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Modelling maintenance effects on manufacturing equipment performance: results from simulation analysis

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Equipment maintenance and system reliability are important factors affecting the organisation's ability to provide quality and timely services to customer. While maintenance remains an important function to manufacturing, it is only recently that attempts have been made to quantify its impact on equipment performance. In this research, an approach of linking maintenance with equipment performance is developed using simulation modelling. The modelling approach involves defining probabilistic models and assumptions affecting system performance, such as: the probabilistic model for the initial failure rate/intensity of the equipment; the probabilistic model for the system deterioration and corresponding effect; the probabilistic model for the random times of corrective maintenance (CM) and preventive maintenance (PM) that takes into the account the types of maintenance plans/policies and the potential dependency between CM and PM times; and the probabilistic model for the random effects of CM and PM on the reliability of the equipment. Using a continuous manufacturing equipment, the model is used to analyse the impact of deterioration, failures and maintenance (policies, timing and efficiency) on equipment performance. It is shown that modelling the effect maintenance provides a basis of evaluating maintenance efforts with the potential application in performance evaluation and decision support while investigating opportunities for manufacturing equipment performance improvement.

Keywords: performance; maintenance; manufacturing; equipment; modelling; simulation

1. Introduction

Though manufacturing equipment is designed to ensure successful operation through the anticipated service life, deterioration commences as soon as it is commissioned. In addition to deterioration, other failures may also occur, especially in the event the equipment is operated beyond its design limits or due to operational errors. As a result, equipment downtime, quality problems or slower production becomes the obvious outcome. These outcomes negatively impact the operating cost, and productivity among other important performance requirements (Muchiri and Pintelon 2011). As asserted by several authors (Campbell 1995; Madu 1999, 2000), equipment maintenance and system reliability are important factors affecting the organisation's ability to provide quality and timely services to customers. Maintenance is, therefore, vital for sustainable performance of manufacturing equipment (Coetzee 1997; Fleischer, Weismann, and Niggeschmidt 2006; Madu 2000).

Maintenance is defined as a combination of all technical and associated administrative activities required to keep equipments, installations and other physical assets in the desired operating condition or restore them to this condition (BSI 1984). Maintenance Engineering Society of Australia gives a definition that indicates that maintenance is about achieving the required asset capabilities within an economic or business context (MESA 1995). They define maintenance as the engineering decisions and associated actions, necessary and sufficient for optimisation of specified equipment 'capability'. The capability in this definition is the ability to perform a specified function within a range of performance levels that may relate to capacity, rate, quality and responsiveness (Tsang 1999).

Though some authors state that there is now higher acknowledgement of maintenance as an important function than ever before (Al-Najjar 2007; Alsyouf 2007), still a complex relationship between maintenance and production does exist (Alsyouf 2004; Dunn 1998; McGrath 1999). The maintenance and the production function are pretty much separated in

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terms of the organisational unit they are embedded in. However, this separation may be less than optimal in situations where the overall performance of organisations is the primary objective (Muchiri and Pintelon 2011).

Extensive research has been carried out over the years on production planning, maintenance modelling and management of unreliable systems (Buzacott and Shanthikumar 1993; Chelbi and Rezg 2006; Das and Sarkar 1999; Dekker 1996; Meller and Kim 1996). However, the tendency of separating maintenance and production is further propagated in theory, where the production planning models assume maximum equipment performance within a planning horizon while maintenance models disregard the impact on production capacity and performance (Aghezzaf, Jamali, and Kadi 2007). Thus, additional effort is required in order to see an integrated or the 'whole picture' of equipment performance (Muchiri and Pintelon 2011).

In many situations, the production and maintenance function cannot operate completely independently. Essentially, by utilising technical systems, i.e. physical assets, some kind of degradation occurs, which without maintenance intervention would lead to loss of function. Thus, the production function generates a demand for maintenance. The maintenance function, on the other hand, tries to remedy loss of function through a technical intervention (Muchiri and Pintelon 2011). Both functions are in essence linked together by their requirement to access the assets for their respective purposes. Mostly, the access of an asset does require some coordination, since the production function and the maintenance function have different and sometimes conflicting requirements regarding the state of the asset for their purpose (Muchiri and Pintelon 2011). For instance, a car cannot be used for driving when a tyre replacement is carried out. On the other hand, measuring oil pressure for condition-based maintenance requires a running engine and may not conflict with the intention to drive the car. This type of interdependence necessitates a mutual coordination for access of assets (Muchiri and Pintelon 2011).

The conflicting interactions between the maintenance and production functions, and resulting influence on equipment performance has elicited research interest. Mathematical and simulation models are usually the most common approaches adopted for analysing these process interactions (Lin, Fan, and Newman 2009). For example, AlDurgam and Duffuaa (2012) propose a mathematical model based on the Markov Decision Process. The model maximises the Overall System Effectiveness (OSE), while considering interaction between process speed, output quality and equipment deterioration. Wudhikarn (2011) also presents a mathematical model for maximising the Overall Equipment Cost Loss (OECL) of a fibre cement manufacturer. In the study, the author investigates the interaction effects between production and maintenance performance measures defined by the Overall Equipment Effectiveness (OEE). The OECL is an extension of the OEE (Muchiri and Pintelon 2008) and incorporates different cost components to the quality metric defined in OEE. Tsarouhas (2012) also proposes a framework based on OEE for analysing the performance of a beverage plant. Alaoui-Selsouli, Mohafid, and Najid (2012) propose the use of a mixed-integer mathematical model incorporating a relaxed Lagrangian heuristic to investigate the conflicting interaction between production demand on the one hand and an unreliable equipment on the other hand.

Mathematical models, however, are associated with several deficiencies that include limited user understanding of the model algorithm thus limiting their use in the manufacturing environment context (Lin, Fan, and Newman 2009; Padhi et al. 2012). In addition, the models fail to explicitly describe the effects of different maintenance policies on the performance measures. Furthermore, production equipment in the manufacturing environment are characterised by complex and dynamic relationships, not just between production and maintenance functions, but by additional external factors such as customer demand or maintenance policies. As a result, mathematical models may not adequately represent the stochastic behaviour of process equipment in the manufacturing environment. Simulation modelling has, therefore, been proposed as a better approach that can address the inherent limitations of mathematical models, especially relating to modelling the performance of complex systems (Kelton, Sadowski, and Sadowski 2002).

Several applications of simulation modelling in the manufacturing environment context are discussed in literature. Lin, Chang, and Chen (2012) propose the use of Activity on Arc (AOA) graphical network model to evaluate the interaction between customer demand on the one hand and equipment reliability, for a footwear manufacturing facility. It is of course intuitive that satisfying a high customer demand may lead to equipment being operated at high production rates, leading to high failure rates. Weigert and Henlich (2009) compare two modelling approaches; firstly, a heuristic simulation model and secondly, a mixed-integer programming solver. The authors apply both approaches to optimise scheduling of assembly processes for a numerically controlled milling table. Huertas et al. (2008) presents an integrated simulation tool and applies it in a case study of a printed circuit board manufacturer to investigate the effect of manufacturing defect on product quality and reliability. Separately, Padhi et al. (2012), and McNamara, Shaaban, and Hudson (2012) demonstrate the use of discreet event simulations (DES) in two different case studies, one involving an automobile manufacturer and the other, a hypothetical unreliable production line. For both cases, the authors use DES to understand the performance of the respective facilities by investigating the influence of important stochastic input parameters. For the simulation models discussed, the role of different maintenance policies and the effects these policies have on performance measures of interest is not very clear.

