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Conceptual framework for smart maintenance based on distributed intelligence

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Abstract: An efficient maintenance strategy will provide more transparency and competitiveness for manufacturers in smart manufacturing era. Even though there have been several maintenance frameworks considering the emerging technologies, they still need to address challenges like big data storage, system resilience, multi-modality sensing, holistic approach, future-proof, generic framework and so on. To address these challenges, this paper presents a smart maintenance framework for shop-floor. First, a brief insight into key properties, performance indicators, levels and enablers of smart maintenance are described. The conceptual framework is based on distributed intelligence and has two major blocks - innate and adaptive intelligence. Tool wear monitoring is presented as a use case.

Keywords: Predictive maintenance, distributed intelligence, human immune system, smart manufacturing, tool wear monitoring

1. INTRODUCTION

Maintenance in smart manufacturing: As manufacturing industry is moving towards the fourth industrial revolution and shifting to smart manufacturing there has also raised the needs for smart maintenance systems. These systems not only should predict future failures but also need to be more resilient and exhibit anti-fragility. An efficient maintenance system would provide the manufacturers competitive advantage and ability to resist market disturbances.

15% of the total cost for a typical organization is spend on maintenance activities (Boston Consulting, 2013). An efficient maintenance strategy would reduce 40% of maintenance cost, 50% of downtime and 3-5% of capital investment (McKinsey Global Institute, 2015). Fortune Business Inside (2019) projects maintenance global market size in its current stage to reach $23 billion in 2026 (30% Compounded Annual Growth Rate). These numbers clearly show the high potential for an efficient maintenance system.

Related Works: Most of the research works presented in the last decade in the field of maintenance in shop-floor focused on integration of the emerging technologies like Big-Data, Internet of Things (IoT), Machine Learning, Cloud computing, Multi-Agent System and Digital Twin.

Data Analytic plays a pivotal role in pushing the traditional maintenance techniques to smarter maintenance. Yan et al. (2017) presents a Big-Data framework with focus on the spatiotemporal properties of the data and invisible information mining from these data. As a similar work, Li et al. (2017) focus on data mining by using 3 groups of models - Statistics, Machine Learning and Heuristic Algorithm. The framework also includes decision support and implementation modules. Luo et al. (2018) focus on a more specific application by utilizing deep learning module for health prediction and considering the impulse response of the machine. All three research works validate their framework on machine wear mechanism (tool wear or ball screw wear).

Data-driven challenges (mentioned below) has encouraged some researchers to utilize Digital Twin. Xu et al. (2019) presents a two stage framework - Virtual & physical stage. Virtual model is trained using Unsupervised Deep Learning and connected to the physical entity using Deep Transfer Learning. Luo et al. (2020) presents a more elaborate multi-domain model considering physical, simulation and experimental model. This hybrid approach is also implemented in predicting the cutting tool wear.

Other researchers have developed frameworks considering solutions based on Internet of Things (Civerchia et al., 2017), Cloud Manufacturing (Wang et al., 2017) and Multi-Agent Systems (Peres et al., 2018).

The framework presented by these researchers are developed for a specific technology or application but as manufacturing becomes complex the developed framework will not be able to provide the necessary support.

Current Challenges: We have identified a list of challenges from recently published literature. These challenges needs to be considered while developing a smart maintenance framework and its implementation in the shop-floor,

- Huge volume of sensor data for maintenance has posed challenge on data management and storage.
- Multi-modality sensing considering heterogeneous data from multi-source is less explored.

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- Frameworks focuses mainly on just a specific part or operation of a machine/system. Also, the methods only focus on constant operating conditions.
- Variation in the consistency of the machine in its life cycle makes it hard for the development of a proper statistical or physical model based method. data driven methods lacks extensive fault data and understanding of equipment physical characteristics.
- Maintenance frameworks are specific to only one maintenance strategies (e.g. condition-based or predictive).
- Maintenance strategies focus mainly on improving the overall equipment effectiveness and ignores other key aspects like energy or resource reduction.
- Current maintenance frameworks don't address new property requirement of the maintenance system like resilience and anti-fragility.

