Simulation-based derived maintenance spares criticality assessment

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Effective inventory control policies for maintenance spare parts necessitates criticality evaluation, which is predominantly done using historical data. This approach disregards uncertainty and risks like changes in reliability and failure rate that maintenance-intensive facilities experience. Therefore, incorporating these anticipated variabilities in the evaluation offers more appropriate and robust maintenance and inventory decision support. Moreover, an assessment considering the contribution of individual spares towards the whole system, based on the various criteria, offers a more comprehensive and accurate criticality analysis. A novel simulation-based spare parts criticality evaluation approach is proposed, integrating maintenance and spares policies of deteriorating multi-component system to derive the information quantifying the various criticality criteria. In addition to the conventional criticality criteria, this study considers the stochastic component dependencies propagating secondary failures (failure interactions) and the respective labour time incurred. Component degradation and dependencies are modelled while forecasting the various criticality criteria values, which are assigned weights based on indices derived through expert analysis. Ultimately the evaluation for each maintenance spare of the system, based on the aggregate criticality index is undertaken to offer a quantitative and robust criticality assignment. The applicability of the proposed approach was demonstrated through a case study evaluating the spare part criticality problem of a turbocharger subsystem in a thermal power plant.

Keywords: Criticality analysis, Maintenance, Spares, Dependency, Simulation, Secondary failure.

1. Introduction

Spare parts management strategy in a multi-unit system is essential towards improving plants availability and maintenance cost reduction (Teixeira, Lopes, and Figueiredo 2018). However, despite its importance, spare parts management retains significant challenges to the system. Spare parts unavailability portends an extended system downtime, with adverse impact on the company's profit (Zhu, Jaarsveld, and Dekker 2020). On the other side, addressing unavailability by maintaining high inventories often results in high inventory costs and consuming the working capital. Furthermore, the decision by engineers, whether to repair or replace a component has profound implications on spare parts management. Lastly, equipment life extension strategies like remanufacturing may be adopted for system or units approaching the End of Life (EoL), which likewise complexify the spares management.

To mitigate these challenges, the formulation of robust Spare part inventory control policies is required. The policies should help in identifying and planning for critical components, ones that impact the system performance (e.g., cost and availability) significantly. Hence, spare parts criticality is an essential aspect of Spare part inventory control policies and management. In literature, several essential criteria are considered in determining critical spares. Such criteria include the failure rate, mean time to repair, spare sourcing lead time, the cost of spares, cost of machine downtime and safety and environmental changes (ISO 17359 2018).

Secondary damage and labour, in addition to conventional criteria, are considered essential factors deriving savings and improving critical spares management. Secondary failure (failure induced damage), is exhibited where component failure may be caused by failure or fault of another component. However, in the conventional criticality analysis approach, each part is considered as a separate unit (independent). Despite notable work in this direction (e.g., Scarf and Deara 2002; Dong et al. 2019), the

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quantification and linking of the secondary consequence to the primary failure (causative) among components, depicting failure dependency is often disregarded. Hence, the propensity of failure retained by such components that effectuate secondary failures in practice should be considered circumspective in increasing their criticality. This is because they increase the unforeseen demand of other spares, prolong the repair times (downtime), increase costs and ultimately adversely affect the overall system performance.

Labour is linked to specificity, a critical spare characteristic subsumed in maintainability. In this case, a specific spare part retains unique maintenance requirements compared to others. For instance, replacement or repair time linked to a particular spare will be different from the others due to its maintainability. Therefore, analyzing the criticality of a spare based on the labour-hours incurred can be advanced as another criticality criterion, depicting specificity of the individual spare part.

A vital aspect for a successful spare criticality analysis represents the derivation of the values representing the various criticality criteria variables like spares demand and lead-times. Information on spares demand, also referred to as Advance Demand Information (ADI), should be available ahead of the actual demand occurrence while deriving inventory policies (Zhu, Jaarsveld, and Dekker 2020). Deriving ADI using historical spares data which remains the predominant method is limited to past events, hence cannot be used for current and future analysis. A simulation-based approach considering maintenance policies is not only based on historical operations but also incorporates future anticipated operational variables in maintenance.

