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Influence of maintenance and operations strategies on the availability of critical power plant equipment: A simulation approach.

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Abstract

Industrial facilities such as power plants often experience significant production losses due to unanticipated failures, suboptimal maintenance, operational activities and challenges in spare parts logistics. Furthermore, they portend loss of reputation, significant societal disruptions and poor manpower utilization. Critical performance measures for power plants, notably availability of the equipment and repair time, directly affect plant economics and reliability. Consequently, maintenance optimization is crucial and requires considering the effects of and interaction between factors such as spares availability, diagnosis time, time between overhaul (TBO) and accurate maintainability. To realistically model such complexities, a discrete simulation model of critical engine subsystems in a thermal power plant is proposed, where various model parameters are derived from actual data and expert input, to optimize diagnosis and repair times, TBO and spares availability, while considering engine availability and total repair time as performance measures. The developed simulation model returns availability of 90.001% and total repair time of 18,313 hours, while the turbocharger is identified as the critical subsystem. Optimizing spares availability is observed to have highest impact on equipment availability with TBO having a similar impact on the total repair time. Interaction of spares availability and TBO is observed to averagely improve the system availability and reduce repair time of the equipment. Utilization and planning of manpower, spares sourcing lead times and quality of repair diagnosis are other areas identified requiring attention. The study quantitatively evaluates the effects and interactions and further enhances maintenance decision making towards optimising the plants' operational and maintenance related factors.

Keywords: Economics, maintenance, availability, optimization.

1. Introduction

1.1 Background

Industrial facilities like power plants are essential in supplying electric power to the population consistently without interruptions. This is amplified when a plant supports critical installations, such as in the health and security sectors. Power supply in such cases should not experience interruptions, since this could lead to high risks along with both social and economic losses. Moreover, most facilities supplying utility grids have contracts specifying hefty penalties in the event of deviation from the supply agreement. This 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 has a pivotal role in contributing to power production interruption. A growing body of literature recognizes the important role of maintenance related downtime, contributing to power plant downtime and subsequently reduced profitability (Alabdulkarim et al., 2011). It follows that addressing maintenance related downtime will considerably reduce power generation interruptions, operational and maintenance (O&M) costs. 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 eventually drive the facility towards achieving the expected power 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. Apart from maintenance strategies optimization, operational aspects such as inventory management, manpower planning and procedures, also require to be optimized to ensure successful plant operations.

1.2 Study aim and motivation for the research

Power plant system reliability is a critical factor in the success of a power generation project. Poor reliability directly affects both the plant profitability and availability to generate power due to plant downtime. Moreover, loss of availability due to critical equipment downtime which may require diverse and intense interventions such us major repairs characterized by high repair times and high spares sourcing lead-times, has a significant impact on the installations economics, tactical and strategic planning. Increased downtime can be attributed to several reasons touching the O&M aspects such as, increased frequency of failures, high lead times in sourcing critical spares, imperfect maintenance, human errors in diagnosis and maintenance and lack of enough maintenance personnel. Considerable studies in this area have considered the main effects of such aspects to the plant performance and thereby applying this results in maintenance decision support while ignoring their interactive nature. Considering previous optimization studies in maintenance, it is becoming extremely difficult to ignore the interactive effects of O&M aspects mentioned above on the plants performance. The aforementioned factors, both individually as well as interactively affect maintenance, where optimizing them would improve the availability of a given power plant, and reduce maintenance time hence improving the economics and performance of the plant.

However, evaluating such complex variables is an arduous task, therefore, a simulation approach is advanced. Hence, the motivation of this study to evaluate the effects and interactions of various maintenance such as CM, PM and operational variables such as spares availability and manpower (technician) capacity to the performance of the power plant, in this study, measured through equipment availability and total repair time.

