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SELECTING THE APROPRIATE PRODUCT MONITORING LEVELS FOR MAINTENANCE OPERATIONS: A SIMULATION APPROACH

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ABSTRACT

The demand for higher product availability has increased through product and service offerings such as Product Service Systems (PSS), where the product is sold for its use rather than the product itself. This has led to pressures on maintenance operations, particularly for out of sight products. Some authors have suggested applying sensors and the use of diagnostics and prognostics to monitor product performance driven by the generally held belief that diagnosing and/or predicting future failure will lead to higher product availability. In this paper, we show the ability of Discrete Event Simulation (DES) to compare between different product monitoring levels. This capability is then applied to an industrial case to investigate whether or not the higher the monitoring level leads to higher product availability.

1 INTRODUCTION

There has been a growing interest in how producers incorporate services into their products offering (Baines, Lightfoot, and Smart 2011). Since the mid-1990s, integrated solutions have grown significantly as companies take advantage of the market demand for more complex solution based products and services (Li. 2011). Such increased awareness has led to the development of the Product Service System (PSS) principle where the focus is on the sale of use rather than the product itself; the customer buys the service and the ownership of the product rests on the manufacturer/supplier (Mont 2002; Phumbua and Tjahjono 2011).

Despite the advantages of new value propositions that PSS offers there are risks. Where suppliers are contracted to supply certain products to purchasers, suppliers will incur any charges due to downtime. As a result, robust methods are required to analyze and enhance maintenance for the provision of good service (Datta and Roy 2011). Product performance is not limited to product reliability, but the wider system performance include inventory and labor.

Simulation has been applied to manufacturing maintenance to increase production throughput. However, a gap exists for simulating maintenance for products in use where modelling maintenance activity is complex, especially when different levels of product monitoring are employed (such as Diagnostics, and Prognostics technologies). This raises the question of whether those technologies assure higher availability or better performance of maintenance operations?

It would seem intuitive that the more sophisticated the maintenance regime, the higher the product availability as a result of better service contract metric performance. As more is known about product performance, through increasing levels of product monitoring, it would be expected that the maintenance regime would enable better availability. Investigations have shown this to not always be the case.

This paper examines overall maintenance system performance on the performance of products (assets) supported in the field using simulation. The research considers the asset performance as well as the availability of inventory and service personnel. In particular an assessment will be made as to whether enhanced product monitoring levels through diagnostic and prognostic technologies are necessarily better than basic reactive maintenance strategies. Table 1 shows the process differences of different monitoring levels.

Table 1: Processes differences between different monitoring levels

Monitoring level	Process description
Reactive	To react when the product has broken down, labor diagnose the product on site, check spares availability and then repair the product (traditional maintenance). This may require two visits from the technician, the first visit is to diagnose the product, and then another visit will be required when the technician gets the spare part if it is available, otherwise the technician will order a spare and when this becomes available he/she will make the second visit.
Diagnostics	On failure the product diagnoses itself and sends feedback information to the maintenance center. The technician will then travel to the product only when the spares are available so that he/she can repair the product.
Prognostics	in this monitoring level the product predicts its failure before it happens. This minimizes the downtime of the product.

2 LITERATURE REVIEW

2.1 Background

Maintenance plays a key role in product performance and availability. It is essential that the maintenance operation is effective and flexible to anticipate unforeseen circumstances so that product availability under PSS can always be guaranteed. The stock inventory for spare parts should be managed efficiently and rapid response time for maintenance must be kept to the minimum. The increased risks have led to the development of technological advances by the manufacturers in order to improve visibility of their products which are located remotely. These technological systems combine sensor and wireless technologies with signal processing and analysis techniques to identify the current and predicted 'health' of a product (Lightfoot, Baines, and Smart 2011).

Dealing with maintenance has been always regarded as a necessity in production to keep equipment in working order, safe to operate, and well configured to perform its task (Duffuaa et al. 2001). Simulation research has been always conducted to improve maintenance operations within a manufacturing context (e.g. Roux et al. 2008; Langer et al. 2010). Few authors have modelled maintenance using simulation outside a manufacturing systems context (Agnihothri and Karmarkar 1992; Cheu , Wang, and Fwa 2004; Riberio, Mauri, and Lorena 2011).

