Assessing Asset Monitoring Levels for Maintenance Operations: A Simulation Approach

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Abstract

Purpose – Asset management has recently gained significance due to emerging business models such as Product Service Systems (PSS) where the sale of asset use, rather than the sale of the asset itself, is applied. This leaves the responsibility of the maintenance tasks to fall on the shoulders of the manufacturer/supplier to provide high asset availability. The use of asset monitoring assists in providing high availability but the level of monitoring and maintenance needs to be assessed for cost effectiveness.

Design/methodology/approach – This research aims to develop a dynamic modelling approach using Discrete Event Simulation (DES) to assess such maintenance systems in order to provide a better understanding of the behaviour of complex maintenance operations. Interviews were conducted and literature was analysed to gather modelling requirements. Conceptual models were created, followed by simulation models, to examine how maintenance operation systems behave regarding different levels of asset monitoring.

Findings – This research indicates that DES discerns varying levels of complexity of maintenance operations but that more sophisticated asset monitoring levels will not necessarily result in a higher asset performance.

Practical implications – The proposed tool supports the maintenance operations decision makers to select the appropriate asset monitoring level that suits their operational needs.

Originality/value – A novel Discrete Event Simulation (DES) approach was developed to provide maintenance operations decision makers to select the applicable asset monitoring level for their particular operations. This novel and unique approach provides numerical evidence rather than reasoning, it proves that the higher asset monitoring level does not always guarantee higher asset availability.

Keywords: asset monitoring, simulation, system behaviour, maintenance.

1. Introduction

Over the last decade, manufacturers, consultants, and businesses, as well as researchers, have been looking to move from producing output (manufactured goods) and instead focus on services (Davies et al., 2007; Vargo and Lusch, 2008). Moussa and Touzani (2010) show that since 2004, research on service has been the most written about subject in leading marketing and management journals.

Due to this new-found awareness for services, new business models have emerged. One such model is the Product Service System (PSS), which is defined as a combined product and service which furthers the established operation of a product by integrating additional services (Mont 2002, Manzini and Vezzoli, 2003). This now means that the responsibility of maintenance activities falls on the shoulders of the manufacturer/supplier where they have to provide a high availability to their customers, for example Rolls-Royce's 'Power by the Hour' where customers are charged on the number of hours flown (Baines et al., 2009). It also means that more efficient maintenance operations are required in order to reduce the downtime and cost and to avoid penalties associated with the unavailability of assets.

Maintenance is a key to product performance and availability. The operation of maintenance must be effective in order to facilitate product availability under PSS contracts. Maintenance operation response times should be minimised and the spares' inventory well managed. Maintenance management plays an important role by reducing equipment downtime and associated cost and unscheduled disruption (Abdulnour et al., 1995). Additionally, maintenance functions support product quality (Ben-Daya and Duffua, 1995) thereby improving the availability, safety requirements, and plant cost-effectiveness levels (Al-Najjar and Alsyouf, 2003).

Efficient maintenance has its own economic objectives (Saranga and Knezevic, 2000). Al-Najjar, (1999) and Kothamasu and Huang (2007) showed that maintenance expenses vary depending on the

industry, accounting for 15-40% of production cost. As most production expenditure can be predetermined, one of the major issues for cost and general performance enhancement is maintenance (Al-Najjar, and Alsyouf, 2003). Savings in maintenance cost will consequently lead to the reduction of product cost as well as providing higher asset availability. It is therefore an important area for research.

Maintenance operations need to be effectively managed in order to meet the contracted level of availability of an asset. Maintenance operations are complex, especially if the manufacturer/supplier has to manage different assets at different locations. Therefore, authors have suggested the application of monitoring technology to monitor asset health (Lightfoot et al., 2011). It has generally been regarded that a higher monitoring level results in higher asset availability. This is based on reasoning and not experimental/empirical data; therefore, further experimental research is required to observe the influence of such monitoring levels on wider maintenance operation systems as a whole. There is an absence of literature on how to assess the effectiveness of asset monitoring when considering assets in a system rather than technology in isolation.

Simulation has been widely used for manufacturing systems including defence, healthcare and public services (Jahangirian et al., 2010). It is defined as "experimentation with a simplified imitation of an operations system as it progresses through time, for the purpose of better understanding and/or improving that system" (Robinson, 2004). Simulation techniques have the capability to analyse the performance of any operating system without affecting the real system. Discrete Event Simulation (DES) is based on events that exist at determined points, and that events will only take place at these points. This method is more appropriate for detailed operations systems where each item needs to be traced within the organisation's dynamics (Robinson, 2004) and so is particularly relevant to maintenance systems. Simulation has been nominated as the second most widely used technique in operations management (Pannirselvam et al., 1999) and has the potential to represent the complexity of maintenance systems. However, when seen in the context of wider manufacturing analysis, the subject of maintenance modelling is poorly covered within literature, particularly on considering different maintenance monitoring strategies.

This paper develops a DES tool to be used by maintenance operations decision makers in order to allow them to select the most appropriate monitoring level of their assets based on analysis rather than reasoning. The tool is specified for supporting complex maintenance operations of products located in different locations (customers' locations). This tool will include resources that may affect the maintenance operations such as asset location, spares availability, labour skills and shifts. To achieve this, the following different monitoring levels will be investigated:

- Reactive maintenance strategy, also known as 'traditional maintenance' (no monitoring).
- Diagnostics maintenance strategy, where the asset is able to diagnose itself and identify the failed part (Medium monitoring).
- Prognostics maintenance strategy, where the asset is able to predict the future failure of a part (High monitoring).

Section 2 of this paper will introduce a literature review to identify gaps in the existing knowledge. Section 3 will be devoted to describe the research methodology applied. The generic requirements in maintenance operation modelling is presented in section 4. The simulation tool is described in detail in section 5. Then, section 6 will present the case study to confirm that all output requirements can be captured by the developed tool. Following that, section 7 will display the case study results and give an analysis. Finally, conclusions drawn from the research undertaken will be discussed.

2. Literature review

Reliability has always been an important aspect in the assessment of industrial products and/or equipment. However, no matter how good the product design is, products deteriorate over time since they are operating under certain stress or load in the real environment that is often difficult to predict.

Maintenance has, thus, been introduced as an efficient way to assure a satisfactory level of reliability during the useful life of a physical asset.

2.1 Maintenance approaches

The earliest maintenance technique of Reactive maintenance (unplanned maintenance), takes place only at breakdowns. A later maintenance technique of time-based preventive maintenance (also called planned maintenance) sets a periodic interval to perform preventive maintenance regardless of the health status of a physical asset. The shortfall of this strategy is the consumption of more spare parts than planned maintenance as part life is not fully utilised. With the development of technology, products have become more and more complex while better quality and higher reliability are required making the cost of preventive maintenance higher. Consequently, preventive maintenance has become a major industrial expense (Jardine et al., 2006). More efficient maintenance approaches such as condition-based maintenance (CBM) are being implemented to handle the situation. CBM enables asset health monitoring through sensing technologies (Grall et al., 2002). It is divided into two monitoring levels, namely Diagnostics; where the machine (Product) diagnoses itself upon a failure and sends feedback information to the maintenance centre and Prognostics, where the machine predicts the failure based on monitoring the machine health status through sensing technologies.

Wang and Christer (2000) have examined a technique for modelling CBM decision making for plant with dual maintenance actions of preventative and replacement. Vardar et al. (2007) designed a queuing-location model to assess the adequacy of after-sales service providers through information from remote diagnosis tools. While assuming the consequences of congestion, the model optimises the place, capability and the service centre category by means of a simulation optimisation based on genetic algorithms. De Smidt-Destombes et al. (2006) have looked into combining CBM as a maintenance policy and the spare part levels. They stated that a maintenance policy, spare part levels, and repair capacity can control the system availability. They presented two analytical approaches to evaluate system availability. Their DES model showed the trade-off between inventory, repair capacity, and maintenance policies for the proposed approaches. This work is one of the few to discuss different operational settings together instead of the common practice in the research where each setting is modelled in isolation. Nevertheless, the coverage of operational settings was limited, e.g. labour availability was excluded. As the complexity of the operational system increases the application of analytical models will be harder.

According to Alabdulkarim et al. (2013), literature on CBM focuses on machine deterioration with the emphasis on machine reliability within a manufacturing plant. Little work has addressed the products within customers' locations. Such complex maintenance operations are beyond the ability of mathematical models due to the complexity and interaction between different subsystems within the wider system over time. As the quantity of the products spread among different customers is relatively high compared to manufacturing systems, travel time is another critical issue. Lastly, the spare part ordering policy and labour availability as these are constraints in such complex systems.

2.2 Suitability of simulation to model maintenance operations

Discrete Event Simulation (DES) has the potential to evaluate different maintenance strategies incorporating all the maintenance operational settings such as asset location, spare part levels, labour availability, travel time to asset, etc. rather than using hard analytical models. The DES approach will enable organisations to select the appropriate maintenance policy (reactive, proactive: where CBM is introduced) suitable for their use from an operational point of view rather than a machine reliability view. The DES technique will enable an understanding of the overall dynamic operation.

