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Cyber-enabled Product Lifecycle Management: A Multi-agent Framework

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Abstract

Trouble free use of a product and its associated services for a specified minimum period of time is a major factor to win the customer's trust in the product. Rapid and easy serviceability to maintain its functionalities plays a key role in achieving this goal. However, the sustainability of such a model cannot be promised unless the current health status of the product is monitored and condition-based maintenance is exercised. Internet of Things (IoT), an important connectivity paradigm of recent times, which connects physical objects to the internet for real-time information exchange and execution of physical actions via wired/wireless protocols. While the literature is full of various feasibility and viability studies focusing on architecture, design, and model development aspects, there is limited work addressing an IoT-based health monitoring of systems having high collateral damage. This motivated the research to develop a multi-agent framework for monitoring the performance and predicting impending failure to prevent unscheduled maintenance and downtime over internet, referred to as for cyber-enabled product lifecycle management (C-PLM). The framework incorporates a number of autonomous agents, such as hard agent, soft agent, and wave agent, to establish network connectivity to collect and exchange real-time health information for prognostics and health management (PHM). The proposed framework will help manufacturers not only to resolve the warranty failure issues more efficiently and economically but also improve their corporate image. The framework further leads to efficient handling of warranty failure issues and reduces the chances of future failure, i.e., offering durable products. From the sustainability point of view, this framework also addresses the reusability of the parts that still have a significant value using the prognostics and health data. Finally, multi-agent implementation of the proposed approach using a power substations for IoT-based C-PLM is included to show is efficacy.

Keywords: Cyber-enabled Manufacturing; Internet of Things; Multi-agent; Prognostics and health management; Remanufacturing.

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1. Introduction

In today's age of connectivity the way human beings interact with technology has been radically redefined by the advent of barcode scanners, radio frequency identification (RFID) chips, product usage sensors, and other mobile communication equipment. The proper use of these technologies enable a system or a group of systems to be monitored and controlled remotely with a network of sensors to ensure safety and better product usage. This new technological framework is popularly known as Internet of Things (IoT), which enables technologies to interconnect physical systems over internet for collaborative activity tracking, information exchange, and execution of physical actions [1, 2, 3]. IoT has been drawing a considerable interest among the researchers in the area of sensor embedding [4, 5], RFID applications [6, 7, 8], and network data security and management [9, 10, 11]. However, most of the applications are limited to consumer electronics and household machines, mainly cellphones, smartwatches, wearable devices, washing machine, lamps, etc. [12, 13, 14, 15, 16].

Two types of maintenance strategies are widely used: time-based maintenance (TBM) [17, 18, 19] and condition-based maintenance (CBM) [20, 21, 22]. TBM model relies on the failure time distribution of a population of components whereas in CBM the amount of degradation of a component is estimated via physics-based or data-driven statistical learning or time series models using real-time sensor data. Monitoring and control of systems are vital for CBM, especially in areas of high collateral damage, such as transportation network, water and gas supply network, and power transmission lines, etc. In these systems the size, geographic location, and the involved weather conditions make the monitoring and maintenance a difficult task resulting in significant investment in terms of labor and resources. Minor disruptions and failures of even small sections of these systems produce massive loss of finances and in many cases human life.

Products once sold or installed are mostly under the consumers' control, with periodic maintenance services provided. The periodic maintenance follows a reactive model rather than a preventive model, where maintenance is mostly carried out after the product fails. In most cases the reactive maintenance employed is the complete replacement of the product without ascertaining the viable life of the failed product's base components. This reactive maintenance method does not consider the fact that the replacement product has the same inherent disadvantages of its predecessor. A sustainable manufacturing environment and economics can only be achieved by ensuring customer trust in the product and services employed and by re-utilizing viable components from older generations. However, the longevity of such a model cannot be promised unless both, the customer and the manufacturer, are assured with the reliability of the reusable components in the system. Some researchers have analyzed the warranty data to determine the reliability of the components and the system [23, 24]. Predictive warranty service is provided by utilizing the reliability information to initiate maintenance action.

