E-Maintenance in the Next Generation of Manufacturing Systems

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Abstract

The US National Research Council in a recently released study has identified reconfigurable manufacturing systems (RMS) as one of top priority technologies in manufacturing in the near future. An RMS theoretically consists of a variety of reconfigurable constituent systems and components (e.g., production lines, machines, controllers, interfaces, and material handlers), as well as methodologies for their systematic design, development, deployment, and diagnosis/maintenance, aiming at making production capacity capable of being rapidly adjusted to fluctuations in product demand and manufacturing functionality. To deploy an RMS, it is necessary to have information systems capable of delivering accurate and pertinent data, information, and/or knowledge to the proper users (e.g., process controllers, staff, operators, technicians, and clients) at the right time, so tasks on hand can be best performed, or informed decisions such as intelligence maintenances made operationally, tactically, or strategically.

To delivery the promises on ordered products, there is an intense pressure on manufacturing industry to eliminate costly unscheduled shutdown maintenances and reduce the failures of production systems. In the exploration of more efficient maintenance and service strategies, the approaches of condition-based proactive maintenance; collaborative maintenance; remote maintenance and service support; provision for real-time information access, and integration of production with maintenance have evolved into a new phenomenon called e-maintenance to meet the needs of the future e-world. This paper introduces the emerging field of e-maintenance by studying its critical elements in support of the deployment of next generation manufacturing systems. For instance, industrial wireless technology and artificial intelligence are two of the enabling technologies in the realization of e-maintenance. The technical issues and challenges involved for deploying these technologies in e-maintenance platform are explained. Finally, a framework for practical implementations is presented in a great detail.

1. Introduction

Growing globalization of markets and individualization of customer demands, fluctuating consumption, increasing pressure on cost and quality create very dynamic marketplaces. In these new and competitive marketplaces, flexibility is necessary but not sufficient attribute for manufacturing systems to be responsive. Flexibility when needed is the new approach that gives manufacturers ability to modify this attribute with their manufacturing systems according to varying conditions. Thus, unnecessary investments are avoided. For instance, a company that is aimed to be a global might face domestic market conditions that demand relatively low product variety. On the other hand, as the customer needs vary from country to country, the same company might face a great deal product variety to produce in order to maintain its international competitiveness. What is needed is the adjustable flexibility not only in producing variety of parts, but also in changing the structure of manufacturing system itself for system scalability, i.e. reconfigurability adaptable to various circumstances. Reconfigurable Manufacturing Systems (RMS) is considered to be a new class of systems to address these challenges in the next generation manufacturing systems.

Reconfiguration implies adding, removing, or modifying specific process capabilities, controls, software, or machine structure, thus an RMS theoretically includes reconfigurable production lines, reconfigurable machines, reconfigurable controllers, reconfigurable interfaces, and reconfigurable material handlers, as well as methodologies

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for their systematic design, development, deployment, and diagnosis/maintenance. One of the key characteristics for a manufacturing system to be reconfigurable is the diagnosibility that is to identify components failure, quality and process problems [1]. For RMS to be deployed and operated successfully, systematic approaches and efficient maintenance strategies are needed to identify root-causes of component failures, to reduce the failures of production systems, to eliminate costly unscheduled shutdown maintenances and to improve productivity as well as quality.

In the exploration of systematic approaches and efficient maintenance strategies, companies have to migrate from their traditional reactive approach, which is to repair when it fails, to a proactive approach, which utilizes preventive and predictive maintenance activities to preclude equipment failures. Predictive maintenance involves monitoring the health and performance of assets and undertaking activities when the assets reach specific conditions. Diagnosis and prediction of failures are carried out based on observed degradations. The essential advantage of this approach is that maintenance is performed only when an indication of equipment deterioration appears, rather than after a specified period of time or usage.

Another critical issue in design and operation of RMS's is to have information systems capable of delivering accurate and pertinent data, information and/or knowledge to the proper places at right time, at right place so that maintenance decisions are made strategically, tactically in synchronization with production. Efficient service and maintenance strategies which provide a manufacturing system with diagnosibility characteristic can happen only by leveraging the latest advancements in Information Technology (IT), Internet, wireless communications, multi-sensor sensing systems and microelectronics. Utilization of e-intelligence in service and maintenance is the key to success.