In addition, DES has been utilised in decision-making mechanisms in asset availability. Ali et al. (2008) carried out an assessment on manufacturing performance in the automotive industry, identifying the bottlenecks and selecting suitable strategies using simulation and optimisation. They looked at why most currently available production systems have disappointing overall availability.

They discovered that this is primarily due to excessive downtime caused by failures of machine/components along with quality problems. Moreover, in order to assess the maintenance performance plan in the manufacturing field, a new approach combining simulation techniques and optimising algorithms has been advocated by Roux et al. (2008).

Meanwhile, emphasis has been given on optimising preventive maintenance in a similar area of manufacturing such as the work done by Oyarbide-Zubillaga et al. (2008). Their primary goal was to search for the optimal frequencies for the preventive maintenance of a multi-equipment system based upon profit and cost factors. Eventually, a Machine Service Support (MSS) System was developed by Ng et al. (2008) allowing an operations and maintenance expert to study and identify disturbances that occur at all locations, however remote.

Besides manufacturing systems, some studies drew attention to maintenance operations outside the boundary of factories. A DES model was created by Greasley (2000) for a company tendering for the operation of a train maintenance depot. By applying the model, the company benefitted in comprehending the operational impacts of a variety of plans and how to meet the demand. Finally, the Finnish Air Forces developed a DES model to investigate the effects of maintenance resources, policies, and operating environments for aircraft availability (Mattila et al., 2008).

Maintenance modelling work entails production as well as business processes as it covers material movement, information and decision making. It is more difficult and complex to model a maintenance operation, since it is not as developed as the manufacturing system operation model mainly due to the fact that in the former, more sub-systems are working together in a complex manner. Usually, the sub-systems, such as production, maintenance staff, and spare parts inventory are modelled separately. In an effort to understand this complex mechanism, Duffuaa et al. (2001) developed a generic conceptual model that best signifies the maintenance in a manufacturing system, and combines various modules together. Other studies formed a conceptual framework which combine maintenance operations in the airline industry (Duffuaa and Andijani, 1999). These models, however, were only conceptual and were not represented using simulation methods which are able to simulate actual performance.

In spite of these examples, there is no discussion on how the service performance is affected by the maintenance of the product in use. The system will become more complex with the maintenance of an asset at a customer site in comparison with the maintenance in a manufacturing system. This is simply due to the availability contract's complexity, caused by the distance between the asset location from the service provider and the availability and location of spares. A single bespoke model was created by Agnihothri and Karmarkar (1992) in order to replicate field services operation with reactive maintenance. The effect of diagnostics/prognostics monitoring technologies on asset maintenance operations has not yet been investigated using simulation modelling beyond reactive maintenance. Recently, Teixeira et al. (2012) developed an online simulation framework of asset health management. This online simulation is beneficial to use whilst a maintenance contract is running. Assessment is lacking by the decision makers as to which monitoring level they should seek using dynamic modelling techniques such as Discrete Event Simulation (DES).

Whilst DES is one of the few tools to replicate product in use maintenance by combining all sub-systems involved that contribute to complexity in modelling, there is little published work in this area (Alabdulkarim et al., 2013). This paper seeks to address this gap by presenting the deployment of simulation across a number of maintenance strategies (asset monitoring levels). In addition, to compare between those assets monitoring levels, to gain better understanding of the maintenance systems when those monitoring are applied.

3. Methodology

In order to understand the behaviour of maintenance system operations using DES, generic requirements for simulation must first be gathered. Two parallel approaches were used. Firstly,

interviews were conducted with academics and industrial practitioners. Secondly, simulation requirements were gathered from papers in the literature. Details on how the generic requirements were gathered (e.g. number of interviews, papers analysed, etc.) and in turn the model inputs and outputs are presented in the next section. A combination of literature search and expert semi-structure interview was used due to the lack of comprehensive models or theories covering this area.

From the generic requirements, three asset monitoring levels were abstracted. These monitoring levels are namely: (1) Reactive Maintenance (RM) as a low monitoring level. (2) Diagnostic Maintenance (DM) as a medium monitoring level. (3) Prognostic Maintenance (PM) as a high monitoring level. These monitoring levels were used to develop three logic flowcharts for maintenance strategies which are analysed in order to understand wider maintenance operation systems' behaviour.

Based on these logic flowcharts, a DES tool was built to represent different monitoring levels (Reactive, Diagnostic and Prognostic). The tool was modelled using the Witness simulation software (Lanner group, 2013), selected for its flexibility and availability. A spreadsheet interface was created and linked to Witness to enable fast model configuration and results collection from the simulation models.

The case study modelled using this DES tool was analysed for different asset monitoring levels (Reactive, Diagnostic, and Prognostic). This provided insight into the case operation as well as ensuring that the outputs from the requirements' phase were captured within the tool.

4. Generic requirements for conceptually modelling maintenance operations

The method applied to gather generic requirements for simulating a maintenance operation system was to conduct expert interviews and analysis of maintenance modelling literature. The semi-structured interviews (Robson, 2002) were conducted with academics and industrial practitioners in the field of simulation, maintenance, and operations management. Interviewees were asked about the level of detail that is required as well as the input and output requirements. Interviews (nine) were conducted until saturation was reached. The latter interviews gathered little additional requirements and served to confirm the earlier findings.

Secondly, literature papers in the field of maintenance modelling were analysed. Ten papers were found to have sufficient levels of detail to warrant inclusion in the analysis (Table 1). The two approaches of interview and literature review were merged into the generic requirements of simulating a complex maintenance operation. Figure 1 represents the level of detail that is required for modelling by functionality, whilst Figure 2 represents the inputs and outputs that were gathered for that functionality. After each input and output in Figure 2 a letter (L) or (I) or (L,I) is shown to indicate from where each requirement is captured, where (L) represents literature review, (I) represent Interviews, and (L,I) means this requirement has been captured through both Literature review and interviews.

> - People: (locations, skills).
> - Equipment: (production, failure modes, location, tools)
> - Monitoring Technologies: (Diagnostics & Prognostics)
> - Spares inventory: (lead time, quantity, etc.)
> - Service level: KPI measures

Figure 1 Level of details of modelling product's complex maintenance operations (adapted from Alabdulkarim et al., 2011)
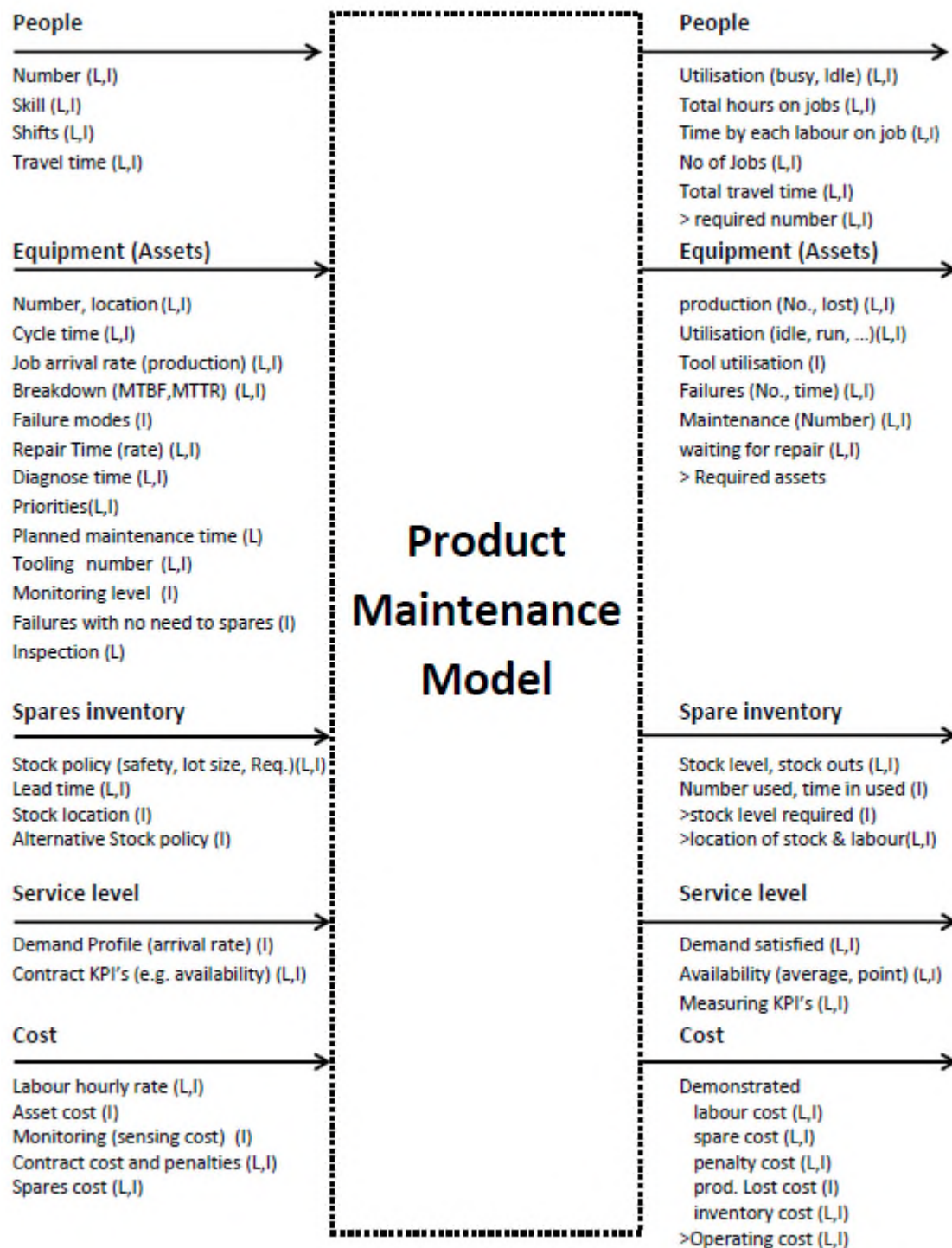
Figure 2 Generic requirements of modelling complex maintenance operations (adopted from Alabdulkarim et al., 2011)

Table 1 Published papers from which the input/output requirements were drawn

Reference	Description
Pruett and Lau (1982)	They used simulation model to better understand the response of highway maintenance systems under various conditions.