Although a networked framework to control and monitor the system with high collateral damage for CBM would be of a tremendous advantage to users, there are only few systems that are designed and built in this manner [25, 26, 27]. The major reason is the enterprise's short-sightedness in choosing immediate profit over long term sustainability. To overcome the above mentioned limitations, in this paper, we propose a sensors embedded monitoring and control approach, using IoT framework, referred to as a cyber-enabled product lifecycle management (C-PLM). First a generic approach for the C-PLM is presented and, then, the implementation using a multi-agent framework is proposed.

The proposed generic C-PLM framework uses a two stage approach for enabling IoT based monitoring. In Stage 1, the traditional products to be serviced with no prior embedded sensor are assessed for remaining useful life (RUL) when brought in for service. The components of good and moderate health are shipped to remanufacturing center for sensor embedding to enable IoT functionality. The unendurable components with end-of-life (EOL) are collected for recycling or a land fill at disposal enter. Stage 2 is completely under prognostic heath monitoring, which is governed by IoT technology. From the C-PLM implementation point of view, a multi-agent framework comprising of hard, soft, and wave agents for a single or multiple systems is also presented. The proposed framework bridges the research gap for developing CBM scheme for systems with high collateral damage value by developing an IoT-based C-PLM framework.

The paper is organized as follows. Section 2 presents the detail architecture of the proposed framework. The tasks of the different agents and the multi-agent framework is presented in Section 3. Section 4 presents two application area of the proposed C-PLM framework. Finally, Section 5 summaries and concludes this paper along with future research directions.

2. The Generic Framework for C-PLM

In general, product lifecycle consists of three main phases: beginning-of-life (BOL), including design and manufacturing; middle-of-life (MOL), including the product uses, service and maintenance; and end-of-life (EOL) where products are recollected, disassembled, remanufactured, recycled, reused, or disposed. During BOL, information flow is quite complete and supported by information systems such as computer aided design (CAD)/computer aided manufacture (CAM), product data management (PDM) and knowledge management (KM) systems. However, the information flow becomes less and less complete after BOL. In fact, for the majority of today's products it is fair to say that the information flow breaks down after the delivery of a product to a customer. As a consequences, the sold products are subjected to corrective maintenance with incomplete and inaccurate product lifecycle information in their MOL.

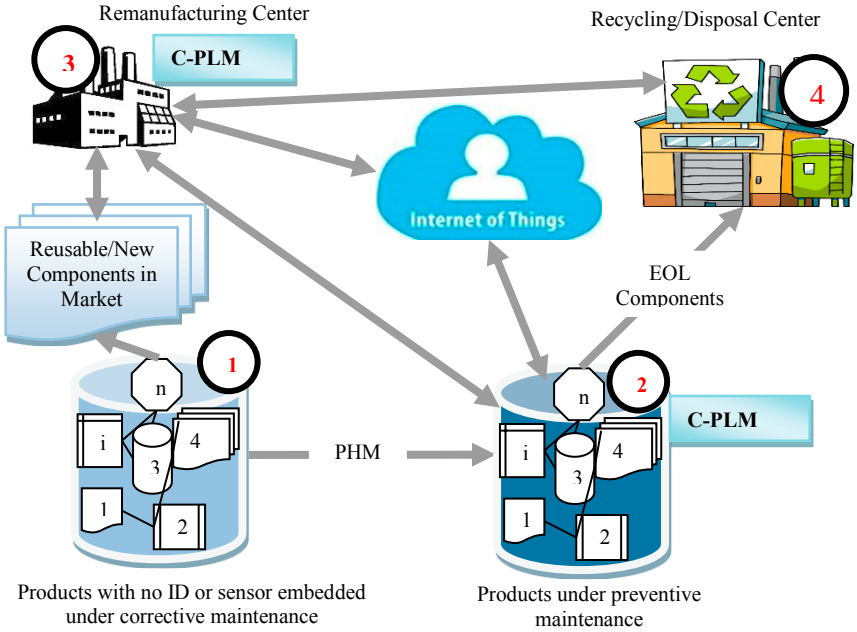

Figure 1. A basic framework for IoT application in PLM: Cyber-enabled Product Lifecycle Management (C-PLM)