This research aims at gaining insights on the performance behaviour of manufacturing equipment subjected to various maintenance policies to counter the effect of deterioration and failure. The purpose is to explore how manufacturing equipment performance results from various interactions between maintenance and production logistics by use of simulation models. Here, the equipment performance is measured using the production output and overall equipment effectiveness (OEE). Further, the modelling approach includes definition of probabilistic models and assumptions affecting equipment performance such as: the probabilistic model for the initial failure intensity of the equipment; the probabilistic model for the system deterioration; the probabilistic model for the random times of corrective and preventive maintenance (CM and PM) that takes into the account the types of maintenance policies and the potential dependency between CM and PM times; and the probabilistic model for the random effects of CM and PM on the reliability of the equipment. The model is used to analyse the impact of equipment operation (and the subsequent effects related to deterioration and failure) and maintenance policies on manufacturing equipment performance (defined by OEE and production output). In this study, we define OEE as the measure of total equipment performance evaluated through analysis of three metrics; availability, performance and quality rate of output. The OEE is calculated using the following equation:

$$\mathrm{OEE} = \mathrm{Availability}\,(\mathrm{A}) \times \mathrm{Performance\ rate}\,(\mathrm{P}) \times \mathrm{Quality\ rate}\,(\mathrm{Q})$$

By integrating the three important metrics commonly associated with manufacturing equipment effectiveness, OEE transforms into a potent tool for performance measurement. This paper is organised as follows: Section 2 suggests the performance modelling approach that considerers the different interactions between the maintenance and production functions. In Section 3, the experimental design and results of different theoretical experiments is discussed. Finally, Section 4 includes the conclusions.

2. The modelling approach

The ability to realise maximum returns from manufacturing assets is affected by several interrelated technical and business factors. Understanding how these factors interact and impact manufacturing performance is essential in ensuring that the asset is operated in a manner that provides desired performance and enables informed performance improvement decisions. However, manufacturing systems performance is affected by many factors that are likely to make performance modelling quite a complex task. In this study, the core of the asset performance modelling is limited to the interaction between production and maintenance. Further, the production planning aspect has been simplified by the simple planning rule of maximising throughput.

The production and maintenance factors considered in the model are conceptualised as shown in Figure 1 (Muchiri and Pintelon 2011). The operation function determines the extent of asset utilisation based on production schedule and

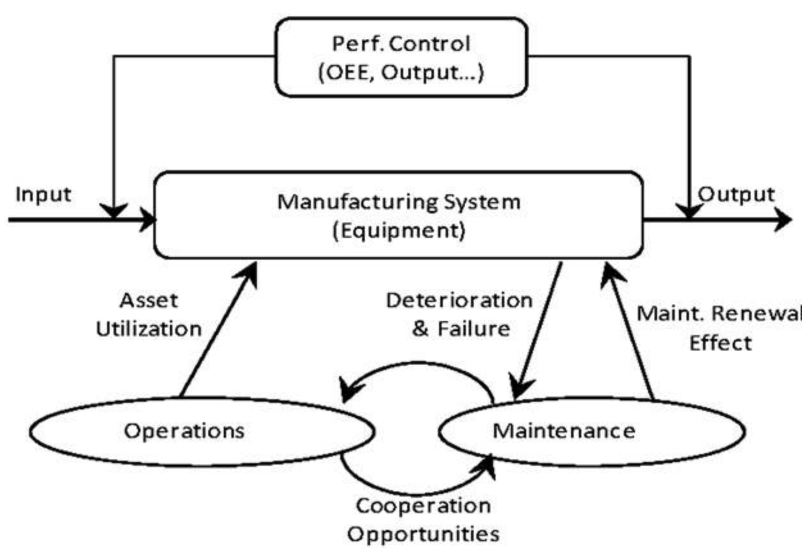

Figure 1. Interactions between equipment operation and maintenance that impacts performance.

market demand. The production schedule also determines the rate of change-over and the set-up time required. The equipment operation initiates condition deterioration and eventual failure, which impacts the quality rate, performance rate and availability, consequently affecting the OEE. This occurrence leads to maintenance demand to restore the equipment to its desired condition. Simulation is used first to mimic the operation of the manufacturing system. Then, the various factors (related to failure, deterioration and maintenance) are represented in the simulation model to quantify their impact on equipment performance. The OEE metric was chosen, due to its ability to simultaneously consider the different aspects of equipment performance related to production and maintenance, and thus, it provides an integrated view of equipment performance (Muchiri and Pintelon 2008).

In the next sections, the modelling approaches used in the simulation models are explained. These methodologies are related to deterioration, failure and maintenance effect modelling.

2.1 *Failure modelling*

Failure can be defined as breakdown, deterioration beyond a threshold level (i.e. a normative failure), decrease in system performance below a critical level or loss of function of system performance (Gertbakh 2000). The main interest in failure modelling is to analyse the effect of failure rate, reliability and availability on equipment performance (Muchiri and Pintelon 2011). The notion of ageing, which describes how a unit improves or deteriorates with time, plays a central role in reliability theory (Lai and Xie 2003). Ageing can be measured in terms of failure rate function, which is a good measure for representing the operating characteristics of the equipment or unit that tends to increase failure frequency as it ages. We assume that equipment deterioration and failure are a factor of equipment utilisation, and thus related to operation time. The failure rate [$\lambda(t)$] is a conditional probability that an item with age t will fail at a time interval [$t,\ t+dt$] (Muchiri and Pintelon 2011). Thus:

$$\lambda(t) \;=\; \lim_{dt\to 0} \mathrm{Prob}\langle t \leqslant\ T \leqslant t+\mathrm{d}t|T > t\rangle/\mathrm{d}t$$

The commonly used type of distribution for increasing failure rate (IFR) with respect to time (age) is Weibull distribution (Johnson and Kotsz 1972; Osaki 1992), which is defined by three parameters namely: shape factor (β), scale parameter (η) and location parameter (γ). When $\beta=1$, a decreasing failure rate (DFR) is obtained. When $\beta\ \approx\ 1$ and $\beta>1$, a constant failure rate (CFR) and IFR are obtained, respectively. If $\gamma=0$, the failure distribution starts at zero and for $\gamma>0$, a guaranteed failure-free period is introduced. The failure intensity [$h(t)$] of a two-parameter Weibull distribution (assuming the location parameter $\gamma=0$) is given by (Muchiri and Pintelon 2011):

$$h(t)=\frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1},\quad \text{Assuming } \alpha=\frac{1}{\eta} \text{ the Weibull failure intensity is given as:}$$

$$h\ (t)\ =\ \alpha\beta\, t^{\beta-1} \quad \text{where } \alpha>0 \text{ and } \beta>0.$$

This is popularly known as the Power Law Process (PLP) for Non-Homogeneous Poisson Process (NHPP) for $\beta>2$ (Doyen and Gaudoin 2004). When $\beta=2$, the failure intensity increases linearly with time (Muchiri and Pintelon 2011). The time in this case is the equipment operation time and not necessarily the calendar time. We assume that the initial failure intensity is a PLP with the failure intensity defined as a power of time.

To conclude, the failure modelling methodology derived above using exponential (for CFR) and Weibull (for IFR) distributions is used in the simulation to model the equipment's failure behaviour and its impact on production performance.