Burton et al. (1989)	A simulation study to evaluate the performance of a job shop plant, where the equipment is subject to failure under different maintenance policies.
Agnihorthri and Karmarkar (1992)	To assist service managers in evaluating the performance of given service territory, to minimise total cost of maintenance.
Albino et al. (1992)	A simulation study to evaluate service performance measures when examining different maintenance policies in just-in-time manufacturing line.
Seal (1995)	Applied spreadsheet simulation technique to model a machine repair problem of a queue with arrivals from finite population.
Al-Zubaidi and Christer (1997)	Developed a building maintenance manpower simulation model for hospital complex to assess the potential gained to be realised using different manpower levels and operational procedures.
Duffuaa and Andijani (1999)	Described the integrated elements of simulation model for (SAUDIA) airlines.
Duffuaa et al. (2001)	Developed a generic conceptual simulation model for maintenance.
Andijani and Duffuaa (2002)	A review paper which examine and evaluate simulation studies in maintenance.
Antoniol et al. (2004)	Assessing staff needs for software maintenance project through queuing simulation.

The requirements collected consist of input and output data shows a similarity between what was obtained from literature and interviews. From literature, input data that is frequently appearing is of course the product reliability data, followed by the maintenance staff levels and their locations, then number of products need to be maintained. Other requirements have been picked such as spare parts and inventory; service level required and cost elements. In terms of outputs, most frequent are number of failures and their total time, number of maintenance performed, staff utilisation, and maintenance operating cost. Other outputs were also picked such as spare parts and service levels.

While in the interviews, it was obvious that the most input data that is frequently mentioned is the product reliability data, followed by the maintenance staff levels and their locations, then number of products need to be maintained. Other requirements have been picked such as spare parts and inventory; service level required and cost elements. In terms of outputs, most frequent are number of failures and their total time, product availability, travel time, and maintenance operating cost. Other outputs were also picked such as spare parts and service levels

The interview data and the literature review were further analysed to identify three generic monitoring levels. These generic monitoring levels were developed using in logical and case insights from the interviewees and can be used as a baseline for Discrete Event Simulation (DES) models to understand the effects of using the monitoring technologies. Figure 3 represents the logic for the monitoring levels, capturing the decision points and the flows of information between stages. The figure shows the common as well as unique elements, for example, travel to asset and diagnose are unique to reactive whilst check for spares availability is common to all models.

The asset monitoring level logic starts at the top of the flow charts (Figure 3) with either a breakdown occurring or the suggestion that a breakdown could occur. When a breakdown occurs in the reactive scenario then a check is made in the model logic to ascertain availability of staff to travel to diagnose and potentially fix the asset. If the asset cannot be fixed then staff wait until spares are available before returning. For the diagnostic logic, the asset self-diagnoses and communicates the fault and staff wait until spares are available before travelling. With the prognostic logic the failure is predicted and a service request is made. Once stock is available for all three scenarios, staff travel to repair or service the asset. Throughout checks are made for tool availability if relevant.
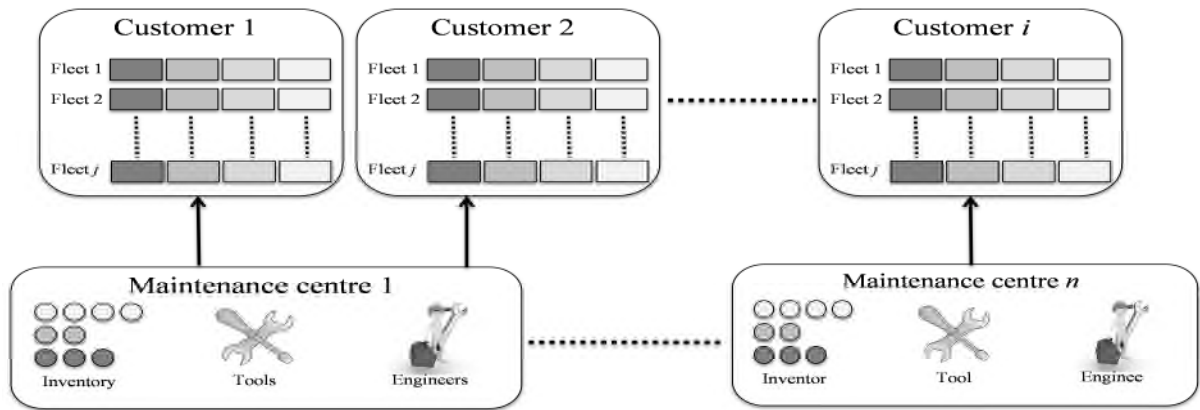
Figure 3 Monitoring level logic flowcharts represented by different flow for Reactive, Diagnostics, and Prognostics strategies.

Figure 4 represents how the complex maintenance operations for products can be modelled. The schematic shows another view on the models created that will need to be created, each having the multiple instances of common elements of fleets of assets, inventory, tools and engineers. The differences between the three maintenance strategies is not discernible in this view as the variants are dependent only on the control strategies shown in figure 3.

Figure 4 Maintenance operational complexity for products

5. Asset Monitoring Levels Simulation Tool (AMLS)

The three monitoring level logic flowcharts were used as the basis of the Discrete Event Simulation (DES) tool. Typically, simulation software packages have a simple built-in breakdown modelling capability for modelling failure and repair. However, according to the requirements gathered, more detail and complexity is required to represent what happens when an asset fails and how it is repaired. For example, each monitoring level treats the breakdown and subsequent repair differently. Each failure mode needs particular labour skills, tools and, more importantly, the required spare part. The developed tool captured such subtleties.

An Excel interface was built and connected to the simulation model in order to allow rapid configuration of the tool and to avoid the need to work with the more flexible and therefore more complex simulation software interface as shown in figure 5. The Witness simulation package was the chosen environment to develop the tool due to its flexibility and availability.
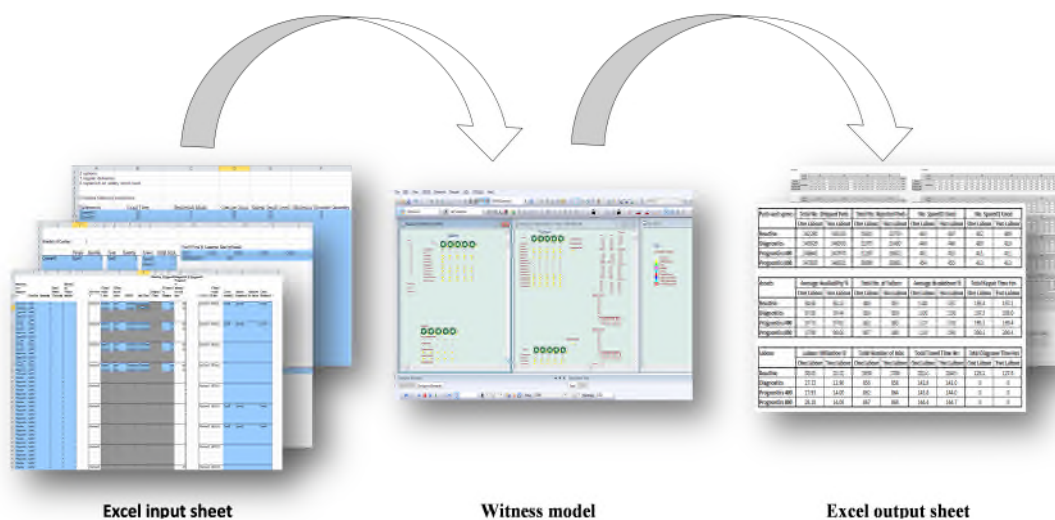

Figure 5 Excel interface with Witness

The interface was created in an Excel spreadsheet. Seven worksheets were used to represent each type of input data as well as resulted outputs as follows:

