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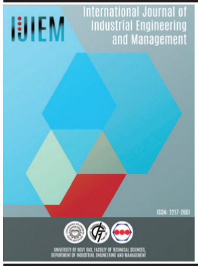

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Maintenance Performance Optimization for Critical Subsystems in Cement Pre-Grinding Section: A Case Study Approach

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ABSTRACT

This paper aims to develop a simulation-based framework to identify critical equipment, critical maintenance and operational factors (e.g., maintenance actions, spare sourcing lead times and fill rate) affecting plant performance (availability and maintenance cost). The study develops a framework that utilizes empirical maintenance data. Pareto analysis is employed to identify critical subsystems, while expert input is incorporated to derive model variables. A full factorial Design of Experiment (DOE) is employed to establish the variables with significant main and interaction effects on the plant availability and maintenance cost. The framework is applied to a real case study of a cement-manufacturing firm, where a simulation model is developed based on the empirical maintenance and operational data while considering the availability and maintenance cost as the performance measures. Simulation results highlight the bucket elevator as the critical subsystem. At the same time, spare parts importation probability, among other parameters like the preventive maintenance interval and utilization of adjust maintenance action, significantly affects the performance (availability and maintenance cost) as main and interaction effects. The research was applied to only one case study, in this case, a cement grinding plant. The study provides a pragmatic reference model framework to practitioners that enhances maintenance decision-making by identifying critical equipment, maintenance and operational parameters and disclosing their effect (main and interaction) on the plant performance (availability and maintenance cost). This study is one of the first to (i) investigate the maintenance and operational factors' main and interaction effects on maintenance cost and (ii) integrate the spare parts importation probability as a factor affecting plant performance. The developed framework assists in determining critical systems to be optimized, considers various maintenance strategies simultaneously, the stochasticity of spare parts availability and replenishment and ultimately discovers the interactions for decision support.

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1. Introduction

Today's cement manufacturing firms face unintended machine downtimes and high maintenance costs, landing to a struggle to sustain their market shares. The quality and output of grinding and milling operations greatly depend on the availability and reliability of the critical subsystems in these systems. The decline in availability and reliability is attributed by machine downtime and other aspects of operations like human error [1] and high spares lead times [2] among other factors, has been shown to significantly affect the productivity and profitability of such systems. Moreover, increased maintenance costs compared to other operational costs in many cement firms are experienced. On the other hand, the impact of machine downtime on plants' availability and

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maintenance cost has been researched over the years due to its criticality [1, 3, 4], resulting in huge losses due to penalties for undersupplies.

Many industrial facilities such as the company under study are faced by extended downtimes, leading to loss of productivity and eventually business reputation due to unmet demands [5]. Factors attributed to the protracted downtime include but not limited to the unplanned failures, the use of various maintenance actions, availability of spares and sourcing options which retain significant lead times.

Maintenance management is employed to address these challenges to increase equipment availability and other industrial performance measures like maintenance costs [6]. Hence, there is a necessity for manufacturing and support processes to have detailed maintenance planning to achieve high plant availability and reduced maintenance cost [7]. In circumstances where critical spares require importation due to their uniqueness in function, industries face high lead times challenges. Therefore, an efficient inventory management of spare parts for production machinery is essential and optimal strategies in procurement, stocking and supply play an important role [7].

The increasing demand for production and pressure for cost reduction in industrial set ups demands continuous maintenance improvement [8]. This involves the optimal use of available maintenance resources including staff, tools, machinery, and money. In many large scales, plant-based industries, maintenance costs can account for as much as 40 per cent of the operational budget [9]. The operational and maintenance related factors such as spares availability, preventive maintenance, maintenance actions have been shown to affect the maintenance cost of industrial plants. Various studies have been conducted on parameters' (corrective and preventive maintenance actions) main effect on availability [9], maintenance cost [10] and [11] on repair time.

However, there is limited evidence in the literature regarding the effects and interactions of these maintenance parameters on the maintenance costs. The reliance of main effects potentially offers a sub optimal decision support hence the need to incorporate the interactions. This is a novel area of research, and little is currently known regarding the effects of the parameters on maintenance cost. There have been no works published so far to the best of the author's knowledge that investigates the effects of operational and maintenance factors on maintenance costs.

While undertaking maintenance, Preventive (PM) and corrective maintenance (CM) inherently utilize spare parts, hence, a cost-effective solution is to consider spare parts and maintenance policies jointly. Different studies have shown the importance and influence of spare parts availability in maintenance cost optimization (e.g., [12], [13]). While considering the sourcing options and their effect on the maintenance costs, the probability of stochastic lead times due to extended sourcing lead times like importing has not received significant attention. Work in this area is extensive but is primarily concerned with the availability, while the effect of the stochastic nature of using either locally or imported spare parts remain unexplored in literature. To incorporate the stochasticity of spare parts sourcing, this study is the first to the author's knowledge to study the impact of the probability of importing spare parts with a view of deriving decision support on the effect of the same to maintenance cost and equipment availability.

In summary, a closer look to the literature, reveals several questions pointing to the research gaps and shortcomings. One of the first questions to arise is if there is a framework that can help the practitioners in establishing critical equipment, operational and maintenance related parameters and understand how they affect the plant performance. It will also be interesting to see whether the probability of spare parts importation has an effect on the plant performance, hence, the need to establish how and if the spare parts importation probability has main effects as well as interactive effects along the other parameters affecting the plant performance. Last but not least, it will also be interesting to see, whether maintenance and operational related parameters have effects on plant maintenance cost. These are questions which are currently unanswered, and hence explored here, deriving the study's original contributions as outlined in the following section.

