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Inventory reduction in spare part networks by selective throughput time reduction

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Abstract:

We consider combined inventory control and throughput time reduction in multi-echelon, multi-indenture spare part networks for system upkeep of capital goods. We construct a model in which standard throughput times (TPT) for repair and transportation can be reduced at additional costs. We first estimate the marginal impact of TPT reduction on the system availability. Next, we develop an optimization heuristic for the cost trade-off between TPT reduction and spare part inventories. In a case study at Thales Netherlands with limited options for TPT reduction, we find a net saving of 5.6% on spare part inventories. In an extensive numerical experiment, we find a 20% cost reduction on average compared to standard spare part inventory optimization. TPT reductions *downstream* in the spare part supply chain appear to be most effective.

Key words: Inventory; spare parts; repair time; maintenance.

1. Introduction

For advanced capital goods such as high-tech manufacturing equipment and medical systems, manufacturers tend to expand their business by offering service contracts for system upkeep during the life cycle (cf. Cohen et al. [2006]). If system downtime is expensive, a service contract typically contains quantified service levels to be attained by the service provider, such as a maximum response time in case of a failure or a minimum uptime per year. We encountered such contracts at Thales Netherlands, a supplier of naval radar and combat management systems.

At the start of the contract, the supplier and/or the user invests in spare parts to facilitate fast repair by replacement of failed modules, the so-called Line Replaceable Units

(LRUs). Since such modules are generally expensive, they are often repaired rather than scrapped. Repairing LRUs usually consists of diagnosis and replacement of a failed subcomponent in a repair shop. It is common to refer to these subcomponents as Shop Replaceable Units (SRUs). Lack of spare SRUs leads to delay in LRU repairs, and longer LRU repair lead times increase the need for spare part inventories. Therefore, there is a trade-off between stocking LRUs and (cheaper) SRUs. Possibly, some SRUs are repairable themselves by replacing cheaper parts. So, we have a so-called *multi-indenture* product structure, see Figure 1. We should decide about the stock levels of all items at all levels in the multi-indenture structure. In the remainder of this paper, we will use the phrases *parent* and *child* to refer to the relations in the multi-indenture structure: In Figure 1, the supply cabinet is the parent of the power supply, and the power supply and air conditioning assembly are children of the supply cabinet. We will use the general term *item* for components at any level in the multi-indenture structure (LRUs, SRUs, parts).

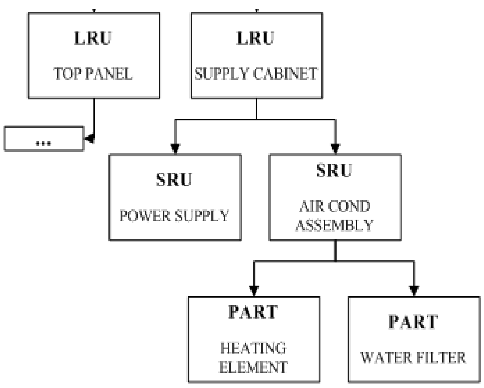

Figure 1. A multi-indenture structure

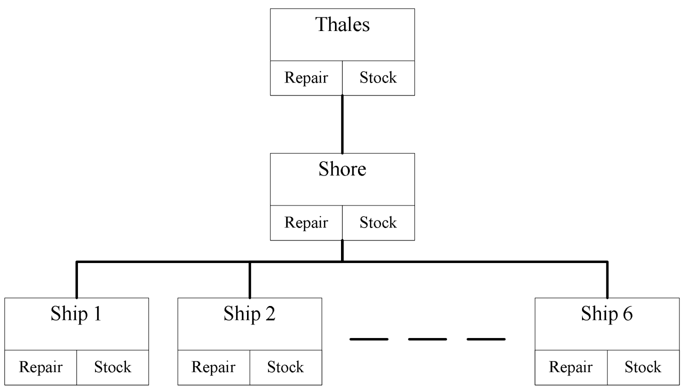

Figure 2. A multi-echelon structure

Because the installed base is usually geographically dispersed, spare parts may be kept on stock at various locations. Spare part stocks close to the sites where systems are installed are important for fast supply in case of a failure. This may lead to several local stockpoints, each dedicated to a certain geographical area containing a part of the installed base. On the other hand, it may be profitable to stock spare parts at a central location in order to take advantage of the risk pooling effect. Therefore, spare part supply systems are usually *multi-echelon* systems as shown in Figure 2. This is an example derived from a case study at Thales Netherlands, where the systems under consideration are naval radars that are installed onboard frigates. Spare parts may be stocked onboard, at the shore organization (close to a harbor), or at Thales Netherlands. In the remainder of this paper, we will use the common term *base* for a site where one or more systems are operational. We will use the phrases *supplier* and *customer* for to the relations in the multi-echelon structure. In Figure 2, Thales is the supplier of the Shore, and the Shore is a customer of Thales. Ready-for-use items are moved from the *upstream* part of the service supply chain (Thales) to the *downstream* part (Ships).

To optimize the initial spare part inventories, Thales uses a commercial tool based on the well-known VARI-METRIC method (cf. Sherbrooke [2004]). If there is evidence during contract execution that the actual service performance will be less than the target (usually in terms of downtime waiting for spare parts), the service provider should take measures. At a tactical level, options are a.o. (i) buying additional spare parts, (ii) reducing repair shop throughput times, and (iii) reducing transportation times of spare parts. In this research, we focus on throughput time (TPT) reduction (of repair and transportation) as alternatives to spare part investment for multi-indenture, multi-echelon spare part networks. At Thales Netherlands, such reductions are feasible at extra costs. It is well known that influencing repair TPT for specific items may have a large impact on the total costs, see Sleptchenko et al. [2005] and Adan et al. [2009].

