Integrated Asset Maintenance: A lab-based demonstrator

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Abstract

The effectiveness of the maintenance scheduling decision depends on the availability of information regarding the remaining useful life of the asset in addition to the asset operating schedule and spares and resources required to carry out the maintenance action. In this paper, we illustrate an integrated asset maintenance approach using a lab-based demonstrator where a washing machine unit is deployed as the “asset”. The condition of the washing machine is assessed using data from a number of embedded wireless sensors to monitor critical parameters. The configuration of the washing machine is monitored using Radio Frequency Identification (RFID) tags. In addition to the condition monitoring platform, the demonstrator includes a supply chain platform with RFID infrastructure to provide real-time tracking information to predict the availability of spare parts within a given time horizon. Information from the condition monitoring platform and the supply chain tracking platform is then fed to a decision support system (DSS) which uses the available information to optimise the total cost of maintenance and decide the following parameters: (a) timing of maintenance, (b) choice of the appropriate spare part, (c) choice of the repair personnel.

Keywords: Maintenance, Condition Monitoring, Demonstrator, RFID, Decision Support Systems, Track and Trace.

1 INTRODUCTION

The management of assets such as facilities and equipment can be a challenging task, and optimizing their usage is critical. When managing assets, decision makers such as engineers, operators, and business managers have to ensure that the assets perform at peak levels, and at the same time, keep capital and maintenance costs down. Consequently, the importance of the maintenance function has increased because of its role in ensuring and improving asset performance and safety [1]. Maintenance scheduling is one of the most important decisions that influence asset performance and utilisation, and this involves deciding the optimal timing of repair or replacement activities. This decision is very much dependent on the maintenance strategy chosen. Maintenance strategies can be broadly divided into two major categories: *corrective* and *preventive*. Corrective maintenance is where assets are run to failure/near failure and the appropriate repair or part replacement action is taken. Preventive maintenance is where appropriate maintenance action is taken before asset failure in order to maintain the asset in specified condition. Preventive maintenance includes time-based preventive maintenance (TBPM) and condition-based maintenance (CBM). CBM typically involves systematic monitoring, inspection, detection, and prevention of incipient failure [2].

Over the past few decades, there has been increasing interest in the area of maintenance modelling and optimization [2-5]. In particular, CBM policies and the study of mathematical models for CBM is growing in popularity since the 1990s [6]. The objectives of these models are (i) to determine the states for which the unit is replaced in order to gain the minimum expected maintenance cost, or (ii) to find the optimal regular/irregular inspection schedule and/or the optimal preventive replacement threshold.

One of the main shortcomings in these models is that they do not consider the problem of “resource” availability and asset schedules sufficiently. Resources here include replacement spare-parts as well as skilled manpower and tools/equipment required to carry out the maintenance action. Spare parts need not be always available thereby leading to a time lag between the order of a spare part and its arrival time. Moreover, while scheduling the maintenance action, one needs to ensure the availability of resources as well as consider the asset operating schedule. The flexibility offered by CBM in terms of scheduling the maintenance is important to gain the benefits of the scheme. The key decision is to decide whether to stop the asset running or to utilise the availability of the asset to plan an appropriate time so that disruptions are minimal. It is therefore important to have an *integrated* maintenance framework that considers not only the asset condition but other factors influencing maintenance scheduling decisions such as the availability of resources required to carry out the maintenance action (i.e. spare parts, personnel, tools, etc). Moreover, it is important to integrate real time information into the decision making process to improve the effectiveness and efficiency.

This research aims to develop tools and methodologies for such an integrated maintenance framework, and in this paper we illustrate a preliminary implementation of the vision of an integrated asset maintenance approach using a lab-based demonstrator.

The paper is structured as follows. Section 2 introduces our point of view of an integrated asset maintenance strategy. Section 3 describes the demonstrator development for integrated asset maintenance. First we introduce the demonstrator architecture, and then the hardware and software are detailed. Finally Section 4 concludes the paper and discusses future prospects.