1. Maintenance Centre:
   ➢ Number of maintenance centres and customers.
   ➢ Travel time from each maintenance centre to each customer.
   ➢ Labour, tools, and spare parts located in each centre.
2. People: assignment of labour to shifts and skills.
3. Shifts: configuration of the number of shifts and durations.
4. Orders: creation of spares, arrival rate and assignment to particular assets.
5. Asset:
   ➢ Breakdown priority for each asset, the higher the number the higher the priority.
   ➢ Monitoring level of reactive, diagnostic or prognostic by asset.
   ➢ Assignment of assets to customers, their quantity and the number of failure modes.
   ➢ Planned maintenance schedule.
   ➢ Failure mode detail including failure according to available or busy time, the Mean Time Between Failures (MTBF), the diagnosis time (reactive only), repair time, and the prognostics (prognostic only: the time in advance that an asset will send feedback information about an upcoming failure)
   ➢ Resources requirement for each specific failure mode: labour skill, tools and spares.
6. Spares: the lead time, safety stock and reorder quantity
7. Results: the tool is able to measure the following results:
   ➢ Assets: Utilisation (Idle, Busy, Down), Downtime is broken down into full details (waiting for resources per asset, actual diagnosis and repair time, travel time per asset ...etc.), Number of failures per asset, Number of asset operations, Production (successful, and lost), Availability percentage per asset.
   ➢ Labour: Utilisation (Idle, Busy), Quantity, Number of jobs, Average job time.
   ➢ Inventory: Spare parts minimum and maximum quantity in the inventory during the model run time, number of each spare used, average time each spare spent in the inventory during model run time.
   ➢ Cost: all cost calculations can be calculated and obtained by the above results.

This tool takes into account different system constraints that may affect the maintenance operations with the flexibility to be reconfigured for modelling different monitoring levels. The simulation based tool can dynamically evaluate how the maintenance operations perform with different monitoring levels.

6. Industrial Case Study

A case study was used in order to demonstrate and test the developed Asset Monitoring Levels Simulation (AMLS) tool. The purpose was to test how the implementation of the generic requirements for modelling complex maintenance operations can be captured by the tool. This case company is a large perishable food importer in the Middle East. It distributes the food (e.g. cheese, vegetables, and chicken, etc.) across Middle East which will be stored in main hub areas ready to be distributed to nearby cities and villages. This company has four main distribution hubs which hold huge refrigerating systems in order to store the perishable food. These refrigerators are huge and their capacities are measured in tons. Refrigeration systems are significant to this company. A breakdown of a few hours in these refrigerators will result in massive losses. Therefore, maintaining these refrigerators is essential for its business.

This company has two large hubs and two smaller hubs. Each of the large hubs have two refrigeration systems while the other two hubs own only one each. The maintenance activities in this company are done in-house. All of the refrigerating systems installed in each of the hubs are similar. Each system installed has four failure modes and each one needs a specific spare part in order to repair it. It is

worth mentioning that these refrigerating systems are working continuously. Figure 6 shows the schematic diagram of the case study details.
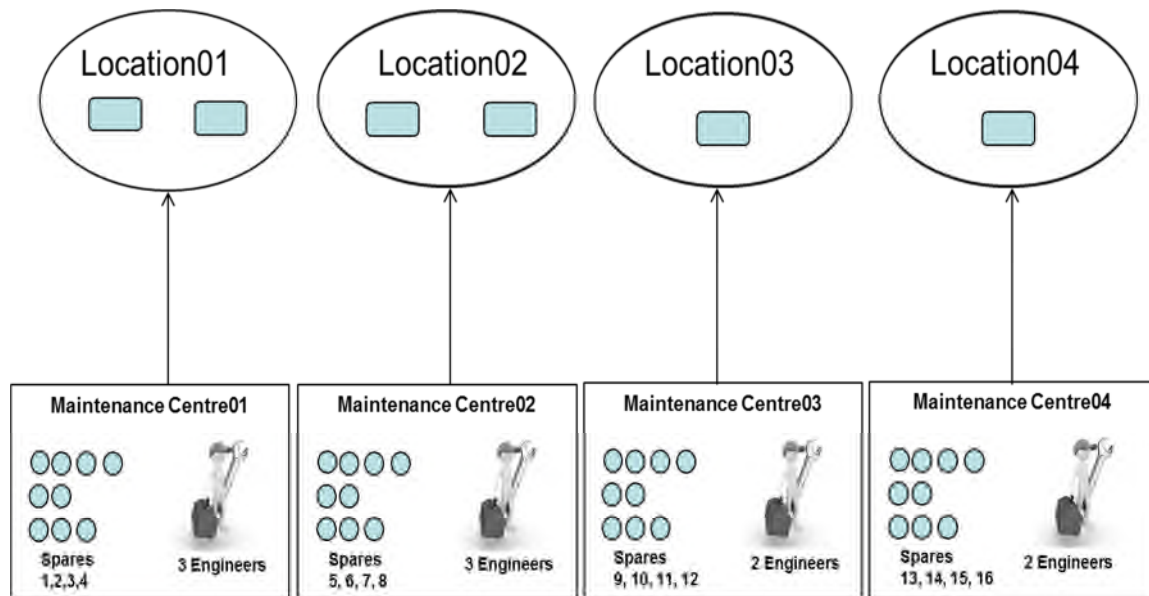

Figure 6 Schematic diagram of the industrial case

Location01 and location02 are the major distribution hubs of the company which have two refrigerating systems with three dedicated maintenance engineers each. Location03 and location04 are identical and have one refrigerator with two engineers on each location on standby for maintenance. The engineers will immediately diagnose and repair the refrigerating system once it fails (Reactive Maintenance). MTBF is relatively high which is typical in refrigerating systems. All data required has been obtained through a face to face interview with the maintenance manager of the company who is a maintenance engineer with experience in the field of refrigerating systems of more than 20 years. Triangular distribution has been chosen to represent MTBF, Diagnose, and repair times for ease of estimation.

All the refrigerating systems installed at all the hubs are by different manufacturers but similar in their failure modes and their associated MTBF. The only differences among these systems are the spare parts related to each failure mode. In this case, this company has 12 different spare parts. Table 2 shows case study information obtained from the case company.

Table 2 Industrial case input data

Location	Location01	Location02	Location03	Location04
No. of refrigerating units	2	2	1	1
No. of engineers	3	3	2	2
No. of failure modes	4	4	4	4
Spare parts	Spare01,02,03,04	Spare05,06,07,08	Spare09,10,11,12	Spare13,14,15,16
Failure mode01	MTBF (mins):Triangular Distribution (86400,259200,518400)			
	Diagnose time (min):Triangular Distribution (60,120,840)			
	Repair time (min):Triangular Distribution (720,1080,1440)			
Failure mode02	MTBF (mins):Triangular Distribution (86400,129600,259200)			
	Diagnose time (min):Triangular Distribution (60,120,840)			
	Repair time (min):Triangular Distribution (720,1080,1440)			
Failure mode03	MTBF (mins):Triangular Distribution (518400,864000,1036800)			
	Diagnose time (min):Triangular Distribution (60,120,840)			
	Repair time (min):Triangular Distribution (20,25,30)			
Failure mode04	MTBF (mins):Triangular Distribution (86400,172800,259200)			
	Diagnose time (min):Triangular Distribution (60,120,840)			
	Repair time (min):Triangular Distribution (60,150,720)			
Lead time	20 days			
Reorder quantity	3 each except for Spare03,07,11,15 are 1 each			
Safety stock	1 for all spares			

The next sub-section will discuss the experimentation set-ups (run length, warm-up period, and number of replications). In addition, it will list the number of experimentations conducted in this case.

6.1 Experiment setup

When a simulation experiment is about to be conducted, a setup for the experiment needs to be made. Experiment setups in simulation are often simulation run length, warm-up period, and number of replication needed.

According to Robinson (2004) there are two different types of simulation models: terminating and non-terminating models. A model will be considered terminating when there is a natural end point to terminate the run length of the model (e.g. bank closes at the end of the day, end of the busy lunch period at a supermarket), whereas the model would be considered as non-terminating when no natural end point exists and the model would only end when the simulation run would be terminated by the user.

The nature of the models to be simulated in this research are non-terminated models. For non-terminated simulation the model output often reaches a steady-state. To reach a steady-state output, the output will gradually go through an initial transient period. Usually, in the beginning of the simulation run, the model is not stable and it builds up until it reaches the steady-state output.

To obtain accurate output results for non-terminated simulations, the user needs to determine the warm-up period. In addition, the user needs to either have a long run or multiple replications. By performing multiple replications and taking the mean of the results, a better estimate of model performance is gained. Performing multiple replications is equivalent to taking multiple samples in statistics. Meanwhile, performing one long run is equivalent to taking one large sample.

