A simulation-based optimization approach evaluating maintenance and spare parts demand interaction effects.

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Abstract

Industrial facilities frequently experience significant production losses due to unanticipated failures, sub-optimal maintenance, operational and spare parts logistics challenges. These among other factors directly affect the plant's performance measures such as availability, repair time and costs. Consequently, optimization addresses such challenges. However, a fundamental problem presented here relates to the need for a framework that assists in the determination of critical system to be optimized, variables that significantly impact the performance of such systems, and subsequently undertake optimization. To realistically model such complexities, a framework that applies the discrete simulation model of critical repairable subsystems, undergoing deterioration is proposed. The study utilises empirical maintenance data, where 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 total repair time and subsequently employed as decision variables for a simulation-based optimization. The proposed framework is demonstrated in a case study of a thermal power plant. Simulation results highlight the turbocharger as the critical subsystem, while spares availability, the time between overhaul (TBO) and reliance on different maintenance strategies exhibit most significant main and interaction effects. The optimization results obtained demonstrate that TBO, spares availability and reliance on various maintenance strategies, provide a significant impact on the reduction of the repair time. The framework enhances maintenance decision making by optimising the plants' operational and maintenance related factors identified.

Keywords: Simulation, maintenance, availability, Semi-Markov process, spare parts availability, diagnosis time.

1. Introduction

1.1. Background

It is essential industrial facilities such as power plants can supply electric power to the population consistently without interruptions. This requirement is amplified when a plant supporting critical installations, such as in the health and security sectors, where an interruption, could lead to significant risks along with both social and economic losses. Moreover, most facilities supplying utility grids maintain contracts specifying hefty penalties in the event of deviation from the supply agreement, which makes it imperative for such power plants to address factors likely to cause interruption of power production and supply. Besides natural disasters and short-supply of consumables like fuel, downtime retains a pivotal role in contributing to power production interruption. A growing body of literature recognizes the significant role of maintenance-related downtime, contributing to power plant downtime and subsequently, reduced profitability (Alabdulkarim et al., 2011; Bouslah et al., 2018). It follows that addressing maintenance-related downtime will considerably reduce power generation interruptions, Operational and Maintenance (O&M) cost. A survey carried out by Jardine and Tsang (2013) reports that maintenance budgets on average are 20.8% of the total plant operating budget. Integrating such measures would ultimately drive the facility towards achieving the expected plant economics due to savings in maintenance and operational costs. Optimal maintenance leads to maximized efficiency and productivity as well as reduced waste in both equipment and personnel usage, which leads to the significance of joint optimization modelling of maintenance, inventory, and manpower also suggested by Van Horenbeek et al. (2013).

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Distinct from maintenance strategies optimization, operational and other aspects such as inventory management, manpower planning, procedures and outsourced maintenance, likewise require to be optimized to ensure successful plant operations. While addressing these aspects, consideration of maintenance quality is vital, because it is influenced by various aspects, while it impacts the equipment reliability and consequently reduced productivity.

1.2. Notations

Throughout this paper, the following notations are adopted.

Decision variables	
A_o	Engine operational availability
T_r	Total repair time (hrs. per year)
Model parameters	
i	Number of maintenance actions
n	Subsystems modelled $n = \{1,2,3,4,5\}$
FS_j	Failure severity for j^{th} severity level
λ_n	Random time to next failure for n^{th}subsystem
T_{d_i}	Random diagnosis time for i^{th} maintenance action (hrs.)
T_{d_n}	Total diagnosis time for n^{th} subsystem (hrs.)
T_{l_n}	Total lead-time for n^{th} subsystem (hrs.)
O_c	Number of Outsourced contractors
t	Simulation time (hrs.)
t_{st_n}	Initial time to failure for n^{th} subsystem
j	Severity levels as per ISO 14224:2016; $j = \{1,2,3,4\}$
ρ_i	Impact factor for i^{th} maintenance action
I	Engine operating time /Running hours
γ, β, η	Location, scale and shape parameters for WEIB (λ_n)
f	Spares availability or spares fill-rate
R_i	Maintenance actions (i ; $i = \{1,2,3,4,5\}$)
T_{r_n}	Total repair time for n^{th} subsystem (hrs.)
T_{r_i}	Random repair time for i^{th} maintenance action
t_{bo}	Time between overhauls(TBO)
t_n	Simulation time (years)
M_{tech}	Mechanical technicians
DT	Downtime (hrs.)

1.3. Study aim and motivation for the research

Power plant system reliability represents an essential factor in the success of a power generation project. A decline in reliability due to critical equipment downtime directly affects both, the availability to generate power and consequently its profitability. Increased downtime can be attributed to several reasons influencing O&M aspects such as increased failure frequency, protracted lead times in sourcing critical spares, imperfect maintenance, human errors in diagnosis and maintenance, and lack of enough maintenance personnel. These factors demonstrate a significant impact on the installation's economics, tactical and strategic planning. The factors above, both individually as well as interactively affect maintenance, where optimizing them would improve the availability of a given power plant and reduce repair and subsequent maintenance time, hence improving the economics and performance of the plant. Moreover, in the plants that retain maintenance records, deriving maintenance optimisation programs utilizing knowledge embedded in this data is not straightforward. The primary challenge faced by many practitioners is the establishment and selection of significant optimization variables affecting equipment performance, from the empirical data, and further implementing an optimization of the variables. The challenge of undertaking maintenance optimization based on significant decision variables derived from empirical data, with the objective of offering maintenance decision support, presents the motivation to this study.

This study proposes a discrete event simulation (DES) model framework that considers the utilization of empirical maintenance data to derive critical subsystems, modelling parameters, and variables. We model a repairable system, whose deterioration is assumed to follow a Semi-Markov Decision Process (SMDP). Design of Experiment (DOE) approach is utilized to quantify the effects and interactions of the variables on equipment availability and total repair time. Markedly, optimization is performed applying the identified significant variables, with an objective of minimizing the total repair time. DES is utilized due to its robustness in dealing with complex, highly variable and uncertain events as a decision support tool also corroborated by (Alrabghi and Tiwari, 2015).

The remaining part of the paper proceeds as follows: Section 2 presents a brief literature review of relevant studies, while Section 3 describes the methodology used for this study. Section 4 presents the results, with a brief evaluation, whereas a summary discussion is presented in Section 5. Finally, Section 6 contains concluding remarks and the proposed future work.

2. Relevant Literature review

The British Standards Institute defines maintenance as, "a combination of all technical, administrative and managerial actions during the life cycle of an item destined to preserve it in or restore it to, a state in which it can fulfil the required function" (EN13306, 2010). This definition enlarges the sphere of maintenance, to cover various tasks encompassed in Corrective Maintenance (CM) and Preventive Maintenance (PM) that incorporate administrative and managerial actions, such as manpower management, spares sourcing and logistics. System reliability, influenced by deterioration, and maintenance strategies performed owing to equipment failure, are critical factors to the realization of a plant's objectives, and overcoming various operational challenges (Jardine and Tsang, 2013). Stochastic models such as Markov models (MM) have proven more robust, in modelling deterioration and failure of equipment owing to their probabilistic nature (Nguyen et al., 2013). Semi-Markov Decision Process (SMDP), contrary to MM which is memoryless, calls for the memory of the process to be renewed each time it attains a state (Dehayem Nodem et al., 2011). Other Markov models, such as time-based Markov models are limited to dealing with time as a deterioration factor. Both the prior severity and the particular maintenance action carried out regarding its quality and harshness, can influence the deterioration of various equipment. An age reduction coefficient can be used to represent the actual influence of maintenance and deterioration on the equipment, (e.g., Duan et al., 2018), or a hazard rate adjustment factor (e.g., Xia and Xi, 2013). To abate the impact of deterioration on equipment, inspections, CM, PM and Overhaul actions are carried out (Bouslah et al., 2018; Rivera-Gómez et al., 2016). However, due to diverse factors, some organizations outsource these maintenance actions, either, to focus on their competencies, or due to technological advances or lack of the required competencies (de Almeida et al., 2015). In an assessment of PM contract maintenance, Wu (2012) proposes two types of outsourcing, where type I, both CM and PM are outsourced and type II, only CM is outsourced.

