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Reducing maintenance cost through effective prediction analysis and process integration

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Asset management is playing an ever increasing role in sustaining the competitive capability of many businesses. Maintenance costs form a large proportion of asset management costs, and a reduction in these costs can represent significant savings to the business. Many software vendors provide various asset management solutions but lack complete horizontal and vertical integration. And with the sizeable number of systems come an equal number of software interfaces. With businesses that subscribe to different CMMS and condition monitoring systems from different vendors, system integration becomes a nightmare. By resolving the integration issue and considering holistic information, asset management can ascend to a new level through effective predictive maintenance. This paper outlines a proposal for integrating condition monitoring systems with a CMMS through the use of emerging technologies. The OSA-CBM framework will be implemented to monitor the condition of an asset for health assessment and predictive maintenance scheduling. Data will be stored in a MIMOSA-derived database, with communications between the OSA-CBM system and CMMS using the open standard MIMOSA OSA-EAI. The underlying foundation is a web services platform which will assist in turning asset condition data into real cost savings.

1. Introduction

The last 30 years has seen the emergence of software products that provide management support for nearly every business area. Enterprise Resource Planning (ERP) systems typically form the core informational systems in most corporations, and Computerised Maintenance Management Systems (CMMS) have been openly embraced by many industries to manage asset maintenance. With maintenance comprising a large portion of the asset lifecycle budget, using enterprise systems to streamline maintenance activities can deliver tangible bottom-line benefits to asset intensive organisations.

Compared with reactive maintenance, condition-based (or predictive) maintenance demonstrates considerable advantages and has become the pioneering maintenance strategy in practice. When assets are critical in the business process chain, condition monitoring is a necessity for the delivery of effective preventive maintenance. In many cases, condition monitoring produces an overwhelming amount of data which is not utilised effectively. Often reporting is confined to immediate condition information, for example, that an asset is in an unhealthy state as it has crossed an alarm threshold. However, this same data can also provide a valuable insight into predicting asset health progression. By employing novel techniques, an optimal predicted maintenance schedule can be generated based on the business requirements.

The benefit of such a predictive maintenance process is obvious, but the integration methodology is not as straightforward. Integration between ERP and CMMS systems has seen the exchange of financial information about assets and maintenance. However, the connection between CMMS and condition monitoring systems still remains largely underdeveloped [1]. Rockwell Automation and Emerson Process Management provide broad asset management solutions that integrate the aforementioned systems, but these solutions restrict businesses to one vendor. Standardisation efforts have seen the Open System Architecture for Condition-Based Maintenance (OSA-CBM) provide a framework for distributed condition monitoring models [2], and the Machinery Information Management Open Systems Alliance (MIMOSA) develop a protocol for the exchange of operations and maintenance data [3]. Due to the infancy of both, the standards have been cautiously received by asset owners.

This paper illustrates a system that will seamlessly integrate the areas of condition monitoring and maintenance management, namely, data acquisition, condition assessment, maintenance prediction, and work order notification. The outcomes of the system are to:

- Demonstrate the end-to-end process for predictive maintenance
- Use open standards for compatibility in integration
- Use advanced health assessment and predictive maintenance techniques

Through the use of predictive maintenance techniques that can use condition monitoring data to more accurately optimise maintenance, productivity of the asset will increase. Further advantages can be seen through potential reductions in maintenance costs through flow on benefits such as less unscheduled maintenance, and less consumption of resources for maintenance.

State of the art technology will be incorporated to achieve these aims. There are several components in the proposed system – a data acquisition module, a condition monitoring and data processing software system, a database for the temporary storage of raw and processed data, and a CMMS. Adopting a standards-based approach, the condition monitoring and data processing system will be based on the OSA-CBM. The database will be derived from work conducted by MIMOSA on asset management information modelling.