In the exploration of more efficient maintenance and service strategies for next generation manufacturing systems, aforementioned facts are converged with other approaches that are condition-based proactive maintenance; collaborative maintenance; remote maintenance and service support; provision of real-time access to information, and integration of production with maintenance have evolved into a new phenomenon. This new phenomenon is called "e-maintenance". E-maintenance is an Internet-based proactive maintenance technology, which consists of remote and real-time evaluation of performance degradation on assets such as equipment, products, and processes [2]. Through e-monitoring, e-diagnosis and e-prognosis, remote manufacturers and customers are supported and ensured of production machine performance and quality of processes.

E-maintenance infrastructure entails various networks to establish real-time communication between computers, programmable logic controllers, and a variety of industrial devices such as I/O modules, motor starters, sensors, and actuators throughout the plant. Remote data transmitting, monitoring and controlling through the network are facilitated by tether-free technologies. Wireless technology within manufacturing industries brings cost reduction (no wiring), flexibility in manufacturing floor layout and information availability. While many issues and challenges remain in the efficient deployment of wireless technology in industry, wireless sensor and control networks play an important role in enabling the e-maintenance platform.

E-maintenance requires the integration of a wide range of technologies. This paper provides insight into this emerging field by looking at its elements that are encapsulated at system level. It also examines pertinent design constraints and the use of certain tools to meet objectives.

2. E-MAINTENANCE – INTELLIGENT MAINTENANCE AND PERFORMANCE ASSESSMENT

A proactive e-maintenance scheme is an interdisciplinary approach that consists of monitoring, diagnosis, prognosis and control processes. The monitoring process involves real-time asset degradation assessment by observation of behavior deviation of machine or system and the detection of abnormal states. Diagnosis identifies the root causes of degradation or failure from the observed machine state symptoms and physical processes. Prognosis analyzes the impact of degradation on the component itself and on the other elements of the production system to predict pending degradations and future system failures. Control is defined as managing rather minimizing, the deterioration by correcting the conditions causing incipient degradations and the conditions leading to future failures. This is based on diagnosis and prognosis results such as adjustment of parameters in the control unit, modifying standard operating procedures or evaluation of operator errors. As a result, decisions can be made and maintenance actions, if necessary, are taken in coordination with the production schedule in an optimum way. These procedures reduce the number of human inspections and unnecessary maintenance activities.

To make the concept clear, a distinction between failure and degradation should be noted. *Failure* is defined as immediate breakdowns (i.e., the end of asset functionality). *Degradations* are associated with deteriorations and can be regarded as symptoms if they are measured, and progressively worsen over time. Unattended they lead to a loss in performance, and ultimately catastrophic failure. Generally, failure takes place after a series of degradations if the cause is aging or wears [3]. Causes (i.e. factors involved in degradation or failure) constitute aging (time-dependent), mechanical wear, environmental effects (e.g., dust, vibration, or thermals), human errors (e.g., improper operation or maintenance deficiencies), and design deficiencies. In addition, component degradation may cause other degradations or failures. Thus, failure is the result of multiple mechanisms. A complete understanding of these multiple failure mechanisms is needed in the analysis and modeling of machine degradation process.

An efficient assessment of machine performance and manufacturing system degradation requires the complete integration of control, maintenance and technical management (CMM) activities [4], which constitute the three main manufacturing islands at the shop-floor level. With this requirement superimposed onto the proactive maintenance processes mentioned above, the conceptual data flow begins with the sensor data collected from equipment control systems and specific sensors. This data is used by both degradation assessment algorithm and prognostic algorithm to perform monitoring, diagnosis and prognosis functions. The resulting performance assessment is sent to technical management and it serves as real-time decision support data for operational planning. Thus, technical management can optimize production by modifying control and maintenance procedures, tools, and materials. For example, fault-tolerant operation of equipment is possible in some cases. Figure 1 illustrates the conceptual data flow. The data, once converted to useful information shared among the manufacturing islands, allows integrated performance assessment and an integrated shop-floor organization.