Another significant aspect of maintenance is the often utilization of spares in both PM and CM actions hence the importance of joint or integrated maintenance and spare policies optimization. Integrated studies considering joint optimization of maintenance strategies and spares/inventory policies, predominantly have focused on specific aspects, such as, evaluating optimal PM optimization (e.g., Lei et al., 2010), optimal production plan (e.g., Ba et al., 2016), optimal inventory holding (e.g., Cai et al., 2017), optimal maintenance policy (e.g., Nguyen et al., 2014). Nevertheless, some studies address diverse aspects, for instance, Rezg et al. (2005), presented integrated modelling and optimization for a randomly failing production unit. Similarly, Lei et al. (2010) presented a modularized Stochastic Timed Petri-Nets (STPNs) model, for system level PM optimization and dynamic maintenance decision making. Gharbi and Kenné (2005) advanced simulation and experimental design to determine the optimal control policies and values of input factors while minimizing total cost of inventory, repair, and PM. Zohrul Kabir and Farrash (1996), presented a simulation model seeking for a joint determination of optimal age replacement and spare part provisioning policy, while Sarker and Haque (2000), developed a simulation model for a system operating with block replacement and continuous review inventory policy. However, much of the research addressing PM (e.g., Roux et al., 2008; Van Horenbeek and Pintelon, 2013), disregard the effect of CM-related failure on the system, which undoubtedly impacts on the equipment reliability, hence affects PM actions and outcome. Moreover, failures addressed using CM, are considered to incorporate spare replacement and following two states "as good as new" (AGAN) and "as bad as old" (ABAO), (e.g., Dijoux et al., 2016; Rivera-Gómez et al., 2016), which does not offer a comprehensive representation of CM actions that may have repairs with or without spare replacement, with random reliability outcome.

Another significant challenge found in considerable studies is the employment of one-factor-at-a-time (OFAT) analysis while analyzing the impact of various factors on the plant performance measures as previously indicated. Subsequently, these results are applied in maintenance decision support, while disregarding their interactive characteristics. As Antony et al. (2003) alludes, despite its popularity, ease of use and precision on the effect of one variable, OFAT offers less precise estimates, it does not consider interrelationships (i.e. interactions) and cannot be used in optimization, challenges overcome by the design of experiments (DOE) technique. Similarly, Bouslah et al. (2018) suggest the interaction effects play an essential role to obtain an optimal trade-off solution while considering an integrated control policy. While considering previous optimization studies in maintenance, it is becoming exceptionally challenging to overlook the interactive effects of various O&M aspects, on the plant's performance.

As regards evaluating the plant's performance, several factors, for instance, repair time taken, availability of manpower resources and logistical challenges involved in spare sourcing, and others, adversely affect the plant's availability (Nguyen et al., 2013). Due to the complex dynamic characteristics of these variables and their interrelationship, the use of classical analytical models in optimization is unsustainable. Hence, the use of simulation techniques, an approach which is also corroborated by various studies (Alrabghi and Tiwari, 2016; Nowakowski and Werbińka, 2009; Rezg et al., 2005), while, Sharma et al. (2011) accentuate that the use of simulation in maintenance optimization has been increasing steadily. Several studies reviewed in this field employing simulation are highlighted in Table 1.

Article	Variables investigated /affecting performance
Li et al. (2013)	Manpower planning
Alabdulkarim et al. (2011)	Manpower availability, equipment usage, spares fill rate. Accurate fault diagnosis
Savsar (2015)	Maintenance policies - age-based (ABP) and block based (BBP)
de Smidt-Destombes et al. (2007)	Maintenance interval, the spare part inventory level and the repair capacity
Scarf and Cavalcante (2012),	Maintenance quality (inspection induced defects, quality of PM and replaced component)
Duan et al. (2018)	Maintenance quality
Bouslah et al. (2018)	Maintenance, quality, and Production-inventory policies

Table 1. Sample summary of simulation-based articles- joint maintenance and spares optimization

Surprisingly, the lack of carefully examining the effects of CM is noted, where most studies consider minimal repair towards bringing a component back to the previous operating state. This aspect is seen perhaps not a complete representation of both maintenance and spare policies, that potentially address component reliability and degradation challenges, both under

PM and CM. Additionally, CM failures which are addressed by various maintenance and spare strategies consequently demonstrate an impact on the PM strategy, due to fundamental and observable reliability changes on the system impacted by the CM actions.

Furthermore, the studies assumed perfect maintenance and considered only one CM maintenance action, i.e. replacement of the failed item. This aspect may not offer a realistic maintenance analysis, because repair actions may not always justify spare replacement, which restricts the research to perfect maintenance. Despite the importance of imperfect maintenance, which mimics real maintenance scenarios, there remains a paucity of evidence on the application of aspects implying imperfectness such as imperfect maintenance, imperfect replacement, and failure diagnosis time, also alluded by Van Horenbeek et al. (2013).

While performing maintenance optimization, most of the studies lack a systematic framework for selecting variables that significantly affect the objective measure, which is subsequently considered as control variables in the optimization program. Such frameworks should consider the interactive effects, where several statistical methods such as full factorial analysis and analysis of variance (ANOVA) offer the means to address this aspect. For instance, Bouslah et al. (2018) employed ANOVA, to illustrate the interactions of variables, while establishing variables that were significant in an integrated production, quality and maintenance control policy.

The first contribution of this paper is to fill the gap in the literature, by developing an integrated framework, derived from empirical data, for the joint optimization of maintenance and spares policy. Specifically, we consider maintenance on different engine subsystems, subject to imperfect maintenance and reliability degradation. The criteria used to select the subsystems, represent the impact to the system performance, in this case, downtime, an aspect corroborated by (Alrabghi and Tiwari, 2015). Moreover, most studies have dwelt on multiple systems, for example, several engines in a plant, whereas our study deals with subsystems within one single engine. The distinctive effect of respective subsystems, such as failure and deterioration, have been overlooked in such models (Alrabghi and Tiwari, 2015), which may lead to generalized and uncomprehensive optimization solutions. In this case, subsystems are inter-linked to form a system, for instance, a power plant engine, has the cylinder, governor, fuel and turbocharger subsystems, which have unique operational and failure characteristics.

Secondly, this paper considers the reliability degradation of distinct subsystems, which typically require the prescription of clear CM strategies. This distinction may not be forthcoming due to imperfect maintenance (imperfect diagnosis and repair) and alternative options available. Hence, the need to explore the value of several maintenance strategies simultaneously, that can be prescribed to the failed subsystems, which is seldom done in research while modelling imperfect maintenance of deteriorating subsystems (Lei et al., 2010).

The third contribution of this paper aims to make the selection of significant variables affecting the maintenance performance measures more judicious, by involving expert assessment and employing statistical techniques to quantify their effects and interactions. Notably, this study will address the aspect of systematic selection of significant variables subsequently employed in a maintenance optimization program. Key plant performance indicators, such as, spares availability, maintenance strategy reliance, and others derived from the empirical data and agreed upon with the plant maintenance team, are subjected to this process.

Lastly, we employ the significant variables as decision variables in a simulation-based optimization with an objective of minimizing the total repair time. A case study approach is adopted to obtain in-depth information and capture the complexities brought by the different variables, derived from plant's empirical data.

3. Methodology

The methodology consists of several steps. Step 1 involves data collection and pre-processing, while Step 2 includes data exploration. Step 3 incorporates identification of the model output parameters, while Step 4 includes extraction of critical variables to be incorporated as input to a simulation model, for evaluating the impact of alternative O&M strategies on power plant availability and repair time. Step 5 entails developing the simulation model and performing simulation experiments, while Step 6, includes evaluating and interpreting the results of the simulation experiments. In this step, significant variables to be employed in the optimization are determined. Finally, Step 7 addresses the implementation of a simulation-based optimization.