For communication, this project will use a web service platform for the integration of these individual components with frequent use of XML (Extensible Markup Language) due to its transparency and thorough support [4]. The OSA-CBM and OSA-EAI standards will influence the message formats for inter and intra-communications between the components.

The paper is organised accordingly: section 2 will provide background information on the technologies used; section 3 will discuss the integration of components; section 4 outlines health assessment and predictive maintenance techniques; and section 5 closes the paper with a conclusion of the outcomes.

2. Technology for system integration

This research considers various progressive technologies to support the process integration effort. The main technologies are discussed below.

2.1. Open System Architecture for Condition-Based Maintenance (OSA-CBM)

The OSA-CBM is a comprehensive communications framework for machinery monitoring and diagnostic systems. Through an Open System Architecture, the OSA-CBM employs a componentised, distributed approach to effectively integrate all CBM processes from data acquisition to maintenance decision making.

OSA-CBM aims to collectively work with the CBM community in standardising a messaging protocol. Benefits include improved ease of upgrading for system components, a broader supplier community resulting in more technology choices, more rapid technology development, and consequently through competition comes reduced prices. However the largest benefit is end-to-end maintenance process connectivity.

Although there is a plethora of COTS (commercial off-the-shelf) condition monitoring software products that can perform health analysis and maintenance prediction, these systems typically have their own interfaces, and a fixed set of system capabilities. The OSA-CBM eliminates the interface concern as it provides an open interface, and the layered structure allows for flexibility in capability.

The OSA-CBM has adopted the OSA-EAI Common Relational Information Schema (CRIS) as its core infrastructure, and many of the OSA-CBM objects correspond to the OSA-EAI's information elements. The structure of the architecture is defined by six generalised functional layers: Data Acquisition, Data Manipulation, Condition Monitoring, Health Assessment, Prognostics and Decision Making. Only the first five layers are implemented in the OSA-CBM, with each of these layers containing three interfaces: Data, Configuration, and Explanation. The Data interface describes data relating to a particular event; the Configuration interface contains configuration information about the module; and the Explanation interface involves information about the device and its setup. The OSA-CBM development team initially focused their efforts on three middleware technologies: CORBA, COM/DCOM, and XML over HTTP. Subsequent development efforts have introduced the OSA-CBM to Java RMI, Microsoft .NET and C++.

The applications of OSA-CBM have been gradually emerging into scientific literature over the last few years. Although the OSA-CBM has been used in ship systems [5], with heavy machinery, industrial processes, and aircraft [6], literature on the framework remains sparse.

2.2. Open System Architecture for Enterprise Application Integration (OSA-EAI)

With the numerous asset management systems offered by different vendors, the process of integration can be problematical as many systems have their own unique data exchange interfaces. This leaves businesses facing a dilemma as different integration techniques bring their own advantages and disadvantages. Purchasing systems from a single vendor leads towards system compatibility, however suppliers may not provide a total asset management solution, and the reliance on one vendor can prove risky. Businesses may purchase a custom bridge that integrates different systems which may prove more cost effective than internally building one, but provides less customisation ability and requires updates for new system versions. Another option is to use a standard specification bridge, which allows businesses to mix different systems with reduced integration costs. However, there may be performance loss compared to a custom solution and vendors must be willing to support the standard.

The absence of a standard for asset management data exchange was a driving factor in the formation of MIMOSA and the subsequent development of the OSA-EAI. The OSA-EAI provides open data exchange standards

in several key asset management areas: asset register management; work management; diagnostic and prognostic assessment; vibration and sound data; oil, fluid and gas data; thermographic data; and reliability information. The interfaces between these seven areas are defined as XML schema, which was chosen for its transparency and wide-adoption by the Internet community. As shown by Figure 1, the OSA-EAI supports both a HTTP client/server model and file import/export model that sit on top of various layers.