Research in this line has predominantly focused on corrective maintenance (CM) and disregarded preventive (PM) and condition-based maintenance (CBM), an approach that may lead to suboptimal decision support. On the one side, despite predominantly considering spare replacement, alternative strategies under CM like repair are disregarded, although they influence spare replacement decisions in real-life. On the other hand, maintenance policies like PM and CBM in real-life, likewise influence the spare criticality criteria like spare demand, labour time and cost. Moreover, the dependency of the various components in terms of failure and operability, subsumed in all the policies, if ignored, may significantly create challenges while considering critical spares. This study, therefore, sets out to develop integrated maintenance and spares policies framework evaluating spares criticality for a multi-unit repairable system. The ADI for a specific spare part is quantified using a simulation-based model. Besides, spare cost, lead-times, labour and secondary failure costs, are quantified using the model. Ultimately, an indexing system is employed to evaluate and rank the criticality of the component. A holistic approach integrating CM, PM and CBM policies simultaneously is utilized. Moreover, alternative options to replacement, like a repair, adjustment and reuse are included (under CM and CBM), along with order-up-to spares provision policy to offer decision support realistically.

2. Related Literature

In undertaking spare parts criticality, three critical aspects are discussed here.

2.1 *Criticality analysis criteria selection*

Various criticality criteria linked to an individual spare part (function and production impact) have been employed, while undertaking spares criticality analysis. Such criterion includes lead time and price (Teixeira, Lopes, and Figueiredo 2018), unit cost, downtime, demand, repair times and the number of potential suppliers (Ilgın 2019). The spares ADI is predominantly influenced by component failure and maintenance actions like replacement and repair undertaken on the repairable component.

However, a multi-unit system demonstrates failure interactions between units, also termed as stochastic dependence. An extensive discussion and list of types of stochastic dependencies are found in Table 2 of (Olde Keizer, Flapper, and Teunter 2017). In this case, the failure or fault of one unit (primary failure) may impact another unit, causing a secondary failure on the other unit(s). Secondary failure is defined by (EN13306 2010), as the failure of an item caused directly or indirectly by a failure or fault of another item. The risks portended, and consequences of secondary damage to system availability and cost can be significant compared to primary failure. Hence, it is an essential aspect while considering the criticality of a component. A study by (Van Horenbeek and Pintelon 2013) incorporated this aspect of stochastic dependency by considering secondary failure for the multi-component system. Besides not acknowledging CBM and undertaking criticality analysis, the study examined secondary failure for only one component, while there are instances where secondary failure may affect more than one component.

Maintainability alludes to the probability that a robust maintenance action (repair or replacement) of a component will be executed within a stated time interval using given resources like tools, engineers with skills and given procedures (Barabadi et al. 2011). Maintainability is significantly influenced by the distinct skills, tools and number of staff required during maintenance of a component. A key performance measure here would include the repair or replace time represented by the labour-hour time; the specific spare incurs during maintenance. A component or spare suffers non-identical repair or replace times compared to others while necessitating unique skills, tools and number of staff. However, studies that have considered this aspect, such as (Eruguz et al. 2018) have lumped the labour costs under the maintenance costs and disregarded the unique characteristics embodied by the different spares individually. Also, opportunistic maintenance (OM) policy which exhibits economic dependence among the units in a multi-unit system, may significantly reduce labour time related to a specific component.

Although extensive research has been carried out using various criticality criteria, no single study exists which incorporates secondary failure and labour time attributed to specific spares as a critical aspect that affects spares criticality analysis.

2.2 *Maintenance based spares advance demand information generation*

Predominantly, two essential methods are distinguished to derive spares ADI. The first method employs historical spare parts data, used in significant studies like (Hu et al. 2017; Teixeira, Lopes, and Figueiredo 2018; Ilgın 2019). However, this method disregards current and future demands and ignores actual inherent maintenance and operational changes expected in a plant. This limitation poses a significant challenge for the process to derive practical and optimal ADI decision support. To overcome these challenges, maintenance driven approach to derive ADI is proposed.

Maintenance policies like block replacement under PM policy and reliance on a corrective replacement under CM may escalate spares requirement (Wakiru et al. 2019). On the contrary, CBM is proven to scale down spare demand (Si, Zhang, and Hu 2017). Hence, a cost-effective solution is to consider spare parts and maintenance policies jointly. To derive spare parts ADI, (Van der Auweraer and Boute 2019) incorporated both PM and CM, while several other studies have employed CBM like (Si, Zhang, and Hu 2017; Wakiru et al. 2020).

