Evaluating the Impact of Spare Parts Pooling Strategy on the Maintenance of Unreliable Repairable Systems

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Abstract: In today's industries, optimal spare parts provisioning plays a critical role towards sustaining the asset's operational capabilities. In this context, spare parts pooling is increasingly mentioned as a plausible approach for optimizing spare parts management, more so for repairable systems. In this sense, several frameworks are proposed in literature, though largely analytical, thus limiting their capabilities with respect to modeling complex repairable systems. Moreover, the nature of interactions often account for aspects such as system reliability, imperfect component reconditioning, repair capacity and spare parts inventory that is multi-echelon in nature. To realistically model such complexities, simulation approaches are often explored. This paper presents a discrete event simulation modeling study. The simulation model mimics the impact of several aspects on unreliable repairable systems. The aspects include the repair capacity, component reconditioning process, and multi-echelon spare part provisioning strategy. Moreover, the influence of spare parts quality aspects is evaluated and demonstrated in the case study of critical system for a thermal power plant.

Keywords: Unreliable asset, Spare parts provisioning, Repairable System, Component Reconditioning.

1. INTRODUCTION

Thermal power plants provide crucial emergency power supply in the power generation industry. A primary advantage of such plants is the relatively short set-up times compared to conventional power generation sources, e.g. hydro-electric power, coal-fired or nuclear powered facilities. In thermal power plants, the unexpected failure of a critical component portends significant revenue losses arising from lost power production or penalty costs attributed to unfulfilled electricity power supply. For this reason, optimal power plant maintenance is quite critical with respect to enhancing the asset's availability. Here, a robust spare parts management strategy is rather critical. Often, spare part unavailability may portend unnecessarily long replenishment lead times and as a consequence, significant production loss.

Thus to mitigate system unavailability occasioned by replenishment lead times, a collaborative spare part provisioning network may be explored. At a higher echelon, the network may extend to the partner with the original equipment manufacturer (OEM) at the highest echelon. Apart from the replenishment challenges, the quality of spare parts and the need for component reconditioning is also quite important. This is essentially the case for repairable systems where a specific component may be refurbished depending on its state at failure. For extensively damaged components, refurbishment is often not possible and as such, a new component may be required. On the other hand, components

with less severe damage may be refurbished and included in the spare parts pool. Moreover, the component quality influences the number of feasible reconditioning cycles. As a result, components of significantly higher quality may undergo more reconditioning cycles as compared to inferior quality spare parts.

In addition, the component reconditioning may restore the component to the as-good-as new (AGAN) state. At the extreme end, the as-bad-as-old (ABAO) restore the component to a state equivalent to minimal repair. For the ABAO, the time to next failure is considerably shortened. Ideally, the reconditioning process varies between the ABAO and AGAN, thus influencing the time to next failure upon restoration (Muchiri et al., 2014). Invariably, this influences component reuse and by extension, spares part replenishment instances.

Thus, optimising equipment performance not only depends on the spare parts provisioning strategy, but is linked to the equipment maintenance strategy. For this reason, a joint maintenance-inventory strategy is often necessary. On the basis of the joint strategy, optimal inventory levels for critical components may be quantified. Nonetheless, evaluating the impact of the equipment maintenance on the optimal stocking level is often not straightforward. Indeed, existing literature detail several quantitative models aimed at determining optimal stocking level while taking into account system reliability. The models are largely analytical and are often

constrained with respect to modelling complex joint spare part inventory – maintenance systems. For such systems, a simulation approach is often ideal and thus the subject of this article.

The remainder of this paper is as follows: Section 2 explores existing analytical and simulative approaches in the context of spare parts pooling – maintenance strategy. Section 3 describes phases of the simulation model. In Section 4, the model design is discussed. In Section 5, different simulation experiments are evaluated with the view of gaining insights on various alternative improvement actions, e.g. enhanced component reconditioning.

2. JOINT MAINTENANCE AND REPAIRABLE SPARE PART INVENTORY MODELS

The work discussed in this article can broadly be viewed in the context of joint maintenance and inventory optimisation frameworks. Such frameworks are not new but nonetheless scarce, more so with respect to repairable systems (Van Horenbeek et al., 2013). Several exceptions include Chen et al. (2006) where a simulation approach evaluating joint inventory provisioning system is discussed. However, the study considers the case for non-repairable spare parts.

