Implementation of Predictive Maintenance Systems in Remotely Located Process Plants under Industry 4.0 Scenario

P. G. Ramesh, Saurav Jyoti Dutta, Subhas Sarma Neog, Prandip Baishya and Indrani Bezbaruah

Abstract Rapid developments in technologies such as Robotics, Digital Automation, Internet of Things and AI have heralded the Fourth Industrial Revolution, commonly referred to as Industry 4.0 (i4.0). Industrial operations and products have since become more competitive and hence more demanding. Systems have also become more complex and inter-disciplinary in nature. Diligent surveillance of operating conditions of such systems and initiation of appropriate actions based on monitored conditions have become indispensable for sustainability of businesses. Significant amount of research is being undertaken world over to meet this requirement of the day. In line with the ongoing research, this paper highlights the need for identifying the needs of condition monitoring preparedness of process plants located in remote places, especially in a logistic sense. Issues related to assessment of the need for the new paradigm in condition monitoring, challenges faced by such plants in the transition from legacy systems to a new system and customisation and optimisation of Predictive Maintenance under Industry 4.0 (PdM 4.0) have been discussed. A Case Study pertaining to remote monitoring of a gas compressor system of a petroleum refinery in North Eastern

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India and a Case Discussion on Basic Technical Requirements for the implementation of Industrial internet of Things (IIOT) based predictive maintenance system are presented to highlight the benefits and issues associated with the radical shift in paradigm from legacy systems to Industry 4.0 based predictive maintenance (PdM 4.0) system. Frameworks for PdM 4.0 system decision making and development are also suggested for supporting future work in this area.

Keywords Industry 4.0 · PdM 4.0 · Condition based maintenance · Predictive maintenance · Remote health monitoring

1 Introduction

Technologies such as Internet of Things, Artificial Intelligence, Cloud Computing, Robotic Automation and Big Data/Data Analytics have brought about a completely new paradigm of conducting business so much so, that this change is being rightly termed in the industrial circles as the fourth Industrial Revolution or in short, "Industry 4.0". In order to maximise the benefits of Industry 4.0, business operations need to transition to the new paradigm in totality which means that maintenance of plant machinery and systems also need to follow at the same pace and mode.

There are multiple challenges in the implementation of Industry 4.0. Today's plant floors need access to a variety of information, but are often burdened with issues around large data volumes, integration of multiple systems, and security. As a result, there is a greater need to share expertise across facilities to optimise safety, production and recovery. Subject matter experts are becoming increasingly difficult to locate and companies need to find ways to use them more efficiently [1]. Remote management allows authorized individuals (specialists, experts) to monitor the automation systems, help diagnose problems, tune loops, optimize processes, and generally improve production [2]. Industrial process plants can be monitored remotely by system architecture having General Packet Radio Service (GPRS) and wireless Internet connection in conjunction with Distributed Control System (DCS), Supervisory Control And Data Acquisition (SCADA) with consequent improvements in reliability, response time, etc. under adverse environmental conditions of process plants for maximizing plant operational conditions [3].

In this chapter, the importance of adoption of Industry 4.0 technologies for Predictive Maintenance of machinery and systems of remotely located engineering plants and aspects related to its implementation are discussed. In Sect. 2 the distinguishing features of remotely located process and manufacturing plants is discussed highlighting the indispensability of their transition to predictive maintenance under Industry 4.0. Frameworks for such a system for large engineering plants that are located remotely are presented in Sect. 3 which will prove useful for further work in this field. Two case studies are presented at Sects. 6 and 7. The first case study is aimed at highlighting the importance of making use of global expertise and resources on an Industry 4.0 platform for process critical machinery based on a case of implementation of such a system for a heavy duty process critical gas compressor of a petroleum refinery in North Eastern India. The second case study brings out the complexity of predictive maintenance systems under Industry 4.0 and highlights the need for comprehensive but optimum specifications for such a system.

2 Remotely Located Process Plants

A number of process and manufacturing plants are situated at locations which pose serious challenges related to supportability of the plant machinery and systems due to logistic constraints. The challenge on account of remoteness of such plants is aggravated by poor connectivity for transportation, geographically scattered locations, inadequate local expertise or resources and, in some cases, poor communication links. Such remotely located plants include oil & gas drilling sites, both land based and off shore, refineries, coal and mining locations, power plants, solar and wind power farms, cement, sugar, chemicals and other process industries. In addition to these stationary plants there are mobile platforms such as ships and aircraft which are required to operate over remote regions which are not easily reachable for logistic support. These platforms too, therefore, can be included in the category of remotely located process plants.

Most of these plants are also large and complex in their equipment or system configurations and operations, thereby posing additional demands on support infrastructure. Comprehensive maintenance strategies are required to be planned, optimised and executed for these plants. Optimal availability of hardware, software and support from remote expert centres as well as deployment of adequate maintenance personnel are some of the essential requirements to ensure requisite standards of reliability and availability [4].

Maintenance of such plants has constantly been evolving driven by the needs of industry and increasingly available technologies and skills. Efforts are being made to make available, details such as, equipment information, failure data, maintenance resources and material availability more readily and develop more and more optimised maintenance decisions. Remotely located plants have benefitted from such developments.

However, in the recent past, there has been radical shift in the paradigm of operation of these plants and such changes have also influenced maintenance philosophies and strategies.

2.1 Industry 4.0 and Changing Operational Philosophies of Remote Process Plants

Technologies such as Industrial Internet of Things (IIOT), Artificial Intelligence (AI), Cloud Computing (CC), Autonomous Robotics, Information and Communication Technologies (ICT) and big data analytics have revolutionised the way Industries can function and have been collectively termed as the fourth Industrial Revolution or Industry 4.0. Industries are leveraging these technologies for their business operations for being more competitive and profitable. The impact of Industry 4.0 technology on business models has been disruptive over the entire value chain.

Under this scenario of increased competitiveness, asset maintenance strategies are also required to be aligned on like terms so that equipment and systems are maintained in requisite states of availability or readiness to match with the overall business expectations.

Engineering assets and operations under Industry 4.0 will have following major components [5]:

(a) Cyber Physical Systems (CPS)
(b) Internet of Things (IoT)
(c) Internet of Services (IoS)

Industries are increasingly configuring their machinery and systems as Cyber Physical Systems (CPS) by employing the above technologies. CPS involves control and surveillance of physical systems through computational and supervisory prowess of computers including web based software resources and expertise. Such web based resources are available as CC applications. Internet of Things (IoT) refers to even the smallest of components or sub-systems that are capable of sending and receiving signals from the internet. Internet of Services (IoS) refers to services that can be provided over the internet and that which can be availed by industries aligned with the concept of Industry 4.0.

Factories that are in line with the above configuration can be called Smart Factories. The Internet of Services and Internet of Things are two basic concepts that should be implemented in factories as a precondition for the smart factory of the future (Fig. 1) [6].

These changing operational scenarios of industries are, in fact, more relevant to remotely located plants since the benefits so derived can offset many of the constraints related to being remotely located.

Industry 4.0 is seen to generally spread from developed countries to developing ones through a rather slow process of diffusion and adoption of constituent technologies [8, 9]. Thus usually different behaviour patterns are seen and perceptions regarding the usefulness of different technologies differ widely from one region or sector to another. Several industries, especially those in the developing economies of the world have commenced application of Industry 4.0 technologies. However, the scope of application is rather non-comprehensive thereby denying the

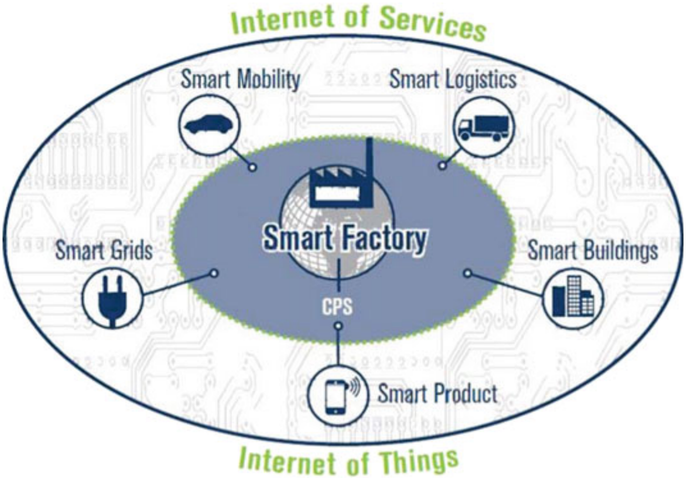

Fig. 1 Schematic representation of a smart factory [7]

possibilities of truly revolutionary changes. For instance, it has been shown by Dalenogare et al. [10] as to how industry in a developing country such as Brazil has not yet taken advantage from some promising technologies such as product big data analysis and cloud services for manufacturing. In fact, benefits to be accrued from Industry 4.0 are largely derived from studies in developed economies. As regards developing countries, more comprehensive studies into how the benefits could be leveraged are required to be undertaken.

