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Impact of resources and monitoring effectiveness on prognostics enabled condition based maintenance policy

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ABSTRACT

In the literature, the role of prognostic information in Condition-Based Maintenance (CBM) policy has been assessed based on the assumptions of perfect condition monitoring and diagnostics. However, effective prognosis require both detection and diagnosis. This research focuses on CBM implementation from a new perspective by using an Excel-based interface integrated with ARENA® based Discrete Event Simulation (DES) to assess and analyse the impact of resources and monitoring effectiveness on the key critical phases in CBM policy. This paper seeks to understand **how** the influence of resources and monitoring effectiveness affect asset availability and overall cost, and to investigate the conditions under which prognostics-enabled CBM could be superior to classic CBM. Without optimisation, prognostics-enabled CBM provided superior technical benefits; **however, with optimisation, overall cost effectiveness was achieved.** The proposed model can provide maintenance decision makers implementing CBM with numerical evidence in assessing the benefits, and adoption of prognostics in their operation.

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Availability; condition based maintenance; discrete event simulation; prognostics and health management; optimisation

1. Introduction

Performance degradation and system failure is a common feature of the complex engineered system. Maintenance plays a critical role in improving the useful life of an asset. Maintenance actions that can either be preventive maintenance (predetermined or condition-based) or corrective maintenance are needed to ensure a satisfactory level of system performance, to minimise the probability of failure occurrence, and to return the system back to the operational state. To meet up with the complexities and provide effective maintenance operations for modern engineered systems, condition-based maintenance (CBM) has been advocated because of its added advantage of performing maintenance actions only when required, increasing system availability and reliability, and reducing maintenance cost, which is a very important goal for business survivability and profitability. The growing popularity of the use of CBM in industries is necessitated by the investigations that indicated that most of the equipment failures that happen in a system are random-related as opposed to being age-related (Amari, McLaughlin, & Pham, 2006). The capability of CBM to detect the random-related failure distinguishes it from other maintenance policies. However, in practice, CBM implementation in industries is still lagging behind the heralded theoretical benefits (Koochaki, Bokhorst, Wortmann, & Klingenberg, 2011; Keizer, Flapper, & Teunter, 2017a; Veldman, Klingenberg, & Wortmann, 2011). As a result, the full capability of CBM has not been achieved in practice, leading to a growing concern about the effectiveness of CBM policy in industries implementing CBM.

Practical implementation of CBM in industries involves using condition monitoring (detection) system to assess and compare the current state of the system against a specified benchmarked parameter, in order to determine when an abnormal operating condition has occurred and perform condition-based preventive maintenance (CBPM) immediately after the anomaly detection. This approach implemented in practice results in some potential loss of the system useful life since when the actual failure of the asset will occur is unknown. Some factors influencing the practical benefits of CBM are required planning time, imperfect condition monitoring, deterioration uncertainty, and skill level of the workforce (Azadeh, Asadzadeh, & Seif, 2014). While CBM provides the opportunity to gain insight into failure evolution, Prognostics and Health Management (PHM) provides failure foresight, thereby enabling advanced preparation for needed maintenance support. PHM has the capability of predicting the actual remaining useful life (RUL) of the system during operation and provides the needed maintenance support for the effective and efficient implementation of maintenance

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actions. PHM is a key enabler to achieve the overall goal of CBM. PHM-enabled CBM improves system design, operational reliability, operational availability, asset maintainability, system safety, logistics support systems for maintenance planning and scheduling, reduces maintenance-induced fault and operating cost, and ensures the optimal use of the useful life of an item (Kim, An, & Choi, 2017, pp. 14–19). **PHM-enabled CBM** approach to maintenance requires using condition monitoring system (detection phase) for anomaly detection, isolating and identifying the fault/failure (diagnostics phase), predicting the remaining useful life (RUL) or the future condition (prognostics phase), and selecting appropriate maintenance actions (Ben-Daya, Kumar, & Murthy, 2016; Guillén, Crespo, Macchi, & Gómez, 2016).

Maintenance resources, such as spare parts, and maintenance personnel, play important role in the effective execution of maintenance actions. The ability to carry out maintenance depends on the availability of maintenance resources and is particularly important when multiple systems or components share a limited set of maintenance resources. The unavailability of resources at the time of maintenance will increase the downtime of the asset or system in the maintenance facility. Hence, it is important to consider the effect of available maintenance resources information in the implementation of CBM.

Over the years, the increasing role of using simulation in the modelling of complex maintenance systems has gained significant popularity in the literature (Alabdulkarim and Ball, 2014; Duffuaa, Ben-Daya, Al-Sultan, & Andijani, 2001; Sharma, Yadava, & Deshmukh, 2011). The main reason for the adoption of simulation approach is its inherent ability to model complex systems that are analytical restrictive, thus providing a more realistic solution to the actual real-world process. Discrete event simulation (DES) refers to the modelling technique where changes in system states can be represented by discrete events (Fishman, 2013). DES has been extensively used in applications, such as manufacturing systems, health, defense, transportation, supply chains, and service industries (Robinson, 2014, p. 10). The capability of DES in modelling detailed operation and item tracking, providing visual interactive environment and experimentation for a better understanding of the system, and providing means of integrating a greater range of factors with adaptable fidelity, make DES more appropriate for modelling complex maintenance systems (Robinson, 2010, Chapter 2; Warrington, Jones, & Davis, 2002).

The objective of this paper is to assess **with and without optimisation** the impact of resources (spare parts and maintenance workers), and monitoring effectiveness (imperfect condition monitoring, imperfect diagnostics, and imperfect prognostics) on CBM using DES on a system-wide level. The monitoring levels considered in this paper corresponds to the key critical phases required in achieving the full capability of CBM, and they are given as:

- Classic CBM, where only condition monitoring is implemented in monitoring the asset.
- Diagnostics-enabled CBM, where diagnostics capability is combined with condition monitoring in monitoring the asset.
- Prognostics-enabled CBM, where condition monitoring (ie, detection of abnormal operating condition), diagnostics (ie, isolation and identification of the abnormal state), and prognostics (ie, prediction of failure evolution (RUL)) are all integrated to monitor the asset.

2. Literature review

2.1. The role of maintenance resources in CBM policy

Effective implementation of various maintenance activities is dependent on the availability of the required maintenance resources, such as spare parts, and maintenance personnel with the right skill set. For example, in a manufacturing plant, when a system cannot be maintained as a result of inadequate spare parts or unavailable maintenance personnel, the production process will be significantly affected. On the dependence of maintenance execution on spare parts availability, maintenance literature generally assumes that spares are constantly available. However, in practice, such assumption does not hold, as considerable lead time is required for spares to be ordered and delivered. The scenario of the joint strategy of spare inventory and CBM using cost objective function and genetic algorithm optimisation was investigated by Xie and Wang (2008) by combining an inspection period (T) with (s,S) ordering policy, and concluded with numerical evidence of the slightly better performance as compared with separate strategy. Wang, Chu, and Mao (2008) considered the optimal benefits of jointly optimising CBM and an (s, S) type spare inventory policy for multiple identical deteriorating systems, where S spares are ordered as soon as inventory spares drop below s. An adaptive inventory policy that incorporates real-time condition monitoring information into spares inventory decision was discussed by Li and Ryan (2011). Keizer, Teunter, and Veldman (2017b) in their contribution discussed that for inventory policy to be optimal, ordering policy for spares can be based on components deterioration level (condition-based) as the (s, S) inventory policy might not necessarily be optimal.

Another important maintenance resource is maintenance workers, who are generally responsible for carrying out maintenance tasks. In practical settings, the number of maintenance activities that can be carried out is dependent on the number of available maintenance workers. Different cases of maintenance worker availability have been considered in the literature, such as when there is a single maintenance worker (Liu, Zhengguo, Xie, & Kuo, 2014) and multiple maintenance workers (Marseguerra, Zio, & Podofillini, 2002). Koochaki, Bokhorst, Wortmann, and Klingenberg (2013) investigated multiple scenarios: with no maintenance worker, with a single maintenance worker, and with multiple maintenance workers using maintenance cost as one of the key performance indicators. In the context of DES, Alrabghi and Tiwari (2016), considered the only spare parts level as maintenance resource in the optimisation of cost in a multi-unit manufacturing system. Similarly, the influence of maintenance resources worker on different maintenance strategies using different levels of spares' availability and two levels of maintenance worker's availability was investigated by Alabdulkarim and Ball (2014). An extensive review of CBM policies for systems under resource dependence is reported in the works of Keizer, Flapper, and Teunter (2017a). While it is true that the important role of maintenance resources in timely maintenance execution has been investigated; however, within the context of CBM, the investigations have been based on the assumptions of perfect monitoring (detection, diagnosis, and prognosis).

2.2. The role of PHM information in CBM policy

In the application of PHM information in the selection of CBM optimal policy using DES, it is observed that only a limited number of literature utilised the benefit of PHM information in the assessment of CBM policy. Wang, Cui, and Shi (2015) developed a framework to assess the general performance of PHM information integration with maintenance and logistics planning in an airline industry. Do, Voisin, Levrat, and Iung (2015) proposed a proactive CBM policy for a deteriorating system considering the impact of both perfect and imperfect maintenance actions, and with inspection based on an adaptive RUL estimation. Camci (2009) demonstrated in his study the beneficial role of incorporating prognostic information in maintenance policy optimisation as compared to the use of thresholds for triggering maintenance actions. Rodrigues et al. (2015) emphasised the importance of taking system architecture into account while using PHM information in maintenance planning with application in aeronautical systems. Huynh, Barros, and Berenguer (2012) used maintenance cost savings to assess when the value of PHM information in maintenance decision making can be advantageous over other maintenance strategies. The benefits of integrated systems health management (ISHM) as an enabler of CBM was discussed by Vandawaker, Jacques, and Freels (2015). The impact of prognostic error on CBM efficiency was assessed by Ma, Kang, Zhao, and Liu (2012). The added value of prognostic information in the selection of optimal maintenance policy was investigated by Van Horenbeek and Pintelon (2011).