2.2 *Deterioration modelling*

In this research, deterioration modelling is developed based on the PF-curve depicted in (see Figure 2), which is derived from reliability centred maintenance (RCM) (Moubray 1997; Pintelon, Gelders, and Puyvelde 2000). The PF-curve represents a follow-up on equipment condition over time. It is based on the fact that most of the failure modes give some sort of indication or warning that they are in the process of occurring or about to occur (Moubray 1997). The PF-curve shows the time instance when the failure commences (potential (P) failure) to the point when the failure (F) actually occurs, and thus the name PF-curve (Muchiri and Pintelon 2011). The analysis of an equipment's or component's condition can potentially help to proactively detect undesirable situations and take appropriate action to prevent complete failure.

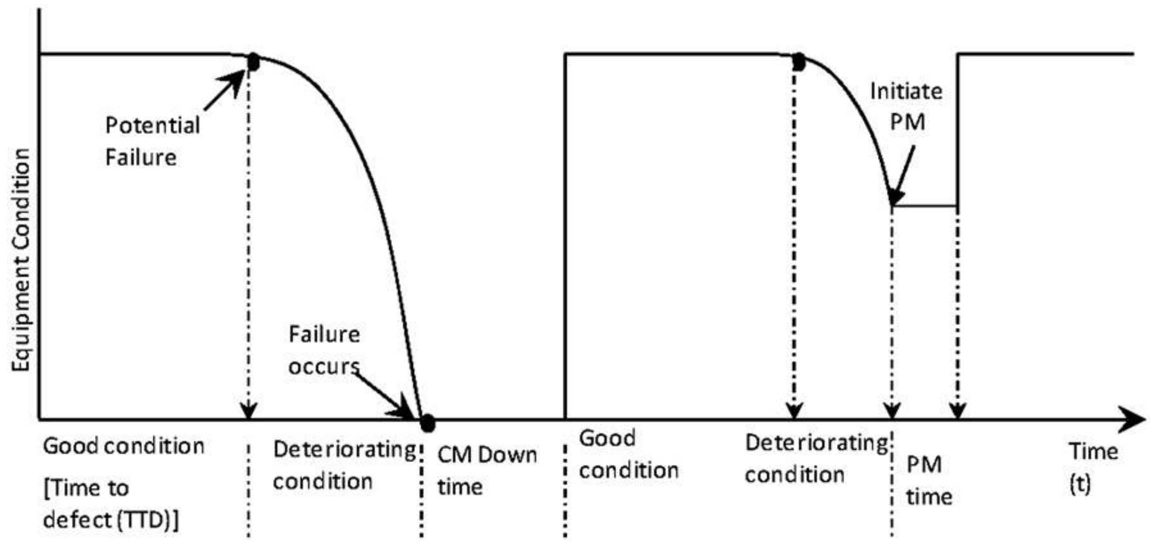

Figure 2. The modified PF-curve showing the state/condition of the equipment.

In this study, the PF-curve concept is modified and used to model the equipment condition, deterioration time and failure. To model the condition of the equipment and its impact on the performance, the PF-curve is defined as illustrated in Figure 2 (Muchiri and Pintelon 2011). The condition of equipment is assumed to be in any of the following three states: good condition, deteriorating condition, down due to CM or PM. The good condition period is the time it takes before a failure mode begins since the previous maintenance intervention. The arrival of a failure mode causes the machine condition to start deteriorating and to run at a reduced speed and a lower quality rate, which are defined in the simulation experimental design. If PM action is not taken during deterioration condition state, the machine breaks down and CM action is taken to bring it back to good condition. If PM action is taken at deteriorating condition state, the equipment does not fail and returns to good condition state (Muchiri and Pintelon 2011).

The use of the modified PF-curve concept also gives a window of opportunity in the investigation of the effectiveness of predictive or condition-based maintenance and the subsequent impact on equipment performance (Muchiri and Pintelon 2011). The impact of condition-based maintenance is investigated together with the other maintenance policies in this research.

2.3 *Maintenance effect modelling*

Maintenance is carried out with the objective of restoration or improvement of condition of the equipment. Maintenance activities play an increasingly central role in the trade-off between the conflicting objectives of the economic service, efficient productivity and safe operation, which drive the industrial world. It is, therefore, necessary to set up proper maintenance measures that evaluate and attempt to control the development of deterioration and as such ensure optimal equipment performance throughout its service life. Thus, to evaluate the maintenance effect on the equipment performance, the OEE is considered. This is because the OEE measure takes into account several ‘system’ uncertainties impacted by equipment maintenance such as product quality rate, performance rate and equipment availability. In addition, system externalities such as high customer demand invariably leads to operating the equipment at high production rates thereby reducing time allocation for maintenance leading to frequent equipment failures. Moreover, important performance metrics such as reliability is implicitly accounted for in the OEE measure via computation of availability.

Modelling the effects of maintenance actions is thus an important first step in assessing the efficiency of the maintenance actions, its impact on equipment condition and eventually the maintenance impact on production and economic performance. To model the effect of maintenance on manufacturing assets, we integrate into the simulation approach the following important maintenance decision-making aspects:

- *What* maintenance needs to be done? (This determines the choice of the maintenance policies that trigger the maintenance actions).
- *How* should maintenance be done? (This determines the degree of improvement or maintenance efficiency).
- *When* should maintenance be done? (This determines the maintenance interval).

2.3.1 *Maintenance type (the 'What' question)*

Maintenance actions are triggered by various policies adopted with respect to the expected failure rate and criticality of the given equipment or process. The maintenance policies investigated in this research are briefly explained below based on (Coetzee 1997; Pintelon and Van Puyvelde 2006; Savsar 2006):

- *Failure-based maintenance (FBM)* – In this policy, CM is done only when the equipment fails. It is a strategy of 'do nothing' and 'wait for failure' and thus it is a purely reactive policy.
- *Time-based (or Use-based) maintenance (TBM)* – is a PM policy where maintenance is carried out at specified time intervals. In between PM actions, CM actions can be carried out when needed.
- *Condition-based maintenance (CBM)* – This is a predictive policy. PM is carried out whenever a given system parameter or condition reaches a predetermined value. The condition of the equipment is measured at predetermined intervals to determine when the component will fail.

2.3.2 *Maintenance efficiency (the 'How?' question)*

Literature proposes some basic assumptions to approximate the efficiency of maintenance actions (Chan and Shaw 1993; Doyen and Gaudoin 2004; Kijima, Morimura, and Suzuki 1988). Two extreme assumptions on the post-maintenance state of an equipment is that the unit is as good as new (AGAN) or as bad as old (ABAO) (Lawless 1983). In ABAO, each repair leaves the system in the same state as it was before failure. In the AGAN, each repair is perfect and leaves the system as if it were new. The reality of maintenance effects is obviously between these two extreme cases. Standard maintenance action reduces the failure intensity, but may not leave the repairable equipment as good as new. The maintenance efficiency in this case is referred to as imperfect maintenance or better than minimal maintenance (Pham and Wang 1996; Shin, Lim, and Lie 1996). Several types of imperfect models have been proposed in literature (Brown and Proschan 1983; Chan and Shaw 1993; Kijima, Morimura, and Suzuki 1988; Malik 1979; Shin, Lim, and Lie 1996; Tseng, Yeh, and Ho 1998; Verrier and Remy 2009).

