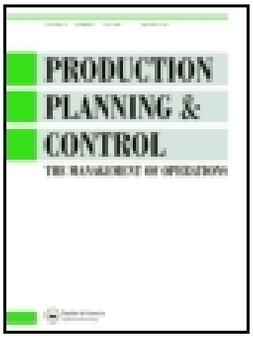

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Integrated maintenance policies for performance improvement of a multi-unit repairable, one product manufacturing system

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ABSTRACT

Planned and unplanned downtime emanating from maintenance, production, and operational function adversely affects the performance of manufacturing plants. This paper develops joint maintenance, production and process/operations control policies integrating Opportunistic Maintenance (OM), which takes advantage of external (operational-related downtimes) and internal maintenance opportunities. The study quantifies the effects of maintenance strategies on the plant's performance, here, the overall equipment effectiveness (OEE), which importantly presents insights on maintenance decision support for production facilities facing significant operational-related stoppages. The study integrates both economic and structural dependence and models the influence of alternative maintenance actions of different maintenance policies, on product quality. The developed model is validated by applying to a multi-unit repairable, imperfectly maintained raw meal grinding system of a cement plant. From the simulation modelling results, integration of the opportunistic maintenance approach, complementary to corrective, preventive and condition-based maintenance strategies, show more enhanced equipment performance, as measured through the OEE.

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KEYWORDS
Preventive maintenance; corrective maintenance; opportunistic maintenance; product quality; OEE; manufacturing system

1. Introduction

1.1. Background

Modern manufacturing organizations experience disruptions like machine unavailability occasioned by equipment failure and other disruptive factors, for instance, operational-related factors like unavailability of raw materials and unplanned major shutdowns. The unplanned and sometimes planned production stoppages can adversely impact the productivity and profitability of manufacturing plants, thus, the need to address the impact of these stoppages on plant availability and production. To wholesomely address these challenges, tracking the critical identifiable performance measurements in manufacturing set up, such as availability (Assid, Gharbi, and Hajji 2015), quality (Alsaleh 2017), repair time (Wakiru et al. 2019c), Overall Equipment Effectiveness (Muchiri et al. 2014) and production (Alrabghi and Tiwari 2016) is essential to ensure manufacturing excellence. Overall Equipment Effectiveness (OEE) encompasses three variants (availability, quality and performance), which are essential while deriving joint maintenance and production decision making support (Gólcher-Barguil, Peter Nadeem, and Garza-Reyes 2019).

There is evidence that maintenance, in conjunction with administrative planning and scheduling of other processes, plays a crucial role in ensuring optimal availability and performance of manufacturing companies (Guillén et al. 2016). Traditionally, the OEE performance metric largely quantifies availability, which is more effectively modelled as compared to metrics such as quality, and performance, which are much more challenging to model. To mitigate these disruptive challenges, different maintenance policies such as corrective maintenance (CM) and preventive (PM), condition-based (CBM) and opportunistic (OM) are employed together to ensure asset availability and performance, while reducing the impact of the various disruptions. However, the policies are considered as 'stand-alone' in most researches, whereas integrating different maintenance policies simultaneously may be argued to offer more robust decision support. The research towards this direction necessitate: (1) incorporating detailed multiple maintenance policies simultaneously and explicitly, where some authors (e.g. Petchrompo and Parlikad 2019) argue would generate robust and insightful decision support, (2) consider modelling reliability of the units which is concurrently affected by the interactions with maintenance policies, and (3) consider dependencies (economic, structural and stochastic).

On the other hand, stochastic deterioration and or failure of units of a system, while interacting either economically or structurally, with alternative maintenance interventions and policies, seemingly influence product quality and associated cost measurable through defective products or rejects

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(Rivera-Gómez et al. 2018). Yet, from a modelling perspective, modelling quality and maintenance aspects are not straightforward and previously has been done in isolation (Sun and Xi 2011)

Traditionally, opportunistic maintenance considers maintenance-related opportunities, and seldom operation/production related stoppages, which, if taken advantage of, could provide additional maintenance window. This will enhance the productivity of multi-unit deteriorating repairable systems (Ma et al. 2020). Moreover, this enhancement is better considered where opportunistic maintenance is undertaken complementary to maintenance policies, such as preventive maintenance, and condition-based maintenance, the latter integrating the influence of both off-line and on-line condition monitoring strategies(Wakiru et al. 2019b). This view of an opportunistic maintenance and production stoppage is considered in the sequel.

The challenges mentioned above motivate the need to evaluate the added value to plant performance, of interacting maintenance interventions and policies while considering stochastic failure degradation of a repairable multi-unit system. An important novelty is the consideration of OM taking advantage of both external (operation-related stoppages) and internal (maintenance or failure related stoppages) opportunities as complementary to the other maintenance policies. Moreover, additional to PM policy, a more detailed abstraction is considered by detailing CM and CBM maintenance policies contrary to the traditional simplification as black boxes, where the type of maintenance interventions is ignored. This constrains the extent to which real-world maintenance decisions can be reached, considering the influence of maintenance practices on product quality.

2. Relevant literature review

2.1. Joint maintenance policies for multi-component systems

Multi-unit or multi-asset system is defined by Petchrompo and Parlikad (2019) as 'a system composed of multiple assets that share common characteristics or resources under the control of an organization or a single-asset system composed of multiple components operating together'. Multi-unit systems exhibit performance dependence a subset of structural dependence; where units operating in series or a network that is made of heterogeneous equipment collectively operating, a failure of a unit dramatically affects the production performance (Olde Keizer, Flapper, and Teunter 2017; Petchrompo and Parlikad 2019). Likewise, Resource dependence, a subset of economic dependency; units share common resources such as workforce and spares, during maintenance.

Recently, a considerable literature has grown around the theme of maintenance policies employed on multi-unit systems to improve equipment availability and reduce production losses. This includes *Corrective maintenance* (CM), which addresses random equipment failure, while *Preventive maintenance* (PM) involves the replacement of equipment or parts using Age replacement policy (ARP) or Block replacement policy (BRP) with or without inspection (Eruguz, Tan, and van Houtum 2018; Peng et al. 2019). *Condition-based maintenance* (CBM) utilizes the information obtained while monitoring and analyzing the condition of a physical asset/unit to recommend maintenance actions for it. Different condition monitoring (CdM) techniques conducted according to a schedule, on request or continuous involve analysis based on lubricant, vibration, temperature and other conditions (Wakiru et al. 2019b). *Opportunistic maintenance* (OM) takes advantage of the plant downtime to carry out maintenance on another unit, which is not necessarily the primary cause of the plant stoppage. Benefits of OM include optimizing cost and reducing equipment downtime (Nguyen and Chou 2018; Do et al. 2019).

2.2. OM in a joint maintenance policy formulation

Traditionally, opportunistic maintenance considers internal maintenance opportunities(IMO), which construes opportunities availed when maintenance is carried out on units of a system, with correlated failure degradation characteristics due to a failure or maintenance of another unit (Xiao et al. 2019). A variant of OM is external opportunistic maintenance (EMO), which considers opportunities availed by non-maintenance related equipment stoppages, for instance, production stoppage (Yang et al. 2018; Sun, Ye, and Zhu 2019).

Several authors have considered the effects of integrating Internal Maintenance Opportunities (IMO) (based on maintenance-related stoppages) as complementary to alternative conventional maintenance policies for multi-unit systems. Examples of these studies include (Iung et al. 2016; Si et al. 2019; Zhou and Yin 2019). Most of the researches, however, do not consider all maintenance policies (CM, CBM and PM) simultaneously, except for the study by Alrabghi and Tiwari (2016). This study, however, simplified the modelling of CBM and CM as 'black boxes', without detailed abstraction, thus overlooking the influence of failure degradation as a parameter for decision support. Moreover, they disregarded influence of performance measures such as OEE and the stochastic failure degradation of the units, hence failed to consider dependencies between maintenance policies and degradation of the multi-unit system.

There is a growing body of literature that recognizes the value of exploiting external maintenance opportunities maintenance (EMO) in multi-unit manufacturing systems. This includes opportunities availed by production stoppages. An example of studies integrating EMO and PM include Xia et al. (2017), which exploit opportunities availed by stoppages attributed to system reconfiguration.

Several other studies integrate both IMO and EMO complementing alternative maintenance policies within the same modelling construct. Zhang et al. (2019) considered CM, OM and PM, where the OM decision is made, not only if a random failure occurs, but also considers the wind speed variations. Assid, Gharbi, and Hajji (2015) advanced a system considering CM and PM, while OM decisions depicting PM taking advantage based on both IMO and EMO (i.e. equipment set up time and production stoppage, respectively).

Other studies that consider both IMO and EMO complementing conventional maintenance policies include (Yang et al. 2018). However, these studies disregard the influence of performance measures like OEE.

The reviewed studies in this Section 2.2 have several limitations; first, they consider perfect maintenance and disregard stochastic equipment degradation, which are essential aspects to be considered for realistic maintenance optimization. Second, they overlook integrating real-world interacting maintenance policies (CM, PM, and CBM) and maintenance interventions, which would offer realistic decision support. Examples of types of maintenance interventions that are often disregarded include replacing, repair and adjustment of components/or systems of a technical asset.

2.3. Maintenance and production optimization

Another critical perspective to consider for technical assets, which is often challenging to consider in maintenance decision making, includes formulating strategies that jointly optimize both maintenance and production. This perspective would be catalyzed by selecting maintenance performance measure(s) or indicator(s) that consider interactions and trade-offs between competing objectives (Wakiru et al. 2019a). While considering the aspect of joint production and maintenance, various studies such as Gólcher-Barguil, Peter Nadeem, and Garza-Reyes (2019), suggest that Overall Equipment Effectiveness (OEE) performance measure integrates both maintenance and production performance aspects for multi-unit systems. Sonmez et al. (2018) argue that the OEE metrics better illustrates the overall productivity of a manufacturing set-up. Hence, OEE offers robust decision support since aspects such as productivity losses, and equipment maintenance are considered within a decision-making framework.

However, in real-life manufacturing systems, product quality may be substantially affected by the operation and deterioration of the manufacturing equipment (Jain, Pistikopoulos, and Mannan 2019; Lozano et al. 2019). Moreover, incidental factors instigated by maintenance actions may be attributed directly or indirectly to affecting the product quality, in terms of quality defects. Such factors include powering down machines during maintenance (e.g. Jain, Pistikopoulos, and Mannan 2019), the effect of deviated system pressure (e.g. Lipiak 2017; Moreira et al. 2018) and maintenance interventions like overhaul that prompt emptying product from the system. Hence, disregarding the influence of interacting maintenance policies and interventions for multi-unit systems may be unrealistic, especially ignoring maintenance influence on production quality defects and rejects.

