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Optimisation of Maintenance Operations Involving Three Integrated Departments at a Local Oil Company in Trinidad

Stefan Harrison [a,Ψ]; Jainarine Bansee[b], and Boppana V. Chowdary [c]

Department of Mechanical and Manufacturing Engineering, The University of the West Indies, St. Augustine, Trinidad and Tobago, West Indies;

[a]Email: stefan_harrison@hotmail.com
[b]Email: jainarine.bansee@sta.uwi.edu
[c] Email: boppana.chowdary@sta.uwi.edu

[Ψ] *Corresponding Author*

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Abstract: *A simulation case study was conducted to assess the utility of predictive maintenance and database management for lean maintenance applications within a Petroleum Company. At this company the maintenance of pumps was performed internally where feasible. The study explored a proposed lean strategy on the operations of three departments related to the maintenance of pumping equipment. These departments were, the Pump Shop, Stores Department and Shipping and Receiving. Rockwell Automation's Arena® simulation software was used to study existing and proposed models of the maintenance system and track the key performance indicators of Flow Time, Waiting Time, and Work-in-Process. Analysis of the performance indicators showed a 76% and a 96% reduction in average Flow Time and Waiting Time, respectively. No difference was determined for Work-in-Process at the 95% confidence interval.*

Keywords: *Simulation Case Study, Database Management System, Predictive Maintenance, Lean Maintenance*

1. Introduction

Beginning from 2014 and extending into 2016, the saturation of the crude oil market led to a fall in global oil prices (IEA, 2019). There were several drivers. The first was, new production techniques that allowed for unprecedented production in the North American shale oil industry. The United States of America for example, increased oil production from around 5 million barrels per day in 2008 to over 9 million barrels in 2015 (Mitchell and Mitchell, 2014). Second, the Financial Crisis of 2007-2008 and the following Great Recession of 2008-2013 caused a weakening of the world economy and reduced capital expenditure (IEA, 2019). Finally, changing government policies in developed nations also served to reduce the growth of demand for foreign oil (Mitchell and Mitchell, 2014). These events contributed to a crisis for numerous oil-producing countries as revenues decreased

In January 2017, international oil producers jointly agreed to supply cuts in an effort to arrest the fall of oil prices and rebalance the global market (Graaf and Michael, 2018). However, the continued volatility of the global oil market means that many oil companies seek to maintain capital discipline with focus placed on productivity improvements and new advances in technology. For the period of 2017-2018, statistics at the oil company showed that more than $188 million dollars were spent on overtime payments to its employees. The reduction of overtime attributable to maintenance activities is therefore one way of improving the firm's productivity.

The study applied a lean approach to the operations of an oil company within the Caribbean region. The chosen approach applies a model based on historical data from the firm's existing maintenance schedule. The subject of the study is the company's pump maintenance and repair job shop, referred to as the "Pump Shop".

A value stream mapping exercise was done in consultation with system experts. The focus of the exercise was the processes within the Pump Shop. Supporting processes within the Stores and the Shipping and Receiving departments were also included in this exercise. Key performance indicators (KPI) were identified and then recorded during this process. This information was used to develop the functional specifications of the system and a model representing its existing state, referred to as the "existing model" (Yorke et al., 2020).

The existing model was constructed and verified under control conditions. Statistical distributions that best fit the collected data were used to represent the inter-arrival time (IAT), number of arriving entities and processing times. The KPI outputs of the existing model were then validated by system experts based on observed metrics.

A proposed model incorporating elements of the suggested optimisation strategy was then generated. With

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consideration to available computing resources, the desired precision of reported KPI, h, was used to determine n_e, the number of replications performed by the existing and proposed models. The value of n_e was estimated using Eq. (1) where n_0 was the number of replications required to derive a precision of h_0 (Kelton *et al.*, 2015).

$$n_e = n_0 \frac{h_0^2}{h^2}$$

The output KPI of the existing and proposed models were compared and assessed at the 95% confidence interval (C.I.) through independent samples *t*-tests conducted using SPSS version 23.

Section 1 discusses the significance of the study to the oil company and the methodology of the research performed. Section 2 reviews the literature regarding the proposed improvement strategy. Section 3 describes the existing system, model development, data collection and the synthesis of the proposed model. Section 4 presents the results of the study and discusses their importance in context of the study. Finally, Section 5 provides the concluding remarks, lists the limitations of the study and offers avenues for future research.