The first contribution of this paper is to fill the literature gap by development of a framework that is derived from maintenance empirical data and experts' judgment. Downtime is the main criteria used in the selection of the critical subsystem after analysing maintenance and reliability degradation of subsystems in various cement plant sections like raw materials handling, material drying, cement storage facilities and packaging. Most studies in literature have considered multiple sections of a single manufacturing plant which may lead to simplified optimization. This study deals with a single section of the plant and offers a deeper dive into factors that affect maintenance performance. In this paper, five subsystems with failure and operational uniqueness are inter-linked to form a system. A case study approach adopted in this paper gives in-depth information on challenges derived from empirical data which can also have a similarity with other manufacturing plants with critical subsystems.

Secondly, the paper considers the stochasticity of spare parts availability among other maintenance parameters like CM and PM actions. These parameters especially spares import probability has been overlooked in many studies that attempt to optimize maintenance cost. In an event where spares are not readily available locally and there is high dependency on overseas manufacturers, the spares import probability become a critical factor and is addressed in this research. The effect of probability utilization of CM actions on availability and maintenance cost comes out clearly in this paper offering a significant decision support to engineering managers. Moreover, no previous study has demonstrated the use of the probability of importation with stochastic respective lead times as observed in the present study.

Lastly, this paper reveals the impact of interactions between various maintenance (PM and CM) and spare strategies on the performance measures, in this case the availability and maintenance cost. Majority of work in this area concerns itself with the main effects of the control variables on the response variables availability and maintenance cost, and as a result offer sub optimal decision support. To the best of our knowledge, our study constitutes the first analysis on the impact of interactions effect of the various maintenance variables on maintenance costs.

The subsequent section of this paper comprises of; section 2; review of relevant literature, section 3; outlined methodology of the research, section4; discussion of the results, section 5; the discussion of managerial implications of the study and finally is section 6 that provides conclusion and recommendations for future study.

2. Literature Review

Maintenance is defined as a function to keep a tool, machine or system in a working condition by proper usage, repairing broken repairable units, replacing components of subsystems to make the repairable items available for use whenever need arises [14]. The effective maintenance practices and strategies has the potential to reduce the risks of catastrophic failures, minimize maintenance costs, increase systems availability, increase productivity, and enhance reliability of the repairable items. Maintenance is a key cost driver in manufacturing industries and maximum effort need to be given in terms of research and development.

In the scope of maintenance, maintenance policies like corrective maintenance (CM) and preventive maintenance (PM) are considered critical to ensure asset performance and operations. Corrective Maintenance (CM) is defined by [15] as unscheduled repairs on reported failures of repairable subsystems or replacement of parts to restore the equipment to As Good as New (AGAN) state while PM was defined by [16] as the scheduled maintenance actions required to operate a system at its acceptable level of performance. Referring to [17], several CM actions has been discussed including repair, replace, inspect, clean and adjust. Various studies has integrated CM and PM in systems' maintenance optimization. For instance, [18], [19] and [20] integrated PM and CM maintenance strategies with lubricants condition monitoring to address the ageing degradation of a multi-unit system, [21] used the two policies in seeking their effects on equipment reliability using a probabilistic model. However, [16] cites disadvantages of CM as unplanned stoppages, spare parts challenges, high repair cost, high waiting, troubleshooting and maintenance times. While considering CM and PM policies, the use of spares while administrating these policies is significant, hence the need to consider joint maintenance and spares policies. Several studies reviewed in this field that employ PM and CM have been highlighted in Table 1.

Studies in literature have integrated the effects of spare parts to various maintenance performance measurements such as availability (e.g. [22]), maintenance time (e.g. [23]) and life cycle cost (e.g., [24]).

Table 1. Summary of reviewed PM and CM articles

Article	Objectives/Outcomes
[15]	To study current maintenance strategies and reliability of critical equipment
[16]	Maintenance strategies and their combined impact on manufacturing performance
[17]	Improving maintenance strategies to reduce the standstill time
[18], [19], [20]	Utilization of maintenance policies to address the degradation of critical subsystems
[21], [24]	To seek the effects of PM and CM strategies on equipment reliability

Other studies have investigated the effect of spare parts lead times on PM (e.g., [25], [26], [27]), effects of spare parts logistics on serviceability of repairable items [28]. These studies and others disregard the effect of stochastic lead times due to spares importation which directly affect the equipment performance.

The aspect of prioritizing the maintenance operations to most critical subsystems has been a factor of consideration by many authors. Criticality analysis help organizations to understand better the systems, subsystems and repairable items that are most essential to their operations. This fosters sound decision making on assets maintenance, project management and upgrade decisions. Recent studies has employed criticality analysis to rank subsystems in their order of maintenance priority, e.g., [29] used a criticality analysis process model to prioritize systems and components, [26] employed the analytic hierarchy process (AHP) to deduce the impact of subsystem failures on human health, risk priority number (RPN) was employed by [30] as key step in reliability centred maintenance (RCM) for conventional milling machine system. Other studies has used pareto analysis including [31], [32], [33] among others. However, the incorporation of experts' views and empirical maintenance data has been i dentified as a potential gap in the ranking of critical subsystems, which is a very underdeveloped area of research.

The over reliance of one-factor-at-a-time (OFAT) in many studies has been a challenge over the past years. The main disadvantage as cited by [34] is that it fails to consider the possible interactions between factors. Moreover, OFAT does not consider interactions and therefore cannot be used in optimization and this challenge can only be overcome by use of design of experiments (DOE) [32] added. Further, considering optimization studies in maintenance, it is becoming exceptionally challenging to overlook the interactive effects of variables that define the plant's performance measurements. To accomplish this, DOE and the Analysis of Variance (ANOVA) are employed to derive the main and interaction effects and establish if the various variable provide significance effect on the response (performance) variable respectively [35]. Work in this area is extensive but is primarily concerned with the main and interaction effects of maintenance related parameters on maintenance repair time and availability. On this subject, no known work seems to exist investigating the main and interactions effects of the parameters on maintenance cost.