Nonetheless, several studies in the literature attempt to link dependent maintenance interventions and policies, with product quality. For instance, Muchiri et al. (2014) utilize deterministic values of quality rates, while Gouiaa-Mtibaa et al. (2018) utilize an increasing deterministic quality degradation rate, tagged to each batch produced. The rate effects an increasing deterministic deterioration due to machine degradation. Jain, Pistikopoulos, and Mannan (2019) used the reliability from a mathematical formula to represent the quality. All the studies, however, regard quality aspects of a product which are de-linked to distinctive maintenance actions undertaken in the system. They further utilize a deterministic approach, despite real-life expectation; the effect of maintenance action on the quality being stochastic (Bouslah, Gharbi, and Pellerin 2018). These assumptions may lead to a significant OEE overestimation of the system and ultimately derive inaccurate production, quality and maintenance policies.

The review of studies in this whole section reveals several common research gaps relating to modelling repairable multi-unit systems in manufacturing setups:

- Modelling various maintenance policies simultaneously (CM, PM, CBM, and OM) while considering system-based dependencies. Furthermore, OM disregarding both IMO and EMO options simultaneously as complementary to conventional maintenance policies.
- Developing models that can be implemented in a real-world system by shunning over-simplifying assumptions. Such assumptions include perfect maintenance, disregarding distinctive maintenance policies abstraction details (e.g. CBM and CM), and stochastic equipment/system degradation.
- Modelling approach that links and incorporates the impact of maintenance policies on the product quality in a multi-unit system producing one product, using OEE performance measure.

The rest of the paper is organized as follows: Section 3 includes the research methodology in two subsections; an exploratory study and a description of the system being modelled. Section 4 details the case study model development, while Section 5 provides the results and discussion, and a conclusion is provided in Section 6.

3. Methodology

We undertake an exploratory analysis to see if these aspects of research gaps in Section 2 are embedded in real-life systems. Hence, we utilize empirical data as a guide to proof of concept. To avoid dealing with the subject in its abstract aspects, we model close to reality to ensure the scalability of the work and research. This section addresses the exploratory analysis of the case study, while Section 4 details the modelling aspect of the case study, given the gaps found in the exploratory analysis and literature.

This study uses maintenance data describing the failure of units, non-maintenance related stoppages, production, and vibration analysis. The data are recorded from the Raw Meal grinding section of a cement plant, over 5 years (2015–2017). The raw meal section contains several equipment/units organized in series, used in the production of clinker, which is further ground in the following section (Cement grinding) to produce cement. These repairable units whose criticality

Table 1. Summary of raw meal grinding section downtime constituents.

	Corrective maintenance (CM)	Preventive maintenance (PM)	Process (PRC)	Circumstantial (CS)	Incidental Shutdowns (ISD)	Power and utilities (PW)
Observations (count)	1108	45	1015	209	6	236
Ave. downtime (h)	1.72	17.40	0.59	21.41	198.98	2.3

Table 2. Sample data extract of raw mill CM and CS events.

Stop date and time	Start date and time	Down-time (h)	Code	Unit	Comments	Failure mode
6/11/2017 15:55	7/11/2017 21:42	29.78	CM	RM	Down to replace broken tension rod for roller #2 and broken upper tension studs for roller #1	Vibration
21/11/2017 6:00	21/11/2017 7:23	1.38	CM	RM	Repaired broken lower tension rod for roller #1	Shearing
2/12/2017 11:38	2/12/2017 23:58	12.33	CM	RM	Replaced broken lower tension rod for roller #1	Vibration
10/12/2017 6:02	10/12/2017 21:22	15.33	CS	RM	Lack of kiln hot gases	N/A
11/12/2017 6:00	11/12/2017 16:39	10.65	CS	RM	Lack of kiln hot gases	N/A
11/12/2017 19:32	12/12/2017 4:22	8.83	CM	RM	Down to replace broken tension rod for roller #2	Vibration

analysis is undertaken in Step 1 of the following section, include the raw mill (RM), bucket conveyor, roller bearing, hydraulic system, fan, weigh feeder, gear lubrication system, bucket elevator, magnetic separator, water pump and bag filter. The unit's event data includes failure (maintenance related) and non-maintenance related downtimes; maintenance actions carried out with comments, details such as the date and time of both the event start and event termination. The non-maintenance related stoppages, further reviewed in Step 3 of the following section, include circumstantial (CS) events like lack of hot gases for the kiln, process-related (PRC) like overload and blockages, incidental major shutdowns (ISD) and unavailability of essential utilities such as power and water (PW). The vibration data contains periodic vibration measurements (velocity in mm/s) and classification for the various units placed under the vibration analysis programme and lastly, the monthly clinker production data.

An exploratory study on empirical maintenance data with expert discussions was undertaken considering maintenance and non-maintenance related downtime experienced by the cement plant. Table 1 presents a summary statistic of the downtimes related to the raw meal grinding section, which is one of the main sections of the plant. It is shown that non-maintenance related downtimes (CS, ISD, and PW) exhibit higher average downtime compared to CM downtime. This situation may offer an opportunity to undertake maintenance (OM), hence, abate failure and reduce failure downtime as also corroborated in Section 2.2 of the earlier review.

To further investigate the feasibility of opportunistic maintenance (OM), we explored the empirical data, where Table 2 provides an extract of the data representing the raw mill (RM), and a critical unit in the section. From the table, as an example, before the occurrence of CS, the tension rod for roller 2 (TSR-2) had failed and correctively replaced a few days before. However, immediately after the CS event, the same component TSR-2 fails and demands replacement. On the other hand, TSR-1 was repaired (welding), and a few days later, it had to be replaced. Three vital aspects are identified here: first, the plant employs various CM interventions such as repair, replacement, and adjustment.

However, the plant fails to consider the different CM interventions, such as 'adjust', an aspect this study envisages to address in Step 1 of the following section. Second, from the comments and consultations, the repair intervention on TSR-1 was wrongly addressed, offering a suboptimal solution leading to failure, earlier than expected. From the maintenance consultation, the tension rod failed before the expected life, depicting that the maintenance efficiency was compromised, with a tendency for a repair tending to as-bad-as-old state. Despite its importance when considered along with maintenance policies in optimizing the performance of repairable systems, maintenance efficiency is not considered. This study further offers an extension (see Step 2 in Section 4) to evaluate maintenance efficiency's effect on plant performance.

Lastly, during the CS or CM stoppage, the plant could have potentially taken the opportunity to inspect the condition of the studs for both TSR-1 and 2, by using vibration analysis monitoring (online or periodic) on the RM immediately before or during replacement action. This potentially would expose the impending failure by picking, for instance, deviation from a predefined vibration threshold; then, maintenance would be scheduled to take advantage of the next production stoppage, which, when undertaken, abates the subsequent failure of TSR-2 that costs the plant downtime of nearly 9 h. Such opportunities advanced by maintenance downtime are not considered, for which we discuss in step 5 of the next Section. Figure 1 illustrates event occurrence

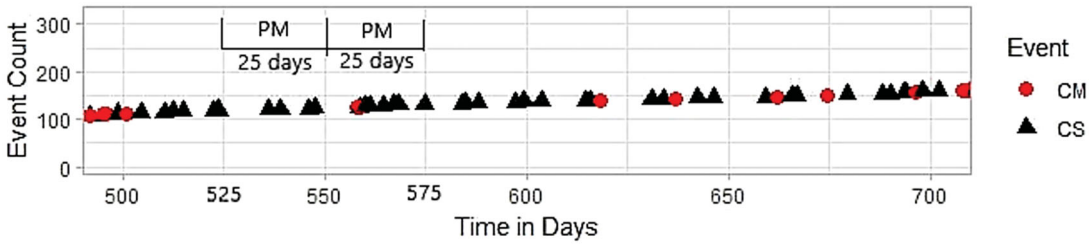

Figure 1. The plot of recurrent CM and CS events for raw mill- RM (Elgin 2019).

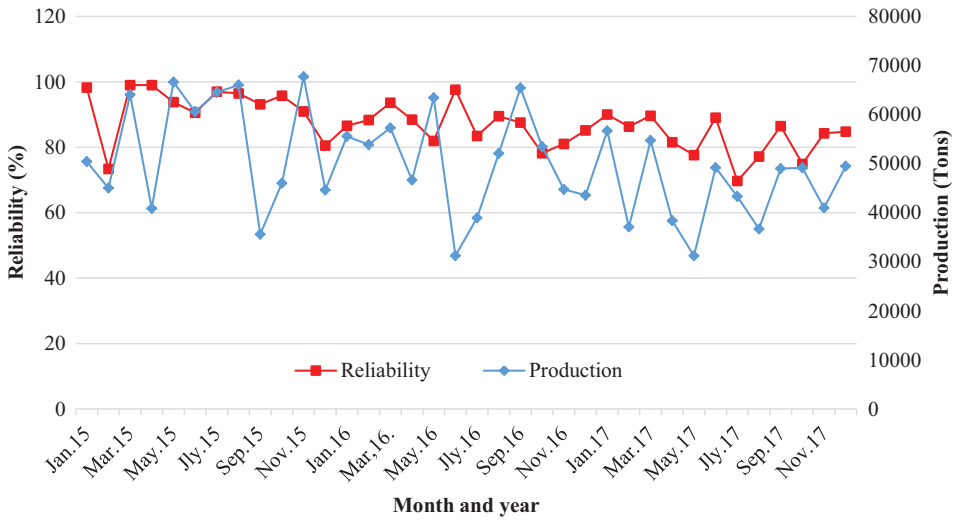

Figure 2. Raw mill trend graph for reliability and production.

according to their time ordering, against a time scale (in days zoomed to cover 500–700 days) since the first failure. A clear trend revealing the occurrence of CS events can be visualized before CM (mechanical) events, in this case availing external maintenance opportunities. Data from Table 2 can be compared with the trend in Figure 1 to derive some conclusion, that both CM and CS event durations could be harnessed for maintenance of equipment on the verge of failure.

Failures that occur succeeding the respective downtime would possibly be avoided, thereby improving the plant availability and efficiency as corroborated by the review in Sections 2.2.1 and 2.2.2. However, the plant does not consider such opportunities as delved in detail in Step 5 of the next section. A closer look at the trend in the empirical data reveal that CS events were occurring close to the 25 days recurring gap (here, e.g. 525, 550, 575 … days) exhibited significant delay duration and if opportunistically seized, PM could be performed while the system is non-operational. This can be achieved for instance, by employing inspection based CBM (online monitoring, e.g. vibrations) strategies to provide an alert on the equipment's condition and subsequently scheduling PM or CM to exploit the next opportunity (occurrence of CS event), an aspect also suggested by (Yang et al. 2018). However, the plant undertakes CBM on an ad-hoc basis and does not consider the use of both periodic and online CBM, which we consider and further discuss in Step 4 of the following section. Taken together, the employment of time-based preventive maintenance (PM) which is undertaken approximately after every 600 h (25 days) could be exploited to inspect and replace some components that are on the verge of failure. The inspection would as well recommend specific maintenance interventions that would be made ready to exploit such internal or external opportunities. This aspect would consider resource dependence by grouping several units that are scheduled to undergo PM at this interval, as discussed in Step 4 of Section 4. Ultimately, as appreciated in the study, various maintenance policies (CM, PM, and CBM) could potentially be employed simultaneously with corresponding opportunistic interventions undertaken while the plant is non-operational, an aspect corroborating the intimations found in Section 2.1.