Lee et al. (2006) described the reactive and preventative strategies that are often implemented in maintenance as a waste. They urged toward using new sensing technologies, such as Diagnostics which can identify product faults, and Prognostics, which monitors the actual health of the product. Lightfoot, Baines, and Smart (2011) advised using product health monitoring technologies as this leads to improved maintenance actions which will in turn lead to a higher availability of products as well as feedback that could improve the design of the product.

In order to analyze the most appropriate maintenance strategy an appropriate technique must be applied. Given that modelling techniques are able to capture the complex and varying nature of systems they are appropriate candidates to carry out such analysis.

2.2 Comparing Different Modeling Approaches

Various mathematical modelling approaches are available from mathematical programming and heuristic approaches. Techniques such as Queuing Theory have been employed as an analytical instrument for varieties of applications, however, suffer a number of weaknesses. Developing queuing systems for analytical models often turns out to be very difficult for reasons of characteristics of service mechanisms, complexity of the system design, nature of queuing discipline or a combination of all these factors.

Simulation is the "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 can be categorized as continuous and discrete. System Dynamics (SD) as a specific form of continuous simulation which represents a system as a set of stocks and flows (Sterman 2000) and is applied at strategic levels where less operational details are required (Borshchev and Filippov 2004).

Discrete Event Simulation (DES) is one of the most widely used approaches (Pannirselvam et al. 1999). If a system is required to be modelled in detail, DES is more suitable than the system dynamics particularly if individual items have to be traced within the system (Robinson 2004); SD is abstract and does not capture the detail of individual transactions (machine breakdown, arrival of parts, etc.).

Another simulation technique known as Agent-Based Simulation (ABS) defined by Shannon (1975) as the process of designing an ABS of a real system and conducting experiments with this model for the purpose of understanding the behavior of the system and/or evaluating various strategies for the operation of the system. In ABS, a complex system is represented by a collection of agents that are programmed to follow some (often very simple) behavior rules. ABS is therefore stronger in social behavior modelling rather than process modelling that is a dominant characteristic of this research.

2.3 Suitability of Discrete Event Simulation

One of the main motivations for developing a simulation model or using any other modelling method is that it is an inexpensive way to gain greater understanding when the costs, risks or logistics of manipulating the real system of interest are prohibitive. Simulation has been used in maintenance by a number of authors including Andijani and Duffuaa (2002).

The most relevant applications of simulation in maintenance systems have been policy testing, scheduling, testing condition-based strategies, assessing cost, assessing availability, staffing levels, ascertaining inventory levels and establishing overall performance (Alabdulkarim, Ball, and Tiwari 2013). Within the literature it is notable that whilst simulation is highly applicable to maintenance assessment the predominant application area is manufacturing. There is conceptually no barrier to using simulation beyond the manufacturing plant, simply there are few reported applications.

It is argued here that DES can be used to support organizational decisions when determining which level of product monitoring should be selected for maintenance operations. DES has the ability to capture the dynamic behavior of such a complex maintenance system. Therefore, it is a suitable approach in supporting organizations in their selection of which level of monitoring to use for their products.

3 METHODOLOGY

3.1 Establish the Modeling Requirements

As a first research step, a literature review was undertaken to collect common modelling requirements and constraints. Next, the authors applied semi-structure interviews (King 1994) to establish the generic requirements to model complex maintenance systems. Qualitative interviews were employed in the exploratory case work prior to the quantitative simulation research to ensure any limitations of literature review alone were overcome.

Nine interviews were conducted with experts from academia and industry. The academic were identified as authors in the field of simulation or maintenance. The industrialists were selected from conferences attendance and existing networks. The interviewees came from the fields of simulation, maintenance, operations management, and business consultation.

The interviews were performed face-to-face as far as possible with telephone interviews used in isolated cases. Interviews were carried out consecutively over several months, and were ceased when the received responses did not offer any new requirements, i.e. the state of saturation was reached. The following sections detail the interviews and the collated requirements. Appendix A provides the full requirements collected.

3.2 Simulation Tool

Simulation, as a quantitative method, is a technique commonly used in operations management mainly because of its ability to capture the complex operational performance. In addition, it provides flexibility in modelling the needs of a wide range of operations from production systems to product performance in the field.

The simulation software, Discrete Event Simulation (DES), is available in various commercial software packages. For this particular study, the software package known as WITNESS (Lanner Group 2014) was used for the simulation. It was selected for its availability to the research team, its flexibility, as well as it satisfies the common requirements of maintenance modelling.