3.1. Data collection

In this study, the analysis uses maintenance data describing failures recorded from thermal power plant engines, over a five-year period. The power plant has fuel oil-driven engines for power generation, which we define as equipment. Each engine consists of several inter-linked subsystems such as a cylinder, turbocharger, and governor. The data contains, subsystem failure occurrences, separate maintenance actions carried out, and components details, such as the date and time of both the failure occurrence and repair finalization. The data was pre-processed using a standardization step following the ISO 14224, to address inconsistencies. In this step, various components were linked to their respective subsystem, while expert consultations were employed where clarity was needed.

3.2. Data Exploration

Following the maintenance data exploration, several aspects are considered towards enabling modelling of the study.

3.2.1. Critical engine subsystems selection

The power plant engine was decomposed into subsystems, from which the four critical subsystems were selected based on failure frequency and the individual contribution to the power lost in megawatts-hours (MWhr) using Pareto analysis. The fifth critical subsystem itemized as ‘others’ incorporated summation of all the remaining subsystems.

3.2.2. Maintenance actions – R_i and subsystem state modelling

Five maintenance actions employed in data exploration were classified following the ISO 14224:2016 classification and categorized on estimated time incurred by the action as corroborated by the maintenance team. See Table 2.

R_i	Maintenance action	Description
i =1	Do almost nothing	Incorporate minor adjustments, may not cause a stoppage, e.g. tightening
i =2	Minor	Incorporate spare replacement bringing the subsystem back to an operational state
i =3	Moderate	Both moderate and major repair actions incorporate logistical lead times during
i =4	Major	spares sourcing and repair actions
i =5	Overhaul	PM action for whole engine overhaul as per the maintenance schedule

Table 2. Maintenance actions classification based on ISO14224:2016

The state of each subsystem is depicted by two variables, a discrete stochastic state FS_j which take the values {1,2,3,4} denoting the operational state, in terms of severity at time *t*, and impact factor ρ_i (hazard rate adjustment factor) which takes a value between 0 and 1, and controls the changes of λ_n at time *t*. In this case, we assume that the stochastic state of the subsystem is dependent on the stochastic prior state FS_j and the maintenance action R_i carried out as discussed in the next section.

3.2.3. SMDP modelling of failure severity states

Failure severity FS_j, is the impact due to R_i on a subsystem, depicting the seriousness or harshness of a failure. This was used to determine the reliability measure attained by a subsystem following a respective R_i and subsequently used for diagnosis whilst selecting appropriate R_i by the maintenance team. While employing SMDP, FS_1 is depicted as causing minor production stop, FS_2, moderate, FS_3, severe and FS_4, an extensive stop in production/operation, as adopted from (ISO 14224:2016, 2016). Low FS_j is assumed to have low T_{r_i}, while high FS_j to have high T_{r_i} due to the intense maintenance action R_i required. Fig. 1 illustrates an example where ideally a subsystem retaining FS_2, should be diagnosed to undergo R_2, but due to imperfect diagnosis, there is the possibility of undergoing one of the other R_i apart from R_5 (mandatory for all subsystems during overhaul). For the purpose of analysis, the assumption that due to imperfect maintenance, FS_2 undergoing R_2, transitions to FS_3, whereas, if perfect maintenance was considered(not in this case), it could transition to FS_1. Following this process, a specific FS_j stochastically transitions to a posterior state between low FS_1 to high FS_4. The scheduled overhaul maintenance reduces the failure severity to FS_1 with some probability of FS_2 which mimics a renewal state (near AGAN) with stochasticity. This process is modelled for all the FS_j with possibilities of subjection to all the R_i.

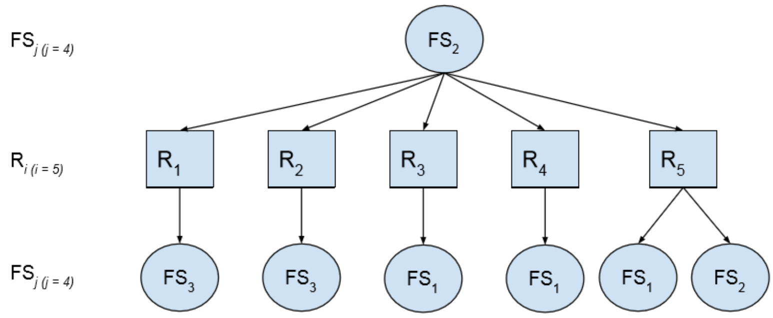

Fig. 1.Sample illustration of FS_2modelling using SMDP

The operating severities	$FS_j\ ; j = \{1,2,3,4\}$
The finite maintenance actions	$R_i\ ; i = \{1,2,3,4,5\}$

3.3. Model output parameters

The model considers two performance measures of interest as the outputs. Firstly, the engine operational availability A_o, is the proportion of time the engine is running compared to total time including downtimes due to failures and overhaul (PM). We use the running hours I against the total running length (includes running hours and downtime). Secondly, total repair time T_r, is the total value of the repair time, accrued by the engine (five subsystems) on purely CM repair processes. This time value excludes the spare sourcing lead-time T_l and diagnosis time T_d delays incurred during the CM activities. The assumption of PM actions having pre-planning therefore, no lead times involved. Equations (3), (4) and (5) provide an annualized average time value based on t_n, which is more intuitive compared to the planning horizon of the plant.

$$A_o = \frac{I}{I+DT} \tag{1}$$

$$T_m = T_d + T_r + T_l \tag{2}$$

$$T_r = \frac{\sum_{k=1}^{n} T_{r_k}}{t_n} \tag{3}$$

$$T_d = \frac{\sum_{k=1}^{n} T_{d_k}}{t_n} \tag{4}$$

$$T_l = \frac{\sum_{k=1}^{n} T_{l_k}}{t_n} \tag{5}$$

3.4. Model parameter extraction

Several model parameters derived for the critical subsystem's analysis include; the time to the initial failure generation t_{st_n}, which represent the time the first failure of a respective n^{th}subsystem occurred. The reliance factor/utilization probability η_i, for the different R_i, was computed from the subsystem failure frequency, while the mean time to repair T_{r_i}, was derived from the maintenance action time classifications using a uniform distribution (due to the classification entailing minimum and maximum time). A probability distribution was fitted for the better random forecast of maintenance interventions that utilized more than 13 hours, to represent R_4. The $t_{bo}$and T_{r_5}, that characterize R_5, were derived from the PM planning manual of the engine. The maintenance team identified T_{d_n}, the estimated time a failed subsystem will incur while being diagnosed to indicate the type of FS_j, hence identify the appropriate intervention or R_i. The time to next failure λ_n, for each subsystem, fitted to a probability distribution, was established by computing the time between repairing the subsystem to operable state up until its next failure. Spares availability *f*, also referred to as fill-rate or instantaneous reliability of spares (Louit et al., 2011), was provided by the plant supply chain, as the estimated probability of the plant holding spares stocks on hand to deal with the maintenance requirement. Sourcing lead-time T_l for both local and imported spares, was derived similarly from the plant supply chain. In the instances requiring spare sourcing, the maintenance data included information on both actual repair and spare sourcing lead times amalgamated, without differentiating the two. Hence, to derive the actual repair time T_r in the model, we subtracted the estimated spare sourcing lead time T_l from the combined actual repair time plus spare parts sourcing lead times derived from empirical data. Therefore, due to the derivation and modelling of this aspect, it is expected that T_l will have an impact on T_r values. An outsourced contractor O_c, is partially involved in the PM (specialised activities), is constrained to working solely during the daytime shift.

3.5. Modeling

A discrete event simulation modeling framework is developed which mimics the subsystems normal running I until failure occurrence and subsequent CM repair action undertaken, while PM is carried out after a time interval t_{bo}. A ρ_i ranging from 0 to 1, was introduced for estimating the subsystem hazard rate adjustment factor (impact of the maintenance action on the λ_n) in each R_i. The extreme values ρ = 0 depict ABAN, while ρ = 1 construe AGAN. SMDP was employed to model the stochastic deterioration process of the subsystems, based on the specific maintenance actions R_i, where initial FS_j values were randomly assigned to the subsystems and posterior FS_j generated as discussed in Section 3.2.3. During the modelling step, the following assumptions are made:

1. Maintenance actions are imperfectly performed, hence, the equipment state does not attain "as good as new" (AGAN) state after maintenance intervention.
2. We consider that two or more subsystems cannot fail simultaneously, because, a single subsystem failure, causes the engine stoppage.
3. Concerning the principle of FS_j transition, we consider only the imperfect maintenance action and the stochastic failure severity of the subsystem.
4. The availability of maintenance technicians is not a constraint. This is because the expert analysis and interviews revealed that the technicians were shared from a pool, hence their availability was not viewed as a constraint.
5. PM incorporates a modularized design for the subsystem's maintenance characterized by spare replacement. Thus, PM is assumed not to incur repair time.