Another critical aspect of the exploratory data analysis subsumes the impact of maintenance on the production of such manufacturing plants. Here reliability is considered as the ability for the system to perform as intended. As illustrated, Figure 2 provides the trend of the raw mill reliability (based on raw mill capacity) and productivity in terms of tonnage of cement per period; there is a clear trend of decreasing reliability and production in the period under

review. A separate review of maintenance and production data, for instance, covering the May–June 2016 period, discloses significant mill failures prompting repair and replacement actions. The raw mill failure occasions stoppage for maintenance intervention, which often affects the product quality, mainly if the maintenance intervention necessitates contact with the product, or disruption of process parameters such as temperature, which interferes with process consistency.

A similar observation occurs during the May–June 2017 period, where analysis of maintenance data shows significant Fan failures. In this case, since the raw mill operates at specified temperatures to attain the right product quality, the failure incidence of the fan aggravates incidental factors like start-stop. The fan failure also exposes the product to elevated temperatures, which ultimately compromise product quality, yielding maintenance-related quality losses. However, one can observe a link between the effectiveness of the maintenance intervention, on product quality, hence a vital modelling variable for maintenance decision support, which is further delved in Step 6 of the next section.

From the exploratory analysis and expert discussion, the findings provide the following insights for further delving. First, the integration of various maintenance policies, CM, PM, CBM, and OM simultaneously with production and quality in a repairable multi-unit system. This should consider both economic (resource) and structural (performance) dependence underpinned as crucial if robust maintenance optimization of the manufacturing system is to be achieved. Secondly, evaluation of the added value by incorporating both IMO and EMO under OM to the plant performance would concretize the need for exploiting such opportunities. Lastly, linking the consequences of various maintenance actions on product quality while addressing the plant performance would ultimately offer vital insights on product quality and maintenance interactions.

4. System modelling

4.1. Notations

Throughout this paper, the following notations are adopted.

4.2. System modelling steps

The study models a repairable system that considers decision making at different abstraction levels of the systems (at both system and component levels) to imitate processes and systems closely. One of the suggested tools by Heath and Yoho (2017), to implement these types of methodologies includes simulation models, while others include mathematical and experimental models. We use discrete event simulation (DES) since it closely models aspects associated with stochastic systems. Moreover, when simulating manufacturing and maintenance, real-life systems may lack enough details of some stochastic events that may include failure of units, repair time and the arrival of non-maintenance related stoppages like lack of raw materials.

We model a raw meal grinding system, where the model is distinguished in seven steps, as described in this section. Step 1 derives the units to be modelled along with their respective modelling parameters while modelling the maintenance efficiency, and unit degradation is described in step 2. Step 3 entails the operational stoppages that disrupt the system operations. Step 4 and 5 specifically address the maintenance policies employed as detailed in Figure 3, which is a schematic block diagram for the simulation model. The shaded blocks represent the 'as-is' scenario with the other blocks as extensions. Step 6 links the maintenance actions to the production quality, while step 7 addresses how the performance measurement is modelled. Lastly, step 8 provides a system model simulation operationalization.

Step 1: Critical equipment in the raw meal grinding section

We consider a repairable production system that constitutes various inter-linked equipment or units. Since manufacturing plants consists of numerous repairable units, we initially undertake a data-driven criticality analysis, to identify critical units to be considered in the modelling approach. The cement raw meal grinding section was decomposed into twelve units and using Pareto analysis, six critical units were selected based on failure frequency and individual contribution to the plant section downtime (h), see Figure 4. The critical equipment E_n included others (E_1), raw mill (E_2), weigh

n	Number of units; $n = \{1,2,3,4,5,6,7\}$	E_n	n^{th} unit
i	Number of maintenance actions; $i = \{1,2,3,4,5\}$	I	Uptime/Operation time (hrs.)
R_i	Maintenance actions; $i = \{1,2,3,4,5\}$	T	Total operation time (hrs.)
k	Number of Operational stoppages	M_p	Production output (Tons)
ν_n	Unit condition vibration analysis classification (%)	α_i	The upper threshold of Quality degradation rate (%)
τ_{PM}	PM interval (hrs.)	α_i^*	Quality degradation rate (%)
τ_I	Derived process losses intervals (hrs.)	t_I	Process losses duration (hrs.)
t_{PM}	PM action MTTR (hrs.)	P_c	System design production capacity (tons/h)
L_v	Vibration measurement threshold	j	Severity levels; $j = \{1,2,3,4\}$
FSV_j	Vibration-based failure severity, j^{th} level	τ_{CBM}	CBM interval (hrs.)
ρ_i	Hazard rate adjustment/impact factor	FS_j	Failure severity for j^{th} level
τ_k	Stoppage interval for k^{th} process (hrs.)	t	Instantaneous system running hours
t_{R_n}	Maintenance action delay for n^{th} unit	A	Availability
λ_n	MTTF for n^{th} unit	P	Performance
t_{S_k}	Stoppage delay for k^{th} process	Q	Quality rate
S_k	Process stoppages; $k = \{1,2,3,4\}$	t_k^*	Time till first k^{th} process stoppage (hrs.)
η_i	Maintenance action reliance/utilization (%)	OEE	Overall Equipment Effectiveness

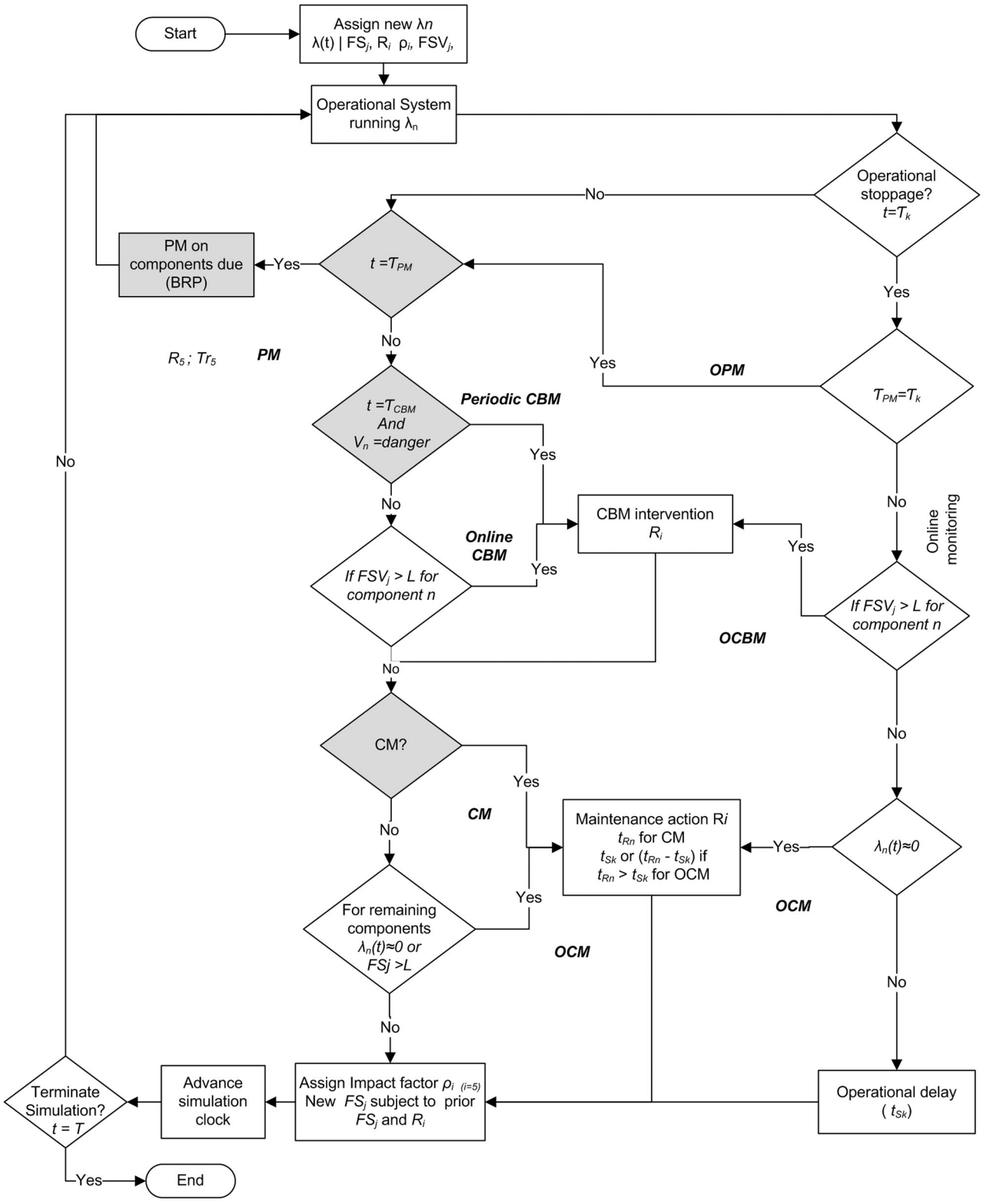

Figure 3. Schematic block-diagram representation of the simulation model.

feeder (E_3), bucket conveyor (E_4), roller bearings (E_5), hydraulic system (E_6) and fan (E_7). The critical units E_{2-7} constitute 93% of total failure frequency and 95% of total downtime, while 'Others'-E_1 includes the sum of the other remaining units.

The repairable system undergoes both corrective and preventive maintenance, where CM involves undertaking repair and replace-maintenance actions or interventions. However, the data exploration phase revealed additional CM actions that may not conclusively fall under the two classes employed, here 'repair' and 'replace' maintenance interventions. For instance, an 'adjustment' intervention is often undertaken, which is usually not as intensive and entails alignment, re-setting, calibration, or balancing a shaft, for

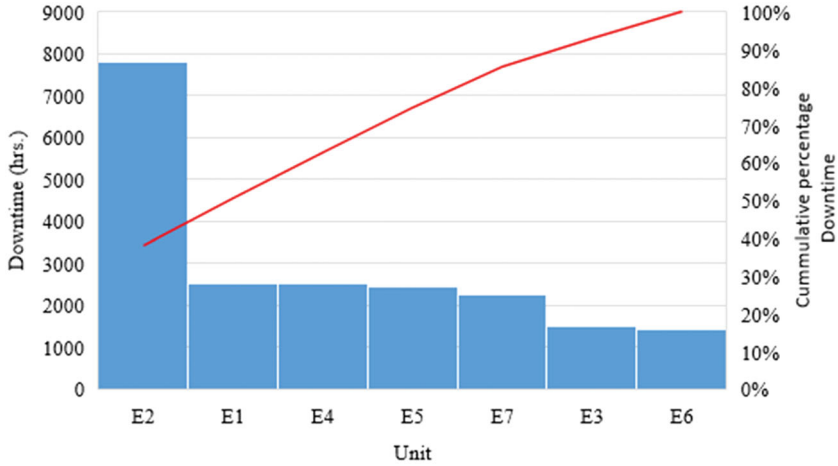

Figure 4. Pareto analysis chart showing downtime contribution for equipment.