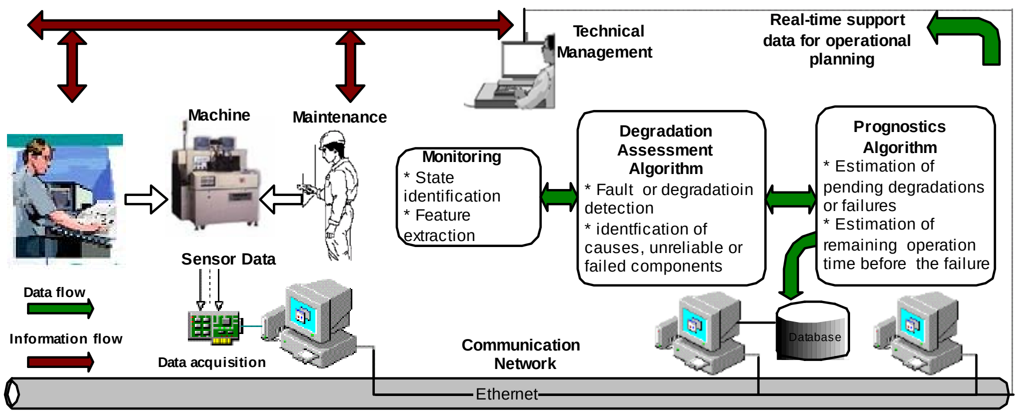

Figure 1: Conceptual data flow

Here, it is important to recognize that accurate, efficient information, available at the right time in the right place, is critical to implement reliable monitoring, diagnosis and prognosis. Accurate information implies an efficient gathering, processing of plant-floor information, and accurate real-time knowledge about what is happening to the process. This is achieved by integrating all machines and products involved in the production. This integration should contain sensors, actuators, controllers, and human interfaces. Efficient representation of the process requires intelligent sensing systems which provide automatic sensing, data acquisition coupled with the subsequent signal/data processing, and evaluation capability. Essential information may be obtained by filtering, refining the data or combining several input signals. This means field components (actuators and transmitters) have embedded intelligence and digital communication exists between them that is the distributed intelligent actuation and measurement (IAM) concept within an integrated shop-floor organization [5].

The key issue with intelligent sensing systems and field components is the communication network. This involves issues of dependability, maintainability, interoperability and subsequently common communication protocol when information is exchanged [5]. Reference [5] conducts the information distribution through a real-time communication system (i.e. fieldbus architecture links to all integrated shop-floor organization activities). Even though fieldbus architecture is seen as a wiring simplification, this approach includes the inherent problems associated with plant wiring such as modularity, installation costs, and expensive maintenance. These issues addressed in detail in the next section, which provides a solution by exploiting industrial wireless technology.

E-maintenance is a tool to facilitate total plant performance management and it evolves from the integration of different activities at different levels. Therefore, an e-maintenance platform requires an analysis in a hierarchical structure. Figure 2 depicts this hierarchical structure and conceptual integration. Shop-floor level, management (business) level, and corporate (enterprise) level are the primary hierarchical steps.