2 INTEGRATED ASSET MAINTENANCE

Maintenance planning plays a vital role in achieving the required asset performance and utilisation. Decisions involved in maintenance planning such as the optimal time to repair or replace will influence availability of the asset and resource utilisation. Deciding on the maintenance schedule will depend on the condition of the asset and needs vital real time information for efficient asset management. With the advent of proactive and predictive maintenance strategies, there is increased need for more information in real time to reap the benefits of such novel strategies. Also with the developments in data capture technologies, it is increasingly possible to gather real time data about the condition of the asset. However, to optimise the maintenance decisions, there are other informational requirements such as resource availability and spare part availability for efficient utilisation of the condition information. Combining real time information and spare part logistics information enables better decision making which leads to reduced downtime, improved resource efficiency and lower life cycle cost.

In this paper the focus is on integrating those different perspectives, i.e. asset condition, resource availability and spare part availability, in order to identify an optimised maintenance plan. A proof-of-concept of this integration is developed in a lab environment to demonstrate the usefulness of different information sources for optimising maintenance activities and decisions. Moreover, this proof-of-concept also demonstrates the usefulness of predictive maintenance done in real time with no spare inventory. We will now describe the set up of the demonstrator.

3 DEMONSTRATOR

This section describes the demonstrator developed as a proof-of-concept to show the concept of integrated asset maintenance. First, the architecture of the demonstrator is described and then the hardware and software components are detailed.

3.1 Overview and architecture

In this lab-based demonstrator, a washing machine unit is deployed as the "asset". The choice of the asset was driven by the fact that it is simple enough to implement, but also complex enough to convey the concept. In fact, in the hospitality sector and laundrette, washing machines are key assets. Moreover, the concept addressed here is also applicable to other industrial assets.

There are six key components in this demonstrator:

1. Condition-monitoring and failure prediction
2. Asset configuration management
3. Spare-parts tracking and prediction
4. Resource scheduler
5. Asset operation scheduler
6. Maintenance DSS

The asset is monitored in terms of its configuration and condition using key emerging Automated Identification and Data Capture (AIDC) technologies. A condition-monitoring platform helps assess the condition of the washing machine using real-time data from a number of embedded wireless sensors to monitor critical parameters such as vibration, temperature, humidity, current, and tilt. In addition to the condition monitoring platform, the demonstrator includes a supply chain platform to show how emerging automated product identification technologies such as RFID can be used for tracking the location of the spare parts the supply chain.

The RFID infrastructure provides real-time tracking information, which is used to predict the availability of spare parts within a given time horizon. Information from the condition monitoring platform and the supply chain tracking platform are then fed to a decision support system (DSS) along with other critical information such as personnel availability and asset (washing) schedules. The DSS uses the available information to optimise and decide the following parameters: (a) timing of maintenance, (b) choice of the appropriate spare part, (c) choice of the repair personnel. The choice is made such that the total cost of maintenance is minimised. The decision support system (DSS) demonstrates the capabilities provided by technology and information systems towards an effective integrated maintenance decision.

The architecture of the developed lab-demonstrator is shown in Figure 1. The asset condition data are gathered using wireless sensors. These data are then visualised using a graphical user interface – *data visualization* – to help decision makers assess the current condition of the asset. The information is also fed to the *asset condition monitoring* component to analyse it and further evaluate the asset health based for instance on comparisons with historical and expected state information of particular components of the washing machine. The predicted failure is the event trigger for the *decision support system* component to set up a maintenance plan. In order to do so, the DSS checks for the availability of the spare parts within the suppliers, using the *Spare Parts Track & Trace* component, but also taking into account the availability of the maintenance engineers (*Resource Planning*) and the asset scheduling (*Washing Machine Scheduling*). After a maintenance activity is performed, the *Configuration Management* component is used to record the maintenance history.