Table 3. Equipment related random maintenance action delay time in hours.

Unit	R_1	R_2	R_3	R_4
E_1	0.5 + EXPO (13.9)	0.5 + EXPO (6.36)	WEIB (0.768,1.16)	UNIF (1, 106)
E_2	2 + EXPO (70.4)	0.5 + WEIB (10.9, 0.653)	UNIF (1.5, 11.5)	0.5 + GAMM (10.2, 0.989)
E_3	2 + WEIB (12.8, 0.645)	0.999 + WEIB (9.83, 0.432)	0.5 + WEIB (11.7, 1.22)	0.5 + EXPO (7.32)
E_4	2.5 + WEIB (26.9, 1.07)	2 + EXPO (24.1)	0.04 + WEIB (0.64,1.02)	0.5 + WEIB (8.76, 0.876)
E_5	0.999 + WEIB (5.94, 0.639)	LOGN (4.04, 5.03)	0.5 + WEIB (7.64, 1.03)	0.999 + EXPO (4.51)
E_6	UNIF (44.5, 50.5)	3.5 + 35 * BETA (0.589, 0.789)	UNIF (1,2.5)	0.5 + LOGN (4.04, 5.03)
E_7	2 + WEIB (46.5, 0.352)	1.5 + WEIB (5.25, 0.796	0.5 + WEIB (5.84, 1)	UNIF (0.999, 161)

example. A 'refit' intervention focuses on actions such as changing the lubricant or cleaning a repairable unit. Hence, to realistically model the repairable system, additional maintenance interventions are defined, such as 'refit' and 'adjust', which are based on the ISO 14224 (2016) and BS EN13306 (2018) standard illustrated in Appendix A.

Hence, we model corrective maintenance as considering four distinct interventions, R_1-Replace, R_2-Repair, R_3-Refit, R_4-Adjust. For each modelled unit E_n, the distinct Mean Time to Repair (t_{R_n}) for a specific intervention R_i, under the CM interventions (R_{1-4}) were derived from empirical data and summarized in Table 3.

Step 2: Maintenance efficiency and unit degradation

To model the effect of maintenance interventions on the units of the repairable system, we assume that the repair process is imperfect; hence, we define a maintenance efficiency model, based on arithmetic reduction of age (ARA) proposed by (Doyen and Gaudoin 2004) and used by (Muchiri et al. 2014). The ARA model is defined by virtual age, in our study λ_n and failure intensity FS_j, which assumes that a specific maintenance intervention reduces the virtual age of a unit to an amount proportional to its age just before repair (Doyen and Gaudoin 2004). We define a hazard rate adjustment factor ρ which assumes a value between 0 and 1 and influences virtual age λ_n at a time instance, t. Hence, we assume that the hazard rate adjustment factor varies from $0 < \rho < 1$, where $\rho = 1$ assumes a perfect maintenance intervention that restores the unit to as-good-as-new (AGAN) state, and $\rho = 0$ is a minimal repair intervention on a unit, which leaves the unit at as-bad-as old (ABAO) state. For modelling purposes, for the Corrective Maintenance policy, we assume that three distinct interventions are possible, 'repair', 'refit' and 'adjust' (R_{2-4}) , which when applied to a unit, yield imperfect maintenance, tends to $\rho = 0$, while a 'replace' intervention, which we denote as R_1 restores the unit to the AGAN state. Likewise, for the Preventive Maintenance policy, the 'preventive replace' intervention, denoted as R_5 assumes that the intervention tends to $\rho = 1$, or perfect maintenance.

To model the unit degradation process, we employ a Semi-Markov Decision Process (SMDP) modelling approach proposed by (Wakiru et al. 2019c), where the effects of varying maintenance actions on a repairable unit are represented with an operating four distinct severity states, denoted FS_j with $j = \{1,2,3,4\}$. The SMDP also considers five finite maintenance interventions, $R_i;\ i = \{1, 2, 3, 4, 5\}$ replace, repair, refit, adjust, and PM. The severity states assume that a minor severity state (FS_1), moderate, (FS_2), severe (FS_3), and extensive (FS_4) are retained by the units following the maintenance interventions. As an example, a 'severe' operating state implies that the deterioration of the unit is critical, hence nearing a catastrophic failure that has severe implications on the operation of the raw meal system. Depending on the type of intervention, the unit is restored, either tending to a less or more deterioration state. For example, a unit with a severe deterioration state, FS_4 if one intervenes and 'replaces' (R_1) the defective component, with a new one, the unit is assumed to be restored to the AGAN state, in our model, FS_1 (restored to a minor severity state).

However, while employing CBM, we assume that the unit degradation varies significantly from that of units undergoing CM and PM. We define four levels of vibration severity thresholds FSV_j with $j = \{1, 2, 3 \text{ and } 4\}$. The first threshold 1

Table 4. Process/operational-related disruptions.

S_k	Stoppage	τ_k	t_k^*	t_{S_k}
S_1	CS	350	600	GAMM (134, 0.505)
S_2	PRC	11160	14616	9 + LOGN (2.72, 7.12)
S_3	ISD	8928	1992	UNIF (7, 99)
S_4	PW	450	624	WEIB (6.74, 0.707)

assumes a 15% deviation from a minimum established threshold for a unit of interest, while FSV_4 assumes a 75% deviation, which means that the vibration of the unit is nearing the maximum established threshold, for which if an intervention is not performed, the unit will fail catastrophically. A subsequent threshold state depends on the type of intervention, where a more thorough intervention such as replace (R_1) performed on a component which state is FSV_4, then we assume the unit to be restored to a lower threshold band, here, FSV_1.

Step 3: Process and operational-related stoppages

We also model different process-related stoppages S_k, earlier described in Section 3, which include circumstantial (S_1), process-related (S_2), incidental major shutdowns (S_3) and unavailability of essential utilities like power (S_4). As illustrated in Table 4, the respective time delay for a process-related stoppage t_{S_k}, is a probabilistic time duration, while, occurrence intervals τ_k, is the time between subsequent stoppages of a specific S_k.

The time of the first instance t_k^*, is the time the first stoppage event was experienced, derived assuming a start date; 01.01.2015 (from the empirical data) as the start of the monitoring period. S_1, S_3 and S_4 were identified as stoppages that can be anticipated and planned for, hence offering external maintenance opportunities. For instance, S_1 related to lack of raw materials such as limestone for raw meal grinding, can be anticipated and planned for a priori. Similarly, power outage and water shortages under S_4, and shutdowns necessitated by other sections like Kiln during the brick lining exercise, which can also be anticipated.

Step 4: Maintenance interventions – R_i and equipment state modelling

During the operation, as illustrated in Figure 3, a continuous evaluation of the system running hours is carried out. If the system running hours is not equal to the time between the occurrences of process stoppage and is equal to the time between PM interventions, it is assumed that a *PM action* is undertaken. Mathematically, this is denoted as ($t = \tau_{PM}$). This intervention exploits the economic dependence by clustering multiple units due for preventive maintenance, where a block replacement policy (BRP) is implemented. For example, the raw mill, fan, and bucket elevator can be maintained preventively considering one PM interval, since, they portray nearly similar inter-failure duration characteristics as revealed from data analysis. PM intervention R_5 is undertaken following a PM interval τ_{PM} (900 h) moreover, repair time under preventive maintenance,t_{PM} of 7 + WEIB (5.89, 0.584), both derived from empirical data.

As the system operates, unplanned failure occurs depending on the empirically derived MTTF of the unit, and the failure is addressed using *corrective maintenance (CM)***.** CM considers the interventions; repair, replace, adjust, and refit maintenance actions, whereas each unit retains a repair time duration t_{R_n} for each specific action, as derived in Step 1. To model CM close to reality, we introduce a utilization parameter which depicts the percentage probability of prescribing the four maintenance actions, which we define by a reliance factor η_i also, derived from the data; η_1=26.4%, η_2=11.1%, η_3=24.4%, η_4=38.1%, respectively for R_1, R_2, R_3 and R_4. Following a unit failure, the various CM actions are stochastically prescribed to address the failure hence depicting imperfect maintenance on the repairable system.

CBM intervention R_6, employs vibration analysis on two units (E_2-Raw mill and E_7-Fan) that retain characteristics monitorable using vibration analysis as derived in Section 3. The current vibration analysis programme is carried out at a predetermined interval τ_{CBM} of 1000 h. To model the CBM intervention, a P–F curve is assumed as illustrated in Figure 5. From Figure 5, point S is assumed to point where a failure starts to occur, and point P depicts the point where one can detect that a unit is failing. Point E is modelled as the point a maintenance intervention is made and finally, F (Functional failure) is the point where it has failed. A periodic CBM is assumed as employed, with the inspections done at intervals τ_{CBM}, after which results are analysed, decisions on the interventions prioritized, maintenance activities scheduled and finally executed at point E. For online CBM, for instance, vibration analysis, as illustrated in Figure 5, the identification of the potential failure is assumed to be detected much earlier, compared to the alternative approach, where a periodic CBM is performed. In this case study, periodic vibration analysis is explored at intervals of τ_{CBM}, where the vibration measurements are categorized into two thresholds; 'pass' and 'danger'. The 'pass' threshold here implies that the condition of the unit is an acceptable vibration amplitude threshold, while the 'danger' threshold would imply that the condition of the monitored unit is beyond acceptable thresholds, hence necessitates an intervention before the unit fails.