Studies thus show that there is significant dispersion between countries in the readiness of their industries in terms of ability to adopt Industry 4.0. The reasons that determine the differences among countries in the ability to adapt to Industry 4.0 require further research: the structure of the industrial sector, its role within each country's economy and differences in business models or management styles even within the same sectors, should be elements of study when looking for the Industry 4.0 drivers [11].

Going forward, enterprise level implementation of technologies of Industry 4.0 encompassing all elements of supply/production/service chain will provide the best results from such an enterprise. The level of application can range from individual machines, individual processes or complete factory in the increasing order of automation or complexity. Also, the level of intelligence embedded in the machines/process/entire factory can range increasing order from merely having an automated control, integration of automated controls of several functions or embedding higher level intelligence in the machines/process/entire factory for autonomous and intelligent functions. This aspect has been well presented by Qina et al., as nine intelligence applications going from low-intelligence and simple automation to high-intelligence and complicated-automation as shown in Fig. 2. From applications I–IX, the production system becomes increasingly automated, flexible, and intelligent [12].

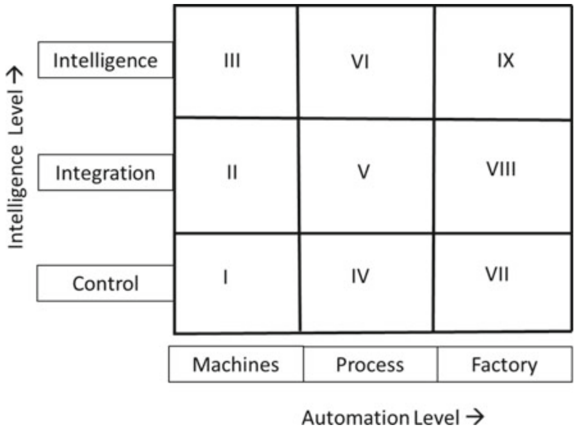

Fig. 2 A categorical framework of manufacturing for Industry 4.0 and beyond [12]

Experts such as Moubray [13] believe that not more than 20% to 35% failures can be prevented by Predictive maintenance depending on whether only condition monitoring inputs or other additional sensing of failure mechanisms are employed. Under this condition, in order to render predictive maintenance under Industry 4.0 to be an applicable and significantly effective strategy for total maintenance, there is a need to combine technology advancement with basic maintenance. Cross-functional working to handle large amount of data, leverage development in technology along with basic maintenance practices will be the key to better maintenance under Industry 4.0.

Augmented Reality (AR) is an important technology of Industry 4.0 and its application for maintenance was known for quite some time. However practical limitations such as lack of adequate knowledge on its application made it difficult for realising its benefits. Now that some of the technological limitations have been overcome and AR seems to be ready to become a tool for industry, it is believed that the scientific community can focus on trying to solve the real industrial problems [14]. This includes maintenance. Technologies like AR and Additive Manufacturing (AM) can provide better way to carry out maintenance operations with respect to a traditional approach as shown in the case of aircraft maintenance [15]. AR can support the operators with user-friendly manuals where virtual models and instructions are mixed with real world, while AM can be useful to avoid large warehouses and cut the logistic chain.

2.2 *Condition Monitoring of Remote Process Plants Under Industry 4.0*

Industry 4.0 assumes limited participation of machine operators in monitoring and diagnosis of manufacturing and technological processes [16]. This is the case not only about machinery and system controls but also about their condition monitoring. Industrial platform for condition monitoring [17] consists of the three major modules: monitoring and feature extraction (MFE), real-time anomaly detection (RTAD) and fault diagnosis (FD). These three modules are also true of conventional or legacy systems. However, the scope and reach of these modules under Industry 4.0 is much extended. MFE module can consist of IIOT based sensing equipment, collection of a large number of sensed and computed data from which feature extraction becomes more accurate and providing better coverage to the maintained system. The MFE information is passed on RTAD which can leverage Artificial Intelligence (AI) and Machine Learning (ML) tools among others to detect anomalies. Likewise FD module makes use of AI, ML at plant locations as well as remote expertise and analytical tools by means of internet communication and cloud resources.

3 Maintenance Frame Work Under Industry 4.0 for Remote Process Plants

Maintenance framework under Industry 4.0 for Remote Process Plants is very much an extension of e-maintenance framework shown in Fig. 3 [4].

The local O&M platform has machinery and systems to be monitored. Monitored condition date are processed in the local platform as far as feasible for detection and prognosis of impending defect conditions. The capacities of local units being limited, remote centres of expertise are configured into the system as

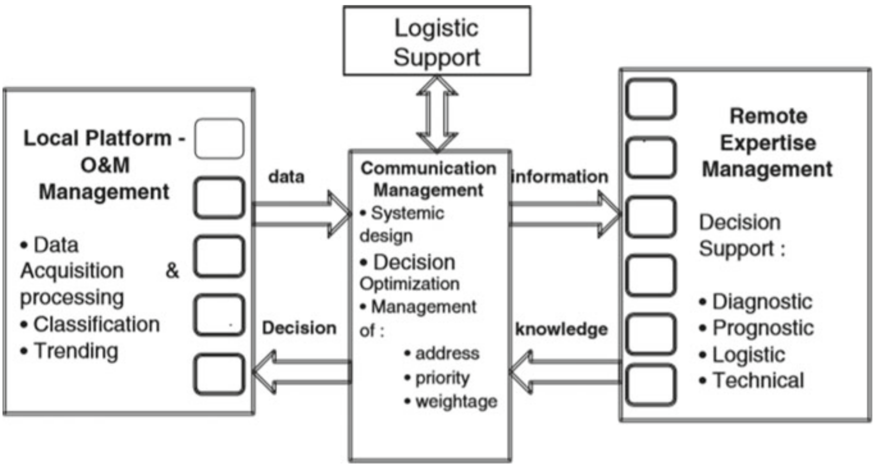

Fig. 3 Framework for e-maintenance [4]

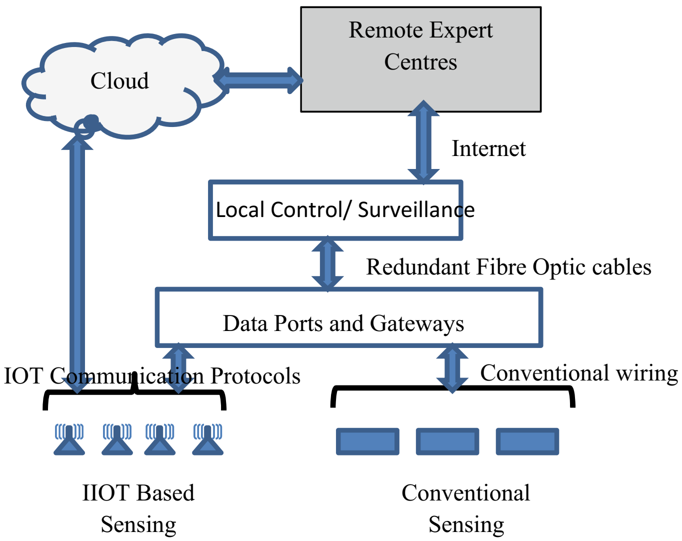

Fig. 4 A scheme for maintenance framework under Industry 4.0

extensions of the local platform capabilities. The communication management module ensures that the overall e-management effort is successfully executed.

Implementation of data collection systems, data analytics and real-time decision making has paved the way for e-maintenance and helped reduce downtime and uncertainty about the current status of the equipment and possible breakdown in the future. Proper use of available technologies will lead towards smart systems which will reduce uncertainty in the decision making process [18].

The above e-maintenance framework is extended using IOT based sensing, cloud technologies as also with effective use of AI and ML. A scheme for maintenance framework under Industry 4.0 is shown in Fig. 4.