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2. Literature Review

Manufacturers are often unable to utilise their existing production capacity at an optimal standard due to process inefficiencies. This is made evident when considering the concept of Overall Equipment Efficiency (OEE). OEE is a quantitative metric used by managers to determine and improve performance efficiency (Piran et al., 2020). It is based on an operation's equipment availability, quality and productivity (Singh et al., 2018). From the literature, the average OEE of companies in the manufacturing sector is 55% (Gopalakrishnan et al., 2013; Singh et al., 2018).

Equipment maintenance plays a key role in optimising process performance (Chowdary et al., 2018; Khasanah et al., 2019). This is due to the direct impact that machine downtime, asset integrity and reliability have on the factors of availability, quality and productivity (Schmidt and Wang, 2016). A lean approach to maintenance therefore holds the potential to improve a firm's OEE (Nhaili et al., 2016). In addition, adequate maintenance procedures contribute to ensuring a safe working environment and minimising the ecological impact of production (Hajej et al., 2017; Khan et al., 2021).

Considerations of safety and ecological impact are relevant due to the common understanding of the social responsibility of industry to stakeholders and the environment. Modern regulatory standards relating to issues of occupational health and safety as well as environmental protection necessitate that firms maintain properly functioning equipment in safe operating conditions (EMA, 2000; OSHA, 2015). Otherwise, firms may face reputational, civil, and judicial consequences due to damage attributable to inadequately maintained equipment. As a result, devising maintenance strategies that optimise performance efficiency and safety are vital for local manufacturers seeking a competitive advantage.

Predictive Maintenance (PdM) is one method of optimising machine utilisation. This approach involves proactively performing servicing operations as required in advance of a predicted machine failure (Ciociou et al., 2017). The utility of this concept can be illustrated using the Potential Failure (P-F) curve which shows the relation between part degradation and time (see Figure 2). A PdM plan allows for the detection and planned correction of potential failure modes in advance of functional failure when machines experience diminished functionality (Entezami et al., 2020; Kamei and Takai, 2011).

The stages of PdM are data acquisition, processing, and assessment (Ran et al., 2019, Resende et al., 2021). Relevant event and condition data, in addition to related metadata, are first collected from a variety of sources. Such sources may include the output from sensors streams, historical data, and original equipment manufacturer (OEM) documentation (see Figure 1).

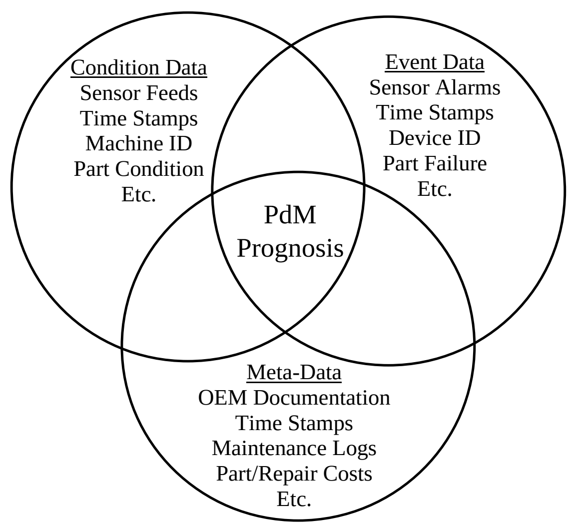

Figure 1. Data Requirements of PdM Prognosis

The raw data are then cleaned and reformatted in the most cost-effective manner allowed by available resources. The last step involves the analysis of the processed data to determine the relationship among the multiple performance parameters and part degradation (Santos et al., 2006; Jiminez-Cortadi et al., 2019). Determining an optimal PdM plan also requires considering factors such as administrative processing costs; time and labour costs related to repair procedures, part replacement and failure analysis; and the cost of lost productivity during servicing operations (Spiegel et al., 2018). Figure 2 shows a potential failure curve. As part degradation increases, there may be a commensurate increase in the associated cost of addressing issues. The nature of the failure mode may be obscured or grow in complexity.

