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# Optimization of a stochastic remanufacturing network with an exchange option

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ABSTRACT

An international manufacturer of industrial equipment offers its customers a remanufacturing service consisting of a refurbishment of the most critical part in order to rejuvenate the equipment. Offering remanufacturing services is in line with a servitization strategy. We develop a strategic decision support tool to optimize the required remanufacturing network. Investment decisions have to be made, not only concerning the number and locations of remanufacturing facilities, but also concerning the appropriate capacity and inventory levels to guarantee specific service levels. These network decisions are influenced by the way remanufacturing services are offered. We consider two service delivery strategies, either a quick exchange of the used part by an available remanufactured one or re-installing the original part after it has been remanufactured. Given the high level of uncertainty, we build a stochastic, profit maximizing model to simultaneously determine the optimal network design and the optimal service delivery strategy for a multi-product, multi-level network for repairable service parts. The rapid modeling formulation with a non-linear objective function subject to non-linear constraints is solved by the differential evolution algorithm. We conduct the analysis for fast and slow moving part types. The model can be easily extended to more general settings, while the case-study provides valuable insights for practitioners.


## 1. Introduction

The large installed base of equipment provides original equipment manufacturers with an opportunity to develop a profitable remanufacturing business. The launch of more extensive warranties and overhaul services relies on remanufacturing activities and fits the current servitization trend in the industrial equipment industry [4,19,5]. Consequently, an increasing number of companies like Bosch and HP are intensifying their remanufacturing activities [10]. Our case-study company is an international manufacturer in the compressed air and generator industry with a renewed focus on remanufacturing. Due to confidentiality reasons the company is referred to as AirGen and financial specifications are omitted.

In order to set up a remanufacturing network, AirGen's management has to decide upon the number and locations of facilities. In addition, appropriate capacity and inventory levels have to be set in order to fulfill the service level agreements (SLA). Furthermore, contractual arrangements made with customers (e.g. regarding the ownership of parts) and the selected service delivery method have an impact on the optimal remanufacturing network design. The goal of our research is to build a model that supports this complex decision making process at the strategic management level.

## 2. Problem description

AirGen's remanufacturing service consists of a refurbishment of the most critical part of the equipment: they clean, rebear and restore the part to an as-good-as-new condition which will extend the lifetime of the equipment. Prior to these refurbishment activities taking place in a remanufacturing facility, an AirGen field technician travels to the customer site to disconnect the worn-out part. Two service delivery strategies are offered. Under a refurbishment with exchange, in short referred to as an “exchange” strategy, the technician replaces the part by an already refurbished one. Contrary, if a refurbishment without the exchange option is selected, or shortly a “refurbishment” strategy, the customer has to wait until its own part is refurbished and the field technician re-visits the site to install the part. With the exchange strategy, AirGen has to deliver a part from stock to replace the worn-out part. This inventory of as-good-as-new parts is replenished either by newly produced parts or by refurbished parts from previous customers. The inventory can be held at the remanufacturing facilities or at a centralized distribution center (DC). There are five locations for opening a remanufacturing facility, while their current production plant and DC are not to be relocated. Fig. 1 represents the potential network structure.

Customers are geographically dispersed but can be clustered into five customer regions corresponding to the five potential remanufacturing facility locations. Preferences for the two service delivery strategies are reflected in different demand and price levels between the customer regions. AirGen wants the model to determine the most profitable mix of both service contracts. Although different part types

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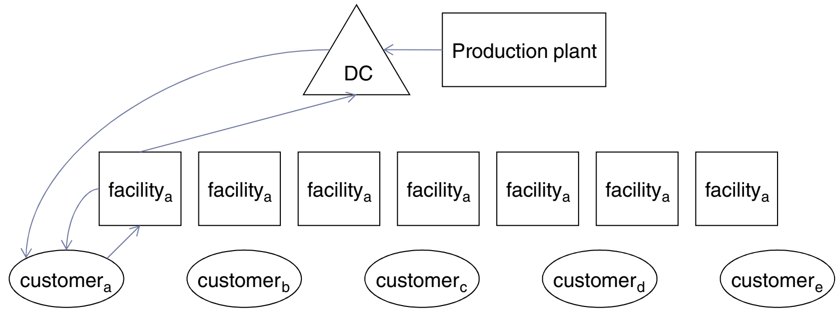


**Fig. 1.** Case study network.

can be refurbished, we group them in two categories to keep the problem traceable: a slow and a fast mover part category. Nevertheless, the model itself is capable of dealing with more than two categories.