To gain insight in the impact of TPT reduction, we first develop expressions for the marginal backorder reduction of LRUs at operating sites as a function of the marginal reduction in TPT of each repair and transport in the service network. We use these expected backorders as criterion, because minimizing these backorders is approximately equivalent to maximizing operational availability, see e.g. Sherbrooke [2004]. Under the assumption of Poisson distributed pipelines, we find that we only need the fill rates of all items in the multi-indenture structure at all locations in the multi-echelon networks for this purpose. Combining these marginal values with a certain discrete step size for the TPT reductions, we develop a heuristic optimization method to balance the investment in TPT reduction to investment in extra spares. In a numerical experiment, we show that a trade-off between spare part inventories and TPT reductions may yield considerable cost savings (20% on average). We find that TPT reductions *downstream* in the service supply chain are particularly interesting. TPT reductions of low level items (SRUs and subcomponents) upstream in the network make little sense. We illustrate our approach using a case study at Thales Netherlands.

In the remainder of this paper, we first discuss related literature and state our contribution (Section 2). We define our model in Section 3. Section 4 shows how we can estimate the impact of TPT reduction for given spare part stock levels. This is input for our optimization heuristic (Section 5). In Section 6, we discuss numerical results from both the case study at Thales Netherlands and a large set of theoretical problem instances that we generated. We end up with conclusions and directions for further research in Section 7.

2. Literature

There is vast amount of literature on optimization of slow moving spare part inventories in multi-echelon, multi-indenture supply chains, see for example Sherbrooke [2004] and Muckstadt [2005]. These models contain many parameters, some of them resulting from underlying decisions. Examples are the location and allocation of repair activities, repair and supply lead times, and item failure rates. In the last decades, several models have been developed that consider some of these decisions jointly. Öner et al. [2010] consider the joint decision of mean time between failures (which can be influenced during product design) and the costs of spare parts during the life cycle for a single item. Joint decisions for spare parts inventories and repair locations, taking into account the costs of resources required, are discussed by a.o. Alfredsson [1997] and Basten et al. [2009]. Rappold and Van Roo [2009] combine the spare part stocking problem with facility location.

Focusing on the relation between spare part inventories and TPTs, there are two streams of literature:

- analysis and optimization of spare parts and repair and supply processes at a *tactical* level, where a selected subset of items is given high priority in repair;
- *operational* optimization of spare part networks by dynamic priority setting in repair and supply, given fixed spare part stock levels and resource capacities.

Within the stream focusing on the *tactical* level, we distinguish the selective use of emergency repair and supply in case of low stocks, and priority setting models with finite repair capacities. In the first area, Verrijdt et al. [1998] use a single item model to show the impact of emergency repairs if the stock level drops below a certain threshold value. Perlman et al. [2001] consider a single-item, two-echelon model with finite capacity repair shops and assume that emergency repair is applied to with a certain probability. Van Utterbeeck et al. [2009], on the other hand, focus on supply flexibility, i.e., the performance improvement if emergency shipments and lateral transshipments are allowed. They use simulation optimization to search the optimal system design and stock allocation, again for a single-item.

The models with finite repair capacities usually model the repair shops as single or multi-server queues with exponentially distributed repair times, see e.g. Gross et al. [1983], Diaz and Fu [1997], and Sleptchenko et al. [2003]. An important issue in this line of research is the trade-off between repair capacity and spare part inventories: Limited capacity leads via high utilization and long TPTs to more spare part stocks. Sleptchenko et al. [2005] introduce priority queueing models for the repair shop where the items are assigned to two priority groups (high or low priority). They show that appropriate priority assignment may lead to a significant reduction in the spare part inventory investment. The idea is to prioritise repair of items with high value and small repair times, so that the work-in-process of these items is reduced with limited impact on other items. A similar idea has been used by Adan et al. [2009], who consider multiple priority classes (>2) in a single-location, single-indenture problem. They develop a method for exact cost evaluation.

At the *operational* level, various priority rules have been examined by simulation. These models assume that all resources are given (spare part inventories, repair capacities) and search for efficiency gain using (i) repair priorities (if a server becomes idle, which item from the queue should be repaired first?), and (ii) dispatch priorities (if an item has been repaired and there are multiple outstanding orders for this item, which order should be filled first?). Regarding repair priorities, Hausman and Scudder (1982) discuss a large variety of rules in a single-location, three-indenture model. The best rules lead to a backorder reduction equivalent to 20% less inventories. Hausman (1984) extends this model to the multiple failure case and finds similar results. Pyke (1990) combines repair priorities with dispatch policies in a simulation study and concludes that priority repair improves the system performance, whereas dispatching priorities usually have limited impact. Caggiano et al. [2006] develop two methods to set repair and dispatch priorities in two-echelon networks within a finite planning horizon. They show that significant gains are feasible in a rolling horizon setting. Tiemessen and Van Houtum [2010] show that operational priorities may yield about 10% cost reduction on top of static repair priorities in a multi-item, single-location model.

The focus in our paper is on the impact of repair and supply differentiation at a *tactical* level. Inspired by the Thales case, we aim for a realistic model, i.e., a multi-item, multi-indenture, multi-echelon setting, whereas many papers address single items models that can be used as a building block only. In contrast to the work on finite capacity models, we do *not* model the repair shops by finite capacity (multi-server) queues for the following reasons. First of all, repair shops often have more similarity to a job shop environment that could be modeled as a queueing network rather than by a multi-server queue. Further, repair capacities are often not fixed or may be fuzzy, because a repair shop may have other tasks than spare part repair only. Also, flexibility options such as working overtime or temporarily hiring personnel may exist. If repair is outsourced, the repair capacity is even unknown, and the repair lead times and corresponding prices are the result of a negotiation process. Therefore, we choose a model in which we may select different options for repair and supply lead time at different prices, without explicit capacity modeling. We encountered this situation at Thales, who offers both a normal repair and a fast repair option to its customers without service contracts at different prices. The same flexibility could be used to optimize the performance for customers having service contracts. This also holds for emergency supply that Thales could apply for certain combinations of items and locations against additional costs.