2.3. The role of simulation in maintenance

Analytical approach, such as Markov models have been extensively used in modelling system states in CBM, but rely on oversimplified and unrealistic assumptions, and becomes intractable and incapable of capturing and representing the dynamic behaviour of complex systems, hence limiting their practical application and implementation in industries (Verma, Srividya, & Karanki, 2016; Alrabghi & Tiwari, 2016). Simulation approach, on the other hand, can be used to solve complex maintenance problems (Alabdulkarim, Ball, & Tiwari, 2013; Alrabghi and Tiwari, 2015; Robinson, 2010), and is based on fewer assumptions and has the capability of capturing complexities and performance analysis of the complex system. This result in realistic solutions that can improve the decision-making process. In addition, since the simulation model allows imitation of the actual process, it can be used to better understand the real world behaviour of the complex system (Sauer, Oppermann, Werner, Wohlrabe, Zerna, Weigert, & Wolter, 2006). The suitability of DES over other simulation techniques for modelling maintenance system include better understanding by visualisation of complex maintenance system in a cost-effective way, the ability to model variability, and its appropriateness for modelling detailed operation systems (Alabdulkarim and Ball, 2014; Alrabghi & Tiwari, 2016; Sauer et al., 2006). Some of the few papers that assess maintenance operations developed with DES using asset monitoring levels were Alabdulkarim and Ball (2014), and Alabdulkarim, Ball, & Tiwari, 2015. They used three different monitoring levels (reactive, diagnostic, and prognostic) to assess the effect of resources on maintenance applications.

It is evident from the literature that considerable attention has been given to the investigation of the role of prognostic information and resources in CBM policy. However, the combined effect of monitoring effectiveness on the three critical phases of CBM implementation, and resources (spare parts, and maintenance workers) were not properly considered in all their works. Most of the research made some assumptions of perfect condition monitoring and diagnostics or no mention of the condition monitoring and diagnostics tools when evaluating the role of prognostic information in CBM (Rodrigues et al., 2015; Ma et al., 2012; Alabdulkarim et al., 2015; Wang et al., 2015). However, it has been reported in the literature that instead of addressing prognosis in isolation, prognosis requires both detection and diagnosis and that the quality of the diagnostics can also affect the prognostics system (Guillén et al., 2016; Jardine, Lin, & Banjevic, 2006; Niknam, Kobza, and Hines, 2015; Saxena et al., 2010). Also since in real-life applications, maintenance and resources are interconnected (Alrabghi, Tiwari, & Alabdulkarim, 2013; Van Horenbeek, Bure, Cattrysse, Pintelon, & Vansteenwegen, 2013), hence it is pertinent to include resources, such as spare parts, and maintenance workers when evaluating maintenance policy. In addition, the monitoring coverage rate (MCR) of condition monitoring, diagnostics and prognostics tools used should also be considered in the evaluation since these tools' effectiveness are gradually evolving and can significantly affect the decision of adopting CBM or not. The combined effects of resources and monitoring effectiveness of CBM implementation have not been fully investigated in the assessment of the value of PHM in CBM policy. This paper intends to exploit the capability of DES approach in modelling complex maintenance systems to provide answers to the following questions:

Research Question 1: How would the influence of resources and monitoring effectiveness affect asset operational availability and overall total cost under CBM policy?

Research Question 2: Under which condition could the added value of prognostic information in CBM implementation be an advantage over classic CBM?

3. Methodology

The aim is to exploit the capability of DES approach in modelling complex maintenance operation to help maintenance operation decision maker to gain a better understanding and to assess the impact of resources and monitoring effectiveness in the adoption of CBM policy based on a practical performance measure of operational availability, and cost. From the three critical phases of CBM implementation, three logic flowcharts that capture the requirements of each monitoring level were developed and analysed in this research work in order to understand the behaviour of complex maintenance operations implementing CBM policy.

A DES tool modelled using ARENA® simulation software (Rockwell Automation, 2015) and Visual Basic for Application (VBA) codes was built to capture the different monitoring levels (Prognostics-enabled CBM, Diagnostics-enabled CBM, and Classic CBM). Although there are many DES software's, the choice of ARENA® software was due to its resilience, programmable capability, **and seamless integration with user-friendly Microsoft technologies for automation purpose**. The degradation model based on non-stationary gamma process model is used in this research to model the degradation process as it is the most common degradation process used in many engineering applications (eg, wear, crack growth etc.) due to its independent increment and monotone sample path properties (Zhang, Lei, & Shen, 2016 and Van Noortwijk, 2009). We adopt condition based ordering policy approach for spare parts ordering with the prognostics-enabled CBM monitoring level, which is based on the value of predicted RUL. If the predicted RUL is greater than the lead time for spares, then spares are ordered, and the downtime of the asset is limited to the time to perform the actual maintenance action. In the case where the predicted RUL is less than the lead time for spares, spares are ordered as well but the total downtime of the asset is increased due to the additional wait time for the spares to arrive before maintenance action could be carried out. Furthermore, for the other two monitoring levels, we adopt (s, S) type spare inventory policy, where S spares are ordered as soon as inventory spares drop below s. Since in practice, condition monitoring, fault/failure diagnostics, and prognostics tools might be unable to detect, diagnose, and predict all faults perfectly, we adopt the approach of using probability to capture the effectiveness of the monitoring tools which is similar to the approach used by Verma, Sridiya, & Ramesh, 2012, and Wang et al. (2015). For example, a condition monitoring detective ability of 0.9 indicates that only 90% of the fault in the system can be detected.

3.1. Classic CBM monitoring level

In classic CBM policy as illustrated in Figure 1, when an abnormal operating condition is detected by the condition monitoring system, the asset is immediately sent to the maintenance centre for inspection, diagnosis, and CBPM. In addition, the absence of diagnostics capability in this monitoring level means that the probability of a human-induced fault in the asset will be increased, particularly during the process of diagnosing the fault. Furthermore, the downtime of the asset is significantly increased as it has been reported in the literature that a considerable amount of time is required for diagnosis (Niebel, 1994).

3.2. Diagnostics-enabled CBM monitoring level

Diagnostics-enabled CBM monitoring level as illustrated in Figure 2 is similar to the classic CBM monitoring level except that the diagnostics unit is triggered when the condition monitoring system detects an abnormal operating condition. The presence of the diagnostics

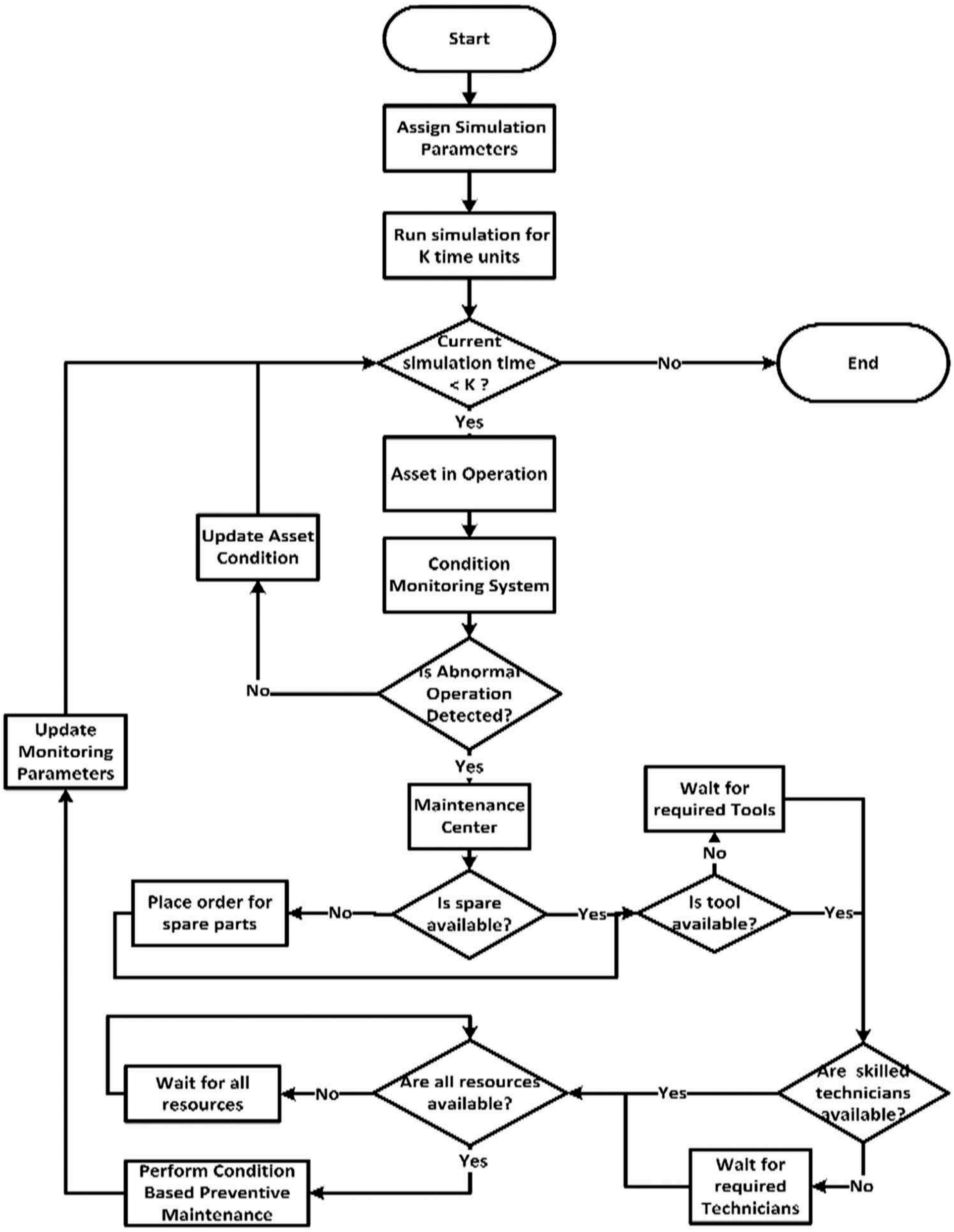


Figure 1. Simulation procedure of classic CBM under perfect monitoring.