Designing a remanufacturing network involves three related strategic sub-problems: a facility location, a capacity and an inventory subproblem. The first decision to be made is where to open remanufacturing facilities. The second decision deals with the number of operators that should be employed at each facility. The third investment decision sets the appropriate inventory level(s) subject to a given SLA, which differs between the refurbishment and exchange service delivery strategies. In contrast to the refurbishment strategy, the exchange strategy requires an investment in inventory of as-good-as-new parts. Not only the level, but also the location of this inventory may be different for fast and slow moving parts. In general, fast moving parts benefit from more decentralized stock locations, while the opposite holds for slow moving parts. Pooling the risk of these highly uncertain items into one central hub can compensate for additional transportation costs. Given the specific characteristics of remanufacturing, we deal with a continuous review one-for-one replenishment inventory sub-problem.

Our focus is on interrelated strategic decisions concerning the network structure: the main questions to answer are the type of service delivery strategy and the number/locations of the remanufacturing facilities. However, these decisions are heavily influenced by the optimal capacity levels at the facilities and the required inventory levels: e.g. cost savings in transportation costs (facility location) may be canceled out by higher operator costs or higher inventory costs. Therefore, it is required to solve the tree sub-problems simultaneously. Tactical and operational decisions such as optimal routing of technicians, transportation batching, work scheduling at the refurbishment centers, etc. are not considered. Consequently, the planning horizon spans multiple years. This integrated approach that leads to outperforming network design solutions in combination with steady state queueing relationships that model lead times and inventory levels is the main research contribution of this paper.

Since all decisions with respect to facilities, capacities, inventories and service delivery strategies influence each other, we propose an integrated solution approach. The complicating factor of uncertainty in demand, processing and transportation times is also taken into account. We formulate a mixed integer non-linear model that integrates queueing relationships and maximizes profit. This rapid modeling approach is solved by a differential evolution search algorithm (see Section 4.7). The focus on the design of a remanufacturing network evidently contributes to the objective of designing sustainable after-market supply chains. After presenting the related literature in the next section, Section 4 clarifies the model. Section 5 presents the results of the case study at AirGen. We conclude in Section 6.

## 3. Related literature

One of the major contributions of this paper lies in its multidisciplinary approach as we integrate facility location, capacity and inventory decisions at the strategic level. Therefore, our work is related to three distinct research streams: facility location, queueing and spare part inventory management literature. Each of these disciplines contains a vast amount of literature. In this section, we do not want to be exhaustive but review the major contributions in each of the three research fields in order to position our research.

The first relevant literature stream is that of the facility location problem (see for example Melo et al. [17] for an extensive overview). Many authors have demonstrated that integrating facility location and inventory decisions can be very rewarding [6,25]. Next to designing a cost efficient supply network, customer service objectives should be taken into consideration, as in the work of Zuo-Jun Max and Daskin [35], Nozick and Turnquist [20] or Mak and Shen [16]. Although both Nozick and Turnquist [20] and Mak and Shen [16] consider stochastic replenishment times, they do not optimize the capacity levels.

The second literature stream deals with queueing networks. Queueing networks are often modeled by using the parametric decomposition approach. The queueing network is decomposed into separate building blocks (i.e. individual workstations or in our case individual facilities in a multi-echelon network). Besides the steady-state waiting time distributions of separate blocks, we have to link the separate blocks by means of linking equations. As such, a linking equation literally links the results obtained at the separate building blocks to obtain the performance of the network as a whole. We refer the reader to Buzacott and Shanthikumar [2], Hopp and Spearman [11], Whitt [32] and [33] for excellent reviews. Using steady state equations as part of an optimization problem can be labeled as a rapid modeling approach [23,24]. These analytical expressions enable us not only to quickly build a mathematical model that represents a production system with realistic dimension, but also to evaluate instantly the performance of this system, allowing us to do a computation intensive optimization process. The use of analytical expressions is in contrast to a simulation technique. This method can also be combined with an optimization process as in Willis and Jones [34], but this would be more time consuming.