To model the effect of maintenance on equipment, we define the maintenance efficiency model based on the arithmetic reduction of age (ARA) models proposed by Verrier and Remy (2009) and Doyen and Gaudoin (2004). The ARA model assumes that maintenance action reduces the virtual age of the equipment to an amount proportional to its age just before repair (Doyen and Gaudoin 2004). This proportion is given by parameter ρ, which represents the maintenance efficiency or degree of renewal. Further, the following notations and assumptions are made in the models (see Figure 3):

- $[T_i]_{i>1}$ – the successive failure times of the manufacturing equipment starting from $T_0 = 0$.
- $[N_t]_{t>0}$ – the number of failures counted up to time t. The failure process of the equipment can be defined equivalently by the random process $[T_i]_{i>1}$ or $[N_t]_{t>0}$.

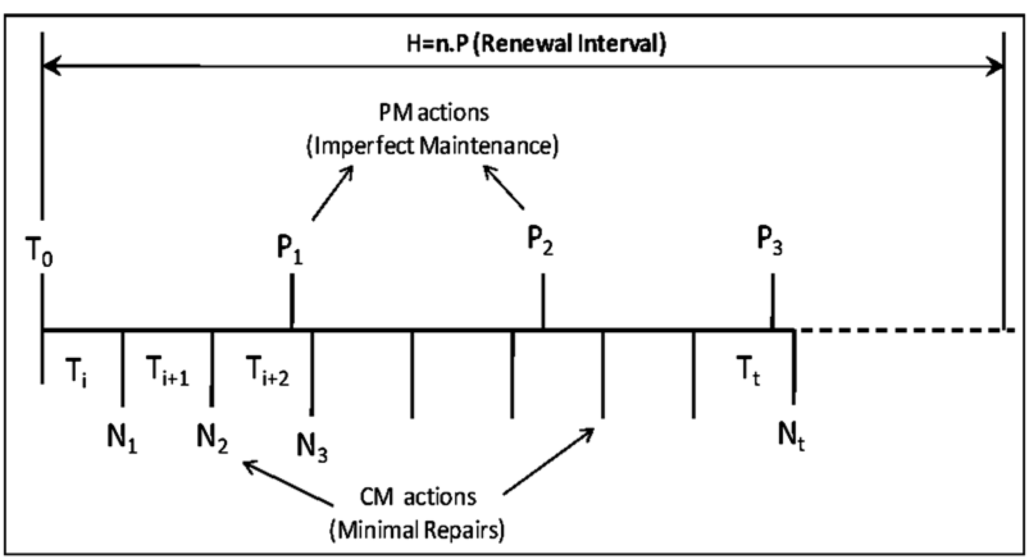

Figure 3. The equipment maintenance timing and maintenance action taken.

- $h(t)$ – is the initial failure intensity of the equipment which is assumed to be of a PLP with the failure intensity defined as a power of time.

The ARA model corresponds to a maintenance action that reduces the virtual age of the equipment of an amount proportional to its age just before repair (Doyen and Gaudoin 2004). This proportion is given by parameter ρ, which represents the maintenance efficiency. The ARA model is defined by virtual age and the failure intensity is given as (Doyen and Gaudoin 2004);

$$h_t = h\left(t - \rho \sum_{i=1}^{N_{t-1}} (1-\rho)^i TN_{t-i}\right)$$

For the maintenance efficiency (**ρ**), it is assumed that (Muchiri and Pintelon 2011):

- $0 < \boldsymbol{\rho} < \mathbf{1}$ **–** is imperfect maintenance
- $\boldsymbol{\rho} = \mathbf{1}$ **–** is perfect repair that makes equipment AGAN
- $\boldsymbol{\rho} = \mathbf{0}$ – is minimal repair that leaves equipment ABAO

For modelling purposes, maintenance is assumed to be minimal (ABAO) for minor CM activities, imperfect for scheduled or CM actions and perfect (AGAN) during scheduled overhauls or turn-rounds. Simulation experiments were carried out to study the effect of different maintenance efficiency levels, and in the various maintenance policies.

2.3.3 *Maintenance timing*

Maintenance timing is influenced by the machine condition (in case of failure or deterioration) or by management through PM or condition-based maintenance intervention. The following maintenance timings are considered in the simulation model (Muchiri and Pintelon 2011):

- CM time-failure occurs at random times and thus cannot be predicted. Thus, CM is done at random times
- PM time:
  - This can be planned maintenance activities and thus they are deterministic.
  - PM time can also be determined by the condition of the equipment according to the results of inspections and degradation or operation control. Thus, random PM can be carried out based on condition monitoring.
  - PM timing can also be influenced by other factors like production schedules where PM is carried out during change-over.
- Condition monitoring time is normally planned and therefore it is deterministic. By planned, we assume a periodic review on the equipment's condition in the absence of 'online' condition monitoring systems. As such, periodic inspection on a degrading asset is instead considered in the simulation experiment to assess the equipment's conditions. The objective here is to investigate the effect of different inspection timings on the CBM policy.

3. Experimental design

To study the dynamics of manufacturing performance, the equipment is subjected to deterioration, failure and maintenance actions in a simulation model developed in the ARENA software. The simulation model consists of four sub-models: the production process, failure mode process, maintenance (PM) process and performance measurement process. The production process sub-model simulates an assumed production system with unreliable equipment. The production process has a continuous supply of raw materials and thus, the production only stops when there is a failure or a maintenance action. The designed production speed for each stage is 10 min/product and the production runs for 24 h/day and 365 days/year.

The failure sub-model simulates the failure process of the machine based on its reliability (determined by the good condition period or time to defect (TTD)), the deterioration time and its maintainability (the latter is determined by time to repair (TTR)).The equipment failure intensity follows the PLP with parameters $\beta = 2$, $\alpha = 1$, the latter parameter described as the reciprocal of the Weibull scale parameter η earlier stated in Section 2.1. To model the condition of the failing equipment and its impact on the system performance, a modified PF-curve is defined as illustrated in Figure 2. The condition of the equipment is assumed to be in any of the following three states: good condition, deteriorating condition or down due to failure (CM) or due to PM. During the good condition period, the failure mode signal, defined as PF signal = 0. During this time, the machine runs at its designed speed (10 min/item) and at a 100% quality rate.

The arrival of failure mode (PF signal = 1) causes the machine condition to start deteriorating and to run at a reduced speed and a lower quality rate. Here, the quality rate is set at 70% with the production speed set at uniform [13,15] minutes per product during the deterioration period. Setting the quality rate at 70% is assumed as a plausible lower bound value with production defects not expected to go below this value. This is based on the assumption that the time from failure inception (PF = 1) to complete failure (PF = 2) is significantly lower compared to the total simulated production time of five years and as such the equipment deterioration is not likely to significantly influence the quality rate. Moreover, assuming constant quality rate simplifies the simulation approach thereby avoiding instances where low quality rate values combine with high production speed giving erroneous OEE performance measures. If PM action is not taken during the deterioration state, the machine breaks down (PF signal = 2) and CM action is taken to restore it back to good condition. If PM action is taken at deteriorating condition state, the machine does not fail and returns to good condition state.

The performance measurement sub-model computes key system parameters that evaluate system performance. These parameters are related to process downtimes, speed loss and quality defects that are used to calculate yearly values OEE. The sub-model also records the production output per unit time. The OEE calculation consists of the planning rate (due to planned downtime), availability rate, speed rate and quality rate (see Figure 4). The quality rate is defined as the ratio of good quality production and total production. The performance (speed) rate is defined as the ratio between the actual production and theoretical production based on standard production rate and the system operating time.