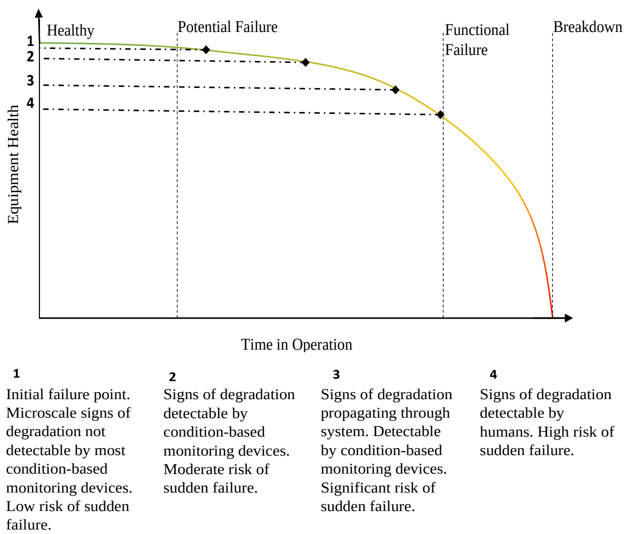

Figure 2. Concept of Potential Failure Curve
Sources Abstracted from Entezami et al. (2020), and Kamei and Takai (2011)

On-board intelligent alarm systems; networked condition monitoring devices; and the analysis of historical data by trained personnel are all tools required by an effective PdM program (Gilabert and Arnaiz, 2006). In recent years emerging Industry 4.0 (I4.0) technologies have also served to enhance the accessibility and utility of PdM (Ran et al., 2019). These technologies include, first, developments such as the use of edge to cloud computing for big data analytics. Second, advances in Information Communication Technology (ICT) provide access to increasingly affordable remote sensor devices (Poszytek, 2021). Third, data-driven decision support services have been enabled by Artificial Intelligence (AI) techniques. Finally, novel advances in Cyber-Physical Systems (CPS) may allow for time and cost-effective transfers of asset information using Open Protocol Communications – Unified Architecture (OPC UA) or in the future Machine to Machine (M2M) communications secured by blockchain software (Ioana et al., 2021; Laabs and Đukanović, 2018).

A database management system for information storage and retrieval therefore presents another possible means of optimising performance efficiency. Maintenance procedures may be linked to a company's Enterprise Resource Planning (ERP) system (Shohet and Nobili, 2016) in keeping with the I4.0 philosophy of integrating computer technology both vertically and horizontally within manufacturing operations (Vaidya et al., 2018). ERP systems may in turn be hosted on cloud servers allowing firms to save costs by outsourcing the maintenance of software, storage and other network infrastructure (Ardito et al., 2019).

Tools such as barcodes, radio frequency identification (RFID) tags, Near Field Communications (NFC) and other technologies used by wireless-enabled devices may allow automated asset information monitoring and control at all levels of an operation (Eckfeldt, 2005; Boriello, 2005; Chongwatpol and Sharda, 2013; Chen, 2017). Research and development are also ongoing regarding PdM systems that utilise Machine Learning algorithms and AI derived models for data-driven decision support based on collected data (Samatas et al., 2021). When applied to PdM, such systems allow for the dynamic adjustment of maintenance scheduling, purchasing, inventory, and production in response to changing operational conditions (Cassingham and Allen, 2008).

A database management system may also benefit maintenance procedures in other ways. For example, relating to tasks such as the efficient organisation and management of the large quantities of OEM technical documentation utilised for condition diagnosis or prognosis (Marques et al., 2021). Storage and retrieval of historical data, inventory document management, and the tracking of part non-conformance by suppliers through invoices are also areas where performance efficiency may be improved. The following case study models the effects of a proposed optimization strategy utilizing historical data from the existing system's preventative maintenance plan.

3. The Pump Maintenance Process

3.1 Description of the Existing System

The Pump Shop conducts pump repair and maintenance to ensure optimal asset reliability (see Figure 3). As part of this process, pumps scheduled for maintenance or those with unexpected breakdowns are delivered to the Pump Shop along with a matching work order. In the case of an unexpected breakdown, the root cause of failure is diagnosed and repaired. Repairs are conducted following the American Petroleum Institute (API) standards and OEM specifications under the safety guidelines of the company's Job Hazard Analysis and Health, Safety and Environment (HSE) procedures. On identifying parts in need of repair or replacement, a request is sent to the Stores Department via a hand written card. This request identifies the spare parts required or the materials needed to fabricate a replacement by the department's machine shop.

On receiving such a request, workers at the Stores Department then proceed to locate the ordered parts or materials within the company's storage facility. Upon location, parts are sent to the Pump Shop along with a delivery note that must be signed by the Pump Shop supervisor. In the event that the parts are not available at the Stores Department, a purchasing request is sent to the Procurement Department, which then orders the parts.

