Simulating the Influence of Spares Replacement and Reuse Strategies on Equipment Availability and Maintenance Cost

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Abstract

The deterioration and subsequent maintenance strategies significantly affect equipment reliability and availability. Spares replacement and or reuse are critical and complement both preventive and corrective maintenance strategies, although sparse work on their influence on maintenance cost and availability has been done. A discrete event simulation model incorporating preventive (PM) and corrective (CM) maintenance actions on multiple critical equipment components are advanced to investigate the influence of reusing and replacing spares on equipment availability and maintenance cost. During PM, spare replacement is modelled using block policy (BRP) or the PM kit. The stochastic component deterioration is modelled following the Semi-Markov Decision Process, where the impact of the maintenance strategy changes the remaining useful life of the components. The proposed study is demonstrated through the use case of a thermal power plant, where components of the turbocharger, one of the critical subsystems, are modelled. The study shows that reusing significantly improves availability but does not reduce cost due to compromising component reliability. The use of the PM kit improves performance significantly compared to using BRP under PM. At the same time, an increase in the PM interval depicts an increase in the maintenance cost and availability. These findings have significant implications while understanding the dynamics of the various maintenance actions and further offering maintenance decision support to enhance the equipment availability and reduce the maintenance cost for critical equipment.

Keywords
Spares, maintenance decision support, Semi Markov Decision Process.

1. Introduction

1.1 Background

Maintenance optimization seeks to balance the resources available at the disposal of the plant with plant availability and cost reduction. Such a balance is not straightforward and often requires in-depth study of the variables that affect the objectives of the plant, including their interactions with each other which subsequently affect the performance. Several salient factors must be considered to address the challenge of optimizing plant availability and maintenance costs to achieve this objective. Equipment usage, degradation, and failure characteristics are essential to prescribe maintenance intervention Mburu et al. (2021) accurately. Similarly, significant are the maintenance interventions such as corrective, preventive, and condition-based maintenance, which significantly affect the state of the equipment/component positively or negatively in case of perfect and imperfect maintenance, respectively Wakiru et al. (2021). Different variants of preventive maintenance (PM) can be followed during an optimization which includes the use of PM kits that offer lower cost and reduce maintenance time, use of newly manufactured spares for PM replacement Chang (2012), and use product-service system (PSS) where the plant purchases, the performance and not the equipment Tukker (2015), and the conventional block-based replacement where components are replaced with new spares.

While considering the factors aforementioned in maintenance optimization, studies such as Savsar (2015) have considered single factor optimization, which follows the main effects of the single maintenance variable. Furthermore, such studies ignore the interactive effects, where several optimization objectives often conflict. Hence, maintenance decision support derived from optimizing one objective may be unreliable, also corroborated by Tian, Lin, and Wu (2012). Moreover, much of the research has not considered and evaluated the effects of various variables such as fil rate, preventive maintenance intervals, reuse, and replacement of spares while utilizing block replacement or PM kits in preventive maintenance strategy on equipment availability and maintenance cost. This indicates the need to interpret the relationship of the various variables to the performance measures that will assist the maintenance manager in wholesomely evaluating the optimization options from an informed position. This leads to challenges in the practical implementation of the optimization results in real life.

1.2 Related literature

Several factors like reliability, maintainability and availability (RAM) remain essential while addressing the maintenance optimization of critical components. The reliability of any component is often determined by the degradation or deterioration that infers the component's failure characteristics. On the other hand, maintenance strategies consider policies that address the reliability aspects of the equipment. It is now well established from a variety of studies that these two aspects(maintenance strategies and reliability) are essential in a maintenance program that considers optimization and further discussed in the following section (Shafiee and Sørensen 2017; Jiang, Chen, and Zhou 2015; Atashgar and Abdollahzadeh 2017). This section reviews literature concerned with equipment failure and degradation characteristics, system or component analysis, and finally, we briefly review appropriate maintenance policies or strategies.

1.2.1 Failure and degradation

Assets are utilized to generate performance that adds value in a business environment; for instance, engines in a power plant are employed to generate electricity. The power is eventually utilized in facilities like hospitals and industries. The assets degrade or deteriorate while being exploited and may experience failure. This deterioration may be measured by increasing the costs of operations and Maintenance (O&M) (Jardine and Tsang 2013; Wakiru et al. 2020).