3.6. Analysis, evaluation, and interpretation

This section encompasses two parts wherein the first part, considers the model results following a one-factor-at-a-time (OFAT) analysis, while in the second part, a set DOE, following a full 2^k factorial design (k as the number of variables/controls to evaluate their effect to the engine A_o and T_r) is conducted and computations of the controls' (here also termed as variables') average effects and interactions generated. The process will follow the 3-factor full factorial experiment with resolution V, as described by NIST/SEMATECH (2012). This resolution or ability to separate main effects and low-order interactions from one another, has the capacity to estimate all main effects and two-way interactions (Sanchez et al., 2006). The significant variables selected during this step meet three conditions; firstly they have both main effects and the corresponding interaction effects, an aspect corroborated by (Mccullagh, 2002). Secondly, they are statistically significant at a significant level of 0.5. Finally, using expert assessment, they are considered significant based on the size and other techniques such as graphical methods.

3.7. Simulation-based optimization

This section outlines the 7-step simulation-based optimization approach based on the conceptual framework proposed by Alrabghi and Tiwari (2016a), further adapted for the optimization phase discussed in this study, as illustrated in Fig. 2.

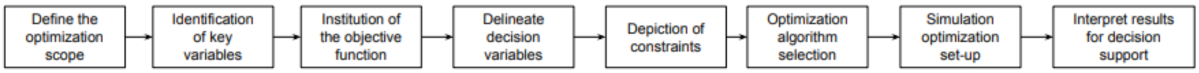

Fig. 2. Schematic framework for simulation-based optimization approach

The first step considers defining the scope of the optimization, which addresses the establishment of the maintenance policies to be employed in the process. The second step involves identifying the maintenance policies and the respective decision variables to be incorporated in the optimization, while the third step, constitutes the formulation of the objective function. Depending on the outcome of the preceding step, the fourth step formulates the constraints. The selection of the optimization algorithm and setting up the required algorithm parameters is performed in the fifth and sixth steps respectively. Finally, the optimization results are evaluated and interpreted while considering the plant/asset's current context. To sum up, the 7-step process is scalable and will offer insights when followed step by step.

4 Results

This section presents the results, brief evaluation and discussion, while a wide-ranging discussion will be dealt with more extensively in Section 5.

4.1. Data collection and pre-processing

The maintenance data from the power plant, recorded in a free text structure was standardized to meet the analysis requirement following the ISO 14224:2016. The classification entailed the equipment class and types Combustion engine (CE) and Diesel engine (DE) respectively, while subsystem classification as illustrated in Table 3.

Equipment class		Equipment type		Sub-units/Subsystems	
Description	Code	Description	Code	Description	Code
Combustion engines	CE	Diesel engine	DE	Cylinder	CYL
				Turbocharger	TC
				Fuel pumps	FS
				Lubrication system	LO
				Exhaust	EXH

Table 3. Sample data standardisation using ISO 14224

The data classification enabled the data to be categorised using the various subsystems utilised for the data exploration discussed in the next section.

4.2. Data exploration

Fig. 3 illustrates a Pareto chart prioritising the engine subsystems in the plant using the individual contribution to the power lost in megawatt-hours (MWHrs). What stands out in the chart is the first four subsystems, i.e. cylinder, governor, turbocharger and lubrication system, which cumulatively contribute 86% of total power lost hence were selected as critical subsystems to be modelled. In this study, the four critical subsystems are modelled with an extra one "others" which is a summation of the remaining subsystems. As regards to maintenance decision support context, explicit strategic focus on the four critical subsystems would potentially improve and enhance the engine performance.

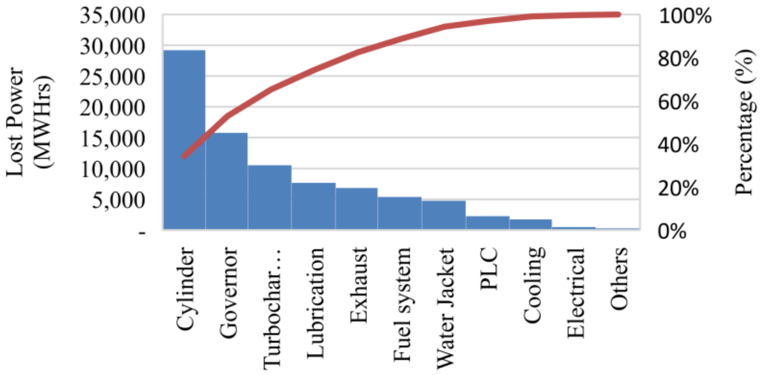

Fig. 3. Pareto analysis for subsystem/components using Power lost

4.3. Model parameter extraction

Table 4 summarises the t_{st_n} and λ_n for each of the critical subsystems selected, where the t_{st_n} was computed based on the assumption of the analysis commencement of January 2011. It indicates the governor has the highest t_{st_n} inferring its less susceptibility to failure during the early running hours, after commissioning compared to other subsystems. The Weibull distribution estimate represented as WEIB (α, β, γ) with the shape parameter β and scalar parameter α and exponential distribution has the mean i.e. EXPO (mean). The Weibull and Exponential distributions were characterized with a third parameter distribution (γ), also known as location parameter or failure free time, which indicates that failures start at a finite time and not at *t*=0, for instance, turbocharger failures (γ = 16). The governor, lubrication system, cylinder and others fit an exponential distribution with a random mean. This signifies failure occurrences that are independent of each other and randomly distributed and could be attributed to high replacement strategy hence tending to near constant or steady state as also corroborated by (Louit et al., 2011).

Subsystem	t_{st_n} (Hrs)	λ_n distribution Parameters	Corresponding p-value	
			X^2 Test	K-S Test
Governor	2,200	EXPO(2.82e+003)	0.341	>0.15
Turbocharger	1,998	16+ WEIB (3.55e+003, 0.854)	0.55	>0.15
Others	640	2 + EXPO (723)	0.316	>0.15
Lubrication	1,260	13 + EXPO (1.28e+003)	<0.005	0.0753
Cylinder	1,800	40 + EXPO (582)	0.477	>0.15

Table 4. Various subsystem time to next failure distributions

The turbocharger subsystem fitted a Weibull distribution, exhibiting a shape parameter β < 1, which indicates that the failure rate decreases over time. The components have their hazard rate decreasing due to less severing strategies for instance replacement that have a lower impact on the λ_n. This is contrary to an intensive regenerative strategy which has a high negative impact on the λ_n due to the strategy characteristics, where the component renewal is near ABAO, hence, lowering λ_n depicts a shorter life experience for the subsystem.

Table 5 provides the different CM actions alongside extracted parameters like the probability of utilisation η_i, repair time classes T_{r_i} and T_{d_i}. T_{r_i} followed the R_i classification as discussed in Section 3.2. Mean time to preventive maintenance (overhaul)T_{r_5} for R_5 had a uniform distribution of minimum 192 hours and maximum 224 hours as depicted from the preventive maintenance schedule. The impact factor ρ_i, acts as a multiplier to the time to the next failure λ_n of an individual subsystem. The ρ_i, was derived from proportionating the respective total λ_n following the approach utilized by Wakiru et al. (2018), which compares and aligns with major repair ρ_4 as 0.80 under the assumption that attaining AGAN status is difficult in deteriorating systems, due to the introduction of errors such as diagnosis, tooling and human related errors. This is based on an empirical analysis of the estimated percentage changes in λ_n of the various R_i, where 0.8 was seen as optimal for R_4. Respective T_{d_i} for the various CM actions were estimated by the plant maintenance team.