Summarized, we aim to contribute the following to the literature:

1. We consider a simple but practical model for the trade-off between spare part stocks and TPT reduction in repair and supply, based on pricing of TPT reduction. This model is suitable for a realistic setting as we encountered at Thales Netherlands, i.e., in multi-item, multi-echelon, multi-indenture networks.
2. We show that we only need all fill rates in the network to estimate the marginal impact of TPT reductions under the assumption that the number of items in repair or resupply at all locations are Poisson distributed.
3. We use these estimates to develop an efficient heuristic for the simultaneous optimization of spare part inventories and repair and supply TPTs. We show that significant cost reductions are feasible (almost 20% on average for theoretical problem instances).

4. We show how the savings depend on type of problem instance and we characterize the type of policies that we typically find. In particular, we see that TPT reductions are most profitable *downstream* in the network.
5. We apply our method in a case study at Thales Netherlands and find interesting savings (5.6% on the inventory investment). The restricted options for reduction of TPTs downstream in the network cause lower savings than in the theoretical experiments.

3. Model, assumptions, and notation

We consider a multi-indenture, multi-echelon spare part network, where our decision variables are both spare part inventory levels and repair and transportation TPTs of all items at all locations in the network. For each combination of item and location, we have a discrete set of TPTs that we may select, and costs are attached to each option.

3.1 Assumptions

We proceed from the standard assumptions as are common in the VARI-METRIC model, cf. Sherbrooke [2004]:

1) System failures occur according to a stationary Poisson process.
2) All failures are critical, i.e., they immediately lead to system downtime.
3) Each item failure is caused by the failure of at most one subcomponent.
4) Repair shops are modeled as $M/G/\infty$ queues, where successive repair TPTs of the same item at the same location are independent and identically distributed.
5) For each item, the fractions of failures that should be repaired at each location in the network are given.
6) All items are as good as new after repair.
7) Requests for spare parts are handled First Come, First Serve (FCFS).
8) We use an (s-1, s) one-for-one replenishment policy for all items at all locations.

9) Any customer location has one unique supplier (except the most upstream stockpoint)

10) Inventories are always replenished from the direct supplier in the multi-echelon structure, i.e., there is no lateral supply between locations at the same echelon.

11) All supply lead times (or: *order-and-ship* times) are deterministic.

With respect to TPTs (repair and supply), we assume:

12) For each combination of item and location, we have a *discrete set* of TPTs that we may select, and costs are attached to each option.

With respect to the latter assumption, we proceed from a standard repair and supply lead time for each combination of item and location, and we consider options for TPT reductions that we may select at additional costs. Without loss of generality, the additional costs per repair are strictly increasing in the repair TPT reduction, and the same applies to the costs per shipment (otherwise, we simply ignore inferior options).

3.2 Notation

We use similar notation as in Sherbrooke [2004] and distinguish input parameters, decision variables, auxiliary variables, and performance measurement (output):

Input:

B = set of all bases, i.e., all locations in the network where systems are installed.

L = set of all LRUs, i.e., all first indenture items.

m_{ij} = demand rate for item i at location j (i=1..I, j=1..J).

r_{ij} = fraction of demand for item i at location j that can be repaired at the same location (the rest has to be returned to the supplier of j for repair).

q_{ki} = fraction of item k failures that is due to a failure of item i.

h_i = costs per year for holding one item i.

$T_{ij}(n)$ = n^{th} option for the repair shop TPT of item i at location j, which is strictly decreasing in n; index n=0 gives the standard repair throughput time

$O_{ij}(n)$ = n^{th} option for the order-and-ship time of item i at location j, which is strictly decreasing in n; index n=0 gives the standard the order-and-ship time.

$C_{ij}^{R}(t)$ = costs per repair if the repair shop TPT of item i at location j is equal to t.

$C_{ij}^{O}(t)$ = costs to move a single item i to location j from its supplier if the standard order-and-ship time is equal to t.

Note that the demand rates m_{ij} are input for all LRUs $i \in L$ and all bases $j \in B$. The demand rates for all other combinations of item i and location j can recursively be found from $m_{ij} = m_{kj} q_{ki} + \sum_{l \in D_j} m_{il}(1 - r_{il})$, where k is the parent of i and D_j denotes the set of all customers of location j.

Decision variables:

s_{ij} = inventory level for item i at location j.

a_{ij} = index of repair TPT of item i at location j.

b_{ij} = index of order-and-ship times of item i at location j.

We denote the matrices of decision variables for all items and all locations in bold face by **s**, **a** and **b**.

Auxiliary variables

$f_{ij}(n)$ = probability density function of the number of items i in the pipeline at location j, i.e., all items in repair or in resupply; we denote the corresponding mean by μ_{ij}.

Performance measurement

$EBO_{ij}(\mathbf{s}, \mathbf{a}, \mathbf{b})$ = Expected backorders of item i at location j under policy ($\mathbf{s}, \mathbf{a}, \mathbf{b}$).

$\beta_{ij}(\mathbf{s}, \mathbf{a}, \mathbf{b})$ = Fill rate of item i at location j under policy ($\mathbf{s}, \mathbf{a}, \mathbf{b}$), i.e. the fraction of demand that can be filled from stock on shelf without delay.

3.3 Model

As in VARI-METRIC, we aim to balance the operational availability and the costs required for holding spare part inventories, and, in our case, the costs of repairs and shipments. As mentioned before, Sherbrooke [2004] uses the sum of the backorders of LRUs at bases (sites where systems are installed) as a proxy for the operational availability. We can interpret this backorder sum as the average number of systems that are down waiting for a spare part. Therefore, we find the following nonlinear optimization model:

$$\begin{aligned} &\underset{\mathbf{s,a,b}}{Min} && \sum_{i=1}^{I}\sum_{j=1}^{J}\left(h_i s_{ij} + m_{ij} r_{ij} C_{ij}^{R}(T_{ij}(a_{ij})) + m_{ij}(1-r_{ij})C_{ij}^{O}(O_{ij}(b_{ij}))\right) \\ &\text{subject to} && \sum_{i\in L, j\in B} EBO_{ij}\left(\mathbf{s,a,b}\right) \le EBO^{Target} \end{aligned} \qquad (P1)$$

where EBO^{Target} denotes a target number of LRU backorders at bases corresponding to a certain operational availability. The expected backorders of item i at location j depend on the probability distribution of the number of items in the pipeline $f_{ij}(n)$ and the stock level s_{ij}:

$$EBO_{ij}\left(\mathbf{s,a,b}\right) = \sum_{n=s_{ij}+1}^{\infty}(n-s_{ij})f_{ij}\left(n\middle|\mathbf{s,a,b}\right) \qquad (1)$$

where the probability density function of the pipeline $f_{ij}\left(n\middle|\mathbf{s,a,b}\right)$ depends on:

- the repair TPT of item i at location j
- the order-and-ship time of item i to location j
- the probability distribution of the backorders (a) of item i at the supplier of location j, and (b) of all children of item i at location j.