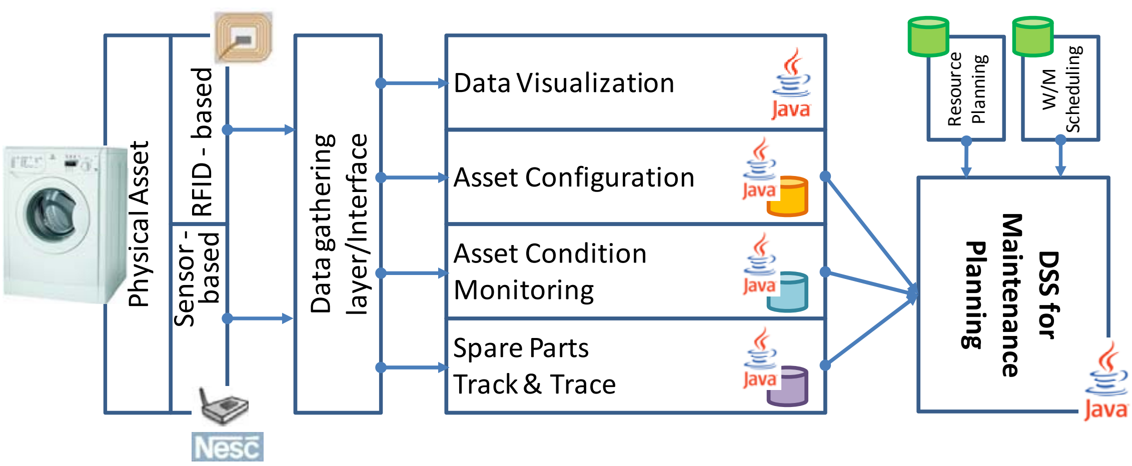


Figure 1. The architecture of the demonstrator

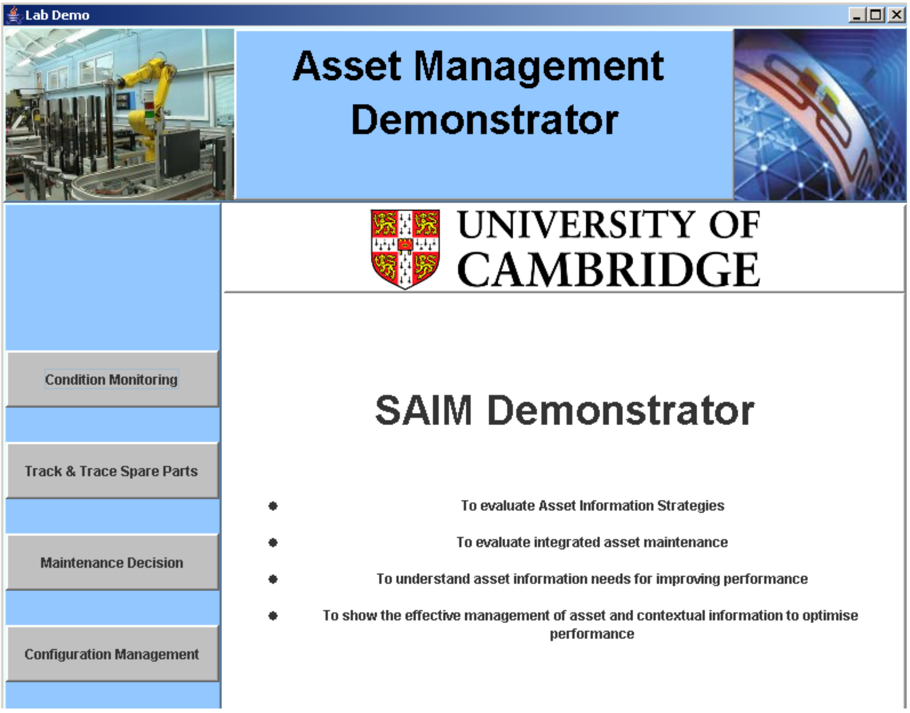


Figure 2. Snapshot of the main window of the demonstrator

The snapshot shown in Figure 2 presents the main window of the developed demonstrator. It is composed of four different modules:

1. Condition Monitoring: To collect sensors data and visualize the asset condition
2. Track & Trace Spare Parts: To predict the arrival time of a given spare part
3. Maintenance Decision: To schedule the maintenance action
4. Configuration Management: To manage the washing machine configurations

In the following sections, the different hardware used to implement the lab-demonstrator as well as the software components are detailed.