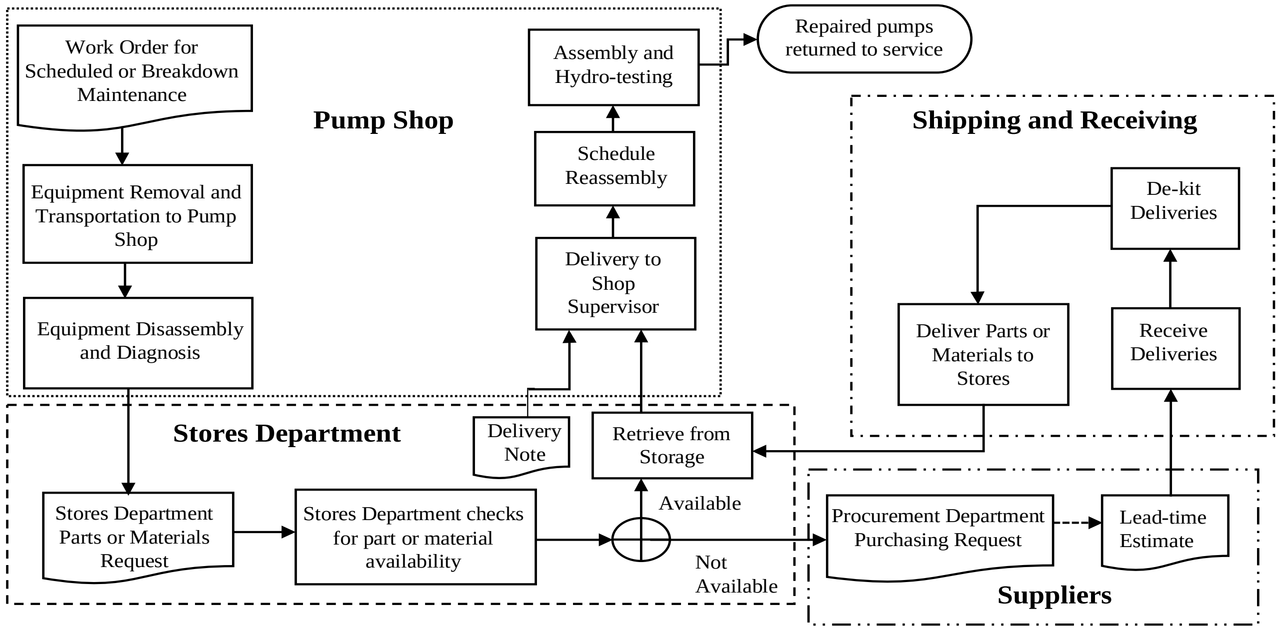

Figure 3. High-level Overview of Pump Maintenance Process Map

The purchasing request is a document which contains the relevant information about the parts required, this includes part specifications and the details of the job that the part is intended to be used for. Once parts are ordered, the Stores Department is then notified of the delivery date via telephone. On delivery of the purchased parts, the Stores Department immediately sends the items to the Pump Shop. The parts sent are kept by the shop supervisor, who is responsible for providing pump technicians with their requested equipment. The processes of part installation, rebuilding and hydro-testing of pumps are then scheduled for the technicians assigned to the job. Once a report of successful completion of the work order is reported to the shop supervisor, the pumps are then returned to service.

3.2 Model Development and Data Collection

The models investigated were formulated using data collected over an eleven (11) month period (see Table 1). Statistical distributions representing the IAT and the number of incoming pumps were determined using Rockwell Automation's Input Analyzer® software. The Weibull Distributions, Eq. (2) and Eq. (3), were used in the existing model to represent the frequency and number of pumps undergoing the maintenance process.

$$\textit{IAT Distribution} = 8 + \textit{WEIB}\,(50.3,\ 0.623) \qquad \text{Eq(2)}$$

$$\textit{Number of Incoming Pumps} = 0.5 + \textit{WEIB}\,(0.804\ ,1.92) \qquad \text{Eq(3)}$$

Data regarding process times were recorded at various stages of the system. Time distributions that best fit the data collected regarding repair processes were then determined by using the Arena Input Analyser® tool (see Table 2).