Indirectly, the backorders of item i at location j depend on all stock levels of item i and all children downwards in the multi-indenture structure, at location j and all locations upstream in the supply chain. The same applies to the repair shop TPT and the order and ship time (and so for the impact of the decision variables a_{ij} and b_{ij}). In METRIC, all pipeline distributions were originally approximated by Poisson distributions. Because this approximation can be quite bad, two-moment approximations for the pipelines have been used in VARI-METRIC (cf. Sherbrooke [2004]). This can be done using a negative binominal distribution, because the variance to mean ratio of the pipelines are usually ≥1. As a more general solution, we use the method of Adan et al. [1995] to fit a discrete probability distribution function to the first two moments of a discrete random variable. Hence, we compute an approximation of all backorders using two-moment approximations for the pipeline distributions. VARI-METRIC only considers the stock levels and not the TPT reduction. For optimization, a simple greedy heuristic is typically applied. That is, starting at all stock levels $s_{ij}=0$ $\forall i,j$, we add in each iteration an item of type i to stock at a certain location j that has the largest ratio of reduction of expected backorders of LRUs at bases and the additional inventory investment. In popular terms, this heuristic is referred to as the *biggest bang for the buck*.

Note that (*P1*) is a large nonlinear integer programming problem having three times as many decision variables as VARI-METRIC: Next to the spare part stock levels s_{ij}, we also have to decide about the repair shop TPT and the order-and-ship time for all combinations of item i and location j. As VARI-METRIC is an optimization heuristic, it is reasonable to expect that problem (P1) cannot be solved exactly in a reasonable amount of time for problem instances with a realistic size. Therefore, we focus on optimization heuristics.

4. Analysis of TPT reduction

Before we develop an optimization heuristic, we first specify the impact of TPT reduction on the expected backorders of LRUs at the bases. Under the assumption of Poisson distributed pipelines, we find the partial derivatives of the total expected backorders of LRUs at bases to any mean repair TPT and order-and ship time in the following way. Under the Poisson assumption, the density function of the pipeline $f_{ij}(.)$ is given by:

$$f_{ij}\left(n\,|\,\mathbf{s},\mathbf{a},\mathbf{b}\right)=\frac{\mu_{ij}^{n}e^{-\mu_{ij}}}{n!} \tag{2}$$

where the mean pipeline μ_{ij} depends on the decision variables $(\mathbf{s},\mathbf{a},\mathbf{b})$. From here on, we will use the shorthand notation (.) if a variable is a function of (some of) the decision variables $(\mathbf{s},\mathbf{a},\mathbf{b})$. Using elementary calculus, we can derive from (1) and (2) that

$$\frac{\partial \mathrm{EBO}_{ij}(.)}{\partial \mu_{ij}}=\sum_{n=s_{ij}}^{\infty}\frac{\mu_{ij}^{n}e^{-\mu_{ij}}}{n!}, \tag{3}$$

which equals $1-\beta_{ij}(.)$, so one minus the fill rate. For a single site model, we have that $\mu_{ij} = m_{ij}T_{ij}$, and so we find using the chain rule for differentiation:

$$\frac{\partial \mathrm{EBO}_{ij}(.)}{\partial T_{ij}}=\frac{\partial \mathrm{EBO}_{ij}(.)}{\partial \mu_{ij}}\frac{\partial \mu_{ij}}{\partial T_{ij}}=\left(1-\beta_{ij}(.)\right)m_{ij} \tag{4}$$

In a *two-echelon, single-indenture* model with location 0 as the supplier of location j, we find:

$$\mu_{ij}=m_{ij}\left\{r_{ij}T_{ij}+(1-r_{ij})\left(O_{j}+\mathrm{EBO}_{i0}(.)/m_{i0}\right)\right\} \tag{5}$$

Applying the chain rule, we find for the derivative to the mean repair TPT and the order-and-ship time at location j and for the mean repair TPT at location 0:

$$\frac{\partial \mathrm{EBO}_{ij}(.)}{\partial T_{ij}}=\frac{\partial \mathrm{EBO}_{ij}(.)}{\partial \mu_{ij}}\frac{\partial \mu_{ij}}{\partial T_{ij}}=\left(1-\beta_{ij}(.)\right)m_{ij}r_{ij} \tag{6}$$

$$\frac{\partial \mathrm{EBO}_{ij}(.)}{\partial O_{ij}}=\left(1-\beta_{ij}(.)\right)m_{ij}(1-r_{ij}) \tag{7}$$

$$\frac{\partial \text{EBO}_{ij}(.)}{\partial T_{i0}} = \frac{\partial \text{EBO}_{ij}(.)}{\partial \mu_{ij}} \frac{\partial \mu_{ij}}{\partial \text{EBO}_{i0}(.)} \frac{\partial \text{EBO}_{i0}(.)}{\partial \mu_{i0}} \frac{\partial \mu_{i0}}{\partial T_{i0}(.)} = \left(1-\beta_{ij}(.)\right)\left(1-\beta_{i0}(.)\right) m_{ij}(1-r_{ij}) \tag{8}$$

Similarly, we find the partial derivatives of the expected LRU backorders at the bases to all mean repair TPTs and order-and-ship times in multi-echelon, multi-indenture networks. To show how, we use $P_{ij,kl}$ for the partial derivative of EBO_{ij} to the mean repair TPT T_{kl}, where

- item k belongs to the multi-indenture structure of item i (i.e., a child of i or a lower indenture item), and
- location l is a location upstream of location j (i.e., the supplier of j, or even more upstream in the multi-echelon structure).