capability in the asset reduces the downtime of the asset in the maintenance centre since the cause of fault would have been identified, isolated, and located by the diagnostic tool. The main benefit of this approach is that maintenance workers are equipped with the knowledge of which components that is faulty, which results in the reduction in time to implement maintenance operation, as well as the prevention of human-induced faults in the asset.

3.3. Prognostics-enabled CBM monitoring level

Prognostics-enabled CBM monitoring level as illustrated in Figure 3 builds on the diagnostics-enabled CBM monitoring level by triggering the prognostic tool to estimate the remaining useful life (RUL) after detection and diagnosis. As indicated in Figure 3, the dashed line represents the path of the identified degraded asset whose RUL is being monitored and recursively updated during the process. In order to set a threshold for which CBPM must be performed, a safety margin (duration of mission completeness) is subtracted from the estimated RUL to yield the prognostic threshold. The decision to maintain the asset or not depends on the value of the predicted RUL with reference to the prognostic threshold. If the predicted RUL is greater than the prognostic threshold, the asset can still be in operation while logistics and administrative support plans, such as the spares required can be ordered, maintenance personnel with the skill set to perform the maintenance can be scheduled ahead of the maintenance task. On the other hand, if the estimated RUL is the same or less than the prognostic threshold, the asset is immediately sent to the maintenance centre for urgent CPBM.

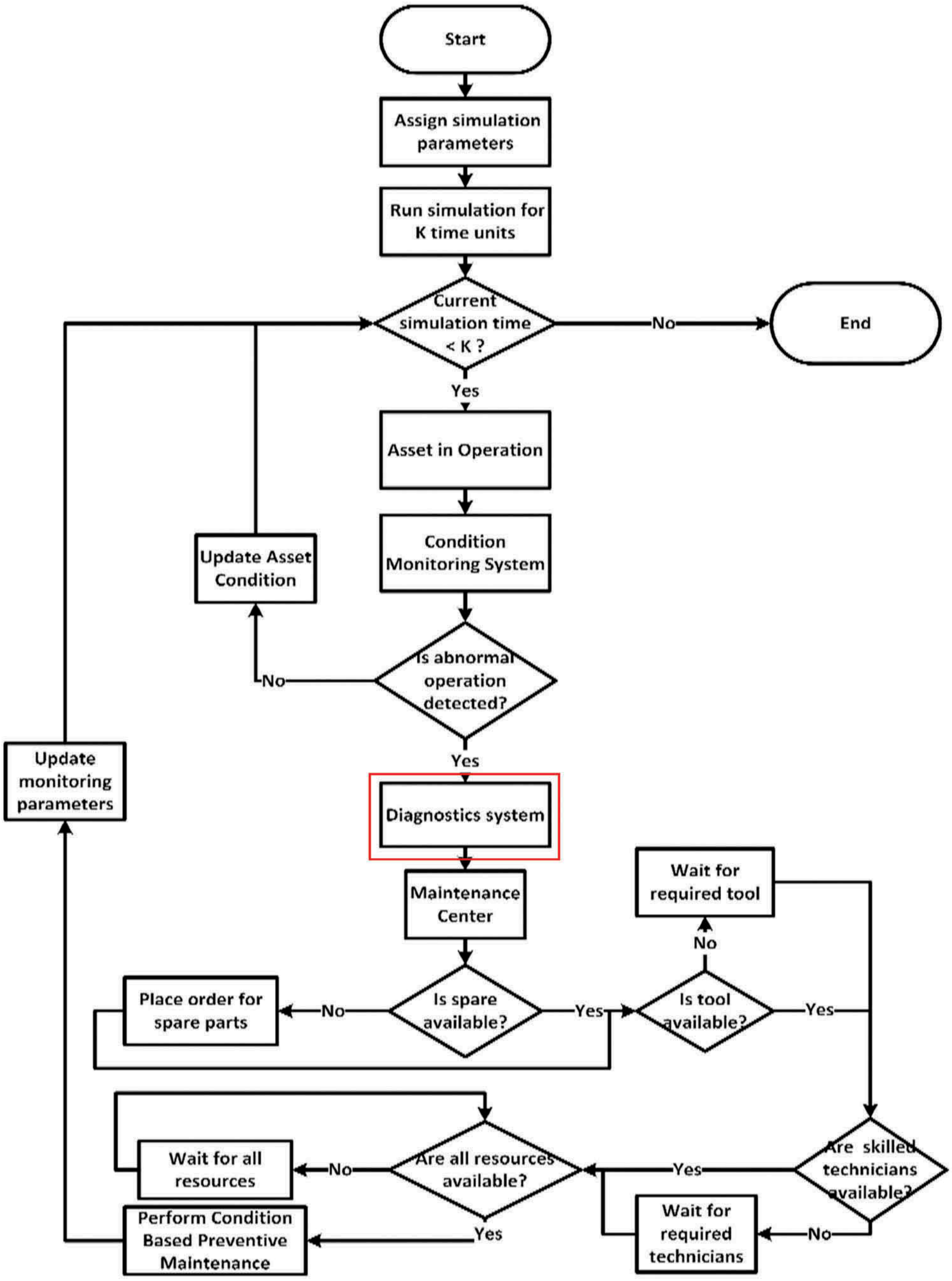


Figure 2. Simulation procedure of diagnostics-enabled CBM under perfect monitoring.

The main advantage of this monitoring level is that prior information is provided by the predicted RUL, which allows optimal use of the asset before failure, as well as allowing required maintenance support to be planned and scheduled in advance before the asset is sent to the maintenance centre. Therefore, this approach improves the uptime of the asset, while the downtime of the asset is significantly reduced. The main advantage of this monitoring level is that prior information is provided by the predicted RUL, which allows optimal use of the asset before failure, as well as allowing required maintenance support to be planned and scheduled in advance before the asset is sent to the maintenance centre.

4. Performance metrics

The performance metrics used in this paper includes overall availability and overall total cost. These performance metrics are discussed extensively below.

4.1. Availability

Availability provides an effective method of evaluating the system efficiency of a maintenance policy since the associated parameters of availability (uptime and downtime) can be accurately measured (Liao, Elsayed, & Chan, 2006). There are mainly three different types of availability identified in the literature, namely: Inherent Availability (A_i), Achieved Availability (A_a), and