Several approaches that mimic as close as possible the system's characteristic time to failure have been developed to model deterioration while undertaking maintenance optimization. A highly adopted approach employs statistical distributions like usual, exponential and Weibull to represent failure characteristics Wakiru et al. (2019a). However, this approach relies on the availability of failure data and other assumptions that offer less interpretability of the studied system. For instance, the Weibull approach retains several limitations; first, the implied assumption that the future is the same as the past, and second, it applies to only one failure mode of an item, which means it cannot predict the life of a part that fails for several reasons or failure modes Sondalini (2009). Approaches employing stochastic methods are used where the complexity of the model might be increased using statistical derived reliability. Such methods include Markov models, Semi Markov, and Hidden Markov, which model the relationship between the observations and hidden states commonly represented using a conditional probability Si et al. (2011). A distinct disadvantage of using these approaches is the state explosion that ultimately makes the optimization too complex to solve Mahfoud et al. (2016).

1.2.2 System and Component level analysis:

While envisaging maintenance optimization, the analysis can be carried out based on system or component levels. A widely utilized analysis at the system level considers interlinked equipment or components, such as a decomposed engine, into divergent equipment/systems such as a cylinder, governor, and oil pump. Several maintenance studies employing the approach include Wakiru et al. (2019b). In contrast, distinct components such as bearings, gear, turbine blade, rotor blade are analyzed while considering the component-level approach. Criticality analysis may be carried out in situations where numerous components are considered to identify components that significantly impact the performance measure. Each component is considered a remote unit (independent) in this analysis approach, and the possible dependency among components may be neglected (Shafiee and Sørensen 2017; Wakiru et al. 2018). The indicated approaches can be considered depending on the expected optimization scope, data availability, and transparent information on all system or subsystem components. However, while modelling the system/subsystem, the combinatorial aspect offers only a general high-level output that could further be used to analyze critical components. On the other hand, the component level analysis offers more intuition insights and mimics the system being modelled to near reality in terms of operability.

1.2.3 Maintenance policies

Failure-based maintenance, also known as corrective maintenance (CM), is frequently employed upon the failure of a component. Whereas it is not advisable to employ CM due to lack of planning and the consequences, it is advantageous where exploitation of the useful life of a component is fully achieved, hence reducing interventions and spare parts consumption Poppe et al. (2017). This can be achieved by replacing the failed components if, after inspection, the component is noted to retain significantly reduced the remaining useful life. Similarly, if a component is deemed to possess significant residual life left after an inspection, the reuse strategy can be advanced. The component, in this case, may be utilized in the same equipment or another similar equipment, especially when new spares are unavailable. However, CM portends high downtime risk because no prior planning has been done. Hence, lengthened downtime can be incurred while sourcing required materials and labour. To overcome this challenge, often enhanced required fill rate for spares or reuse strategy under the CM activities may be effective. To address the challenges posed by the CM strategies, preventive maintenance (PM) is advanced, where planned replacement of the components is scheduled either on a use-based or time-based approach, for instance, after so many running hours of equipment. Due to the inherent PM characteristics, the time taken for maintenance and the costs incurred is reduced compared to CM. However, the PM interval may be optimized to ensure, on one side, the components are not replaced early so that their useful life is not fully utilized (over maintenance), or on the other side, if the PM interval is extended, fewer failures would occur and hence reduce the CM interventions significantly. Notable variants concerning PM replacement are the utilization of preventive maintenance kits, frequently referred to as repair kits, which are cost-effective and offer reduced replacement time due to their inherent, intrinsic characteristics. Several studies on the PM kits concept ABB (2013) and Hu et al. (2018) can be found here.

1.3 Study aim and motivation

Remanufacturing strategies such as reuse and reconditioning have always been considered part of maintenance strategies. The use of these often-interchangeable strategies (reuse and replace) in conjunction with other maintenance strategies such as repair and reconditioning would require a trade-off while seeking an optimal performance of an asset. Based on the adopted strategy, the trade-off represents the quantified value of equipment availability gain or loss and reduced maintenance cost. Reuse strategy is often employed in installations that require ageing equipment to perform optimally. In such a case, the maintenance functions seek to lengthen the life of a component beyond the expected end of life (EOL). This is further considered in cases prompted by obsoleteness of some equipment and or components, which are no longer being produced or manufactured. Additionally, replacing such components with an advanced design would be costly for modification and possible inherent failures due to the design change afterwards. Furthermore, the maintenance cost represents a significant cost component on the total life-cycle cost of the equipment; hence the use of reuse and recondition strategies are employed Wakiru et al. (2018).

This study seeks to quantify the effect of reuse and replacement strategies and the PM interval on the availability and maintenance cost for a turbocharger whose deterioration is assumed to follow a Semi Markov process. The study further exposes how the different preventive maintenance strategies utilizing BRP or PM Kits can be relied upon to improve equipment performance. Therefore, this study contributes to maintenance optimization research by developing a framework to empower the links between the various variables engraved in optimization models.
The study extends the work of Wakiru et al. (2018a); nonetheless, several aspects differentiate the current study from the previous. This study incorporates the maintenance cost performance measure, while the previous study presented repair time. Moreover, the previous study modelled the turbine rotor as a single component while undergoing the repair strategy. The turbine rotor is disassembled, and various components such as turbine blades, rotor shaft, turbine wheel, compressor wheel, and complete turbine rotor system are incorporated separately in the model. This aspect in the current study is advanced after consultations with the maintenance function and the OEM. Finally, in the current study, the bellows were expunged since, after consultation, it was established that for comprehensive analysis, the component did not directly affect the turbocharger but affected the engine; hence, it could be unaligned wholly to the turbocharger.