3.3 Spreadsheet Interface

DES modelling is fairly complex and not many are well versed with the software. To allow the researcher to easily and effectively use simulation it was decided to develop an interface for data entry feeding directly into WITNESS for different industrial cases (Alabdulkarim, 2014). In addition this allowed the results to be in an easy to use format. In view of this, an Excel spreadsheet (Microsoft Office) was selected because it is flexible, easy to use, easily available and the researcher is familiar with the software.

4 TOOL DEMONSTRATION

An industrial case study was used to demonstrate and test the developed tool. The purpose was to test how the implementation of the generic requirements for modelling complex maintenance operations can be captured by the tool. Additionally, the research aims to better understand such complex maintenance operations with different product monitoring levels

The purpose of the experiments carried out are firstly to ensure that the developed tool can mimic the current (As-Is) complex maintenance operations and the effect of different monitoring levels on the current situation. Secondly, other experiments have been carried out to assess if the tool can absorb the changes of some factors as well as to gain more insight and understanding of how these factors affect the complex maintenance operations.

The key interest here is to investigate the effect of a single factor on the system outputs to explore how this affects the system behavior. This research is not about studying the factors mixture to evaluate their effect on each other as could be found from Factorial Experiment (FE).

From the earlier requirements gathered during the interview phase, broadly three main factors were identified; 'product' equipment, labor, and inventory. Based on these factors it would be intuitive to understand the effect of Mean Time Between Failure (MTBF), labor levels, and travel time from/to maintenance center. In addition, in the case of Prognostics level, it is important to understand the effect of applying different Prognostics Windows (PW), i.e. the time in advance the maintenance center should know about a future failure. Spare part lead time is an important factor, the effect of which needs to be understood.

4.1 Industrial Case

This case presents a utility company in a middle eastern country. It owns multiple utility stations over the country. These stations have assets (products) that always need to be in an operational condition to provide the citizens with its services. Breakdowns of these assets are critical and need to be resolved immediately.

As agreed with the case company, the data of the operations will be provided to the researcher from one of its maintenance centers. This maintenance center serves four stations scattered in the city, and each station has multiple identical assets. These assets were deemed to have three categories of failure mode and each one of those failure categories has associated spare parts (e.g. failure mode 1 needs spares 1 and so on). The first station has 23 assets, the second station has 26 assets, the third station has 18 assets, and the fourth station has 31 assets. Data for this case was obtained directly from the company's computerized system. The data needed was identified and explained in an initial meeting with the case company who then sent the researcher the required data. Bearing in mind that this case is for the adoption of Diagnostics technology to monitor the company's assets rather than the current Reactive approach, the diagnosing time was estimated by maintenance engineers as diagnosing activity is done by sensing technologies. In this maintenance center there are eight maintenance engineers (labor) to maintain those stations. The following Figure 1 shows the schematic diagram of the case and Table 2 provides the input data used in modelling this case. The travel times in Table 2 were calculated based on the average time from receiving a failure note until the failure is attended by an engineer.