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 intended to retain it in, or restore it to, a state in which it can perform the required function” (EN13306, 2010). This enlarges the scope of maintenance beyond fixing worn or broken components, to incorporate various tasks included in corrective maintenance (CM) and preventive maintenance (PM). CM is carried out after failures have occurred and have been noted, while PM is carried out following repeated analysis or evaluation of degradation (EN13306, 2010). Amongst others, PM tasks include condition based maintenance, where maintenance is triggered either by detection of deviation from the standard equipment condition or by testing/inspections. PM often includes predetermined maintenance via scheduled maintenance, replacement and tests. The CM and PM tasks incorporate administrative and managerial actions, such as manpower management, spares sourcing and logistics. System reliability and maintenance optimization are critical towards any plant’s realization of its objectives and towards overcoming various operational challenges (Jardine and Tsang, 2013). System reliability and maintenance optimization, are related to some extent, where variables contributing to equipment reliability are similarly maintenance related. Component failure severity, for example, which affects equipment reliability, is inherently influenced by the accuracy of diagnosis and subsequent, the maintenance action intensity. Plant availability, a critical maintenance optimization objective, is significantly affected by logistical challenges involved in spare sourcing, which portend higher downtime due to characteristically long sourcing lead times. Due to the complex dynamic characteristics of these variables, using classical analytical models in optimization is not sustainable, and hence simulation techniques are used, an approach which is also corroborated by various studies (Alrabghi and Tiwari, 2016; Nicolai and Dekker, 2008; Nowakowski and Werbińka, 2009). Sharma et al. (2011) accentuates that the use of simulation in maintenance optimization has been increasing steadily. Several studies in this field are reviewed in the next section.

To determine the components influencing maintenance costs and the availability of the turbines in the wind farm, Li et al. (2013) simulated the operation, failure occurrence and maintenance of the wind turbines. The study classified pitch, gearbox and generator as having high downtime, while pitch and electric system had high failure frequency, and further, they concluded that for optimality, manpower planning needs to be addressed. Alabdulkarim et al. (2011) modelled field maintenance where maintenance is carried out in remote and observed that maintenance performance (availability) was affected by asset use, labor availability, spares availability and provision of accurate fault diagnosis. Virtanen et al. (2001) built a model depicting aircraft maintenance types and flight operations. The study argues that aircraft availability was sensitive to manpower capacity which, in turn, was dependent on the type of maintenance carried out. Using a simulation modeling approach where different PM scheduling techniques are evaluated while using multi-criteria decision making (MCDM) in the decision-making process, Eslami et al. (2014), while modelling an imaginary manufacturing line composed of two series machines, argue that the best PM schedule incorporates a system plan, line conditions and complexities. Savsar (2015) used discrete event simulation (DES) to determine the effects of age based (ABP) and block based (BBP) maintenance policies on power plant availability, where he found ABP yielded better results than BBP. In a study of aircraft engine maintenance planning, (Razavi, 2015) identified lowest total, average grounding and waiting times, and shorter average queue length which is operational in nature, as the desirable performance indicators.

Three important themes to be considered while addressing maintenance optimization emerge from the studies discussed so far: (1) maintenance related costs, (2) equipment availability and (3) maintenance strategies. In an interesting analysis, Roux et al. (2013) argues that, while considering maintenance optimization, maximizing availability is better than other criteria such as maintenance cost. In the reviewed studies no attempt was made to quantify the effects of the various variables on equipment availability and maintenance or repair time. Moreover, the studies have generally dwelt on the systems, for example engines, and seldom evaluated critical subsystems constituting the system, for instance, for a power plant engine, cylinder, fuel system and turbocharger. This study, while modelling critical subsystems, seeks to quantify the effects and interaction of the spares availability, technician capacity, TBO, impact factor and diagnosis time due to major repair action on engine availability and total repair time, which are key plant performance indicators.

2 Methodology

The methodology consists of several steps. Step 1 involves data collection and pre-processing, Step 2 involves data exploration. Step 3 includes extraction of critical variables to be incorporated as input to a simulation model evaluating the impact of alternative O&M strategies on power plant availability. Step 4 entails developing the simulation model and performing simulation experiments, while Step 5 includes evaluating and interpreting the results of the simulation experiments.