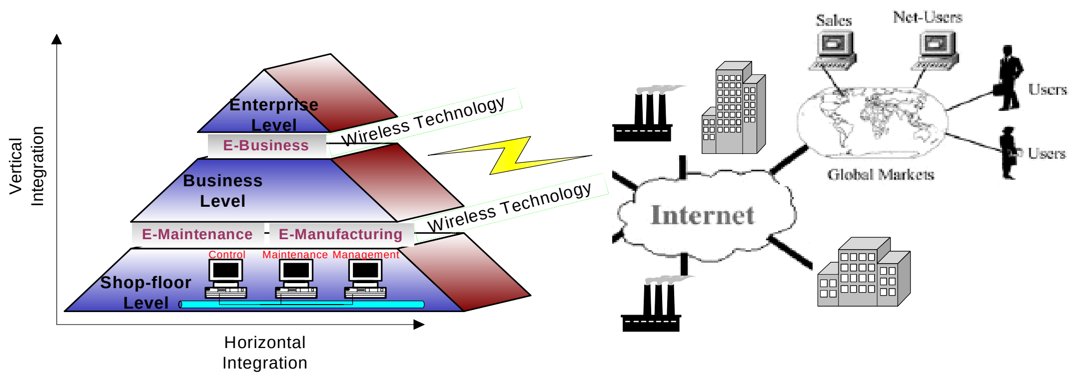

Figure 2: Integration of activities at different hierarchical levels.

At the shop-floor level, monitoring how rapidly the machine degrades requires continuous on-line measurements. Since it is difficult to extract the relationship between performance measurements and a specific component or software errors, total machine health and performance monitoring involves several techniques to be employed, each dedicated to a specific area and integrated to the machine [6]. E-maintenance platform employs both on-line monitoring and off-line monitoring (historical). Information technology (IT) intelligence is an enabling factor for all these activities. Real-time computer processing, rapid data interpolation and automatic logical decision-making provide the intelligence.

Obtaining information from the monitoring process requires an interpretation of the measured parameters based on past and present equipment operation and knowledge equipment’s fault signatures. Accurate interpretation helps identify symptoms, trends, and provides a diagnosing degradation causes. To handle these extremely complicated processes effectively, e-maintenance utilizes artificial intelligence (AI). Real-time application requires fast, accurate, and efficient diagnosis. This imposes a number of limitations on AI applications. These issues, and possible solutions, are further investigated in the following sections.

All aforementioned activities at the shop-floor level provide local service and maintenance within a manufacturing facility. However, the e-maintenance platform utilizes the Internet, wireless communications, and web-enabling technologies as a multi-media information environment for global service and maintenance operations. The information and knowledge on productivity, diagnostics, and service evaluation gathered through these local activities could be shared among several manufacturing plants at different locations [7]. This requires an integration of IAM with agent-based communications. For instance, a predictive intelligent tool (i.e. the ‘watchdog’ agent, a neural computing algorithm developed by [7], provides remote and real-time performance evaluation, and degradation assessment for machines. It enables digital maintenance diagnosis and could be networked via the Internet for remote access.

At corporate level, e-maintenance provides a multi-source environment for known manufacturing plant failure trends, their causes, and proven solutions by remote networking. This helps overcome some limitations on AI applications when used for fault detection and diagnosis (i.e., expert systems have a better-defined failure domain). In addition, e-maintenance distributes knowledge on diagnosis and service activities to remote sites for collaborative maintenance, which brings cost-effective and logical decision-making yielding high productivity. The technical collaboration through e-maintenance could be used as input during, product design or system development. The data collected over time could provide valuable metrics in developing design criteria (reliability, maintainability, supportability, and serviceability) within the context of system life-cycle engineering.

A global proactive maintenance system is a core element of a world-class manufacturing company. The e-maintenance infrastructure extends the integration of activities at the shop-floor level (i.e. CMM concept) through a set of enterprise processes [8]. The full integration of e-maintenance with manufacturing activities (e-manufacturing) and enterprise activities (e-business) provides a holistic approach in evaluation of the complete performance.

The realization of an e-maintenance platform is achieved by integrating wide range of technologies including sensory devices, reasoning agents, wireless communications, virtual integration, and interface platforms [2]. This paper discusses the two core elements; wireless technology including sensor networks and artificial intelligence in the next sections.

3. Industrial Wireless Technology

The application of wireless technology to e-maintenance specifically involves wireless sensor and control networks. Manufacturing facilities typically use wired networks as the data transmission medium for condition monitoring and automation applications. Traditionally, hard-wired transducers are connected to multiplexers, which are networked to a diagnosis unit. But the networks that run on wire cable have several limitations. Wires have high costs associated with installation, maintenance, troubleshooting and upgrading. It is difficult to reconfigure for changes in the production environment. Cables may pick up electromagnetic interference resulting digital data errors. Wires are vulnerable to age, breakage and bad connections.