However, these studies have several limitations: Firstly, the studies predominantly consider replacement of the spares solely under all policies to derive ADI. However, disregarding other maintenance actions like repair may offer suboptimal decision support since these maintenance actions likewise influence the demand for spares. Moreover, tracking the reliability of the component which is affected by such maintenance actions is seldom modelled. Secondly, the studies have not incorporated all the maintenance policies (PM, CM, CBM and OM) together while deriving spares ADI. In real life, the various maintenance policies are employed simultaneously, hence disregarding their interactions would potentially offer enervated decision support.

2.3 *Parts criticality classification techniques*

In literature and practice, several techniques, either qualitative or quantitative, incorporating single or multi-criteria methods, are employed for spare criticality and classification. Well applied qualitative classification techniques include ABC which uses the 80-20 rule (the Pareto principle) and Vital, Essential and Desirable (VED) (Hu et al. 2017). ABC classification, primarily influenced by cost (Hu et al. 2017) may be unable to provide a functional classification when other criteria linked to each item, like lead time and inventory cost, become essential. While VED analysis tolerates subjective and biased judgments of the users (Cavalieri et al., 2008).

AHP addresses the limitation of a single criterion by utilizing both qualitative and quantitative factors and defines critical ones via a hierarchical structure (Teixeira, Lopes, and Figueiredo 2018). Due to imprecise information, fuzzy logic is incorporated with weights (e.g., (Ilgın 2019)) The reader is referred to (Hu et al. 2018) for an extended discussion of the techniques. Fault Tree Analysis (FTA), dynamically incorporates failure dependency and spares. The reader is referred to (Ruijters et al. 2019) for a comprehensive FTA model benchmark. However, this technique is inept to simultaneously consider uncertainty and random influence of maintenance actions and component reliability changes.

All research in this direction has largely employed qualitative techniques and are based on the historical information of spare demand data and lead-time data, which is subject to change with time. Hence cannot be relied upon for future planning, due to dynamic changes that affect both the system's maintenance, operation and supply chain (internally and externally). Moreover, the employment of qualitative techniques introduces bias and subjectivity, which may ultimately lead to suboptimal decision support.

To mitigate these challenges, simulation, which considers system stochasticity and translates all variables quantitatively is now increasingly being employed (Van der Auweraer and Boute 2019; Wakiru et al. 2019, 2020). This study aims to contribute to this growing area of research by developing an innovative simulation-based model for criticality analysis of a multi-unit repairable system. The use of simulation modelling for robust decision support allows: first, the consideration of uncertainty associated with various maintenance-related parameters like the time between failures and repair times. Secondly, the integration of all the maintenance policies (CM, PM, CBM and OM) and the unit degradation to represent reliability. Conclusively, the model is capable of deriving individualized spare parts demand information, contribution to secondary failure cost, labour time, lead time and total spare cost.

The remaining part of the paper proceeds as follows: Section 3 describes the methodology adopted, while Section 4 demonstrates the results and discussion from the case study. Finally, Section 5 concludes the paper.

3. Methodology

The methodology adopted in this study consists of four steps as described in this Section.

3.1 *Data collection and pre-processing*

This study utilizes maintenance data considering six years (2011- 2017) on failures from a thermal power plant remotely located in Eastern Africa. The study represents an advancement of published work (Wakiru et al. 2019) where the availability and maintenance repair time were evaluated and the turbocharger identified as a critical subsystem. The turbocharger has n components. Here, $n = 11$, i.e. bearings, gaskets, Lube oil pipe, nozzle rings, turbine diffuser, turbine rotor, base plate, turbine blades, turbine wheel (disk and blades), compressor wheel and others.

3.2 *Parameter extraction*

Failure analysis was carried out for the various n components of the turbocharger based on the empirical maintenance data. The multiple parameters derived, are described and employed in the subsequent Section 3.3. They included the random time to next failure (λ_n) and the cost for each of the components (See Table 1). Time to repair (Tr_i), diagnosis time (Td_i) and probabilistic utilization (η_i) for CM and PM are shown in Table 2. Similar parameters for CBM (Tr_i^c, Td_i^c and η_i^c respectively) are shown in Table 3. Lastly, holding cost rate of 0.2 €/hr/component and labour rate of 10€ per hour for maintenance were also derived from data and expert consultation.

3.3 *Simulation modelling*

The simulation model schematically illustrated in Fig. 1 is further described in Section 3.3.2. The model mimics the failure generation and intervention for components whose description, λ_n and costs are illustrated in Table 1.