The remaining part of the paper proceeds as follows: Section 2 describes the methodology adopted, while Section 3 demonstrates the results and discussion from the case study. Finally, Section 4 concludes the paper and offers future directions.

2. Methods

The methodology adopted in this study consist of four steps. Step one involves the collection and pre-processing of the data. Step 2 allows for the extraction of the various variables to be employed in the simulation model. Step 3 involves developing the simulation model and carrying out the simulation experiments, while Step 4 will include evaluating and interpreting the results.

2.1 Data collection and pre-processing

This study utilizes maintenance data on failures from a thermal power plant remotely located in Eastern Africa. The data for the components constituting the turbocharger, i.e., base plate, bearings, gaskets, Lube oil pipe, others, and turbine rotor system (disassembled to turbine blades, turbine wheel, and compressor wheel) considering six years (2011- 2017) were used from the subject thermal power plant.

2.2 Parameter extraction

The turbocharger was decomposed into its components, failure analysis was carried out for the various components, and maintenance/recovery strategies parameters were extracted. The various parameters include the time to subsequent failure, spare costs for each component, repair time for respective (CM and PM) strategies, labour rate per hour for maintenance, failure frequencies, and PM kits costs.

2.3 Simulation modelling

The simulation model mimics the failure generation and intervention for components of the turbocharger, as illustrated in Figure 1.

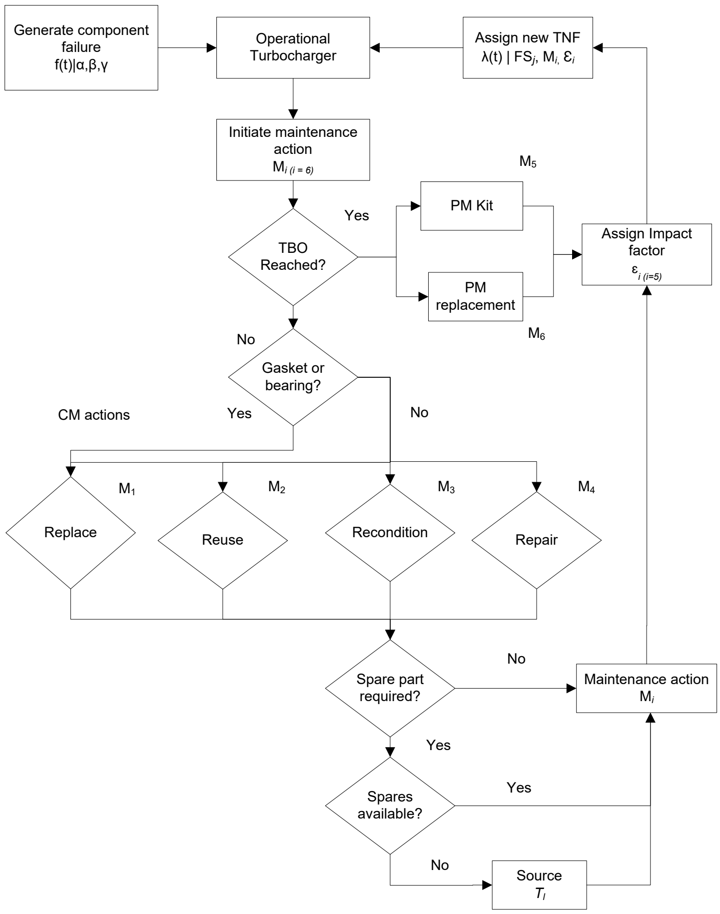

Figure 1. Conceptual representation of the simulation model

While the turbocharger is running, preventive maintenance, in this case, replacement of all components, is done at scheduled running hours τ (PM interval) of the engine. While running, random unplanned failures employ corrective maintenance that includes several maintenance interventions. The first CM strategy is the replacement of failed components with a newly manufactured spare, which is mandatory for bearings and gaskets. In contrast, other components possess probabilistic utilization of the other strategies. This aspect is influenced by the fill rate, where if the spare is unavailable, it is sourced, hence incurring sourcing lead time. Reuse strategy is also employed for components that can be sourced from equipment either decommissioned or opportunistically waiting for other spares hence not operating (Table 1).