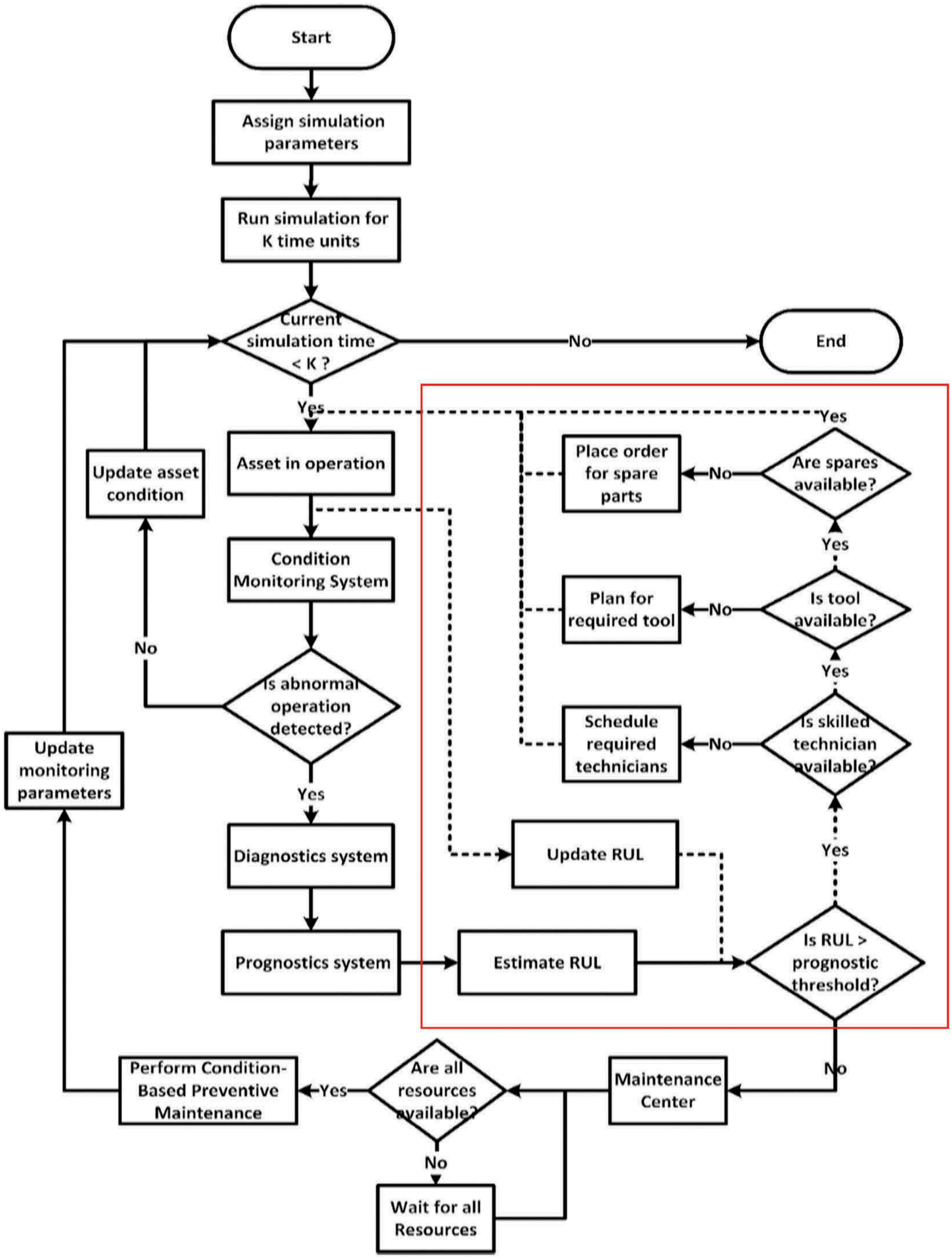


Figure 3. Simulation procedure of prognostics-enabled CBM under perfect monitoring.

Operational Availability (A_o). Their differences are shown in Table 1. MTTF is the Mean Time To Failure, MTTR is Mean Time To Repair, MTBM is Mean Time Between Maintenance, MMT is Mean Maintenance Time (combines Corrective Maintenance (CM) duration and Preventive Maintenance (PM) duration), and MDT is Mean Delay Time (combines CM duration, PM duration, logistics delay duration, and administrative delay

Table 1. Characteristics of the different types of availability.

	Parameters				
		Downtime			
Availability type	Uptime	Corrective maintenance	Preventive maintenance	Logistics delay	Administrative delay
$A_i = \frac{MTTF}{MTTF + MTTR}$	√	√	×	×	×
$A_a = \frac{MTBM}{MTBM + MMT}$	√	√	√	×	×
$A_0 = \frac{MTBM}{MTBM + MDT}$	√	√	√	√	√

duration). Since the maintenance actions considered in this paper include both CM, CBPM, logistics, and administrative delay time, A_o has been chosen as the availability performance metric as it provides the means of assessing both maintenance effectiveness and efficiency (Pascual & Kumar, 2016).

4.2. Cost

Maintenance cost takes significant proportions of the total operating cost in industries (Cigolini, Fedele, Garetti, & Macchi, 2008; Turan, Ölçer, Lazakis, Rigo, & Caprace, 2009). Hence, maintenance managers are interested in minimising maintenance cost while assuring a satisfactory level of equipment availability and reliability. Due to high initial set-up cost of CBM technologies, CBM is presently adopted and implemented in industries where reliability and safety are of highest priority. In this research work, which is based within the context of CBM, the initial set-up cost of CBM installation is excluded from the overall total cost as it has been reported in the literature that it has a predictable offsetting effect on the maintenance cost (Koochaki et al., 2011). The explanation of each cost parameter used in this research is given in details as follows:

- CBPM Cost (C_{CBPM}): The cost incurred when executing preventive maintenance based on the condition of the asset. It is expressed as:

$$C_{CBPM} = \sum_{i=1}^{n} (N_{PMi} \times C_{PMi}) \tag{1}$$

N_{PMi} is the total number of CBPM actions carried out on component i, and C_{PMi} is the cost of CBPM action on each failure mode (i) of the component.

- Corrective Maintenance Cost (C_{CM}): The cost incurred when corrective maintenance is executed on the asset. It is expressed as:

$$C_{CM} = \sum_{i=1}^{n} (N_{CMi} \times C_{CMi}) \tag{2}$$

N_{CMi} is the total number of CM actions carried out on component i, and C_{CMi} is the cost of CM action on each failure modes (i) of the component.

- Spare Parts Cost (C_{SP}): The sum of the cost of ordering spare parts and the respective holding cost. It is expressed as:

$$C_{SP} = C_{OS} + C_{HC} \tag{3}$$

$$C_{OS} = \sum_{j=1}^{n} (N_{COj} \times C_{DCj}) \tag{4}$$

$$C_{HC} = \sum_{j=1}^{n} (N_{HCj} \times C_{HCj}) \tag{5}$$

C_{OS} is the ordering cost for each component j, C_{HC} is the holding cost incurred in storage, N_{COi} is the total number of spares ordered for each component j, C_{DCj} is the delivery cost of each component (j) ordered, N_{HCj} is the total number of spare parts for each component (j) in storage, and C_{HCj} is the holding cost of each component j. Hence, the overall total cost can be expressed as:

$$\textit{Overall Total Cost} = C_{CBPM} + C_{CM} + C_{SP} \tag{6}$$

5. Case study

The case study used in this research is a published case study (Wang et al., 2015), which consists of four civic airlines with airplanes that fly between four base stations, each airline has spares inventory system with a fixed capacity, the airplanes are identical as they are produced from the same production line, and for each maintenance task, and only one spare is taken from the spare parts inventory. The data used in the published case study is shown in Table 2, which details the airline network formulation, component information, fault modes, criticality, and repair information, and the spare capacity distribution of each airline base. It should be noted that the components which have no PHM function have been removed from the data in Table 2. The RUL variables for the two components follows the symmetry triangular distribution of TRIA(0,500,1000) for component 1, and TRIA(0, 1500,2000) for component 2. The **total** delivery cost of each spare ordered is #200, **and the holding cost for each spare is assumed to cost #20**, and the lead time for delivery is 50 hours. The deterioration of the airplanes gear and aero engine at time t, $t \geq 0$ are denoted by $X_G(t)$, and $X_E(t)$. The mean of the gamma distribution is given as $MTBF \cong \frac{\alpha}{\beta}$ (Pham, 2006, Chapter 2). Since the failure rate is constant, the shape parameter $\alpha = 1$ (Pham, 2006, Chapter 2), and given the MTBF values, as shown in Table 2, we can estimate the value of β for both the gear and aero engine. For the simulation of the gear degradation process, we used $\alpha_G = 1$ and $\beta_G = 2 \times 10^{-3}$, while for the simulation of the gear degradation process, we used $\alpha_E = 1$ and $\beta_E = 6.667 \times 10^{-4}$. We fix the detection threshold value at 0.6 to indicate when the abnormal operating condition is detected, while the failure threshold is fixed at 1.

In addition, to adapt the case study for the purpose of this research, we define some synthetic

Table 2. System configuration parameters [Adapted from Wang et al. (2015)].

Airline network formation				
Airline name	Code	Main base	Fleet size	Daily flight hours
Qantas airways	QF	SYD	21	206
Qatar airways	QR	DOH	9	85
Korean air	KE	ICN	7	65.5
Singapore airlines	SQ	SIN	7	64
Component information				
No	Name	Quantity	MTBF (h)	PHM function
Component 1	Transmission gear	1	500	YES
Component 2	Aero engine	1	1500	YES
Fault modes, criticality, and repair cost information				
No	Number of failure modes	Fault rate percentage	Criticality	Repair costs
Component 1	3	0.75	#1,000	#300
		0.2	#2,000	#500
		0.05	#4,000	#1,000
Component 2	3	0.65	#2,500	#100
		0.3	#2,500	#100
		0.05	#2,500	#100
Spare capacity distribution of the airline bases				
Part number	SYD	DOH	ICN	SIN
Component 1	8	5	3	4
Component 2	4	3	2	2

parameters to capture the duration of the maintenance actions. The CBPM duration follows a triangular distribution of TRIA(3,4,6) hours. The CM duration follows the same triangular distribution of TRIA(6,8,12) hours. The diagnosis duration follows a triangular distribution of TRIA(2,3,4) hours. We assume **that** at each airline base, **at least** two maintenance engineers **are required for performing maintenance-related tasks**, and the route of each airline is as shown in Figure 4. All the activities (disassembly, replacement, reassembly, and testing) are lumped together to represent the total duration of each maintenance action except the diagnosis duration, which is necessary to account for the diagnostic ability incorporated in both prognostics-enabled and diagnostics-enabled CBM monitoring levels. The primary goal of this simulation study is to demonstrate and assess the potential benefits of PHM as an enabler for CBM implementation under the influence of resources (spare parts, maintenance workers), and varying monitoring effectiveness, using practical performance measures of overall A_o, and overall total costs.

5.1. Simulation setup

The required setup parameters when doing a simulation experiment includes; warm-up period, simulation run length, and the number of replications. Simulation models can either be terminating or non-terminating (Robinson, 2010, p. 138). While terminating simulation model reaches a natural end, non-terminating simulation model reaches steady-state. The nature of the case study follows a non-terminating simulation model since the airplanes are expected to fly their different routes consecutively day after day. In order to ensure simulation stability, it is required to determine the warm-up period where all transient behaviours inherent in the simulation would have disappeared.