From the data, we define the 'pass' classification of the unit ν_n, where $n = 2$ and 7 (depicting the raw mill and fan, respectively) based on its condition as measured using the velocity of its vibration. The first classification probability denoted as ν_2 models the percentage of observations in which the vibration measurements for the specific unit, in this case, the drum of the raw mill, is within the acceptable condition, which we refer to as a 'pass' condition, derived empirically from the data. From the empirical data, 90% of the observed measurements for the raw mill were within the acceptable levels, hence, $\nu_2 = 90\%$. This means that 10% of all vibration measures for the raw mill drum were not within acceptable thresholds. For the fan unit, 70% of all measurements, ν_7 were within acceptable thresholds, with 30% of $(100\% - \nu_7)$, outside acceptable thresholds. In the instances where the vibration measurements are outside acceptable

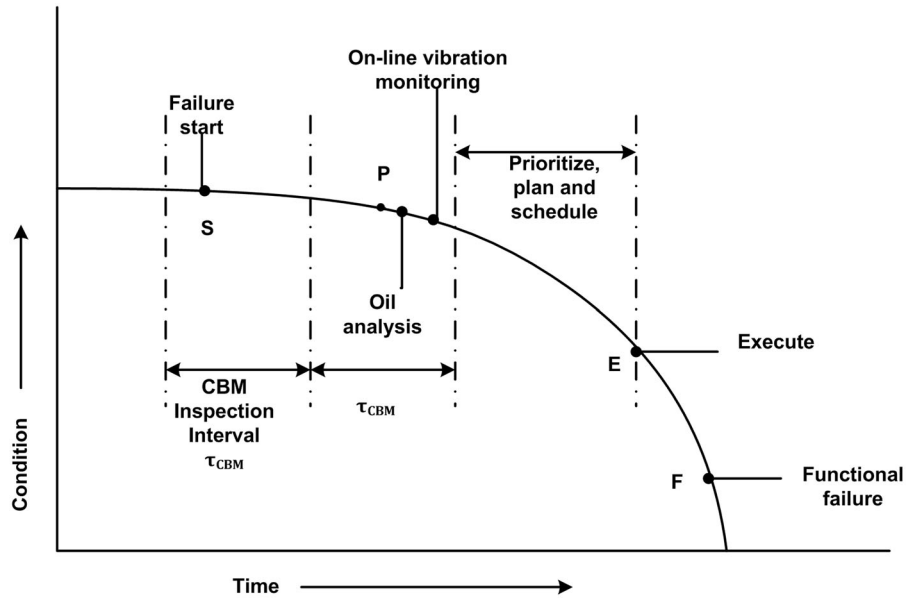

Figure 5. P–F curve illustrating both periodic and on-line CBM.

thresholds, adjust (R_2) or refit (R_4) maintenance actions are prescribed, incurring respective t_{R_n} as shown in Table 3.

As discussed in Section 3.1, the plant employs only the periodic condition monitoring; hence, we extend the modelling approach to consider online monitoring with the modelled maintenance interventions. In this case, we define failure severity states assuming pre-knowledge of the deterioration of the component as per the measurement of vibration intensity. Here, we define failure severity states, FSV_j which vary from 1 to 4. The severity state here improves or deteriorates further depending on the former severity state and type of maintenance intervention. For instance, a unit retaining a moderate severity FSV_3 (vibration retaining 50% deviation of the vibration threshold) undergoes adjust maintenance action(R_4), the severity reduces by one level to moderate severity FSV_2 which means the balancing or alignment performed on the vibrating unit reduces the vibration intensity.

The FSV_j is employed to determine the deterioration state of a respective unit following a maintenance intervention. It allows decision-makers to audit the quality and effectiveness of the maintenance intervention. For instance, in the above case, decision-makers would rate maintenance intervention as useful. However, considering the same unit retaining FSV_3 state undergoing a refit (R_3) maintenance action, which would indicate imperfect diagnosis and maintenance, the severity would deteriorate to significant severity FSV_4, whose maintenance intervention would be rated as ineffective.

Step 5: Opportunistic maintenance considering IMO and EMO opportunities

In this section, we extend the maintenance interventions to include opportunistic maintenance (both internal and external maintenance opportunities) as complementary to the previously derived policies in the preceding step 4.

The process-related stoppages defined in Step 3 and the maintenance interventions in Step 4 are employed together to exploit the IMO and EMO. While the system is running, we assume that if a process stoppage occurs and the simulation time is close to the PM interval ($t \cong \tau_{PM}$) and the anticipated process stoppage duration is equal or higher than the PM action duration, ($t_{R_5} \leq t_{S_k}$), the external maintenance opportunity ($t = \tau_k$), is exploited and Preventive Maintenance intervention, denoted, R_5 undertaken. We introduce a continuous online condition monitoring (CBM) approach, which extends the CBM strategy of periodic monitoring at the case raw meal section. The system is monitored continuously in this instance when operational. In the event the vibration threshold of the monitored unit is equal or above a set limiting threshold, denoted as L_v, two alternatives arise:

- Option 1: If the simulation time is close to the occurrence of a process-related stoppage ($t \cong \tau_k$), we carry out opportunistic maintenance for the unit, while taking advantage of the process related stoppage (EMO) that occurs at ($t = \tau_k$).
- Option 2: If the vibration threshold is higher than L_v for a unit known a priori based on the online monitoring, the opportunistic maintenance exploits the unplanned failure of a different unit which fails within the same window of opportunity. In this case, CM interventions R_i are employed to restore the unit to a less severe failure state FSV_j.

However, if the running time is not equal to CBM interval denoted mathematically as, $t \neq \tau_{CBM}$, the system continues running till the next unplanned failure occurs on any of the units E_n, where we assume various CM interventions R_i are prescribed, based on their percentage utilization derived empirically from the data of the cement plant, η_i.

To introduce an internal maintenance opportunity, we assume that during the CM intervention on the nth equipment, the virtual age or MTTF $\lambda_n(t)$ of other units not undergoing CM are evaluated using on-line monitoring. Hence, if

the virtual age of the unit, $\lambda_n(t) \approx 0$, we take the opportunity to intervene while exploiting the downtime (and repair time) of the failed unit. Similarly, if $\lambda_n(t) \approx 0$ for a unit and the respective time to repair is less than the process related delay ($t_{R_n} \leq t_{S_k}$), then we intervene correctively while taking advantage of the stoppage of S_k, when ($t = \tau_k$). Additionally, if the repair time is equal or more significant than the stoppage duration ($t_{R_n} \geq t_{S_k}$), the opportunistic corrective maintenance (OCM) utilizes the duration t_{S_k}, while the balance duration of $t_{R_n} - t_{S_k}$, is utilized for non-opportunistic CM intervention.

It is important to note that OM based on external maintenance opportunities, specifically considers process stoppages S_k which are known a priori, for instance, because of a scheduled production stoppage. In this case, S_1, S_3 and S_4 as depicted in Step 3.

Step 6: Modelling the link between maintenance actions and product quality

This study attempts to link the impact of various maintenance actions R_1, R_2 and R_5 to product quality. We define a quality degradation rate α_i representing the production percentage rate attributed to sub-optimal maintenance actions R_i. We assume that sub-optimal maintenance actions may lead to a failure that demands a maintenance intervention, in which the product (cement) quality is compromised. In this case the quality degradation rate $\alpha_i = 0\%$ implies no quality defects generated, while $\alpha_i = 100\%$ tends to higher quality rejects in terms of tonnage. Taking this to consideration, α_i is assumed to be equivalent to the unreliability of a unit, where the unit reliability is computed as the ratio of the total run time to the actual run time affected by the various non-maintenance-related downtime (e.g. lack of storage space, idleness, lack of utilities and process stoppages). The specific contribution by the maintenance actions R_i on the lost production on a month-to-month basis due to quality, is derived empirically from the data, as a random distribution. For example, quality defects attributed to a 'replacement' intervention, R_1 is α_1^*=UNIF $(0.5, \alpha_1)$. The parameters of the random distribution assume that for R_1, a minimum of 0.5% of the production is lost due to the effects of sub-optimal maintenance intervention. The distribution sets an upper threshold of $\alpha_1\%$, which depends on the type of intervention. The percentage of quality defects is modelled against a desired production capacity for the cement mill, P_c to derive the total production defects.

Specific distribution values of quality degradation, for the maintenance interventions derived empirically from the data, includes, $\alpha_1^* =$ UNIF (0.5, 29.5) for the 'replace' intervention, $\alpha_5^* =$ UNIF (0.5,2) for PM intervention, and $\alpha_2^* =$ UNIF (0.5,24.5) for the 'repair' intervention. For modelling purpose, the quality degradation considers two units of the section, which includes, E_2 (raw mill) and E_7(Fan). These systems were observed as influencing product quality more significantly compared to other systems of the raw meal section. This means, following a repair intervention on $\boldsymbol{E}_2$, the production of defective product retains a random rate of UNIF (0.5, 24.5) %.

Step 7: Performance measurement

Following the elucidation in a previous study by Wakiru et al. (2019a) which highlights availability and OEE as critical maintenance objectives for mining and manufacturing facilities, where raw meal section falls within this category. The Overall Equipment Effectiveness (OEE) is included in the modelling framework to measure the performance of the manufacturing equipment.

Equation (1) illustrates the computation of OEE, where availability is computed by comparing the uptime (I) to the total time (T), further defined in Equation (2). The performance rate, in Equation (4), defines the ratio of the net uptime to the uptime, where, to compute the net uptime, by subtracting changeover and process losses from uptime value. Following expert consultations, minor stoppages with downtimes of less than 45 minutes were categorized as process-related losses that did not render the system non-operational. Therefore, a process loss is computed considering minor stoppages that do not render the system non-operational by a delay time distribution, $t_l =$ EXP (0.55) h, at an interval of $\tau_l = 51$ h, derived by fitting the probability distribution.

However, since the study relates to the production of one product, i.e. cement in this instance, the changeover losses are not considered. The quality rate Equation (5) considers the system production, which is attained excluding defective production, against the total production (summation of both system and defective production) on the milled product linked step 6. The performance is based on the Mill production M_p characterized by production capacity P_c of 135 tons/hr.

$$OEE = A \times P \times Q \tag{1}$$

$$A = \frac{Uptime}{Total\ time} \times 100 \tag{2}$$

$$Uptime = Total\ Running\ time - Downtime \tag{3}$$

$$P = \frac{Uptime - Changeover\ and\ process\ losses}{Uptime} \tag{4}$$

$$Q = \frac{Total\ production - Random\ and\ quality\ defect}{Total\ production} \times 100 \tag{5}$$

Step 8: Simulation model

We integrate all the policies CM, PM, CBM, and OM above in one simulation model and evaluate the system performance. The model is developed and executed through ARENA simulation software, integrating model inputs derived from the empirical data.

5. Results and discussion

In this section, the results of the model depicting the 'as is' scenario are discussed, followed with results depicting the impact of implementing CM and PM policies within an opportunistic maintenance framework. The second part of the results addresses the systematic extensions quantifying the respective value of the integrated opportunistic

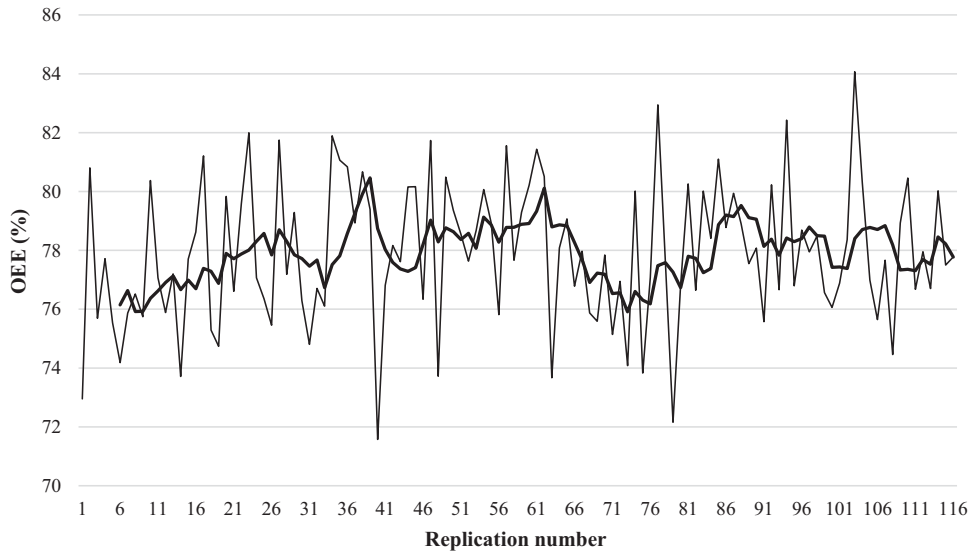

Figure 6. Variability of the objective function – OEE.

corrective, preventive and condition-based maintenance policies on the performance of a cement mill system modelled in this study.