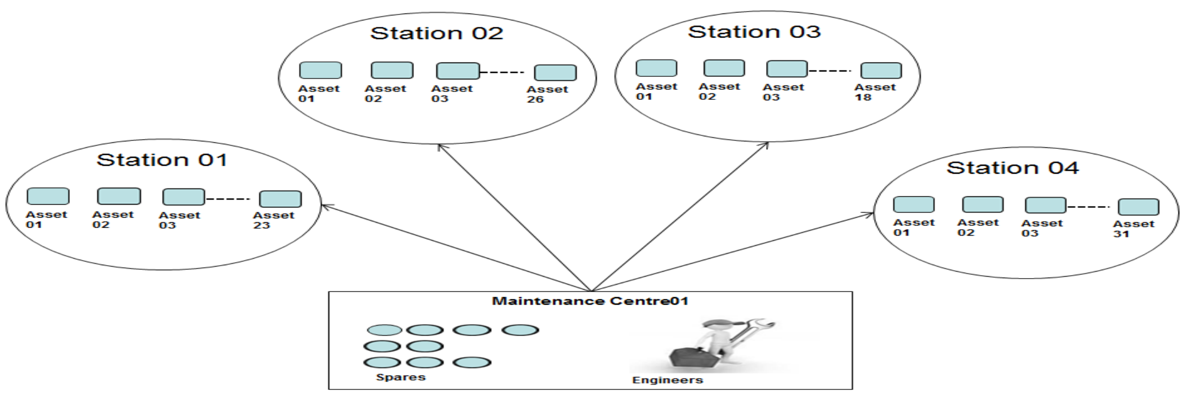

Figure 1: Schematic diagram of the case study

4.2 Case Study Experiment Setup

The simulation experimentation setup of run length, warm-up period, and replications was established. In this case study, The run length of ten years was decided upon as multiple failures of each failure mode will occur during this run length. Moreover, the case company would like to assess its maintenance operation over such a long run. The warm-up period has been decided to be for three years (three year warm up, ten years run length). Warm-up period was verified by a time-series method suggested by Robinson (2004) and the output measure is the labor utilization. The number of replications has been decided based on a combination of rule of thumb suggested by Robinson (2004) and the confidence interval method. Table 3 shows that for two replications the deviation is over 6% but after three replications the deviation falls to less than 2% which is sufficient and no further replications are required.

Table 2: Input data of the case study

Location	Location01	Location02	Location03	Location04
No. of assets	23	26	18	31
Travel times (Hrs)	6.3	5.8	7.3	8.6
No. engineers (Labor)	8			
No. of failure modes	3			
Spare parts	Spare01, Spare02, Spare03			
Failure mode01	MTBF (mins):Triangular Distribution (211896,332424,697248)			
	Diagnose time (mins):Triangular Distribution (2880,10080,15840)			
	Repair time (mins):Triangular Distribution (429.6,536.4,861.6)			
Failure mode02	MTBF (mins):Triangular Distribution (478224,675864,815184)			
	Diagnose time (mins):Triangular Distribution (4320,8640,23040)			
	Repair time (mins):Triangular Distribution (523.2,792,1152.6)			
Failure mode03	MTBF (mins):Triangular Distribution (297432,894888,1145016)			
	Diagnose time (mins):Triangular Distribution (7200,12960,18720)			
	Repair time (mins):Triangular Distribution (578.4,1222.8,2080.8)			
Lead time	30 days			
Reorder quantity	5 each			
Safety stock	1 each			

The calculations were based on the (As-Is) model, and the output measure used for this calculation was the average availability percentage of assets. Combining the rule of thumb and the confidence interval method, the researcher has decided to select three replications to be used in this case.

Table 3: No. of replication calculations based on the confidence interval method.

			Significance level	**5.0%**		
				Confidence interval		
Replication	Result	Cum. mean Average	Standard deviation	Lower interval	Upper interval	% deviation
1	79.37	79.37	n/a	n/a	n/a	n/a
2	78.59	78.98	0.552	74.02	83.94	6.27%
3	79.41	79.12	0.462	77.97	80.27	1.45%

A set of experiments was conducted for this case. These experiments were based on the discussion raised in section 4.1. The experiments made for this case is listed in Table 4. Three scenarios (Reactive, Diagnostics, and Prognostics) were compared for each of the experiments. Furthermore, different Prognostics Windows (PW) were applied. Eight different experiments were applied with three monitoring levels. A Prognostics level has been applied with three different PWs which are (PW=500 min, PW=1000 min, and PW=43500 min). These different PWs were decided to assess different levels of PW on maintenance operations. Bearing in mind that three replications for each scenario have been decided, the total number of simulation runs for this case total 120. The analysis of the results obtained will be presented and followed by a validation process.

Table 4: Experiments conducted.

No.	Experiment description
1	As-Is
2	Labor reduction
3	No travel time
4	Spares lead time reduction by 50%
5	Increase MTBF by 50%
6	Decrease MTBF by 50%

4.3 Results and Discussion

This section presents and analyses the results of the different experimentations made on the industrial case. Figures 2 and Figure 3 show the comparisons of availability percentages and the number of failures occur on the different experiments. The analysis of each experiment will be presented in the sub-sections that follow