Present Work: In order to fulfill these challenges, we proposes a smart maintenance conceptual framework. Initially, we provide the base for the development of the framework by giving insights to the properties, performance indicators, levels and enablers of a smart maintenance system (Section 2). The proposed framework is based on two major blocks of intelligence - innate and adaptive (Section 3). The developed framework is further explained by considering tool wear monitoring as a use case (Section 4).

2. SMART MAINTENANCE - REQUIREMENTS AND ENABLERS

In this section, we propose the key properties, levels , performance indicators and enablers of a smart maintenance system. These act as the foundation on which we develop our conceptual framework.

2.1 Key Properties

We propose 4 key properties which need to be taken into consideration while designing a smart maintenance system. Some properties (Robustness and Pro-activity) are innate properties of the system which are present in the system before a failure occurs. These properties help the system by preventing/prolonging the occurrence of the failure. Some properties (Resiliency and Anti-fragility) are adaptive properties of the system which are activated after the failure has occurred. As an adaptive property, the system can choose to be more resilient or anti-fragile. Anti-fragility is preferable than resiliency.

Table 1. Key properties for a smart maintenance system

Property	Property Type	Definition
Robustness	Innate	Ability to resist failure
Pro-activity	Innate	Ability to predict failure and act ahead of time
Resiliency	Adaptive	Ability to recover from failure to the same state
Anti-fragility	Adaptive	Ability to recover and be more robust after failure

2.2 Maintenance levels

Considering the stages of implementation of the maintenance strategies in the shop-floor, We propose 6 levels of maintenance (Fig. 1) in the shop floor (Inspired from Lee et al., 2020 and Metso et al., 2018). These levels could help manufacturers to understand how much evolved their maintenance policies are in present. With the understanding of the current stage, the manufacturers could aim to raise above the ladder.

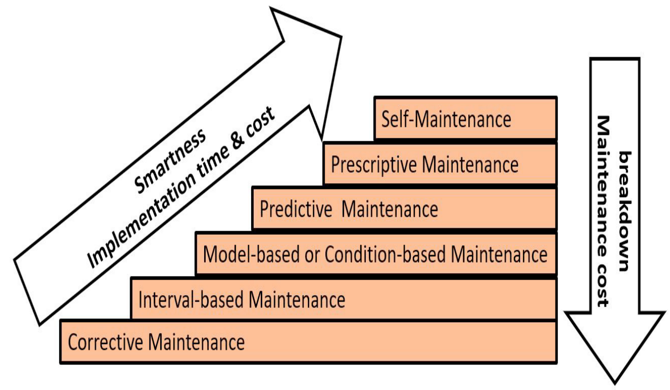

Fig. 1. Six levels of maintenance strategies

- *Level 1 - Corrective Maintenance :* Maintenance is carried out after a fault/breakdown occurred
- *Level 2 - Interval-based Maintenance:* Maintenance is carried out during a specific time period (e.g. every week, every month) irrespective of the condition of the system
- *Level 3 - Model-based or Condition-based Maintenance :* Maintenance is carried out based on a mathematical or simulation or sensor data-driven model of the system
- *Level 4 - Predictive Maintenance :* Maintenance is carried out based on predictive model (developed using historical data) and the current machine condition (sensor data)
- *Level 5 - Prescriptive Maintenance :* Maintenance is carried out considering the current state of the machine and the work flow schedule
- *Level 6 - Self Maintenance :* Maintenance is carried out by the system itself considering its current state and work flow

In practice, shop-floor doesn't exist in one specific level. Critical equipment in a machine, expensive machines and bottle-neck system mostly will be in a higher maintenance level than other less important machines.

2.3 Key Performance Indicator (KPI)

The evolution of KPIs for measuring a maintenance system is presented below, along our proposal of a new KPI.