Wireless technology used within manufacturing and maintenance industries promises cost reduction, manufacturing floor layout flexibility, information availability and enables new applications. Wireless networks have lower installation and maintenance costs than wired lines and reduce connector failures. Ease of replacement, simple reconfiguration, and rapid commissioning are the other advantages. In wireless networks, radio transceivers, that send and receive, are used to exchange radio signals. Encoding electronic signals from sensors onto radio waves is called modulation. The transmission of these radio signals, reception, and translation to recover original sensor information constitute the basic description of the data flow.

E-maintenance requires both real-time monitoring and control applications sharing information about the equipment at the shop-floor. Currently, many users in the manufacturing industry are reluctant to apply wireless data networking for real-time control applications, as opposed to more common applications in monitoring, due to performance and security concerns. Control is more time critical, thus demanding high-speed data rates. Even though wireless technology has made impressive progress in commercial communications, industrial deployment remains limited due to the technology’s ability to handle harsh industrial environments [9].

Listed next are the key characteristics for deploying wireless technology in real-time performance degradation monitoring and control applications within e-maintenance [10]:

Data Integrity: There must be sufficient error checking capability to ensure that the data received is identical to the data transmitted.

Data Security: Data should be protected against jamming, interceptions, and eavesdropping. Interference occurs when devices share the same frequencies. The Federal Communication Commission (FCC) requires that such signals be distributed over a wide band using spread spectrum technology (SST). By using advanced modulation, encoding and encryption techniques, security goals can be achieved.

Deterministic Latency: In control, the update rate for an actuator could involve a very short time. If an updated signal is not received on time, the wireless control system should have the intelligence to respond smoothly.

Data Rate: The minimum data transfer rate required is dependent on the quantity being monitored. The rate is low for slowly changing temperatures, higher for vibration. The minimum data transfer rate is the Nyquist frequency of the upper cut-off frequency times the number of sampling bits for analog-to-digital (A/D) conversion [11]. For example, in vibration monitoring, the upper cut-off frequency of 5000 Hz is usually considered sufficient. In order to digitize the vibration information, the sampling rate must be at least 2.56 times the upper frequency bound to enable the Fast Fourier Transform (FFT) calculation. Thus, for a 27-bit A/D conversion with the constant is taken as 4 instead of 2.56, then the net data stream is 5000 Hz X 4 X 27 b = 540 kbps. In addition to monitoring, real-time control can also be considered. This can include continuous updates from actuators and an allowance margin for control command dropout. Thus the minimum data rate can reach 2 Mb/s. In wireless communication, as the speed of data transmission (throughput) increases, radio frequency signals supply less energy per bit, negatively affecting reliability. Reducing the data rate also reduces the error rate.

Functionality and Nodes Supported: Coverage flexibility increases with larger numbers of sensor nodes. If a node becomes unavailable in wireless network, a new connection should be established without creating either a time or throughput problem. A network system must be capable of operating without human intervention (i.e. it is self-configuring, self-calibrating, self-identifying, and self-organizing) for optimal network performance and fault recovery [9].

Noise Immunity: Data throughput is negatively affected by noise. Collision avoidance and packet retransmission techniques are available for signals blocked by interference. But these techniques require considerable power and can generate interference for other systems [9]. Better solutions are needed.

Mechanical Reliability: Rugged industrial environments affect the reliability of wireless data transmission. High and low operating temperatures (-40^o to 70^o), high humidity levels (95% at 40 ^{o}), potentially explosive situations, vibration, and metal equipment affecting the transmission path are problems wireless technology may encounter in industrial environments.

Power Requirements: The power requirement involves two areas, transmission power and processing power. Long distances and interference problems increase the demand for transmission power. Encoding techniques need to be developed for reducing processing power. Better-designed antennas and receivers would help reduce power needs. Also, long-lasting and reliable power sources are needed to overcome power drain issue at sensor nodes.