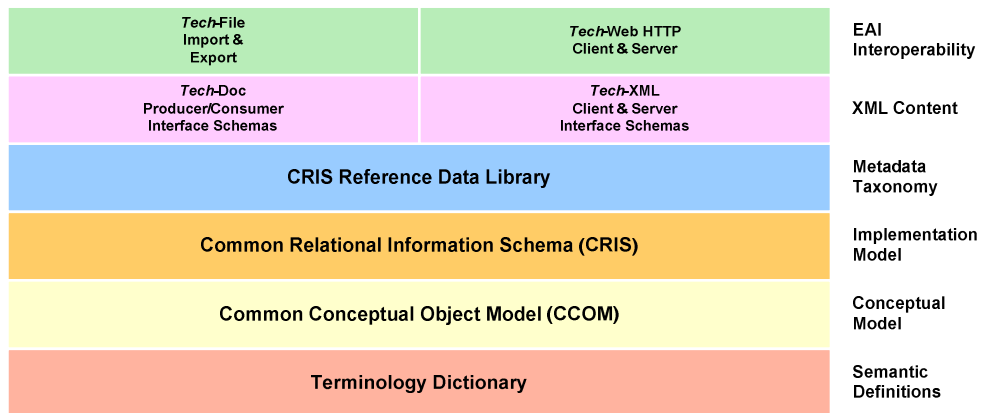


Figure 1. MIMOSA OSA-EAI layers

Compared with the OSA-CBM, the OSA-EAI provides the architecture for static data archiving and storage. It targets inter-system interfaces in allowing data exchange between different asset management systems. ISO is currently considering the adoption of the OSA-EAI and the OSA-CBM as standards in their respective areas.

2.3. Web services

The goal of web services is to provide a dynamic distributed computing environment independent of platform or programming language. Providing a communications methodology for distributed components, web services use several XML-related technologies such as Simple Object Access Protocol (SOAP), Web Service Definition Language (WSDL), and Universal Description, Discovery, and Integration (UDDI) [7]. SOAP provides a lightweight communications protocol that defines the message format, encoding rules, and a representation for remote procedure calls. WSDL is an interface description language and describes the access protocol and operation information of the web service. UDDI provides directory registry and search capabilities for web services.

2.4. Summary

The development of the above systems has been partly due to the ubiquitous use and standardisation of Internet-related technologies. The OSA-CBM and OSA-EAI both implement XML-related solutions to provide communication support to asset management systems. Web services provide a robust, distributed service architecture that facilitates effective communication between components. Together, these technologies provide a sufficient foundation for this research.

3. A structured framework for process integration

3.1. Predictive maintenance process chain

To meet business requirements, an end-to-end process chain for predictive maintenance is proposed. The process chain defines what processes are required to support predictive maintenance, and the information resources utilised. It is defined by six steps as illustrated in Figure 2: 1) monitoring the asset through hardware sensors; 2) assessing the health of the asset from the condition; 3) considering the calculated reliability and business maintenance objectives to predict maintenance requirements; 4) issuing maintenance work orders; 5) managing the maintenance process; and 6) updating the financial information.

The first process in the chain is acquiring data about the condition of an asset. Sensors typically relay the condition data through filters and amplifiers and finally to a data acquisition device connected to a computer. Sensor technology has matured over the years, and many monitoring techniques are now possible. Vibration, current signature, temperature, pressure, oil composition, and thermography are all proven analysis techniques that are available to maintenance engineers. A data acquisition system provides the interface between the sensor data and the condition monitoring system.

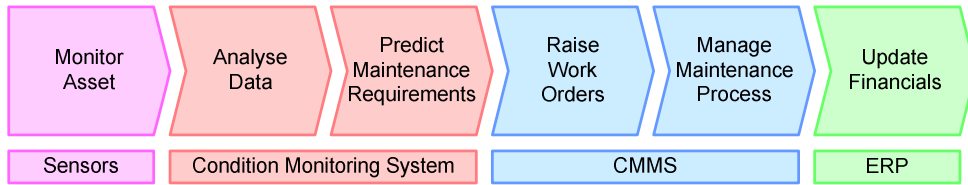


Figure 2. Predictive maintenance process chain.