To study the effect of the various maintenance policies on equipment performance, simulation model was defined for each policy in the maintenance sub-model. The policies investigated in this study are the FBM, traditional periodic maintenance (TBM) and CBM. In FBM policy, maintenance is only done when a failure occurs and therefore it is unplanned maintenance. For any failure that occurs, CM is carried out with repair time assumed to be triangular distributed with a minimum of 1.5 days, mode of 2 days and maximum of 2.5 days (Triangular 1.5, 2, 2.5). The CM actions carried out in FBM is assumed to have random effects on equipment age and condition. In the simulation experiments, different efficiency levels of FBM are tested. For TBM policy, the PM actions are planned for a given PM interval. The intention of setting the PM interval is to eliminate wear out failures characterised with an IFR. However, depending on the PM interval timing, some failures may occur especially considering a sub-optimal PM interval. Thus, in the simulation modelling approach, different PM interval timings are considered ranging from 30 to 900 days. The PM time is assumed constant at 1 day per PM action. For any failure occurring within the PM interval (i.e. before the planned PM time), CM is done with a repair time of triangular distribution of Tria (1.5, 2 and 2.5) days. For these failures (i.e. that occur before the PM interval), the next PM date is recalculated as per the PM interval.

The CBM policy is based on evaluating the condition of the equipment, which is defined by the PF signal in the model. If PF signal is 1 (with failure mode), a PM action of 1 day is taken. Else, no action is taken. The important decision variable in this case is the monitoring interval since failure can occur in between for large intervals. The CBM policy is dependent on the observable failure modes and the duration of the deterioration period. Simulation experiments are carried out with different monitoring intervals (e.g. 1 day and 5 days). The summary of the other assumptions made in maintenance effect studies is shown in Table 1.

To evaluate the effect of the various maintenance policies, different variables are used in each experiment. Each simulation experiment considers a production period of five years (24 h/day and 365 days/year), where the five years operation period is assumed to represent the equipment life. For each simulation, 100 replications were made and the average performance per year was evaluated. The 100 replications allow a large sample size to be considered thus reducing the 95% confidence interval half width. This in turn minimises the resulting variability for the performance statistic, i.e. production output and OEE.

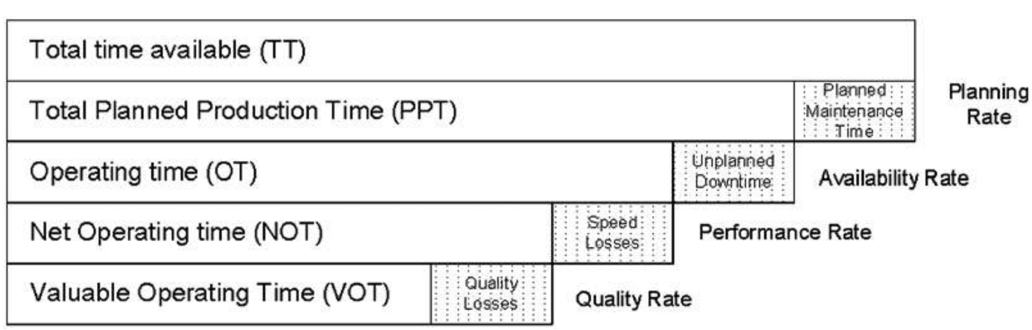

Figure 4. The OEE metric used in performance analysis.

Table 1. The parameters used in the maintenance policies' effect experiments.

M/C state/condition	PF signal	Duration (days)	Processing times	Quality rate (%)
1. Good condition	0	Variable [TTD]	Constant [10]	100
2. Deteriorating condition	1	• Exp (2) • Variable [Det.Time]	Unif [13, 15]	70
3. CM down time	2	Trial [1.5, 2, 2.5]	–	–
4. PM down time	2	Constant [1] day	–	–
5. Condition monitoring time	0 or 1	No equipment down time	–	–

3.1 *Experiment 1: maintenance policies' effects*

To study the effect of the defined maintenance policies on performance, the time to defect (TTD) was varied from 2 to 120 days. This range was chosen to show the effect of each policy at both high and low equipment reliability. From the results (see Figure 5(a)), FBM policy was found to have the worst performance (OEE) especially at high failure rates (i.e. low TTD values). This is attributed to low availability due to high unplanned downtimes that demand more repair time. The OEE values are also lower due to the high rate of deterioration that affects quality and speed rate. With the introduction of PM (TBM), there is significant performance improvement due to elimination of wear-out failures, thus a reduction of failure rate and deterioration effects. However, with the improvement of equipment reliability (increased TTD of 30 to 50 days), the performance becomes the same for both TBM and FBM policy. When the equipment has high reliability, the FBM policy has a higher performance than TBM policy. At this phase, the PM actions do not have any effect on equipment failure mode and just introduces additional and 'unnecessary' downtime. These results justify the notion that for some equipment, the failure modes are not age-related and no amount of PM can effectively manage these failures. Using time interval in the maintenance strategy would, therefore, have little or no impact on reliability. We may also conclude that the law of diminishing returns takes effect with the amount of PM carried out.

The CBM policy was found to produce the best performance of all the other policies. Since CBM aims at determining the condition of the equipment before any action is taken, unnecessary downtime is avoided especially when the equipment is in good working condition. The success of this policy is dependent on the technology involved and by condition monitoring intervals. This is demonstrated by results for 1 and 5 days intervals. It shows that when the interval is long, some failure modes may develop and eventually lead to failure without being detected. For short

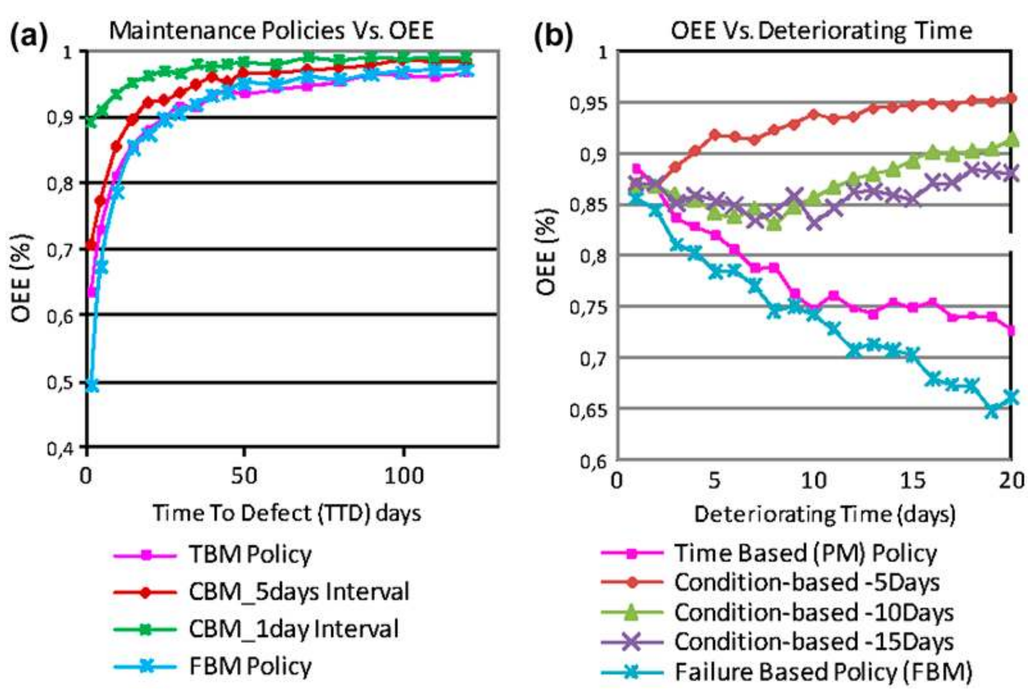

Figure 5. Equipment performance (OEE) with (a) varying maintenance policies (b) with varying deterioration time.

monitoring intervals, the only downtime experienced is due to maintenance action (when needed) while the unplanned downtime is eliminated. Much of CBM technology involves monitoring equipment while in operation. This leads to high availability and high production effectiveness. Further, when potential failure is identified at an early stage and corrected, no much speed loss and rejects are generated and therefore the equipment works at high effectiveness. These results suggest that investment in predictive maintenance is likely to improve asset productivity and avoid unnecessary maintenance. However, as the reliability of the system increases, the performance of the production system reaches a steady state for all policies with a very small difference between them. The benefit of CBM at this state is highly reduced (minimal). Therefore, a trade-off between cost of failure and CBM efforts is necessary to justify CBM use.