3.2 Hardware

The demonstrator hardware consists of the following parts:

1. Sensors for condition monitoring
2. RFID infrastructure for configuration management
3. RFID infrastructure for supply chain parts tracking

We shall now describe each of these elements in detail.

3.2.1 Condition monitoring technologies

The condition monitoring platform consists of four different sensor nodes positioned at different parts of the washing machine, i.e. Drum, Motor, Water Inlet and body (cf. Figure 3). The parameters monitored include vibration, temperature, current, humidity and tilt (cf. Table 1). The condition monitoring information is stored in a database and can be accessed remotely.

The sensor nodes used are manufactured by CrossBow Technologies[1], and consist of MICAz MPR2400CA motes with appropriate sensor boards attached to them. There are four sensor nodes that transmit the washing machine condition's data to two MIB510 base stations.

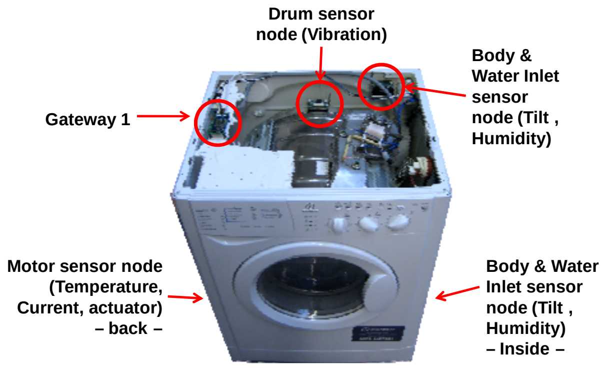


Figure 3. Deployment of sensors on the washing machine

Table 1. Sensors board used for asset condition monitoring

Asset components	Parameters	Sensors board used
Drum	Vibration	MTS310
Body	Tilt	MTS310
Water Inlet	Humidity	MTS400
Motor	Temperature	MDA300
Motor	Current	MDA300

[1] www.xbow.com/

3.2.2 Asset configuration

For real-time monitoring of the asset configuration, RFID tags were attached to various parts (motor, water inlet and drum) of the washing machine and RFID readers are used to detect the tags at key observation points. The RFID tags are embedded with IDs that uniquely identify each of the parts. The tags used were manufactured by Alien Technology and they operate within the EPCglobal UHF Class 1 Gen 2 (ISO 18000-6C) protocol. These are passive squiggle tags and operate in the 865.6-867.6 MHz frequency band. Alien Technology readers were used to read these tags, and small antennas were placed inside the washing machine. The RFID reads are streamed to the asset configuration database to keep track of the current washing machine configuration.

For instance, if a part is replaced, the configuration of the washing machine will be automatically updated in the asset configuration database as the RFID readers will detect a change in the ID sent by the RFID tag attached to the new part. This process enables recording of maintenance or repair action. This knowledge is crucial for decision-making since it allows obtaining accurate information on which parts are installed as well as their maintenance history. Although sensor nodes can be used to identify the parts they monitor, they are too expensive to be placed in every relevant part. Furthermore, we are interested in testing RFID tagging inside the machine due to the challenging metal environment and also as a proof-of-concept for the use of this technology for automated asset configuration management.

3.2.3 Spare parts Track & Trace

Logistics of spare parts for maintenance is different to other materials, because unavailability may lead to downtime and financial loss. However, keeping the spare part available well before the failure will incur higher inventory holding cost and the chance of obsolescence.

The demonstrator includes a working model of a spare part supply chain, which is achieved by moving shuttles on a conveyer path that represents a mini supply chain (cf. Figure 4). The shuttles carry spare parts, which are tagged with RFID tags. RFID readers are placed at various points to observe the location of the spare parts in the supply chain. The tags were provided by QinetiQ and the readers from Sikit and Impinj, operating also under the protocol EPCglobal UHF Class 1 Gen 2. The collected data are then processed by the Track and Trace model to predict the spare parts arrival time (described later in section 3.3.3) [7].