To process signal data from the sensors, the condition monitoring system will analyse the data to determine the condition of the asset. The analysis can determine deterioration from the original healthy state by comparison to an initial baseline. Determination of an unhealthy condition is followed by a fault diagnosis to trace the root cause.

By understanding the past and present condition of an asset, a judgement about its reliability can be provided. The reliability of the asset provides an indicator to the health of the asset, and can be used to predict when failures will occur (see section 4). Combining this information with a company’s maintenance strategy allows the system to optimise the maintenance plan.

Once a condition-based maintenance plan is developed, work orders can be generated by the CMMS. This action will allocate resources to the maintenance work order, schedule operations, and organise documentation. Subsequent management of the maintenance work is conducted by the CMMS for management of inventory and budgets. Cost information, such as resources and inventory consumed, capital expenditure, wages accrued, and incidentals are passed onto the enterprise resource system for financial reporting.

There are several properties that the entire system should reflect:

- The processes should be timely. Changes in the asset condition that affect the maintenance requirements are conveyed in time.
- The system should have event-driven processes. By interacting seamlessly, user intervention is minimised.
- The process should have flexibility. Feedback from the CMMS should adjust parameters and settings.
- The overall system must be secure. Authentication ensures compromised data is not accepted.

The proposed system design sits in the condition monitoring section covering the data analysis and maintenance requirement prediction processes. It additionally encompasses the communications between the adjacent information resources (sensors and CMMS).

3.2. System design

Figure 3 illustrates the different components in the system and their relationships. The design is based on the five layers of the OSA-CBM, and the creation of a decision support module that determines the maintenance requirements. Information is passed from the sensors, through the data acquisition layer, and to any other relevant layers through the OSA-CBM XML schema. The Maintenance Support layer will provide condition-based information to the CMMS through the OSA-EAI XML Schema. All of the XML communications is supported by a web services platform.

A database, which is based upon the OSA-EAI CRIS, supports the information storage requirements of the OSA-CBM modules. Each module has direct access to the information in the database.

The main two components, the communications and database, are discussed in more detail below.

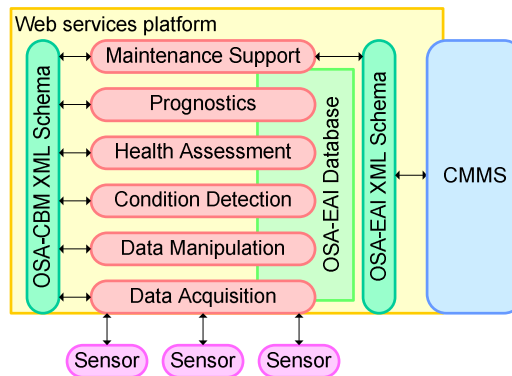


Figure 3. System components.

3.2.1. Communication

A critical aspect of the system is the implementation of communications, as most of the issues that justify the system can be identified by the immaturity of the communications between systems. Communication issues are relevant at three points: 1) data acquired from the sensors feeding into the OSA-CBM system; 2) intra-communication between different modules in the OSA-CBM system; and 3) the reporting of information from the OSA-CBM system to the CMMS.

The data passed from the sensors can be received either offline or online. Offline data can be received by means of a file or database, in which the file structure or database design must be clearly presented. In the case of data that can only be interpreted through the manufacturer's software tools, the process of data acquisition may not be completely automated. Online (or real-time) data acquisition requires additional devices to connect the sensors and the computer. Software drivers must be written for each hardware data acquisition device to provide access to the sensor readings.