3. Research Methodology & Data Analysis

The methodology employed in this paper consists of several steps including data collection, data pre-processing, data exploration, model parameters extraction and modelling. This section describes the mentioned steps in the following sub-sections. Figure 1 illustrates the mentioned methodological steps.

Five maintenance actions 'Adjust', 'Repair', "Replace,' 'Clean' and 'Inspect' actions form the correc-

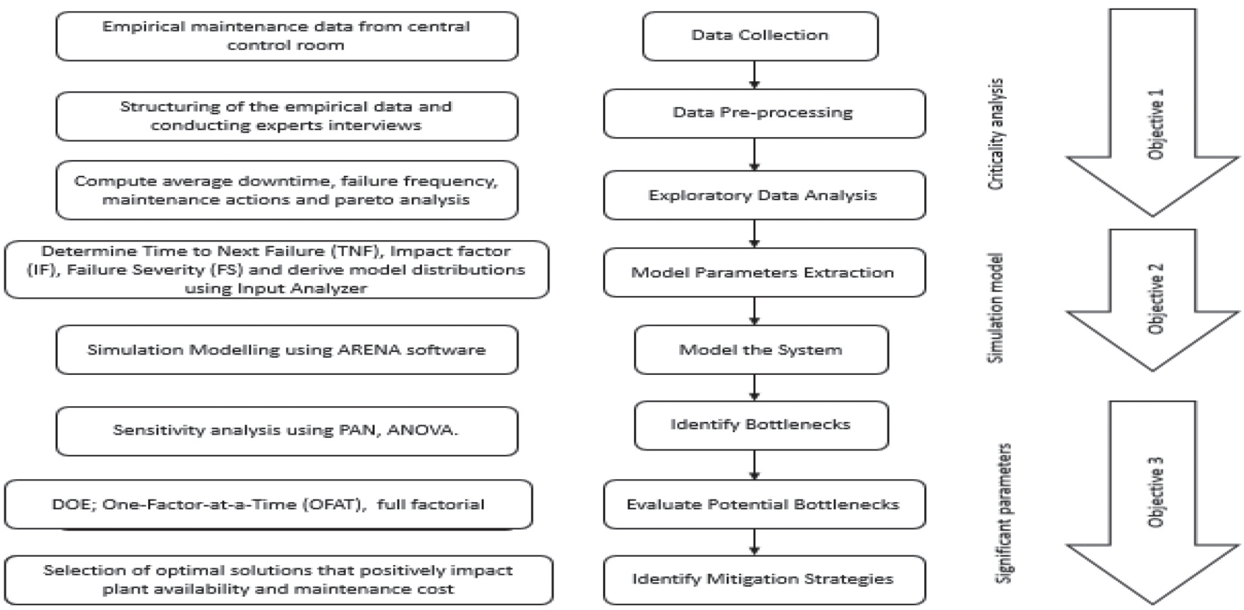

Figure 1. Methodological steps

tive maintenance, CM while the planned preventive maintenance, PM occurs after every 8760 hours of running (i.e., once annually). The failure of the critical subsystems in this section poses high risks in the organization including high maintenance costs, excessive labour utilization, low sales volumes and ultimately decreased profitability.

3.1 Data Collection & Pre-processing

The data collected in this study is the maintenance data captured in the central control room between 2015 and 2020, i.e., 6 years of operation equivalent to 52, 160 hours. The data comprises of the subsystem, stop, and start time, the section responsible for the downtime and the failure description. The data indicates the time when the mill was running and when it was down due to various reasons.

3.2 Exploratory Data Analysis

Data exploration was performed to inform various aspects of consideration in modelling. From data exploration, the system was broken down into 5 major subsystems as described in Table 2.

3.3 Model Parameters Extraction

Various model parameters were extracted for all the subsystems based on each failure characteristics. Table 3 illustrates a sample of model parameters from each subsystem after data exploration. TIF was the time when a subsystem initially failed in the first year of the study period. TNF is the time between failures and was represented by a random probability distribution.

All the repairable subsystems undergoes both PM and CM where CM involves various maintenance actions based on [20] and [37]. Under CM, five maintenance actions (R_i) were considered and modelled, Repair- R_1, Adjust- R_2, Clean- R_3, Inspect- R_4, and Replace- R_5. A 'repair' action refers to the actions taken to restore a repairable item into functional state. 'Adjust' action relates to tasks such as calibration, reset and shafts-motor alignment without necessarily stopping the machine. 'Clean' action includes removal of debris, unclogging of pipes and other parts of conveying components. 'Inspect' action refers to examination of a repairable item for conformity by measuring, observing, or testing relevant characteristics of a repairable item. The 'replace' action entails

Table 2. Subsystems and their descriptions

Subsystem	Purpose
Cyclones	This unit is primarily used to separate cement particles from the gas stream.
Recirculation fan	Provides the appropriate air volume to sweep the ground cement components from the mill to the separator, balance the material layer thickness inside the mil, control mill outlet temperature, maintain pressure difference in the mill and control the product fineness.
Roller Press	Used as a pre-grinding unit before the ball mill to reduce the particles size of the raw materials, i.e., clinker, gypsum and pozzolana.
Roller press Bucket elevator	Chain bucket elevator is used to convey the product of the roller press from a low level to an elevated level where separation occurs. It is essential in transportation of materials with high density and strong abrasiveness, and relatively hot as in this case study.
Separator	The function of the separator is to separate the fine-sized cement particles from the coarse-sized to avoid material condensation and overgrinding in the mill and improve the mill grinding efficiency.

