subscribed for taking action on the alerts. The alert raised stored in the database until the status is open. Audit process can find out if some alerts are not being actioned.

IV. KEY STRATEGIES FOR AI ENABLED PREDICTIVE MAINTENANCE

A. Classification and sub-classification of data

Classification and sub-classification of data is the key to successful predictions and impact analysis. In a large enterprise, there are huge number of sensors, so when selecting right set of sensors for a given component and sub-component is the key to successful perdition. The grouping and sub-grouping simplifies the complex relationship into simple system and sub-system. This helps in quick understanding of the specific component rather than analyzing all the sensor data.

B. Logical Grouping

The logical grouping can be derived from the variable naming convention or applying static rules. Using NLP/patter matching the categorization can be done. This logical grouping will help in creating the ontology and deriving relationships as demonstrated in Figure 2.0.

C. Behavioral grouping

Behavioral grouping will be based on entities having similar regimes. This is based on dynamic states of components, for example in an automobile industry engines with similar performance on fuel consumptions can be grouped into common category etc. Figure 3.0 demonstrates how engines with high value of utilizations states are grouped. Figure shows 52% are of Type-3 engines. Types are determined by the type of engines such as heavy truck engines, medium truck engines etc. Such grouping helps in identifying how many percentage of engines are always having high level of entropy, and this can be sent as an input the intelligent predictive maintenance system which can determine using the logical grouping what components needs to be monitored to identify the wear and tear for maintenance.

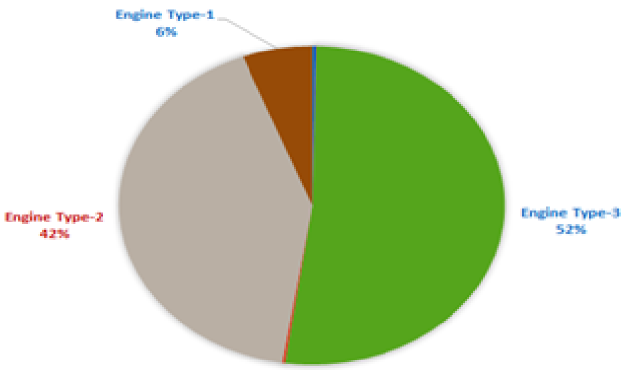

Fig. 3. Similarity behavior grouping

D. Predicting maintenance at the edge by detecting anomalies

Detecting anomalies is the first step in determining if maintenance would be required for the given machine component. Sensor data from the PLCs are captured which can be processed using digital twin to identify anomalies.

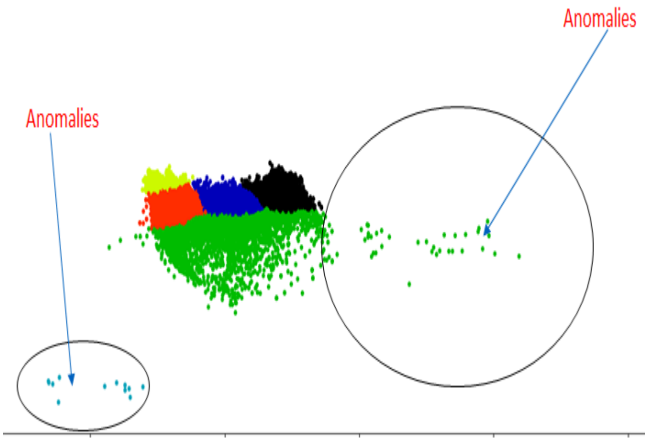

Fig. 4. Anomalies detection

Figure 4.0 shows the how the anomaly can be analyzed. The circle areas demonstrates the anomalies.

E. *Predictive maintenance at the edge by visual inspection*

Computer vision can be applied at the edge to do visual inspection for identifying structural defects. The computer vision is equipped with AI and machine learning capabilities to quickly identify the defects. This strategy can be applied to equipment which requires visual inspection. High resolution camera can be installed near the equipment which requires visual inspection. Captured images are send to the IoT edge device which can measure any deviations using combination of image processing algorithms and deep learning.

F. *Predictive maintenance at the intelligent analytics hub*

At the intelligent analytics hub predictive models can use a combination of supervised and un-supervised models to predict the anomalies, and based on the predictions the recommendation system uses information from asset database, problem resolution systems to arrive at the correct recommendations and generates alerts.

V. Conclusions

The AI enabled predictive maintenance demonstrates a scientific approach which not only addresses the current challenges of predictive maintenance but also simplifies the complexities involved in a highly sensor based system. The self-supervised-learning capabilities, ontology, graph models along with the powerful edge computing abilities shows a lot of potential to address the machine breakdown, operational cost overhead, and failure prevention accurately and effectively in an automated way. The intelligent analytics hub also widely usable to many areas. The value of smart manufacturing can be only realized when the machines operate without failures and wear-out is managed at the right time providing better controlling system, and at the same time addressing scalabilities to cope up with future growths.

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