For repairable systems, the METRIC (Multi-Echelon Technique for Recoverable Item Control) is one of the earliest analytical model in this context (Sherbrooke, 1968, Sherbrooke, 1986). Extensions to the METRIC models include aspects such as asset reliability and constrained repair capacity (Muckstadt, 1973, Diaz and Fu, 1997). Other models evaluating the effect of component failure and repair times on system availability and spare part demand are recently discussed (Mirzahosseinian and Piplani, 2011). However, the aforementioned models are largely analytical and as such constrained with respect to modelling complex multi-echelon spare part provisioning systems. For instance, the models ignore the influence of maintenance aspects such as component reconditioning, imperfect repair process and spares part quality (i.e. percentage of component discarded at repair). Such aspects influence the system availability, spare parts demand, total replenishment cost and by extension, the optimal stock pooling strategy.

Nonetheless, incorporating the aforementioned aspects in analytical models is often not straightforward. Thus several authors propose simulation approaches. For instance, Wen (2009) discuss a discrete event simulation model for a closed loop multi-echelon repairable system where spare part demand is initiated based on equipment failure. However, the model assumes that all failure modes necessitate component replacement. In reality, this is often not the case given that some failure modes require minimal repair actions. Moreover, the impact of imperfect repair on spare part provisioning is also ignored, thus constraining possible insights with regards to the simulated system.

Cavalieri et al. (2008) discuss a decision making framework for spare parts management and mention the importance of component reconditioning with respect to component reuse

based on wear state at failure. Thou not mentioned in their article, the number of repair cycles a component can feasibly undergo is also important and invariably influences the spare part replenishment demand. It is also intuitive that the component reconditioning and reuse are implicitly linked to the quality of spare parts used. These aspects are explicitly included in the simulation model proposed in this article. By modelling these aspects, it is possible to gain interesting insights with regards to complex inventory-maintenance provisioning systems within a multi-echelon spare part provisioning network.

3. MULTI-ECHELON REPAIRABLE INVENTORY MODEL

The joint maintenance and spare parts pooling strategy modelled here consists of 5 steps, depicted in Fig. 1. In Step 1, the replenishment process is triggered by component failure. In the model, failure is generated from the component characteristic lifetime distribution derived from empirical thermal power plant failure data (see Table 1). Once failure occurs, diagnostic tests are initiated to ascertain the type of failure and level of component damage. Depending on the failure severity, minor repair actions are undertaken without the need for component replacement. For severe damage, component replacement becomes necessary. The diagnostic and repair process constitutes Step 2 and respective times sampled from triangular distribution (see Table 1).

In Step 3, the component replacement process is performed. Here, a three-echelon spare parts provisioning system is modelled. Intuitively, the first echelon represents in-house requisition. If the required component is out-of stock, the requisition is referred to the partner at a higher level. The model includes one partner although more partners may be added to the network. If the partner's inventory is out-of-stock, the requisition is sent to the component supplier or OEM situated at the highest echelon. The replenishment process is carried out on a one-by-one basis. Moreover, the replenishment lead times also influence the system availability depending on the echelon the spare part is sourced. As such, more production loss is expected where the component is sourced from the OEM as compared to either in-house or from the partner. Moreover, several replenishment options are possible with different cost impacts. Thus, emergency spare part replenishment from the supplier/OEM at the high echelon is considerable more costly compared to regular replenishment from the same, i.e. supplier/OEM.

In Step 4, the defective component is sent to repair centre for refurbishment. Intuitively, the decision whether to refurbish the component depends on its state at failure. Thus, a proportion of retrieved component are refurbished while the rest are discarded. In Step 4, component sent for refurbishment may undergo several reconditioning cycles with varying repair efficiency. In the model, we assume that the number of repair loops depends on two aspects; (1) the component state at failure and (2) the component repair efficiency. Here, we assume that component of better quality (e.g. sourced OEM) undergo more reconditioning loops as