A framework for predictive maintenance in line with the above overall framework for maintenance under Industry 4.0 of plant machinery and systems of a remotely located plant is shown in Fig. 5. Sensor and other acquired real time data, historical data, environmental data and asset design data are used by the system represented by the above framework for presentation of processed information in the following forms:

(a) Indication of Asset performance: Key Performance Indicators (KPIs) are defined as a set of quantifiable and strategic measurements in a Performance Monitoring System (PMS) that reflects the critical success factors of an enterprise [19]. Performance data collected through an array of IOT based sensors as well as classical sensors, wireless or wired, are processed against data from other sources to provide information that indicate the performance of the asset on suitable HMI or recorder. Both the number of equipment and the number of sensors are limited to the bare minimum in legacy systems with

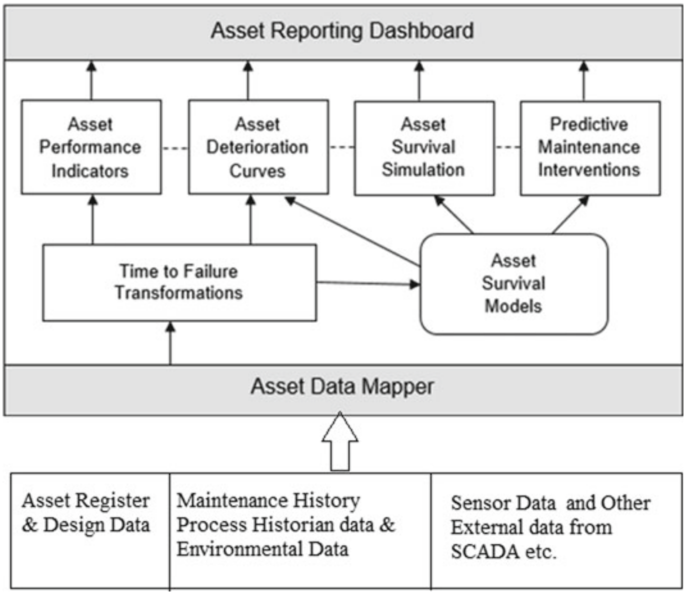

Fig. 5 Schematic diagram of the asset predictive maintenance framework using IIOT

manual modes of monitoring. However, with IOT and wireless based communication of performance parameters, the number of parameters and equipment under coverage can be significantly increased, thereby improving the effectiveness of health monitoring, trending, analysis and predictive maintenance.

(b) Indication of Asset deterioration curves: This feature provides static and dynamic factors that can help explain asset and process failure, and their relative importance. Risk of failure of an asset at given time is also analysed and presented. Feature engineering can be carried out to capture degradation over time by using techniques such as Regression, binary and multi class classification, survival analysis and anomaly detection. In doing so, solution provider will find out the features, which shows degrade pattern with significant predictive power. Technologies of Industry 4.0 such as Artificial Intelligence (AI) and Big Data Analytics can help in making use of all collected data, interpreting suggested trends and continuously improve upon prognosis of failure.

(c) Results of simulation of asset life or survival: The effects of various asset maintenance scenarios, probability of an asset that survive beyond a given time, prediction of failure probability over time are some of the useful simulation that can be undertaken and presented for the maintenance team.

(d) Recommendations for predictive maintenance interventions: The predictive maintenance recommendations are based on collection of a large quantity of data involving multiple KPIs from multiple equipment and processing the same by making use of technologies of Industry 4.0. Unlike legacy systems where maintenance decisions were based on very few KPIs and equipment being monitored in standalone modes, in systems under Industry 4.0, decisions are more dynamic, wholesome and robust through extensive analysis of data, simulation, modelling and application of AI/ML. AI/ML tools if rightly understood and applied by the maintenance decision maker, may unravel the mechanisms or trends behind many of the "sudden/unexpected failures". Further, there is a need for careful determination of the kind of data that is required to be acquired and processed in order to be able to maximise the desired outcomes from the predictive maintenance system.

4 Transition to PdM 4.0 from Legacy Maintenance Systems

A few studies have been conducted regarding the issues connected with the adoption of Industry 4.0 on legacy systems. In one such study, interviewees mentioned that the main adoption challenges are the analysis of data generated, integration of new technologies with available equipment and workforce, and computational limitations as also changes in company's business model through the integration of internal resources with complementary activities of their partners and other cluster companies [20].

One of the features of most remotely located industries is their complexity of systems in terms of their configuration, diversity, size, criticality and inability to provide long breaks in production. This complexity renders transition of legacy maintenance systems of these equipment and systems to Predictive Maintenance under Industry 4.0 (PdM 4.0).

Legacy machine tools are often isolated, not well-equipped with modern communication technologies, and with lack of open Application Programming Interfaces (API). It is therefore difficult to monitor and control the entire production process [21] using legacy systems. It is difficult to easily monitor legacy systems, which can introduce inefficiency and generate higher cost of sensor integration [22]. As a solution, industries can reconfigure their legacy systems into "smart legacy machines". However there are challenges for identifying standard IOT architecture, and establish clearly the benefits of the transition. Industries are also concerned about protection of their data when exposed to a cloud or internet-based architecture [23].

For large plants especially those located in remote areas, progressive conversion of legacy machines to smart legacy machines is a good option, while also moving on to completely Industry 4.0 machines and systems during replacement and modernisation projects. A discussion of a case of requirements for implementing IIOT based predictive maintenance decision support system for a petroleum refinery has been presented later in this chapter. Until a complete change over, there will be a long transition phase having a mix of old and new for which engineers of such remotely locate large plants need to gear up.

5 Customisation of PdM 4.0 Solutions to Remote Process Plants

As mentioned earlier, remotely located large engineering plants be it, process or manufacturing plants, renewable energy farms or ships have unique customised designs, set of equipment, systems and operating philosophies. The set of objectives and constraints including logistics for such industries are also unique. Therefore there is a need to customise PdM 4.0 solution also for such industries. Off the shelf solutions are bound to be sub-optimal due to inadequate coverage and challenges of integration.

5.1 Integration of PdM 4.0 Features During System Design

In order to achieve customisation, the ideal option would be to integrate PdM 4.0 during design of a plant. The plant machinery and systems should be compatible, supportable and integratable with PdM systems. However, this is seldom possible practically since the rates of obsolescence of plant machinery systems and PdM systems are very different. Hence customisation efforts are required to take into consideration a mix of legacy and new equipment for design of PdM 4.0.

5.2 Optimisation of PdM 4.0 Solutions for Remote Process Plants

Major objectives of PdM 4.0 for a remotely located process plant would be maximisation of plant availability, equipment and process reliability, safety and minimisation of costs. However depending on the nature of the plant, there will be several minor objectives as well. All objectives have importance for certain stakeholders at certain times. Many of the objectives would compete with each other resulting in trade offs and not single optimum solution. Similarly there are major and minor constraints in achieving the objectives. Obviously, designing a PdM 4.0 platform for such plants will be a multi-objective, multi-constraint decision optimisation problem. A sample framework for multi-objective Condition Based Predictive Maintenance (CBPM) problem is shown in Fig. 6 [24].

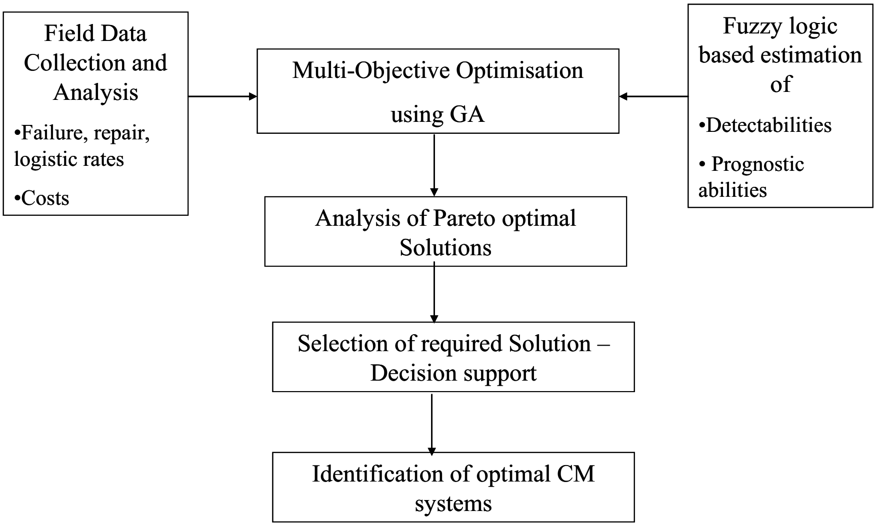

Fig. 6 A framework for multi-objective CBPM problem [24]

As shown in the figure, a Multi-Objective Optimisation Problem (MOOP) is solved with inputs from field data and Detectabilities and Prognostic abilities. The latter two, explained briefly below, are derived based on data or from experts with the help of Fuzzy Logic Framework. Solution to the MOOP consist of a set of optimal points each differing from the other with trade-offs. The decision maker selects that solution which would be the most optimum under the prevailing conditions. This solution corresponds to the set of parameters that would define the CM system that would be selected.