In this case study, the run length has been decided to be five years, this is to ensure that during the period decided, useful information about the maintenance task and sufficient CBPM and CM would have occurred in the fleet. In order to specify the warm-up period, we follow the approach described by Robinson (Robinson, 2010, p. 138) and

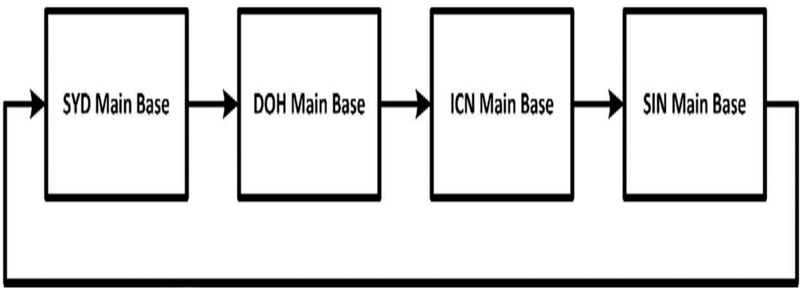


Figure 4. Movement of airplanes across the four main bases.

implemented by Alabdulkarim et al. (2015) in their paper. They used one of the output measures to visually decide the start of the steady state behaviour of the system. Hence, we used maintenance personnel utilisation to decide the warm-up period. The time series diagram as shown in Figure 5 with 10 replication length (indicated by different lines) indicates that the warm-up period should be set as **2.22** years (**20,000** hours).

The number of replication was decided based on the confidence interval method. The overall operational availability of the airplanes under perfect monitoring simulation model for the prognostics-enabled CBM policy was used for the calculation of the number of replications. Hence, based on the calculated number of replications using the confidence interval method, 100 replications was used for the case study.

5.2. Model verification and validation

Model verification and validation is a required, and prerequisite step to the experimental analysis of the simulation model (Andijani and Duffuaa, 2002). The process of verification ensures the correct mapping between the developed model and the system being represented by the model, while validation ensures that the developed model closely represent the behaviour of the real-world system. Model verification was done by utilising the animation facilities provided by ARENA® simulation software. The animation facilities enabled model logic to be verified by observing and following the path of the entity.

The validation step was based on sensitivity analysis suggested by Greasley (2004). He stated that "if a simulation model has been built for a system . . ., performing sensitivity analysis is particularly appropriate". He argued that "if there is little variation in output as a consequence of a change in input then we can be reasonably confident in the results". In this paper, sensitivity analysis was performed by observing the effects of input parameter variation (resources and monitoring effectiveness) on the model results. Additional validation was performed by discussing the model logic and results with experts in the field of simulation. The model logic and results were deemed to be logical, representative, and explainable.

5.3. Maintenance manager user-friendly platform for maintenance analysis

An Excel-based interface was developed to provide an easy and convenient way to analyse the simulation of the different CBM monitoring levels. Three interfaces corresponding to each monitoring level were developed in this paper. The approach uses VBA code written in excel to automate the process of providing input to the ARENA model, as well as exporting the output to the Excel interface. This approach is similar to the approach implemented by Saltzman and Mehrotra (2004). The Excel

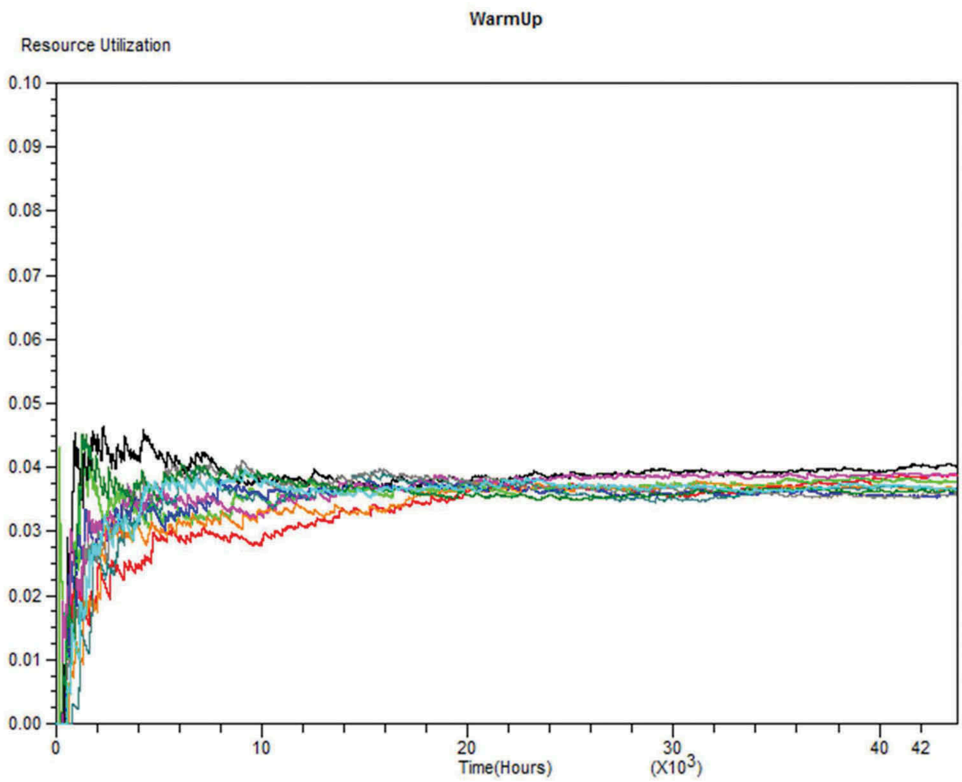
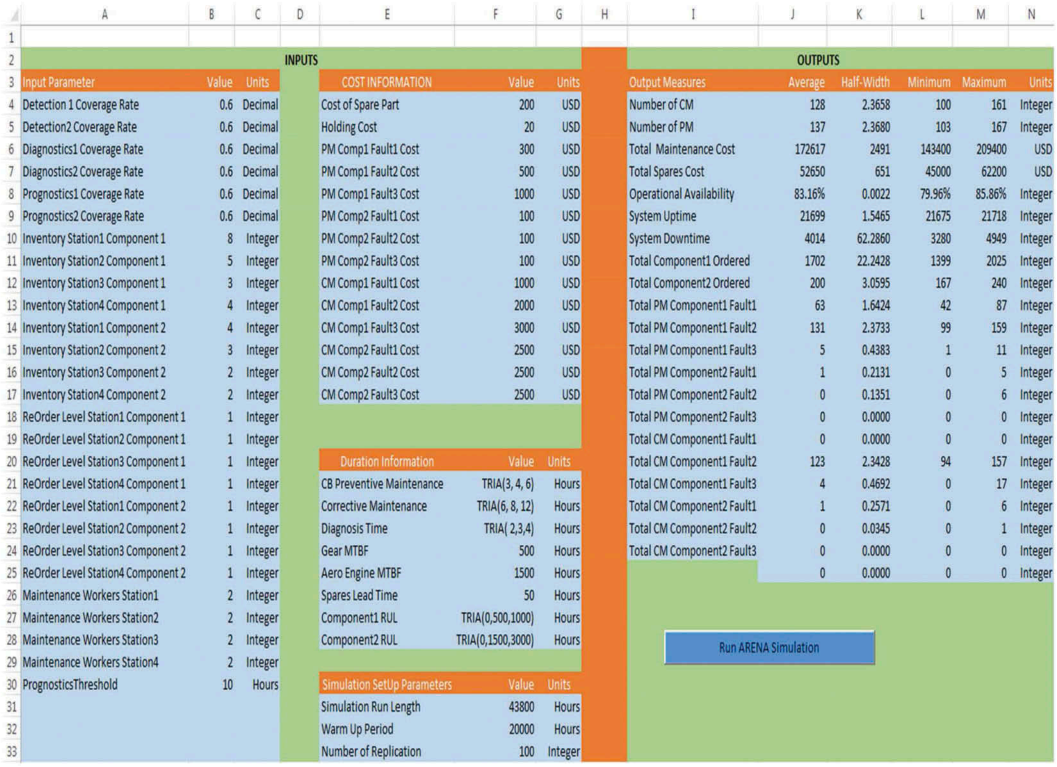


Figure 5. Warm-up period using time series plot of maintenance worker's utilisation.