Table 1. Notations utilized in the study

i	Number of maintenance actions	I	Turbocharger running hours
M_i	Maintenance strategies	A_o	Operational availability (%)
$\mathcal{E}_i$	Age renewal factor	T_m	Total maintenance time (hrs.)
τ	Preventive maintenance interval	PM_{pol}	Preventive maintenance (PM) policy
η_i	Reliance factor/index	C_{s_n}	Spare cost for n^{th} component
FS_i	Hazard rate/Failure severity	T_{r_i}	Recovery/repair time (hrs.)
C_m	Total maintenance cost (K€)	T_l	Sourcing lead time (hrs.)
C_s	Total spare cost (K€)		
C_L	Total labour cost (K€)		

This is commonly termed as cannibalization, though in this study, more dominant are spares stored from previously decommissioned or reworked turbochargers. A repair strategy is used where the component's failure state is repairable, returning it to its functional condition. Reconditioning strategy is also employed where the cores of the components are availed, and the OEM or an agent can restore components and avail with some warranty. In this study, it is assumed that the reconditioning is done after failure occurrence. Preventive maintenance (PM) is modelled following two options; where the first involves replacing the components with newly manufactured spares. In contrast, the second, a preventive maintenance kit is utilized along replacement of components not included in the kit, following the lapse of the τ. The maintenance actions/strategies M_i modelled include replacing (M_1), reuse (M_2), recondition (M_3), repair (M_4), PM using the kit (M_5) and PM employing new spare replacement (M_6) as block replacement policy (BRP). To model the maintenance strategy frequency of usage, reliance factor $\eta_{i=1,2,3,4}$ is introduced, which indicates the percentage usage of the specific M_i.

The effective age renewal factor or the impact of the respective recovery/maintenance strategy on a component's remaining useful life is depicted using an impact factor $\varepsilon_{i\ (i=1,2,3,4,5,6)}$ (note $\varepsilon_5 = \varepsilon_6$), which range from 0 depicting ,as bad as old, (ABAO) and Ɛ=1 ,as good as new, (AGAN). A hazard rate FS_jAn index indicating the severity or seriousness of a component failure state is introduced, with a stochastic transitioning severity state of a component prior to and after maintenance action. Posterior ε_i, depends on the prior severity state and the maintenance strategy impact hence depicting a multi-state system (MSS). A Semi Markov Decision process is employed to model deterioration of the components, which considers the observed partial degradation that influences the component's posterior state after maintenance intervention. The maintained component is assigned the new Ɛ and ρ and subsequently continues to run till either next PM or CM.

2.4 Evaluation and interpretation
For this study, the critical performance measurements include the turbocharger operational availability $A_o$and the total maintenance cost C_m. A sensitivity analysis is performed to ascertain the impact of reliance on replacement and reuse strategies separately. Additional analysis on the effect of the PM interval is also done. During the analysis, the indicated variables will be varied as follows: PM_{pol}(1-PM replacement, 2-PM kit), τ (9,600 – 14,400 hrs.), replace reliance η_1(50% - 74%) and reuse reliance η_2 (7% - 11%). The values of $\eta_1$and η_2 are utilized alternately, summing up to 85% (total probability utilization of the two strategies in real-life operations).

3. Results and Discussion
3.1 Modeling, verification, and validation
3.1.1 Model parameters
The model parameters adopted from the case established in the paper (Wakiru et al. 2018) τ, 12,000 hours; ε_1,90%; ε_2, 40.5%; ε_3, 43.94%; ε_4, 55.59%; ε_5,95%; η_1,62.71%; η_2, 9.33%; η_3, 22.03%; η_4, 5.93%. Other parameters extracted from data and maintenance schedules included the respective component's new spares costs $C_{s_n}$and distributions depicting the time to subsequent failure λ_n. Such distributions included WEIB (α, β), BETA (α, β), with shape parameter β and scalar parameter α while exponential distribution has the mean and TRIA with the minimum, average and maximum. Additional parameters included sourcing lead time T_l, repair/recovery time T_{r_i} for each maintenance strategy.

3.1.2 Modeling
The performance measures turbocharger availability A_o and the total maintenance cost C_m are defined by equations (1) and (2) respectively as follows:

$$A_o = \frac{I}{I+T_m} \qquad (1)$$

$$C_m = \sum_{k=1}^{n} C_{L_k} + \sum_{k=1}^{n} C_{S_k} \qquad (2)$$

Since the model starts with no activity, attaining a steady-state is essential. To address the issue of large half-width, the number of replications was computed from the initial 10 replications generating half-width of ± 6.15%, in our case approximately 100 replications leading to ±2%. A warm-up period of 10000 hours was employed, while the replication length was 105,120 hours, equivalent to 12years of operation.
h_o= half-width from ,initial, number n_o of replications
h = $n_o \frac{{h_o}^2}{h^2}$ = 10*$\frac{6.15^2}{2^2}$ = 94.55

3.2 Simulation results

Table 2 illustrates the model results categorized, firstly considering PM with complete spares replacement, while the second considers the employment of the PM kits.