compared to counterfeit parts. Moreover, the reconditioning efficiency influences the 'time to next failure'. Thus, minimal repair (ABAO) shortens the observed time to next failure as compared to the AGAN repair action. Reconditioned components revert back to the spare parts pool depicted in Fig.1. In Step 5, component that cannot be feasibly reconditioned are discarded.
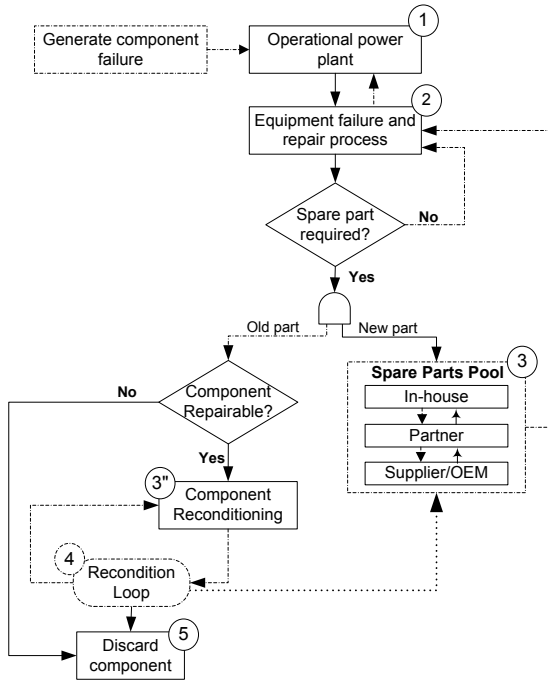

Fig. 1. Spare parts provisioning process for the thermal power plant.

4. SIMULATION MODEL DESIGN

4.1 Model assumptions and parameters

In the simulation model several assumptions are defined:

(1) The time to the next observed failure depends on the type of spare part used. Thus a new part restores to the AGAN state. For the reconditioned component, imperfect repair is assumed varying from $0 \leq \eta \leq 1$, where 0 equates to ABAO and 1 equates to AGAN state. Reconditioned parts revert back to the in-house spare parts pool;

(2) The repair resources within the network are shared and constrained with respect to capacity;

(3) Better quality parts undergo more replenishment circles as compared to more inferior quality parts. Moreover, the spare parts quality is assumed to influence the severity of component damage at repair;

(4) Component cannibalism is ignored and all spare parts are assumed sourced from the OEM or contracted suppliers. Moreover, we assume that the OEM/suppliers always have spare part stock at hand.

Table 1 depicts a sample of input parameters implemented in the simulation model.

Table 1. Overview of model input parameters

Parameter	Input distribution
Uptime (component A) [days]	WEIB [0.618, 38.59]
Uptime (component B) [days]	WEIB [1.3, 52.32]
Diagnostic and repair times [hrs.]	TRIA [1,2,5]
In-house replenishment delay [hrs.]	TRIA [0.1, 0.5, 2]
Partner replenishment delay [days]	EXPO [2]
OEM replenishment delay [days]	EXPO [10]

4.2 Simulation model design

The multi-echelon spare part pooling network is modelled in Arena, discrete event simulation software (Kelton et al., 2014). The model consists of seven sub-models as per the processes depicted in Fig.1 and discussed in Section 3. The sub-models include: component failure module; diagnostic and repair module; power generation module; component replenishment module; reconditioning module; spare parts pooling module and system restoration module. Figure 2 depicts the underlying processes for spare part requisition from the OEM.
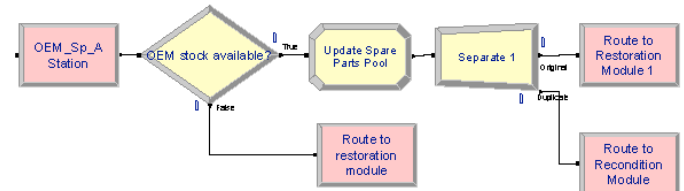

Fig. 2. Component replenishment from the OEM

In the simulation model, a replication length of 1000 days is implemented. Moreover, a total of 10 replications are implemented for each replication length. Component requisition from the spare parts pool is also as described in Fig. 1 where an echelon query procedure is followed. The query starts with in-house request and transits up the echelon to the supplier/OEM.

4.3 Simulation model performance measures

In the simulation model, several performance measures are implemented which include the system availability, production loss and spare part replenishment cost. The latter, i.e. replenishment cost is evaluated at the three echelons, i.e. in-house, partner and at the OEM/supplier.