INPUTS

	Input Parameter	Value	Units
4	Detection 1 Coverage Rate	0.6	Decimal
5	Detection2 Coverage Rate	0.6	Decimal
6	Diagnostics1 Coverage Rate	0.6	Decimal
7	Diagnostics2 Coverage Rate	0.6	Decimal
8	Prognostics1 Coverage Rate	0.6	Decimal
9	Prognostics2 Coverage Rate	0.6	Decimal
10	Inventory Station1 Component 1	8	Integer
11	Inventory Station2 Component 1	5	Integer
12	Inventory Station3 Component 1	3	Integer
13	Inventory Station4 Component 1	4	Integer
14	Inventory Station1 Component 2	4	Integer
15	Inventory Station2 Component 2	3	Integer
16	Inventory Station3 Component 2	2	Integer
17	Inventory Station4 Component 2	2	Integer
18	ReOrder Level Station1 Component 1	1	Integer
19	ReOrder Level Station2 Component 1	1	Integer
20	ReOrder Level Station3 Component 1	1	Integer
21	ReOrder Level Station4 Component 1	1	Integer
22	ReOrder Level Station1 Component 2	1	Integer
23	ReOrder Level Station2 Component 2	1	Integer
24	ReOrder Level Station3 Component 2	1	Integer
25	ReOrder Level Station4 Component 2	1	Integer
26	Maintenance Workers Station1	2	Integer
27	Maintenance Workers Station2	2	Integer
28	Maintenance Workers Station3	2	Integer
29	Maintenance Workers Station4	2	Integer
30	PrognosticsThreshold	10	Hours

COST INFORMATION	Value	Units
Cost of Spare Part	200	USD
Holding Cost	20	USD
PM Comp1 Fault1 Cost	300	USD
PM Comp1 Fault2 Cost	500	USD
PM Comp1 Fault3 Cost	1000	USD
PM Comp2 Fault1 Cost	100	USD
PM Comp2 Fault2 Cost	100	USD
PM Comp2 Fault3 Cost	100	USD
CM Comp1 Fault1 Cost	1000	USD
CM Comp1 Fault2 Cost	2000	USD
CM Comp1 Fault3 Cost	3000	USD
CM Comp2 Fault1 Cost	2500	USD
CM Comp2 Fault2 Cost	2500	USD
CM Comp2 Fault3 Cost	2500	USD
Duration Information	**Value**	**Units**
CB Preventive Maintenance	TRIA(3, 4, 6)	Hours
Corrective Maintenance	TRIA(6, 8, 12)	Hours
Diagnosis Time	TRIA(2,3,4)	Hours
Gear MTBF	500	Hours
Aero Engine MTBF	1500	Hours
Spares Lead Time	50	Hours
Component1 RUL	TRIA(0,500,1000)	Hours
Component2 RUL	TRIA(0,1500,3000)	Hours
Simulation SetUp Parameters	**Value**	**Units**
Simulation Run Length	43800	Hours
Warm Up Period	20000	Hours
Number of Replication	100	Integer

OUTPUTS

Output Measures	Average	Half-Width	Minimum	Maximum	Units
Number of CM	128	2.3658	100	161	Integer
Number of PM	137	2.3680	103	167	Integer
Total Maintenance Cost	172617	2491	143400	209400	USD
Total Spares Cost	52650	651	45000	62200	USD
Operational Availability	83.16%	0.0022	79.96%	85.86%	Integer
System Uptime	21699	1.5465	21675	21718	Integer
System Downtime	4014	62.2860	3280	4949	Integer
Total Component1 Ordered	1702	22.2428	1399	2025	Integer
Total Component2 Ordered	200	3.0595	167	240	Integer
Total PM Component1 Fault1	63	1.6424	42	87	Integer
Total PM Component1 Fault2	131	2.3733	99	159	Integer
Total PM Component1 Fault3	5	0.4383	1	11	Integer
Total PM Component2 Fault1	1	0.2131	0	5	Integer
Total PM Component2 Fault2	0	0.1351	0	6	Integer
Total PM Component2 Fault3	0	0.0000	0	0	Integer
Total CM Component1 Fault1	0	0.0000	0	0	Integer
Total CM Component1 Fault2	123	2.3428	94	157	Integer
Total CM Component1 Fault3	4	0.4692	0	17	Integer
Total CM Component2 Fault1	1	0.2571	0	6	Integer
Total CM Component2 Fault2	0	0.0345	0	1	Integer
Total CM Component2 Fault3	0	0.0000	0	0	Integer
	0	0.0000	0	0	Integer

Run ARENA Simulation

Figure 6. Developed excel interface for prognostics-enabled CBM simulation and analysis.

interface for prognostic-enabled CBM monitoring level, which automatically controls the execution of the developed ARENA®-based simulation model is shown in Figure 6. The other two interfaces are similar to the interface, as shown in Figure 6.

6. Experimentation results and analysis

In the different scenarios considered, Monitoring Coverage Rate (MCR) of each monitoring levels is varied between 0.6 and 0.9, this is used to reflect the minimum and maximum acceptable detective, diagnostic, and predictive ability of the monitoring tools. Since in practice, MCR is never 100%, we exclude MCR value of 1 in the analysis of the results. In the case of prognostic-enabled CBM monitoring level, there are six MCR variables (two condition monitoring tools, two diagnostics tools, and two prognostics tools) to give an indication of the effectiveness of the monitoring tools, each having values uniformly varying between 0.6 and 0.9. For the diagnostics-enabled CBM monitoring level, there are four MCR variables (two condition monitoring tools, and two diagnostics tools), and two MCR variables (two condition monitoring tools) for the classic CBM monitoring level. These MCR's captures the two critical components of the airplanes highlighted in the description of the case study.

6.1. *Monitoring levels under fixed resources, increased resources, and decreased resources*

The monitoring levels investigated were compared under fixed (As-Is), increased (50% increment), and decreased (50% decrement) number of required spare parts, reorder level, and maintenance engineers using the performance metrics of overall operational availability, and overall total cost. Therefore, different scenarios corresponding to different MCR value with a step change of 0.1 of one MCR variable at a time were used to define the number of **simulations** to be run. Based on this method, a total number of 16 **simulations** were required for the classic CBM monitoring level, a total number of 52 **simulations** for the diagnostics-enabled CBM monitoring level, and a total number of 76 **simulations** for the diagnostics-enabled CBM monitoring level. Since it will be very difficult to explore all the possibilities of the MCR variables manually, optimisation has been included in **Section 6.3** in order to select the optimum combinations of MCR variables and maintenance resources. The first 4 scenarios in each monitoring level correspond to identical step increment of the MCR variables (with values from 0.6 to 0.9, and a step increment of 0.1). To evaluate all the scenarios, a separate application within ARENA® called Process Analyzer (PAN) was used. PAN enables multiple scenarios to be run using the different values for input controls, while a set of output controls

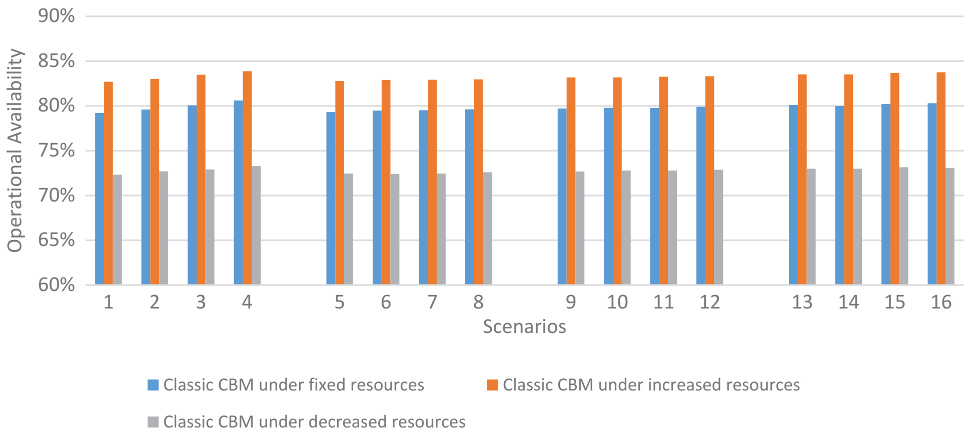


Figure 7. Effect of MCR under classic CBM policy with fixed resources, increased resources, decreased resources on operational availability.

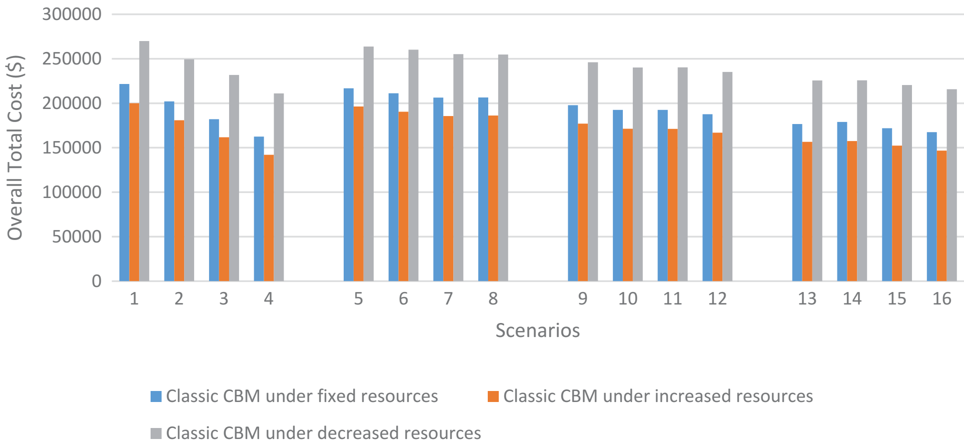


Figure 8. Effect of MCR under classic CBM policy with fixed resources, increased resources, decreased resources on overall total cost.

(operational availability, and overall total cost) of each scenario are evaluated after each run, and used to compare the best scenario among all the results.

The effect of MCR on A_0 under classic CBM monitoring level is shown in Figure 7, while the results obtained using the metric of the overall total cost is shown in Figure 8. Figure 9 shows the comparison of the different resources and monitoring effectiveness on diagnostic-enabled CBM monitoring level using the performance metric of operational availability. In terms of the overall total cost under diagnostic-enabled CBM monitoring level, Figure 10 indicates that increasing resources has a noticeable effect in the reduction of the overall total cost as compared to fixed and decreased resources scenarios. The effect of MCR on A_0 under prognostic-enabled CBM monitoring level is shown in Figure 11, while the corresponding result obtained using the metric of the overall total cost is shown in Figure 12.