This research can be contributed to providing a life-cycle management framework in MOL phase to develop prognostics health and management (PHM) capabilities for the systems having high collateral damage values. The proposed C-PLM framework can be a reference model for product lifecycle management (PLM) and economical sustainability, as shown in Figure 1. This generic framework for C-PLM includes:

- development of remanufacturing and sensor embedding processes in components and parts (center 3);
- development of prognostics and health management (PHM) capabilities to predict impending failure and prevent unscheduled maintenance and downtime (center 2);
- development of remaining useful life (RUL) and real-time reliability prediction based on different dominant failure mechanisms by including information from new, reused, and repaired components (center 1, 2, 3); and
- development of IoT based framework to monitor sensor network and schedule automated preventive maintenance.

A detailed description of each block for the proposed framework is given below.

2.1. Remanufacturing and Sensor Embedding

Center 3 depicted in Figure 1 represents the remanufacturing center of the framework under study. The process starts with diagnosis of products with no sensor embedded under corrective maintenance in stage 1. Diagnosis extracts fault-related information and examines the remaining useful life of components. The reusable components with significant RUL are sent back to the remanufacturing center for repair. To understand of potential failure mechanism, reusable components with significant RUL is deployed with dedicated sensors. Based on the dominant failure mechanism, dedicated wired or wireless sensors are embedded to components for analyzing vibration, lubrication, temperature, pressure, moisture, humidity, loading, speed or/and environmental data etc., and to monitor attributes that are essential for CBM.

The unendurable components are sent to the disposal center 4 for recycling/landfill. The replacement of those components are fulfilled from external suppliers of used/new components embedded with sensors. Thus, the model is aimed at determining the optimal utilization of the used components in realizing economical sustainability of the product. If ID's and/or sensors can be embedded in a part and a product, it is possible to trace the part and products throughout their lifecycle for reliability and value predictions.

2.2. Prognostics and health management (PHM) capabilities

Smooth and trouble free use of products for a long period of time requires two type of maintenance: (i) fixed or regular maintenance (such as; denting-painting, lubrication, etc.), and (ii) maintenance due to breakdown or degradation in the configurations. The latter can be achieved through corrective maintenance and preventive maintenance. Preventive maintenance is divided into types: time based maintenance (TBM) and condition based maintenance (CBM). TBM relies on the failure time distribution (e.g., normal, exponential, Weibull distribution, etc.) of a population of components, which may not capture the current health status of a single component. In contrast, condition-based maintenance measures the amount of degradation of the components through in-situ sensing and is also able to generate impending failure alerts based on either pre-set functional or reliability levels. The maintenance types can be utilized in prognostic health monitoring of a product, where the understating of current health of the constituent components is essential.

In this research, both corrective and preventive maintenance are proposed. We propose corrective maintenance to the products that failed and are absorbed for remanufacturing. During the remanufacture, we deploy dedicated sensors across critical components for monitoring the product's performance and enable it for CBM. For an easy appraisal, a flow chart of PHM that describes techniques to build prognostic health monitoring capability in the product is outlined in Figure 2.

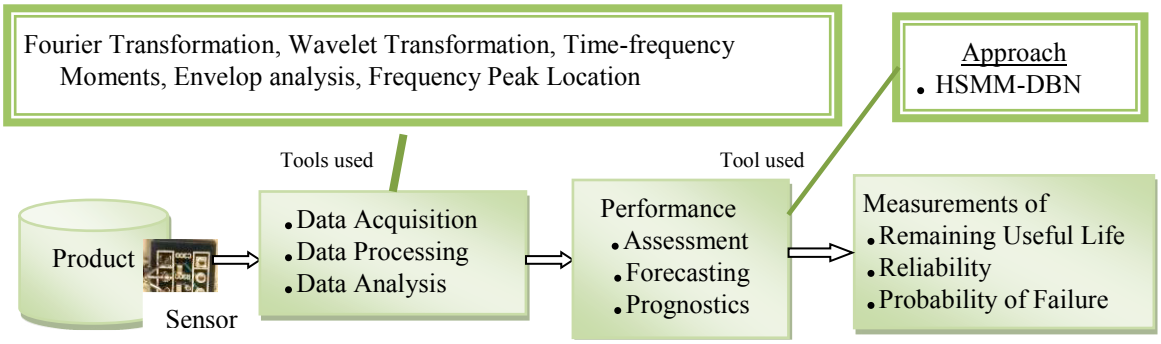

Figure 2: Flow chart of prognostics health monitoring: tools used in data fusion and feature extraction, performance prediction, real time condition measurement