Interoperability and Standards: Wireless components from different suppliers must be compatible. A variety of wireless networking standards exist in the market such as, IEEE 802.11a, 802.11b, 802.11g, Bluetooth, HomeRF-2, HiperLAN2. Each has merits and shortcomings. There is a great need for a standard protocol. Bandwidth availability and compliance with FCC regulations constitute the main items in the evolution of such a standard.

Obviously advances are still needed in power consumption, reliability, integration, cost, functionality and bandwidth efficiency to produce a desirable wireless system [9] as detailed in Table 1.

Table 1 Desirable characteristics for wireless networks

MAXIMIZE	MINIMIZE
Data Rate (bits/second/hz)	Latency (sample rates & updates)
Range (distance)	Bit Error Rate (BER)
Volume (sensors/area)	Power Demand
Security (time to access)	Cost ($ per bit per Hertz)

4. Artificial Intelligence

Artificial Intelligence (AI) is defined as a computer system mimicking “human” intelligence i.e., executing learning and problem solving through knowledge gathering. In the equipment service field, the challenges tackled by AI technologies include segmentation, classification, prediction, and decision-making. These are extremely complex processes involving large amounts of diverse data. AI technologies can monitor products and processes; detect incipient failures; diagnose possible faults; predict pending degradations and potential future system failures; determine preventive or corrective action and produce a cost-effective repair plan.

Expert systems are widely employed for fault detection and diagnostics in equipment maintenance. Here, a knowledge base is used to obtain relationships between measured values and failures. The knowledge base is constructed by acquiring experiences of human experts. However, it is difficult to acquire knowledge about all possible machine failures from such experts and then organize the information obtained. Moreover, the expert systems can not adapt to dynamic environment conditions. Thus, expert systems are restricted to problems with well-defined failure domains [7].

Neural networks approach is another AI software technique used in fault detection and diagnostics, particularly for pattern recognition, data classification, and trend analysis. This technique has the ability to learn from examples and is adaptive as opposed to the traditional "programming" approach that is to follow a set of instructions in solving problems. Neural networks learn based on the data sets given for training or on initial experiences including input patterns and the correct interpretations of those patterns. Neural networks can create their own representation of the information they receive during the learning period. They can filter out input noise and exhibit robustness under changing operating conditions [12]. A disadvantage is that the learning set examples must be carefully selected, otherwise the network might function incorrectly. Also, since neural networks learn how to solve problems by themselves, their operation can be unpredictable.

Since expert systems and neural networks each have specific merits and weaknesses, one method used alone may not perform satisfactorily. However, one can complement the other. Therefore, combining the systems and forming a hybrid, such that the expert systems supervise the neural networks, is the preferred approach for applying AI to industrial equipment diagnosis applications.

One of the major challenges in monitoring processes and machines is tracking the degradation of a large number of sensors and detecting multiple-sensor failures. The degradation or failure of sensors in a network could result in false indications of machine or process failure. Reference [12] proposed a solution by developing a methodology, based on a hybrid combination of AI and statistical techniques, for intelligent sensor data validation, fusion and sensor failure detection. The technique handles subtle sensor problems such as drift, multiple simultaneous failures, and detection of sensor degradation. Here, a hybrid AI system combines neural networks fuzzy logic (i.e. neural-fuzzy adaptive networks) for adaptive prediction. Thus, AI software techniques are used in handling multiple sensors associated with complex machine monitoring.

More learning data and better knowledge of machine and process failures will improve the results obtained with the systems just mentioned. E-maintenance, by networking remote manufacturing plants, provides a multi-source knowledge and data environment. Known failure trends, causes, and proven solutions are used to expand the knowledge base of the hybrid AI systems, thus enabling them to perform at maximum efficiency.

5. EXPERIMENTS WITH E-MAINTENANCE

The industrial implementation and evaluation of e-maintenance at the shop-floor level is prototyped in [4]. The experimental platform consists of (1) an intelligent manufacturing system (IMS) that runs a process and (2) a maintenance platform (TEMIIS) that accommodates a local data center. The process run by IMS regulates a water level in a closed loop. The experiment includes communication of Control, Technical Management and Maintenance experts on the Ethernet through TCP/IP to assess process performance and remotely maintains IMS service in the cases of degradation on process components. Three Experts Control, Technical Management and Maintenance interact with each other as shown in Figure 3 to achieve the overall goal.