The trend of the results indicate that the scenario under increased maintenance resources generally improves the performance metrics of overall A_0, and of overall total cost as compared to scenarios under fixed resources, and decreased resources across the different types of monitoring levels. However, superior performance is observed with prognostics-enabled CBM monitoring level as compared to other monitoring levels. In addition, the results obtained using the metric of overall total cost indicates that **the integration of prognostics information** have a noticeable effect in the reduction of overall total cost within the manufacturing system. The reason for this phenomenon can be attributed to the integration of prognostics, which minimises unused component useful life, thus ensuring that the useful life of the components are almost used to the full before maintenance. Also, since the ordering system under prognostics-enabled CBM is condition-based (based on RUL information) as discussed in Section 3.3, the number of spares parts ordered are reduced. As a result of all these factors, the overall total cost is reduced as less frequent preventive maintenance and corrective maintenance are carried out under prognostics-enabled CBM policy when compared to classic CBM and diagnostics-enabled CBM, and the reduction of spare parts cost brought about by spares ordering policy which is based on PHM

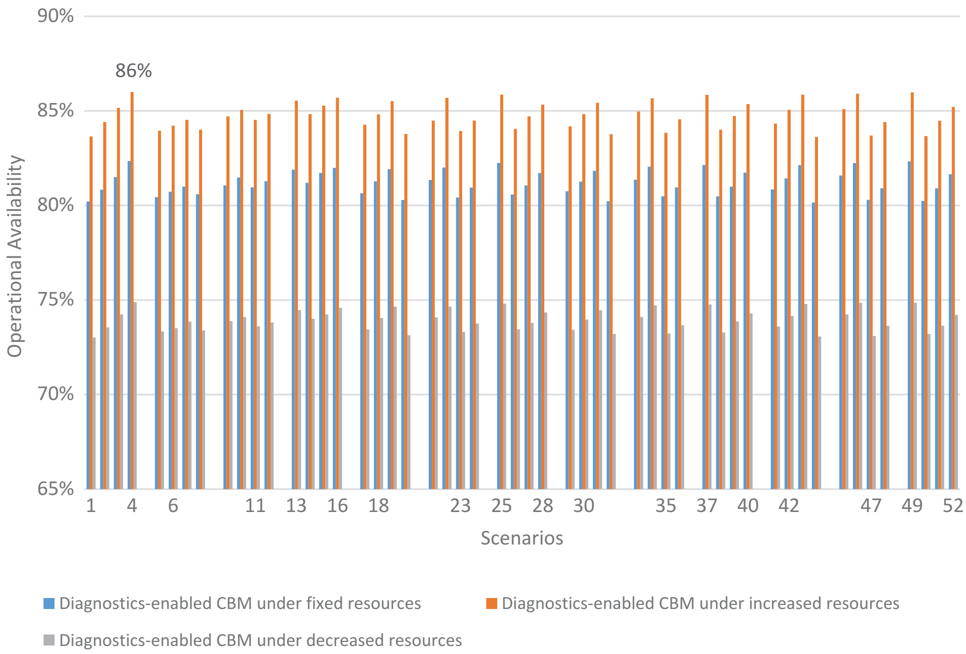


Figure 9. Effect of MCR under diagnostics-enabled CBM policy with fixed resources, increased resources, and decreased resources on operational availability.

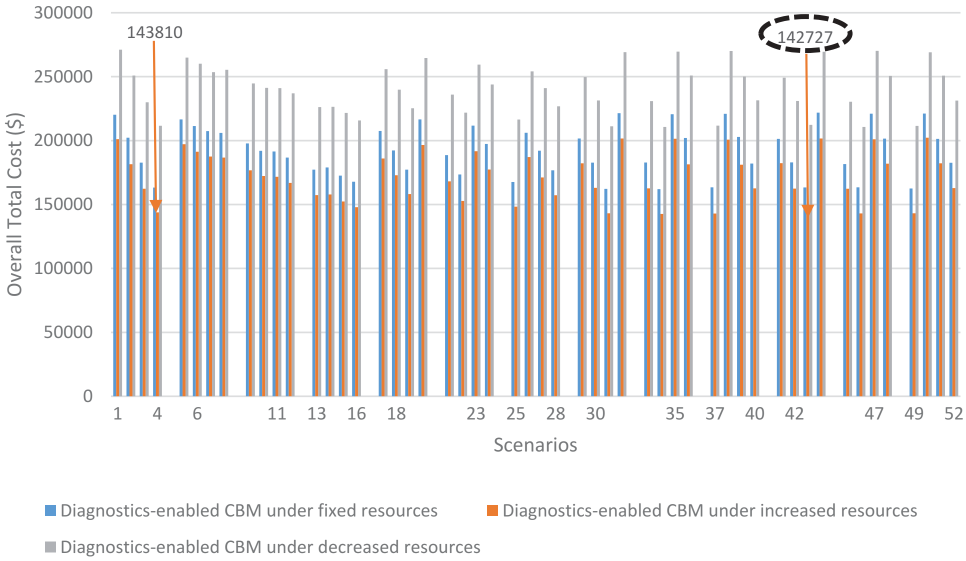


Figure 10. Effect of MCR under diagnostics-enabled CBM policy with fixed resources, increased resources, and decreased resources on overall total cost.

information. In addition, as indicated in Table 2, the cost of performing each maintenance action (preventive and corrective maintenance) for each failure mode is a fixed cost. Hence, in this research work, the maintenance cost will be constant irrespective of the maintenance engineers hired. In future research work, this assumption can be relaxed to allow for the inclusion of the cost of adding additional manpower to the number of maintenance engineer. Hence, the reduction of overall total cost is mainly as a result of the reduction in the number of maintenance task carried out, and the reduction in the number of spares ordered due to the RUL information provided by the prognostics system.

To justify the need for optimisation for optimal parameters settings, the black dotted **circle** in Figure 10 under diagnostics-enabled CBM monitoring level indicates that the lowest overall total cost was obtained in scenario **43**, while the highest overall A_0 was obtained in scenario 4 in Figure 9. Hence, the above illustration indicate that there are still more possible combinations that could be further explored with the use of optimisation to intelligently search for an optimum combination of maintenance resources and monitoring effectiveness that minimises the selected objective function.

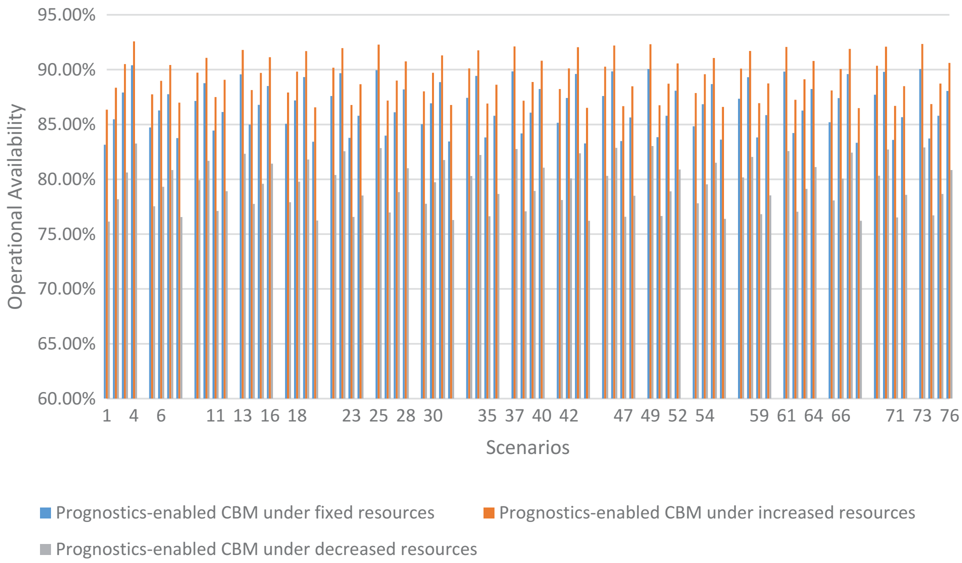


Figure 11. Effect of MCR under prognostics-enabled CBM policy, with fixed resources, increased resources, and decreased resources on operational availability.

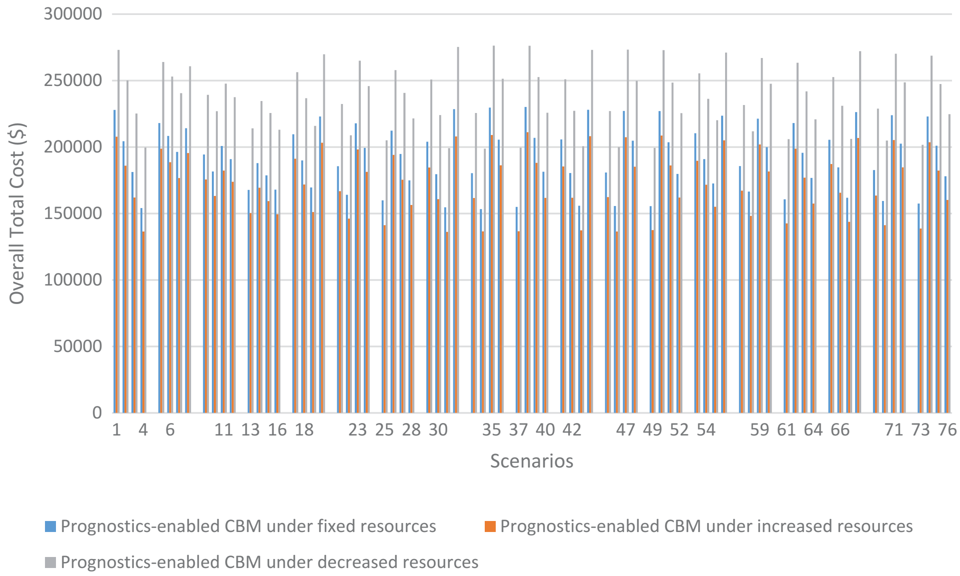


Figure 12. Effect of MCR under prognostics-enabled CBM policy, with fixed resources, increased resources, and decreased resources on overall total cost.