In the process of optimisation, it is essential to identify or create certain parametric metrics for desirable features of the PdM 4.0 system and quantitatively ascertain how they could influence achievement of objectives of PdM 4.0. For instance, the ability of a PdM system to be able to detect the onset of a defect or impending failure and also its capability for prognosis and diagnosis of defects are important requirements for any user. Based on this premise, a study has proposed two metrics, detectabilty and prognostic ability and has undertaken a multi-objective optimisation using these metrics as variables. The influence of these variables on one of the objectives, namely, to minimise unavailability is shown in Fig. 7. It may be observed that the detectability and prognostic ability averaged for the constituent sub systems show an increase with increasing cost.

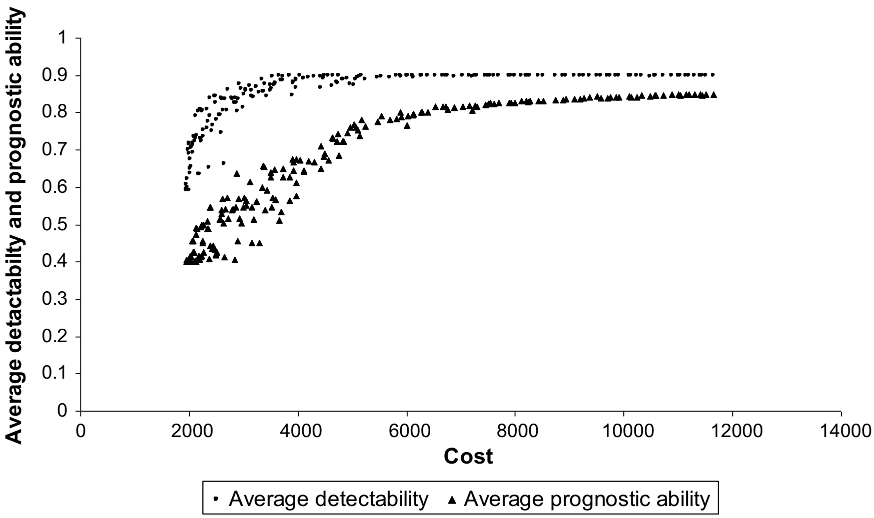

Fig. 7 Cost of PdM versus average detectability and prognostic ability [14]

6 Case Study I: "a Process Critical Equipment of a Petroleum Refinery in North Eastern India Integrated with Industry 4.0 Based Predictive Maintenance System"

6.1 Introduction

Presently online machine monitoring system installed in critical equipment in the refinery is equipped with machine protection system (MPS) apart from diagnostic facility. MPS consist of transducers (vibration, position, temperature, flow, pressure, speed, etc.) with continuous, permanent monitoring instruments installed which are capable of sending alarm and shutdown commands to the machinery control system. MPS thus uses real time measurements and data to automatically shut the machine down when conditions degrade beyond pre-set alarm limits. MPS can be taken off-line and automatic shutdown can be disabled if so desired. Many users would want to disable auto shut down using MPS for the fear of shutdowns due to false alarms.

In this case study, two situations (with and without MPS auto shutdown) encountered in a critical machinery in a major Petroleum Refinery in North Eastern India will be discussed. It will be shown that leveraging global technical expertise and resources pertaining to health monitoring in the realm of Industry 4.0 in case of such critical equipment can provide optimum maintenance decision support to the plant personnel instead of merely depending on an auto shutdown facility.

6.2 *Basic Information of Equipment Installed with Machine Monitoring System*

The equipment discussed in the case study pertains to a set of 03 in numbers Makeup Gas (MUG) compressors (Fig. 8) installed in Hydrocracker Unit (HCU) unit of the refinery. MUG Compressor is a high pressure 3-stage Reciprocating compressor of Hydrogen service. The Makeup H_2 compression section consists of three identical parallel compressor trains, compressing makeup H_2 from the H_2 plant to the reactors. Three compressors are required to run simultaneously at 240% collective load for achieving the maximum load requirement of the HCU Plant.

Equipment Data

Machine: Reciprocating Compressor
Power Rating: 3 MW
Manufacturer: NuovoPignone
Model: 4HF/3
No Cylinders: 4
Service: Make Up Hydrogen

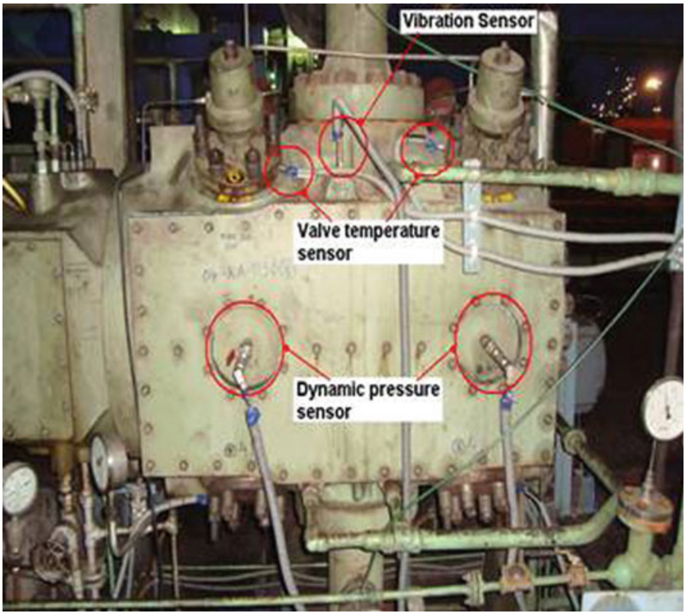

Fig. 8 Picture of one of the cylinders of make up gas compressor with installed sensor of PROGNOST system

No Stages: 3
1st Stage: 19.5/45.6 kg/cm^2 a
2nd Stage: 45/100.8 kg/cm^2 a
3rd Stage: 100/189.1 kg/cm^2 a.

Features of PROGNOST Monitoring System Installed in the Refinery

- Real time data collection.
- Database system.
- Data Management.
- Trend storage.
- Data archive management.
- Analysis of Historical data.
- Data export into MS-EXCEL etc.
- Anomalies banner, that is, a logbook containing errors recorded by the system.
- Thermo dynamical and Mechanical simulations modules.

Basic Reciprocating Compressor Monitoring Parameters

- Suction and Discharge temperature, vibration and pressure of cylinders.
- Vibration and Mechanical looseness.
- Piston Rod run out and drop.
- Temperature of main bearings.
- Crosshead and Crosshead pin parameters.
- Piston rings wear of all stages.
- Rider rings wear of all stages.
- Main packing's temperature.
- Frame vibrations.
- Lube oil system temperature.

The PROGNOST Machine Protection System of MUG Compressor is based on parameters as indicated in Table 1.

When the safety threshold is violated, the automatic shutdown of the machine may be implemented for protection against costly failures. The PROGNOST machine shutdown is based on a voting feature where users during installation can define a group of parameters (Online monitoring recorded data), which when satisfied independent of each other, can trigger a machine shutdown.

The diagnostics system allows comparison of the measured values with the expected values generated by the model. The software processing unit analyses all changes in the thermodynamic condition of the compressors and updates the expected values in real time. Every displayed parameter has four different associated states indicating its condition: Green, Yellow, Orange and Pink. The green state indicates that the value of the measured parameter is normal/good; The Yellow state indicates that the value is at the upper/lower limit of a predefined criticality

Table 1 MUG compressor parameter

Parameter	Description
Crosshead slide vibration	• Threshold monitoring of RMS vibration for 36 segments per revolution • Threshold monitoring of RMS vibration per revolution (1 segment)
Dynamic cylinder pressure	Threshold monitoring of peek to peek dynamic pressure per revolutions
Dynamic Rod drop	Threshold monitoring of peek to peek piston rod vibration for 8 segments per revolutions
Frame vibration	(i) Threshold monitoring of RMS vibration for 36 segments per revolution (ii) Threshold monitoring of RMS vibration per revolution (1 segment)
Alert and shutdown with plausibility check prior to alarm	The plausibility check is a feature that avoids costly false trips that could result from faulty sensors or loosened instrument connections within the loops
Unsafe alarm in case of non-functional loop or system	Any non-functional loop or system feature informs any loosened instrument loops

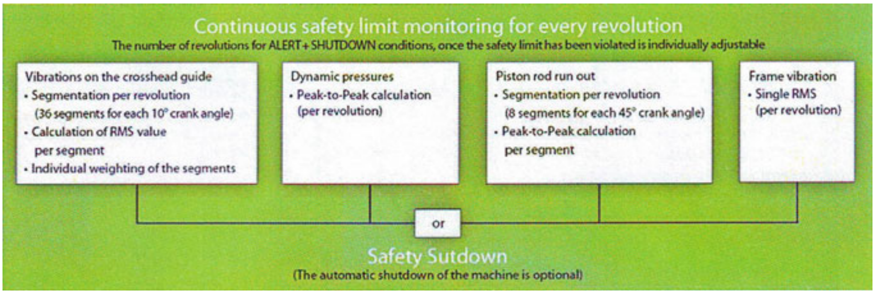

Fig. 9 Schematic diagram relating MPS parameters versus safety shutdown

range; the orange state indicates that the value is at the upper or lower limit of the predefined high criticality range; the Pink state indicates that the value has reached/ crossed the set safety limits of predefined criticality range. With MPS on line, Pink State indicates crossing safety limits and will trigger machine shut down command. The shutdown logic for the compressor is shown schematically in Fig. 9. In the above compressors MPS have been kept offline.

