Embedded intelligence supporting predictive asset management in the energy sector

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Abstract

In recent years and across a myriad of industries, there has been a realisation that in order to optimise the Remaining Useful Life (RUL) of assets and to maintain optimal system level performance whilst assets age and at times with growing and dynamic loading demands, a transition to predictive maintenance from reactive and traditional condition based monitoring and maintenance is required to achieve return of investment (ROI) and performance targets. A sector driven by security and a need to defer investment within the asset base is the Energy sector. After a brief introduction to maintenance process's in the oil and gas domain, this paper presents a novel approach to hierarchical predictive maintenance of assets in through a distributed architecture, represented as domain knowledge-based system, that provides a viable solution for systems containing similar multiple assets

1 Introduction

Year-round energy industry fields require the routine and permanent presence of a condition and performance monitoring (CPM) system [1], designed to maximise production uptime and asset availability. CPM systems respond to the asset manager's need to continuously demonstrate 'fitness for service'; and improve understanding of asset condition, which obviously support the decision making process for de-rating, process optimisation and scheduling for remediation and rectification task. Furthermore, there is also a requirement to provide enough evidence based knowledge to support the extension of the design life of components, and justifications tie with brown fields.

In addition, technological improvements have allowed oil and gas developments to emerge into deep and ultra-deep waters [2][3], introducing an operating environment not encountered in shallow water. Following this trend, it is essential to understand the various uncertainties associated with operation in these new environments, and accept full accountability for the economic consequences. Subsea well system repairs and interventions also become more expensive and are associated with longer delays due to availability and mobilization times for required intervention vessels, particularly in ultra-deep water environments.

The short and long term effectiveness and efficiency of the maintenance management and undertaken maintenance activities affect directly key performance indicators, KPIs, such as

1. Availability. How many assets are ready for operation?
2. Reliability. Maintenance should be the number one priority to ensure reliability, as it has been considered key to successful subsea operation in the oil and gas sector.
3. Life Cycle Costs. A neglected maintenance service is more expensive as the failing equipment needs to be replaced, reducing the life cycle of the equipment and increasing their cost. The main target is to optimize the schedule maintenance service and the cost needs for life cycle of asset considering the failures per equipment per time of operation.
4. Safety. The safety parameters of assets need to fulfil the safety standard and these parameters have to be defined for all assets. It is needed to measure all safety parameter per asset per maintenance level and after repair. The asset is available for operation if this measurement is 0%.
5. Asset Manager Satisfaction. A more effective and long lasting maintenance will have a direct impact on the asset manager satisfaction, as the asset availability is affected by the status monitoring and maintenance of the equipment.

To better manage these KPIs and support asset managers with a systematic work process for successfully managing technical risk and uncertainties, this paper presents a knowledge representation framework for end-to-end intelligent asset maintenance system and process, and presents groundwork developing a maintenance knowledge-based model describing the oil and gas environment and similar industrial scenarios.

2 Maintenance processes in the oil and gas industry

Maintenance of complex industrial assets, such as FPSO processing facilities, underwater wells, pipelines etc. is a complicated and important task. Current and future maintenance activities include methods such as scheduled, on-condition monitoring, and predictive maintenance. Figure

1 illustrates briefly the different types of maintenance and the flow of actions for each one [4].

Traditionally, maintenance is performed based on a time, usually related to safety critical items like valves and ESD system condition. During this maintenance regime, records