3.3.1 Degradation

The effective age renewal factor or the impact of the respective recovery/maintenance action on a component's remaining useful (virtual) life is depicted using an impact factor $\rho_{i\ (i=1,2,3,4,5)}$ (note $\rho_5 = \rho_6$). The impact factor ranges from 0 depicting "as bad as old" (ABAO) and ρ=1 "as good as new" (AGAN), while the study adopts the work of Wakiru et al. (2018) as illustrated in Table 2.

Table 1. Turbocharger components cost and MTBF

Component	Time to next failure -λ_n (hrs)	Cost (€)
Others	116 + WEIB (2.1e+003, 0.562)	68600
Gasket	178 + EXPO(3.6e+003)	43644
Bearings	161 + EXPO(5.21e+003)	9698
Base plate	16 + WEIB (1.39e+003, 0.486)	13644
LO Pipe	76 + WEIB (1e+003, 0.711)	40373
Turbine Rotor	1.21e+003 + EXPO(4.55e+003)	1318
Turbine Blades	1.21e+003 + EXPO(1.64e+003)	2443
Comp. Wheels	1.21e+003 + EXPO(1.12e+003)	12328
Turbine Wheels	9.67e+003 + EXPO(1.6e+004)	575.4
Nozzle Rings	1.1e+004 + EXPO(8.72e+003)	135972
Turbine Diffuser	1.25e+004 + EXPO(6.59e+003)	800

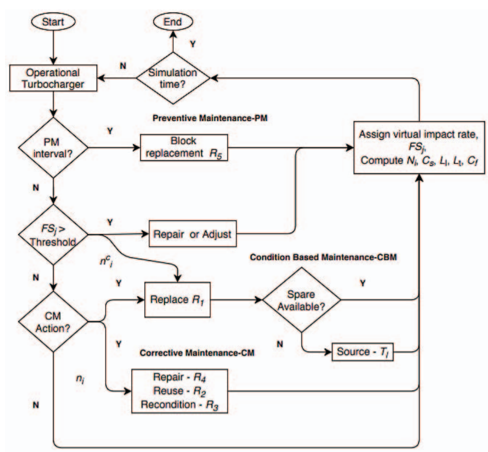

Fig. 1. Conceptual representation of the simulation model

We introduce a hazard rate FS_j, which indicates the severity state of a component before and after maintenance action. FS_j depends on the prior severity state and the maintenance strategy impact hence depicting a multi-state system (MSS).

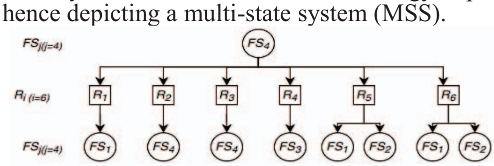

Fig. 2. Failure severity transition states using SMDP approach

A Semi Markov Decision process is employed to model the deterioration of the components considering the partially observed degradation which influences the posterior state of the component after maintenance intervention. A sample trace of a component with a hazard rate FS_4 undergoing different maintenance actions is illustrated in Figure 2.

3.3.2 Maintenance policies

As shown in Fig. 1, while the turbocharger is running, Preventive maintenance (PM) R_5, which involves the replacement of the components, following the lapse of the PM interval τ_{PM}=12000 hours are scheduled. While running and $t \neq \tau_{PM}$, random unplanned failures may occur and corrective maintenance (CM) undertaken which includes several maintenance interventions $R_{i(i=1,2,3,4)}$. R_1 entails the replacement of failed components (mandatory for bearings or gaskets), while other parts have a probabilistic utilization (η_i) of the CM strategies (R_{1-4}) are indicated in Table 2.

Table 2. Preventive and Corrective Maintenance actions

R_i	Tr_i (Hrs)	Td_i (Hrs)	η_i	ρ_i
R_1	EXP (11.15)	0.5	0.630	0.900
R_2	EXP (5.01)	0.5	0.110	0.405
R_3	EXP (9.07)	0.8	0.070	0.439
R_4	EXP (6.76)	1.0	0.190	0.656
R_5	UNIF (30,52.5)			0.950

The spare replacement follows the periodic (s, S) inventory policy, where if stock in hand is lower than reorder level (s), an order quantity (the difference between the maximum and stock in hand) is placed and sourced, incurring sourcing lead time Tl_n. In this case, the lead times in hours for Turbine blade is UNIF (5,24), others UNIF (2,4), turbine rotor UNIF (2,12), while the remaining units retain UNIF (4,8).