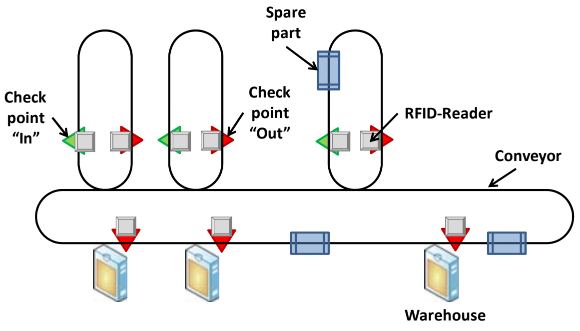


Figure 4. Supply chain demonstrator

3.3 Software

The demonstrator software consists of the following parts:

1. Condition monitoring
2. Configuration management
3. Spare parts tracking and prediction
4. Resource management
5. Decision support system

The following sections describe in detail these different modules.

3.3.1 Condition monitoring

The software architecture used for the condition monitoring platform is based on Moteworks 2.0 from Crossbow Technologies. The architecture enabled us to effectively implement and deploy the developed platform. The architecture is layered and can be divided into three primary layers or tiers. In the context of the integrated asset maintenance implementation, the tiers in Figure 5 are described below.

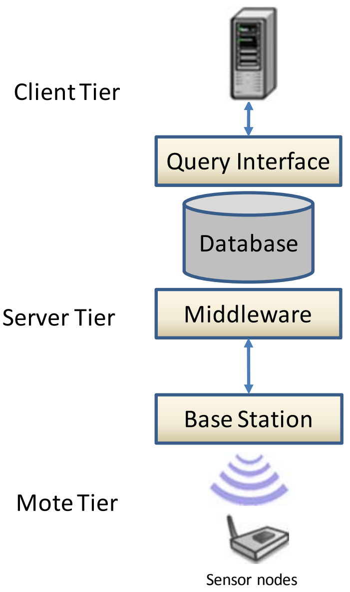


Figure 5. System architecture for condition monitoring [7]

The *mote tier* consists of the physical layer i.e. the different sensor nodes and base stations. As described in Section 3.2.1, the sensor nodes are based on MICAz from Crossbow Technologies, and their main characteristics are an 8 bits micro-controller, 128 KB of Flash memory, 4 KB of SRAM and a 2.4 GHz IEEE 802.15.4 wireless transceiver. The sensor nodes form a low-power wireless multi-hop mesh network. The sensors collect data about the temperature, current, humidity, tilt and vibration of the various components of the washing machine. These data are then transmitted to the next tier (server tier) through the radio stack. The mote's software was specifically re-programmed for the purpose of the demonstrator.

The *server tier* consists of a computer with the Moteworks middleware (*Xserve*). A local Xserve running on the computer communicates with the base station over a serial port and interprets the raw binary data obtained from the base station. The interpretation of the data can be configured using a simple eXtensible Markup Language (XML) file stored in the Xserve's configuration directory. The configuration script provides ample flexibility to control the storage and the pre-processing of the received data, such as converting to meaningful engineering units or simple filtering. The middleware is configured to convert the binary data to decimal values and to store time stamped sensor data in a defined relational database implemented on a Postgresql database. This stored data can then be accessed by client applications over the Internet by subscribing to various data streams.

Finally, the *client tier* consists of the application processing and analysing the condition monitoring data for statistical anomalies. In our case, two different applications connect to these data and process them for further analysis. First, the *data visualisation* application which allows displaying the different asset condition parameters into plots through graphical user interfaces.

The process of vibration analysis and plotting is described below to illustrate the first type of application. The same reasoning is also applied to the different condition parameters. The second type of application is the Decision Support System developed to optimise the maintenance plan and will be described in section 3.4.5.

For vibration analysis, the sensor node with the MTS310 board is placed on the outer covering of the rotating drum (cf. Figure 3). The raw data denoting acceleration is measured from the acceleration sensor ADXL202E on the MTS310 sensor board along two perpendicular horizontal axes X and Y. These raw values are converted into milli-gravity (mg) units using the equation (1) given below.

$$accel = \frac{data - zerogdata}{onegdata - zerogdata} \times 1000 \qquad (1)$$

Where, *accel* is the value of acceleration in mg, *data* is the raw data obtained from the sensor; *zerogdata* is the raw data when acceleration is zero and *onegdata* is the raw data when acceleration is one g (9.8 ms^{-2}). The sensor is sampled at 256 Hz and 8 sampled values for each of the X and Y directions are sent in a single packet, whereby 32 packets are transmitted every second utilizing 12.5kbps of the communication channel.