The second experiment involved the effect of varying the deterioration time in the various maintenance policies. For this experiment, the TTD was assumed to be exponentially distributed with Expo [15] days while the CM time and PM time remains unchanged at Tria [1.5, 2, 2.5] days and 1 day, respectively. For TBM, the PM interval remains at 25 days while in CBM, the monitoring interval is experimented with 5, 10 and 15 days. As show in Figure 5(b), the success of the CBM policy is highly dependent on the monitoring interval and the deterioration duration when the failure mode can be identified. With deterioration duration of 1 day, there is no much difference between the different policies though TBM has the highest OEE and FBM the lowest. With increase in deterioration time, the CBM of 5 days increases in performance as an indicator that failure modes are easily identified and prevented. After a deterioration duration of 15 days, the CBM of 5 days reaches its peak OEE performance of 95%. For CBM of 10 days, the effect of condition monitoring on OEE is only felt when the deterioration duration passes 10 days. Likewise, observations are made for CBM of 15 days. This confirms the importance of deterioration information (failure mode and duration of deterioration) before implementing predictive maintenance policies or CBM. Otherwise, the CBM policy can be highly ineffective in improving reliability and overall performance. Both the FBM and TBM have decreasing OEE with increase in deterioration duration. The FBM have the worst performance since extra deterioration time leads to more speed and quality losses. Reduction of PM interval is likely to improve performance, though may not compete with the benefits of CBM use. The findings correspond largely with observations in practice and therefore they are not particularly revealing as such, but underline the validity of the modelling approach encouraging further experimentation.

3.2 *Experiment 2: maintenance timing effect*

This experiment was conducted to study the effect of maintenance interval on equipment performance. This is important especially in deciding the optimal PM interval for a given equipment in TBM policy. To study the impact of PM timing in TBM policy, the PM interval was varied from 30 to 900 days in steps of 30 days. For TBM policy, it is assumed that PM downtime = 1 day and CM downtime = Tria[1.5, 2, 2.5] days. Should a failure occur between the PM intervals, a CM action is taken. The PM action is assumed to renew the condition of the equipment to AGAN while a CM action is a minimal repair that is assumed to leave the equipment ABAO. Here, the maintenance efficiency is set at 100% for PM and 0% for CM actions, respectively, in the maintenance sub-model. As shown in Figure 6(a), there exists an optimal PM interval (120 days in this case) that results from a trade-off between the PM downtime and the CM downtime. The results demonstrate the intuition that too much PM is likely to result to high PM downtime while less PM is likely to result to high CM downtime. The optimal PM interval is observed at the lowest total equipment downtime. Figure 6(a) compares to the commonly known maintenance optimisation curve derived from operation research (OR) techniques, which is used to determine the optimal PM interval that minimises the maintenance cost (Gertbakh 2000; Nakagawa 1981, 2005). This illustrates the utility of maintenance simulation modelling in decision support.

Some of the insights we can derive from this analysis is that a slightly longer PM interval (than the optimal interval) is better than a shorter PM interval. With shorter PM interval than the optimal interval, the curve for total downtime is very steep indicating a sharp increase in total downtime. From the analysis of the performance rates (see Figure 6(b)), the maximal OEE is observed at the optimal PM interval, where the availability rate equals the planning rate. A possible decrease in CM downtime is likely to shift the optimal point to the right and thus a higher optimal PM interval. Similar observation is expected for an increase in PM downtime. It is worth noting that different PM intervals can be obtained from different criteria. For example, it is likely to have different optimal PM interval for a minimised downtime from an optimal PM interval for a minimised total maintenance cost (from optimal age replacement model). Thus, it is important to balance the cost and benefit of PM action in TBM policy in such multi-criteria decision scenario. The simulation approach developed in this research can potentially be useful in such multi-criteria decision scenarios.

3.3 *Experiment 3: the effect of maintenance efficiency*

These experiments were conducted to study the effect of maintenance efficiency on equipment performance. Maintenance is assumed to cause a renewal to the age of the equipment thereby reducing the failure rate. When maintenance has no

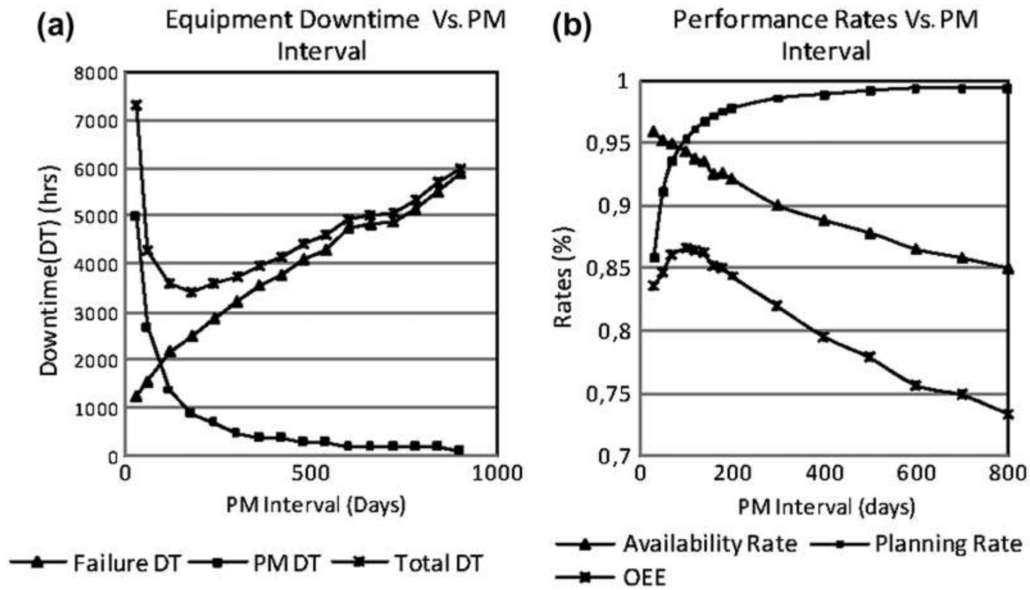

Figure 6. The impact of PM interval on equipment performance (a) effect on downtime (DT) (b) effect on effectiveness rates.

effect on failure rate, the efficiency is 0% (minimal repair – ABAO). Else, maintenance is assumed to cause complete renewal (AGAN) with an efficiency of 100% or imperfect maintenance with a renewal efficiency of less than 100%. It is assumed in this study that maintenance efficiency is an important decision variable that should be considered together with maintenance policy and interval while optimising the performance of manufacturing equipment. Likewise to experiment 2, the maintenance efficiency (i.e. AGAN and ABAO) is incorporated in the maintenance sub-model in the simulation approach.