6.3 *Case Study I (Part 1): Compressor System with MPS Auto-Shutdown ‘OFF’*

In this case, the MPS Auto-Shutdown for the compressor system was put ‘OFF’.

6.3.1 Problem Description and Prognostic System Logging System Alerts

On the 23-Jan-2013, HCU load was at maximum load with the three MUG compressors running with compressor numbers:

- 04-KA-03B at 100% load
- 04-KA-03A at 70–85% load
- 04-KA-03C at 50% load.

On the morning of 23-01-2013, 11 AM, compressor KA-3A was started. The PROGNOST-NT system released several SHUTDOWN alarms approximately 13 min after the start of the compressor. With reference to the Figs. 10 and 11, the

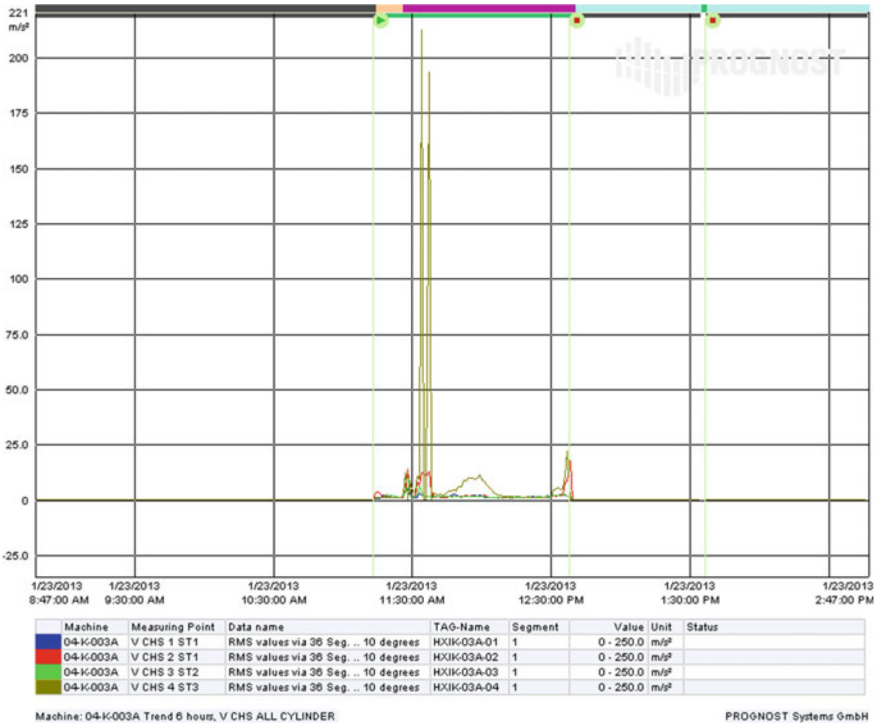

Fig. 10 PROGNOST-NT system all stage crosshead slide vibration trend for the period 23-Jan-2013

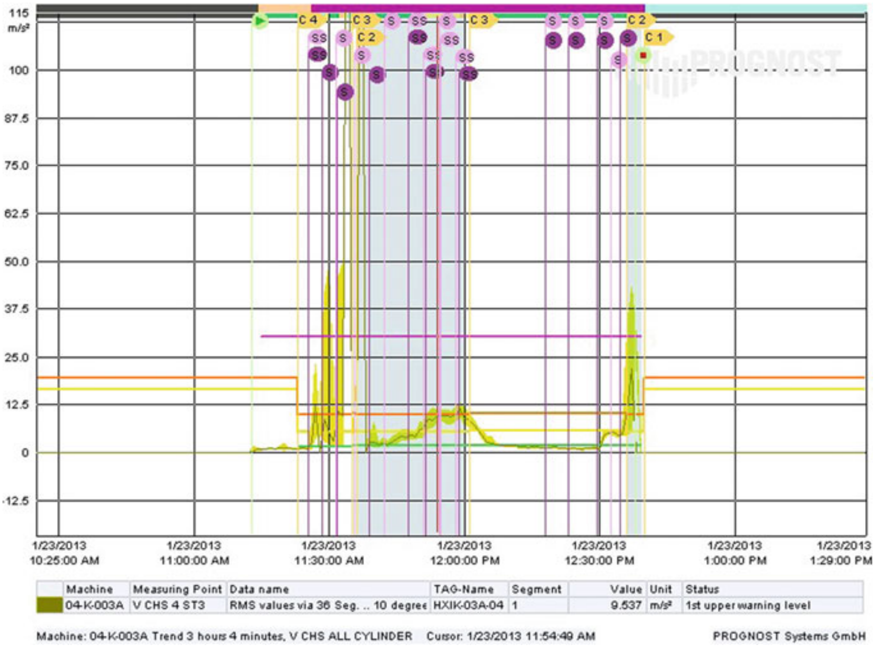

Fig. 11 PROGNOST-NT system 3rd stage crosshead slide vibration RMS trend for the period 23-Jan-2013

crosshead slide vibration on cylinder 4 (third stage) were on a high level and much higher than all other cylinders. Even on other cylinders, e.g. on cylinder 3 high crosshead vibration were recorded and SHUTDOWN alarms were released as well. However the compressor continued to operate since Auto Shutdown feature of MPS had been switched 'OFF'.

After few minutes abnormal sound from the compressor was heard. The compressor was stopped and opened for inspection by the maintenance team. Cross-Head side cover was opened and white metal chips were found. The cross head gudgeon pin was found seized and cross head overheated and burnt. Pictures of damaged parts are shown in Fig. 12. MPS generated warning signals around 20 times for stopping the compressor but the same was ignored by operation team and machine was continued running suspecting false alarm and fearing negative impact on production if stopped unnecessarily

6.3.2 Defect Analysis

The burnt condition of the crosshead indicated lack of lubrication in the crosshead gudgeon pin. Rod reversal allows lubrication to both sides of the cross head pin and the present damaged condition indicated lack of rod reversal in the 3rd stage. The

Fig. 12 Parts of MUG Compressor showing marks of damage

absence of rod reversal in 3rd stage (Cyl 4) during startup resulted in damage of crosshead and high vibration alert. The Hydrocom stepless flow control on the crank end side (CE) of cylinder 4 was unloaded while the head end side was loaded from the beginning of the run at 11:12 am until 12:37 pm. Such a condition is unusual and typically both sides of the piston will be equally loaded to avoid such an unbalanced situation.

6.3.3 Discussion

If the MPS system was on line, this catastrophic failure could have been avoided. Remote expertise could have been accessed using cloud or direct internet resources. The above failure resulted in the replacement of the Crosshead, crosshead shoes, small end bushing, and main bearings along with complete overhauling of the machine. Total approximate cost for the refinery in damage repair of components was INR **5788348** and in Machine overhauling was INR **660000**. In addition the machine was down for 30 days due to non-availability of spares resulting in the plant operating at part load.

6.4 Case Study I (Part 2): Compressor System with MPS Auto-Shutdown 'ON'

In this case, the MPS Auto-Shutdown for the compressor system was kept ON.

6.4.1 Problem Description

On the 23-May-2014, HCU load was at 95% with the Three MUG compressor running with compressor

04-KA-03B at 100% load
04-KA-03A at 50–70% load
04-KA-03C at 50% load

On the morning of 23-05-2014, 9.45 AM, PROGNOST-NT system released several alerts: 'Drive Train Crosshead/Piston Rod/Piston damage', CYL1 ST1 with correlation: 66, 3% and more" in the Cyl 1 stag 1 of 04-KA-003B. At 12.51 pm, PROGNOST-NT system released several safety shutdown alerts for the crosshead vibration of 1^{ST} Stage Cyl 1 of 04-KA-003B.