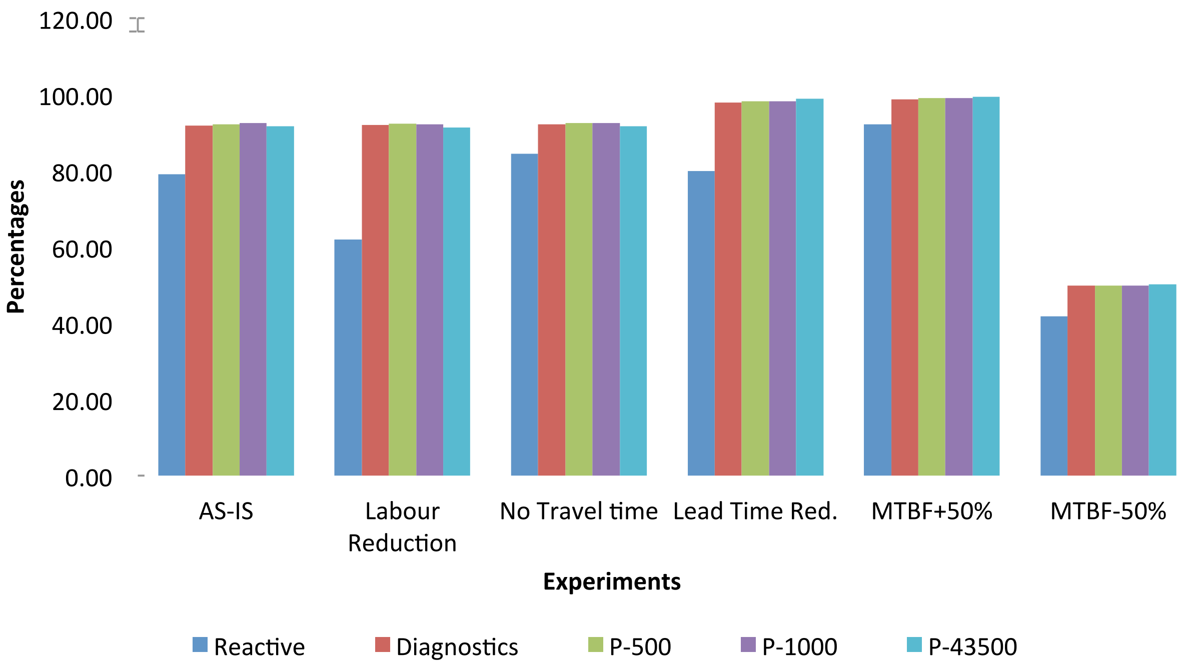

Figure 2: Availability percentages across different experiments.

The As-is situation shows (Figure 2) that the Reactive level gives about 79% of availability. A sharp increase of availability to 91.9% is reached when the Diagnostics level is applied. This is due to travel time (Reactive level needs two travel times for repair as explained earlier) in addition, the manual diagnosing time in this industrial case is very high. Moving to the Prognostics level with a PW of 500 minutes (P-500) only an increase of 0.35% has been gained compared to Diagnostics. Applying a PW of 1000 minutes (P-1000) gave an increase of 0.55% compared to Diagnostics. The availability is almost the same between Diagnostics and Prognostics levels due to the travel time is the same in both cases as well as the manual diagnosing process is eliminated.