6.2. Comparison of all the CBM monitoring levels

In this section, comparison is made among the considered monitoring levels implemented in this research work (prognostics-enabled CBM, diagnostics-enabled CBM, and classic CBM monitoring levels) based on the performance metrics of overall A_0, and the overall total cost. In order to ensure a fair comparison, only **the results from** the first 4 scenarios, corresponding to the uniform increment of 0.1 (from 0.6 to 0.9) across all the MCR variables for each monitoring level are used. The best result (highest value of the overall A_0, and lowest value of overall total cost) are shown in bold for each level of maintenance resource, and different MCR variables. The comparison as tabulated in Table 3 showed that the added value of PHM information in CBM policy is highly significant. It resulted in consistent improvement of A_0 across all different monitoring and resource levels for prognostics-enabled CBM monitoring level. However, the benefit of PHM information in the reduction of the overall total cost is dependent on the prognostic tool achieving sufficiently high MCR value.

6.3. Optimisation of monitoring levels

As discussed in Section 6.1 and illustrated by the **black** dotted circle line in Figure 10, it is quite difficult to explore all the feasible dimensional space, and

Table 3. Comparison of monitoring levels in CBM based on overall A_0 and total cost.

Resource level	Scenario	Operational availability (%)			Overall total cost (#)		
		Classic CBM	Diagnostics-enabled CBM	Prognostics-enabled CBM	Classic CBM	Diagnostics-enabled CBM	Prognostics-enabled CBM
Fixed resources	1	79.21	80.21	**83.16**	221,700	**220,261**	227,900
	2	79.60	80.83	**85.47**	**202,014**	202,279	204,375
	3	80.07	81.50	**87.92**	182,034	182,730	**181,193**
	4	80.61	82.35	**90.40**	162,510	163,218	**154,101**
Increased resources	1	82.70	83.65	**86.35**	**199,982**	201,160	207,774
	2	83.01	84.41	**88.35**	**180,877**	181,520	185,953
	3	83.48	85.16	**90.51**	**161,813**	162,373	162,046
	4	83.88	86.00	**92.58**	142,064	143,810	**136,486**
Decreased resources	1	72.32	73.02	**76.15**	**269,904**	271,049	273,088
	2	72.70	73.55	**78.18**	**249,369**	250,874	250,119
	3	72.91	74.24	**80.62**	231,760	230,009	**225,182**
	4	73.29	74.89	**83.26**	211,013	211,592	**199,647**

choose the best combinations of the decision variables (MCR, and maintenance resources) using PAN to minimise the selected objective function. Hence, the need for optimisation. In this research work, the minimisation of the overall total cost is selected as the objective function, subject to the requirement that the overall A_0 should be greater than or equal to 80%. The optimisation was carried out using OptQuest® package in ARENA®. OptQuest® uses a combination of heuristics, such as tabu search, scatter search, and neural network to intelligently search for an optimum solution (Kelton, 2010). The following are the notations used in the optimisation model: j is the number of component in the system, g is the number of airline base in the system, and A_O^D is the minimum acceptable value of A_0 in the manufacturing system.

The sets in this module are as follows: G is the set of all airline bases, and $g \in G$. J is the set of all components that are being monitored, and $j \in J$. Decision variables related to the optimisation problem are: MCR_{jg} is a discrete variable that denotes the MCR of component j in airline base g with a discrete step size of 0.1, R_{jg} is a discrete variable that denotes the re-order level of component j in airline base g with a discrete step size of 1, S_{jg} is a discrete variable that denotes the order quantity for spare parts of component j in airline base g with a discrete step size of 1, M_g is a discrete variable that denotes the number of maintenance engineer in airline base g with a discrete step size of 1, and x_{jg}^{ML} denotes the type of monitoring level selected ($ML \in$ {0,1,2}, where **0** denotes CBM monitoring level, **1** denotes diagnostics-enabled CBM monitoring level, and **2** denotes prognostics-enabled CBM monitoring).

The optimisation problem can be mathematically represented as:

$$\text{Minimize} \quad Overall\ \ Total\ \ Cost \tag{7}$$

$$\text{Subject to } MCR_{jg_{min}} \leq MCR_{jg}\left(x_{jg}^{ML}\right) \leq MCR_{jg_{max}}\ \forall j \in J, \forall g \in G \tag{8}$$

$$R_{jg_{min}} \leq R_{jg} \leq R_{jg_{max}}\ \forall j \in J, \forall g \in G \tag{9}$$

$$S_{jg_{min}} \leq S_{jg} \leq S_{jg_{max}}\ \forall j \in J, \forall g \in G \tag{10}$$

$$M_{g_{min}} \leq M_g \leq M_{g_{max}}\ \forall g \in G \tag{11}$$

$$A_0 \geq A_O^D \tag{12}$$

Equation (7) is the objective function, which is a simulation model output that minimises the overall total cost of the airline case study operation, which includes: (i) cost of CBPM, (ii) cost of corrective maintenance, and (iii) cost of spares. Equations (8–11) are constraints on the decision variables or input controls, which represents the boundary for the decision variables; namely MCR (minimum value of 0.6, and maximum value of 0.9), reorder level (minimum value of 0, and maximum value of 2), order quantity of spare parts (minimum value corresponding to 50% decrement, and maximum value corresponding to 50% increment of the spare capacity distribution as shown in Table 2), and maintenance engineer (minimum value of 1, and maximum value of 3), respectively. Equation (12) defines the constraints on the simulation model output of A_0 ($A_O^D = 0.8$). As indicated in the case study description, the number of parameters for the components and the base stations were set to two and four respectively. Table 4 presents the overall total cost reduction, as well as the optimal parameter values of maintenance resources obtained for each monitoring level. From the data presented in Table 4, we can see that prognostics-enabled CBM monitoring level achieved the best overall total cost reduction as compared to other monitoring levels.

7. Conclusion and future work

In this paper, we have investigated the influence of resources and monitoring effectiveness of CBM policy based on the three critical parts of CBM, detection, diagnosis, and prognosis using the performance metrics of operational availability and

Table 4. Comparison of optimisation results of the monitoring levels.

	Monitoring level		
Optimisation results	Classic CBM	Diagnostics-enabled CBM	Prognostics-enabled CBM
Objective function			
Overall total cost(#)	130,610	128,003.33	115,160
Monitoring coverage rate			
Component 1 detection tool	0.9	0.8	0.8
Component 2 detection tool	0.8	0.9	0.8
Component 1 diagnostic tool	–	0.9	0.7
Component 2 diagnostic tool	–	0.8	0.8
Component 1 prognostic tool	–	–	0.9
Component 2 prognostic tool	–	–	0.8
Order quantity for spare parts			
Qantas airways component 1	11	10	10
Qantas airways component 2	6	6	5
Qatar airways component 1	8	7	7
Qatar airways component 2	5	5	3
Korean air component 1	5	5	2
Korean air component 2	2	2	2
Singapore airlines component 1	6	5	5
Singapore airlines component 2	3	3	1
Re-order level for spare parts			
Qantas airways component 1	2	2	2
Qantas airways component 2	2	2	2
Qatar airways component 1	2	1	2
Qatar airways component 2	1	1	2
Korean air component 1	2	1	1
Korean air component 2	2	2	1
Singapore airlines component 1	2	1	1
Singapore airlines component 2	2	1	1
Base maintenance engineer			
Qantas airways	3	3	2
Qatar airways	3	3	2
Korean air	2	3	1
Singapore airlines	3	2	1

overall total cost to quantitatively assess the technical, and economic benefits of the value of PHM in CBM using a published case study example on a system-wide level. Additionally, we **incorporated optimisation to find optimal parameter settings (MCR and maintenance resources) for each monitoring level**. The research questions raised at the onset of this research work is subsequently answered based on the quantitative results obtained from the case study.

Research Question 1: How would the influence of resources and monitoring effectiveness affect asset operational availability and overall total cost under CBM policy?

Resources (spare parts and maintenance engineers) and monitoring effectiveness have a noticeable effect on both overall operational availability and overall total cost. The performance metrics of operational availability increases (decreases), as well as the overall total cost decreases (increases) with increased (decreased) resources with improved monitoring effectiveness of the monitoring tools across all the monitoring levels.

Research Question 2: Under which condition could the added value of prognostic information in CBM implementation be an advantage over classic CBM?

Without optimisation, the integration of prognostic information in CBM policy results in superior technical performance benefit. However, the economic benefit of prognostic information can only be realised when the monitoring effectiveness of the prognostics tool (dependent on both diagnostics and condition monitoring tools) attains sufficiently high value. On the other hand, with the implementation of single-objective optimisation, the added benefit of incorporating prognostics for cost-effective maintenance was realised as a result of optimal maintenance resources settings. The result obtained clearly showed that prognostic-enabled CBM monitoring level achieved the best overall total cost reduction when compared to other monitoring levels investigated.

Future work will investigate the additional cost of hiring more or fewer maintenance engineers as part of the overall total cost. Also, multi-objective optimisation considering both operational availability and overall total cost performance metrics as objectives will be investigated with the developed simulation framework. Further analysis using multi-objective optimisation will provide maintenance operations decision makers more flexibility in adapting their changing circumstances to match their business environment.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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