However, the sensor data obtained in the time domain must be converted into the frequency domain to provide a frequency spectrum for vibration analysis of the drum during a washing cycle. This is achieved by transforming the acceleration values into the frequency domain using Short Time Fourier Transform (STFT). A rectangular moving window function is used to simulate a digital spectrum analyzer.

$$X(m,k) = \sum_{n=-\infty}^{\infty} x(n)\, w(n-m)\, e^{-2j\pi kn} \qquad (2)$$

Equation (2) gives the transformation used to convert the time domain acceleration data from the sensor into the frequency domain. In Equation (2), $X(m,k)$ are the values in the frequency domain, $x(n)$ are the sample values in the time domain, *k* is the frequency index, *m* is time index and w is the window function. As the signal is real, the frequency range of our analysis is limited to half the sampling rate (Nyquist frequency) i.e. 128 Hz. The frequency spectrum obtained from the vibrating drum is shown in Figure 6.

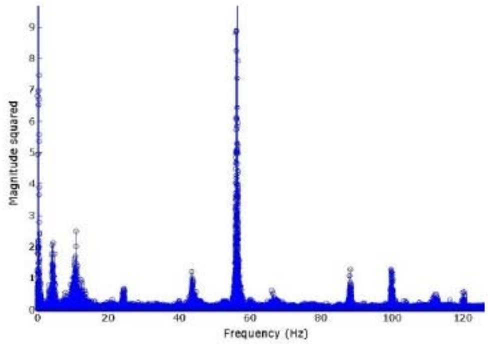


Figure 6. Vibration spectrum of drum from acceleration data obtained in a single washing machine cycle

3.3.2 Configuration management

The configuration management application in this demonstrator aims to manage the washing machine structure throughout its operational life. The application allows identifying the current configuration of the washing machine, but also covers the elements of change controls. This would help the asset manager to keep track of any modification of the washing machine configuration.

In a context of maintenance management, not only the information about the physical structure of the washing machine is captured, but also all the information related to the different maintenance actions performed on the washing machine. These pieces of information are highly important to improve the maintenance plan scheduling, such as maintenance action duration, necessary tools, skills to perform the maintenance action, and so on. For that purpose, a data model for asset information management is developed and then implemented in a database (cf. Figure 7).

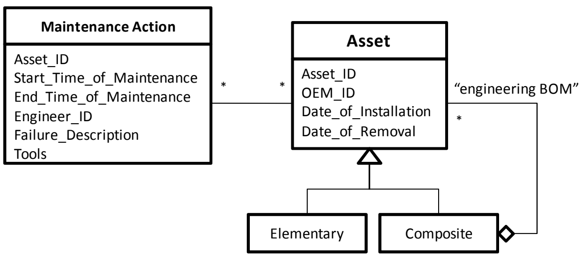


Figure 7. Data model for managing asset maintenance

The information stored on this database describes the asset structure and the maintenance action. Regarding the asset structure the set of information gathered is: Asset Component Identity, Date of Installation, Date of removal, and Original Equipment Manufacturer Identity. While the set of information gathered to describe the maintenance action is: Start Time of Maintenance, End Time of Maintenance, Maintenance Engineer Identity, Failure Description and Necessary Tools. This data model is instantiated each time a maintenance action is required on the washing machine. The part to be replaced is detected with the RFID reader and the set of related information are displayed to the maintenance engineer. Same for the new spare part, it is detected through the RFID reader and the maintenance engineer could modify any piece of information corresponding to this specific part. As soon as the failed part is replaced, the maintenance engineer record the information regarding the maintenance action, failure description, tools, etc. and then the asset configuration will be updated. A new configuration of the washing machine is then available with the new spare part.