Lastly, the spare part inventory literature has paid special attention to multi-echelon repairable networks due to both the applicability and complexity of these networks. In his seminal work, Sher-Brooke [26] formulates a technique to find the base stock level that minimizes the expected number of back-orders in a two echelon parts network with ample repair capacity. This METRIC model has been adapted by many authors to make it applicable to more realistic settings. Muckstadt [18] extends the model to the MOD-METRIC that allows multi-indenture parts. The VARI-METRIC model that is based on the work of Graves [8] and further improved by Sherbrooke [27], allows for a higher variability in the distribution of the back-orders. A highly restrictive assumption of these multi-echelon models is the conjecture of infinite repair capacity. The research on multi-echelon capacitated repairable networks was started by Gross et al. [9]. Diaz and Fu [7] optimize the inventory levels for multiple items in a network with limited repair capacity, general repair times and a demand rate that depends on the repair backlog. The work of Sleptchenko et al. [28] is probably the first that simultaneously optimizes the repair capacity and the inventory decisions. Also Caggiano et al. [3] focus on both capacity and inventory decisions in a multi-echelon network, however, they consider the level of capacity and inventory as given and search for an optimal allocation of the resources based on real time data.

To the best of our knowledge, only Rappold and Van Roo [22] and van Ommeren et al. [21] have simultaneously optimized the capacity, the inventory and the facility locations in a multi-echelon repair network with uncertainty. Although van Ommeren et al. [21] take into account demand uncertainty, they do not consider stochastic processing times and they do not use queueing theory. The setting of our research is comparable to that of Rappold and Van Roo [22], but it differs on some key aspects. Whereas Rappold and Van Roo [22] allocate a fixed amount of inventory between the different stocking locations, we determine the required inventory level endogenously based on utilization levels and variances in demand and production processes, while fulfilling given SLA's.

Contrary to earlier work on repair network optimization in which only one delivery strategy is considered, we consider two delivery strategies, viz. exchange and refurbishment. The service provider incurs different costs and generates different revenues depending on the opted delivery strategy. As such, cost minimization is not a valid objective and consequently we maximize profit. Recently, increased interest to incorporate environmental concerns in the objective function for network design can be observed, e.g. Wang et al. [31].

## 4. Mathematical model

In this section, we formulate our mathematical model which is in line with a rapid modeling approach. We derive a profit maximization model with constraints and non-linear, steady state queueing relationships. First, we outline the notation and assumptions used in the model (Section 4.1). In Section 4.2, we derive the network flow rates that are used throughout the three strategic sub-models: the facility location sub-model, the capacity (queueing) sub-model and the inventory sub-model. Although we formulate one integrated model that solves these sub-models simultaneously (Section 4.6), the three sub-problems are first clarified separately in Sections 4.3 to 4.5. The optimization procedure is briefly discussed in Section 4.7.

### 4.1. Notation and assumptions

We consider a single indenture service part network with facilities that can be opened at locations chosen from a fixed, predetermined set of potential facility locations $f\in\{1,\ldots,F\}$. For AirGen's network in Fig. 1, we have $F=7$ and the production facility ($f=6$) and DC ($f=7$) are always open. A decision about how many and where to open remanufacturing facilities still has to be made. As it is AirGen's policy to serve all customer demand, parts that cannot be remanufactured have to be replaced by new parts. Consequently, demand for refurbishment service can be satisfied either by remanufactured returned parts or newly produced parts. As the production facility is located near the centralized DC, all newly produced parts are stocked at the DC from where parts are sent to customer regions. The third party logistics company (3PL) who is responsible for all the transportation activities ships on a one by one basis, resulting in a single unit batch size through the network. Remanufacturing facilities have capacity constraints that are determined by the capacity sub-model. Although infinite capacity is assumed at the 3PL, the DC, the field technicians and the production plant, both costs and variable processing times are taking into account. For all processing times, we assume general distributions.

Customer demand exists for different types of parts, also known as different stock-keeping units (SKUs). The number of SKUs is denoted by $c\in\{1,\ldots,C\}$, with $C=2$ in the AirGen case study: $c=1$ for the fast mover category and $c=2$ for the slow mover category. Similar to many authors e.g. Diaz and Fu [7], we assume that each customer region experiences a Poisson distributed demand with an average arrival rate $D_p$ for parts $p$, which is different for slow and fast moving parts (low vs. high volume). Given the different demand levels in the different customer regions and for different SKUs, we define a part $p$ as a unique combination of a SKU and a customer region. Specifically for the AirGen case, there are five customer regions and two SKU resulting in an index $p\in\{1,\ldots,P\}$ with $P=2\times5=10$.