3.1 Data collection

In this study, the analysis uses maintenance data describing failures recorded from thermal power plant engines. 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 cylinder, turbocharger and governor. The data was recorded in a free text format and collected over five-year period and includes subsystem failure occurrences, failed subsystem and components details including date and time of occurrence. The data also includes repair actions performed on the failed subsystem, the date and time the repair was finalized, and so on. Owing to data inconsistencies, it was pre-processed using a standardization step following the ISO 14224. Data was pre-processed linking the various components with their respective subsystem as well as expert consultations were done where clarity was needed.

3.2 Data Exploration

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

(a) Engine subsystems

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 (MW) using pareto analysis. The fifth critical subsystem itemized as 'others' incorporated summation of all the remaining subsystems.

(b) Repair actions

Four repair actions used in data exploration were classified using estimated repair time incurred by the action as corroborated with the maintenance team: (1) do almost nothing takes minimum 0 to at most 1 hour repair time, includes minor adjustments for instance tighten components and may not cause stoppage, (2) minor repair taking minimum 1 to maximum 7 hours may not incorporate spare replacement bringing the subsystem back to operational state, but may cause deterioration to another level of failure severity, (3) moderate repair taking 7 to at most 13 hours considers partial spare replacement and other CM actions and (4) major repair that takes over 13 hours invariably requires spares replacement. Both moderate and major repair actions incorporate logistical lead times during spares sourcing.

(c) Failure severity

This depicts the seriousness or harshness of a failure which was used to determine reliability measure attained by a subsystem following respective repair actions and subsequently used for diagnosis towards appropriate repair action. Low failure severity will have low repair time while high failure severity is assumed to have high repair time due to an intense repair action needed. In an ideal diagnosis situation, subsystem with low failure severity is directed to a lower intense repair action such as do almost nothing or minor repair actions, while one with a higher severity to high intense repair actions. The various repair actions have probability of increasing or decreasing the failure severity of the subsystem from low index 1 to high with index 4. The scheduled maintenance (PM) reduces the failure severity to almost 1 which mimics a near renewal state (near AGAN-As Good as New).

3.3 Model output parameters

The model will have two performance measures of interest as the outputs. Firstly, the engine availability also known as Operational availability, is the proportion of time the engine is running compared to total time including shutdowns due to failures and planned maintenance. It is the probability that an item will operate satisfactorily at a given point in time when used in an actual or realistic operating and support environment. We use the running hours against the total running length. Secondly, total repair time, is the total value of the repair time accrued by the engine (five subsystems) on purely repair process. This time value excludes the spare sourcing lead time and diagnosis time delays in the corrective maintenance.

3.4 Model parameter extraction

For the critical subsystems selected for analysis, several parameters derived included time to the initial failure generation which is the time the first failure of a respective subsystem occurred. Subsystem failure frequency against the four defined repair actions was extracted, which was subsequently utilized to derive the utilization probability of the different repair actions. The mean time to repair (MTTR) for the respective repair actions was derived from the repair-action time classifications using a uniform distribution (due to the classification entailing minimum and maximum repair time) while the major repair, a probability distribution was fitted due to the infinite upper value of >13 hours. Time between overhaul (TBO) and MTTR for PM were derived from the preventive maintenance planning manual of the engine. Performing the maintenance task, though, does not absolutely eliminate the failure from occurring, but it does delay it and may lessen the severity when it does occur depending on the respective repair action carried out. The estimation of impact of repair actions on the subsystem risk of failure was modelled using "Failure Severity" parameter, which was initially randomly assigned to the subsystems. Depending on the type of repair action (do almost nothing to major repair) carried out and the prior failure severity (low-1 to high-4), posterior severity will be modelled. The diagnosis time, is the estimated time that a failed subsystem will take while being diagnosed to indicate the type of failure severity hence identify the appropriate intervention or repair action, the latter identified by the maintenance team. Time to next failure (TNF) for each subsystem was determined by computing the time between repairing the subsystem to operable state up until its next failure. The time data was fitted to a probability distribution for the CM actions. Other parameters such as frequency of failure repairs that utilized spares were derived to give the probability of spares requirement for each CM action. Spares availability p also referred to as instantaneous reliability of spares (Louit et al., 2011), was introduced and provided by the plant supply chain, as the estimated probability of the power plant having stocks on hand to deal with the maintenance requirement. Sourcing lead-time for both local and imported spares was derived similarly from the plant supply chain. Manpower resource planning and scheduling including shift schedules for the main maintenance personnel was retrieved from the maintenance planning schedule. This included the estimates of maintenance staff engaged in both PM and CM repair actions in the respective two shifts per day.