Equivalently, $Q_{ij,kl}$ denotes the partial derivative of EBO_{ij} to the order-and-ship time O_{kl}, Then we can recursively compute all partial derivatives under the assumption of Poisson distributed pipelines. Figure 3 shows how the partial derivatives of the expected backorders of LRU 0 at base j to the repair TPT of SKU i (child of LRU 0) at location 0 (supplier of j). It is straightforward to modify this scheme for the order-and-ship times.

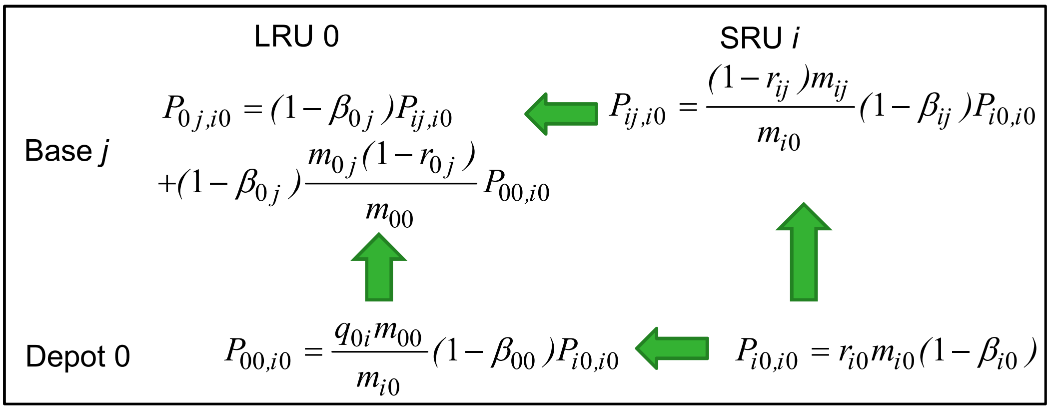

Figure 3. Computation scheme for the partial derivatives of LRU backorders at bases.

We observe that we only need the fill rates to estimate the impact of TPT reduction of all items at all location under the assumption of Poisson distributed pipelines, which is straightforward and fast to compute. Our approach is exact for multi-indenture, multi-echelon networks under Poisson distributed pipelines. However, it is known that the true pipeline distributions may clearly differ from Poisson distributions. We have also observed this, particularly if we need probabilities from the tail of the pipeline distributions. Unfortunately, we could not find reasonable expressions for the partial derivatives under two-moment approximations for the pipelines. In the next section, however, we will see that we do not use the exact values of the partial derivatives, but only use their ranking to select the most promising option (repair or shipment) for TPT reduction.

5. Optimization heuristic

At first sight, we can easily extend the standard greedy heuristic for spare part optimization by adding extra options for TPT reduction. We estimate the impact of repair TPT reduction of item i at location j by an amount $\left\{T_{ij}(a_{ij})-T_{ij}(a_{ij}+1)\right\}$ on the total LRU backorders using the partial derivatives as found in the previous section: $\left\{T_{ij}(a_{ij})-T_{ij}(a_{ij}+1)\right\}\sum_{k\in L}\sum_{l\in B}P_{kl,ij}$. This is obviously an approximation, but it gives us a good idea on the impact of TPT reduction. We compare this impact to the additional costs we face, being the additional repair costs times the number of repairs per year: $\left\{C_{ij}^{R}(T_{ij}(a_{ij}+1))-C_{ij}^{R}(T_{ij}(a_{ij}))\right\}m_{ij}r_{ij}$. So, we have the following simple approximation for backorder reduction per euro $\Delta_R(a_{ij})$ due to repair TPT reduction of item i at location j from $T_{ij}(a_{ij})$ to $T_{ij}(a_{ij}+1)$:

$$\Delta_R(a_{ij})=\frac{T_{ij}(a_{ij})-T_{ij}(a_{ij}+1)}{\left\{C_{ij}^{R}(T_{ij}(a_{ij}+1))-C_{ij}^{R}(T_{ij}(a_{ij}))\right\}m_{ij}r_{ij}}\sum_{k\in L}\sum_{l\in B}P_{kl,ij} \tag{9}$$

The backorder reduction per euro due to order-and-ship time reduction $\Delta_O(b_{ij})$ equals

$$\Delta_O(b_{ij}) = \frac{O_{ij}(b_{ij}) - O_{ij}(b_{ij}+1)}{\left\{C_{ij}^O(O_{ij}(b_{ij}+1)) - C_{ij}^O(O_{ij}(b_{ij}))\right\} m_{ij}(1-r_{ij})} \sum_{k \in L} \sum_{l \in B} Q_{kl,ij} \tag{10}$$

We denote the standard backorder reduction per euro from VARI-METRIC, due to adding a spare part *i* at location *j* to stock, by $\Delta_S(s_{ij})$. Now a logical extension of the greedy VARI-METRIC heuristic is to add all options for TPT reduction, and to select at each iteration the decision that yields the highest backorder reduction per euro spent. This can be either adding a spare part to stock, or a discrete step reduction in repair TPT, or a discrete step reduction in order-and-ship time. Unfortunately, this heuristic does not work well, since TPTs and stock levels are not independent: If we add stocks, the impact of TPT reduction decreases. We typically see in this heuristic that we initially decide to reduce many TPTs, because there are hardly any spare part stocks and so the impact of TPT reduction is high. Is spare part stock levels are zero, any hour reduction of TPT is an hour reduction in system down time. Later on in the algorithm, when we add spare parts on stock, we find out that the impact of these TPT reductions decreases, and finally we may even end up with a solution that is worse than VARI-METRIC, ignoring he options for TPT reduction. So, we have to find another heuristic.