Reuse strategy R_2, is employed for components that can be sourced from equipment either decommissioned or opportunistically waiting for other spares hence not operating. Repair strategy R_4 is used where the components failure state is repairable, and the component can be brought back to its functional condition. Reconditioning strategy R_3 is also employed where the cores of the components are availed and the OEM or an agent can restore components and avail. In this study, it is assumed that the reconditioning is done after the failure occurrence. Selective online condition monitoring under CBM-R_6, oil analysis affecting the bearing and vibration analysis on the lube oil pipe, turbine rotor and bearings is undertaken while the system is running.

Table 3. Post CBM interventions characteristics

CBM intervention	Tr_i^c (Hrs)	η_i^c	Td_i^c(Hrs)
Adjustment	UNIF (4.45, 7.56)	0.18	2
Repair	UNIF (2, 16)	0.19	2
Replace	WEIB (7.53, 1.22)	0.63	2

Based on the hazard rate threshold set ($FS_j \geq 4$) for Lube oil pipe and ($FS_j \geq 3$) for the turbine rotor and bearings, CBM intervention whose characteristics are illustrated in Table 3 is undertaken. Replacement follows the same periodic (s, S) inventory policy.

3.3.3 Components dependencies

Stochastic dependence is employed to depict failure interactions between the components via failure induced damage. This paper adopts the failure interactions defined by (Van Horenbeek and Pintelon 2013) and is ingrained in all policies that include replacement action (PM, CM and CBM). Two scenarios are considered when a component fails. In the first scenario, no secondary failure is considered; hence only the replacement of a primary-failed part is undertaken. In the second scenario, replacement of both primary and secondary-failed unit(s) is considered, thus extending the work of (Van Horenbeek and Pintelon 2013), which only considered one secondary failed component. The probabilities of having a particular failure scenario at the failure of component i $(p_{R_1} = (p_{R_{1a}} = 0.85, p_{R_{1b}} = 0.15))$. This implies that for replacement maintenance, the primary failed component is replaced at a probability of 85% of the actions, while both primary and secondary damaged components at 15%.

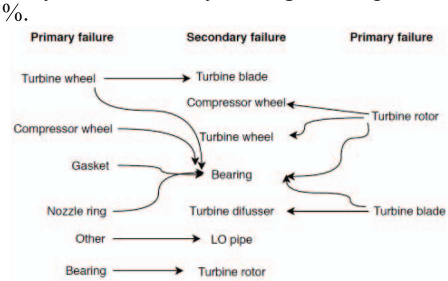

Fig. 3. Conceptual representation of primary and secondary failure dependencies

Fig. 3 links the antecedent primary failure to the consequential secondary failure. For instance, a breakdown of the turbine rotor may lead to secondary failures of the compressor wheel, turbine wheel and bearing. Structural dependence is ingrained by the fact that the maintenance of any unit of the system necessitates the other units to be dismantled at the same time. In this case, undertaking maintenance simultaneously rather than individually decreases the maintenance cost and downtime since all the components must be dismantled. Hence, in all the scenarios, economic dependence under opportunistic maintenance (OM), is exhibited in the combined opportunistic setup cost/time (e.g. downtime opportunity, maintenance set-up and repair).

3.4 *Evaluation and interpretation*

The simulation model is employed to derive the annual spare demand (*N*), total spare cost (C_s), average lead time (L_t), average labour time (L_l) and secondary failure cost (C_f), linked to a specific component or spare. We employ criteria levels also evidenced in other studies like (Teixeira, Lopes, and Figueiredo 2018). The respective derived values are indexed based on the Criticality index (*CI*) Eq. (1) and criteria levels, which are derived from the expert review, are shown in Table 4.