3.5 Modelling

A discrete event simulation modelling framework which mimics aspects such as subsystem failure generation, subsequent undertaken repair actions (CM and PM) and normal running until the next failure occurrence was developed. An impact factor ε ranging from 0 to 1, was introduced for estimating the subsystem hazard rate (impact of the repair action on the TNF of the subsystem) in each repair action. The extreme values $\varepsilon = 0$ depict 'as bad as old' while $\varepsilon = 1$ construe 'as good as new' (AGAN). Probabilistic modelling was performed to model the deterioration process of the subsystems based on the specific repair actions utilized.

3.6 Analysis, evaluation and interpretation

This section encompasses two parts where in the first part, the model results following "as is" basis are considered while in the second part, a set design of experiment (DOE), following a full 2^k factorial design (k as the number of variables to evaluate their effect to the engine availability and total repair time) was conducted and computations of the main effects and interactions generated. Main effect is the effect of one variable on the performance measure, while ignoring the effects of all other variables, for instance the effect of increasing TBO to the engine availability ignoring other variables. An interaction is the effect of one variable on the performance measure, whilst depending on the level of another variable.

4 Results and discussions

4.1. Data collection and pre-processing

The maintenance data from the power plant was recorded in a free text structure and required standardization to meet the data structural requirement. Data standardization was done following the ISO 14224:2016. This enabled the data to be categorized using the various subsystems which was output for the data exploration discussed in the next section.

4.2. Data exploration

Figure 1 illustrates a pareto chart prioritizing the engine subsystems in the plant using individual contribution to the power lost in Megawatts (MW). What stands out in the chart is the first four subsystems i.e. cylinder, governor, turbocharger and lubrication system 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. In the maintenance decision support context, explicit strategic focus on the four critical subsystems would potentially improve and enhance the engine performance.