As the problems in the previous heuristic are caused by the generally decreasing impact of TPT reduction in the spare part inventories, it seems better to construct a heuristic that considers TPT reduction while stock levels are *de*creasing rather than increasing. The basic idea is the following. First, we apply VARI-METRIC using the standard TPTs $T_{ij}(0)$ and $O_{ij}(0)$. Then, we improve this solution by exchanging the spare parts having the least added value for TPT reductions having the most added value. The spare part having least added value is the last one we added to stock in the VARI-METRIC algorithm. We search the best (set of) TPT reduction(s) compensating the loss of availability by removing the latter spare parts. If these TPT reductions are feasible at less costs per year than the holding cost of the removed spare part, we accept the exchange. We continue until no improvement is found. So, our basic algorithm is as follows:

Basic optimization heuristic

1) Initialize the decision variables: s_{ij}=0, a_{ij}=0, b_{ij}=0 (i=1..I, j=1..J).
2) Use VARI-METRIC to optimize the spare part stock levels for the TPTs $T_{ij}(a_{ij})$ and $O_{ij}(b_{ij})$ (i=1..I, j=1..J). Keep track of the order in which spare parts are added to stock (item i, location j). Let us denote that list by (i_n, j_n), being the type of item i_n and the location j_n that has been added to stock in iteration n (n = 1..N). Compute all partial derivatives $P_{ij,kl}$ and $Q_{ij,kl}$
3) Consider exchanging spare part (i_N, j_N) for TPT reduction. The cost savings per year are h_{i_N} . Set the additional costs for TPT reduction equal to C^{TR} = 0. Set i^*=i_N and j^*=j_N

   a. Recompute the expected backorders and the partial derivatives that have changed (that is, for all combinations of (i) items in the same branch of the multi-indenture structure as i^* (parents and children), and (ii) locations in the same branch of the multi-echelon structure as j^* (customers and suppliers). If the sum of expected LRU backorders at bases is greater than or equal to the target EBO^{Target}, then go to Step b, else go to 3c [1].

   b. Select the best TPT reduction from the options a_{ij}, b_{ij} by selecting (i^*, j^*) from

$$(i^*, j^*) = \underset{(i,j)}{arg\,min}\left\{min\left(\Delta_R(a_{ij}), \Delta_O(b_{ij})\right)\right\} \tag{11}$$

   If the minimum is attained for a repair TPT reduction, then set $C^{TR} := C^{TR} + \left\{C^R_{i^*j^*}(T_{i^*j^*}(a_{i^*j^*}+1)) - C^R_{i^*j^*}(T_{i^*j^*}(a_{i^*j^*}))\right\} m_{i^*j^*} r_{i^*j^*}$, and

[1] This will never occur in the first iteration, but may happen in next iterations.

$a_{i^*j^*} := a_{i^*j^*} + 1$

else set $C^{TR} := C^{TR} + \left\{ C^O_{i^*j^*}(O_{i^*j^*}(b_{i^*j^*} + 1)) - C^O_{i^*j^*}(O_{i^*j^*}(b_{i^*j^*})) \right\} m_{i^*j^*}(1 - r_{i^*j^*})$, and

$b_{i^*j^*} := b_{i^*j^*} + 1$.

Return to step 3a.

c. If $C^{TR} < h_{i_N}$, the costs of TPT reduction are less than the cost savings of removing a spare part, whereas we attain the target backorder level. Accept this exchange and go to Step 4. Otherwise, ignore the exchange, keep item i_N on stock at location j_N and STOP.

4) $N := N\text{-}1$; If $N \geq 1$ and there are still options for TPT reduction left, then consider the next spare part for exchange to TPT reduction: Go to Step 3.

Because we only have to update a limited number of partial derivatives each time we modify spare part stock levels or TPTs (Step 3a), the algorithms requires limited computation time (from a fraction of a second to various minutes, depending on the size of the problem).

The basic heuristic stops if it is not cost effective to exchange a *single* spare part for one or more pieces of TPT reduction. A straightforward *extension* is to consider an exchange of two or more spare parts simultaneously for pieces of TPT reduction. In principle, we can continue until we run out of either options for spare part reduction or options for TPT reductions, whatever comes first (usually the TPT reductions come first). This may seriously increase the computation times, however. As a compromise, we consider exchanging multiple spare parts for one or more pieces of TPT reduction, until the next best marginal effect of TPT reduction according to criterion (11) is less that the impact of removing the next spare part, being the total increase in LRU backorders at the bases divided by the decrease in costs h_{i_N} .

An obvious drawback of our heuristic is that we do not know how close we are from the optimum. An optimal algorithm, however, is not easy to find. An option is an approach similar to the method by Basten et al. [2010] for the integration of decisions for repair locations and resource locations (Level of Repair Analysis) and spare part inventories. Such an approach is out of scope for this paper (see also Section 7). Advantages of our heuristic are its simplicity and speed, such that we are able to analyze models of realistic size. Moreover, the construction of the heuristic guarantees that we only find solutions that are as least as good as the standard VARI-METRIC procedure without considering TPT reductions.

6. Experiment and results

In this section, we design a numerical experiment to analyze the savings that can be obtained using joint optimization of spare part inventories and TPTs and to characterize its type of policies. We give our experimental design in Section 6.1, and discuss our results in Section 6.2. We illustrate our method in a case study at Thales Netherlands (Section 6.3).

6.1 Experimental design

We focus on two-echelon, two-indenture networks. The holding cost rate is 25% of the item value per year. We vary the size and type of the problem in terms of number of items (LRUs and SRUs), number of bases, average demand rates per LRU, average repair times, repair costs, order-and-ship costs, and target availability, see Table 1.