Table 3. Subsystems time characteristics

Subsystem	Time to Initial Failure (TIF) (Hrs.)	Time to Next Failure (TNF) (Hrs.)
Cyclones	7632	9.64e+003 + 7.9e+003 * BETA (0.164, 0.141)
Recirculation fan	1512	NORM (3.03e+003, 2.2e+003)
Roller Press	168	GAMM (1.24e+003, 0.507)
Roller press Bucket elevator	1924	WEIB (354, 0.501)
Separator	3360	EXPO(2.89e+003)

getting rid of an old item and installing a new one. In this case, the machine is restored to As Good as New (AGAN) state. Table 4 below provides a summary of mean time to repair (MTTR) for different subsystems derived from empirical data.

Table 5 below shows various maintenance actions and utilization, MTTR and failure frequencies.

Figure 2 shows a Pareto chart obtained from data driven criticality analysis aimed at identifying the critical subsystems for consideration while modelling the system. Roller press and Bucket elevator constitutes 90% of total downtime and the other three constitutes 10%. The researcher decided to model all the subsystems to identify basis of further study.

From figure 4, the subsystems (E_n) included Cyclones (E_1), Recirculation fan (E_2), Roller press (E_3), Bucket elevator (E_4) and Separator (E_5).

3.4 System Modelling

3.4.1 Notations

Throughout this paper, the notations in table 6 are adopted.

Figure 3 is a schematic representation of model conceptual framework that mimics the real system in terms of running and maintenance.

To model the subsystems' availability and reliability degradation, the approach of [29] is adopted where impact factor (IF), with values of 0 to 1 and failure severity (FS) is introduced. IF in this case is a variable that impacts the life of the subsystem based on the maintenance action carried out. FS follows a Semi-Markov decision process (SMDP), influenced by the last maintenance action carried out on a subsystem.

Table 4. Related random maintenance action delay time in hours

Subsystem	R_1	R_2	R_3	R_4	R_5
E_1			2.04 + EXPO (0.525)		
E_2	GAMM (1.39, 3.95)	1 + EXPO (4.03)	UNIF (0.12, 6.72)	2.35 + WEIB (2.52, 1.98)	2.13 + 4.41 * BETA (0.936, 1.05)
E_3	1 + 20 * BETA (0.554, 1.12)	24 * BETA (0.524, 2.97)	1 + WEIB (2.75, 1.12)	1.02 + 5.71 * BETA (1.73, 1.31)	4 + 11 * BETA (0.486, 0.524)
E_4	5 * BETA (0.497, 0.499)	WEIB (3.46, 1.34)	1 + WEIB (2.72, 0.833)	1 + WEIB (3.57, 0.809)	UNIF (2, 24)
E_5	5 * BETA (0.497, 0.499)	8.92 * BETA (0.643, 1.28)	1 + WEIB (2.89, 1.96)	UNIF (2, 5)	2 + 8 * BETA (0.807, 0.765)

Table 5. Maintenance actions MTTR, failure frequencies and percentage utilization

Maintenance Action	MTTR (Hrs.)	Failure Frequency	% Utilization
Repair	7.19	69	34
Adjust	3.69	67	33
Clean	3.52	28	14
Inspect	5.09	18	9
Replace	12.79	22	11

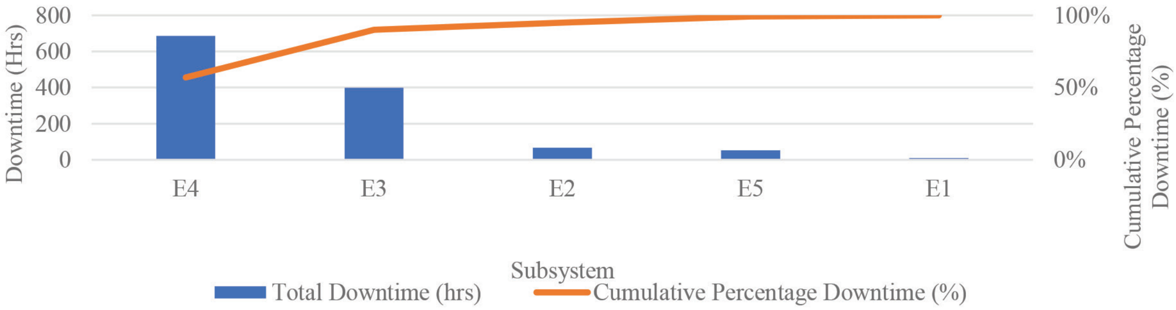

Figure 2. Pareto Analysis Chart reflecting the effect of downtime to subsystems

Table 6. Notations

Response Variables	Description
A_M	Mill Availability
C_{TM}	Total Maintenance Cost (KES)
Model Parameters	Description
R_i	Maintenance Actions; i = {1,2,3,4,5}
η_{ri}	Maintenance Actions Utilization (%)
f	Fill rate
ρ_i	Import Probability
T_{PM}	PM Interval
E_n	n^{th} subsystem
n	Number of subsystems; n = {1,2,3,4,5}
i	Number of maintenance actions; i= {1,2,3,4,5,6}
FS_j	Failure Severity for j^{th} level
j	Severity level; j = {1,2,3,4}