Machine Availability : Historically, KPI for maintenance is measured as the percentage of actual production time to potential production time. This gives us as an idea of the time lost due to maintenance. Some other variants for understanding machine availability are Down time, Mean Time Between Failures (MTBF), Mean Time To Repair (MTTR) and so on. Planned Maintenance Percentage and Schedule Compliance gives an idea of the efficiency of the maintenance strategy implemented.

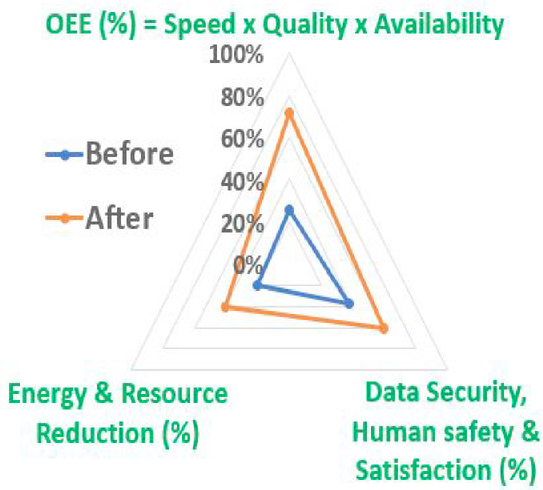

Fig. 2. Smart Maintenance Radar Chart

Overall Equipment Effectiveness (OEE): This is a widely used KPI for maintenance (Kechaou et al.,2022). OEE not just takes into consideration the machine availability but also the impact of the maintenance on the product quality and the production speed (1).

$$OEE = Availability * Quality * Speed \tag{1}$$

Other variance of OEE are Overall Operations Effectiveness (OOE) and Total Effective Equipment Performance (TEEP) which reduces the machine availability considering operator performance and production planning time.

Smart Maintenance Radar Chart: Even though OEE cover the impact of maintenance on some aspects of the shop-floor performance beyond machine availability, It still misses the impact of maintenance in some areas which affect the production cost and safety. We propose a Smart Maintenance Radar Chart which considers aspects like energy consumption, Resource reduction, data privacy, human safety, and satisfaction. The radar chart has three axes (Fig. 2) considering the possible difference of impact on the axes due to maintenance. For example, a maintenance strategy considering the improvement of OEE only will have a negative impact on the resource utilization or human satisfaction. An ideal maintenance strategy should consider the improvement of all three axes. The manufacturers could provide different weights to each axis depending on their priorities. OEE and Energy & Resource Reduction are a quantitative data and the Third axis on Security, Safety and Satisfaction is a qualitative data.

2.4 Maintenance Enablers

Enablers are the technologies that aid in the improvement of maintenance activities. Recent technological enablers are linked with the advanced of digitization of industries and the convergence of physical assets with its virtual counterpart; i.e., Cyber-Physical Production Systems (CPPS). Conceptually CPPS represent future industrial automation and its desired functionalities fall in the so called "self-x" properties (Lee et al., 2015).

A 5C-CPPS architecture is proposed by Lee et al. (2015) to illustrate the different phases required to implement CPPS from the connection to the configuration itself (self-x properties). We use this work to map various technological enablers related to maintenance operations as shown in Fig. 3 and listed below:

(1) *Smart connection:* Includes physical devices (e.g., Sensor networks, gateways, physical assets) and standardized technology and protocols (e.g., OPC-UA, MQTT) to acquire relevant information from the shop-floor.
(2) *Data to information:* Considers methods to store (distributively) encrypt (cyber-security), process (in the edge) and analyze data (data analytics). This data becomes relevant information to be used by the maintenance system.
(3) *Cyber:* The analysis of the information from the shop floor is supported by distributed computation i.e. artificial intelligence (Multi-Agent Systems) and Cloud computing, providing: decentralization, modularity and scalability to the system. The use of real time simulations (digital twin) allows forecasting of future scenarios e.g. to artificially create data that can be used by the maintenance system. The use of augmented and virtual reality technologies has been also popularized as a digital tool to increase engagement and interaction between the operator and the shop floor.
(4) *Cognition:* In this phase enough information is provided to diagnose a maintenance problem (if some) and to support the decision making of the operator.
(5) *Configuration:* In this phase the system is expected to at least partially execute a maintenance operation, providing healing mechanisms to the physical assets, controlling and setting up necessary parameters and adapting current maintenance operations.