Repair Action	T_{d_i} (hrs)	T_{r_i} (hrs)	η_i (%)	ρ_i	ISO 14224:2016 classification
Do Nothing	0.15	0 - 1.0	16%	$\rho_1 = 0.65$	Minor
Minor Repair	0.50	1.0 - 7.0	57%	$\rho_2 = 0.75$	Moderate
Maoderate Repair	0.7	7.0 - 13.0	15%	$\rho_3 = 0.85$	Severe
Major Repair	2.0	Over 13.0	12%	$\rho_4 = 0.80$	Catastrophic

Table 5. Repair time for various repair actions

Table 6 presents the various parameters used while addressing the spare inventory and logistics. The percentage requirement of local and import sourcing, as well as the respective lead times, were provided by the experts from the plant maintenance and supply chain departments.

Maintenance action	Spares needed (%)	f (%)	Spares sourcing			
			Local (%)	Lead-time (Hrs)	Import (%)	Lead-time (Hrs)
Moderate repair	80.19	90	10	1 - 5	90	36-120
Major repair	100.00	90	5	4 – 24	95	120 –1080

Table 6. Spares availability and sourcing lead times

4.4. Model

The developed model mimics the operation of the engine, where the performance measurements were $A_o$and T_r. Fig. 4 illustrates the conceptual representation of the model.
The model was run with a replication length of 105,120 hours equivalent of 12 years, reflecting the age and the first planning horizon based on the planned useful life. The industry average design engine lifespan is estimated to be 20-25years. Hence, this correlates to the lifetime of similar engines. For each simulation, 55 replications were made which allowed a large sample size to be considered, hence reducing the 95% confidence interval half width of the performance measures Tr (from $\pm$45.00 to $\pm$5.00) There was no significant variation in the percentage change of the half width beyond 55 replications.

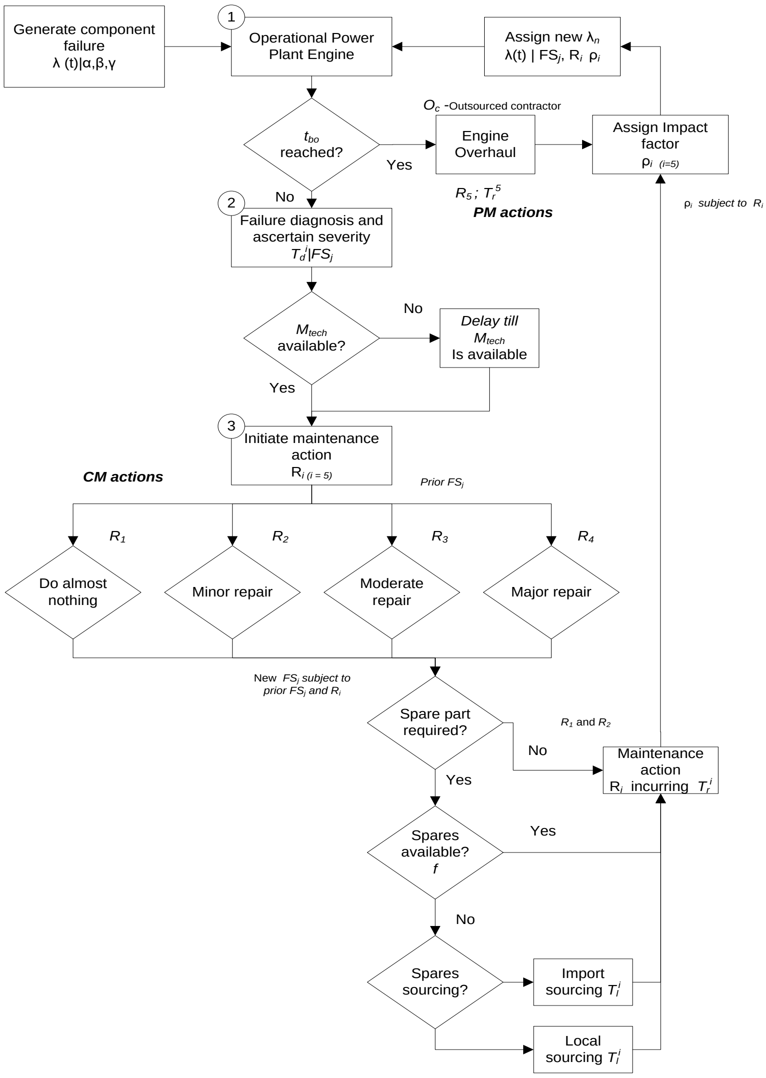

Fig. 4.Conceptual representation of a discrete event simulation model

4.5. *Analysis of results*

4.5.1. *Model results*

The model generated A_o of 90.001%, and T_r of 1,526 hours per year respectively. The achieved A_o and $T_r$using the model were close to the empirical values as analysed from the data of 92% and 1,621 hours respectively. This may be attributable to the stochasticity in the modelling parameters. However, the generated A_o is very close to the empirical value of 92%. Thus, we can assume that our model is a valid representation of the modelled processes in the power plant. Further evaluating the individual contribution to T_r, the cylinder, turbocharger and governor subsystems, each contributed 23.2%, 19.9%, 18.1% respectively of the total as depicted in Table 8.

Subsystem	T_{r_n}	T_{l_n}	T_{d_n}	T_{m_n}
Turbo charger	303.38	128.58	9.99	441.95
Governor	275.89	122.40	8.46	406.75
Cylinder	354.24	10.28	20.10	384.62
Lubrication	254.00	13.04	7.76	274.80
Others	338.61	520.64	34.30	893.55

Table 7. Summary of subsystem times variables

It should be noted; the values indicated are average values over the simulation time t_n. The consolidative characteristic of “other” subsystems as seen in Table 7 is attributed for the high

T_r and T_l, hence not incorporated in the analysis for individual subsystems in this section. The turbocharger incurs the highest T_m compared to the other critical subsystems. Both the turbocharger and governor subsystem indicate high T_l, implying substantial failures characterized by spares sourcing requirement. This could offer a pointer towards, the need of a more plausible strategy, that could incorporate spares inventory, reuse, recondition, or cannibalization strategies, if possible, to overcome the challenge. Cylinder subsystem has high T_d, possibly attributed to the complexity of the assembly, that often require disassembly to diagnose internal components failure in the subsystem.

t_{bo} (hrs.)	A_o (%)	Annualized time over t_n (hrs.)				The frequency of utilization over t_n					
		T_r	T_l	T_d	$T_r + T_l$	R_1	R_2	R_3	R_4	R_5	$\sum_{i=1}^{4} R_i$
7000	82.79	1763.51	415.23	83.39	2178.74	236	818	221	152	18	1427
8000	91.60	1735.11	429.22	84.44	2164.33	280	824	225	154	17	1483
9000	90.01	1526.13	685.23	80.88	2211.36	256	833	232	165	15	1486
10000	87.00	1376.3	929.83	79.51	2306.13	230	857	246	165	13	1498
11000	87.60	1187.11	1222.13	70.57	2409.24	193	883	254	175	11	1505
12000	87.56	1175.89	1442.13	76.69	2618.02	205	991	264	187	11	1647

Table 8. Annualized times and frequency of utilization for R_i while varying t_{bo}tbo

It can be seen from Table 8, obtained by carrying out an OFAT analysis, that increasing the t_{bo} gradually decreases T_r in a non-linear manner. As a result of extended t_{bo}, the frequency of R_5 utilization (renewal instances) declines and more failures requiring CM interventions occur as represented in the last column of Table 8. Additionally, this aspect is confirmed by the marked increase in the utilization of various R_i under CM, for instance, R_2 (818-991), R_3 (221–264) and R_4 (152-187). The increase in T_l observed, can therefore be related to the increased utilization of both R_3 and R_4, which subsequently demand replacement of spares that incur high lead-times, an aspect demonstrated by the increase of T_l. Hence, an objective and realistic analysis show the CM related repairs incurring more time ($T_r + T_l$) and more activity $\sum_{i=1}^{4} R_i$, which is logical and corroborated by various studies. Further review demonstrates an inconsistent variation of A_o indicating the possible effect of other variables. However, a general increase is noted from 82.79% to 87.56%. A similar analysis indicates that increasing f improves A_o, while T_r increases and T_l decreases respectively. To explicitly understand the level of dependency between the variables while impacting the performance measures, a full factorial orthogonal design experiment is employed as discussed in the following section.