Table 1. Data Regarding Pump Arrivals and Servicing Times

Pump Arrival [Week]	IAT [Hours]	No. of Pumps	Servicing Start Date	Servicing Finish Date	Servicing Time [Hours]
1	0	1	23/01/2013	25/01/2013	29.5
2	40	1	28/01/2013	30/01/2013	29.6
3	72	1	06/02/2013	08/02/2013	28.8
4	64	1	14/02/2013	18/02/2013	26.1
4	8	1	15/02/2013	19/02/2013	30.8
5	32	1	19/02/2013	19/02/2013	32.3
6	48	1	25/02/2013	27/02/2013	33.1
6	16	1	27/02/2013	01/03/2013	31.0
12	344	1	11/04/2013	19/04/2013	32.5
13	48	1	17/04/2013	02/05/2013	32.6
15	104	1	30/04/2013	06/05/2013	32.4
15	16	2	02/05/2013	07/05/2013	26.5, 30.7

Table 2. Processes and Representative Time Distributions

Processing Time	Processing Time Distribution
Check for availability of parts/materials (Hours)	NORM(5.39, 2.04)
Order placed for part/material (Hours)	TRIA(1.09, 5.86, 10.9)
Lead time for expedited part order (Days)	TRIA(6.5, 13.1, 22.5)
Available part/material delivered to shop (Hours)	TRIA(1.18, 2.09, 2.6)
Inspection time (Minutes)	TRIA(10, 16.8, 19)
Recording Receipt (Minutes)	NORM(20, 4.97)
Transport to storage address (Minutes)	15 + 17 * BETA(1.99, 1.5)
Disassembly and Diagnosis of equipment (Hours)	NORM(2.98, 0.093)
Assembling repaired equipment (Hours)	1.48 + 3.52 * BETA(3.43, 5.08)
Machine Setup (Hours)	NORM(1.02, 0.182)
Part Processing (Hours)	TRIA(2, 4.33, 6)
Part Post Processing (Hours)	0.34 + WEIB(1.25, 4.29)
Work order travel time from Pump Shop to Stores (Hours)	0.44 + 1.37 * BETA(2.95, 2.91)

3.2.1 Model Formulation Assumptions

During the process of model formulation, certain assumptions were applied to the proposed model. These were:

- Suppliers were assumed to consistently fulfil orders without unexpected delays,
- Suppliers were assumed to correctly fulfil orders with zero errors,
- The machine shop was assumed to fabricate parts with zero defects,
- Functional parts were categorised as ‘Good’ and non-functional parts as ‘Bad’,
- Reliability engineers were assumed to identify issues in advance of unexpected breakdowns, and.
- Reliability engineers were assumed to consistently identify the correct PdM prognosis.

3.2.2 Model Development

It was determined that 2,190 replications were required to achieve the degree of precision desired of the existing model (see Eq. (1)). Due to the nature of the Pump Shop, where a preventative maintenance schedule required continuous activity, the model was designed to be a non-terminating simulation. The run length of the model was set at 90 days, composed of 8-hour work days, to allow the system to achieve steady state conditions (Kelton et al., 2015).

Truncated replications were utilised to prevent initialisation bias from affecting the reported KPI. This was done through the application of a 25 day warm up period. This warm up period was determined by using Arena Output Analyzer® to plot a time dependent chart of KPI over the 90-day period. Through examination of the plot, 25 days was conservatively estimated as the time after which the system entered steady-state conditions (Kelton et al., 2015). The existing model included the modules described within Table 3, with application of the

Table 3. Selected Arena® modules and descriptions of their usage in the existing model

Create	A module used in the existing model to represent the arrival of pumps at the Pump Shop (see Figure 4). The statistical distributions for IAT, Eq. (2); and quantity of incoming pumps, Eq. (3), were determined by using Arena Input Analyser® on the data provided in Table 1. The results were input into the model.
Decide	A module used to determine the following processes an entity is passed through based on a specified condition or attribute. They were used for example to differentiate whether a part was available in the inventory by comparing the number of parts requested to the quantity held in the inventory.
Route	A module which transferred entities to a user-specified station with the option of defining a transfer delay to simulate travel time. For example, work orders from the Pump Shop requesting parts and materials of the Stores Department were transferred by route module, ‘Route to Stores’ (see Figure 4).
Station	A module used to define areas which correspond to the physical or logical location where processing occurs. In Arena®, it is the location within a model to which a route module sends entities. For example, the station module, ‘Machine Shop’ (see Figure 4), represents the location where replacement parts are fabricated.
Separate	A module that duplicates an incoming entity and transfer the copy to other areas of a model. For example, the separate module, ‘Separate Good and Bad Parts’ duplicated entities which were passed on to other processes as either ‘Good’ or ‘Bad’ parts (see Figure 4)..
Match	A module that combines a specified number of entities waiting in different queues into a single group. The match module, ‘Match Pump Parts’ was used in this model to represent the matching of original pump components with new replacements (see Figure 4).
Dispose	This module removes entities from the system and may record entity statistics before the entity is disposed. Repaired pumps exited the system via the dispose module, ‘Return to Service’ (see Figure 4).
Assign	A module used to alter variables within the system or attach and modify entity specific attributes. For example, the assign module, ‘Assign ID’, gave the attribute ‘a_ID’ to pumps which allowed the model to make decisions based on that attribute’s value.
Process	A module that detailed the operations performed on an entity over a specified time period and utilised resources. They were categorised in the models as either value added (VA) or non-value added (NVA). The ‘Assembly and Testing’ process module represents the reconstruction of pumps with parts that have been replaced or repaired.