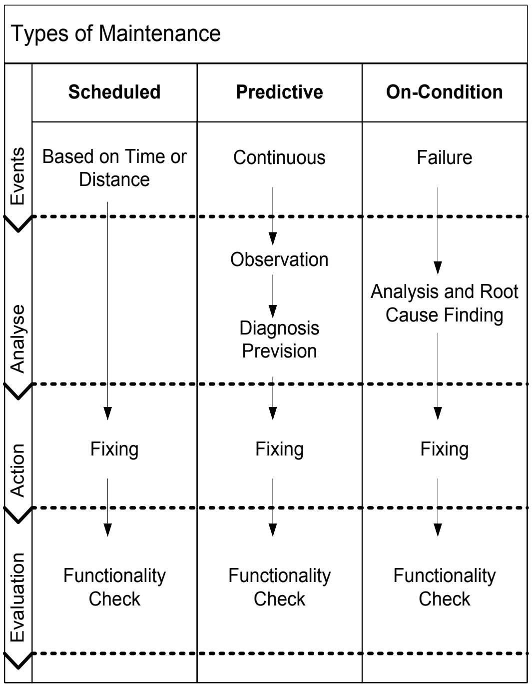

Figure 1 Types of maintenance and their succession of events

from all assets must be kept and stored efficiently. This task is time consuming unless a modern well system control and data gathering system is available. There is also the fact that an asset will deteriorate just as quickly if it is unused as it would if it was being operated every day. Only the items which deteriorate will vary. Condition monitoring is achieved by checking the operation of the equipment and only changing something if it shows signs of wear beyond pre-set limits. The checking is often done using on-board monitoring and storing the data gathered in a computer system for downloading at the maintenance facility. Unlike condition monitoring systems, predictive maintenance is directed to analysis of current equipment state with the object to reveal some possible emerging problems, thus preventing failures via adjustment of parameters, change of parts, tuning, etc. beforehand, and it leads to lower expenses for device maintenance, because failures can damage devices severely sometimes.

The predictive maintenance regime requires access to the condition of the assets, by not only looking at the data, but also at the knowledge that can be extracted from these data. Embedded decision making agents that contain reasoning algorithms can optimise the long term management of heterogeneous assets and provide fast dynamic response to events by autonomously coupling resource capabilities with alarms in real time.

The problem, however, is that, at present, CPM applications are mono-domain, targeting only system (i.e. flowlines, or control systems), and therefore it leaves the platforms in isolation and limits the potential of multiple coordinated actions between adaptive collaborative systems.

In a standard information flow, the main use of the data acquisition systems is to gather information from sensor data. In order for embedded tools to support the decision making process and interoperate, it is necessary that they have the capability of dealing with and understanding the highly dynamic and complex environment where these networks are going to operate. These decision support tool are therefore constrained to the quality and scope of the available information.

Shared knowledge representation between embedded tools is therefore necessary to provide them with the required common situation awareness. Two sources can provide this type of information: the domain knowledge extracted from the expert and the inferred knowledge form the processed sensor data. In both cases, it will be necessary for the information to be stored, accessed and shared efficiently by the deliberative agents in ‘near’ real time. These agents, providing different capabilities and working in collaboration, might even be distributed among the different platforms or sharing some limited resources.

3 Data flow in maintenance processes

Since maintenance-related processes rely on relevant information, comprehensive and timely information delivery from the embedded data gathering systems to the individuals involved in the maintenance can significantly benefit the process. This makes automated maintenance system, which can integrate maintenance-related information from many sources, highly desired in order to give appropriate maintenance support. All these variety of data contributing to the maintenance process are represented in the data flow illustrated in Figure 2, which represents the typical life cycle of maintenance activities [4].

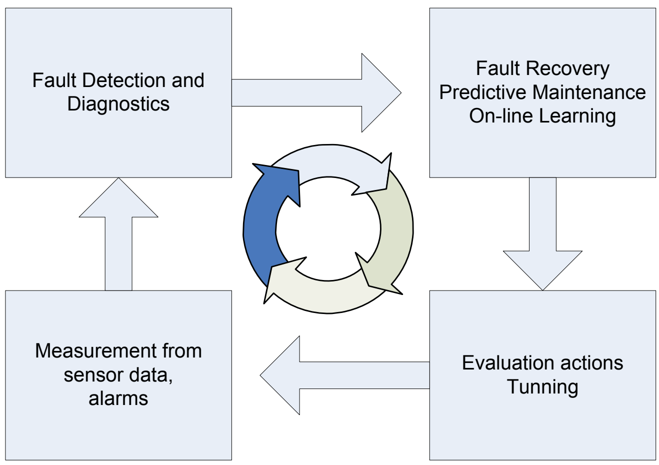

Figure 2 Flow diagram of maintenance processes

Looking at the maintenance environment, the knowledge is embraced by interactions among systems, system observers, observables, engineering objects and instruments, and the complex system interactions must be dispatched into infrastructural layers based on knowledge system, which must be dedicated to human and data communications. The collective vocabularies must be associated with the communication crossing the layers in the problem solving environment. This synthesis of information would impact on knowledge technologies employed today for solving engineering problems encountered in the maintenance domain.