4.5.2. Full factorial effects and interactions experiment results

A 3-factor complete factorial design experiment was carried out, to determine significant variables. The respective variable ranges illustrated in Table 9, were prepared according to the procedure used by (Sanchez et al., 2006; Zhu et al., 2017). An analysis of the effects and the respective p-value for different ranges was done in addition to expert consultation while assessing the appropriateness of the ranges as seen in Table 11. The ranges were computed using the model parameters derived as described in Section 4.3. We utilize the ranges adopted in both the full factorial experiment (in this Section 4.5.2) and the simulation-based optimization in Section 4.6.

Variable	Values	Ranges	
t_{bo}	9000	7,000	12000
ρ_1	0.65	0.52	0.78
ρ_2	0.75	0.60	0.90
ρ_3	0.85	0.68	0.99
ρ_4	0.75	0.60	0.90
η_2	57	45.6	68.40
η_3	15	8.00	22.50

T_{d_1}	0.15	0.07	0.23
T_{d_2}	0.5	0.25	0.75
T_{d_3}	0.7	0.35	1.05
T_{d_4}	2	1.00	3.00
f	90	72	99
O_c	1	1	2

Table 9. Variables ranges used in the optimisations

The criteria employed to identify the significant variables, considered, first, that the variable has both, the main effect and corresponding interaction effect, secondly, the P-Value confirms the variable(s) is statistically significant at the significance level of 0.05. Also, to visualise the error size of an effect, graphical methods were used, while, plots of residuals were used to check for model adequacy. The simulation was carried out using 55 replications, and results depict average values, using resolution V to estimate the average effects and interactions. Table 10 provides a sample of generated average main and interaction effects on the A_o and T_r from the designed experiment, while a detailed list is shown in Table A1, in the appendix.

		t_{bo}	f	η_2	η_3	$t_{bo}+f$	$\eta_2+\eta_3$	$t_{bo}+\eta_2$	$f+\eta_2$	$t_{bo}+\eta_3$
A_o	Δ (K€)	5.87	19.4	11.99	5.59	12.52	1.5	-1.95	-0.66	-1.89
	Prob > |t|	<0.0001	<0.0001	<0.0001	0.0004	<0.0001	0.0446	0.0225	0.0134	0.0267
T_r	Δ (K€)	-612.33	548.14	716.62	-209.83	-92.07	-42.38	-94.96	-379.9	78.58
	Prob > |t|	< 0.0001	< 0.0001	<0.0001	0.0010	0.01850	0.0038	0.0160	<0.0001	<0.0001

Table 10. A sample of significant main and interaction effects

As Table 10 indicates, an increase in t_{bo}, will averagely increase the A_o by 5.87% while decrease the T_r by 612.325 hours. The improvement of A_o is because of compensated repair time by lengthened running or operation time *I* due to a decline of PM activities as also seen in Section 4.5.1 and Table 8. The availability of spares potentially reduces the subsystem downtime due to spares sourcing lead times T_l which positively impact I, hence improve the A_o. An increase in η_2 will averagely increase A_o (11.99%) and increase T_r (712.62 hours). This indicates, that increased reliance of R_2, offers a negative impact on T_r attributable to the fact that R_2 incorporates solely repair without spares requirement, hence the modelled T_r retains higher value.

Considering interaction effects, for instance, the interaction of t_{bo} and f causes a significant change in A_o and a modest decrease of T_r by a factor of 12.52% and 92.07 hours respectively. This infers that the effect on f by t_{bo} positively affects the performance of the engine A_o and T_r. Similar interaction to some extent is seen between η_2 and η_3 with a modest improvement on T_r and a modest change on A_o. This implies that the t_{bo} effect on A_o does not depend on the effect of f, signifying that t_{bo} has a negative effect at high f but a positive effect at low f. While evaluating the impact on T_r, the effect of t_{bo}, to some extent depends on the effect of f, where f has a negative effect at high t_{bo} but a positive effect at low t_{bo}. The main and interaction effects are presented in Table A1. To evaluate the variable ranges employed in this exercise, we employed three sets of ranges and confirmed they gave same results in terms of significance of the variables. A sample of the evaluation is shown in Table 11.

Variable	50%:100%:150%		80%:100%:120%		90%;100%:110%	
	Effect	p-value	Effect	p-value	Effect	p-value
f	1464.18	0.0000	548.14	0.0000	718.52	0.0000
t_{bo}	-1361.4	0.0000	-612.33	0.0000	-242.15	0.0000
η_3	708.7	0.0007	-209.83	0.0001	88.79	0.0000
$t_{bo} * f$	-421.5	0.0000	-92.07	0.0185	-68.72	0.0003
$f * \eta_3$	-282.18	0.0002	-112.27	0.0350	-31.9	0.0244
T_{d_2}	70.10	0.8840	29.70	0.8451	26.26	0.7426

Table 11. Evaluation of different variable ranges scenarios

In summary, it can be concluded from the DOE performed, that the variables significantly impact T_r, hence the critical performance measurement selected to be employed in the optimization. Subsequently, the significant variables established included, t_{bo}, η_2, η_3, and *f*. Due to the interactive characteristics of the significant variables, an optimization considering them jointly and several constraints, is advanced employing a simulation-based optimization as discussed in the next section.

*4.6 Simulation-based o*ptimization

The simulation-based optimisation framework described in Section 3.7 is followed here step by step:

1. Defining the scope of the optimization

The simulation-based optimization addresses the subsystems identified and modelled as per Section 4.3. In this case study, the optimization scope will include the total repair time and fill rate which addresses the spares policy.

2. Applicable maintenance policies and decision variables for optimisation

The decision variables established as significant in Section 4.5.2 are considered for the maintenance optimisation. The variables include the time between overhaul t_{bo} addressing PM policy, fill rate f that deals with the inventory policy. Other variables addressing the CM policy include the maintenance strategy reliance factors η_2 and η_3. However, O_c, the number of outsourced contractors will be included despite not being in the DOE performed in Section 4.5.2, because we view it as an essential aspect, that could influence downtime caused by PM strategy and subsequently influence CM policy in terms of reliability. Table 12 presents the summary of the decision variables and the possible number of solutions.

Variable	Ranges		Possible choices	Revised choices	Remarks
t_{bo}	7,000	12,000	5000	5000	No change
η_2	45	68	230	23	Changed from step 0.1 to step 1.0
η_3	8	22	140	14	Changed from step 0.1 to step 1.0
f	81	99	18	18	No change
O_c	1	2	2	2	No change
Possible solutions			**161,000,020**	**57,960,000**	

Table 12. Variable ranges and the possible number of solutions

3. Objective function formulation

The critical policies to consider based on the variables selected in Step 2 include the repair times, maintenance strategy reliance and spare parts availability. The effect of spares availability is incorporated in T_r, since it introduces lead time and affects the repair time due to multiple handling. In the same way, the maintenance strategy reliance effect would be noticed in generating T_r. Hence, minimizing the total repair time will be the only objective.

4. Constraints definition

Two constraints are defined, the first considers η_2 and η_3, as illustrated in Table 5. Both constitute a combined 72% (57% and 15% respectively), hence we formulate the constraint as $\eta^*_2 + \eta^*_3$=72%. Secondly, to ensure the optimization considered a better scenario than the base, we define A_o to be more than the base value of 90%, as depicted in Section 4.5.1, hence, the problem can be formulated as follows:

Minimize: $T_r = \frac{\sum_{k=1}^{n} T_{r_k}}{t_n}$

Subject to:

$A_o \geq 90\%$

$\eta_2 + \eta_3 = 72\%$

5. Optimization algorithm

We employ OptQuest for the optimization problem at hand, which offers the possibilities to optimise simulation experiments employing neural network filter and apply heuristics known as tabu search and scatter search (Kelton et al., 2010). Moreover, it offers both the option of setting up goals for explicit handling of bounds enforced on output values and the graphical output presentation that enhances interpretation. Furthermore, it is employed, to gain insights, while considering the consistency the variable bounds, as previously employed in Section 4.5.2.