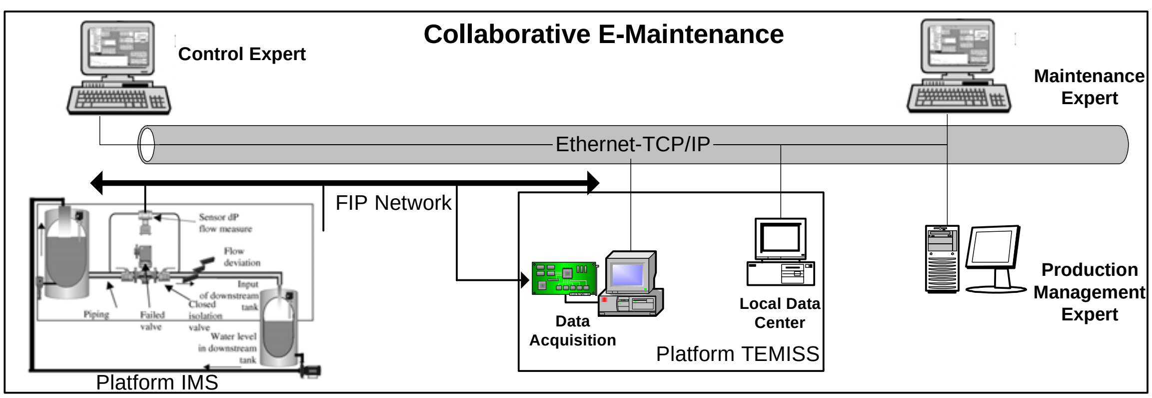

Figure 3: Experimentation of e-maintenance

Connected to Ethernet local data center acquires, processes, and stores the real-time data gathered from local measurement and control devices. It also keeps the degradation information resulting from monitoring and diagnosis. An efficient, reliable representation of the production process is achieved with embedded intelligence in the field components (actuators and transmitters), IAM, and digital communications through FIP network. The distribution of artificial intelligence across the process is provided with multi-agent System (MAS) modeling. The embedded agent-based system consists of monitoring, diagnostic, communications, and synchronization agents assigned to each data flow and process activity. Mobile, platform-independent agents search for; access and retrieve the data and other information located in the local data center; and manage information exchange among the experts. IBM's Aglet Software Development Kit is used to create the agents. These Java-based agents can roam the Internet, visit the databases, perform computation tasks and carry the results back to the end-users

The local data center also contains the production system performance models that characterize operational and degraded states to obtain a prognosis evaluation. These models are automated, but are also accessible to human experts. Thus, an integrated reasoning environment is established that exploits the human expertise and computerized reasoning for fault detection and prognosis. In order to achieve an integrated decision-making procedure, Bayesian networks are used to create complex statistical models in decision support.

Though this e-maintenance experiment was only performed at the shop floor level, it could be developed to include business and enterprise levels in a hierarchical structure. Indeed, experimental platform is still under development by the author. Future development may well include the application of industrial wireless technology to the platform to more fully realize e-maintenance.

6. SUMMARY

This paper examined the e-maintenance strategy and reviewed some of the ongoing research work. The application of proactive maintenance strategy to the e-maintenance platform was analyzed. The critical elements and issues of intelligent maintenance systems were explored.

E-maintenance can bring more efficient maintenance and service strategies to today's competitive manufacturing industries worldwide. E-maintenance brings just-in-time maintenance to just-in-time production. It employs computer-based systems to predict the pending downtime. This allows plant management to synchronize maintenance with production, maximizing process throughput and minimizing downtime costs.

Advancements in both wireless sensor networks and distributed AI through intelligent actuation and more adaptive automation systems will realize e-maintenance applications in the manufacturing industry. Measurable, positive impact of e-maintenance on throughput and productivity will make easier for management to justify investments in this emerging technology.

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