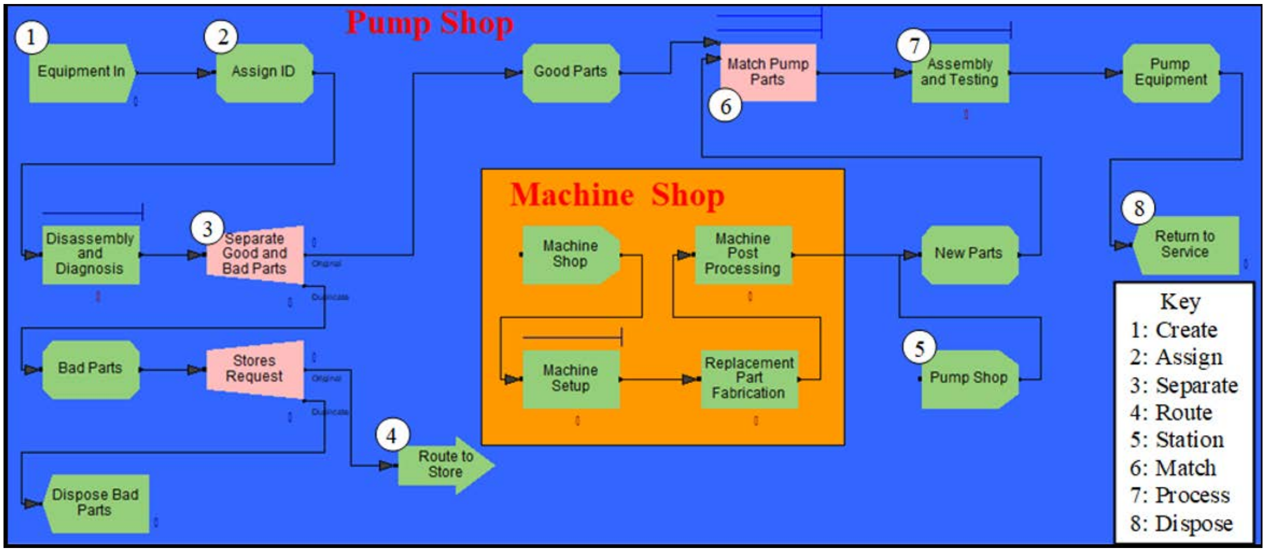

Figure 4. Existing Model, Pump Shop Arena® Modules

previously determined initial conditions and the assumptions listed (see Sub-section 3.2.1). Figure 4 shows the existing model with the Pump Shop Arena® modules.

3.2.3 Proposed Model

The effects of applying PdM and a database management system were investigated through the synthesis of a proposed model based upon the following strategy. First, the use of a database management system was modelled as a reduction in the time spent on data entry and information retrieval tasks such as searching for a part's storage location. Second, the effect of PdM activities was reproduced by having arriving entities which initially entered the model at the Stores department in the form of a parts request. This represented a process where the analysis of historical and condition monitoring data was conducted in parallel with machine operations and allowed the maintenance department to form a prognosis regarding machine failure modes. This ensured that the parts and materials required for repairs were secured prior to the initiation of maintenance activities. The initial conditions of IAT, number of pumps on arrival, number of replications, run length, and the duration of the warm up period were the same as the existing model. Table 4 shows the selected Arena® modules and descriptions of their usage in the proposed model.