4 Knowledge-based system for maintenance domain

Maintenance as any other engineering process is a human effort to change or facilitate a kind of environment in order to make that environment more suitable or responsive to perceived human needs and wants. Such an effort results many kinds of physical outputs; it may define, design, develop or maintain a system. Many actors take part in engineering. One group are engineers; others are managers; still others are ones who create artefacts such as numerical models according to specifications. Much knowledge is derived from human observations, designs and experiments. They all only know what they know when they need to know it. From a computing perspective, there must be a knowledge management, which encapsulate its meta-systems in whatever forms showing how knowledge is grounded from a level of engineering to a level of business organization that manages the engineering processes.

Knowledge-based system enables logical extensions to be made to integrate information. Therefore, the knowledge concept is given a special attention in this paper, as it is considered a driving element of the intelligent maintenance system. Starting from the basic definition of knowledge-based system, this task abstracts and extends it in the maintenance domain for the oil and gas. Possibly this knowledge system should be constructed with a number of different layers to represent different aspects of the system as maintenance activities.

The main objective of this work is to establish the knowledge-based system of the maintenance domain in a coherent infrastructure interacting with humans, systems, data, devices, communications, objects to achieve or problems to solve, as well as tools that support all this, including computers, web, and data networks.

Before establishing the main requirements for the maintenance knowledge-based system in a coherent infrastructure for all involved interaction, some aspects and systematic concepts need to be considered.

- There is no one correct way to model a domain— there are always viable alternatives. The best solution almost always depends on the application and the possible extensions.
- Development of the knowledge-based system is necessarily an iterative process.
- Concepts in the system should be close to objects (physical or logical) and relationships in the domain of interest, e.g. asset maintenance domain. These are most likely to be nouns (objects) or verbs (relationships) in sentences that describe the domain.

In other words, deciding the use of the knowledge-based system, and how detailed or general the system is going to be will guide many of the modelling decisions. Among several viable alternatives, one aspect will be determined to work better for the projected task, be more intuitive, more extensible, and more maintainable. Furthermore, the knowledge-based system is a model of reality of the world and the concepts in the system must reflect this reality. After the initial version of the knowledge-based system is defined, it will be evaluated and debugged it by using it in applications or problem-solving methods or by discussing it with experts in the field, or both. As a result, the initial model will be revised. This process of iterative design will likely continue through the entire lifecycle of the knowledge-based system.

4.1 Model for predictive maintenance

As it has been discussed, predictive maintenance for assets in the oil and gas environment is a knowledge intensive task, usually performed or supervised by human experts. The primary objective of a predictive maintenance process is to improve equipment reliability by identifying problems before they cause failures, further damage and increase the cost of the asset. The secondary objective is to provide advance warning of developing problems before these equipment fail catastrophically during a production run. In other words, its goal is predicting when and what maintenance actions are due in order to avoid an unexpected breakdown of the system. Considering all aspects involved in the realization of the predictive maintenance, Figure 3 illustrates all inputs and outputs considered in the intelligent maintenance process of a system.

The results from the embedded tools, annotated sensor data, serve as an input for the prediction and diagnostic task to produce optimum fault detection. The output from diagnostic and prediction serve as input to the planning task involving sub-tasks such fault recovery and on-line learning, if it is adequate. The different tasks described in Figure 3 and their decomposition into subtasks can be used as the basis for constructing the model. If a list of knowledge roles, which serve as input/output in these tasks, is formulated, the most important ones, which can be taken by different knowledge types (domain concepts, relations or rules), are:

- Parameter. A measured or calculated quantity whose value can detect abnormal behaviour
- Source. Something that can be observed or detected.
- Symptom. A negative source.
- Norm. Expected values of a parameter for normal condition

- Discrepancy. A quantified difference to the norm.
- Fault. Cause of symptom
- Location. Where a symptom or fault is found
- Action. An activity to eliminate a fault or to improve situation.