We integrate all the policies CM, PM, CBM and OM above in one simulation model and evaluate the system performance. The model is developed and executed through ARENA simulation software, integrating model inputs derived from the empirical data.

As shown in Figure 6, the moving average is computed from the objective function (OEE) recorded while the simulation is run repeatedly. At the 90th replication, the moving average line insinuates to stabilize; hence, the number of replications was set to 90 to ensure a better estimate of OEE. Moreover, the half-width retained by OEE reduced from ±2.064 to ±0.53155. We modelled a simulation time of 26,280 h, which represents a 3-year horizon depicted from the empirical data. Since the model commences without any entity, a warmup period of 12,000 h was set to ensure all entities are in the system when statistics collection commence.

5.1. Scenario 1: 'as-is', considering the influence of corrective and preventive maintenance

Implementing the modelling framework discussed in Sections 3 and 4, some of the results are illustrated in Table 5. The results from our modelling framework are comparable to empirical averages of parameters such as availability, performance, and quality, with the deviations below 10% (8.21%)compared to the empirical values, therefore suggest that the model mimics the flow and reality of the system (Kelton, Sadowski, and Swets 2010).

The 'as-is' scenario considers only PM and CM maintenance policies. Online CBM is not considered in this scenario, since as currently the case for the cement facility, only scheduled or periodic CBM policy is implemented in an ad hoc manner. The as-is or currently implemented maintenance strategy at the cement mill assumes that units of the cement plant are inter-dependent; hence a failure of one unit

Table 5. Comparison of simulation results.

Scenario	A_o (%)	P (%)	Q (%)	OEE (%)	Mill production (K Tons)
'As is'	55.11	97.95	100	53.98	811.80
Empirical	59.60	98.00	100	58.41	883.80

renders the other parts of the cement mill, non-operational. Moreover, the current maintenance practice considers a PM interval of 900 h for critical units such as the raw mill (E_2) and fan (E_7), while other sub-systems considered non-critical are maintained correctively (relying on the CM policy).

To verify that the model behaves as expected, we varied the PM interval from 300–2000 h, while evaluating the influence of this variation on system performance, for our case, measured through availability and performance metrics. As depicted in Figure 7, the OEE gradually decreases following a similar trend with the availability metric, as the PM interval increases. This trend is expected in practice since extending the PM interval means that more components deteriorate and fail in-between the intervals, which in turn increases the expected CM downtime. Consequently, this also negatively influences the availability of the system. The link between availability and PM planning is also corroborated in literature, for instance, in Chang and Lee (2020) where they show how sub-optimally defining a maintenance interval, ultimately influences the availability of technical systems negatively.

For quality, intuitively, since the cement mill ignores the influence of maintenance-related quality defects, our model generates a 100% quality rate. For the performance rate, it is influenced by the low process loss, since, as described in Equation (4), it retains similar measurement metrics (in this instance, uptime which is influenced by the system downtimes) as also shown in Equation (2).

From the as-is modelling results, we can observe that assuming a quality rate of 100%, is unrealistic as it ignores the influence maintenance interventions has on the quality of the manufactured products. Moreover, the low availability of the cement raw mills presents an opportunity for designing more optimal maintenance strategies, which take

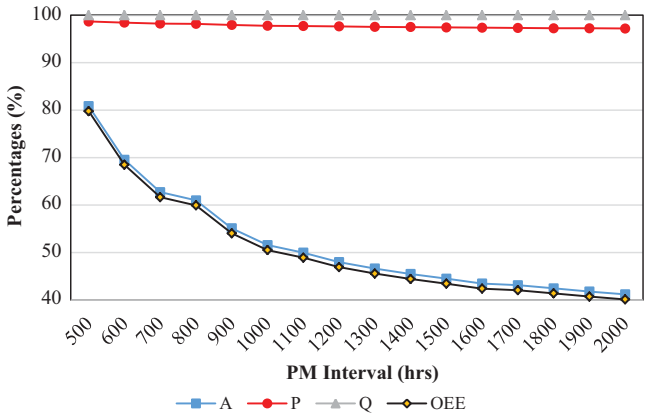

Figure 7. The effect of varying the PM interval on performance rates and OEE for the 'as-is' model.

advantage of process-related stoppages, which also motivates this study. This aspect is also demonstrated clearly in the exploratory analysis discussed earlier in Section 3.

5.2. Improvements to the 'as-is' maintenance strategy

Because of the flaws of current maintenance practices at the raw meal section, illustrated through the results of the 'as-is' scenario, it was essential to model improved maintenance strategies. In this case, we incorporate all the maintenance policies in the system, which now includes CM, PM, CBM and OM (considering both EMO and IMO). In addition to the mentioned improvements, several parameters are re-defined, as indicated in the exploratory study in Section 3. This includes PM interval changed to 600 h while we introduce the quality degradation rate that links the maintenance actions to the product quality. The PM interval of 600 h was derived not only estimated from the exploratory study (Section 3), but also from a sensitivity analysis where the interval was varied from 300 to 2000 h as shown in Appendix B.

Considering scenarios alongside, the improvement attributable to CBM and employment of OM based on EMO undoubtedly, demonstrates the significance of considering external maintenance opportunities in improving the performance of the system. Moreover, the results demonstrate the added value derived from the application of the developed approach. The results based on the developed model, insinuate performance improvement where A_o and OEE improves by 22.08% and 15.07%, respectively. As alluded by Smith and Mobley (2008), World-class levels of OEE start at 85% based on the following values: 90% unit availability × 95% performance efficiency × 99% rate of quality = OEE of 84.6%, hence the mill with improvements nears the performance expectations.

a. Impact of maintenance policies on performance

To study the effect of maintenance intervals on the system performance, the experiment varying the PM (τ_{PM}) and CBM (τ_{CBM}) intervals from 300 to 2000 h was undertaken. This is an important aspect, especially in deciding the optimal PM and CBM interval for a given system. As shown in Figure 8(a), an increasing τ_{PM} insinuates a decline in OEE while a marginal decline in OEE is observed when τ_{CBM} increases. This result substantiates the insight that shortened τ_{PM} potentially result in high PM downtime while an extension leads in high CM downtime (Arts and Basten 2019).

On the other hand, the OEE marginal performance decline while gradually increasing τ_{CBM} can be attributed to moderate increased failures. In this case, failure modes discovered using CBM are now addressed primarily by PM and CM actions due to the less utilization of CBM. This scenario increases a unit's deterioration; hence failure rate increases moderately as depicted by a moderate increase of CM downtime. Second, it provides an insight into potential 'over maintenance' concerning employing CBM at low intervals. Since both online and periodic CBM are considered, there is some intuition that possibly employing one of the two approaches, would, in this case, offer optimal solutions. Therefore, the total effect infers extending τ_{PM} would cause the OEE to decrease at higher intervals. On the other hand, gradually increasing the CBM interval is seen to decrease the performance at higher CBM intervals marginally. These results seem to be consistent with other research, which found that extension of PM and CBM intervals leads to higher unit deterioration hence reduced system performance.

To investigate the effect of the CM policy on the performance, we increase the instances of the 'repair' and 'replace' maintenance interventions under a CM strategy, from 4% to 32%. An increase in a replacement maintenance action may imply predominantly replacing components that fail, with parts in AGAN condition, while performing minimal repair. As shown in Figure 8(b), increased utilization of the 'replace' action improve the OEE of the system, while an increase in utilization of the 'repair' action does not significantly change the OEE. The observed increase in performance due to higher utilization of the 'replace' intervention can be attributed to the renewal effect enhanced on the units as a result of the higher application. This signifies the positive impact of the replacement of units which infers a renewal effect which possibly improves the MTTF and hence reduces failures ultimately improves the performance.

To investigate the effect of integrating both the PM and CBM and CM policies, we varied the PM and CBM intervals alongside varying the replace-maintenance action utilization from 20% to 100%. Extending the CBM intervals means that failure modes observed in condition monitoring will now be mainly dealt with by the CM actions. In this case, the increase in replace-maintenance action utilization ensures the units are renewed; hence lower failure rate is observed, leading to performance improvement. This derived synergy could be exploited by plants especially when one of the strategies is unavailable. For instance, the plant could employ an enhanced CBM to augment minimal 'replace' actions due to a lack of new spares or inferior performance spares available. On the other hand, in case of lack or faulty condition monitoring tools or programmes, the plant may enhance the replacement actions to ensure lengthened CBM intervals do not affect the performance. On contrast,

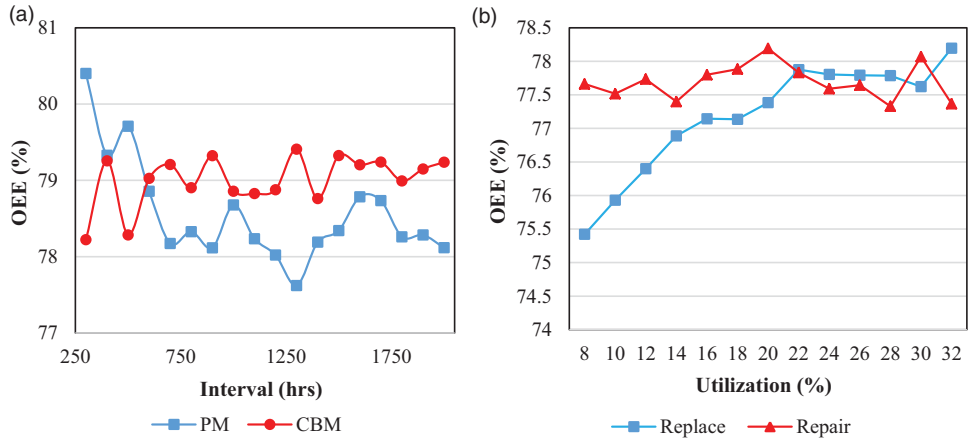

Figure 8. The effect of varying (a) PM and CBM interval and (b) replace and repair-maintenance action utilization on performance using the extended and improved model.

extending the PM interval while increasing the utilization of the replace action derives a contrary effect. At lower replace action utilization, extension of the PM interval significantly increases the CM downtime, eventually reducing the system availability and ultimately the OEE. Extending the PM interval intuitively leads to increased CM actions, hence reduced application of replace action directly infers an increase in utilization of other CM actions such as repair and refit which are time-intensive. This also negatively impacts the unit reliability hence increased failure and downtime, which negates the system performance in terms of both OEE and availability.

b. Effect of maintenance efficiency on the performance

In real life, an extension of the PM interval for the system intuitively leads to over-reliance on CM maintenance actions, evidenced by an increase in CM downtime, to bring the units to an operable state (Wakiru et al. 2019c). For better system performance in such a case, the maintenance efficiency of the CM actions should be at an appropriate level to address the system challenges like increased failure rates. In this case, it is essential to investigate how varying the different maintenance efficiencies and PM interval would affect the system performance. To probe the influence of maintenance efficiency on the plant performance, the efficiency of the 'repair' maintenance intervention, was varied from 20% to 80%. Here, we consider a situation where the management may decide to increase the utilization of a more thorough 'repair' strategy, because of reasons such as lack of spares, hence the repair action becomes critical to addressing the system performance when PM interval is extended.