2.3. RUL and reliability predictions capabilities

The remaining useful life (RUL) or real-time reliability of the components under prognostics and health monitoring is predicted by formulating model-driven statistical learning method that exploits the stochastic properties of Bayesian networks and Markov model. Considering the merits of hidden semi Markov model (HSMM) over hidden Markov model (HMM) [28, 29], and also the encouraging results by formulating a hierarchical HMM based model as dynamic Bayesian networks (DBNs) [30], we propose the implementation HSMM-DBN for state of health and RUL estimation. The proposed model utilizes DBNs to represent the hidden-states in HSMM in terms of a set of random variables. The purpose of DBNs playing as a HSMM is to infer the hidden states that evoke in time by using sequenced observed variables that are generated by these hidden-states [30]. Focusing on the Bayesian network (BN) structure, the proposed HSMM-DBN eliminates the major drawback associated with learning BN, where the search space is huge and Bayesian network learning algorithms usually adopts greedy search heuristics, which easily gets stuck in a local optimum [31]. One of the major problems in the application of evolutionary algorithms (EA) for learning Bayesian

networks is the directed cyclic graph formation during the intermediate phases. While generating any intermediate networks it is not sure as to the feasibility of candidate networks (i.e. directed acyclic graph (DAG)).

In the proposed approach, the ant colony system (ACS) will be used to resolve the problem of formation of cyclic graphs. The formation of cyclic graphs can be avoided only when precedence ordering is known such that, every node coming earlier in the order, can be the parent of following nodes. Thus the problem becomes exactly like a traveling salesmen problem (TSP) that was very efficiently solved by ACS [32]. Moreover, HSMM-DBN will utilize minimum description length (MDL) metric as a measure of the goodness of the candidate Bayesian network. Taking MDL as a measure of the quality of the individual network and best ordering found by application of ACS, the evolutionary programming (EP) based search process for an optimal DAG will be employed. The proposed strategy forms a precedence order of the nodes of Bayesian networks, which reduces the string length to ${}^{N}C_2$ (instead of N^2). After the optimal ordering is found using ACS, EP search process is employed to search for the best Bayesian network.

The next objective is to estimate RUL or reliability information of a product that indicates impending failure based on past observed data. For instance, remaining useful life of a component by backward recursive equation in hidden semi Markov model (HSMM) [33] is,

$$RUL_i = \alpha_{ii}[D(h_i) + RUL_{i+1}] + \alpha_{i,i+1}[RUL_{i+1}] \tag{1}$$

where, RUL_i is reaming useful life at state "*i*", $D(h_i)$ is state duration in health state h_i and α_{ii} are transition probability from state "*i*" to "*j*". Here; $D(h_i)$ is depend on mean life ($\mu(h_i)$) and variance ($\sigma^2(h_i)$) of health state "*i*", and total life of the component $T = \sum_{i=1}^{N} D(h_i)$ as,

$$D(h_i) = \mu(h_i) + \left\{\frac{(T - \sum_{i=1}^{N} \mu(h_i))}{(\sum_{i=1}^{N} \sigma^2(h_i))}\right\}\sigma^2(h_i) \tag{2}$$

Further, the reusability of the component can be determined if RUL is greater than the estimated second life [34].

$$RUL = MTTF - t_1 \tag{3}$$

where; $MTTF$ refers mean time to failure, t_1 is age of the component.