In this industrial case, the run length was decided to be for five years. This decision was agreed by the case company and the researcher as a sufficient number of breakdowns will occur during such a period for each asset. while, the warm-up period was decided to be for one year (one year warm up, five years run length). This was based Time-series inspection suggested by Robinson (2004). He stated that one of the model output should be measured through the model running time and the modeller can decide visually where the steady-state of the system starts. By doing so, the warm-up period needed can be decided. For this research, the authors decided to use labour utilisation as an output measure to decide the warm-up period as the labour utilisation is associated with the asset breakdown which is the main concern for this research. Figure 7 shows the Time-Series diagram.
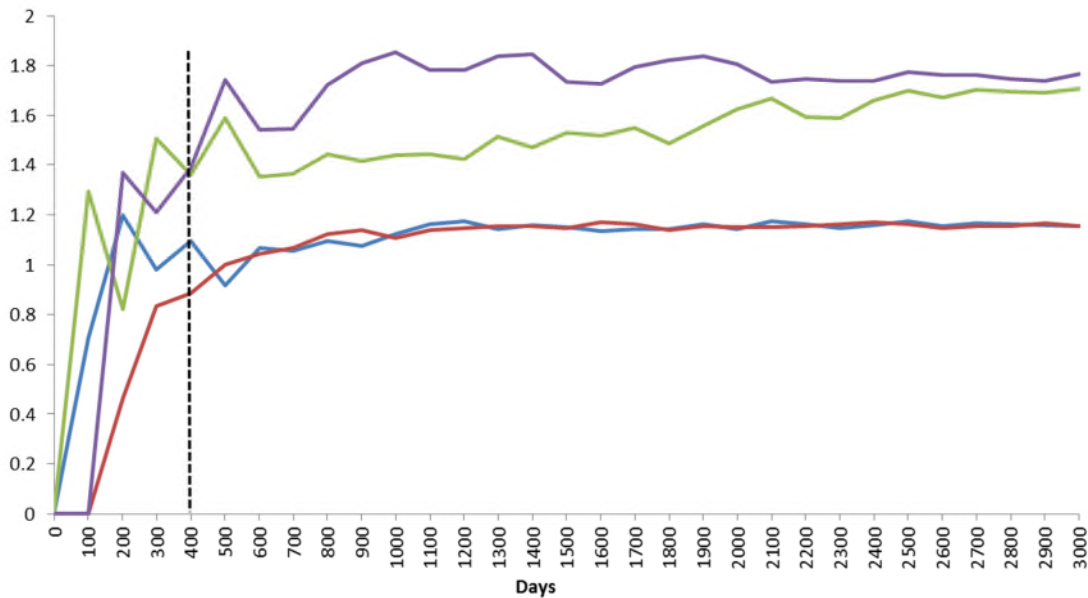

Figure 7 Time-Series diagram to measure the warm-up period

The number of replications was decided based on a rule of thumb (three to five replications) suggested by Pidd, M. (2004) and Robinson (2004). In addition, the researcher has calculated the required number of replications based on a confidence interval method. Table 3 confirms that two replications are sufficient as the deviation is less than 1%. The calculations were based on the (As-Is) model, and the output measure used for this calculation was the average availability percentage of the refrigerators. Combining the rule of thumb and the confidence interval method, the researcher decided to select three replications to be used in this case. The input distributions for the model were derived from case company data and the resulting model behaviour shows low overall output variability. Hence, whilst a higher number of replications could be performed, the behaviour of the model only necessitates a low number of replications.

Table 3 No. of replications calculation based on the confidence interval method

				Significance level	5.0%	
				Confidence interval		
Replication	Result-Availability %	Cum. mean Average	Standard deviation	Lower interval	Upper interval	% deviation
1	98.32	98.32	n/a	n/a	n/a	n/a
2	98.29	98.31	0.021	98.11	98.50	0.19%
3	98.23	98.28	0.046	98.17	98.39	0.12%

A set of experiments have been conducted for this case. These experiments were made to test different situation to assess the AMLS tool. Those experiments are shown in Table 4.

Table 4 Experiments conducted for the industrial case

No.	Experiment description
1	As-Is
2	Labour reduction to one at all locations
3	Travel time 240 (mins)
4	Travel time 720 (mins)
5	Increase the MTBF by 50%
6	Decrease the MTBF by 50%
7	Increase spares lead time and decrease Min. reorder quantity

Three scenarios (Reactive, Diagnostics, and Prognostics) were compared for each of the experiments. Furthermore, different Prognostics Windows (PW) were applied.

Seven different experiments were applied with three monitoring levels, while the Prognostics level has been applied with three different PWs which are (PW=400 min, PW=1000 min, and PW=86400 min). These different PWs were to assess different levels of PW on maintenance operations. In addition, a significant PW value (PW=86400 min) was decided to assess the scenario when PW > spares lead time (this was only applied when experimenting with the spare lead time). Bearing in mind that three replications for each scenario were decided, this makes the total number of the simulation runs for this case come to 84 runs. Figure 8 shows a snap shot of the model while running.
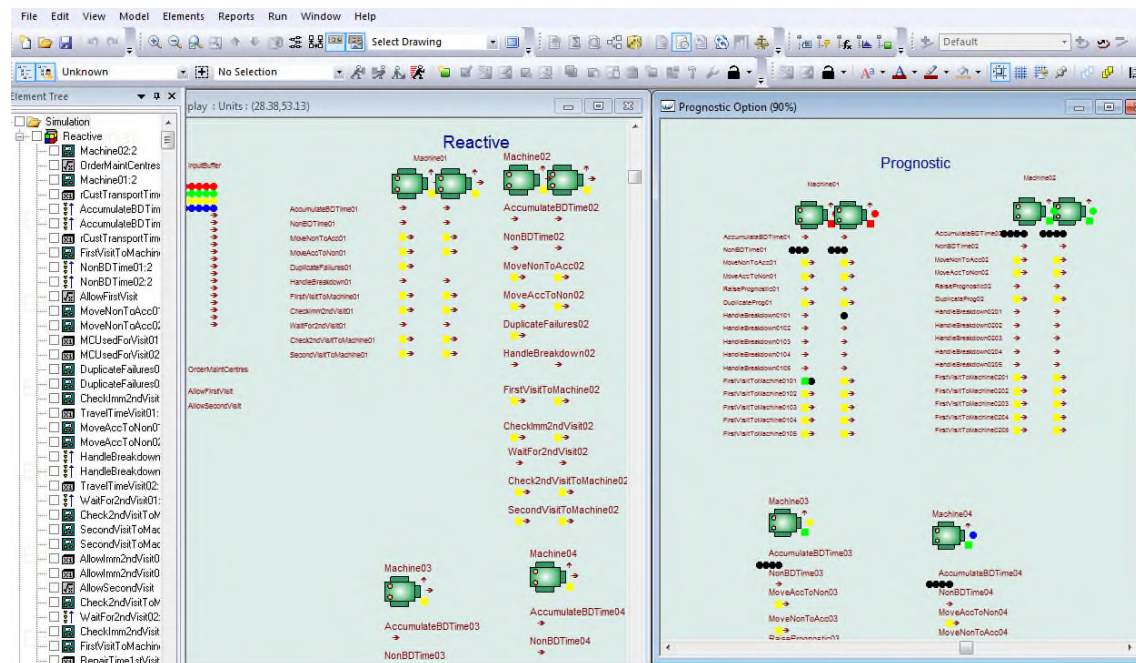

Figure 8 snapshot of the AMLS tool while running

Following this, the analysis of the results obtained will be presented and followed by a validation process.

6.2 Results and analysis

In this section, the results of the different experimentations for the industrial case will be analysed and discussed. A comparison between experiments conducted in all the three monitoring levels will be presented and discussed here. Due to the length of the results obtained, the discussion will focus on

applying the comparisons of different monitoring levels based on the main measures of availability percentages, breakdown percentages, number of failures and labour utilisation percentages. Other metrics such as idle percentages, busy percentages for refrigerators and labour are collectively reported in these main metrics.