Obviously, different routings for each part $p$ are possible across the network in Fig. 1. A routing is defined by a sequence of operations $o\in\{1,\ldots,O_{pr}\}$ that are performed on part $p$ in one or several facilities $f$. In Fig. 1 possible routings for a specific part (SKU) to fulfill demand in region "a" are shown. Note that we only show routings for returning parts through remanufacturing facility one. However, we allow that parts returning from customer region "a" are sent to remanufacturing facilities 1, 2, 3, 4 or 5. More specifically, a part can be sent from a customer region to one of the five remanufacturing facilities, from where it is either directly returned to that customer (one echelon network structure) or sent through the DC (two echelon network structure). Apart from these routings for used parts, there are also routings for flows of newly produced parts at the production facility, possibly assigned to each of the five customer regions. We need this source to satisfy total demand for overhauling parts when the volume of returns is insufficient. So parts that are not refurbished, will be automatically replaced by new parts.

To distinguish between the two service delivery strategies, all routings are duplicated resulting in a set of routings $r\in\{1,\ldots,R_p\}$ for the refurbishment strategy, and a set of routings $r\in\{R_p+1,\ldots,2R_p\}$ for the exchange strategy. In the AirGen case each part $p$ (SKU-customer region combination) will have two potential routings for returned parts for each of the five remanufacturing facilities and one routing for newly produced parts. These 11 routings are duplicated such that the first 11 routings are used for the refurbishment without exchange ("refurbishment routings") and the last 11 routings for the refurbishment with exchange strategy ("exchange routings"). Note that the additional inventory of parts for the exchange strategy is only needed along exchange routings. The inventory of as-new parts is always held either at the facility that remanufactures the parts or at the DC, so there is no local stock at customer regions.

Within these settings, we determine the optimal network structure and the optimal delivery strategy for each customer region, while fulfilling the main constraints of SLA and demand volume. Optimality is defined as maximal profit during a period $T$ in steady-state. The model formulation relies on three groups of decision variables:

1. binary variables $Y_f$ decide on the opening and closing of facilities $f$ (facility location sub-model)
2. integer variables $s_f$ decide on the number of operators in each facility $f$ (capacity sub-model)
3. continuous variables $\tau_{pr}$ decide on the flow of parts $p$ assigned to a routing $r$ (commonly used in all sub-models).

The first group of decision variables is used in Section 4.3 to open ($Y_f=1$) or close ($Y_f=0$) a remanufacturing facility $f$. The remanufacturing activities are quite labor intensive, so we use the number of operators $s_f$, the second group of decision variables, as a determinant for the capacity level at facility $f$ (Section 4.4). Finally, the routing fractions $\tau_{pr}$, commonly used in the three sub-models, determine the amount of parts $p$ along a routing $r$, expressed as a percentage of total demand for part $p$, i.e. demand for remanufacturing service for a specific SKU in a specific customer region. This third group of decision variables defines the optimal flow of fast and slow moving parts by making a trade-off in the three sub-models between costs for transportation, production, capacity and inventory. Given the high importance of these flow rates, we first describe them before formulating the three sub-models. We remark that although we do not have a specific decision variable to determine the inventory levels in the network, these inventory decisions depend on the three groups of decision variables. Based on the values for these decision variables we derive the lead times for each part type. These lead times are used to determine the inventory levels. Since we offer a strategic decision support tool, the objective function, as well as all cost, time and flow rate parameters are usually (and also in the case study) expressed in a common time period $T$ of one year. We do not use a multi-period model, but instead we select a representative period of one year, which is assumed to reflect the steady state conditions that hold in the long term planning horizon.