To investigate the effect of maintenance efficiency in TBM policy, the experimental set-up remained unchanged. The efficiency of PM is varied from 100% to 20% while the PM interval is varied from 30 days to 800 days. Minimal maintenance (0% efficiency) is done in case of a failure between the PM intervals. As shown in Figure 7, the maintenance renewal efficiency has a highly significant impact on performance and optimal PM interval. With reduction of efficiency, there is obvious reduction of OEE which can be attributed to increase in failure rate. There is also an interesting trend of the shift of optimal PM interval to the left with reduction of PM efficiency. With 100% PM efficiency, the optimal PM interval is 120 days while with 40% PM efficiency the optimal PM interval is 60 days. This is an indication that equipment receiving lower renewal efficiency would demand more PM actions (or shorter PM intervals) to improve their performance (reliability, availability and OEE). The other performance insight that can be derived from the results is the relationship between renewal efficiency and the PM interval. For example, with a target OEE of 80%, a 60% PM efficiency would require 100 days of PM interval while a 100% PM efficiency would require around 400 days of PM interval to meet this target. Assuming different maintenance efficiencies have different costs, integrating renewal efficiency in maintenance cost and performance optimisation would be valuable in decision support.

In addition to the renewal effect expected in PM actions, management can decide to renew the equipment during CM actions. In the second experiment, the renewal effect caused by CM actions is investigated in addition to the renewal efficiency of the PM action. The PM action taken in the predetermined interval is assumed to have a 100% renewal efficiency. For the CM actions taken in case of a breakdown, the efficiency is varied from 0 to 80% as shown in Figure 8. It is found that introduction of renewal efficiency in CM actions cause a significant improvement in equipment performance. This is more evident when the PM interval is large and thus the effect of PM is minimal on the equipment. The results suggest that a 20% renewal efficiency on every CM action would give better results than PM actions taken on optimal PM interval of 120 days. With a CM renewal efficiency of 20% and above, the equipment performance is better-off without periodic PM interventions. Increment of PM actions, for PM interval less than 100 days, causes a reduction of system performance. With longer PM interval, it is only the CM effect that is dominant and thus the maintenance policy equates to FBM. These are very interesting results that demonstrate the utility value of CM actions, which target to improve the reliability of an equipment. The value of CM actions with renewal efficiency is especially interesting when a high percentage of equipment failures are not directly related to the age of the equipment. In this case, no amount of PM can effectively manage the failures and thus effective FBM policy can be a solution.

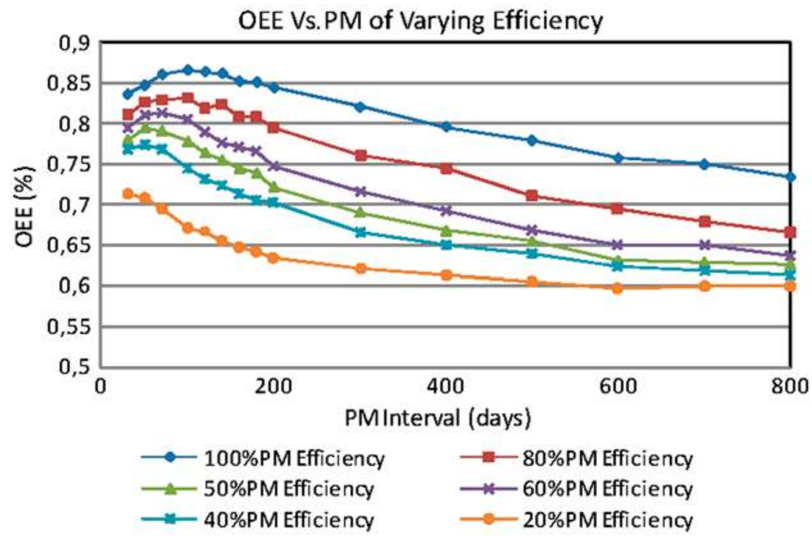

Figure 7. The effect of varying PM efficiency on performance in TBM policy.

Moreover, the results confirm some intuition that interfering with a good equipment (through PM actions) is not appropriate in some cases; condition monitoring and effective CM actions may give better results (Andy and Karalexis 2009).

The other aspect investigated in maintenance modelling is the effect of renewal efficiency in CBM. In CBM policy, it is assumed that the failure mode observed during condition monitoring is corrected using PM action. Should a failure occur between the monitoring intervals, a CM action is carried out. The two important decision variables in this case is to determine the renewal efficiency in both PM and CM actions. In the first experiment, it is assumed that the PM actions have renewal efficiency while the CM actions are minimal repairs (ABAO). The experimental design is the same as in TBM expect for the condition monitoring that is done during uptime. A PM action generated from CBM is assumed to take 1 day and CM downtime has a triangular distribution (Tria[1.5, 2, 2.5] days). The monitoring interval is varied from 3 days to 300 days and performance is recorded as shown in Figure 9. In Figure 9(a), the effect of CBM with varying PM efficiency and minimal repair for CM actions is shown. It is confirmed that the effectiveness of CBM policy is dependent on the monitoring interval. A short monitoring interval ensures that all failure modes are identified in good time and eliminated through PM actions. With the increase of monitoring interval, there is sharp decline of OEE due to failure occurrence and subsequent CM actions. With longer monitoring intervals, a significant difference is

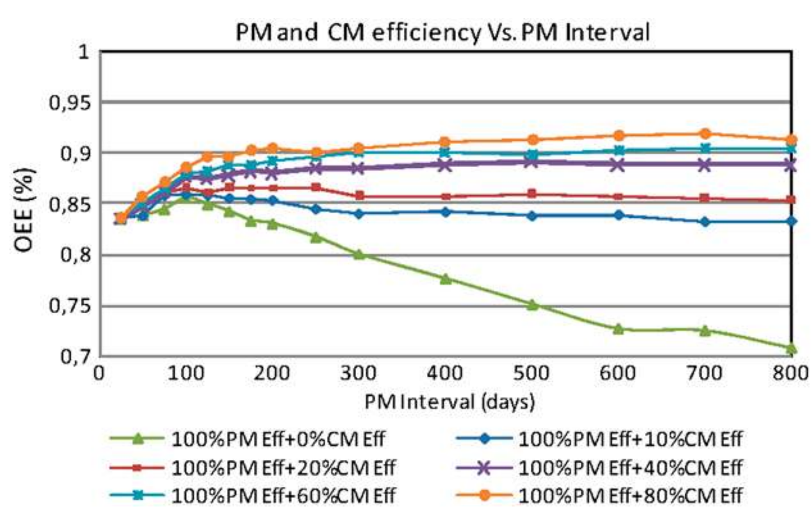

Figure 8. The effect of varying PM efficiency and CM efficiency on performance in TBM policy.