4. Simulation Results and Discussion

Table 5 summarises the KPI output by Arena® for the existing and proposed models. A reduction in average Flow Time (FT) and Waiting Time (WT) was determined by comparing the KPI of the existing and the proposed models. The WT changed from 28 to 1 ± 1 hour and FT from 38 to 9 ± 1 hour. The average Work in Process (WIP) however showed no difference between the existing and proposed models. Independent samples of t-tests determined that the difference between the reported WT of the existing model was significant at the 95% C.I., (M = 22.28, SD= 10.94) and proposed model (M = 0.64, SD = 1.17); t (29.66) = 10.77, $p < 0.001$. The difference noted in the FT of the existing model (M = 34.96, SD = 15.94) and proposed model (M = 9.99, SD = 2.12); t (30.03) = 8.51, $p < 0.001$ was also determined to be significant at the 95% C.I

Table 4. Selected Arena® Modules and Descriptions of Their Usage in the Proposed Model

Create	A module used in the Proposed Model to simulate the production of a predictive maintenance schedule. The distributions for IAT and quantity on arrival were identical to those used in the existing system. This module created work orders that first entered the Stores department (see Figure 5), before eventually being transferred to the Pump Shop shown in Figure 6.
Clone	This module was used to duplicate an incoming entity and transfer the copy to specified Labels at other areas of the model. Clones of completed work orders entered the Pump Shop as pumps.
Label	Pumps entered the Pump Shop only after replacement parts were confirmed to be available. The Create Module in Figure 4 was replaced by a Label Module in the proposed system. Pumps scheduled for maintenance entered the Pump Shop through a Label Module (see Figure 6).
Hold	This module was used to detain an entity in a queue until a specified condition is fulfilled. For example, work orders were detained in a Hold Module until parts or materials were reordered (see Figure 5).

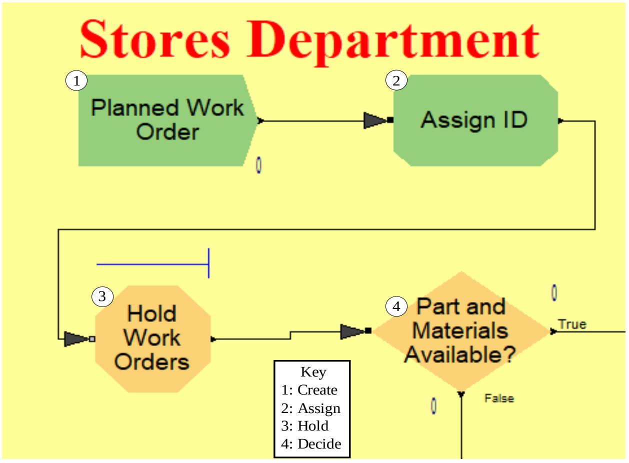

Figure 5. Proposed Model, Planned Work Orders Initially Enter the Stores Department

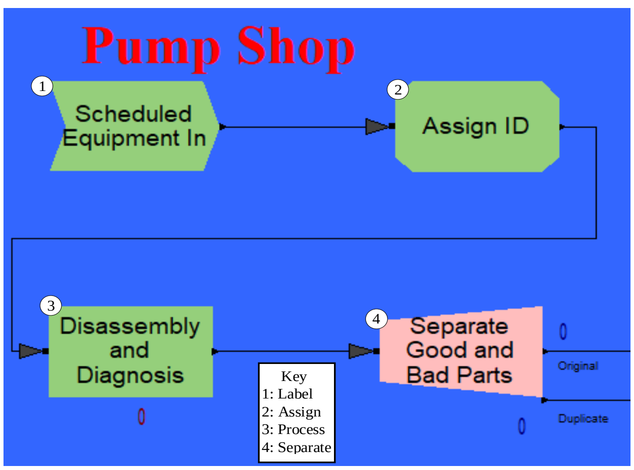

Figure 6. Proposed Model, Pumps Scheduled to Enter Pump Shop Based on the PdM Prognosis

Table 5. KPI of the Existing and Proposed Models

KPI	Existing Model	Proposed Model	Precision
Work in Process	1	1	± 1 pump
Waiting Time	28	1	± 1 hour
Flow Time	38	9	± 1 hour

From these results it could be determined that the implemented strategy allowed for a reduction in the average time that pumps were down due to maintenance. WT was reduced by 96% and the FT of pumps through the maintenance department were diminished by 76%. These time savings were primarily due to modelling condition prognosis as a task carried out in parallel to machine operation. A reduction in FT occurred even without decreasing the time allotted to disassembly and diagnosis which, in the proposed model, would have been applied to verify the prognosis. The simulated database management system reduced the time pumps waited for the completion of setup related activities in the Stores Department in addition to shipping and receiving. While not accounted for within the model as such tasks were simulated as occurring in parallel with machine operation, maintenance tasks can also require consultation with large volumes of OEM technical documentation utilised for condition prognosis. In practical usage, this presents another area of benefit posed by a database management system.