3.3.3 Supply chain tracking and prediction

A tool is developed to track and predict the location of a spare part in the supply chain. This tool is based on the Track and Trace model developed within the BRIDGE EU-Project[2]. The developed mathematical model is based on expected object behaviour (defined by the transition model) and observation information across the supply chain (defined by the observation signals and the sensor model). Given a set of object observation signals, the model generates a location probability distribution, which expresses the estimate of the object's current or future location.

A first order hidden Markov model is then used to predict the time and location of arrival of a particular spare part in the supply chain. On querying the supply chain for a particular spare part type, it is possible to obtain the probable arrival time of the spare part at a particular point in the supply chain. It is also possible to track the movement of spare parts in the supply chain, hence enabling real time planning of any disruptions in the supply chain.

The model describes the relation between successive states (usually corresponding to locations) of the spare part and models the uncertainty under which the observed state reflects the actual state of the spare part. Using these as a basis, the model enables the inference of tracking information based on the available spare part observations that the tracking system provides.

3.3.4 Resource management

For efficient maintenance management, it is vital to have the right person with the right skills at the right time. Also, using predictive maintenance, it is possible to plan the maintenance at a time when the washing machine is available for maintenance. This will allow minimum disruption to the existing processes, while allowing maximum utilisation of the asset. Information regarding resource availability and asset schedule will enhance the optimisation of maintenance scheduling. It is assumed that the washing machine schedule is discrete and maintenance is possible only when the machine is idle or failed and when resources are available. Combined optimisation of resource availability and asset availability, along with the flexibility offered by predictive maintenance, it is possible to increase the efficiency of maintenance decisions and cost reduction. For this purpose, a database is developed to store the information about the work plan of the maintenance engineers as well as the scheduling plan of the washing machine. The database includes the availability time and skill set of the technician. Using this database, it is possible to choose the right available person to carry out the maintenance plan in real time when degradation or abnormal behaviour is detected.

3.3.5 Decision Support System

The DSS combines various information, both real time and historical, to provide in efficient maintenance decisions. One of the key features of the DSS is to optimise the maintenance plan. The DSS is a simple expert system using simple if-then rule based algorithm for making decisions. The DSS converts real time information coming from sensors into real time plots for assessing the condition of the asset. Threshold of degradation is set in the DSS and it is possible to monitor the operating trend of the washing machine in real time. For that purposes, the washing is monitored continuously. Once the threshold of degradation is reached, the remaining life is calculated and it is possible to plan the maintenance before failure. The DSS queries the spares supply chain with the part needed. The obtained information consists of a list of spares with their respective arrival times. This gives rise to two possible scenarios:

1. Spares arrive before failure: When the spare parts arrive before failure, the DSS finds the optimal time of maintenance by choosing the required resource, optimal spare part and asset availability. The optimality is based on minimised cost.
2. Spare arrive after failure: When the spare parts arrive after failure, the DSS chooses an optimal time of maintenance and the optimal spare (with minimum holding time) with respect to resource availability.

The optimal choice of spare part will allow for minimum holding time while making sure the spares and resources are available before complete failure. This combination jointly optimises the spare inventory, maintenance scheduling and resource management, at the same time maximising the asset utilisation, while minimising the disruptions to other process. The DSS uses cost as the optimisation constraint. The time dependant factors such as spare arrival and inventory holding time, operating in degraded state are converted in to costs.

In order to optimise the maintenance plan, the following costs are used,

1. Cost of operating in degraded state C_d
2. Cost of spare part C_{sp}
3. Cost of inventory (spare holding) C_i
4. Cost of labour C_l
5. Cost of idle time when the machine fails before spare arrives C_{idle}

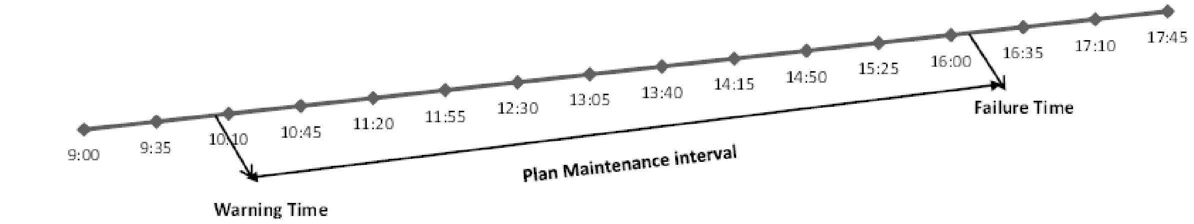
The optimisation problem can be now represented as:

$$Minimise\ \ TC(c) = C_d + C_i + C_l + C_{idle}$$

subject to spare and resource availability, and asset availability, where $TC(c)$ is the total cost function for the maintenance action.