The crosshead vibration signal of 1^{ST} Stage Cyl 1 of 04-KA-003B showed an increase vibration value of 23.27 m/s^2 from previous recording of 7 m/s^2 (Fig. 13). Normal RMS value for the Crosshead should be below 15 m/s^2.

The PROGNOST-NT system had released several SHUTDOWN alarms for immediate shutdown of the compressor. The vibration trend indicated a major breakdown in the crosshead of 1^{st} stage Cylinder 1 of 04-KA-03B. To analyse the

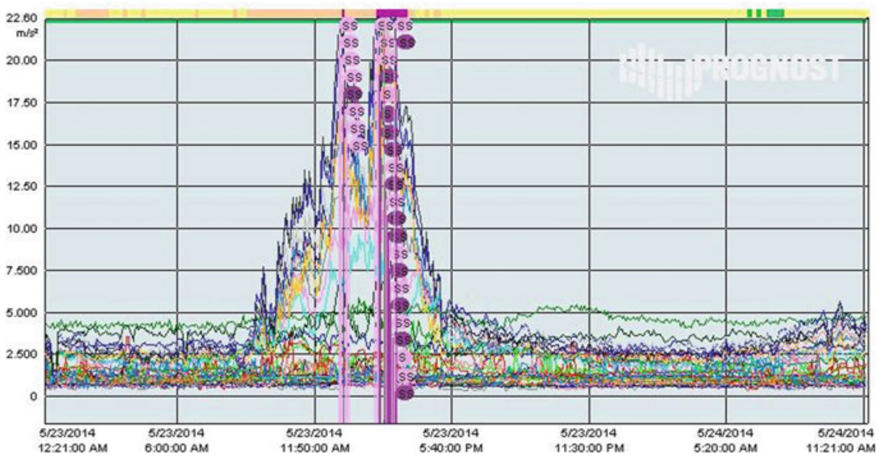

Fig. 13 PROGNOST-NT system 1st stage Cylinder1 crosshead slide vibration RMS trend on 23-May-2014

defect different available trends were analysed from PROGNOST online monitoring system.

The Operation department of NRL reported that no process related abnormality could be recorded in the HCU control room and the trends indicated normalcy in the compressor behavior. No physical abnormality like metallic sound, looseness could be heard. Vibration in Crosshead location in 1st stage Cyl 1 was also checked with offline Vibration Analyzer. The readings were in the range of max 1.8 mm/s and were Normal. The other cylinder readings were also recorded with the Vibration Analyzer and were found to be similar. The ring buffer signals also confirmed that some abnormal vibration signals are being recorded for the VCHS CYL 1 STAGE 1 of 04-KA-03B.

After deliberating with the OEMs of the equipment and PROGNOST, the maintenance team further investigated the issue and the Crank case NDE and DE side vibration signal was trended and analyzed offline. The vibration trend for the period was stable and no abnormal reading was recorded. It was concluded that vibration sensor was generating erroneous data. As anticipated, sensor was found loose and after the tightening of the CHS vibration came down to normal level. There was yet another occasion when a false signal was received due to a faulty sensor. The sensor was replaced and the defect was ruled out after similar analysis.

6.4.2 Discussion

If MPS were online, it would have shut the compressors down resulting in unnecessary production losses. Sudden shutdown of the machine may lead to an emergency situation, if not handled properly may have adverse effect on reactor catalyst leading to catalyst life reduction.

6.4.3 Conclusion

While there are several equipment in a refinery system that may be considered as non-critical and/or having redundancies, there are quite a few process and production critical, large equipment such as the one in this case study. It is essential to prevent catastrophic failures of such equipment that are bound to have large repair costs and time. Hence it may not be prudent to leave preventive shutdown to an automated local safety devise such as MPS discussed in this case study. It was seen in Case Study 1(Part 1) that not having consulted the remote external experts led to the catastrophic failure of the compressor. In the Case Study 1 (Part 2), it was observed that based on consultations with the external domain experts/OEMs, it was found that the fault signals were indeed fault and thus unnecessary interruption of the plant was averted.

Therefore, in the case of process or production critical large equipment, it will be prudent to employ continuous health monitoring by expert agencies although located geographically at distant locations by leveraging the benefits of IIOT and other Industry 4.0 technologies such as Cloud resources and AI. Cost effective solutions can be identified and optimized for such a facility. Any unplanned shutdown of the compressors results in unnecessary production losses. Sudden shutdown of the machine may lead to an emergency situation, if not handled properly may have adverse effect on reactor catalyst leading to catalyst life reduction.

Spurious tripping of 1 no's MUG compressor with three compressor running in NRL Hydrocracker plant would result in plant upset and reduction of load. On the other hand, any spurious tripping of 1 no's MUG compressor with two compressors running in NRL Hydrocracker plant would result in second stage down of the Hydrocracker Unit and in worst case unit shutdown. Hydrogen 2–3 MT (costing around 1.8 Lakhs/MT) in the system will be flared apart from generation of slope and unconverted oil. Hence, continuous monitoring of parameters by external agencies under I4.0 scenario and taking corrective action accordingly will derive value from the technology. Further, organisation will learn from the root cause analysis carried out by external agencies on different conditions.

7 Case Study II: Implementation Requirements for IIOT Based Predictive Maintenance System Under Industry 4.0 in a Remotely Located Petroleum Refinery

In this section, configuring of IIOT based predictive maintenance system as a part of a larger Integrated Business Performance System in a typical remotely located petroleum refinery in North Eastern India will be discussed. The aspects of this system for the refinery would apply for other industries also reasonably well. As suggested earlier, application of Industry 4.0 technology on a business-wide scale is bound to have radical improvements in performance and in redefining the overall business paradigm of remotely located industries. A typical Integrated Business Performance System under Industry 4.0 is shown in Fig. 14.

As it can be seen, the proposed Integrated Business Performance System provides seamless flow of data, practically unrestricted capability for analysis and valuable flow of information to support business operations. With such information integration, dashboards for monitoring and control by senior echelons of the management are also achieved with ease.

The Integrated Business Performance System, as the name suggests, includes all operations of the business enterprise, including business systems and plant systems. Control, Condition Monitoring and Predictive Maintenance will be parts of this overall architecture, taking care of the plant systems.

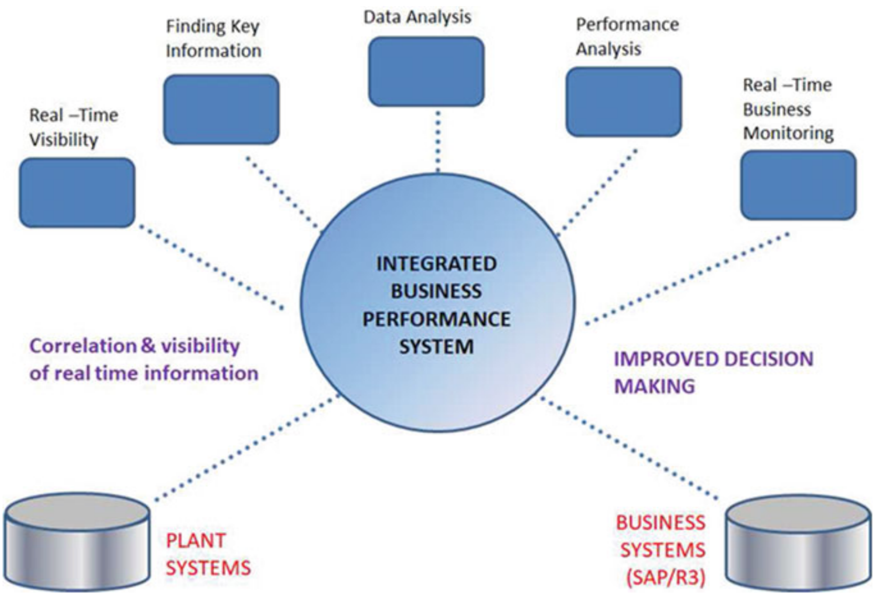

Fig. 14 Integrated business performance system proposed for a typical remotely located petroleum refinery

7.1 Plant Systems

A typical petroleum refinery has more than 4000 rotating equipment such as, pumps, motors, turbines, compressors, blowers and mixtures and over 10,000 static equipment such as, Reactors, Columns, Pressure Vessels, Furnaces, Cooling Towers, Valves, Pressure/temperature Safety valves and steam traps. Monitoring the health of these with conventional operator driven preventive and time based inspection is not sufficient. Legacy systems have always had unexpected breakdowns, long logistic delays and repair times leading to poor utility factor. As partial remedial measures these industries had to maintain large inventories and standby workforce. Industry 4.0 technologies now offer a much needed solution to these plants for providing much higher levels of plant RAMS.