The configuration of the modules in the OSA-CBM system influences the amount of internal communication between the components. As the OSA-CBM has been designed to allow a flexible distributed environment, there could be up to six different communication instances (one for each layer) for the one OSA-CBM system. Whilst the OSA-CBM supports various middleware technologies as outlined in section 2.1, this system uses a web services platform based on SOAP. This choice is due to the integration with the OSA-EAI, which is largely based on XML.

For each layer, the OSA-CBM provides three XML schemas – one for each of the layer interfaces: Data, Configuration, and Explanation. Certain concepts defined in the OSA-CBM XML schemas relate to objects in the OSA-EAI CRIS. This simplifies the process of saving information to the database.

The MIMOSA OSA-EAI also conveniently fits into the web services platform as all communications is performed through XML. Several XML schemas support the different services in each of the seven areas that the OSA-EAI covers (see section 2.2). The top Maintenance Support layer exclusively uses the OSA-EAI specification to communicate with the CMMS as this layer is not officially defined by the OSA-CBM. Hence, information will be passed

As configuration feedback may be provided by the CMMS to the OSA-CBM system, the Configuration service of the OSA-CBM will be implemented.

3.2.2. Database

The MIMOSA OSA-EAI defines the Common Conceptual Object Model (CCOM) which provides the description of various objects in the standard, their properties, and their relationships to other objects. Above the CCOM (see Figure 1), MIMOSA provides an implementation-level model - the Common Relational Information Model. The CRIS defines the types and naming conventions for the entities in the CCOM. The CCOM and CRIS models provide the basis for constructing the database that will be implemented in this project.

The incentive to use a database based on the OSA-EAI object model stems from the inherent compatibility with the data exchange mechanism. As the XML schema used in the web service communication relies on the OSA-EAI object model, there will be a natural reduction in development time as type conversion and checking is reduced.

The trade-off is an increase in the complexity of the database. Due to the design of the standard, the OSA-EAI attempts to deliver a generic approach in managing asset data. The generic approach found in the standard, results in two potential concerns for this system: 1) further database development may be required as the OSA-EAI does not consider data specific to an application; and 2) the increased complexity of the system as extraneous information is included. The resolution for both issues is for an accurate data modelling process to be conducted to determine the relevant data items for the system. The results are then merged with the OSA-EAI data model to form the final database.

With the ability to distribute different modules, the location of the database becomes an issue, particularly when a sizable amount of data needs to be transferred. Different modules may require access to the database, such that the database cannot be tied to an individual module. Depending on the production environment, a distributed database solution may alleviate sizeable data requests.

3.3. System Assessment

To present a viable business case, the system must have measurable and applicable metrics by which its performance can be assessed. One of the business drivers of the project is to *reduce maintenance costs*, and the budgeted and actual costs after implementation can be considered a sound indicator. As the system aims to schedule maintenance more efficiently and effectively using health prediction technologies, it logically follows that the amount of unplanned maintenance should decrease. Thus the *resources consumed through unplanned maintenance* can be used to provide an indicator of the success of the system. As unplanned downtime is reduced, the *availability* and/or the *productivity of the asset* should increase. A direct comparison of these measures with pre-integration values may not reflect the actual performance, as the metrics rely heavily on various assumptions.

4. Advanced equipment health prediction methodologies

An accurate maintenance decision largely relies on accurate asset health prediction through the adoption of effective diagnosis and prognosis techniques. There are numerous health prediction techniques discussed in the literature [8, 9] and relevant methods will be implemented into the Health Assessment and Prognostics layers of the OSA-CBM structure depicted in Figure 3. These health prediction techniques typically require data inputs such as condition monitoring data, process and performance data, and failure history data. The combination of asset health prediction together with financial and business requirement data assists in supporting effectual predictive maintenance decision making.

4.1. Health Assessment

Diagnosis plays a primary role in the Health Assessment layer of the system. The Health Assessment component will determine if the health of an asset is degraded, and if so, generates a fault diagnosis report. Fault diagnosis techniques are mature and can assist in the discovery of the fault severity, root cause, and subsequent guidance in enhancing maintenance [10, 11].