Figures 9, 10 and 11 show the comparisons of average availability percentages, breakdown percentages, and number of failures on different experiments. A discussion of each experiment will be presented as follows:
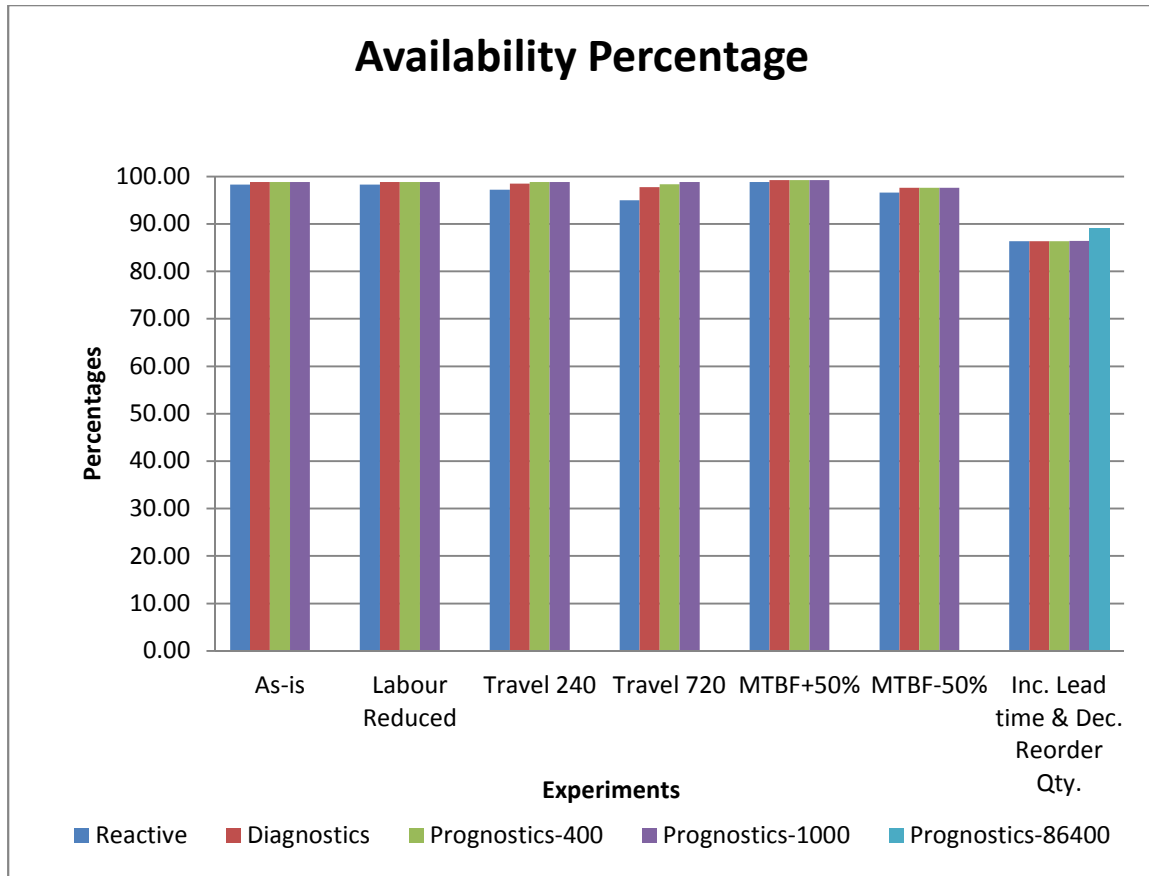

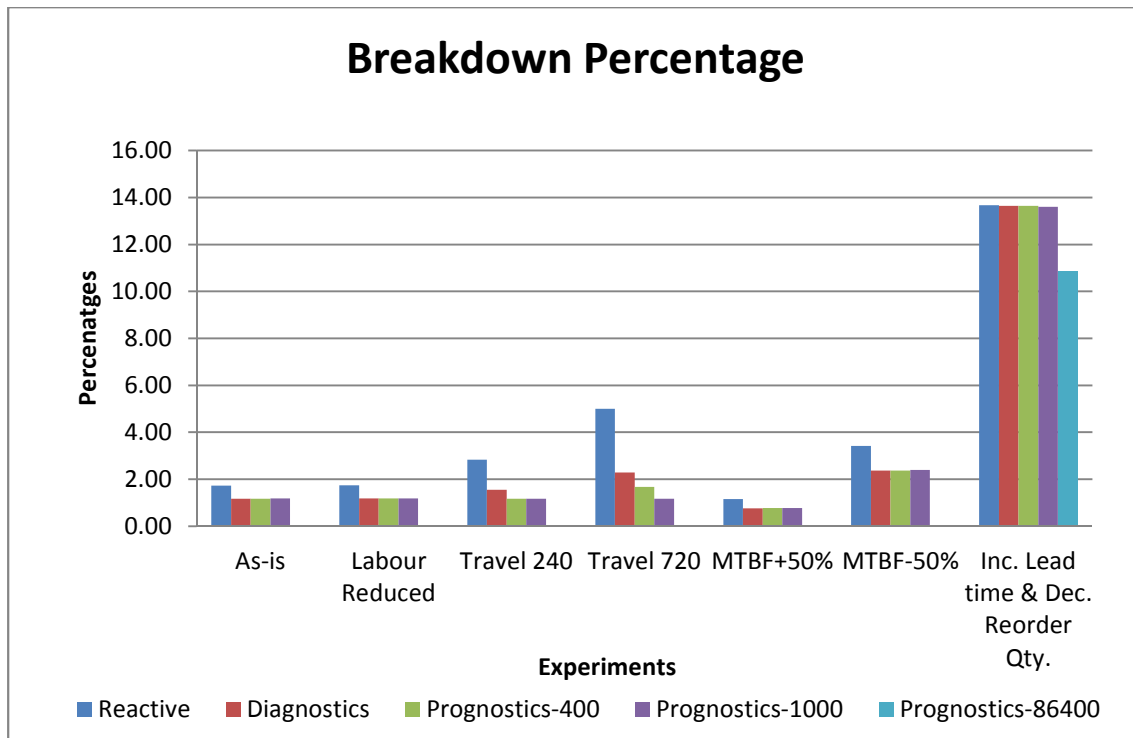**Figure 9 Availability percentages across different experiments**

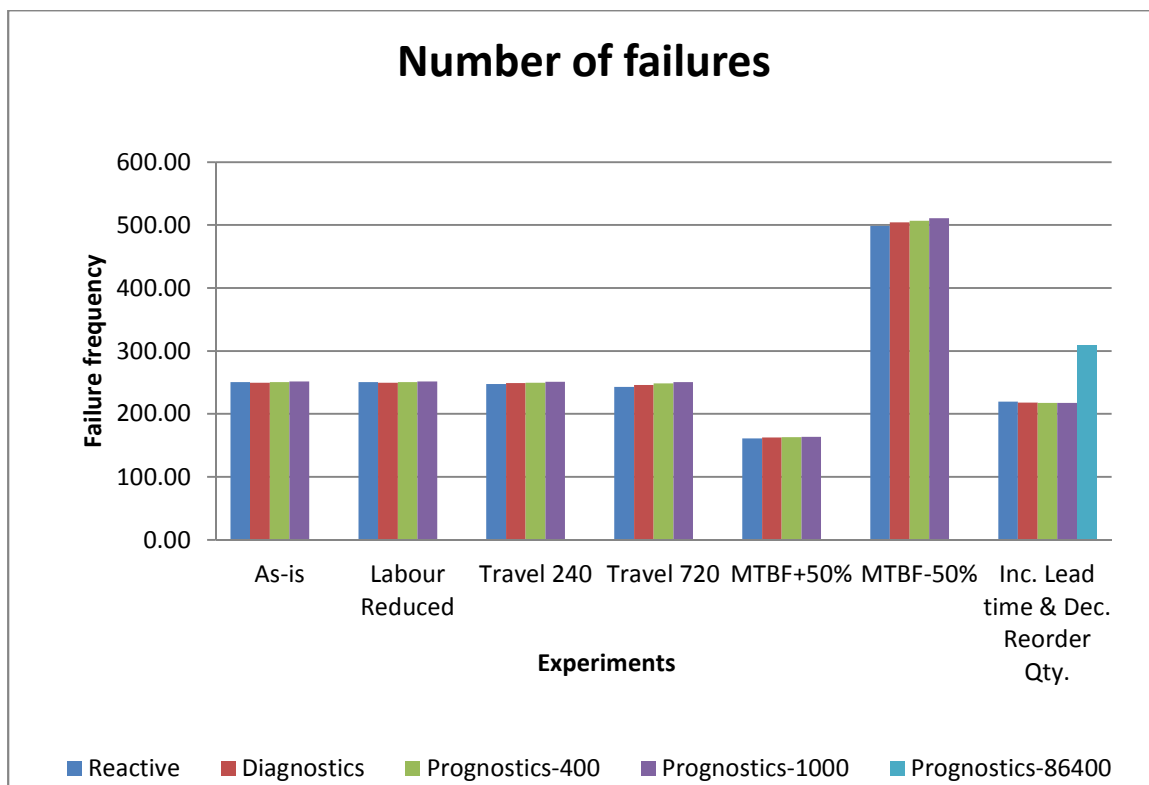**Figure 10 Breakdown percentages across different experiments**

Figure 11 Number of failures across different experiments

- **As-Is scenario and Labour reduction**

As this case is about maintaining the refrigerating system and taking into account the high MTBF for such systems, this explains the high availability already obtained. As-Is and labour reduction scenarios were combined in the discussion here as they provide the same results. The number of labour in the As-Is scenario is clearly more than the company actually needs. When this was raised to

the case company, the reply was that having more labour is preferable compared to losing perishable food which is worth significant amount of money due to a breakdown. In addition, the labour costs are low. Consequently, the researcher decided to conduct another experiment with the minimum number of labours (one labour) at each maintenance centre. The results of the As-Is and the labour reduction are the same.