The system availability is derived from the following equations:

$$A_s = \sum_0^T \frac{TTF}{TTF + TTR} \qquad (1)$$

In Eq. 1, the time to failure (TTF) is linked to the type of component used and the component repair efficiency. As mentioned, the efficiency varies from the AGAN to the ABAO repair states. The time to repair (TTR) influences the system downtime and is further decomposed into components such as system start-up/shut-down time, diagnostic time, repair time, and spare part replenishment lead time. The time (T) represents the simulation time, i.e. replication length of 1000 days implemented in the simulation model.

The replenishment cost evaluates the economic implication of spare part reordering. Here, the cost can be decomposed into two cost components; (i) cost of regular re-order and (ii) emergency order cost. Emergency re-order assumes an instance where failure occurs and spare part is requisitioned from higher echelons, i.e. the partner or the OEM. During the replenishment lead time, production loss is incurred owing to system downtime. Regular replenishment cost assumes component reorder from higher echelon while the system is operational. The total replenishment cost is defined through the equation:

$$C_{rep}^{tot} = [C_{inh} + C_{part} + C_{OEM}] \times N_{req} \qquad (2)$$

The in-house, partner and OEM replenishment cost components are decomposed as follows:

$$C_{inhse} = N_{req}^{inhse} \times F_{inhse} \qquad (3)$$

$$C_{part} = \left(N_{req}^{reg} \times F_{part}^{reg}\right) + \left(N_{req}^{eme} \times F_{part}^{eme}\right) \qquad (4)$$

$$C_{OEM} = \left(N_{req}^{reg} \times F_{OEM}^{reg}\right) + \left(N_{req}^{eme} \times F_{OEM}^{eme}\right) \qquad (5)$$

The cost factor F varies depending on the type of requisition. For instance, emergency requisition from the OEM is assigned a higher factor compared to regular requisition from the partner. The factor models logistical complexities during the requisition process, e.g. the need for expensive courier services for emergency replenishment. In the simulation model, the total number of spare part requisitions (N) are tallied and factored in the respective cost functions depicted in (2-5).

4.4 Simulation model verification

In this phase, the model is verified through sensitivity analysis. Here, the effect of increasing in-house/partner spare part inventory is evaluated. Moreover, the effect of enhancing the reconditioning cycles for the retrieved component is evaluated. These effects are evaluated with respect to the

power plant availability, power production loss and replenishment cost. Table 2 depicts results of the sensitivity analysis.

Table 2. Overview of the sensitivity analysis results

Parameter	Spare part Inventory		Component Recondition
	In-house	Partner	Repair cycles
	(+200%)	(+200%)	(+100%)
System availability	+8.3%	-0,3%	+3%
Production loss	-33.5%	+0,9%	-12.2%
In-house replenishment cost	+38.9%	+1%	-30.2%
Partner replenishment cost	-11.3%	-1,9%	-32.5%
OEM replenishment cost	+33.8%	+6.7%	-27.1%
Total replenishment cost	+28.3%	+5.5%	-25.9%

The results shows that increasing the in-house spare part inventory by 200% compared to the base case (i.e. as-is situation) positively influences the power plant availability by a proportion of 8%. Moreover, the power production loss is significantly reduced, i.e. by a margin of 33%. However, the improved system availability is at the detriment of total replenishment costs where an increase of 28% is noted. The high cost is attributed to the fact that in the simulation model, more components are sourced from the OEM/supplier as compared to the partner. This is also attributed to the fact that the partner stock is constrained and thus in the event of stock-out at the partner, parts are sourced from the OEM. During instances of partner stock out, the in-house stock is sourced directly from the OEM, often at a higher cost.

On the other hand, enhancing the partner inventory by 200% does not significantly influence the system availability and production loss. However, compared to the base case, the replenishment costs are significantly lower compared to the enhanced in-house case. This is attributed to lower direct replenishment demands from the OEM as compared to the enhanced in-house case. This result is not surprising given the fact that with enhanced inventory at the partner, the thermal power plant has the option of cheaper replenishment option in the event of failure as compared to having to order from the OEM in the event the partner experiences stock outs.

It is also observed that enhancing the reconditioning cycles positively influences the power plant performance measures. Here, the system availability is enhanced by 3% while the replenishment cost is reduced significantly, by a margin of 25% compared to the base case. This is intuitive given that more component reconditioning avoids the cost of emergency replenishment, either from the partner or the OEM. Moreover, the system downtime attributed to spare part stock out is reduced given that reliance is largely on the reconditioned parts whose replenishment time (or reconditioning time) is often lower than the emergency

replenishment lead time. This highlights the advantage of using superior quality components, e.g. sourced from the OEM in the plant installation.