In this experiment, we retain all the other maintenance efficiencies at 100% and review the impact of varied repair efficiency. As shown in Figure 9(a), when we vary the PM interval and repair efficiency, the results show that at lower PM interval, the system performance is high. However, it declines at about 700 h and to some extent, stabilizes after 900 h. When low PM interval is maintained, the units are renewed frequently using the PM policy; hence, reduction of failures is expected. This, in turn, reduces the system dependence on the CM actions, and high performance is attained. However, as the PM intervals are extended, the system performance declines considering the different repair efficiencies. This may signify that for the management to predominantly enhance the use of a robust repair-maintenance action, the PM interval should be kept at lower levels. The results confirm some intuition that extending the PM interval in some cases is not appropriate if no robust CM actions are employed to address the increased failure rate introduced into the system.

Similarly, we varied the PM interval from 300 to 1300 h, while the replace-maintenance efficiency was varied from 20% to 100%, depicting the management's decision to rely on replacement of deteriorated parts, as a maintenance strategy. As shown in Figure 9(b), higher levels of 'replace' efficiency, and shorter PM interval yields a high overall system performance (OEE). However, as seen, at an extended PM interval, the performance declines. This can be attributed to the fact that reduced replace significantly affects the system performance when the PM interval is extended. Intuitively, to attain high system performance while extending the PM interval, the replace-efficiency should be significantly high to derive the unit's renewal effect, which is reduced due to the PM extension.

These results considering both replacement and repair-maintenance efficiency, demonstrate the value of implementing specific robust corrective maintenance interventions such as 'replacement' of a unit which ensures the reliability of the unit is retained high to as-good-as-new state. This offers the best CM actions in improving system reliability and performance when the PM interval is extended. The present results are significant in at least two significant respects. First, considering situations intuitively, where failures are not precisely associated with the age of the units, CM actions with a higher renewal effect could be essential to increasing the availability, hence OEE of a system. Lastly, the incorporation of both replace and repair actions is not only realistic but also demonstrates the synergies the two maintenance

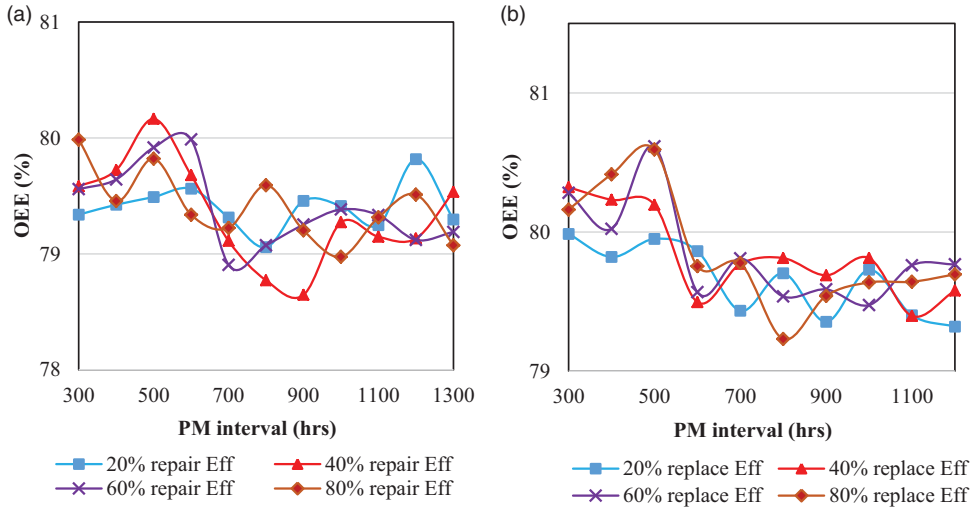

Figure 9. The effect of varying PM interval (a) repair maintenance efficiency and (b) replace maintenance efficiency on system performance using the extended and improved model.

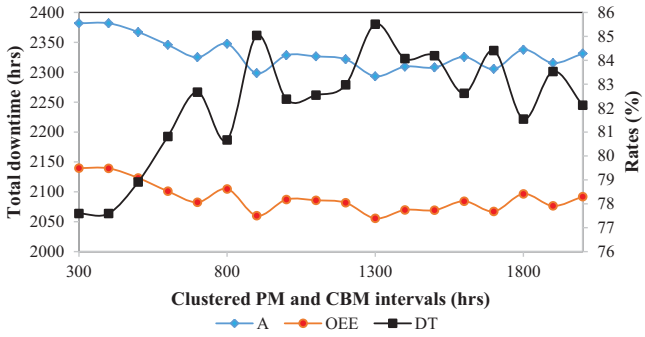

Figure 10. The effect of clustered PM and CBM interval to system OEE and downtime.

actions extend to ensure better system performance, with a balanced, realistic influential effect from each CM action.

c. Effect of economic dependence on the performance

To evaluate the effect of economic dependence, where the periodic CBM and scheduled PM are clustered and performed within the same intervals. This is undertaken assuming the plant undertakes condition monitoring of the critical units while the system is in operation, just before the production stoppage, for preventive maintenance. For instance, an opportunity to undertake CBM on the Fan based on the vibration threshold when the raw mill is nearing PM.

As depicted in Figure 10, clustering both PM and CBM intervals exhibit a slight decline in OEE and stabilize from 900 h. This effect is likewise evidenced by the availability, while the total downtime increases and fluctuates at the same interval. In this case, extending the clustered intervals, failure modes observed during CBM, and the renewal of units under PM will predominantly be addressed using CM actions due to less application of CBM and PM. Therefore, a critical aspect that needs to be investigated while deriving economic dependence by clustering the PM and CBM intervals retains the effect of maintenance efficiencies of the various CM maintenance actions.

The critical decision variables here are both replace and repair-maintenance actions under CM. The replacement efficiency was varied from 20% to 100%, while the clustered intervals from 300 to 1300 h. In this case, we assume that the replacement efficiency is low, for instance, when maintenance staff are not thorough in the replacement action. An example such as inappropriate torquing or tightening of the replaced parts, or unable to ensure proper sealing is attained will retain low replace efficiency. On the contrary, we assume that perfect replacement will retain a high replacement efficiency.

The results show that lower replacement efficiency yields a significant decline of OEE as the clustered intervals are extended. An intuitive reason for this might be that the extension of the clustered interval reduces the usage of PM policy, leading to high usage of CM actions, hence an increase in the CM downtime. Moreover, this can be linked to the negative impact that the lower replace efficiency inflicts on the unit's reliability for instance, loose torquing which may eventually cause vibrations, leading to a high frequency of failures. This is an indication that a system extending the clustered intervals reduces the renewal impact the unit derives while exploiting PM based Block Replacement Policy (BRP) policy; hence the replacement efficiency should be high to counter the increased failure rate. On the contrary, despite an increase in the application of CM actions as the PM and CBM intervals are extended, the repair-maintenance efficiency marginally affects the system performance because of the simultaneous usage of the replace efficiency in the system.

This result is interesting, and further support the idea of integrating different CM actions such as replace and repair simultaneously for optimal decision support, in a situation warranting clustering the PM and CBM intervals. This is mainly attributed to the reduction of total downtime, which improves the system availability and ultimately improves the OEE. These results are interesting and demonstrate the importance of integrating various maintenance actions under CM, which endeavour to boost the reliability of the units.

Since the extension of the clustered intervals means that CM policy becomes dominant, it follows that integrating the different maintenance actions under CM would maintain the system reliability.

d. Impact of maintenance actions on the performance and product quality

To examine the impact of defined maintenance actions on the production quality, we assume that suboptimal maintenance actions lead to an increase in the quality degradation rate. We evaluate the impact of replace-maintenance action on the quality rate of the system by varying its utilization from 2% to 32%, while we vary the PM interval from 300 to 1300 h.

For clarity, we represent the variation of the replace maintenance action utilization with 4% and 8% for a lower scale and 28% and 32% to represent the higher scales. As shown in Figure 11(a), at lower PM intervals, the quality rate is high at both the lower and higher values of replace utilization. This may be attributed to the dominant renewal PM effect, which the units undergo more times compared to CM's actions. This insight corroborates the real-life expectation that shorter PM intervals will lead to better performance of the system by increasing the use of PM and significantly reducing the CM utilization. Thus, the impact of the replace-maintenance action is not significant at lower values of PM interval. Considering the higher PM intervals, the quality rate significantly declines between 450 and 650 h for the higher values of replace utilization, which stabilizes after about 700 h of PM interval.

Despite the small quality rate changes evidenced in Figure 11(a) due to varying the replace maintenance action, the ultimate quantity of defects is significant. For instance, the decrease of quality rate due to implementing the '4% replace' action and varying the PM interval, translates to an increase in production quality defects of approximately 2823 tones (the equivalent of €191,964) per year. Further analysis considering the clustered PM and CBM interval while varying the replace maintenance action utilization generated a similar effect.

However, it would be essential to evaluate the effect when the CBM interval is extended while assuming the renewal and reliability challenge is addressed by increasing the robust maintenance action like replacement. This experiment retained PM interval as a constant, varied CBM interval from 300 to 1300 h and the replace maintenance action utilization from 2% to 32%. As shown in Figure 11(b), the quality rate generally improved as the CBM interval was extended for all the replace utilizations. The extension of CBM interval infers that the failure modes are not discovered frequently and hence the system relies on mainly CM to mitigate these failure modes. However, an increase in replacement action's utilization inherently improves a unit's reliability; in this case, failed components are replaced with new ones; hence the unit demonstrates longer MTTF. In this case, the use of CBM can be extended since the condition of the unit being monitored is most of the time in better condition due to the continual renewal of the unit using the replace-maintenance action. These support previous research into this domain area, which links the unit's condition and replacement, where increased renewal of a unit using replace-maintenance action can be exploited to extend the condition monitoring intervals.