In order to calculate the reliability function, the Kaplan-Meier method provides the equation as [34];

$$R(t_i) = \prod_{j=1}^{i} \frac{n_j - r_j}{n_{j-}} \; ; i = 1, \dots, m \tag{4}$$

Where; $R(t_i)$ is estimated reliability at time "*i*", *m* is total number of data points, *n* is total no of units. Here it is determined by using r_j (number of failure in the jth data group) and s_j (number of surviving units in the jth data group) as,

$$n_j = n - \sum_{j=0}^{i-1} s_j - \sum_{j=0}^{i-1} r_j \tag{5}$$

2.4. IoT based framework

The IoT framework connects the smart components and parts, i.e., parts and components embedded with sensors for exchange of information. One of the major challenges in the information exchange is the security of the information as per the Industry 4.0. Hardware embedded security authentication protocols are required to maintain the data privacy and avoid malicious data injection. The interchange of sensor data and external data from similar equipment enable smart data-driven heath monitoring and prognostics via cloud based computing. The data processing can also be carried out at a central location or distributed over geographical areas based on requirement. In the next section, the implementation of the generic framework using multiple agents is presented.

3. C-PLM implementation as a Multi-agent Framework

The C-PLM architecture proposed in the previous section can be abstracted in three layers: 1) material flow layer, 2) information flow layer, and 3) logic and control flow layer, as shown in Figure 3. The material flow layer is similar to the physical layer in network architecture. The material flow consists of servicing of parts and components to be monitored. One of primary actions in the material flow layer is sensor embodiment in the legacy components of high or moderate reusable value or replacing the faulty legacy component with new smart component.

The second layer is the information flow layer. This layer is similar to the network layer. The information from various stages in the material flow layer get exchanged with the central processing center or cloud. This layer also uses authentication protocols for security and privacy of the data. The center layer is the logic and control layer which is a similar to the application layer. This layer is used to make all major health and management decisions. This also provide user interface for health information retrieval. This layer can be centralized or distributed over could.

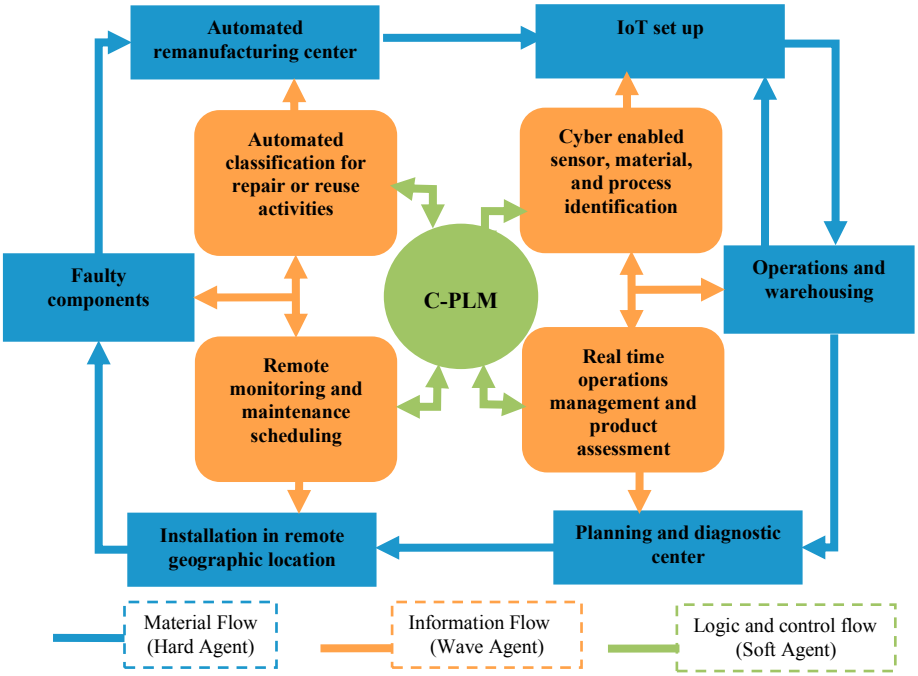

Figure 3: Capabilities and functions of the proposed cyber-enabled product lifecycle management

The C-PLM layers can be implemented as a multi-agent based system that interacts among three basic agent: hard agent, soft agent, and wave agent. The hard agents deals with material flow management for diagnosis, remanufacturing, IOT set up, and installation of new components. The soft agent is either software programs installed on the device or cloud to control the device. It has numerical or soft ability to control the actuation of device. The third agent of the proposed framework is wave agent, which deals with information flow and communication with other machines, i.e., severs, and cloud via internet, machine to human, or human to machine, as shown in Figure 4. A descriptive methodology of the multi-agent framework is given below.