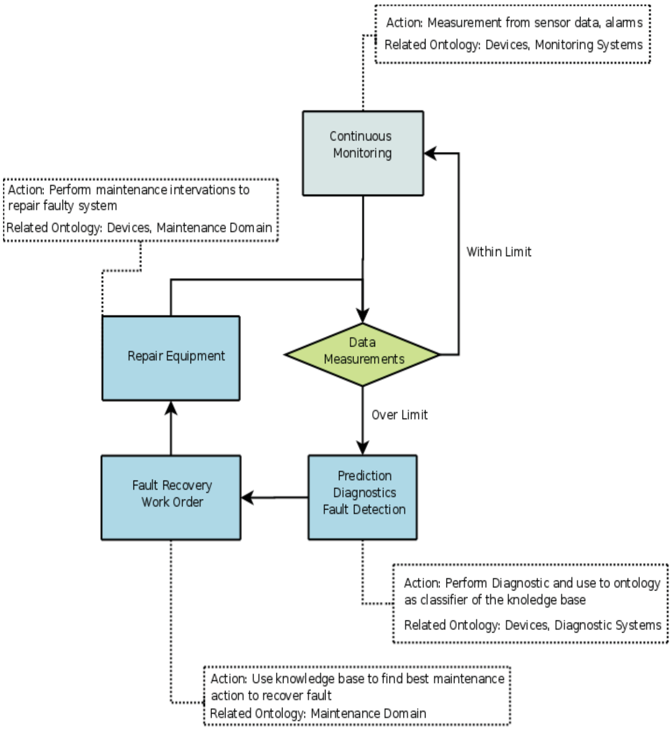

Figure 3 Inputs and outputs involved in predictive maintenance

These knowledge roles could represent the meta-concepts in the knowledge-based system, and they will express the relation task-domain (fault detection – well system). As it can be observed in Figure 3, several domain knowledge models (i.e. ontologies [5][6]) can be constructed for the scenario maintenance of the oil and gas environment. One could be the model of the wells, other one could encapsulate the maintenance activities, fault detection and diagnostic could be described in a different model, and so on. These models are defined as the domain models, which represent knowledge of the domain independently of their use. However, the application of the predictive maintenance knowledge-based model will employ existing domain models using concepts and relations from these models to optimize the knowledge transfer.

It is on these layers of domain models where data are collected, distributed and measured, reports are circulated; and groups are participating and communicating with one another. Data in a physics based infrastructure cannot be explained merely as a consequence of a differing coherence of an assertion. They depend on who makes the assertion, where the sensors are situated, where the data are channeled, how the data are stored and filtered, or what methods are used to understand and explain an observed phenomenon. Therefore, the knowledge-based system is systematically constrained by the physics based infrastructure. The priori knowledge for the model design must be closely inherent to understandings of physical systems, as well as practical experience with the systems. A problem solving process for a given application can then be supported by the "content" of the priori system information. Another interactive layer is human oriented.

An engine's maintenance is no longer just a traditional event of a repair – call an engineer in with parts and tools to fix it. It is a matter of how to detect the first sign from the engine, so something is known priority if there is a need for preventing the "disasters". Engineers can properly analyze equipment failures and forecast the probability of the same equipment failing in the same asset or other units, or undertake the processes, such as data collection, data clustering, testing, fault or defect diagnosis, planning spare parts, making recommendations, reporting major factors affecting a system' s life, all in a technical and timely manner. All layers are meaningful and usable only when a system observer participants in a particular communication. Whether a maintenance engineer can exploit in elliptical or anaphoric resolution is depending in part on the role that the engineer has most recently played in the communication in the physics-based infrastructure.

The domain model is a description of real-world things of interest and consists of a set of conceptual classes, their associations and attributes modelled with knowledge-based class descriptions. In the case of assets in the oil and gas domain, the domain model consists of faults that can be caused other faults. A transient fault can be defined as failure event, while a permanent fault is described by a failure event. Furthermore, a condition monitoring methods are employed to predict failure states, and triggers a predictive action. Predictive maintenance action can be classified as a subclass of a proactive maintenance type similar to a scheduled maintenance action. Proactive maintenance action reduces possibility of a fault. In case of a failure state, reactive maintenance action, or on-condition, restores the system state to normal. Proactive and reactive maintenance actions are subclasses of maintenance actions. All these concepts related to the asset maintenance domain are illustrated in Figure 4, and it can represent the initial knowledge model to anchor the collaborative approach in the knowledge model design.