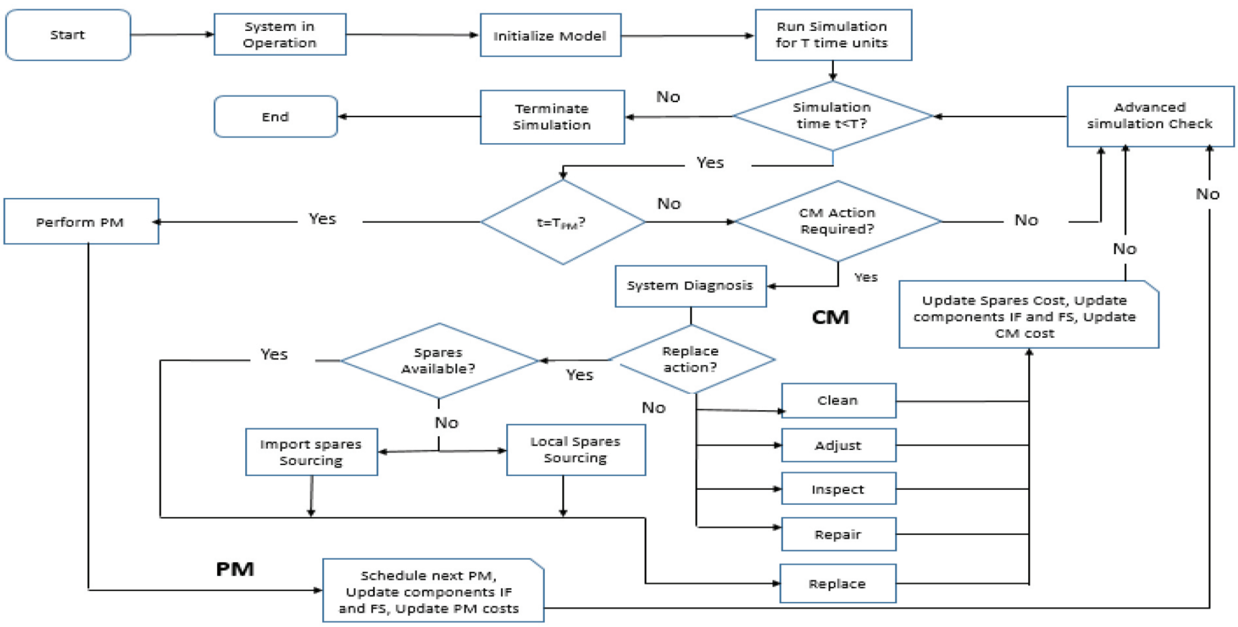

Figure 3. Conceptual framework of the pre-grinding system model

3.5 Performance Measures

Two performance measurements; Availability (A_M) and Total maintenance cost (C_{TM}) were derived from the simulation-based model as illustrated in equations (1) and (2) respectively. The availability of the pre-grinding system is a percentage of grinding hours and both grinding hours and downtime. Downtime is a contribution of PM, CM actions and time spent while sourcing spares. The Total maintenance cost is a combination of both spares and labour costs.

$$A_M = \frac{\text{Grinding Hours}}{\text{Grinding Hours+Downtime}} * 100 \quad (1)$$

$$C_{TM} = \frac{\text{Labor Cost (PM+CM)+Spares Cost(PM+CM)}}{\text{No.of years}} \quad (2)$$

3.6 Simulation Model

PM and CM maintenance strategies were integrated in one model to derive the performance measurements explained in 3.5 above. The simulation model involves a collection of methods and applications to mimic the real pre-grinding system and ARENA simulation software was used to integrate various inputs from empirical data.

4. Results

The model was set to run for 52,160 hours, equivalent to 6 years of production period. While running the model at 10 replications, the availability Am half width was ±7 while the desired half width was ±2. To achieve the desired half width, the following formula (3) was used, and the model was run at 120 replications {equation (4)}.

$$n = \frac{n_O * h_O^2}{h^2} \tag{3}$$

Where n is the number of the desired replications, n_o is the number of current replications, h_o is the current half width and h^2 is the desired half width.

$$n = \frac{10*7^2}{2^2} = 120 \text{ replications} \tag{4}$$

4.1 Model Results

As shown in table 7, availability of 79.3% and total maintenance cost of KES 24489K was generated from the simulation model. Expected mill availability and total maintenance cost from empirical data was 82% and KES 25640K respectively. The results validate the model with acceptable range of±10% [36].

Table 7. Comparison of simulation results

Scenario	A_M (%)	C_{TM} (1000 KES)
'As is"	79.3	24489
Empirical	82	25640

The impact of PM interval was evaluated by varying the intervals from 4380 hours to 13140 hours. From Figure 4, it is illustrated that as PM interval increases, C_{TM} increases with decrease in A_M. CM actions are mostly utilized that are more expensive and the activities of CM results to high downtime thus reducing the subsystems availability. The vertical dotted line is the reference point for T_{PM} from empirical data. C_{TM} increases from KES 12 million to KES 46 million while A_M decreases by 32.57% from 90.49% to 57.92%.

From figure 5, η_{r1} was varied from 24% to 44%. The impact of this variation reduced the C_{TM} by KES 5 million from KES 27 million to KES 22 million. The mill availability, A_M was slightly affected as it dropped by 1% from 79.6% to 78.6%. The marginal decrease of system reliability was attributed by initiative-taking response to breakdowns by the maintenance teams because the PM interval is not yet reached. With reduced MTTR and lack of waiting time for spares in terms of lead times, AM was not significantly affected, and this confirms that the reliance of spares importation can impact the downtime due to high lead times as in this case study.

The effect of varying the import probability, ρ_i was evaluated by varying ρ_i from 0% to 20% as shown in Figure 6. The vertical dotted line represents the import probability utilization from the empirical data, at 10%.

4.2 Full Factorial Effects and Interactions Experiment Results

To investigate the influence of effects and interactions of the various responses under research, OFAT, 2-factor full factorial and analysis of Variances (ANOVA) was conducted. Table 8 shows the variables ranges used in the experiments.