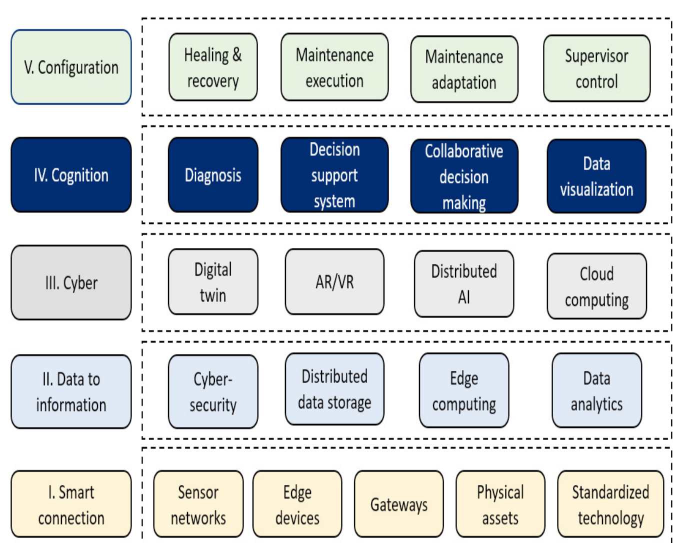

Fig. 3. Novel enablers of maintenance activities and its relation to the 5 cognition phases of CPPS

3. SMART MAINTENANCE FRAMEWORK

We propose a novel framework for smart maintenance system. The framework is designed considering the key

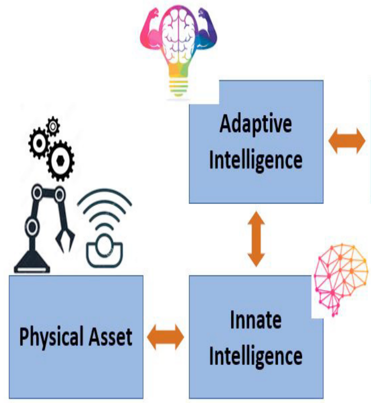

Fig. 4. General overview of the smart maintenance framework

properties required for smart maintenance (Section 2.1) and has the ability to reach the highest maintenance level (Section 2.2). The framework has drawn inspiration from the human immune system for developing a future proof system. Human immune system has a distributed intelligence with innate & adaptive immunity and a extensive collection of memory cells for all pathogens what could attack the human body.

3.1 General Overview

The smart maintenance framework consists of 4 blocks (Fig. 4),

(1) *Physical Asset:* This block takes care of all the activities carried out by the physical asset namely system robustness, sensing and actuation.
(2) *Innate intelligence:* This is the first stage of the maintenance system and activities are performed near the physical asset. In an efficient system, most of the maintenance activities are carried out by just the first two blocks. If required, Innate system asks the help of the adaptive system.
(3) *Adaptive intelligence:* The adaptive intelligence provides the required support to the innate component in term of developing the properties of resiliency and anti-fragility.
(4) *Knowledge Base:* It acts as the library for the adaptive components. All developed models by the adaptive components are stored in this block.

The interaction within/between these blocks are highly distributed (Fig. 5). Some of the emerging technologies that support these interactions are multi-agent Systems, swarm learning and federated learning.