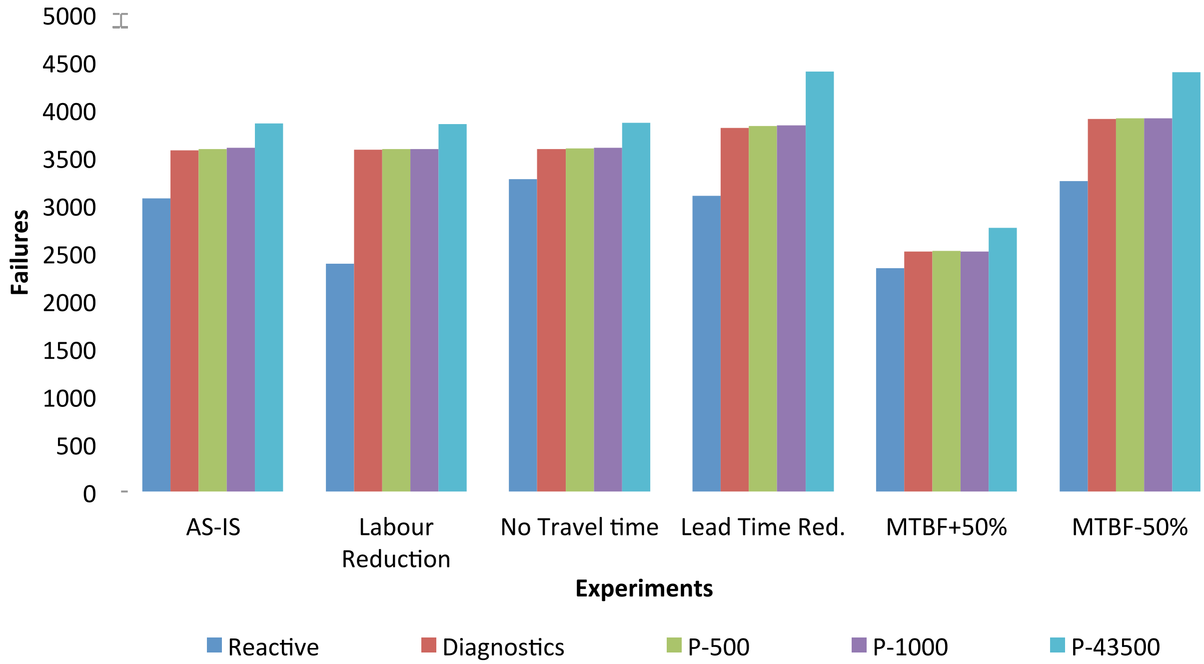

Figure 3: Number of failures across different experiments.

A longer PW was applied (P-43500) to more than the spares lead time of 30 days to assess its impact. A drop in the availability occurred as it gives the same availability as in Diagnostics. This is due to more frequent repairs (more than is actually needed) which have been made due to the lengthy PW selected. Another experiment was conducted to assess the impact of labor reduction where labor was reduced from eight to six. This shows a further drop of 17.25% in availability in the Reactive level compared to the As-is situation. However, other monitoring levels gave almost the same availability as in the As-Is.

The number of failures (Figure 3) in the As-Is situation increases as a higher monitoring level is applied. With higher monitoring level the availability increases and therefore more failures can occur. Moving from the Reactive to the Diagnostics level, an increase of 507 failures was made and that is simply due to repairs being carried out faster when Diagnostics technologies are implemented. From Diagnostics (P-500) a slight increase of 14 failures occurred while a further 9 failures took place moving to (P-1000) compared to (P-500). Longer PW (P-43500) gave the highest number of failures as it increases the failures by 259 compared to (P-1000). In the same manner, when the labor reduction experiment was applied a further decrease in the number of failures was made as a lower availability was obtained. Other monitoring levels almost have same level of number of failures as in the As-is situation.
Comparing the Reactive level in this experiment with the As-is, it can be noted that availability has risen by 5.23% as a result of removing the travel time. Comparing other monitoring levels with the As-is, it shows that generally little improvement was gained. Likewise, the number of failures were expected to increase moving from the As-is situation as in this experiment travel times were removed. Reactive shows the highest number of failures where other levels show a slight increase moving from Diagnostic to Prognostics in the same experiment. Reducing the spare parts lead time by 50% shows that in the Reactive level a 0.74% increase in the availability was gained compared to the As-Is. An increase of about 6% in availability was achieved in all other levels compared to the As-Is with the exception of the lengthy PW (P-43500) which gave a 7% increase. In all experiments conducted, the number of failures was seen to be greater as a higher monitoring level was applied.

Two experiments were carried out to assess the implications of increasing and decreasing the MTBF as made in previous cases. Firstly, increasing the MTBF by 50% was assessed. Logically, an increase of availability percentages was expected compared to the As-Is. Thus, a rise in availability from the As-Is model was gained. Decreasing the MTBF by 50% gives a drop of 37% in availability in Reactive while other monitoring levels dropped by about 42%.

The number of failures dropped generally in the MTBF+50 experiment while there was an increase in MTBF-50% compared to the As-is. Reactive gives the least number of failures; the higher the monitoring level the higher the number of failures occurred. When the PW was set to 43,500 minutes, an obvious increase of failures occurs.

4.4 Validation

The validation took place between the researcher and the company's maintenance planner. The full results from the simulation were provided to the company, many of which have been presented above. Actual company performance data cannot be presented here for confidentiality reasons other than the asset availability. The validation focused on comparing the results of six experiments from Table 3. As a baseline the current performance of the company was compare with the as-is model output. First confidence was established in the as-is situation to in turn permit discussion of the results from remaining five experiments of labor reduction, no travel time, reduced spares lead time, increased MTBF and reduced MTBF. Each of these were examined first for the current reactive scenario and then for credibility of changes resulting from diagnostic and prognostic scenarios.