Table 2. Simulation base results

Model approach	A_o	C_m (K€)
PM approach I	94.019%	1,005.2
PM approach II	93.176%	977.75

As shown in Figure 2, the PM kit (PM approach II) reduces the total maintenance cost by 27.45 K€ compared to BRP (PM approach I). This could be attributed to the cost advantage the PM kit retains, when utilized, an aspect also corroborated by (Saccani et al. 2017). However, approach II generates moderately reduced availability, which may probably be attributed to a moderate increase in repair time, occasioned by components that demonstrate their reliability negatively affected. This is because the approach I entrench significant probability to install higher values of FS_j compared to approach II. However, overall availability compared with the actual empirical of 92% show minimal deviation which is attributed to lack of Condition-based Maintenance (CBM) strategy utilization.

3.3 Sensitivity analysis results

Sensitivity analysis was carried out following the objectives of the study as depicted in Section 1.3. The first experiment evaluates the reliance on replacing strategy, while the second evaluates a reuse strategy. The final experiment evaluates the influence of PM interval.

3.3.1 Replacement strategy- η_1 reliance

From results depicted in Figure 2, it is demonstrated that reliance on a replacement strategy η_1, minimally reduces A_o and moderately increases the C_m. The reduction of A_o may be attributed to the increased downtime time occasioned by the increase in sourcing lead time for the unavailable spares as per the fill rate *f*. The employment of this strategy, as expected, retain a disadvantage of incurring higher spare costs, which negatively impact C_m as also seen in Figure 2. This is because the spares utilized are newly manufactured, increasing the spare cost. However, high utilization of replacing beyond 68% is shown to increase significantly A_o and reduce C_m in approaches I and II (See Figures 2a and 2b). A trade-off area of retaining η_1 (55% - 68%) indicates optimum A_o and C_m for such a case study.

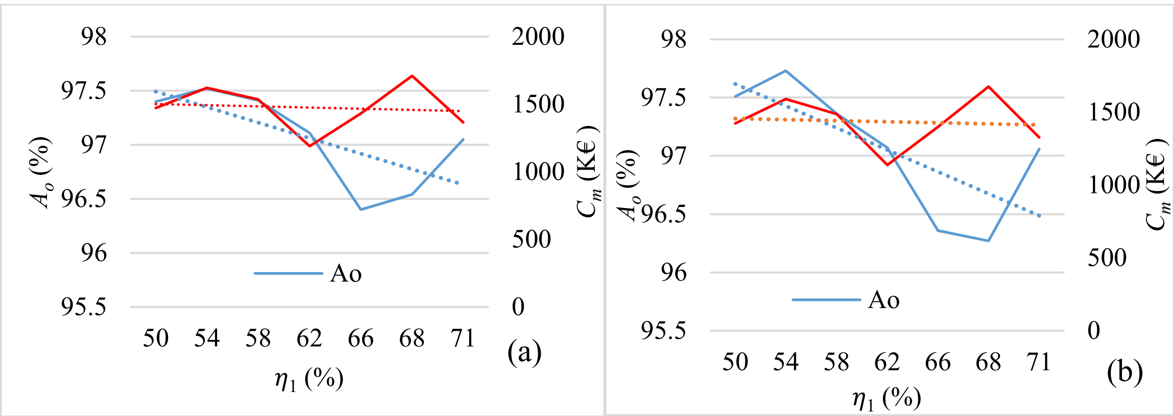

Figure 2. Variation of replacing strategy η_1 reliance, when utilizing (a) BRP and (b) PM kit

3.3.2 Reuse strategy- η_2 reliance

While investigating the effect of reliance on reuse strategy while using block replacement policy in PM, Figure 3(a) shows a marked decrease in the A_o and stagnation of C_m. However, when using a PM kit (approach II), as seen in Fugue 3(b), a significant improvement of A_o (increase) and an increase in C_m is noted. The increase in η_2, firstly reduces the repair time due to significantly low sourcing lead times while utilizing reusable spares. However, due to the utilization of this strategy, it is expected that the system reliability is compromised hence the non-linear behaviour of the curves as demonstrated in both approaches I and II as shown in Figures 3a and 3b, respectively. To employ such a strategy, caution should be observed while addressing the reliability transition of the reused components or equipment.