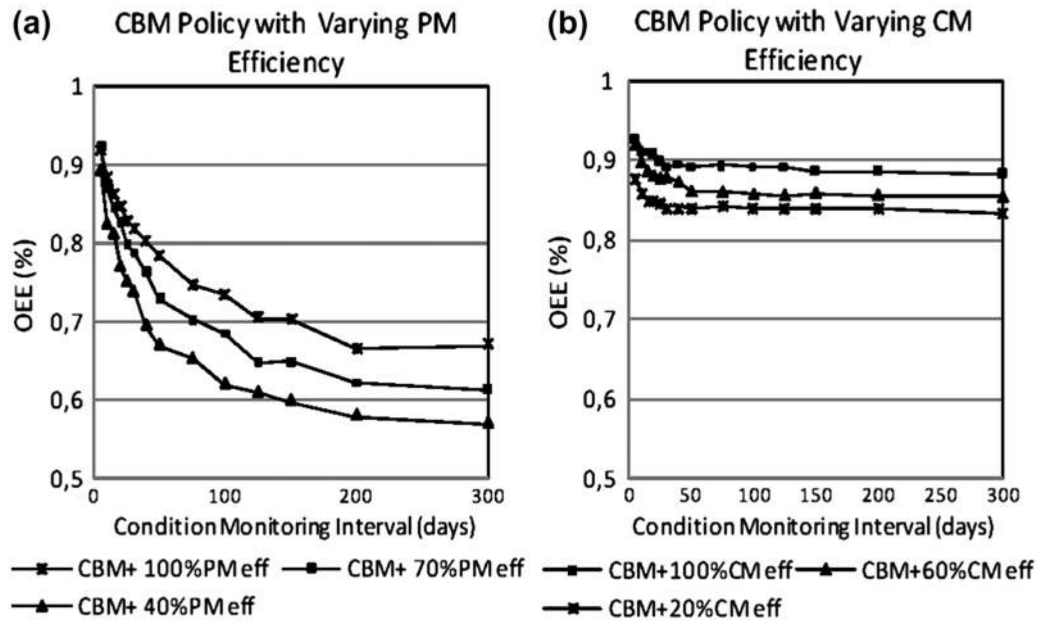

Figure 9. The effect of CBM policy with varying monitoring interval and (a) varying PM efficiency + ABAO CM (b) varying CM efficiency.

observed among the various efficiency levels of PM actions. However, the results are an indication that long monitoring intervals are not meaningful in CBM policy as many failure modes will go unnoticed till the equipment breaks down. In Figure 9(b), the effect of introducing renewal efficiency in CM actions is shown. In this experiment, both the PM and CM are assumed to have equal renewal efficiency. Likewise, the effect of CBM policy is only felt when the monitoring interval is small. For longer than 50 days interval, it is only the effect of CM efficiency that maintains the performance at the same level. Thus, with long monitoring intervals, the equipment is running on a FBM policy. A big difference in performance is observed with CM efficiency and without CM efficiency for longer monitoring intervals. This explains the difference between curves in Figure 9(a) and (b) and demonstrates the potential of effective CM actions. Further, it is observed that though monitoring interval is the most important decision variable in CBM, the efficiency of maintenance carried out is also significant.

The final analysis involved comparison of the different maintenance policies (FBM, TBM and CBM) with varying maintenance intervals and renewal efficiency in the same experimental set-up. As shown in Figure 10, different maintenance policies lead to different equipment performance. The CBM policy provides the best results when the

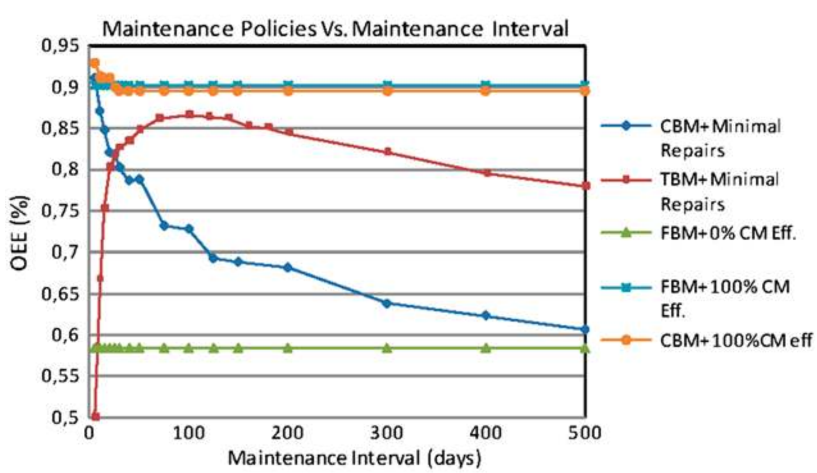

Figure 10. Comparison of different maintenance policies with different efficiency levels.

condition monitoring interval is small. This is an indication that CBM policy is only effective for a well-defined monitoring interval, beyond which CBM policy is not meaningful. The analysis of TBM policy demonstrates some interesting results of the optimal PM interval that maximises the equipment performance. This is a demonstration that a trade-off between PM and CM downtime exists. A similar trade-off is known to exist between failure cost and PM cost. The most surprising results are obtained from the analysis of CM renewal efficiency. In FBM policy, where CM is carried out exclusively, it is shown that introduction of renewal efficiency has a highly significant impact on equipment reliability and performance. With 20% CM efficiency, the equipment's performance equals the optimal PM interval renewal of 100%. This came as a surprise due to the fact that introduction of minimal CM renewal efficiency can potentially lead to high performance improvement. With little effort to effect some renewal in every repair, there is increment in failure inter-arrival time, and thus some failures are averted. In combining different policies, for example a combination of CBM and repair efficiency, this modelling approach demonstrates that better equipment performance is expected over traditional periodic maintenance (TBM). The modelling approach opens further research opportunities on integrated maintenance cost and equipment performance optimisation. By assigning cost to the different levels of renewal efficiency, it is possible to assess different combinations of policies in terms of cost and equipment performance.

4. Conclusions

The results from these simulation studies demonstrate the importance of quantifying and modelling the effect of maintenance on manufacturing systems. This can potentially support decision-making on what kind of maintenance need to be done (policy), how it should be carried (renewal efficiency) and how frequent (timing) in order to improve performance against other factors like maintenance cost and total system profitability. It was demonstrated how the various maintenance policies lead to different equipment performances. Perhaps, simulations like the ones used in this paper may serve as a first line evaluation of new maintenance concepts before committing them to practice.

For example, it was shown that the success of the CBM policy is highly dependent on the deterioration duration. With minimal deterioration duration, CBM is not effective and thus other policies may provide better equipment performance. In addition, the CBM policy provides the best results for small condition monitoring intervals. This is an indication that CBM policy is only effective for a well-defined monitoring interval, beyond which CBM policy is not meaningful. This observation is important in that, as much as condition monitoring provides real-time information on equipment's health, CBM actions have to be planned, especially for off-line condition monitoring. Also, from simulation experiments on renewal efficiency considering CM, TBM and CBM, it was found that the introduction of minimal renewal efficiency per CM action can potentially lead to a high asset performance improvement. Thus, modelling the effect of maintenance provides a basis of evaluating maintenance efforts with the potential application in performance analysis and decision support on performance improvement.

The main challenge, however, is the direct application of this approach in practice. First, the equipment failure rate is highly influenced by both maintenance and operating practices. The failure mode is, therefore, a complicated mixture of normal wear and tear (due to ageing) and random effects (due to operating practices). This complicates the determination of failure distribution and intensity. However, the theoretical simulation work illustrates the importance of equipment knowledge on failure and deterioration; the impact of maintenance on performance; and the need for integrating operation and maintenance practices in asset performance analysis and optimisation. The developed approach provides a strong incentive for further research where the simulation approach is extended to manufacturing systems consisting of several inter-linked equipment. This potentially allows the performance evaluation of entire production systems. Although, the OEE was chosen as the performance criterion in this study, sufficient reason exists to re-evaluate this principle choice and to allow for other types and combinations of indicators, like cost in future research.

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