Table 4. Indexing criteria levels

Index	Annual demand	Spare cost (€)	Lead time (hrs.)	Labour time (hrs.)	Sec. failure (€)
1	< 5	< 10000	< 2	< 10	< 10000
2	< 10	< 50000	< 5	< 20	< 20000
3	< 20	< 100000	< 10	< 30	< 30000
4	> 20	> 100000	> 10	> 30	> 30000

$$CI_n = N_n^* * C_{s_n}^* * L_{t_n}^* * L_{l_n}^* * C_{f_n}^* \qquad (1)$$

To closely mimic the unexpected eventualities as the system ages with time and evaluate the impact of unforeseen failures, we assume the system ageing leads to a reduction of the virtual age of each component. We introduce a virtual age impact rate ρ^*, which reduces the λ_n. In this study, we use 50%, 70% and 90% as the variants, while 100% depicts the base case scenario. As an example, a virtual age impact rate of 50%, represents a reduction of λ_n for the component by 50% with time.

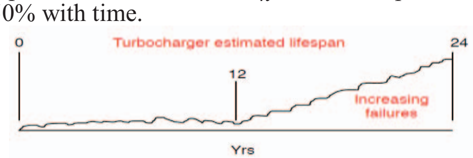

Fig. 4. Turbocharger lifetime modelling

For brevity, we compare six parts shown as critical in the base case ($\rho^* = 100\%$) in the subsequent analysis. We consider the estimated lifespan of the turbocharger of 24 years, and model the last 12 years assuming an increased failure rate through ρ^*, as shown in Fig. 4.

4. Results and discussion

In this section, the criticality criterion results, and the criticality ranking is demonstrated and discussed.

4.1 *Model development and validation*

We model with ARENA software and consider the second half of the turbocharger lifespan (12 years≅ 105,120 hours) operation as the simulation time. A warmup period of 40000 hours is used to attain a steady-state since the model starts with no activity. To address the issue of large half-width, the number of replications was computed using Eq. (2) from the initial 10 replications generating half-width of ± 2369.2, in our case approximately 135 replications were leading to ±650. Where h_o= current half-width from "initial" number n_o of replications, while n is the required replications to attain a half-width of h.

$$n = n_o \frac{{h_o}^2}{h^2} = 10*\frac{2369.2^2}{650^2} = 135 \qquad (2)$$

4.2 *Criticality criterion results*

Table 5. Criticality values for base case scenario ($\rho^* = 100\%$)

Component	N	C_s	L_t	L_l	C_f
Turbine Wheel	4	174,576	1.08	83.4	1,749
Turbine Blades	4	274,400	8.72	11.42	7,694
Turbine Rotor	2	119,596	4.39	26.71	17,509
Nozzle rings	2	27,288	5.84	33.90	858
Comp. Wheel	4	161,492	5.34	7.05	1,959
Turbine diffuser	2	19,396	3.88	26.57	7,701
Lube oil pipes	22	12,658	2.48	5.24	2,229
Others	16	12,800	3.73	14.91	1.292
Bearings	7	17,101	2.19	22.21	41,784
Gasket	7	9,226	4.08	14.66	3,839

From the criticality criterion values for the base case scenario shown in Table 5, Lube oil pipe is depicted to retain the highest demand for new spares. This could be attributed to the fact that the plant may have opted to employ failure-based maintenance (FBM) strategy on the component, for instance, due to low spare cost or negligible consequences of its failure. Considering spare costs, despite low demand on components like turbine blades and compressor wheel, the total spare cost attached is depicted to be significant due to the unit cost of the respective component. The results appear to make sense and to be compatible with our expectations. The results on average labour time show that components retaining lower demand incur higher average labour time.

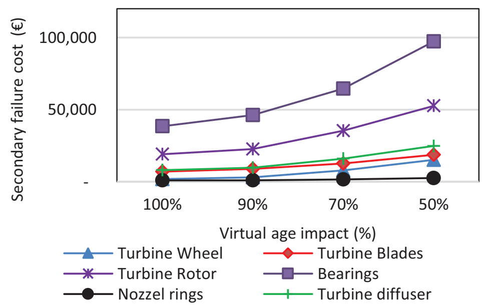

Fig. 5. Secondary failure cost comparison with varying ρ^*

This may be attributed to the fewer instances the components require intervention as may be inferred from the low demand of spares. The turbine blade is shown to retain the highest average lead time while bearing the lowest lead time. As expected, the turbine and bearing exhibit the highest contribution to the secondary failure cost. This finding arises from the fact that the two components retain a high failure interaction, while the turbine rotor failure also, adversely impacts several other parts. As ρ^* decreases, depicting an increase in component failures, as expected, a general increasing trend of the spares demand is demonstrated. This is primarily attributed to the dependence of spares demand on the failure rate. Like the spares demand results, secondary failure cost linked to various components, as shown in Fig. 5, increases as the failure rate increases.