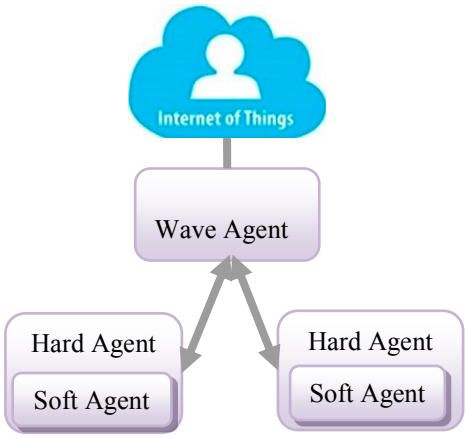

Figure 4: A nested agent based representation of Multi-agent Framework

3.1. Hard Agent

A crisp way to define the hard agent is to conceive it in terms of the actual physical thing, itself, such as the sensor embedded system components. The hard agent is responsible for all the physical design and development in the framework and to collecting information related to corrective and preventive maintenance of the system. Hard agents can be further divided into three sub agents, such as service agent, fault diagnosis agent, and remanufacturing agent.

3.1.1. Service Agent

The main task of this agent is to collect sensor data embedded to the system and to differentiate them into different categories. This categorization is based on corrective and preventive maintenance of the system. This agent also analyses the data collected from the embedded sensor to check which parts or products are subjected to frequent maintenance and then accordingly assign them a rank.

3.1.2. Fault Diagnosis Agent

Once the service agent identify the components subjected to maintenance, the information is passed on to the fault diagnosis agent to explore the root cause of the failure. This failure can be either due to the fault in the manufacturing processes or the design of the products and so on. The agent then directs the products to the relevant units for the maintenance or replacement based on the remaining useful life of the component. This agent also gathers feedback from the different units and on the basis of the feedback performs the simulation to check whether the modification/corrections made in the system has fixed the problem or not. If the simulation shows that the problem still exists, this agent then passes on this information to the relevant unit. This process of feedback continues to assist the units until the problem is completely resolved.

3.1.3. Remanufacturing Agent

The information gathered by the fault diagnosis agent is passed on to the remanufacturing agent. As soon as it receives the information about the reason for maintenance, this agent decides how this can be fixed the faulty components with replacement of reusable components having significant remaining useful.

3.2. Soft Agent

The soft agent is either software programs installed on the device or are on cloud to control the device. This agent ensure the functional and systems requirement to the framework. Constructing the soft agent refers to coding the program on the *thing* itself in the memory of the device using an *API* or coding a program on cloud to attain the reliability predictions and PHM capabilities in the system and the data security and accuracy defined for sensor data and network management.

3.3. Wave Agent

The third and last kind of agent proposed in this framework is called wave agent, which is defined as any hardware or software that enables sensing of any statics or kinetics, communication with other machine, communication with severs, cloud, internet, and so on. This agent interacts with hard and soft agents and ensures a speedy transfer of real-time system information using things via machine to machine, machine to human, and human to human communication reducing lags and waits to lower cut offs.

4. Application Area

In this section, the implementation of C-PLM framework for various infrastructure and utility services with high collateral damage value are presented.