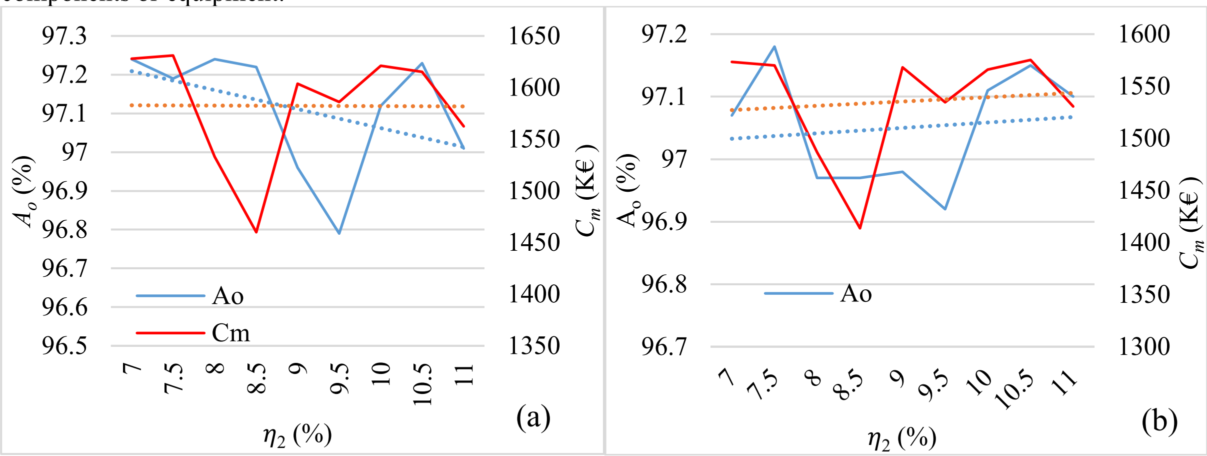

Figure 3. Variation of reuse η_2 strategy reliance, when utilizing (a) BRP and (b) PM kit

3.3.3 PM Interval- τ variation

Figure 4 illustrates the changes in both A_o and C_m while varying the PM Interval τ and utilizing the BRP and PM kit, see Figures 4(a) and 4(b), respectively. An increasing trend of τ shows a remarkable increase in A_o. This can be attributed to the extended time of running for the turbocharger before the planned stoppage for PM.

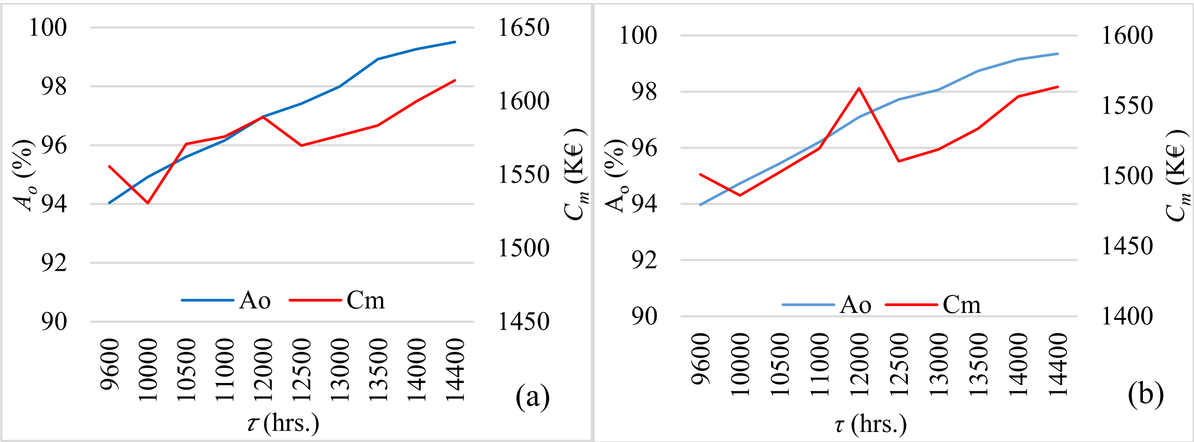

Figure 4. Variation of PM Interval τ strategy when utilizing (a) BRP and (b) PM kit

However, this extension produces a negative impact on the components failure rate since the reduced renewal process leads to a significant failure rate dealt using CM interventions which are costly, hence the increase in C_m. The non-linear characteristics of the C_m the curve indicates potentially external factor (s) interacting with τ. However, while considering optimal τ, this aspect requires consideration. Further, the trade-off between the performance measure preferences of the maintenance team should cautiously be considered, in collaboration with organizations' changing maintenance objectives, while determining the optimal value of τ.

3.3.4 Spares fil rate sensitivity - *f* reliance

As shown in Figure 5, the change (increase) in the fil rate, which infers high availability of spares for replacement, increases both the availability (A_o) and C_m while implementing either approach (approach I-BRP or approach II-PM kit). As expected, the availability of spares will reduce the downtime contribution of spare sourcing lead times hence increasing the availability. On the flip side, the subsequent increased use of spares will undoubtedly increase the maintenance cost. However, while utilizing approaches II (Figure 5b), the C_m is lower than the approach I which retain complete PM replacement or BRP. This is attributed to PM kits that provide a cost advantage by being lower in cost than new spare parts sourced separately.