7.2 Predictive Asset Health Monitoring

Monitoring the health of plant systems is fundamental to Predictive Maintenance. Some of the health monitoring objectives under Industry 4.0 for the refinery are as follows:

(i) Reduce the downtime.
(ii) Prediction of potential failure.
(iii) Dashboard for maintenance and Operation staff for monitoring of asset health accessible from mobile as well as in PC.
(iv) Continuously display real-time operational status, running hours, predictions such as Remaining useful life, Time to failure and predictive alerts as they occur and when the as the running states of the equipment changes.
(v) Automated alert actions triggered by maintenance diagnoses from ML predictive analytical platform and equipment Prediction of failures and performance variations.
(vi) Dashboards, Drill Down, unit wise segregation of sensors and equipment.
(vii) Alerts and events.
(viii) The predictive system should have self-learning features for providing real time signature based diagnosis and prognosis.

Coverage of condition monitoring equipment is an important element in the design of monitoring systems. Coverage has two broad implications: the range of equipment and systems to be covered and the number of signatures or parameters to be covered. Typically coverage of following equipment and parameters are some which are envisaged in a petroleum refinery under Industry 4.0:

(i) Steam traps wireless acoustic sensor for immediate failure detection and steam loss KPI monitoring in Power & Utility offsite.
(ii) Pumps, compressors, Air pre heater, Motor& FD/ID Fan monitoring—Pressure, vibration, temperature, bearing temperature in co-relation with other process historian data and analytics.
(iii) Pressure safety valves for Gas leakage monitoring in Utility Area.
(iv) Cooling towers Pump and Gearbox vibration monitoring and prediction of failure along with cooling tower performance monitoring.

With reference to Fig. 14, the outputs that are expected from the asset predictive maintenance framework will be briefly discussed here.

(a) *Asset Performance Indicators Requirement*: As brought out above, there are several equipment in the refinery and multiple KPIs pertaining to each one of them. With remote sensing based architecture including IIOT for Industry 4.0, the number of parameters and equipment under coverage can be significantly increased as shown in Table 2 as compared with legacy systems. KPIs pertaining to typical pumps in the refinery are shown in the table as a sample. Similar lists of KPIs are drawn up for all equipment and systems.

Industry 4.0 technologies not only make measurement and transmission of KPIs in large numbers feasible but also facilitate processing of such large amount of data using Artificial Intelligence (AI)/Machine Learning (ML)/Data Analytics and generate information immensely useful for predictive maintenance. The role of these technologies will also be leveraged to ensure integrity of data and reliability of information so generated.

Table 2 Comparison of parameters (KPIs) that is available continuously in legacy systems and Industry 4.0 compatible systems in remote sensing based coverage including IIOT in the refinery

Legacy systems with manual recording	Industry 4.0 compatible systems under remote sensing including IIOT
a. Measurements (periodic recording) i. Number of operating hours ii. Pressure (input & output) iii. Temperature (input & output) b. Manual Computations or using hand held equipment i. Delivery head ii. Electrical power	a. Measurements (defined as time series) i. Number of operating hours ii. Motor current iii. Pressure (input & output) iv. Flow (input & output) v. Temperature (input & output) vi. Vibration (for major & critical pumps) b. Direct Computations (defined as time series) i. Delivery head ii. Electrical power c. KPIs average i. Average current during ON stages d. KPIs consumption i. Energy consumption ii. Flow e. KPIs efficiency i. Total efficiency ii. Ratio energy/flow = Energy performance indicator iii. Ratio cost/flow = Financial performance indicator iv. Savings if operated with variable speed drive f. KPIs deviation to design i. Deviation to design power ii. Deviation to nominal flow iii. Deviation to nominal head iv. Deviation to optimal efficiency

Connected with the above requirement of measurement and display of information following features are also included with the aid of technologies such as AI and ML:

(i) Equipment and System Diagnosis
(ii) Dashboard for maintenance engineers.

Typically following are some of the features that will also be included in the dashboard:

- Remaining Useful Life.
- Remaining Useful Life (% of Expected Life) with Age and installation date,
- Time to Failure Prediction within a given time window.
- Survival models for the prediction of failure probability over time.
- MTBF. MTTR, OEE, open work orders.
- Short and detailed report about equipment health to be made accessible from web and mobile devices with maintenance recommendations.

- Figures from Operational metrics such as motor run-hours, no of starts/stops, Ambient temperature and wet bulb temperature and Humidity.
- Spare parts material code and no should be linked with sap current stock availability.
- Pattern recognition or other machine learning techniques for detecting anomalies/predicting failures.
- Performance correlated to a slowly degrading metric—Temperature Bearings Motor windings, Pressure or Delta P of plugging filters in pump, Vibration, amplitude, discharge pressure variation over a time period with same load etc. to be compared in the platform in real time in streaming model.
- All key personnel to be alerted on their mobile device and email about overall Asset health score or developing problems in critical assets when threshold is breached.

(b) *Asset deterioration curves*: Following are some of the features of degradation that are considered in modelling and presentation of results:

- Speed Reduction from Design RPM at rated power
- Design Discharge Pressure versus Actual Discharge Pressure
- Temp Difference between Bearing temp and Ambient Temp in time series
- Difference between (Discharge Pressure—Inlet Pressure) in time series
- Number of times the temp exceeds a threshold value over a number of days
- Peak and RMS value Vibration Pattern over a period (Say In last 10 Days)
- FFT plot reading from Raw feed of vibration sensor in a time period
- Moving Average Voltage and Current drawn over a time series points
- Use feature cross and Static data and frequently updated data
- Remove highly co related and duplicate features in feature engineering
- Degradation pattern in speed, efficiency, pressure, load, heat, noise etc. to be tracked and monitored.

(c) *Asset survival simulation*: Following are some of the simulation that are undertaken as decision support for refinery maintenance team:

- Effects of various asset maintenance scenarios
- Probability of an asset that survive beyond a given time
- Prediction of failure probability in a certain given interval of time.

(d) *Predictive maintenance interventions/recommendations*: The feature provides predictions about the assets at greatest risk of impending failure, so shifting the maintenance regime from fail-and-fix to predict-and-prevent by issuing work order, schedule maintenance rules (alarm, alert or maintenance call). The technical scope of a predictive maintenance decision support platform for a typical refinery under Industry 4.0 envisages a vast domain.

Some of the major technical requirements of such a predictive maintenance decision platform are as follows:

- Fixing and monitoring of KPIs of Throughput, Yield/Production, Profitability, Cost, Target vs Actual Scenario, historical performance, Equipment Overall Efficiency, Health Indices, Probability of failure calculations, Reliability modelling, Failure Reasons, Reliability parameters MTBF/MTTR calculation, trends, spares consumptions, and performance curves of equipment integrated with notifications
- Real Time Performance Based Surveillance based on Stability Modelling for any process and equipment parameter and performance curve
- Root Cause Analysis with integration of relevant data
- Automation of plant-wide repository for all corrective and preventive action taken
- Provision of an analytical platform that can provide a foundation of capability within the refinery for application of Statistics, Data Mining, Reliability, Survival, Discrete Event Simulation, optimisation capabilities to generate in-plant solutions by the utilization of huge amount of data collected
- Provision of tools to track the effectiveness of maintenance
- Provisioning for predictive, prescriptive of cognitive analytics. It should have ANN libraries for image processing, Deep Neural Net, SVM, CNN and all traditional ML algorithms
- Provisioning connectivity to DCS and SCADA systems through open protocols like OPC.

Data set for predictive maintenance of assets: The nature and quantity of data required for predictive maintenance analysis would differ from one application to another. For the case of a refinery, some major categories of data that would be necessary are as follows:-

- Static Data—Equipment Make, Model, Configuration, best practices and OEM recommendations
- Frequently Updated Data & Usage History: Age of asset in days, failure history and the preventive maintenance schedules of assets, KPIs for asset performance tracking
- Maintenance Data: Maintenance/breakdown details, service history
- Time series Data: KPIs that are needed as function of time
- Feature Engineering: Collection of data which are collated in the form of averages, linked data (such as ambient temperature, bearing temperature and vibration) in order to draw better inferences about the health of machinery.