6. Simulation optimisation set-up

The optimisation using OptQuest was done with varying the number of replications from 5 to 55 for each simulation, allowing OptQuest to test for the statistical significance between the average objective function of our best previous and current simulation, whose intention is to rule out inferior solutions. The optimisation process was only stopped and results retrieved when no change is noted on the optimal solution after 200 simulations. The T_r baseline before the optimization is 1,526.1 hours as seen in Section 4.5.1.

7. Results and discussion

Fig. 6 illustrates the optimisation results, which indicates the best value being attained at the 186th simulation and no further change seen.

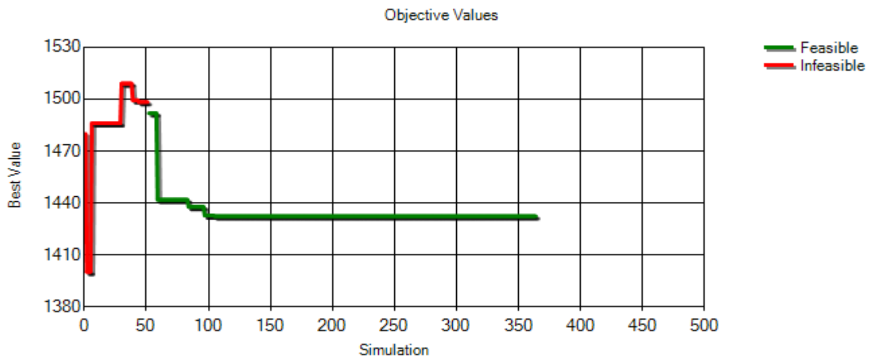

Fig.6. Graphical representation of the optimisation results

The optimisation resulted in more than 30 solutions where the T_r is more than 1% below the base line value. Table 13 presents the top ten optimal solutions. From these results, we can see that optimality is attained while enhancing PM, spares availability, while, a modest change in the reliance of minor and moderate repair strategies. Scenario I generated the highest A_o and power generated as production output for the engine.

Scenario	A	B	C	D	E	F	G	H	I	J
T_r	1432.30	1432.74	1437.65	1437.70	1438.48	1440.06	1440.44	1441.84	1442.37	1444.35
t_{bo}	12000	12000	12000	12000	11976	11976	12000	12000	12000	12000
η_2	58	58	58	58	58	58	58	58	58	58
η_3	14	14	14	14	14	14	14	14	14	14
f	99	99	99	99	99	99	99	99	99	99
O_c	2	2	2	2	2	2	2	2	2	2
A_o	91.21	91.01	91.43	91.29	91.42	91.32	91.14	91.47	91.44	91.23
Power Generated	87135	86940	87340	87203	87336	87232	87061	87382	87348	87149

Table 13. Optimization parameters while minimising T_r

The values of η_2 and η_3 in the optimized scenarios, indicate more reliance on minor repair actions (η_2). This was expected, because of the inherent characteristics of the minor repair actions, which exhibit lower repair times and no spare sourcing lead time. O_c in this case depicts a higher value of 2, which can be attributed to the fact that the outsourced capacity is only available during the daytime shift, hence the increase by 1 to ensure availability of the resource.

As far as reviewing the optimisation results is concerned, there is strong concurrence that enhancement of t_{bo}, f, leads to optimization of the plant's performance measures. An implication of this is, firstly, the possibility of re-evaluating the t_{bo} to optimize the planned maintenance effectively, based on the lifecycle of the subsystems. Secondly, spares inventory challenge if overcome, shows a potential positive optimization solution, an outcome also corroborated by Kennedy et al. (2002). In this case, an introduction of different inventory policies such as consignment stocking, employing other recovery actions such as reconditioning and adoption of industrial symbiosis, would probably ensure spares are available throughout and could positively impact on the optimization. A caution here would involve carrying out a cost-benefit analysis to balance the cost and improvement on either A_o or T_r as also corroborated by Alabdulkarim et al. (2011). Furthermore, due consideration should be taken on probable risks that accompany enhanced f such as increased risk due to spare costs, insurance costs, pilferages and storage space requirement.

5. Discussion

The initial model analysis results are significant in at least two significant respects. In the first place, they guide the practitioner while selecting the critical subsystem, where in our case, the turbocharger is picked based on total maintenance time. In the second place, they offer insights on the bottlenecks suffered by the plant using various maintenance policies. Among the subsystems' identified through the approach as critical regarding portended time characteristics, such as repair time, lead-time to procure spare parts and diagnosis includes the turbocharger, cylinder and governor. Hence, such subsystems necessitate further investigations with a view of identifying robust maintenance strategies, which seeks to optimise operational availability. The proposed simulation is demonstrated as useful for decision support as observed from the results illustrated in Section 4. As an example, as described in Section 4.5.1 (Table 7), the turbocharger and governor, exhibit lengthier lead-time delays based on the modelled stochastic spare part sourcing lead times. An implication of this is the need to investigate further the specific spare part inventory that frequently requires to be sourced, either locally or imported from the original equipment manufacturer (OEM). In real-life, determining the stocking policy is not straightforward in the absence of a decision support framework, owing to the stochasticity of time characteristics like repair, diagnosis, and sourcing lead times. Moreover, the interaction effects between the stochastic spare part availability and other variables, influence the stocking strategy, yet modelling this aspect and evaluating its influence on system availability is somewhat challenging. However, from the simulation model, it is observed that it is possible to derive insights on such interaction effects through the simulation modelling approach. For instance, the turbocharger and governor which exhibit longer sourcing delays could benefit through initiatives like prioritised stocking, Just-in-Time (JIT) or consignment stocking from the OEM/local agent.

Moreover, for the above, utilisation of condition monitoring techniques such as oil analysis or vibration analysis on such subsystems, potentially can provide early warnings that assist the plant in advanced planning of spare parts sourcing, a strategy similarly suggested by Eruguz et al. (2018). While addressing the diagnosis delay and accuracy for critical subsystems such as the cylinder and turbocharger, the plant could re-train the technicians and bring in better diagnostic technologies, which could enhance better detection of failure severities as this aspect in most cases is influenced by technician knowledge and experience, an observation also corroborated by Wang (2012). This improvement would also yield better repair strategies, for instance, a component replacement for high severity failures.

Importantly, modelling stochastic failure diagnosis T_{d_i} times, despite its insignificant impact on T_r in this case, illustrate the significance of this seldom utilized maintenance downtime constituent, as a modelling variable which influences the quality of the maintenance action, an aspect also corroborated by Van Horenbeek et al. (2013). Further investigations concerning T_d would lead to unearthing aspects such as the suitability of a technician skills, their response time, maintenance quality, availability of tools, and could further examine automation of decisions as concerns the use of sensor or historical data, aspects also corroborated by Bousdekis et al. (2015). This aspect could be addressed by employing appropriate fault diagnostic systems, for example utilizing thresholds such as RUL and hazard rates to trigger decisions of appropriate interventions under CBM, an area the authors view for future work.

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 systematic determination of significant variables, employing various techniques, based on the main and interaction effects demonstrates a plausible framework. It lays emphasis that the 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. Graphical methods, additionally provide a valuable means of allowing information in the data and the mind of the expert to interact appropriately, an aspect also corroborated by (Kleijnen et al., 2005).

Taken collectively, these results suggest it is essential to optimise variables jointly since the decision variables or controls can interact with each other and yield a sub-optimal solution. For instance, as seen in the results in Table 9, variable such as η_2 and f negatively affected T_r individually, based on their individual main effects on T_r. However, when their interactions were considered, their combined beneficial influence on T_r was positive. As an example, the combined effects of η_2 and f generated a decrease in T_r despite both having negative effects individually. Hence, this suggests that performing optimization based on a single variable (or the OFAT approach) could eventually lead to sub-optimal maintenance optimization, and by extension, considerable modelling time owing to repetitive OFAT experiments. This observation corroborates to a greater extent the findings by (Sarker and Haque, 2000) who suggested that this type of model using interactions is applicable in maintenance strategies of multiple components in maximizing service levels, similarly considered in this study.