In the As-Is and labour reduction scenarios, it can be noted that Diagnostics and Prognostics in general give slightly better availability than Reactive. This improvement of 0.55% is small compared to that of the Reactive level which in this case is already achieving high availability. The reader might be surprised to discover why the Diagnostics and Prognostics levels in these scenarios provide exactly the same results. Figures 12 and 13 explain the reason behind this, particularly as there is no travel time and that all the resources needed, such as labour and spares, are always available.
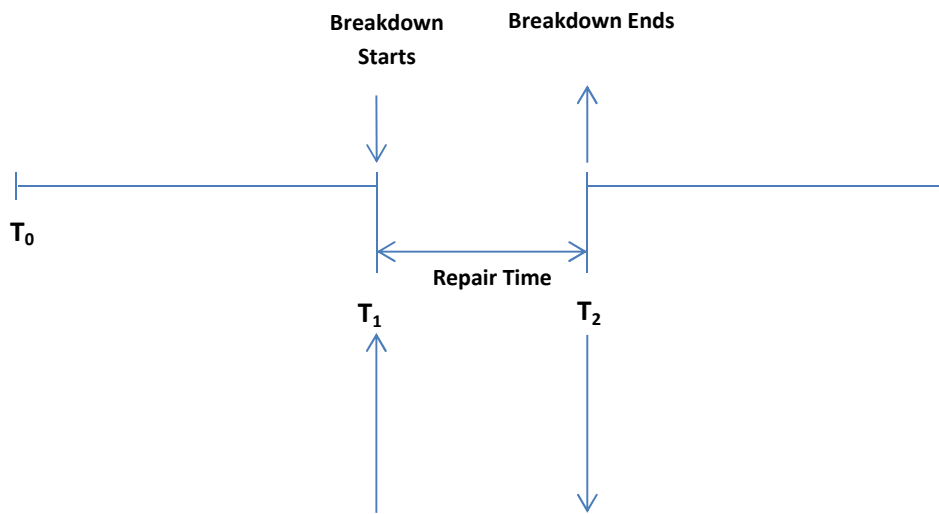
Figure 12 Diagnostics level case when no travel time and all resources available
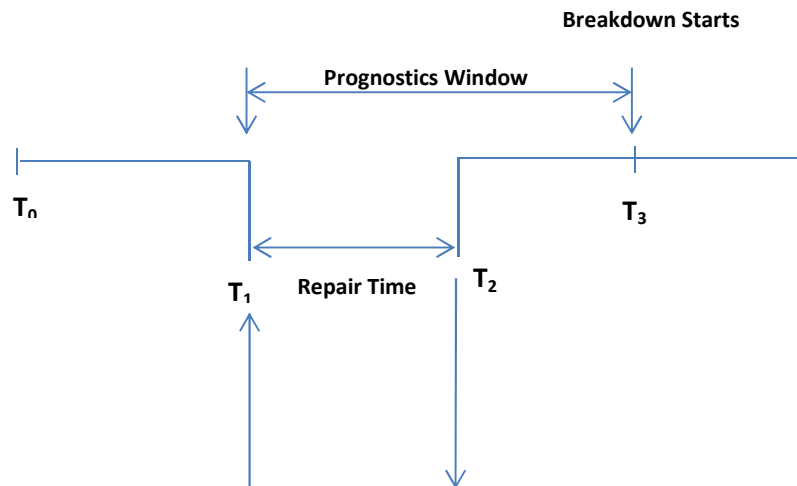
Figure 13 Prognostics level case when no travel time and all resources available

Figure 12 shows that in the case of the Diagnostics level applied, where all resources are available and there is no travel time to the product, then the failure is supposed to happen at T_1. As there is no travel time and resources are all available then the repair will start at T_1 until T_2 as there will be no waiting for resources at all.

Figure 13 explains what happens when the Prognostics level has been applied where all resources are available and there is no travel time to the product. Failure is expected to happen at time T_3 but as the Prognostics Window (PW) is applied, the resources should be triggered at T_1. Repair activity will take place immediately at T_1 by stopping the product and carrying out the repair activity. Downtime for both Diagnostics and Prognostics in this particular case will be the same. The only difference is that in the case of Prognostics the repair time will be shifted earlier but the magnitude of repair time will be the same. This explains the reason why Diagnostics and Prognostics give the same results in the first two experiments (As-Is and Labour reduction). Breakdown percentages reflect the opposite direction of availability percentages which is correct as the sum of both the availability and breakdown percentages comes to 100%.

The number of failures, as seen in Figure 11, increase as the higher monitoring levels are applied. This is as the availability increases which logically increases the number of failures occurring.

Table 5 Labour utilisation percentages for As-Is and labour reduction experiments

Monitoring levels/Labour	As-is				Labour Reduced			
	Location01	Location02	Location03	Location04	Location01	Location02	Location03	Location04
Reactive	1.16	1.12	0.85	0.89	3.48	3.37	1.70	1.78
Diagnostics	0.78	0.77	0.57	0.63	2.32	2.30	1.15	1.25
Prognostics-400	0.78	0.77	0.57	0.63	2.35	2.30	1.15	1.25
Prognostics-1000	0.79	0.78	0.57	0.63	2.36	2.32	1.15	1.25

Table 5 shows the labour utilisation percentages in both experiments. Location01 to Location04 represent the labour utilisation percentages at each maintenance location of case 01. As can be seen, utilisation percentages are very low; however, this was expected due to the nature of the maintenance activities and the high number of labour utilised. The labour are used during the job time to carry out other non-maintenance activities. These activities were not modelled as the priority was always for the maintenance of the refrigerating systems.

The Reactive shows higher utilisation percentages as expected due to the labour diagnosing and repairing the product, whereas in other levels the diagnosing activities are carried out by the monitoring technologies installed. Labour utilisation increased when the number of labour was reduced to one at all locations.

- **Travel time 240 (min) and travel time 720 (min)**

In these experiments two levels of travel times (240 minutes and 720 minutes) were applied from the As-Is model. The reason behind the choice of these travel levels was to have one travel time (240 minutes) below all the Prognostics Windows applied in these experiments (P-400, P-1000) and the other travel time (720 minutes) to be between the PW applied in order to assess the effect of travel times on the PW.

In the case of the 240 minutes travel time, it can be noted that the higher the monitoring level is applied then the higher availability is gained. However, in the Prognostics level as the travel time is below all of the PWs, it can be seen from Figure 8 that there is no improvement in the availability which will be gained among the different PWs applied. In contrast, when the 720 minutes travel time is applied it is clear that when the PW is more than the travel time (P-1000) then more availability is achieved, whereas when the PW is less than the travel time then the availability decreases. Travel time has a clear effect on the product availability performance and the developed tool has enabled a better understanding of this effect. As discussed earlier in other experiments, breakdowns reflect the opposite percentages to the availability which is reasonable.

The number of failures increases slightly when higher monitoring levels are applied. However, in the case where the travel time is 240 minutes, the number of failures is the same between P-400 and P-1000. In the case of 720 minutes travel time, the number of failures has increased a little between P-400 and P-1000.

Table 6 Labour utilisation percentages for travel time experiments

Monitoring levels/Labour	Travel 240 minutes				Travel 720 minutes			
	Location01	Location02	Location03	Location04	Location01	Location02	Location03	Location04
Reactive	2.14	2.10	1.61	1.64	4.06	4.04	3.07	3.10
Diagnostics	1.27	1.27	0.94	1.01	2.27	2.24	1.67	1.78
Prognostics-400	1.28	1.27	0.94	1.01	2.28	2.27	1.69	1.79
Prognostics-1000	1.29	1.28	0.94	1.01	2.31	2.28	1.70	1.79

Table 6 shows the labour utilisation when travel time is applied. It is obvious that the utilisation percentages increased as the travel times were included with the Reactive level giving a higher utilisation than other levels due to manual diagnosing activities. As the number of failures increases slightly towards higher monitoring levels, the utilisation percentages increase as well. When the travel time is longer (travel 720 minutes) an obvious increase in the utilisation is noticed.

- **MTBF+50% and MTBF-50%**

These experiments were conducted to assess whether the developed tool is also able to grasp the changes in the MTBFs as it would be of interest to the research to assess the effect of MTBF on different monitoring levels. Firstly MTBFs in this case study have been increased by 50%. Then, another experiment was done when the MTBF is decreased by 50% from the As-Is model.

In the MTBF+50% experiments, a slight performance improvement has been achieved in terms of availability percentage from the As-Is model. In the Reactive level this has increased the availability by 0.57% from the As-Is model while the improvements were 0.41% for the rest of monitoring levels. These improvements were only slight due to the fact that the base model (As-Is) is already achieving a very high availability. Still higher monitoring levels give slightly better availability than the Reactive level. Diagnostics and Prognostics levels achieved the same availability levels for the same reasons that were discussed in the As-Is model when both levels gave identical availability results.

When the MTBF-50% experiment was conducted it shows a drop in the availability in general from the As-Is model. The Reactive level in MTBF-50% availability dropped by 1.70% from the Reactive in the As-Is with other levels dropping from the As-Is model by almost 1.20%. Again, with the MTBF-50% experiment, Diagnostics and Prognostics levels show that they achieve a slight increase of 1.04% in availability than the Reactive level.