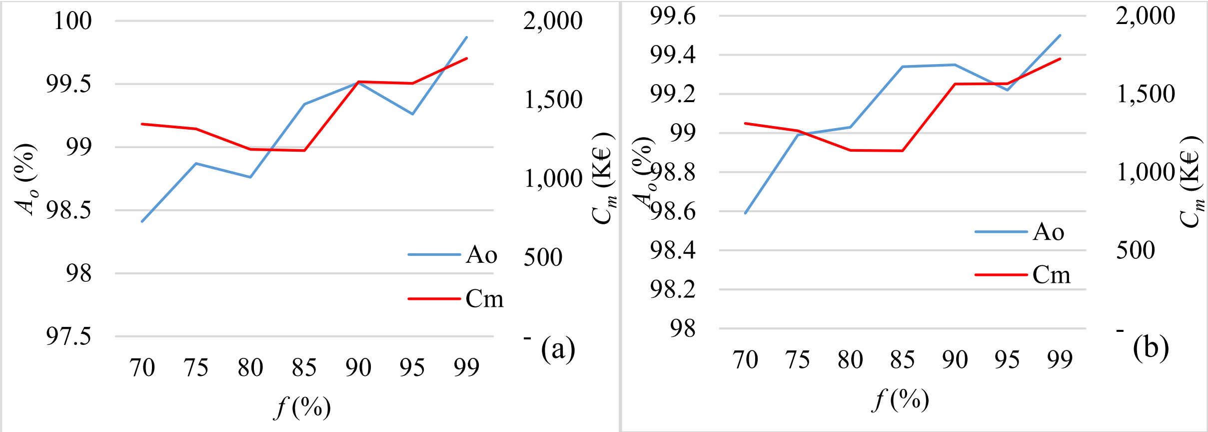

Figure 5. Variation of fill rate when utilizing (a) BRP and (b) PM kit

In summary, the enhanced replacement strategy will ensure the components in operation continuously retain high reliability; hence, if they are reused, the reliability retained within will ensure longevity and reduced failures. This subsequently will offer a reduction of the C_m if both reuse and replace strategies can be employed in a hybrid approach to complement each other. Another downside of the replace strategy is the possibility of replacing components whose whole life is not fully exploited, and hence, the reliance on newly manufactured spares during both the PM and CM activities, complemented with the high instantaneous availability of the inventory, undoubtedly will increase C_m. These approaches would indirectly relate to replacing components before fully exploiting their residual life, an exercise that may be referred to as ‚over maintenance.‚

3.4 Summary

Some of the issues emerging from these findings relate principally to the importance of accurately establishing the accurate time to make a specific maintenance intervention to mitigate what was earlier highlighted as ‚over maintenance‚ and unplanned failures. An approach should be derived for such a plant to either consider the severity or the mean residual life of the component while deciding when to intervene with a specific maintenance strategy/policy. Hence, further work is required to consider these two aspects, i.e., the component severity (hazard rate) and remaining useful life (RUL) in maintenance intervention decision-making. This combination of findings considering the influences of η_1, η_2 and τ on both A_o and C_m provides some support for the conceptual premise that reliance on a single decision variable or main effects leads to sub-optimal maintenance optimization. It is then prudent for maintenance managers to investigate all possible decision variables that demonstrate the potential to be included in the maintenance program. The evaluation should address both effects or impacts on the performance measures and their interaction characteristics. This will inform the maintenance team on the essential decision variables to consider, hence, deriving a wholesome and accurate optimization outcome. From the sensitivity analysis, it has been demonstrated that enhanced utilization of the reuse strategy offers better optimization outcomes compared to replace strategy. However, using both strategies under a hybrid approach forms a substantial issue for future work.

4. Conclusion

The present research aimed to examine the effects of reliance on reuse and replace maintenance strategy, the PM interval, and the PM kit on both the Turbocharger availability and total maintenance cost. The results clearly show that reliance on a single variable for optimization would lead to the sub-optimal outcome. These findings provide significant implications for understanding how the investigated decision variables should be incorporated in the optimization processes. The insights gained from this study will assist the maintenance managers while prudently selecting the maintenance variables that will significantly affect their maintenance programs, especially as concerns optimization where various decision variables constitute the maintenance objective function.

To attain near empirical performance measures, subsequent work incorporating the analysis of effect and interactions, condition-based maintenance, and utilization of an RUL threshold for maintenance intervention decision making is proposed.

Acknowledgement

Special appreciation to the anonymous power plant and maintenance staff.