The key concept of this model is the *MaintenanceType,* which is triggered from the occurrence of fault, and depending on the nature of the fault (*ExistingFault* or *IncipientFault*) the maintenance type is classified into two different and disjoint *CorrectiveMaintenance* or *PredictiveMaintenance.* Associated to each *MaintenanceType* individual, there is a *WorkOrder*, which lists the variety of *MaintenanceActivity* that are necessary to recover or repair the fault. The main relationships associating these concepts are:

- *Fault RequiresMaintenanceType MaintenanceType*
- *MaintenanceType hasWorkOrder WorkOrder*
- *WorkOrder hasFirstMaintenanceActivity MaintenanceActivity*

- *MaintenanceActivity hasNextMaintenanceActivity MaintenanceActivity*

As part of the collaborative design process of the knowledge-based model, feedback can be taken from several participants. It can be considered that the sub classification of the maintenance actions to proactive and on-condition is unnecessary, as these options can be represented as instances of the maintenance action class. Furthermore, the maintenance schedule could be associated to the respective maintenance actions.

The main objective of condition monitoring techniques is to predict at least on failure state, but the condition monitoring method could not trigger any maintenance action. The condition monitoring is associated with some limited number of failures, and only the failures can be prevented by the maintenance action. Also, each failure state could not be associated with a condition monitoring method.

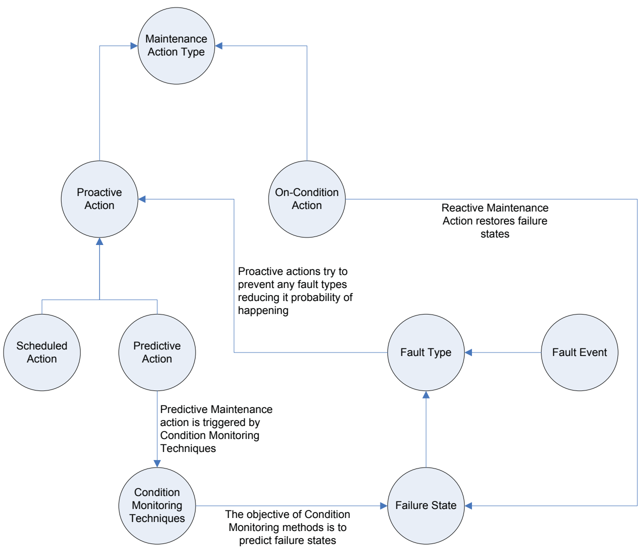

Figure 4 Initial knowledge-based domain model for predictive maintenance

Looking at Figure 4, there could be some doubts about the differences between the failure state and failure event. A fault is a possibility for or an existence of a failure event or state. However, an event is really a state change of some system. Therefore, an event can be described with the resulting state or a state with the causing event. Potential events of interest affecting assets in the oil and gas domain in the shape of a FMEA is depicted in Table 1

Event	Effect Duration	Event Duration	Occurrence
Fatigue	Dynamic, Vibration	Continuous	Continuous
Excessive loading	Static, Quasi-Static, Dynamic	Short or Continuous	Sudden
Shock loading	Vibration	Quick	Sudden
Force monitoring	Static, Quasi-Static, Dynamic	Change, Drift	Continuous
Shape monitoring	Static	Long	Regular
Third party interference	Dynamic, Vibration	Quick, Change	Sudden
Fluid properties	Static, Quasi-Static, Dynamic	Change	Sudden
Leak	Dynamic, Vibration	Change	Sudden

Table 1 Characteristics of events and effects considered in the knowledge-based model

5 System Architecture

This knowledge-based system should be constructed with a number of different layers to represent different aspects of the system, for information integrating for intelligent monitoring, which is founded on a multi-tier architecture and a common terminology based on knowledge-based system. Figure 5 shows the architecture for information integration. From bottom to top there is an abstraction and aggregation process in place, which abstracts from low-level, proprietary information to higher-level information, which is enriched by the semantics embedded in the knowledge-based model.

- Real-World Information. The bottom layer accesses real-world data, which is acquired from sensors or whose digital representation is stored in databases (e.g. in some database of the domain stakeholder, in Geo Information Systems, or also on the Web). The key challenge for data acquisition and later integration on this layer is heterogeneity.
- Semantic Transformation. On the second layer software parsers and adapters are located, which transform the real-world information into a common language. The output of the diverse software parsers and adapters is stored in the distributed repositories. It is important that the semantics of this generated data (relations and properties of referenced objects) is described consistently with the predictive maintenance domain model.