In the proposed model, the predictive maintenance plan further contributed to time and cost savings by allowing parts and materials to be secured prior to initiating repair activities at the Pump Shop. However, the success of the predictive maintenance plan was based on the assumption that maintenance personnel correctly predicted pump failure modes with sufficient lead time for obtaining the parts and materials needed for repairs. In this light, the importance of customer-supplier relationships to maintenance performance in relation to the timely procurement of spare parts (Mehdi et al., 2021) should be noted. This is because prompt intervention is required to circumvent the possibility of predicted part degradation leading to more complex and expensive to repair failure modes.

This correct prognosis of pump failure is a point of interest as PdM requires the analysis of not only event and condition data, but also the related metadata. The model presents a somewhat idealised scenario of consistently accurate fault prognosis. In reality, failure modes may result from multiple factors compounding themselves into a complex problem or masking the root cause of failure behind seemingly benign or unrelated issues. The emerging and novel technologies for real-time condition monitoring, decision support, and the analysis of big data are therefore important factors in making PdM feasible for companies (Selcuk, 2017).

5. Conclusion and Future Work

The aim of this research was to assess the potential of PdM and database management systems in optimizing the maintenance procedures of a large Petroleum company. Rockwell Automations Arena® Simulation software was used to model procedures within the existing Pump Shop, Stores and Shipping and Receiving Departments. The KPIs of FT, WT and WIP were compared between the existing and proposed models. The observed differences were subject to statistical tests using SPSS.

The study showed that the measures proposed resulted in the significant reduction in average FT and WT by 76% and 96%, respectively. The models indicated an improvement in operations and a reduction in machine downtime due to the alterations to maintenance activities without significant changes to WIP. However, the systems modelled did not take into account the variability in the models of pumps maintained or the differences in the families of parts or materials required.

The use of a database management system contributed to the improved FT and WT by reducing time spent on non-value-added document handling tasks. This was based on the assumption that the relevant departments were able to be easily integrated into the company's existing ERP system. The PdM plan also reduced FT and WT, having the required parts and materials available. This was due to simulating the accurate prognosis of failure modes. This element of the proposed strategy assumed that the Pump Shop would have the trained staff, technology, and data to correctly detect machine failures and the type of fault likely to occur. It was assumed that there would be sufficient lead-time to procure necessary parts prior to machine failure.

For undertaking this research, several limitations of the research were identified, including:

- Variations in the type and model of parts and materials were not considered.
- The reliability of local suppliers was not considered.
- Variations in the type and model of pumps entering the system were not considered.
- The probability of unexpected machine breakdown occurring prior to entry into the proposed model's Pump Shop was not considered.
- The costs of materials entering the Pump Shop were not considered.

Based on the study findings, future work should address:

- The reliability of local suppliers to support PdM operations across the variety or parts, materials and models of pumps.
- The effect of Just-in-Time manufacturing as a proposed strategy.
- The feasibility of implementing a database management system for organisation and control of the company's collection of OEM technical documentation.
- The feasibility of integrating the Maintenance, Stores, and the Shipping and Receiving Departments into the company's existing ERP system.
- The effectiveness of discrete event simulation to investigate optimising maintenance operations of a larger sample of local manufacturing firms.

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Authors’ Biographical Notes:

Stefan Harrison *is a doctoral student reading for a PhD in Manufacturing Engineering at The University of the West Indies, Trinidad and Tobago, St Augustine Campus. His research interests include cyber-physical production systems, lean manufacturing, and simulation modelling.*

Jainarine Bansee *has over 20 years of diversified industrial experience in the process and manufacturing environment and has served for over fifteen years as a faculty member. Currently he is a developmental engineer at the Faculty of Engineering at The University of the West Indies, Trinidad and Tobago, St Augustine Campus.*

Boppana V. Chowdary *is Professor of Mechanical Engineering and the Deputy Dean of Graduate Studies and Research, The Faculty of Engineering at The University of the West Indies, Trinidad and Tobago, St Augustine Campus. His research interests include production technology, product design and development and CAD/CAM).*

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