Experimental factor	**low value**	**high value**
Number of LRUs	25	100
Average number of SRUs per LRU	0.5	2
Average demand per LRU per base m_{ij} (per year)	0.05	0.25
Number of bases	3	10
Average repair time T_{ij} over all items (year)	0.05	0.25
Repair costs as a percentage of the item value	15%	30%
Order-and-ship costs in €	100	500
Target availability	0.95	0.99

Table 1. Experimental factors

For each setting, we generate randomly 25 problem instances as follows.

1) We draw the demand per year per base for each LRU m_{ij} ($i \in L$, $j \in B$) from a continuous uniform distribution around the mean (see Table 1) with minimum demand rate 0.002.
2) We randomly assign the SRUs to LRUs using equal probabilities.
3) If an LRU has one or more SRUs, the probability that no SRU needs to be replaced upon LRU failure is always 0.1, whereas the remaining 0.9 probability mass is allocated to the SRUs based on a continuous uniform distribution (giving the cause probabilities q_{ki}).
4) We draw the *net* value per item from a shifted exponential distribution with lower bound €400 and mean €6000; the *gross* LRU value includes the net values of its SRUs.
5) All items can be repaired at the central depot ($r_{ij} = 1$ if j represents the central depot). At the bases, the repair probabilities r_{ij} only depend on the item i and are drawn from a continuous uniform distribution on the interval [0.1, 0.9].

In all cases, we consider the following options for TPT reduction (Table 2):

Repair TPT		**Order-and-ship time**	
TPT reduction	**Cost increase**	**TPT reduction**	**Cost increase**
25%	40%	50%	100%
50%	100%		
75%	700%		

Table 2. Scenarios for repair TPT reduction and order-and-ship time reduction

We use fewer options for order-and-ship time reduction, because these times are usually much smaller than repair TPTs. Altogether, our experiment consists of 2^8 (8 experimental factors) * 25 (random problem instances per setting) = 6,400 problem instances.

6.2 *Numerical results*

6.2.1 Savings percentage

First we compute the cost savings from including throughput reductions as decision variables in the optimization. That is, we compute the total costs as specified in the goal function of optimization problem (P1) in Section 3 after optimization to the total costs after Step 1 of our algorithm (i.e., application of VARI-METRIC using standard TPTs only). Over all 6,400 problem instances, we find average cost savings of 19.8%.

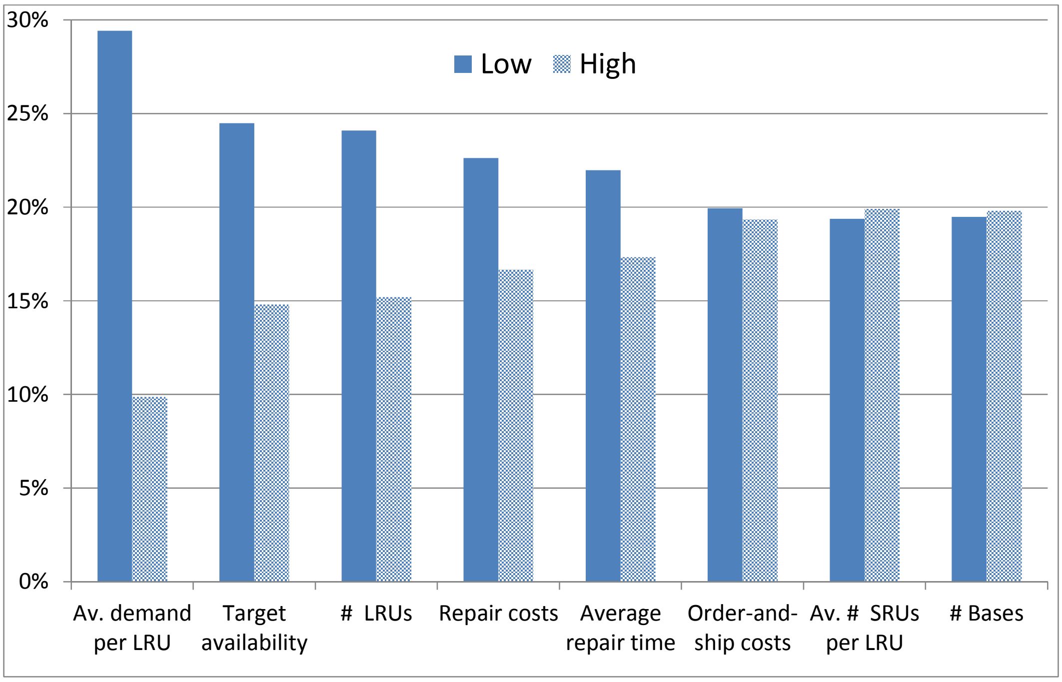

Figure 4. Impact of the experimental factors on the average cost savings (see Table 1 for the high and low settings per factor)

Figure 4 shows the impact of the experimental factors as displayed in Table 1 on the cost savings, sorted by magnitude of the impact. We observe that the average demand per LRU has the highest impact on the savings: TPT reduction is particularly profitable if demand is low. This makes sense, because repair and order-and-ship costs increase proportionally in the demand, whereas spare part holding costs increase less than proportionally because of the portfolio effect. Further, the savings percentage decreases with the target availability, the number of LRUs in the system, the mean repair costs, and the mean repair time. The impact of the average availability and the number of LRUs is remarkable. In both cases, the average downtime allowed per LRU decreases. A possible explanation is that low downtime requirements per LRU lead to high spare part stock levels, and then the impact of TPT reduction is relatively low. The other factors (average number of SRUs per LRU, number of operational sites, order-and-ship costs) have a marginal impact on the cost savings. We expect that higher order-and-ship costs would lead to less reduction in order-and ship times and so to less cost savings. We do not see this in the savings percentage, but we see it in the type of policy that we choose. We will discuss these policies in more detail below (Section 6.2.2).