- Aggregation & Persistence. On the aggregation and persistence layer, repositories and databases are integrated, and with them the distributed information as well.
- Predictive Maintenance Domain Model. This model represents an XML-based data model, which uses description logics for specifying the terminology of the predictive maintenance domain, as well as oil and gas domain.
- Distributed Reasoning [7]. The distributed reasoning layer comprises so-called reasoners, which is described as a software-based inference engine that analyses and interprets information by deriving additional data using description logic.
- Intelligent Services. On the top layer application, services and so-called maintenance agents are located, which are software agents, that can autonomously collaborate with each other in order to analyse certain fault situations and in order to support in corresponding decision making tasks (e.g. predictive maintenance: when to generated a maintenance working order for an asset based on symptom analysis).

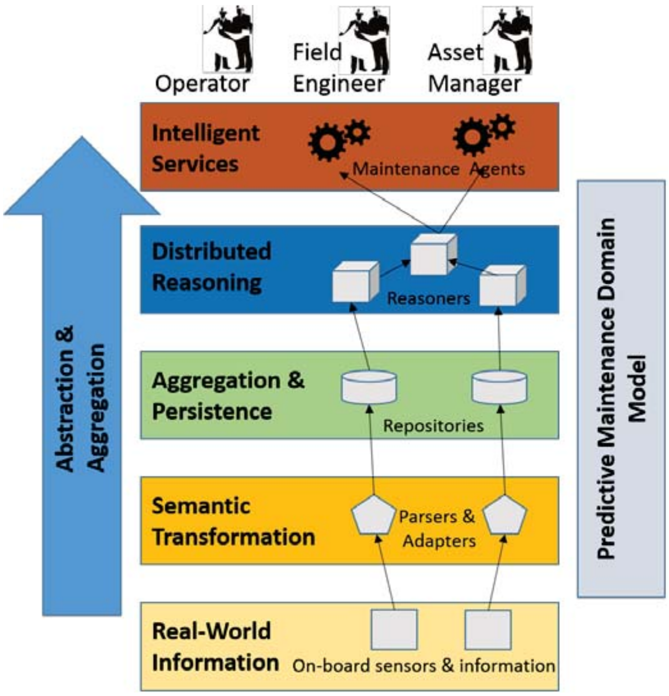

Figure 5 Layered architecture for integrating distributed monitoring data

4 Conclusions

A novel approach to hierarchical predictive maintenance of assets in the oil and gas domain has been outlined. Through a distributed architecture, represented as domain knowledge-based system, it provides a viable solution for systems containing similar multiple assets. The domain model represents models of many aspects of the system (including a physical decomposition among others) and maps to Key Performance Indicators (KPI's). The approach allows fault diagnosis from intelligent embedded tools to be performed at different levels within the oil and gas distributed system and the most appropriate modeling choices to be used for particular problems. The abstract nature of the models reduces the computational overheads, and therefore the models could be implemented at the lowest level in a decentralized approach. The combination of quantitative and qualitative fault diagnoses will allow a greater range of system faults to be tackled. Therefore, a maintenance engineer will benefit greatly from an automated maintenance system, which can integrate maintenance-related information from many sources, such sensor data, design information, diagnostic output from on-board diagnostic systems, thus providing appropriate maintenance support

Furthermore, one of the benefits of the approach presented here is the extended querying that it provides, even across heterogeneous data systems. The meta-knowledge within an knowledge-based system can assist an intelligent search engine with processing your query. Part of this intelligent processing is due to the capability of reasoning that makes possible the publication of machine understandable meta-data, opening opportunities for automated information processing and analysis. For instance a diagnostic system, using a model of the system, could automatically perform a root cause analysis, suggesting the location of a fault in relation to the happening of symptoms and alarms in the system. The system may not even have a specific sensor in that location, and the fault may not even be categorised in a fault tree. The reasoning interactions within the model are provided by the intelligent embedded tools, which enables the domain's logic to be specified with respect to the context model and executed to the corresponding knowledge, i.e. the instances of the model.

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