Table 7 Labour utilisation percentages for MTBF+50% and MTBF-50% experiments

Monitoring levels/Labour	MTBF+50%				MTBF-50%			
	Location01	Location02	Location03	Location04	Location01	Location02	Location03	Location04
Reactive	0.79	0.74	0.56	0.60	2.28	2.26	1.72	1.72
Diagnostics	0.51	0.50	0.38	0.40	1.59	1.56	1.15	1.21
Prognostics-400	0.51	0.50	0.38	0.40	1.59	1.57	1.15	1.22
Prognostics-1000	0.51	0.51	0.39	0.40	1.60	1.59	1.16	1.23

Table 7 shows the labour utilisation when experimenting with MTBF. Obviously more labour utilisation will be shown for the case of MTBF-50% as more failures occur. Generally, the Reactive gives higher utilisation, while the utilisation in the case of Diagnostics and Prognostics gives a very slight increase of 0.01% in some cases as the number of failures increases.

- **Increasing spares lead time and decreasing minimum reorder quantity**

In the base model the spares lead time was 20 days on average. With this lead time in the As-Is model, high availability has been achieved due to the reason that MTBF obtained from the company is relatively high as well as the spares always being available every time a failure occurs. Thus, the researcher has decided to examine the effect of increasing the spares lead time to 60 days. Also, the minimum reorder quantity of the spares has been set to one to establish a starving inventory situation.

A new PW of 86400 minutes (60 days) is added to this experiment (P-86400) to test if the PW > spares lead time would be reflected on the product performance.

A significant drop in availability was seen from the As-Is model which was about 98% to 86% at all monitoring levels when the lead time of spares was increased. However, setting the PW to 86400 minutes in this experiment gives a higher availability among all levels of monitoring as it increased from 86% to 89%. Diagnostics shows a very slight increase over the Reactive level by 0.03%. Diagnostics and P-400 gives the same availability, while P-1000 has increased the availability from P-400 by 0.04%. The spares lead time has shown its effect on setting the PW.

The number of failures has also increased slightly when moving to higher monitoring levels. However, it shows a sharp increase when P-86400 has been applied which is associated with the availability increase.

Table 8 Labour utilisation percentages for increasing lead time and decreasing reorder quantity experiments

Monitoring levels/Labour	Inc. Lead time & Dec. Reorder Qty.			
	Location01	Location02	Location03	Location04
Reactive	0.96	0.91	0.85	0.89
Diagnostics	0.63	0.60	0.57	0.63
Prognostics-400	0.63	0.60	0.57	0.63
Prognostics-1000	0.63	0.60	0.57	0.63
Prognostics-86400	0.78	0.80	0.93	0.98

Table 8 shows the labour utilisations for this experiment. It is evident that the utilisation percentages in general have dropped compared to the As-Is model. This was based on the shortages in the spares inventory due to the lengthy lead time. A higher utilisation was achieved when the PW was set to 86,400 minutes (60 days) as the resources were triggered in advance to match the spares lead time. This was obvious due to the higher availability achieved.

After analysing and discussing the results obtained from the developed tool for the industrial case01, a better understanding of this particular complex maintenance operation has been developed using the proposed tool. Travel time and spares lead time play important roles in deciding the PW as their effects were assessed in this industrial case study.

Also this case has provided a better understanding for the product monitoring levels when travel times are not involved, and other maintenance resources are available (labour and spares) as in this case Prognostics levels will not have any more advantages than the Diagnostics level. In the next section, the validation of these results will be discussed.

6.3 Validation of results

A web meeting was held with the maintenance manager of the case company to discuss the output obtained from the tool. The meeting started by asking the maintenance manager about his estimates of the average availabilities of the refrigerators and the labour utilisations in the current maintenance operations. The reply was 96% as an average refrigerating availability with about 70% labour utilisation. After this the result graphs were presented to discuss the reliability of these outputs obtained from the tool according to his experience from reality.

The differences of the manager's estimates and what was obtained from the tool were discussed. Both the researcher and the manager agreed that the difference of about 2% on the availability was acceptable and that it was due to several reasons. These reasons are that the manager's estimate was based on experience and was not based on actual calculations. Also, the input data was based on the manager's experience and was not obtained from a computerised system due to the simple fact that they do not currently have a computerised system to log all their maintenance activities. It is worth

mentioning that, in the data collection stage, the researcher asked the case company to use their paper records to obtain accurate data rather than expert estimation, but the request was refused due to internal reasons.

A significant difference was observed on the labour utilisation between the manager's estimate and what was obtained from the tool. This issue was discussed, and the outcome of these discussions was that according to the maintenance manager they are assigned to other maintenance and non-maintenance activities during their working hours and that is why the maintenance manager gave an estimate of 70%. The manager agreed with the current utilisation obtained by the tool as these utilisations were calculated according to the maintenance of refrigerators only. When asked about why more labour is used than needed in each station, the reply was those labour costs are very low compared to the significant cost of the perishable goods that might be lost if a breakdown occurred. The manager mentioned that the case company is satisfied with its current maintenance strategies and that it is not willing to adopt the monitoring technologies.

All other experiments were shown and discussed with the manager during the web meeting. The manager was not an expert in monitoring technologies but states that all the results obtained are sensible, logical and explainable.

7. Discussion and conclusion

The move towards more efficient maintenance strategies has been driven by the need to eliminate waste and increase the asset availability to customers. Recently, the pressure for high availability has increased in asset management. Manufacturers, suppliers, and maintenance contractors are more concerned about asset availability particularly in the case of Product Service Systems (PSS) where the sale of the asset use is demanded rather than the sale of the asset itself. Authors such as Lightfoot et al. (2011) have suggested that sensing technologies to monitor the health of the asset would increase asset performance. Logical reasoning has been used to date to justify higher asset monitoring will deliver better overall system performance but this is not supported by empirical, experimental data. The contribution of this paper is to seek to verify this using simulation approach through using the developed Asset Monitoring Levels Simulation (AMLS) tool.

Simulation, in particular Discrete Event Simulation (DES) has the characteristics to discern complex operations. A review of literature has identified an absence of dynamic tools to assess complex maintenance operations. This research started by gathering the required input and output of such complex models. This paper gathered the generic requirements for modelling complex maintenance operations (by interviews and literature). These requirements were built into a Witness simulation package representing the different monitoring levels (Reactive, Diagnostics, and Prognostics). An Excel interface has been developed for rapid model configuration which could also assist inexperienced users to insert their input and get their output without using simulation software directly.

The developed AMLS tool enables assessment of complex maintenance operations by examining the implications of different asset monitoring levels for different fleets of assets, asset locations, labour requirements, shift patterns, spare parts inventory, etc. The tool also has the flexibility of assigning different priorities for each asset, as well as different monitoring levels for each asset in the same model.

The work contains a number of limitations, some of which are the basis for future work. Firstly, the model logic assumes perfect monitoring, information records and staff competence. As companies improve the reliability of their assets and develop more effective response strategies then the issues correct diagnosis and no fault found (NFF) become more apparent. This modelling work did not consider sensor failure, NFF, loss of information, incorrect information on the availability of spares, failure to repair the assets due to mistakes or repairs triggering further faults. This could have been modelling through increasing the breakdowns or adding control logic. In this phase of the work it was

considered that the additional complexity was not necessary to understand the basic dynamics of a system but in future more insightful modelling could be conducted. Secondly, the experimentation was by changing one factor at a time rather than a design of experiments. This was considered acceptable as the purpose was to demonstrate the potential of the simulation approach rather than to provide solutions to optimise the scenarios performance. The development of optimisation techniques would be valuable from a knowledge perspective and the outcome of the optimisation would benefit the focal company. Thirdly, a wider range of applications needs to be considered in order to understand the generalisability of the modelling approach. From the experience of authors the modelling could be most valuable where it is acceptable to trade-off cost with maintenance strategy rather than the extremes of accepting break-fix approach or being a requirement to ensure near continuous operation for critical systems. Finally, a greater consideration of the contract metrics rather than simply simulation metrics needs to be considered; the simulation model shows performance from the supplier point of view of maintaining assets but is not in the format of potential availability contracts that demand availability at certain points in the day or average availability over set periods.

A case study tested the AMLS tool functionality and shows that key behaviour of entities could be captured through modelling. The results through different experiments uncovered that higher performance does not always result from the application of higher monitoring levels. This is only true in some of the scenarios examined. Evaluating the effect of the number of labour has an impact on the performance of the maintenance operations. It is noticed that when availability increases then the number of failure and the number of spares used increases accordingly. Of particular note were the high labour availability and their very fast response times due them being on-site rather than off-site. As a result of the three potential constraints of assets, people and spares it was shown that the availability and response times of people does not impact on the overall performance significantly. Another potential constraint of spares availability did not affect overall performance due to the local stocking policy and relatively fast replenishment time. Therefore the performance of each individual asset in isolation was most influential on their overall uptime.

There has been little simulation research reported in the area of field maintenance, an in particular the trade-off of asset monitoring levels. Previous work has largely focused on analytical models which do not capture and therefore do not provide insight to the dynamics of an operation when considered more holistically and not simply asset focused. This research has novelty in demonstrating an understanding of the effect of asset monitoring levels on maintenance operations when considered as a system rather than a collection of assets. The work recognises the complexity by considering asset monitoring levels in maintenance as part of a wider operational system in which there are multiple constraints due to asset capacity, labour capacity and spare part availability.

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