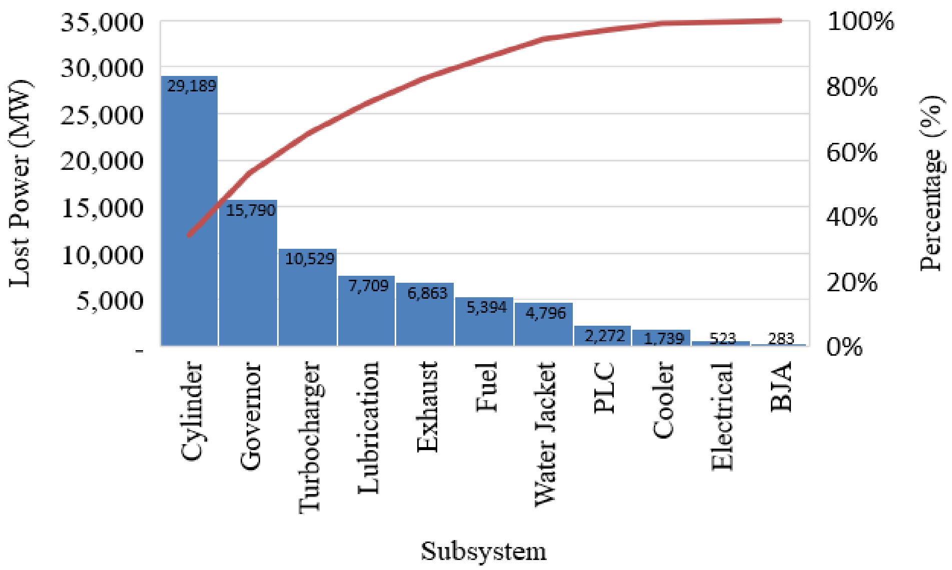

Figure 1.Pareto analysis for subsystem/components using Power lost

4.3. Model parameter extraction

Table 1 summarizes the time to the initial failure and the time to the next failure (TNF) for each of the critical subsystems selected. The computation of the time to the initial failure was done with an assumption of the analysis commencement of January 2011. Table 1 shows the governor has the highest value of time to first failure inferring its less susceptibility to failure during the early running hours after commissioning compared to other subsystems. Time to next failure (TNF), mainly mimicked Weibull and Exponential distribution's parameters. The Weibull distribution estimate represented as WEIB (α, β) with shape or slope parameter β and scalar parameter α and exponential distribution has the mean. The TNF distributions had a third parameter distribution (γ) also known as location parameter or failure free time. γ 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. A continuous distribution bounded on the lower side which 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.

Subsystem	Time to initial failure (Hrs)	Time to Next Failure(TNF) 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 1. Various subsystem time to next failure distributions

The turbocharger subsystem fitted a weibull distribution, attributable to the aging and wear out effect. The subsystem exhibit shape parameter $\beta < 1$, which indicates that the failure rate decreases over time. This happens if there are significant defective components failing early leading to strategic interventions hence failure rate decreases over time as the defective components are either replaced or maintained accurately. The components have their hazard rate decreasing due to less severing strategies for instance replacement that have lower impact on the RUL hence slight improvement of the TNF. This is contrary to intensive regenerative strategy which has a high negative impact on the RUL due to the strategy characteristics where the component renewal is near ABAO, hence shorter life experience to the subsystem.

Table 2 provides the different corrective repair actions alongside extracted parameters like probability of utilization, repair time classes and MTTR. MTTR followed the repair action classification as discussed in Section 3.2. Time utilized under the preventive maintenance (overhaul) had a uniform distribution of minimum 192 hours and maximum 224 hours as depicted from the preventive maintenance schedule manual.

Repair action	Repair classification (hrs)	Probability %	MTTR
Do Nothing	0 - 1.0	9%	UNIF (0,1)
Minor Repair	1.0 - 7.0	48%	UNIF (1,7)
Moderate Repair	7.0 - 13.0	24%	UNIF (7,13)
Major Repair	Over 13.0	19%	13 + EXPO (39.6)

Table 2. Repair time for various repair actions

The impact factor (ε) which is the percentage the interaction of the prior failure severity and repair action done is introduced to act as a multiplier to the normal operating or running hours, which is also known as the time to the next failure (TNF) of an individual subsystem. ε adopted for the 'do almost nothing' repair action was 0.65, 'minor repair' 0.75, 'moderate repair' 0.85, 'major repair' as 0.80 and 'overhaul' as 0.95, while diagnosis time in hours were 0.15,0.5,0.7 and 2.0 for the respective CM actions, which was estimated by the plant maintenance team. The impact factor was derived from proportionating the respective total TNF, comparing with major repair as 0.80 under the assumption that attaining AGAN status is difficult in deteriorating systems due to introduction of errors such as diagnosis, tooling and human related errors.

Table 3 presents the various parameters used in the spare inventory and logistics for instance the probability of requiring spares for the respective moderate and major repair actions. 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 (%)	Spares availaibility (%)	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 3. Spares availability and sourcing lead times

4.4. Model

The model mimicking the operation of the engine was developed, where the performance measurements were engine availability and total repair time. Figure 2 shows a simplified schematic model block representation of the developed model. The model developed is evaluated initially on an "as is" basis and then a design of experiment analysis is carried out, further discussed in the next section.