5. DESIGN OF SIMULATION EXPERIMENTS

5.0 Simulation experiments and results

In order to gain insights on the factors influencing system availability and replenishment cost, four simulation experiments are implemented. The system availability and replenishment cost are computed from equations 1 – 5. In first experiment, the percentage requirement for a new/reconditioned component during repair is varied. As mentioned, the need for a new component depends on the level of component damage, often a function usage, equipment operation, component quality, or efficiency of the last repair action carried out by the technician. Thus, low percentage requirement is ideal with respect to enhancing the system availability and minimising the replenishment costs. Figure 3 depicts the results of the first experiment. As expected, low component requirement either through enhanced repair efficiency or use of superior parts positively influence both the system availability and replenishment cost. Moreover, a break-even point is reached at 75% system availability where at this performance level, the replenishment cost is minimised at 3357 units (e.g. euros).
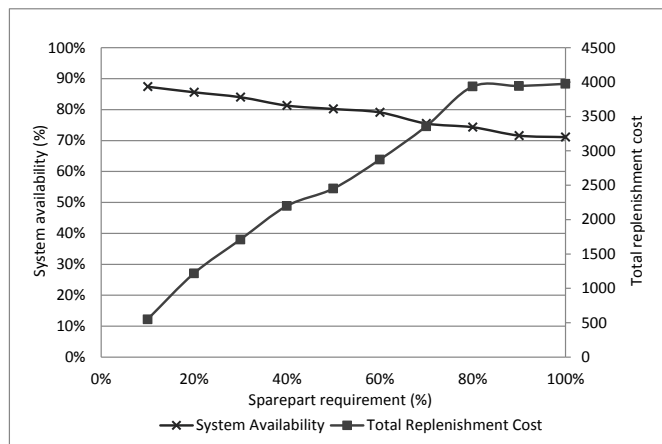

Fig.3.   Effect of percentage spare part requirement

In the second experiment, the number of reconditioning cycles is varied. This experiment evaluates the possible effects of enhanced reconditioning loops through use of high quality components, prompt maintenance intervention or enhanced repair actions. Figure 4 depicts the results where increased reconditioning cycles is seen to positively influence both the system availability and replenishment cost. This stems from the fact that implementing intervention measures leading to reduced component damage at repair or use of more superior component at repair reduce the need for emergency part replenishment and as a result, lowering the system downtime and emergency replenishment cost.
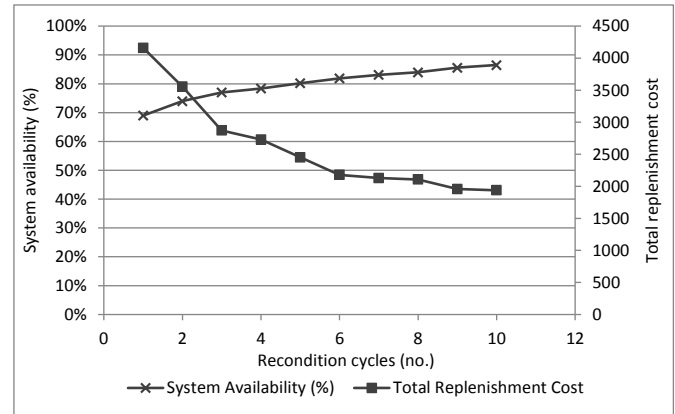