4.1. Power grid application

Health monitoring of power grid components, which leads high collateral damage with failure of equipment, is a critical from the continuous service point of view. In general, the important equipment in a power grid are the transformers, circuit breakers, relays, current and potential transformers. Each

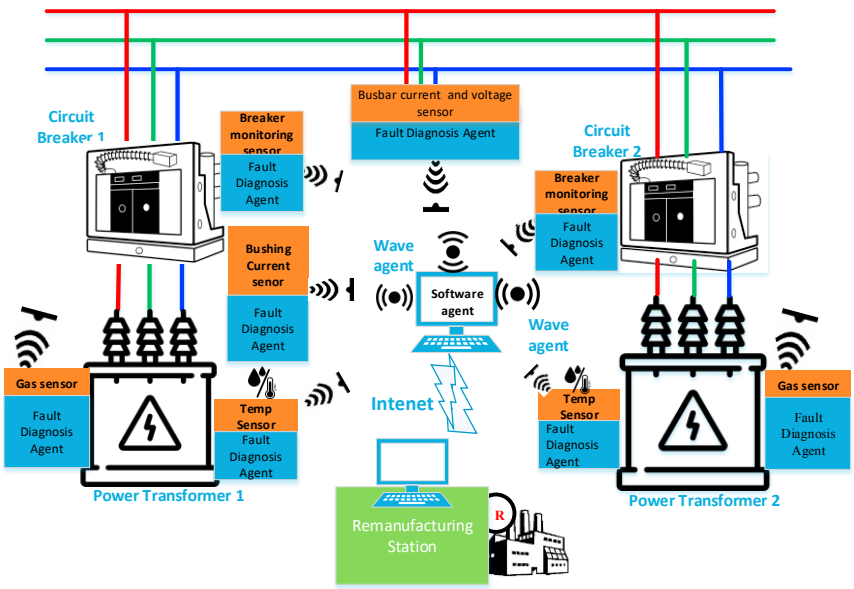

Figure 5: A pictorial view of end-to-end implementation case

component can be subdivided in to multiple subparts for health monitoring and implementation of the C-PLM architecture.

For example, the transformer can be divided into winding, insulation, and bushing and these parts along with embedded sensors will represent the hard agents. Various different sensors can be embedded into the transformer windings, insulation and bushings, such as, thermocouple, partial discharge sensor, accelerometer, gas sensors, pressure sensors etc., to monitor fault parameters. Similarly, the circuit breaker can be embedded with current sensors for analyzing the switching arc for contacts health. Further the bus bars' health can also monitored by analyzing the current and voltage profile with power spectrum analysis. These parameters can be collected by the service agent, an embedded system with memory, and classify them into different categories using the on board look up table or cloud. This classification of failure is based on type of fault and available corrective and preventive maintenance scheme of the component. This service agent can also analyze and maintain a record of the maintenance data onboard to check which parts or products are subjected to frequent maintenance and rank them while communicating the information to the fault diagnosis agent for fault diagnosis. The fault diagnosis agent explores the root cause of the failure and determines RUL of the component. The remanufacturing agent, which is the remotely located monitoring station, receives the fault, remaining life information and the reason for maintenance. Then based on the criticality of the component, the agent decides the approach for repair or replacement of the faulty components with reusable components having significant RUL. All these components are integrated using the internet and corresponding maintenance management software, i.e., the wave agent and software agent, for real-time maintenance action.

4.2. Transportation network

The C-PLM implementation for the transport network can be have multiple directions. 1) Health monitoring of the transport vehicles in real-time, and 2) health monitoring of the goods. The IoT based approach will enable the transport companies to keep a track of the goods and vehicle conditions and schedule CBM on their way by informing the service centers. The packages and goods can be embedded with RFID tags, vibration, and temperature sensors for real-time health data. The vehicle's computer can implement the C-PLM and can communicate to the cloud for monitoring current health and predict RUL.

5. Conclusion

The paper proposes a generic framework for C-PLM using IoT-based protocol, as the communication medium, for lifecycle management of the products having high collateral damage values and where monitoring and control of systems in real-time are vital as well as challenging to human capitals. The proposed framework conceives IoT solutions in middle-of-life (MOL) phase of products for monitoring the performance and predicting impending failure, preventing unscheduled maintenance and downtime. The application of the proposed solution in a smart power transmission substation and transportation network are presented that can be monitored and controlled remotely. Further, this generic framework can be utilized in a wide range of industrial services such as; railway lines, oil and water pipelines, etc. As a future direction of the research we will include more specific task oriented agents to address other different aspects of IoT problem such that the proposed framework can be further extended to fit into different scenarios and resolve the complex issues

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