In addition to the above basic structure of Predictive Maintenance Framework, following are some of the major features that are included in a predictive maintenance decision framework for better technology and resource utilisation and enterprise level outcomes:

(i) Asset data mapping and modelling: Mapping of operational, environmental, historical and age related data are done for generating information that point more precisely to equipment/system health. This data mapping can support

Table 3 Sample asset score

Asset Score	Status
9–10	Good
6–8.9	Close monitoring
3–5.9	Action required
0–2.9	Danger

regression models (for predicting RUL, failure time), classification models to predict failure within a given time window, models for flagging anomalous behaviour, Survival models for the prediction of failure probability over time.

(ii) Machine learning based asset health score in dashboard: Using tools of AI and ML, the decision support system can generate certain scores representing the health an equipment or system. This information, when available in the platform for access by maintenance team or on the dashboard for senior management, can serve as a valuable decision making tool.
A sample asset score is shown in Table 3:

(iii) Operational & enterprise reporting automation and dashboards: One of the important requirements of a Predictive Maintenance Decision Support System under Industry 4.0 is a very versatile and rich reporting system. The reports range from direct real time recorded data, data from direct computations, alarms, trends, diagnosis, maintenance reports and dashboard summaries. In order that the benefits of such a decision support system is fully realised, it is necessary to devote adequate attention to the development and configuration of dashboards, HMIs and other reporting mechanisms. For example, a dashboard vibration analysis of typical rotating equipment in a refinery will present the following:

- Time, Frequency Domain Analysis and Phase Analysis
- Bode Plot, Waterfall Plot, Polar Plot, Orbit time base plot
- Enhanced fast Fourier transform
- Constant percentage bandwidth (CPB) and Selective envelope detection (SED)
- Vibration Trend Analysis
- Vibration Spectra and Time waveform Analysis
- Detection of bearing fault harmonics (BPFO/BPFI harmonics) by suitable anomaly detection technique or referring to fault frequency database
- Waterfall full spectrum
- Vibration severity recommendations as per ISO 10816 and ISO 13373.

(iv) Cyber security requirements: The platform is normally developed based on industry-standard, secure software development practices. Implementation of cyber security best practices in accordance to international IT and OT standards (ISO 27001, IEC 62443, NIST SP 800 etc.) are complied with for better inter-operability as well as to ensure integrity and security of data. Necessary safeguards specific to the plant and user department are also built in. However care is to be exercised to ensure that utility of the system and ease of operation is not hampered while instituting security measures.

(v) Safety Requirements: It is needless to state that the system as complex, critical and expensive as the Integrated Business Performance System should have all safeguards against hazardous material in the refinery, electric hazards, fire, vibration and mechanical shock or impact.

7.3 Suggested IIOT Architecture for a Refinery

Based on the foregoing discussions, a suggested architecture for a petroleum refinery is shown in Fig. 15. IIOT based sensors as well as conventional sensing equipment pick up signals from operating equipment and systems in two independent distillation units. The signals are transmitted through a set of switches and gateways to dual redundant cabling, firewalls and then to cloud based and remote infrastructure. Control signals are also sent to the distilling plants through the same network.

7.4 Conclusion

In modern refining practice where reliability, availability, productivity and foremost safety are the main point of concern, traditional operator driven approach has its draw backs to meet all these criteria fully. So modern approach of IIOT based Industry 4.0 techniques will definitely help to improve the plant's safety and reliability along with other production related parameters. In order to achieve the same, it is necessary to employ Industry 4.0 technologies in a comprehensive, optimal and plant-wide manner as brought out earlier in this chapter and also in the above case study. While it would be desirable to have high-intelligence and complicated-automation in maintenance as brought out in Sect. 2.1, constraints such as intial/recurring costs and human resources/factors need to be borne in mind while finalising the scope for the PdM 4.0 systems.

7.5 Future Work for Implementation of IIOT Based Industry 4.0

Knowhow of IIOT based Industry 4.0 is in itself a challenge. Training of management and operators is a first step of the implementation process. To reap the benefits out of the system the detail engineering part can be outsourced to agencies with expertise in data acquisition and processing technologies. Software Solution

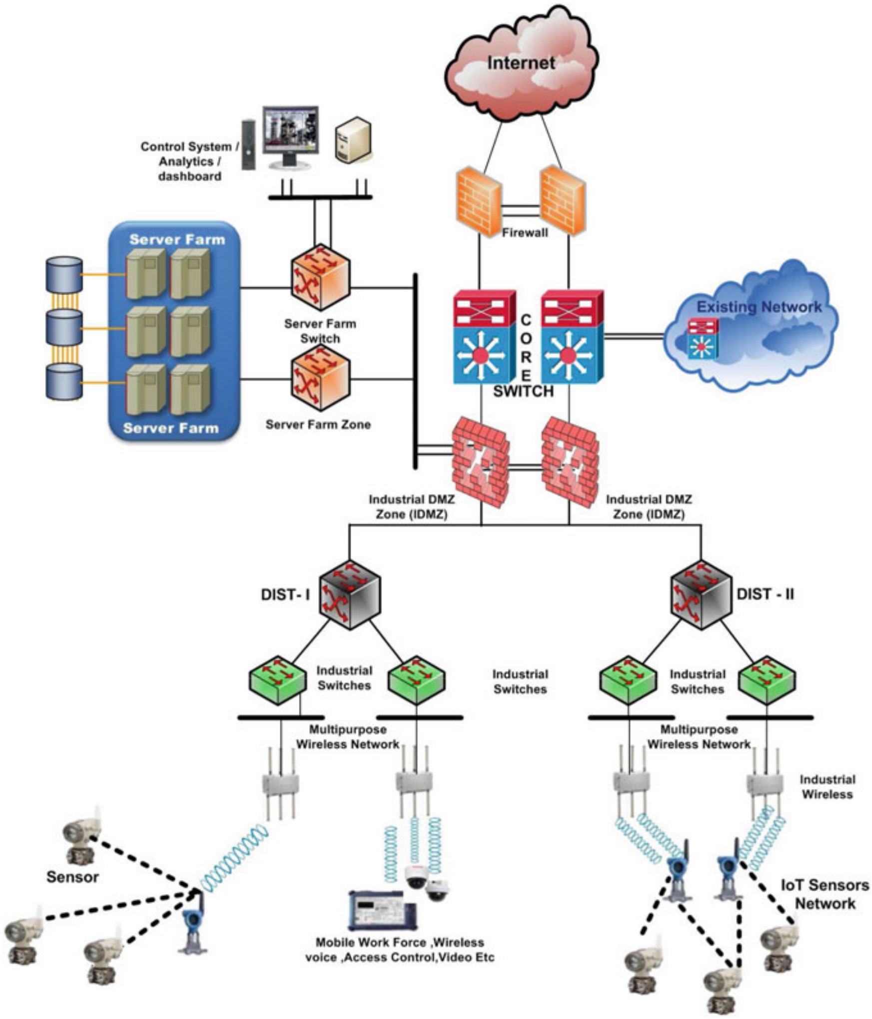

Fig. 15 Suggested IIOT architecture for a refinery

providers in the market can come up with the complete solution and customised packs as per requirement of plant management. The various milestones are described below:

(i) Identification of the requirements- Identification of the critical assets which we want to monitor remotely.
(ii) Choosing the technology-As mentioned earlier, there are service provider companies who can provide various sensors technologies, data acquisition, processing and presentation techniques for IIOT based Industry 4.0.

(iii) The plant management will choose the right technology and train its employees on it.
(iv) Post implementation, it will be necessary to institutionalise maintenance of the system and validation of data as per actual situation.

8 Conclusion

Industry 4.0 is being adopted by manufacturing and process industries in keeping with the global industrial and research trends. Maintenance, as an indispensable element of industrial operations, will also have to align its practices, hardware and frameworks in line with this global trend in order that industries reap the full benefit of Industry 4.0. There is a large dispersion between countries, regions and sectors when it comes to the extent of implementation of Industry 4.0. This dispersions will reduce with greater acceptability and readiness for the constituent technologies on the part of industries worldwide. However, it is amply evident that a comprehensive implementation of Industry 4.0 leveraging all relevant technologies will provide immense mileage that can truly be called the fourth Industrial Revolution. In this chapter, unique considerations for maintenance management of those manufacturing and process plants that are located remotely are discussed. Such remote locations come with an array of challenges which can be effectively handled with the advent of Industry 4.0. Further, application of Industry 4.0 in maintenance is not only desirable but also indispensable for industries to remain competitive. Transition to Predictive Maintenance Under Industry 4.0 (PdM 4.0), especially in respect of legacy systems is a universal challenge and needs to be handled appropriately as also discussed in this chapter. Case studies presented in this chapter highlight the benefits of using technologies of Industry 4.0 such as IIOT, AI, Cloud resources and Automation for better RAMS and hence increased productivity and competitiveness.

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