4.2.1 Main Effects Results

An analysis was conducted to evaluate the main effects of independent variables on the main perfor-

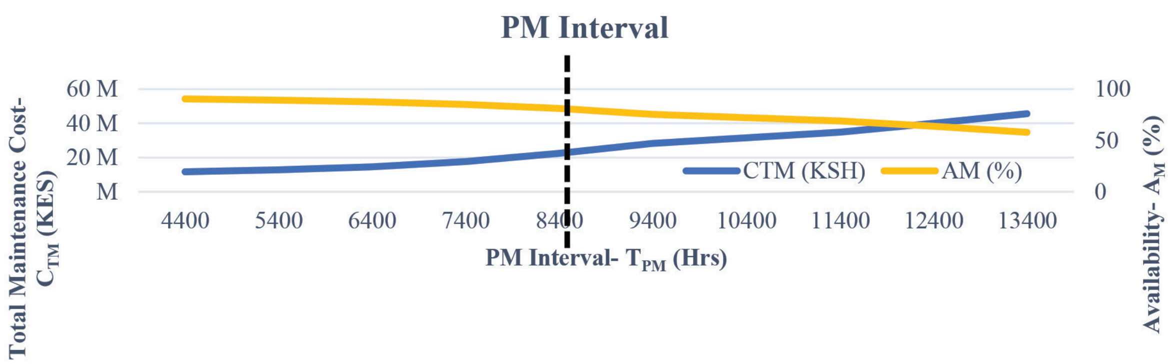

Figure 4. The effect on mill subsystems performance by varying T_{PM}

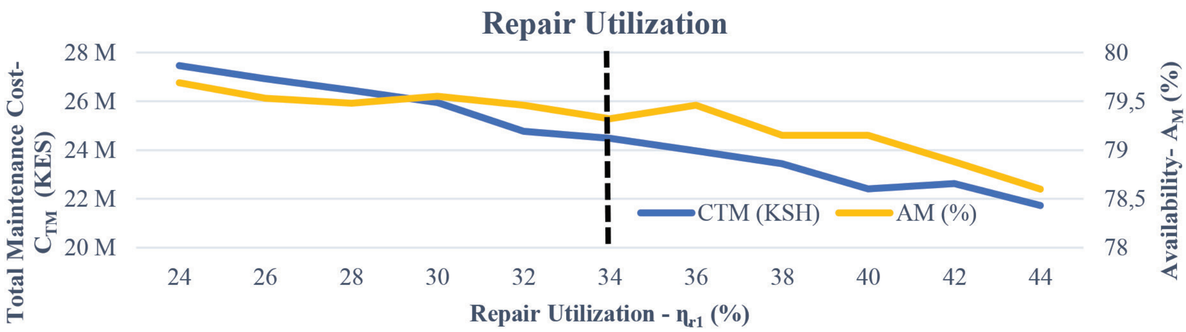

Figure 5. The effect on mill subsystems performance by varying utilization of repair action (η_{r1})

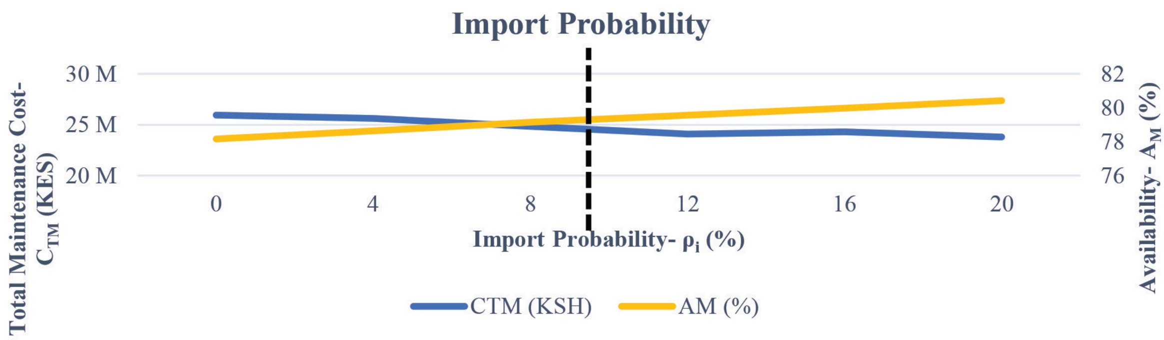

Figure 6. The effect on mill subsystems performance by varying import probability (ρ_i)

Table 8. Variable ranges as used in experiments

Control Variables	Model Value	Ranges	
		Min	Max
Pm Interval (Hrs.)	8760	4380	13140
Fill rate (%)	70	49	91
Import Probability (%)	10	0	20
Repair Utilization (%)	34	25.5	42.5
Adjust Utilization (%)	33	25	42
Clean Utilization (%)	14	10.5	17.5
Replace Utilization (%)	11	8.25	13.75

mance measures. As shown in table 9, T_{PM} reduced the system A_M by 32.09% when PM interval was varied from 4380 hrs. to 13140 hrs. This is because when T_{PM} is prolonged, corrective maintenance becomes the major maintenance strategy to be utilized, which is expensive and leads to high downtime, therefore, C_{TM} increases by KES 33,057K because of increased C_{TM} actions. The adjust utilization, η_{r2} reduces C_{TM} by KES 5,065.8K since no spares are needed in adjustment and A_M is slightly affected as adjustment is done on-run. By holding more spares, the fill rate, f increases cost by KES 1,240K but slightly affects A_M. η_{r3} reduces maintenance cost because the maintenance actions do not require spares. However, increasing ρ_i increases A_M by 2.49% simply because spares are available for replacement.