Condition deterioration contributes towards maintenance by revealing the condition progression. Deterioration models use condition monitoring information to provide condition trending and projection. The models are based on the estimation of health deterioration and progression (e.g. wear, cracks, and corrosion). Changes in monitored parameters are analysed to identify asset performance deterioration and malfunction of equipment components. Signal features from time and frequency domains can be used as trending parameters. The overall time domain features, such as peak-to-peak value, root mean square and kurtosis, are sensitive to condition variations in most scenarios. The frequency domain features extracted from band limited signals, such as band amplitude, can reveal the condition of specific components.

Multiple parameter analysis is another advanced technique that considers the relationship of different parameters [12] derived from either different physical signals, e.g. current, temperature, pressure, or from different bandwidths signals, e.g. vibration [10].

4.2. Prognostics

While diagnosis techniques endeavour to explain past history, prognosis techniques attempt to predict future condition progression. Reliability analysis is one approach often used in prognostics. It generally uses long-term failure data to produce reliability-related measurements, such as mean time to failure (MTTF). Reliability factors are usually estimated and adjusted with respect to the failure history of a given system. Factors such as failure interaction and repair effects, are considered by certain reliability models [13-15] to produce a more accurate prediction. Alarm limits for preventive maintenance can be derived using hazard and reliability functions [16].

Besides using failure history data, reliability prediction models can be enhanced by adopting condition monitoring data. The Proportional Hazard Model (PHM) combines historical data and environmental condition data for the prediction of system hazards [17]. In certain instances, the Proportional Covariates Model (PCM) has demonstrated a better capability of reliability prediction [18]. PCM estimates system hazards with historical data and response condition symptoms of asset.

4.3. Maintenance Support

Maintenance support involves providing timely, relevant, and accurate maintenance information for decision making. A multiple criteria approach is the most common technique, which attempts to optimise maintenance schedules based on several parameters. These parameters can include reliability and expected costs [19], resource availability, timing with other projects, losses due to outages, safety permits for personnel [20]. Other models include condition-based criteria using a range of techniques, such as mathematical modelling [21], fuzzy logic [22], and neural network [23]. These models use aggregated condition parameters, such as overall health, rather than direct sensor readings. There is a lack of models that provide consistent integration from condition monitoring through to maintenance decision making processes. The development of standard framework through the OSA-CBM should assist in the development of integrated models for maintenance decision support.

5. Conclusion

The integration of condition monitoring data with maintenance management systems can provide a valuable strategic advantage in asset management. By understanding the condition of an asset, predictive maintenance techniques can help significantly reduce maintenance costs. Although solutions by asset management software vendors exist, the software system interfaces are typically not open, making integration and customisation difficult. A system was proposed that utilises open standard architectures for condition monitoring systems and asset management data exchange. Both the OSA-CBM and MIMOSA OSA-EAI standards support XML-based technologies, which leads to the natural adoption of a web services communications platform. The condition

monitoring modules can be configured with advanced models to determine effectively the asset health and reliability for the purposes of predictive maintenance.

Glossary

CBM	Condition-Based Maintenance
CCOM	Common Conceptual Object Model
CMMS	Computerised Maintenance Management System
COM/DCOM	Component Object Model/Distributed Component Object Model
CORBA	Common Object Request Broker Architecture
CRIS	Common Relational Information Schema
ERP	Enterprise Resource Planning
HTTP	HyperText Transfer Protocol
Java RMI	Sun Java's Remote Method Invocation
MIMOSA	Machinery Information Management Open Systems Alliance
OSA-CBM	Open System Architecture for Condition-Based Maintenance
OSA-EAI	Open System Architecture for Enterprise Application Integration
SOAP	Simple Object Access Protocol
UDDI	Universal Description, Discovery, and Integration
WSDL	Web Service Definition Language
XML	Extensible Markup Language

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