Fig. 4. Effect of enhanced reconditioning cycles

In the third experiment, the impact of component reconditioning efficiency is evaluated. This experiment evaluates the influence of superior reconditioning process for components retrieved during repair. As mentioned, the reconditioning efficiency varies between the ratio $0 \le \eta \le 1$, i.e. the ABAO and AGAN states. Figure 5 depicts the impact of varying reconditioning efficiency on the system availability and total replenishment cost. From the results, an increase in system availability is observed with increasing recondition efficiency. Moreover, a decreasing trend in the total replenishment cost is noted beyond a repair efficiency of 0.5. This implies that at lower repair efficiency, the time to next failure is significantly diminished thus initiating higher demand for new spare parts. In such instances, more requisitions are expected upstream, either from the partner or the OEM/supplier, thus high replenishment costs.
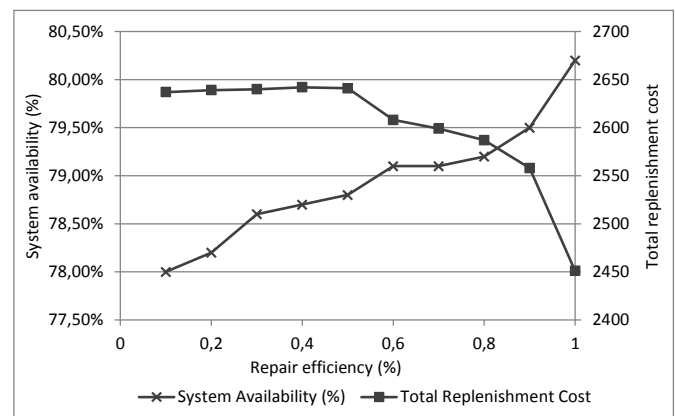

Fig. 5. Effect of component repair efficiency

In the fourth experiment, the system availability and total replenishment cost is optimised. Here, the OptQuest, an Arena tool is applied. The OptQuest embeds several optimisation techniques, e.g. Tabu search to efficiently derive the optimal solution from the multi-dimensional solution space (Kelton et al., 2014). In particular, the total replenishment cost is minimised under several constraints including:

$$85\% \leq system\,availability \leq 99\% \qquad (6)$$

$$2 \leq recondition\,cycles \leq 5 \qquad (7)$$

$$40\% \leq sparepart\,requirement \leq 95\% \qquad (8)$$

Figure 6 depicts the 30 best optimisation results where the lowest replenishment cost is achieved at a system availability of 87.5%. However, one also notes a random variation in the system availability at different replenishment cost. This variation is influenced by the nature of input parameter combinations. A sample of input parameters for the best solutions is depicted in Table 3.
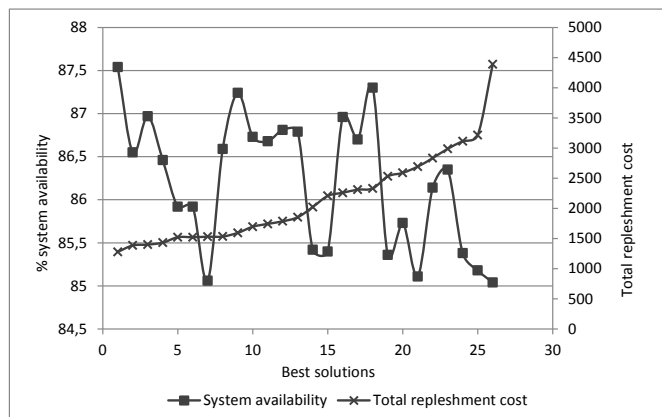

Fig. 6. Trend overview of best optimal solutions

From Table 3, the best results suggest an optimal combination with balanced in-house and partner inventory (5 spare parts), 40% spare part requirement, 40% repair efficiency and high repair cycles (5 loops). Here, one may deduce that the use of components allowing more reconditioning cycles in combination with balanced spare parts pooling strategy yields relatively high system availability at minimised replenishment cost.

Table 3. Spare part pooling optimisation results

Spare part Inventory		Component Reconditioning		
In-house	Partner	Spare part required (%)	Repair efficiency (%)	Repair cycles (no.)
5	5	40	40	5
5	5	42	42	5
2	5	40	40	5
2	5	40	40	3
3	5	40	40	5

To conclude, the simulation study demonstrates how different input parameters influence the system performance measures, here, the system availability and total replenishment cost. In particular, we demonstrate that the multi-echelon spare parts provisioning strategy is influenced by several aspects such as the component reconditioning process, the spare part quality, and reconditioning (repair) efficiency. Here, the spare part quality is implicitly evaluated through the decision variables; percentage component requirement and number of reconditioning cycles. In particular, the simulation study

highlights the importance of considering imperfect repair in the context of component reconditioning. This is considered an important extension to existing studies evaluating joint maintenance and inventory systems. Proposed extensions to this study will evaluate the impact different maintenance policies on multi-echelon spare part provisioning systems.

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