References

Atashgar, Karim, and Hadi Abdollahzadeh., A Joint Reliability and Imperfect Opportunistic Maintenance Optimization for a Multi-State Weighted k-out-of-n System Considering Economic Dependence and Periodic Inspection. *Quality and Reliability Engineering International* 33 (8): 1685–1707, 2017.

Chang, Yu Sang., Strategy, Structure, and Channel for Global Leaders of Industrial Service: A Flow Chart Analysis of the Expanded Value Network., *International Journal of Services Technology and Management* 17 (2/3/4): 138, 2012.

Jardine, A.K.S, and A.H.C Tsang, *Maintenance, Replacement, and Reliability*. Second. Boca Ranton, FL: CRC Press, Taylor & Francis Group, 2013.

Jiang, Yunpeng, Maoyin Chen, and Donghua Zhou., Joint Optimization of Preventive Maintenance and Inventory Policies for Multi-Unit Systems Subject to Deteriorating Spare Part Inventory., *Journal of Manufacturing Systems* 35: 191–205, 2015.

Mahfoud, H., A. El Barkany, A. El Biyaali, H. Mahfoud, A. El Barkany, and A. El Biyaali., ,Preventive Maintenance Optimization in Healthcare Domain: Status of Research and Perspective., *Journal of Quality and Reliability Engineering* 2016: 1–10, 2016.

Mburu, Stanley M, James M Wakiru, Peter N Muchiri, and Liliane Pintelon, Maintenance Impact on Geothermal Drilling Operations. A Case Study Approach. *American Journal of Industrial and Business Management* 11: 183–201, 2021.

Poppe, Joeri, Rob J.I. Basten, Robert N. Boute, and Marc R. Lambrecht, Numerical Study of Inventory Management under Various Maintenance Policies., *Reliability Engineering and System Safety* 168 (June): 262–73, 2017.

Saccani, Nicola, Filippo Visintin, Renata Mansini, and Marco Colombi., Improving Spare Parts Management for Field Services: A Model and a Case Study for the Repair Kit Problem., *IMA Journal of Management Mathematics* 28 (2): 185–204, 2017.

Savsar, Mehmet., Availability Analysis of a Power Plant by Computer Simulation., *International Journal of Electrical, Computer, Energetic, Electronic and Communication Engineering Vol:9,* 9 (4): 495–98, 2015.

Shafiee, Mahmood, and John Dalsgaard Sørensen, Maintenance Optimization and Inspection Planning of Wind Energy Assets: Models, Methods and Strategies, *Reliability Engineering and System Safety* 000: 1–19. , 2017.

Si, Xiao Sheng, Wenbin Wang, Chang Hua Hu, and Dong Hua Zhou. ,Remaining Useful Life Estimation - A Review on the Statistical Data Driven Approaches, *European Journal of Operational Research* 213 (1): 1–14, 2011.

Sondalini, Mike, *Plant and Equipment Wellness*. Engineers Media., 2009.

Tian, Zhigang, Daming Lin, and Bairong Wu. ,Condition Based Maintenance Optimization Considering Multiple Objectives, *Journal of Intelligent Manufacturing* 23 (2): 333–40, 2012.

Tukker, Arnold., Product Services for a Resource-Efficient and Circular Economy - A Review. *Journal of Cleaner Production* 97: 76–91, 2015.

Wakiru, James, Liliane. Pintelon, Peter.N Muchiri, and Peter Chemweno, Maintenance Optimization: Application of Remanufacturing and Repair Strategies, *Procedia CIRP* 69 (May): 899–904, 2018..

Wakiru, James, Liliane Pintelon, Peter N. Muchiri, and Peter K. Chemweno, A Review on Lubricant Condition Monitoring Information Analysis for Maintenance Decision Support., *Mechanical Systems and Signal Processing* 118: 108–32, 2019a.

Wakiru, James, Liliane Pintelon, Peter N. Muchiri, and Peter K. Chemweno., A Simulation-Based Optimization Approach Evaluating Maintenance and Spare Parts Demand Interaction Effects, *International Journal of Production Economics* 208 (December): 329–42, 2019b.

Wakiru, James, Liliane Pintelon, Peter N. Muchiri, and Peter K. Chemweno.,Integrated Remanufacturing, Maintenance and Spares Policies towards Life Extension of a Multi-Component System., *Reliability Engineering & System Safety* 215 (November): 107872, 2021.

Wakiru, James, Liliane Pintelon, Peter N. Muchiri, Peter K. Chemweno, and Stanley Mburu., Towards an Innovative Lubricant Condition Monitoring Strategy for Maintenance of Ageing Multi-Unit Systems, *Reliability Engineering & System Safety* 204 (December): 107200, 2020.

Biography / Biographies

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