With regard to the optimisation results in section 4.6, the results indicate that the total repair time would be optimized by considering firstly, the CM related factors (i.e., the maintenance strategies to rely on and the spares availability), and secondly the PM-related factors (TBO and Outsourced maintenance). Concerning the reliance on different maintenance strategies, the results show that a slight increase in minor repair with a small decrease in reliance on moderate repair actions would contribute to an optimal solution. This result may be explained by the fact that minor repair retains a lower repair time strategy with no spare requirement. As for the spares availability, the results are as expected, were to reduce repair time, spares availability should be guaranteed. However, this aspect requires further investigation considering the operational context of different plants, where a trade-off may be required between stocks level, holding costs, pilferage and spares shelf-life. Concerning TBO, the results indicate that for this case, the increased interval would offer lower repair time. The observed decrease in T_r could be attributed to the modelling approach of the time variants T_r , T_d and T_l as indicated in Section. Moreover, the possible interference of protracted T_l, thereby reducing respective T_{r_n}cannot be ruled out. However, an introduction of other performance measure such as total maintenance cost or time that amalgamate the time incurred ($T_d, T_r$and T_l), will undoubtedly cause this observation to change.

From the optimisation results, contract or outsourced maintenance during equipment overhaul as currently implemented at the power plant negatively influenced the total repair time for the power plant. This influence was due to limitations such as availability timelines of the outsourced resource (often only during one shift), or the type of outsourced maintenance service. For the latter, two types of maintenance services are outsourced, wherein the type I, both corrective and preventive maintenance services are outsourced, and in type II, only, CM is outsourced. The availability limitation is observed as negatively impacting the overhaul time since repairs would otherwise have been performed during both the day and night shifts. Secondly, outsourcing only PM services limits the maintenance repair processes, since the outsourced resource are deprived of valuable insights which could be derived from performing CM actions. As an example, root causes of chronic subsystem failures which are correctively repaired could be missed during PM actions, yet such root causes could be appropriately addressed during the CM actions by the outsourced resource, who are more specialised in maintaining the critical subsystems. This finding is also demonstrated by Wu (2012), where he suggests that attention should be given while selecting the type of outsourced resource for plant maintenance. He argues that for better maintenance processes, organisations should outsource type I services (CM and PM). Further, the ageing process of the subsystem could be a factor to consider during outsourcing, where a balance between in-house and outsourced maintenance. As an example, ageing components may require more outsourced maintenance services. This observation corroborates findings by Bazargan (2016), who recommended a combination of in-house and outsourced in such circumstances.

The proposed methodology is generalizable and can be scaled to fit different applications that constitute multiple subsystems. Table 14 illustrates several potential applications, indicating the respective sector, system, and possible subsystems. It is essential to bear in mind that the application of this proposed methodology to various applications, for instance, the manufacturing sector would require some adaptations to suit the operational context. Firstly, the identification of the system to be investigated, for instance, the cement mill/grinder in a cement plant. Secondly, for the identified system, a precise segmentation of the subsystems constituting it (indicated in the "sample subsystems" column in Table 14). The third aspect will involve the adoption of the methodology as highlighted in Section 3, where maintenance data is collected, preprocessed and explored. From the data exploration, plants exhibiting numerous subsystems, prioritisation based on the performance measures employed, for instance, downtime, may be employed to establish critical subsystems. For the identified subsystems, the different model parameters are extracted from empirical data and expert assessment while the performance measures and objective functions are formulated for the simulation model. Expected differences would emanate while modelling due to the differences in the operational context. For instance, some plant set-ups constitute redundant or buffer subsystems to guarantee continuous operations, an aspect that should be considered (Rezg et al., 2005).

Sector/Industry	Sample System	Sample subsystems
Manufacturing	Cement mill	Weigh feeder, conveyor system, mill/grinder, elevator, water system, air, and blower system
Exploration	A drilling rig (fossil/geothermal/offshore)	Air system, a hoisting system, power supply, top-drive/rotary table, well monitoring system.
Aviation	Turbofan engine	Air intake/compressor, combustion chamber, Turbine, exhaust system, ignition system, engine fuel system, lubrication, exhaust system

Table 14. A sample of different possible applications of the proposed methodology

6. Conclusion

The present study was designed to develop a methodology that commences with empirical data, to analyse the effects and interactions of various maintenance and operational factors and their impact on the optimisation of the engine total repair time using a simulation model. The case study of a thermal power plant was advanced with consideration of repairable subsystems with both PM and CM actions. The subsystem deterioration problem was formulated stochastically integrating the previous subsystem severity influenced by maintenance actions. Further to identifying the turbocharger as critical among the subsystems using total maintenance and repair time, the study has shown that the different subsystems have different repair, diagnosis and lead time's characteristics offering different impacts to their life cycle times. Spares availability, reliance on minor and moderate repair strategies and TBO were demonstrated to have the most potent effect on total repair time. The analysis results while evaluating the model, conceivably support the hypothesis that interactions of the variables play a role in influencing the performance measures. The optimisation exercise which openly supports the relevance of interactions. indicates that t_{bo}, spares availability and maintenance strategies reliance as essential ingredients. These findings have a significant implication in understanding parameters that require further investigation while carrying out maintenance decision making, whereby, if enhanced, would greatly improve the maintenance strategies, resource allocations and ensure priorities are set right to improve the availability of the engine and eventually the plant economics. 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. Moreover, the simulation-based experiments and optimization on real power plant data verify the validity and robustness of the developed technique.

Several limitations of the present study should be acknowledged, which should be dealt with in detail in future studies. For example, modelling shared resources like technicians amongst several systems, which could offer decision support concerning the same. Another limitation of the study is based on the fact that it considered only PM and CM policies, whereas additional maintenance and restorative strategies identified like condition monitoring, spares reconditioning, and reuse of spares could be incorporated. An optimisation extension utilising the failure diagnosis remains a possible aspect interesting to be investigated about the human factor effect on maintenance. Other studies will be needed to investigate the impact and balancing of in-house and outsourced maintenance, to develop a full picture of outsourced maintenance

Table A1. Main and interaction effects considering T_r.

Effect	Estimate	D.f	Sum of Squares	F Ratio	p-value	Significant
t_{bo}	-612.325	1	1499767.6	384.4216	0.00000	Yes
f	548.138	1	1201818.9	308.0512	0.00000	Yes
η_2	716.62	1	2054176.9	526.5282	0.00000	Yes
$f * \eta_2$	-379.9	1	577303.6	147.9749	0.00000	Yes
$t_{bo} * \eta_3$	78.58	1	49404	31.1416	0.00000	Yes
η_3	-209.828	1	176110.32	46.3816	0.00010	Yes
$\eta_2 * \eta_3$	-42.38	1	3591.71	36.6776	0.00380	Yes
$t_{bo} * \eta_2$	-94.96	1	36069.6	9.2454	0.01600	Yes
$t_{bo} * f$	-92.073	1	33909.4	8.6917	0.01850	Yes
$f * \eta_3$	-112.273	1	25210.2	9.8302	0.03500	Yes
$t_{bo} * f * \eta_2$	76.0376	1	23126.8	5.9279	0.04090	Yes
$t_{bo} * T_{d_2}$	54.12	1	11715.9	3.0856	0.11710	No
$\eta_3 * T_{d_2}$	35.02	1	4907.7	1.2925	0.28850	No
T_{d_2}	26.26	1	531.99	0.1401	0.74260	No
$\eta_2 * \rho_2$	-60.735	1	14755	0.0741	0.79240	No
ρ_2	-50.76	1	10308.3	0.0518	0.82570	No
T_{d_3}	37.35	1	5580.09	0.0478	0.83250	No
$T_{d_2} * T_{d_3}$	-29.24	1	3418.74	0.0293	0.86840	No
$f * \rho_2$	-29.248	1	3421.7	0.0172	0.89890	No
$\eta_3 * T_{d_3}$	15.71	1	987.22	0.0085	0.92900	No
$t_{bo} * \rho_2$	-6.15	1	151.3	0.0007	0.98020	No
$t_{bo} * T_{d_3}$	28.3	1	3204.13	0.1784	0.68020	No

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