6.2.2 Type of policy

To examine the type of policy we find for the TPTs, we measure the degree of TPT reduction in a single problem instance by the weighted average percentage TPT reduction with the number of (repair or transportation) jobs as weights. We distinguish between the levels in the multi-echelon system and the levels in the multi-indenture structure. Obviously, we find most TPT reduction in the problem instances with the highest savings (see Section 6.2.1). Apart from that observation, the following observations are interesting:

- The average reduction in repair TPT is 8.5% for all upstream repairs and 24.8% for all downstream repairs. Clearly, we have most TPT reductions *downstream* in the network.
- We observe most TPT reduction for repairs downstream (at the bases) when repair costs are low and repair time are high (38% reduction).
- We hardly use repair TPT reduction of SRUs at the central depot (6.4% on average). We find the most reduction in case of few bases and low demand rates (still only 12.7%).
- The average reduction in order-and-ship time between central depot and bases is 25%.
- Despite of the order-and-ship costs having little impact on the savings (see Figure 4), the type of policy depends on the order and ship costs. The average TPT reduction is 34% if

the costs per shipment are €100, and 16% for order-and-ship costs of €500. So, we indeed reduce the order-and-ship times less if the costs are higher.

6.2.3 Impact of scenarios for TPT reduction

We first analyze the impact of using repair TPT reductions and order-and-ship time reductions only. If we only consider repair TPT reductions and no order-and-ship time reductions, we still get significant average cost savings, namely 14.9% instead of 19.8%. If we limit the options to order-and-ship time reductions, the average cost savings are 3.3% only. It is remarkable that the joint effect of repair TPT reduction and order-and-ship time reduction is larger than the sum of the separate effects.

Next, we analyze the impact of the number of scenarios for TPT reduction (i) by excluding scenarios for repair TPT reduction: we only allow cutting repair TPTs in half at twice the costs (ii) by adding scenarios for TPT reduction. In the latter case, we considered the following options for both repair TPTs and order-and-ship times (Table 3):

Repair TPT		**Order-and-ship time**	
TPT reduction	**Cost increase**	**TPT**	**Cost increase**
10%	10%	10%	10%
25%	40%	25%	40%
50%	100%	50%	100%
60%	300%	60%	300%
75%	700%	75%	700%

Table 3. Scenarios for repair TPT reduction and order-and-ship time reduction

If we reduce the number of options for TPT reduction, the average savings decrease from 19.8% to 16.0%. Under additional options, the average savings increase from 19.8% to 22.3%. So, the number of discrete steps in TPT reduction has impact, but it is not very large. We already achieve significant gains with a single alternative option for TPTs only.

6.2.4 Three-echelon, three-indenture systems

To examine whether our findings remain valid for other network types, we designed a similar experiment for three-echelon, three-indenture networks. The cost savings have the same magnitude were somewhat higher on average (24.8%), but the other findings are similar to two-echelon, two-indenture systems. The only new finding is that we observe a larger impact of the multi-indenture structure on the cost savings. Higher savings are feasible for the combination of more SRUs per LRU and more subcomponents per SRU, so for a "heavier" multi-indenture structure (29.2% savings). We particularly observe a higher reduction in repair TPTs as well as order-and-ship times downstream (and particularly for LRUs).

6.3 Case study

To evaluate our method in a practical setting, we collected data for a part of a radar system at Thales Netherlands. The data are related to a service contract covering six radar systems onboard of six frigates. Spare parts are supplied in a three echelon system from Thales Netherlands via a shore organization to the frigates. Spare parts may be stocked ands repaired at each of the three levels. The subsystem consists of 114 different items, spread over two indenture levels (LRUs and SRUs). The item values vary from a few hundreds of euros to more than €100,000 (LRU including SRUs). The options for TPT reduction are:

- Repairs at Thales Netherlands can be processed via a "fast channel" at extra labor costs (>€1,000), yielding repair TPT reduction of 50% on standard values of several months.
- Order-and-ship times from Thales Netherlands to the Shore can be reduced from 14 days to 7 days at limited extra costs (extra transport by an express courier service).
- Order-and-ship times from the shore organization to the ships can be reduced from 5 days to 2 days, but this yields huge extra costs, since an additional helicopter flight from the Shore to a frigate on a mission is needed.

Application of our heuristic yields 6.3% savings on the spare part holding costs at extra repair and order-and-ship costs equal to 0.7% of the original inventory investment, so we have a net saving of 5.6%. Note that this is *not* a percentage over the total spare part holding, repair and order-and-ship costs, since we were not able to specify repair and order-and-ship costs for the standard TPTs. In fact, we only need the additional costs of TPT reduction to apply our method. Although the savings are relevant for Thales Netherlands given the amount of money involved, it is clear that the savings are considerably less than the average that we observed in our theoretical experiments. We have the following explanation for this:

- The theoretical experiments show that TPT reduction downstream in the network is usually most profitable. However, Thales Netherlands can only influence repair times at the own site, since both the shore and the ships are part of the customer organization. Therefore, we only considered repair TPT reduction *upstream* in the supply chain.
- The same applies to the order-and-ship times: reducing order-and-ship times downstream is extremely expensive (helicopter flights) and therefore no realalistic option. Only TPT reductions upstream are feasible at reasonable costs.
- We have only two options for repair TPTs, namely either a normal or a fast repair. As shown in Section 6.2.3, this reduces the potential for cost savings.

7. Conclusions and directions for further research

In this paper, we developed a heuristic for the joint optimization of spare part inventories and TPTs in repair and supply based on pricing of TPT reductions for multi-item, multi-echelon, multi-indenture spare part networks. Our heuristic is easy to apply and yields significant cost reductions compared to the standard VARI-METRIC method for spare part optimization where TPTs are fixed. We find that it is particularly profitable to reduce TPTs *downstream* in the supply chain. Repair TPT reduction of lower indenture items upstream in the supply chain is least useful.

As further research, we suggest to develop a method for exact optimization of this model to provide a benchmark for the performance of our heuristic. The approach as applied by Basten et al. [2010] for the joint optimization of the spare part provisioning and Level Of Repair Analysis (LORA) problem seems to be most promising. However, we expect that an exact method require more computation time, so that it will not be suitable to solve problem instances of practical size.

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