The significant increase in secondary failure cost related to the bearings, could in part be explained by the high cost of the turbine rotor assembly, the component retaining failure interaction with the bearing. Considering the average lead time, all the components retain a modest increase in lead time. This increase may correlate to an unprecedented surge of spare demand rendering the reorder level under the current inventory policy inadequate.

4.3 *Criticality ranking*

Comparing the criticality ranking of six components while varying ρ^*, is shown in Fig. 6. A general increasing trend of *CI* is seen as the system experiences an increase in component failures.

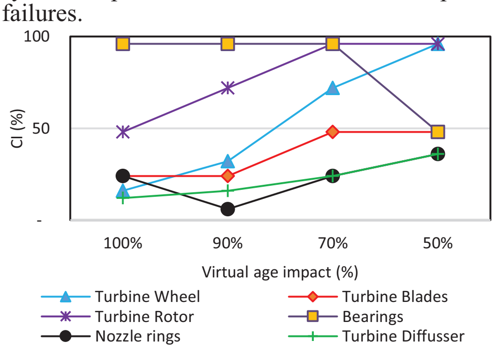

Fig. 6. Criticality index comparison

Components like turbine rotor and blades are depicted to retain modest *CI* at the base case and significantly increases as the failure rate increase. This is most likely attributable to the effect of failure increase of the components, which increases the distinct aspects like labour time and secondary failures contributions explicitly. This finding demonstrates that aspects like maintainability of a spare and skill set required under labour time and secondary failure offer exploitable criteria in criticality analysis. However, the bearing ranked as critical in the base scenario (ρ^*=100%), retains a stagnant *CI* at all the impact values, with a decrease at $\rho^* = 50\%$. This decrease in CI may directly be attributed to lower average labour time incurred by the bearing. This is probably not a mere coincidence and in fact, may indicate economic dependency via OM, where an intervention related to the bearing is opportunistically undertaken when a different component is under maintenance.

On the flip side, an analysis of the *CI* while disregarding labour time (L_l) and secondary failure cost (C_f) was done. The study demonstrates components like LO pipes and others are considered critical. On the contrary, the two parts are not shown as significantly essential in our developed approach. This can be attributed to the predominant dependence of the *CI* on the spares demand, in the analysis disregarding C_f and L_l. This signifies that the conventional techniques like ABC classification have a limitation of retaining bias towards spare demand quantity and cost, which may offer suboptimal decision support.

From the results, this study suggests that labour time and secondary failure costs are significant criteria that should be inculcated while undertaking spare criticality analysis. This implies the need for a plant to initially track and link various labour related times incurred, skills and tool requirements for maintenance of specific components. Moreover, keen evaluation of the root causes of each component's failures may enable accurate differentiation of the primary and secondary causative actions or components. This will be required to ensure maximum benefits are accrued from these criteria in the analysis.

The results underline the significance of the unforeseen failure rate while undertaking a criticality analysis. The variation of *CI* and failure rate changes implies that the criticality of a component may significantly change, hence affirming the importance of considering the futuristic system expectations like ageing. Moreover, organizations may want to consider anticipated changes like increased use of alternative strategies like repair in place of replacement and alternative suppliers with different lead times and spare costs. This simulation model demonstrates the potential to incorporate such changes in the analysis, forming part of the future work.

From the study results, the bearing, turbine rotor, turbine blades and turbine wheel (disk and blades) are depicted as critical in all the failure variance categories ρ^* retaining 50%, 70% and 90%. Interestingly, the identified critical components in practise are considered collectively to constitute a turbine rotor assembly. This finding, while preliminary, suggests that consolidative, the turbine rotor assembly is most critical. Since this study focussed on the second half of the turbocharger life, other interventions linked to EoL treatment, like spares remanufacturing and 3-D printing may provide more alternatives to address the spares challenges like cost and reliability, offering robust decision support. This provides a sound foundation on which future research can be built.

5. Conclusion

This study has shown that employment of a simulation-based approach in deriving the criticality criteria values, offers more robust decision support. Moreover, expected and unforeseen future system, maintenance and operational changes, are considered. The simulation-based framework has demonstrated that by incorporating all maintenance policies (i.e., CM, PM, CBM and OM), a more practical ADI is attained leading to optimal solutions. This study has been one of the first attempts to incorporate the contribution of a component to labour time and secondary failure costs of a system in the criticality criterion.