5.3. Managerial implications

Many manufacturing plants with repairable multi-unit systems employ various maintenance and operational policies often without considering all the policies together. As highlighted in the exploratory study and the system scenario modelling, disregarding non-maintenance related downtime adversely affects the performance of the system. Therefore, it is prudent to consider both maintenance and non-maintenance downtime while addressing challenges affecting system maintenance and overall performance. For manufacturing plants operating repairable systems, addressing this aspect may significantly improve both the uptime and overall performance of the system.

The employment of CBM portends significant benefits to a manufacturing plant as corroborated in this case study where vibration analysis has been utilized. Despite the study

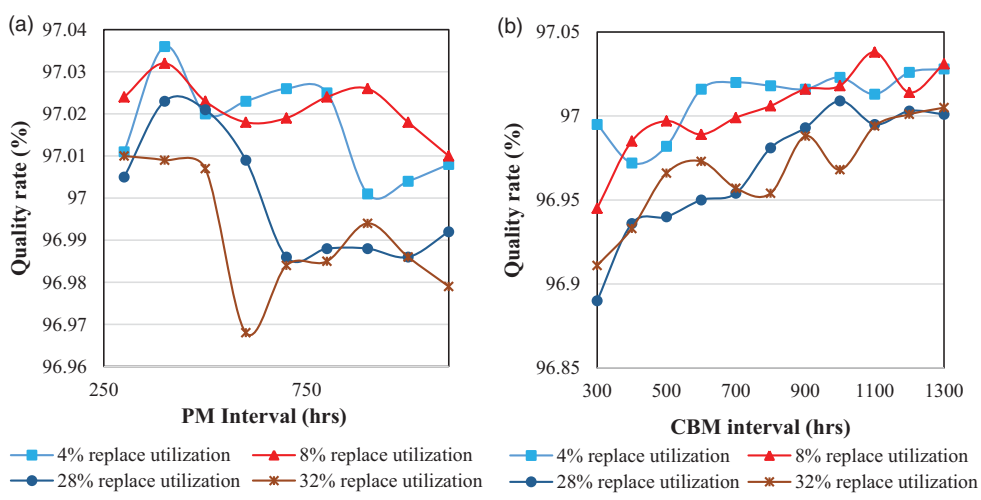

Figure 11. The effect of maintenance action on the quality rate with varying replace maintenance action utilization and (a) PM interval and (b) CBM interval.

employing a selective strategy where only two units are monitored, it has been shown that maximizing the effect of the CBM policy would incorporate the introduction of on-line monitoring to ensure real-time intervention and offer accuracy with little or no human interaction. In this case, maintenance intervention decision making based on the condition monitored would consider the use of remaining useful life or hazard rate of the unit. However, comprehensive benefits from using opportunistic CBM (OCBM) may be influenced by the plant's preparedness to undertake CBM, which requires advanced provision or fast sourcing of spares, tools and skilled workforce. The integration of other condition monitoring techniques like oil analysis, acoustic emission, pressure and thermography, undoubtedly provides synergetic solutions and enhances maintenance decision support as also corroborated by (Wakiru et al. 2019b).

Moreover, as advanced in this study, harmonizing or clustering the CBM and PM interval offers an opportunity where resource dependence, a subset of economic dependence, is exploited. As advanced, periodic condition monitoring just before preventive maintenance may provide invaluable information on the unit's condition and ensure units with a high probability of failure are maintained during PM. It has been shown that to derive high performance while extending the clustered intervals, demands high maintenance quality under CM maintenance actions like replace and repair because CM interventions dominate in such cases. These results differ from Muchiri et al. (2014), who found that higher PM efficiency derived higher system performance. This result may be explained by the fact that this study integrates the renewal effect in both PM (preventive replacement) and CM using replace efficiency. On the other hand, Muchiri et al. (2014) assumed a single CM action that initially retained 0% efficiency. This reveals the importance of maintenance quality while considering integrated maintenance policies for repairable systems. However, further work is required to establish the viability of this finding, especially an evaluation of the trade-off the maintenance team would need to undertake between maintenance cost and reliability of the units and system in general.

The employment of opportunistic maintenance that considers both internal and external opportunities offers a definite value addition when integrated into the plant's maintenance and planning strategies. A salient feature of the OM involves integrating advance information sharing by developing clear and comprehensive sharing across the organization for seamless planning by the plant and other departments. Importantly, to harness the external maintenance opportunities, information sharing is vital. However, most plants operate in silos (Al-Douri and Tretten 2017), where each department distinguishes itself in terms of responsibilities, and hence, information sharing with another department may not be forthcoming. For instance, the operational function is concerned more with productivity, at the expense of reliability of the equipment and vice versa. This aspect often negates the opportunities that could be seized to ensure improved plant performance. Therefore, this study demonstrated how information sharing, for instance between production and maintenance functions, renders the maintenance department efficient to schedule maintenance activities in sync with production schedules comprehensively. This finding has important implications for developing an information-sharing based system where real-time information is shared across the organization. Similarly, the introduction of a centralized or integrated system whose platform ensures all departments can view other department's plans and exploit opportunities such as advanced in this study.

The impact of maintenance policies and actions to the production quality is an area which has been advanced in this study. The maintenance team, importantly, should comprehend that maintenance has a vital role in ensuring quality production and reduction of product rejects and reworks. The results show improved quality rate when CBM interval is extended while an increase in replace action utilization is made. Despite the positive effect on the unit's reliability, it prudent for the maintenance team to undertake a cost–benefit analysis to understand the trade-off represented here since the cost of new inventory is expected to increase significantly. However, taking all together, it might be paramount for the maintenance team to incorporate an additional performance indicator that depicts the production quality lost due to maintenance related issues like failures and incidental shutdowns. With this accountability, not only will the plant generate accurate quality loss data but also ensure the maintenance team address aspects that may help mitigate such losses.

Maintenance quality, which is inferred in this study by the maintenance efficiency, has in the recent past, attracted interest in the maintenance field. When a plant attains a high maintenance quality, the maintenance efficiency improves, and significant savings can be realized. For instance, it enables extending PM and CBM intervals not only lead to maintenance cost savings but also improve the plant performance. The quality of the maintenance would significantly impact system performance; hence, steps should be placed to ensure high-quality maintenance interventions. Such steps would require re-training of maintenance staff, incorporation of product-related services under the product-service system, like maintenance contracts, advice and consultancy for units which in-house maintenance staff are inadequate to maintain.

An automated software solution can be employed for analyzing downtime, which provides enhanced visibility of the issues that affect plant availability and production loss. It is a cost-effective method of tracking production stoppages and improves the analysis capability to understand better the most critical causes of unplanned stoppages and production slowdowns. It can increase plant efficiency by isolating production under-performance and putting actions in place to maximize production equipment, which can be measured over time. It forms part of a continuous improvement programme to improve operational efficiency and increase overall productivity.

This study applied the proposed methodology to the raw meal grinding section of a cement plant. This methodology is both generalizable and scalable for different multi-unit

Table 6. A sample of the potential application of the methodology.

Sector/industry	Sample system	Sample subsystems	Sample EMO	Quality measure
Wind energy	Wind turbine	Electrical system, Generator, gearbox, mechanical brake, rotor blades, drive train, yaw system, hydraulic system	Wind speed, low power demand	Power Quality.
Manufacturing	Tea processing	Humidifier, Vibro sorter, fibre sorter, furnace, drier, rotor vane, roller, CTC machine	Lack of utilities (fuel, water)	Quality of tea processed (quantity)

system applications, and also transferable to other sectors. However, several adaptations will be necessary to suit the operational contexts of the various applications. In the first place, the establishment of the system to be investigated is critical. For instance, the wind turbine in the Wind Energy sector would form a system, as illustrated in Table 6. Second, it entails the identification of critical subsystems or components, dependencies exhibited, for instance, by configuration characteristics (series, parallel, or hybrid).

Lastly, is the adoption of the methodology as described in Section 4, where model parameters are derived from empirical data and expert assessment. In this case, it will be prudent to establish aspects in the system under study, correlated to the advanced methodology. For instance, in the wind turbine case, factors to consider while deriving OEE performance measure, availability may be derived from the operational time, while performance represented by the power coefficient (related to power and wind speed), and the quality parameter by the power quality (related to voltage, amplitude and frequency of the power). The EMO opportunities could include a decline in wind speed and power demand in the utility.

6. Conclusion and future research

This research's first aim was to develop a modelling framework that considers maintenance policies (CM, PM, CBM, and OM) simultaneously for a repairable manufacturing system. The study integrated a block replacement policy under PM, while CM was extended from the traditional 'replacement' maintenance intervention, which assumes that a deteriorated component is replaced with a component/spare, in the as-good-as-new state. We introduce alternative maintenance interventions, which include 'replace', 'repair', 'adjust', and 'refit'. A CBM strategy is modelled, considering both online and periodic policies and further, we integrate both internal and external maintenance opportunities under an opportunistic maintenance policy. The model was employed to derive the added value of such a framework. The second aim of this study was to model close to real life, the stochastic system degradation, and distinctive abstraction details of maintenance policies. A Semi-Markov decision process and the arithmetic reduction of age models were employed to derive stochastic system degradation that considered the former state of a unit and the actual maintenance action undertaken. While evaluating the economic dependence, the framework not only included the grouped PM interval but also clustered PM and CBM interval was evaluated within the context of integrating various maintenance policies. The final objective of the study was to link and incorporate the impact of maintenance policies on product quality. In this regard, the study introduced the quality degradation rate that linked the CM policy (both replace and repair-maintenance actions) and PM policy to the product quality of the multi-unit system. In general, the maintenance model proposed in this paper can help the maintenance manager derive decision support by understanding the influence of taking advantage of opportunities during operational or maintenance stoppages. Furthermore, the proposed modelling framework supports decisions, for instance, understanding the influence of maintenance interventions on product quality, as aspects not well addressed in the literature.

Introduction and explicit modelling of CBM policy by incorporating various condition monitoring techniques like lubricant condition monitoring and thermography simultaneously, while considering both online and predetermined periodic condition monitoring application for most of the units in a system, offers an aspect for future study. Further extension of the model to incorporate maintenance cost as a performance measure while considering maintenance inventory management for component spare parts and lubricant (as a spare item), would offer more insights and assist the maintenance practitioners in cost-benefit analysis and eventual trade-off in selecting optimal strategies.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Appendix A. ISO 14224:2016 maintenance activities

Activity	Use	Activity	Use
Replace	C,P	Modify	C,P
Repair	C	Test	P
Adjust	C,P	Combination	C,P
Refit	C,P	Other	C,P
Service	P	Check	C
Overhaul	C,P	Inspection	P

Key: C: Corrective maintenance; P: Preventive maintenance

Appendix B. Sensitivity analysis for 'as-is' model using PM interval