Table 9. Main effects sizes of the control variables

Control Variables	Main Effect Sizes on Performance Measures	
	A_M (%)	C_{TM} (KES)
T_{PM}	-32.09	33,057.1 K
η_{r2}	-1.06	-5,065.8 K
f	-1.72	1,240.0 K
η_{r3}	-0.13	-1,437.6 K
ρ_i	2.49	-1,769.2 K
η_{r1}	-1.11	-5,797.5 K
η_{r5}	0.12	1,986.2 K

4.2.2 Interaction Effects Results

Referring to table 10, T_{PM} has the interactions with major effects on both performance measures A_M and C_{TM}. For instance, interaction between T_{PM} and η_{r2} and T_{PM} and η_{r1} has major saving in C_{TM}. This is because both η_{r1} and η_{r2} do not incur spares cost. T_{PM} alone had a major increase in cost. This is because any time the system goes through PM, labor cost increases due to demand of high skilled personnel to do the replacements as well as expensive spares.

The interactions with >95% confidence interval was considered. T_{PM} + η_{r2} and T_{PM} + η_{r1} had major effect on both A_M and C_{TM} . $T_{PM} + f$, and $T_{PM} + \rho_i$ had effect on A_M only while T_{PM} + η_{r5} had effect on C_{TM} only. PM interval twice a year that equates to minimal utilization of repairs and adjustments in between the PM intervals and maximum utilization of spares import probability results to positive gain in both performance measures.

5. Discussion

The initial results of the model analysis provide several significant aspects to the practitioners and academia. In the first place, the model provides a pragmatic reference model practitioners can use to identify critical subsystems and parameters. The identification of the bucket elevator and the roller press as critical shows the subsystems require more focus in terms of maintenance activities to improve the mill performance. This model is unique as it provides for stochasticity of the system, an aspect important while mimicking real life system operations and analysis.

While considering the effect of PM Interval as shown in Figure 6, the analysis intimated that an increase in the PM interval significantly increased the C_{TM} while there was a decrease in A_M. An extended PM interval means a reduced frequency of undertaking Preventive maintenance. This directly affects the reliability of the different parts maintained due to the reduced renewal effect. The reduced PM action means extended usage of parts before replacement. This has two cardinal effects, firstly, the use of corrective maintenance in increased in this case and secondly, increased failure is expected. These two issues inherently lead to increased downtime which causes the reduction of availability while increased corrective maintenance actions which are inherently time and cost-intensive eventually lead to high maintenance costs. This same phenomenon is seen while

Table 10. Interactions effects sizes and P-Values of control variables using Full Factorial and ANOVA

Control Variables	Interaction Effect Sizes		P-Value	
	A_M (%)	C_{TM} (KES)	A_M	C_{TM}
$T_{PM} + \eta_{r2}$	-0.83	-3,742.9 K	0.042	0.000
$T_{PM} + f$	-1.30	1,086.0 K	0.001	0.270
$T_{PM} + \eta_{r3}$	-0.06	-1,091.0 K	0.888	0.267
$T_{PM} + \rho_i$	1.89	-1,547.5 K	0.000	0.112
$T_{PM} + \eta_{r1}$	-0.83	-4,304.5 K	0.043	0.000
$T_{PM} + \eta_{r5}$	0.12	1,517.8 K	0.605	0.039
$\eta_{r2} + f$	0.22	-293.3 K	0.938	0.925
$\eta_{r2} + \eta_{r3}$	0.05	-23.8 K	0.979	0.945
$\eta_{r2} + \rho_i$	-0.12	718.1 K	0.966	0.817
$\eta_{r2} + \eta_{r1}$	-0.15	-311.2 K	0.951	0.862
$\eta_{r2} + \eta_{r5}$	0.01	-128.9 K	0.973	0.913
$f + \eta_{r3}$	0.05	-23.8 K	0.986	0.994
$f + \rho_i$	-1.46	820.0 K	0.616	0.793
$f + \eta_{r1}$	0.23	-189.6 K	0.950	0.945
$f + \eta_{r5}$	-0.24	-228.9 K	0.954	0.889
$\eta_{r3} + \rho_i$	-0.08	355.3 K	0.979	0.910
$\eta_{r3} + \eta_{r1}$	0.11	404.9 K	0.969	0.923
$\eta_{r3} + \eta_{r5}$	-0.01	-589.9 K	0.970	0.998
$\rho_i + \eta_{r1}$	-0.16	907.6 K	0.978	0.798
$\rho_i + \eta_{r5}$	0.06	-741.3 K	0.927	0.957
$\eta_{r1} + \eta_{r5}$	-0.01	-55.6 K	0.991	0.934

investigating the effect of Repair Utilization illustrated in Figure 7. The results showed that an increase in the utilization of the repair maintenance action significantly increased the C_{TM} while there was a marginal decrease in A_M.

While investigating the effect of spare parts Importation probability on the plant performance, Figure 8 shows the results while varying ρ_i. The plant availability, A_M increases from 78.2% to 80.4%, the latter resulting from maximum ρ_i utilization. A_M is increased if spares importation is maximized since the replaceable items are customized to fit the purpose and this ensures spares availability during downtime. Perhaps the most significant finding is that the dependence on local spare sourcing, especially when the installed system is of a special category like the system under study, retains protracted lead times. This intriguing result is because of the requirement by the local suppliers to customize the spares compared to original equipment manufacturers who retain system knowledge and capacity to manufacture spares within considerable lead times. For the system under study, spare importation is advantageous in both cost and lead times, hence the maintenance cost reduction, C_{TM} by KES 2 million. These findings cannot be extrapolated to all types of industrial plants as it is important to bear in mind the type of spare parts and the possible localized solutions required. For spare parts that retain such characteristics, it will be important for the practitioners to consider the importation probability as it significantly improves plant performance.