3.2 Physical Asset

The Physical Asset block consist of 3 key modules,

1. System Robustness: This module helps in improving the robustness of the system. Predominant activities are carried out during the design stage of the physical asset. Some examples of improving the system robustness includes,

- Tougher and more resistant material properties
- Smart programming to deal with possible errors
- Fail safe mechanisms to prevent failures

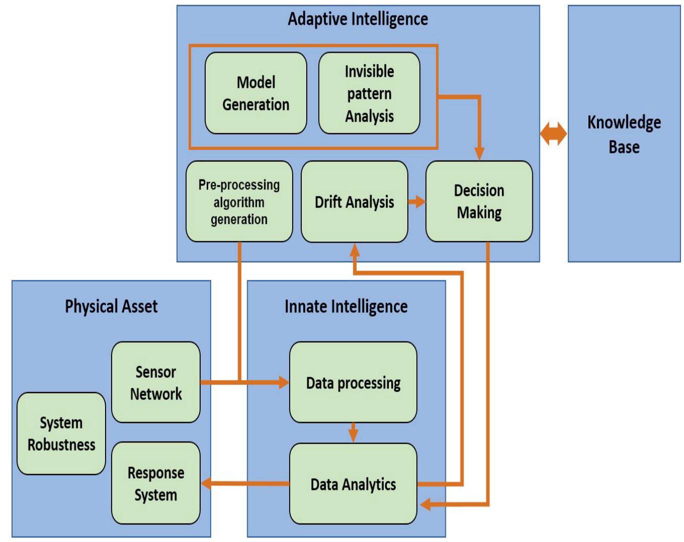

Fig. 5. Smart maintenance framework

This is an iterative process and not just restricted to design stage of the system. The iteration is carried out considering the information from the innate component.

2. Sensor Network: This module takes care of sensing and data acquisition process. A wide variety of sensors could be utilized for maintenance activities for measuring vibration, energy (power & current), acoustic, temperature, pressure, load, speed, ultrasonic, and torque. With the implementation of Internet of Things, the monitoring devices could abstract the measured value and passed it through a gateway (messages into data packets).

3. Response System: This performs the instructions provided by the Innate intelligence on the physical asset. This could be as simple as providing alarm signals to as complicated as actuators performing self-maintenance. Some common response systems includes PLCs, Control Systems, User Recommendation Systems, Virtual & Augmented Reality (VR/AR) and so on.

3.3 Innate intelligence

Innate intelligence (local intelligence) is developed and maintained by the Adaptive intelligence (global intelligence), but it's the first layer of protection for the maintenance system. It is physically near to the physical asset. An enabler used for this implementation is Edge Computing. It consists of two modules,

1. Data processing: This module converts the sensory data into structured data. The processing algorithm is developed by the Adaptive intelligence block. The sensory data could include semi-structured data (e.g., XML) and unstructured data (e.g., Images, Voices, Videos). Useful features are extracted from these data.

2. Data Analytics: This module converts the extracted features into useful information. This information is also converted into actionable instructions or sent to Adaptive intelligence for further analysis. A generic algorithm followed is presented below,

data is compared with existing model,

if data within threshold value **then**
  data is deleted
else if abnormal data identified in past **then**
  Sent command to the response system
  abnormal data is deleted
else
  Send the abnormal data to Adaptive Intelligence
end if

This module helps the system to be proactive and respond before failure occurs.

3.4 Adaptive intelligence

Adaptive intelligence is the main engine of the maintenance system. It develops models, initially considering historical data or simulation model and later adapts the developed model considering the new abnormal data. An enabler used for this implementation is Cloud Computing.

1. Model Generation: A model is generated from historical data &/or multi-physics simulation (with boundary condition mapping). The model is tested under different parameters for potential failures. The model is then validated for failure prediction. Another approach for generating virtual model include development of physical degradation model. This developed model can be further modified by experiments on the physical asset.

2. Pre-processing algorithm generation: This module considers historical sensory data from different sensors to create algorithms for structuring the data. The algorithm includes data cleaning, reduction, and transformation. The data could be characterized using its spatiotemporal properties. Later, various techniques could be used for structuring the data, including semantic web, ontologies, feature extraction, expert knowledge, clustering.