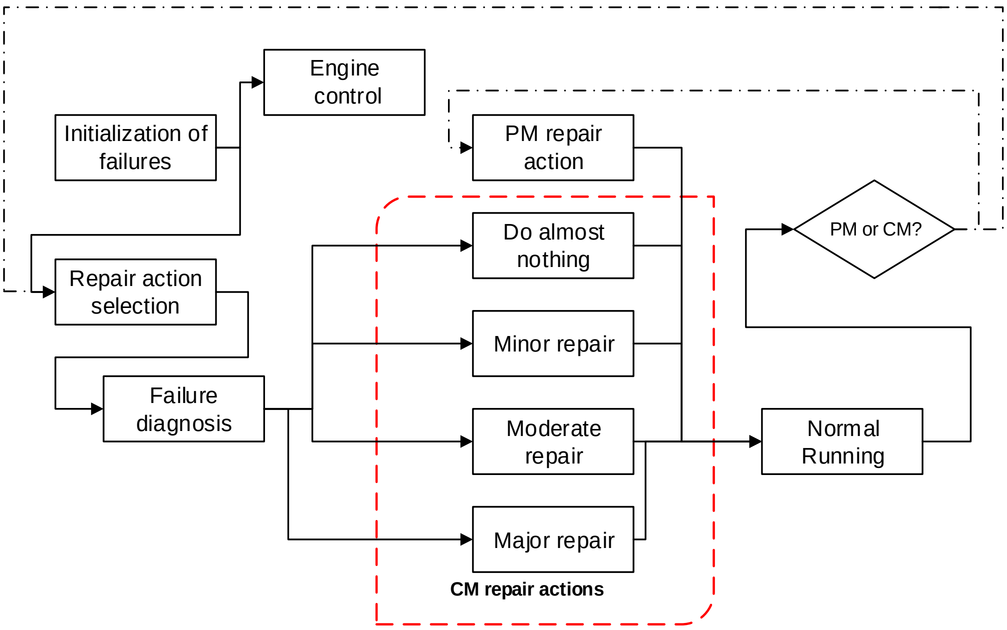

Figure 2.Schematic block representation of discrete event simulation model

4.5. Analysis of results

(a) Model results

The model generated an engine availability of 90.001% and total repair time of 18,313 hours. The availability achieved using the model was lower than the actual 92% which is attributable to the fact that strategies like condition monitoring which have potentially positive impact on TNF were not incorporated. To a certain extent the use of distribution estimations increases the variability of the results. Further evaluating the total repair time generated of 18,313 hours, the lubrication subsystem had the highest repair time, followed by governor and turbocharger each contributing 23.2%, 22.2%, 19.5% respectively of the total as depicted in Table 4. Despite "other" subsystems incurring the lowest repair time, it had the highest values for both lead-time and diagnosis time, which contribute 58.29% and 3.8% of its individual total maintenance time. Further, Table 4 shows different time variables incurred by each subsystem cumulating to total maintenance time which incorporates repair, spares sourcing lead-time and diagnosis time. The turbocharger incurs the highest total maintenance time compared to the other critical subsystems. Both Turbocharger and governor subsystem are characterized with high sourcing lead-times implying substantial failures requiring spares sourcing hence, 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. Cylinder subsystem has high diagnosis time which can be attributed to the complexity of the assembly which often require disassembly to diagnose internal components in the subsystem.

Subsystem	Repair Time (Hrs)	Lead-Time (Hrs)	Diagnosis Time (Hrs)	Total Maintenance Time (Hrs)
Turbo charger	3,562.02	1,596.96	119.9	5,278.88
Governor	4,059.56	1,514.38	101.55	4,927.14
Cylinder	3,048.00	123.31	241.2	4,615.76
Lubrication	4,251.25	156.49	93.15	3,297.64
Others	3,311.22	6,247.69	411.55	10,718.81

Table 4. Summary of subsystem times variables

The technician (manpower) utilization for both 6am to 6pm and 6pm to 6am shifts were 6.40% and 6.44% respectively, while scheduled utilization, which is the average number busy divided by the average number available was 8.59% and 13.62% respectively. These values, which apply for one engine, are low because the technicians are shared resources utilized by the whole plant with several engines. Nonetheless, the values imply similar utilization despite the day shift having two technicians while one in the night.