While reviewing the second phase where main and interaction effects are determined, the results doubtlessly, despite dependent on the case study characteristics, has some reliable conclusions. The parameters with significant main effects included T_{PM}, ρ_i, η_{r1}; η_{r2} and f as shown in Table 8. However, while considering the interaction effects, the effect sizes significantly change, laying the emphasis of the need to explore factor effects concurrently. Significant interaction effects are discovered between various parameters like T_{PM} and ρ_i, T_{PM} and η_{r1}, T_{PM} and η_{r2}, and T_{PM} and f (See Table 10). It is worth noting that the interactions provide important insights on parameters that when considered separately would provide improved performance but when interactively considered the perceived improvement is reduced. However, on the other hand several interactions show an improved performance of the grinding mill. These results emphasize that practitioners and analysts must explore factor effects concurrently to understand how their simulation model behaves when its factors are changed. Despite the use of p-values, information about the size of an effect and its possible error must be allowed to interact with expert knowledge. Taken collectively, these results suggest it is essential to optimize variables jointly since the decision variables or controls can interact with each other and yield a sub-optimal solution.

As for the managerial implications. this study incorporated two maintenance policies, CM and PM and four maintenance actions, repair, replace, clean, and adjust. Spares availability as well as import probability was also considered to identify their implications in maintenance performance of the cement grinding system. From the exploratory study, PM was conducted once a year while fill rate and spares importation was not put into consideration. Maintenance actions were selected based on technicians' judgement during CM. In this study, all the mentioned factors were evaluated in simulation-based model and deductions made. The approach in this study has portrayed a great benefit of implementation of stochastic utilization of various maintenance actions during CM and validated the best PM interval, scientifically evaluated instead of the old Ad Hoc maintenance approach employed by many manufacturing plants.

The impact of spares sourcing, lead times and fill rate has been identified as factors that directly affect the overall performance of maintenance performance in manufacturing industries and therefore cannot be ignored. The Ad hoc maintenance practices may not give the best outcome of plants' performance and therefore the model proposed in this study can help the maintenance manager to make the best decision. The linkage of both CM and PM strategies while considering the impact of spares sourcing, lead times and fill rate offer sound decision support to engineering and production functions and are aspects not well addressed in literature. Our results, concurring with [37], emphasize the importance of incorporating these parameters into routine maintenance planning practices.

In addition, the study has brought out clearly a need to consider interactions between maintenance policies and maintenance actions to determine which combination improves system reliability and availability whilst reducing maintenance cost at the same time without compromising on the profitability of the business. The application of full factorial and ANOVA experiments in the study has given better understanding unlike reliance of main effects alone. Relying on main effects only as has been a norm in Ad Hoc maintenance policies may not offer a workable solution to emerging problems in manufacturing industries.

It is important for the engineering managers to apply more scientific approaches while evaluating the best maintenance strategies to solve complex maintenance challenges and to holistically evaluate different maintenance options before engaging the repairable items to maintenance actions. This study has shown that having PM schedule at least twice a year and utilizing the 'repair' and 'adjust' maintenance actions between the PM interval will result to high plant availability and reliability due to minimal downtime and prolonged life of the repairable items and cut maintenance cost to almost a half. This method has a lot of potential to be used in various scientific fields. The findings from this study can be applied in all manufacturing industries that has repairable items and therefore it is not limited to cement manufacturing firms.

6. Conclusion

The main goal of the present study was to develop a framework that commences with empirical data, whose first aim was to derive the critical equipment. The second aim was integrating spare parts importation probability in the framework as a factor and investigate its impact on the plant performance. Lastly, the study aimed to develop and undertake the main and interactional effects of various operational and maintenance related parameters on the availability and maintenance cost of the plant.

The investigation of the critical equipment in the plant has shown that the bucket elevator and roller press were the critical equipment in the cement plant section under study. Moreover, the use of repair and adjust maintenance actions were the most utilized in the maintenance of the plant section. On the other hand, the relevance of the spare parts importation probability is clearly supported by the current findings which show that it significantly affects the plant performance (availability and maintenance cost). The third major finding of this study was that the PM interval, spare parts importation probability, filrate, adjust maintenance action utilization were found to have significant effects on the plant performance.

The analysis results while evaluating the model, conceivably support the hypothesis that interactions of the variables play a role in influencing the performance measures. Taken together, these findings suggest a role for the spare parts importation probability along with other maintenance related parameters and strategies in affecting the plant performance. These findings have significant implications for the understanding of how the various operational and maintenance related parameters affect the plant performance, in this case availability and maintenance cost. Hence, if enhanced, would greatly improve the maintenance strategies, spare parts provisioning strategies and ultimately improve the plant availability and reduce the maintenance cost. This combination of findings provides some support for the conceptual premise that while carrying out maintenance optimization, a balance of decision variables used, need to be struck by considering their effects, interactions and expert knowledge. The research lays a groundwork for future studies into other maintenance strategies with their possible interactions towards an in-depth optimization model.

The research lays a groundwork for future studies into other maintenance strategies with their possible interactions towards an in- depth optimization model. Moreover, simulation-based experiments and optimization on real cement plant data verify the validity and robustness. This study was limited to using one case study of the cement plant, however, despite of its limitation, the study certainly adds to our understanding of the influence of the aforementioned parameters to the industrial plant's performance. Further investigation and experimentation into other maintenance policies like opportunistic maintenance, condition-based monitoring is strongly recommended. Moreover, further research in other parameters like workforce utilization as well as lead times to evaluate their effect on maintenance cost and availability, is therefore, an essential next step in research.

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