3. Invisible pattern Analysis: This module tries find out the relationship between the extracted features and invisible factors. The invisible factor might include sensory data like environmental temperature, humidity, or energy consumption etc., production data like product quality, production speed, etc. or worker data like staff working efficiency. After the relationship mining is performed a causality analysis is carried out.

4. Drift Analysis: The abnormal data sent by the innate intelligence helps in identifying data drift or concept drift. Once identified, the existing model is updated, and sent to innate intelligence for adaption. A copy of the developed model is also stored in the knowledge base.

5. Decision Making: This module decides which type of analysis should be carried out with the historical, theoretical, experimental, or simulation dataset. The module chooses the algorithm based on the dataset from the knowledge base. The Decision Making takes into consideration the Smart Maintenance Radar Chart and the maintenance planning & scheduling.

3.5 Knowledge Base

All the existing models and algorithms are stored in the knowledge base. The library is also constantly updated with new models developed by the adaptive intelligence and by expert knowledge. An enabler used for this implementation is Cloud Storage. A shorter list of existing models and algorithms available in the knowledge base is listed below,

- Statistics [regression analysis, cluster analysis, discriminate analysis]
- Machine Learning [supervised, unsupervised, semi-supervised, reinforcement]
- Heuristic [genetic, artificial neural network, fuzzy logic systems, case-based reasoning]
- Diagnosis [decision tree, support vector machine, association rules]
- Prognosis [fuzzy logic prediction, deep neural network, match matrix prediction]
- Hybrid approach [Kalman filter, particle filter, ensembled learning]
- Planning & Scheduling [particle swarm optimization, ant colony optimization, bee colony algorithm]

4. USE CASE - TOOL WEAR MONITORING

Wear monitoring is an important activity for shop-floor consisting of many CNC machines. Researchers have done extensive research in this aspect with particular focus on tool and ball screw wear (see related works in section 1). Tool wear monitoring is considered here as a use case to better understand the different blocks of the framework.

Physical Asset : The system robustness could be improved by careful choosing of the tool material, tool shape, tool design, chip-breaker design etc. The IoT Sensors network includes vibration, temperature, acoustics, and energy/current sensor. Considering the abnormal data from the IoT sensors (e.g. high temperature on work piece surface) the innate intelligence provides command to the response system. These commands include, automatic slow down of the spindle speed, start coolant supply or increase the amount of coolant, power off, alarm signal to the operator.

Innate Intelligence : Statistical feature of the signals like mean value, max-min point, standard deviation, kurtosis RMS, Skewness etc. are extracted. These features are then compared with the existing model to determine if the values are within the threshold. New abnormal data are sent to adaptive intelligence for further analysis. This module also predicts the tool life and sends the information to physical asset.

Adaptive Intelligence : Initially, the tool wear model is developed considering tool wear mechanism, Finite Element Method and experiments (varying machining parameters like spindle speed, feed rate etc.). This model is then validated with historical sensor data. The sensor data especially, vibration and acoustic are pre-processed to extract only the important features. The pre-processing is performed both in time and frequency domain. Once the model is validated, it is checked for data or concept drift when an abnormal data is received (e.g., due to change in tool supplier). Once drift is identified, the decision-making module decided on the perfect algorithm to develop a more adaptable model. The developed model is then sent to Innate Intelligence.

Knowledge Base : It provides the required library for data pre-processing and development of a more adaptive model. The newly created model is also stored for future reference.

5. CONCLUSION

The key contribution of the paper and take away points are listed below,

- The paper provides new insights to key properties, different levels, Key Performance Indicators and enablers for a smart maintenance system
- The paper proposes a novel framework considering the above mentioned insights based on human immune system
- The framework consist of 4 blocks, with two major blocks of intelligence - innate and adaptive
- Tool wear monitoring is considered as the use-case for better understanding of the framework

future work will focus on implementation of the developed framework in tool wear monitoring for wear prediction and smart maintenance.

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