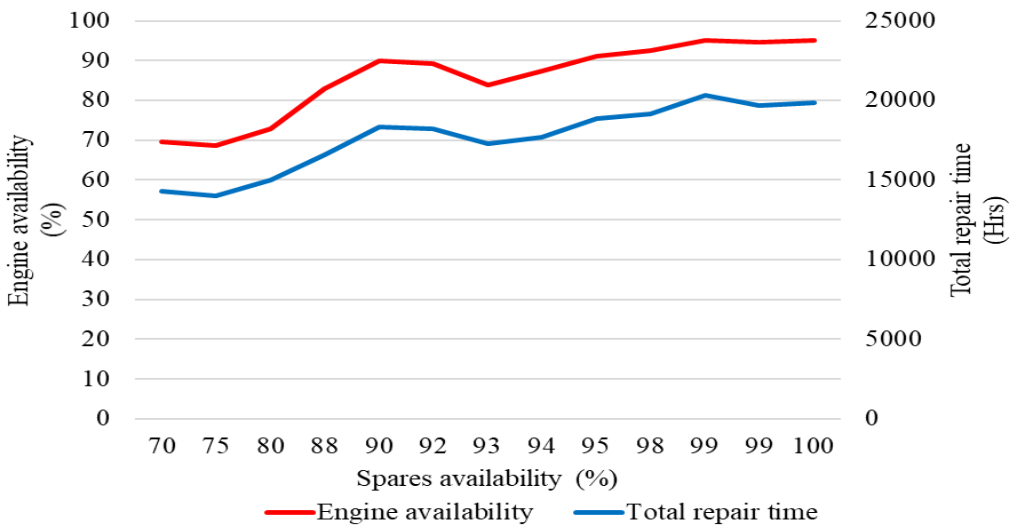

Figure 3.Plot showing effect of varing spares availability on performance measures

This implies that the night shift technician is stretched as he is utilized at the same level of two technicians during the day shift, hence higher scheduled utilization. The plant could possibly consider three shifts (6am-2pm, 2pm-10pm and 10pm-6am) to balance the utilization with the maintenance activities anticipated and ensure proportionate scheduled utilization. Moreover, adopted strategy may require to be flexible, as the plant would require more personnel in specific shifts during certain days to ensure other repairs for the other engines either in random repairs or scheduled maintenance are done.

It can be seen from Figure 3 that increasing the spares availability increases both the engine availability and total repair time. A similar analysis of TBO indicates that increasing TBO generates mixed results giving improvements and decline of both performance measures at different values. This is a rather interesting outcome which requires further investigation to explicitly understand the level of dependency between the variables while impacting the performance measures, hence the use of a full factorial experiment as discussed in the next section.

(b) Full factorial effects and interactions experiment results

Process analysis was carried out by varying different parameters such as TBO (7,000 – 12,000 hours), major repair diagnosis time-D_{t4} (0.5 – 3.5 hours), technician capacity-T_c (1 – 4 persons), spares availability- p (80% - 95%) and major repair impact factor- ε_4 (0.6-0.9). Table 5 provides the generated average main effects on the engine availability and total repair time from process analysis step. An increase in TBO from low to high, will averagely improve the engine availability by 1.19% while reducing the total repair time by 6,570.07 hours. An increase TBO means the subsystems, less frequently undergo PM which inherently is time intense, hence reduced repair time and further translates to higher engine availability due to increased running time. Despite improvement in spares availability generating high positive effect on the engine availability up to an average of 20.46%, it has a relatively high negative impact on the total repair time averagely increasing by 5,962.11 hours.