The study dealt with a case study incorporating a limited number of components included in a turbocharger, representing a limitation of the work. Notwithstanding the relatively limited sample, this work offers valuable insights into the innovative approach of criticality analysis and ranking that is scalable and generalizable. An extension of this work could consider expanded link beyond the first layer of primary and secondary failure.

References

Auweraer, Sarah Van der, and Robert Boute. 2019. "Forecasting Spare Part Demand Using Service Maintenance Information." *International Journal of Production Economics* 213 (July). Elsevier: 138–49.

Barabadi, Abbas, Javad Barabady, and Tore Markeset. 2011. "Maintainability Analysis Considering Time-Dependent and Time-Independent Covariates." *Reliability Engineering & System Safety* 96 (1). Elsevier: 210–17..

Dong, Wenjie, Sifeng Liu, and Yangyang Du. 2019. "Optimal Periodic Maintenance Policies for a Parallel Redundant System with Component Dependencies." *Computers & Industrial Engineering* 138 (106133). Elsevier: 1–9.

EN13306. 2010. "Maintenance-Maintenance Terminology." *British Standards Institution*.

Eruguz, Ayse Sena, Tarkan Tan, and Geert Jan van Houtum. 2018. "Integrated Maintenance and Spare Part Optimization for Moving Assets." *IISE Transactions* 50 (3). Taylor & Francis: 230–45.

Horenbeek, Adriaan Van, and Liliane Pintelon. 2013. "A Dynamic Predictive Maintenance Policy for Complex Multi-Component Systems." *Reliability Engineering and System Safety* 120. Elsevier: 39–50.

Hu, Qiwei, John E. Boylan, Huijing Chen, and Ashraf Labib. 2018. "OR in Spare Parts Management: A Review." *European Journal of Operational Research* 266 (2). Elsevier B.V.: 395–414.

Hu, Qiwei, Salem Chakhar, Sajid Siraj, and Ashraf Labib. 2017. "Spare Parts Classification in Industrial Manufacturing Using the Dominance-Based Rough Set Approach." *European Journal of Operational Research* 262 (3): 1136–63.

Ilgın, Mehmet Ali. 2019. "A Spare Parts Criticality Evaluation Method Based on Fuzzy Ahp and Taguchi Loss Functions." *Eksploatacja i Niezawodnosc* 21 (1): 145–52.

ISO 17359. 2018. "Condition Monitoring and Diagnostics of Machines - General Guidelines."

Olde Keizer, Minou C.A., Simme Douwe P. Flapper, and Ruud H. Teunter. 2017. "Condition-Based Maintenance Policies for Systems with Multiple Dependent Components: A Review." *European Journal of Operational Research* 261 (September). North-Holland: 405–20.

Ruijters, Enno, Carlos E Budde, Muhammad Chenariyan Nakhaee, Mariëlle Stoelinga, Doina Bucur, Djoerd Hiemstra, and Stefano Schivo. 2019. "FFORT : A Benchmark Suite for Fault Tree Analysis." In *29th European Safety and Reliability Conference*, edited by Michael Beer and Enrico Zio, 878–85.

Scarf, Philip A, and Mohammed Deara. 2002. "Block Replacement Policies for a Two-Component System with Failure Dependence." *Naval Research Logistics (NRL)* 50 (1): 70–87.

Si, Xiao-Sheng, Zheng-Xin Zhang, and Chang-Hua Hu. 2017. "An Adaptive Spare Parts Demand Forecasting Method Based on Degradation Modeling." In *Data-Driven Remaining Useful Life Prognosis Techniques*, 405–17.

Teixeira, Catarina, Isabel Lopes, and Manuel Figueiredo. 2018. "Classification Methodology for Spare Parts Management Combining Maintenance and Logistics Perspectives." *Journal of Management Analytics* 5 (2). Taylor & Francis: 116–35.

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

Wakiru, James, Liliane Pintelon, Peter Muchiri, and Peter Chemweno. 2020. "Integrated Maintenance Policies for Performance Improvement of a Multi-Unit Repairable, One Product Manufacturing System." *Production Planning & Control*, 1–19.

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

Zhu, Sha, Willem van Jaarsveld, and Rommert Dekker. 2020. "Spare Parts Inventory Control Based on Maintenance Planning." *Reliability Engineering & System Safety* 193.