Given that the company has a reactive operation then numerical comparison could be carried out for this scenario only. Within the limits of confidentiality, the summary average variation between actual and simulation performance was only 3.3% with no significant outliers. Specific, it is possible to reveal that the Average asset availability from the simulation (91.87%) compared favourably with company actual (88.6%). This was deemed sufficiently close to establish credibility. The planner expressed satisfaction in the credibility of the reactive modelling, both as-is and for the impact of changes.

For the diagnostic and prognostic scenarios qualitative comparisons were made. The planner elaborated that this tool assumes ideal Diagnostic operations as no fault was found and the wrong diagnosis were not modelled. In other words, sometimes the sensing technology will sense a failure and it will be reported, but when labor attends the fault they will discover that the asset is working smoothly. This requirement for 'no fault found' was not captured from the literature or expert interviews that led to the creation of the tool. Apart from this assumption the planner signalled acceptance of credibility of the remaining results for diagnostics and prognostics.

5 CONCLUSION

This paper has considered whether advanced sensing and monitoring strategies can offer better asset performance in Product Service System (PSS) type scenarios than a simple reactive maintenance strategy. Simulation was the chosen tool to assess maintenance systems and was applied to a utility company. The results showed a comparison between reactive, diagnostic and prognostic maintenance strategies.

It is clear that simulation can identify differences in the product's dynamic performance in complex maintenance operations when different monitoring levels are applied. This paper has shown how different product monitoring levels can be discerned by simulations. It also showed that higher monitoring levels do not guarantee higher product availability as different system constrains (such as: spares inventory, labor levels, travel time, etc.) affect the maintenance operations.

Future work in this area needs to be carried out on assessing some of the troublesome factors that are emerging in industry. Such as the significant problem of no fault found has to be considered, either as a result of sensor malfunction or incorrect diagnosis. This impacts on the use of staff time, the replacement of modules, the potential repeat visits for unsolved problems and the pressure on the supply chain to repair modules and supply new stock. Finally consideration has to be given to the nature of experimentation to uncover whether design of experiments can uncover further interesting behavior in these types of systems.

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A INPUT AND OUTPUT REQUIREMENTS ESTABLISHED

	Input Requirements		Output Requirements
People	Number, Location (L,I)	People	Utilisation (busy, Idle) (L,I)
	Skill (L,I)		Total hours on jobs (L,I)
	Shifts (L,I)		Time by each labour on job (L,I)
	Travel time (L,I)		No of Jobs (L,I)
Equipment	Number, location (L,I)		Total travel time (L,I)
	Cycle time (L,I)		Required number (L,I)
	Job arrival rate (production) (L,I)	Equipment	Production (No., lost) (L,I)
	Breakdown (MTBF,MTTR)(L,I)		Utilisation (idle, run, …) (L,I)
	Failure modes (I)		Tool utilisation (I)
	Repair Time (rate) (L,I)		Failures (No., time) (L,I)
	Diagnose time (L,I)		Maintenance (Number) (L,I)
	Priorities (L,I)		Waiting for repair (L,I)
	Planned maintenance time (L)		Required assets
	Tooling number (L,I)	Spares inventory	Stock level, stock outs (L,I)
	Monitoring level (I)		Number used, time in used (I)
	Failures with no need for spares (I)		Stock level required (I)
	Inspection (L)		Location of stock and labour (L,I)
Spares inventory	Stock policy (safety, lot size, Req.)(L,I)	Service level	Demand satisfied (L,I)
	Lead time (L,I)		Availability (average, point) (L,I)
	Stock location (I)		Measuring KPI's (L,I)
	Alternative Stock policy (I)	Cost	Labour cost (L,I)
Service level	Demand Profile (arrival rate) (I)		Spare cost (L,I)
	Contract KPIs (e.g. availability) (L,I)		Penalty cost (L,I)
Cost	Labour hourly rate (L,I)		Prod. Lost cost (I)
	Asset cost (I)		Inventory cost (L,I)
	Monitoring (sensing cost) (I)		Operating cost (L,I)
	Contract cost and penalties (L,I)		
	Spares cost (L,I)		

* where L indicates the requiremet collected from the literature review, I indicates the requirements collected by interview

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