In order to choose the optimal plan, the DSS checks for each spare part, the availability of asset and resource, and calculates the total cost involved. This will provide the decision maker a range of options for doing maintenance at a convenient time. The cost of operating in degraded state is associated with operating the machine in the degraded state until maintenance is carried out. The spare holding cost is related to the spare holding time, which is between the availability of spare part until maintenance. If the cost of operating in degraded state is much higher, then the DSS will schedule the maintenance as soon as the spare and resources are available, much before failure. If there is less loss in performance due to degradation, the DSS will schedule the maintenance closer to the failure time, choosing the later arrival spare part, thus maximising the usage life. On the other hand, if the cost of inventory is high, the DSS plans the maintenance as soon as the spare becomes available. Thus by varying the costs, it is possible to simulate the various optimal solutions for the decision maker

[2] www.bridge-project.eu/



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Time	9:00	9:35	10:10	10:45	11:20	11:55	12:30	13:05	13:40	14:15	14:50	15:25	16:00	16:35	17:10	17:45

Optimisation parameters

- Spare parts
- Maintenance Time

Constraints

- Residual life
- Spare part arrival time
- Labour availability

Minimise Costs

- Inventory cost
- Cost of operating in degraded state
- Cost of spare part
- Cost of labour
- Cost of machine failure

Figure 8. Washing Machine Schedule

Figure 8 illustrates a typical planning of the maintenance action by the DSS. The figure shows the asset availability, warning time (threshold of degradation) and the remaining time left for planning maintenance before failure. The output of the DSS is the maintenance plan which consists of the optimal time of maintenance, appropriate spare part and the resource allocated. Also the DSS allows real time monitoring of the condition of the asset and the real-time location of spare parts in the supply chain. The corresponding output of the developed software is shown in the snapshot Figure 9. It shows the maintenance plan for the washing machine component "Motor" and the spare part to replace the motor has a corresponding ID "00000000C000001000000009". The residual life of the motor is expected to be for "Thursday December 18 at 11:08:00". So the optimal maintenance would for the "Friday December 19 at 9:00:00". This maintenance action will be performed by the "Engineer3" and will cost "£159"; this includes the cost of holding the spare parts, the cost of the washing machine operating in a degraded state, the cost of the machine idle time, the cost of labour and the cost of the spare part. It has to be noted here, that these figures are not actual but used to run tests with the DSS tool.

Figure 9. Snapshot of the DSS output

4 CONCLUSION

This paper essentially describes the set up of a preliminary asset management demonstrator and research facility. Although at this stage the demonstrator focuses very much on maintenance planning, the forward vision is to extend this to cover all the key decisions along the asset's usage life including design and implementation of service contracts.

This facility will enable development and testing of novel algorithms and techniques for data filtering, condition assessment, diagnosis, prognosis, and integrated maintenance planning.

On the hardware side, the facility will enable analysis of the implications of using different data capture technologies. For instance, we plan to extend the condition monitoring platform with RFID-integrated sensors and compare it with the existing data capture platform (separate configuration and condition monitoring). In addition, the facility will be used to perform a comparison of different product data management approaches. Furthermore, the washing machine demonstrator will be used to demonstrate the implications of different types of service contracts on organisational performance. This will help answering key questions such as:

- How would the asset manager use current asset, contract, resource and supplier information to manage contractual performance obligations?
- How would the asset manager achieve better management through modifying resource & spare part availability?
- How would the asset manager use the current information structure to award new service contract levels?

5 ACKNOWLEDGEMENT

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