Measurement	TBO	Spares availability	Major diagnosis time	Technician capacity	ε_4
Engine Availability	1.19	20.46	-0.92	0.00	0.05
Total Repair Time	-6,570.07	5,962.11	-97.20	0.00	102.84

Table 5. Computed main effects of the parameters

The availability of spares potentially reduces the subsystem downtime due to spares sourcing lead times which greatly impact the engine running hours, hence improve the availability. This high index possibly addresses moderate and major repair actions bottlenecks by decreasing sourcing lead times, which could lead to high utilization, thus an increase in the total repair time. An increase in the major repair diagnosis time (D_{t4}) will averagely reduce engine availability by 0.92% and decrease total repair time by 97.20 hours which is negligible. These mimics increased time to ensure thoroughness in diagnosis and possibly reduction of human errors during this exercise. This has a relatively negligible positive impact on the repair time where more accurate repairs can be done on the failed subsystem and potentially reduce repeat jobs translating to a substantive reduction of the total repair time. Technician capacity (T_c) variation has no impact on both performance measures. This is attributed to the sharing of resources amongst the engines in the plant without dedication or specialisation. Increasing the value of the impact factor due to major repair action (ε_4) improves the engine availability by 0.05% and increases the total repair time by 102.84 hours. This depicts a reduction of human errors hence subsystem has lengthened running time before next failure which improves the engine availability. The model mimics mostly the retention of the respective failure severity on subsystems undergoing major repair hence a high probability for the next failure to be diagnosed towards the moderate or major repair which are time intense, which results to an increase in the total repair time.

Table 6 presents sample computed interactions on the engine availability and total repair time by the various parameters. The interaction of TBO and p causes a decrease of both engine availability and total repair time by a factor of 0.22% and 1,051.26 hours respectively. Surprisingly, despite both TBO and p having positive effect or impact on the engine availability, their interaction generates a negative effect. Furthermore, despite p having a negative effect on total repair time, the interaction generates a positive effect on the same.

Measurement	TBO + p	$p + D_{t4} + \varepsilon_4$	$p + \varepsilon_4$	$p + D_{t4}$ + TBO + ε_4	$p + D_{t4} + \varepsilon_4$
Engine Availability	-0.22	0.54	0.33	-0.22	0.33
Total Repair Time	-1051.26	-29.86	48.78	-113.66	48.78

Table 6. Computed sample interactions of parameters

This implies that the TBO effect on the engine availability does not depend on the effect of p, signifying that TBO has a negative effect at high spares availability but positive effect at low spares availability. While evaluating impact on total repair time, the effect of TBO to some extent depends on the effect of spares availability, where spare availability has a negative effect at high TBO but positive effect at low TBO. Increasing TBO and spare availability will decrease both the engine availability and total repair time and vice versa. The same analysis can be done on the computed interactions, which offer worthwhile information for maintenance optimization decision support.

5 Conclusion

The present study was designed to determine the effects and interactions of various variables on engine availability and total repair times using a simulation model. Further to identifying the turbocharger as critical among the subsystems using total maintenance time, the study has shown that the different subsystems have different repair, logistic and diagnosis times characteristics offering different impacts to their life cycle times. Spares availability was indicated to have the strongest effect on engine availability followed by TBO, while TBO had strongest effect on total repair time followed by an interaction of both TBO and spares availability. The interactions analysis while evaluating the model conceivably support the hypothesis that interactions of the variables play a role influencing the performance measures. These findings have a significant implication for the understanding parameters that require further investigation while carrying out maintenance decision making. These aspects 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 variables used need to be struck by considering their effects and interactions. The research will serve as a base for future studies and a more in-depth optimization model.

Future work could potentially involve optimization of the critical components of the subsystem incorporating additional maintenance and circular economy restorative strategies identified such as condition monitoring, spares reconditioning and reuse while incorporating cost element to improve the maintenance performance measures.

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