### 4.2. Flow rates

As explained in the previous section, our model formulation relies on routings and corresponding flow rates. Recall that in our setting a technician travels to the customer site, disassembles the used part and sends it to a remanufacturing facility. Due to the early involvement of the service provider in the remanufacturing process, the potential return flow equals the demand level (not taking into account possible rejections due to quality problems). The total demand for refurbished parts at a certain customer region during the planning period $T$ equals $T*D_p$, where $D_p$ is the demand rate per time unit for $p\in\{1,\ldots,P\}$. When $\tau_{pr}$ is the fraction of the demand $D_p$ assigned to a routing $r$ for used or new parts, we can define the arrival rate of parts $p$ at such a routing as

$$\lambda_{pr} = \tau_{pr} D_p. \tag{1}$$

Note that depending on the different demand levels, we have distinctive flow rates for fast and slow moving parts. As we cannot take back more units than the level of demand for remanufacturing service, the total fraction assigned to routings $r$ for used parts cannot exceed 100%

$$\sum_{r=1}^{2R_p} \tau_{pr}\chi_{pr} \le 1 \qquad p = 1,\ldots,P \tag{2}$$

with $\chi_{pr}=1$ for routings $r$ handling used parts and $\chi_{pr}=0$ otherwise (i.e. routings for new parts). Therefore, the number of used parts coming from the customer is bounded by total demand. This inequality equation also allows for accepting less returns in the network than the maximum volume of $T*D_p$, if it is more economic to provide new parts instead of delivering remanufactured ones. Due to quality problems, some parts will be disposed of at a scrap rate $\omega_{pro}$. Thus, the average arrival rate of part $p$ at operation $o$ in routing $r$ can be written as

$$\begin{aligned} \lambda_{pro} &= \lambda_{pr} && \text{if } o = 1 \\ \lambda_{pro} &= \lambda_{pr}\prod_{\dot{o}=1}^{o-1}\left(1-\omega_{pr\dot{o}}\right) && \text{if } o > 1 \end{aligned}.$$

Since total demand must be satisfied, new parts are necessary to replace scrapped or uncollected parts. These are supplied by the routings $r$ for new parts. As total demand must be met exactly by remanufactured and/or newly produced parts, we have to require that total output of the system equals the demand, or

$$D_p = \sum_{r=1}^{2R_p} \lambda_{prO_{pr}}\left(1-\omega_{prO_{pr}}\right). \tag{3}$$

Note that by summing across all refurbishment routings without exchange ($r\in\{1,\ldots,R_p\}$) and with exchange ($r\in\{R_p+1,\ldots,2R_p\}$), the decision on the fractions $\tau_{pr}$ may result in a mixed policy of both delivery strategies.

The remainder of this section is organized as follows. First we develop the three sub-models: the facility location problem, the capacity problem and the inventory problem. Then these sub-models are integrated into an overall model for profit maximization.

### 4.3. Facility location sub-model

The first sub-model deals with the number and location of facilities that must be opened. We use a fixed set $F$ of potential facility locations $f$. The decision variable $Y_f$ is used to either open ($Y_f=1$) or close ($Y_f=0$) a facility $f$. The locations are selected based on different cost components: fixed facility costs (FC), transportation costs (TC) and production costs (PC).

$$FC = \sum_{f=1}^{F}\left(FFC1_f + FFC2_f s_f\right)\; Y_f. \tag{4}$$

$$TC = T\sum_{p=1}^{P}\sum_{r=1}^{2R_p}\sum_{o=1}^{O_{pr}} \lambda_{pro} UTC_{pro}. \tag{5}$$

$$PC = T\sum_{p=1}^{P}\sum_{r=1}^{2R_p}\sum_{o=1}^{O_{pr}} \lambda_{pro}\left(UPC_{pro} + \omega_{pro} UDC_{pro}\right). \tag{6}$$

The fixed facility costs (FC) during each planning period $T$ consist of two parts: a fixed overhead cost $FFC1_f$ (e.g. depreciation charges, administration and management) and a fixed cost $FFC2_f$ associated with the number of operators $s_f$. The transportation costs related to operation $o$ are determined by the volume ($\lambda_{pro}*T$) and a unit transportation cost ($UTC_{pro}$) that depends on the transportation distance. The production costs ($PC$) account for the unit processing costs ($UPC_{pro}$: new production or remanufacturing) as well as the disposal cost of scrapped units.

Opening or closing facilities will impact which routings can be used to fulfill demand. When a facility is closed, no flow of parts is allowed along a route $r$ that requires facility $f$. Hence, we can write

$$\tau_{pr} = 0 \quad \text{if } \exists f : Y_f = 0 \wedge \sum_{o=1}^{O_{pr}} \varsigma_{prof} = 1 \tag{7}$$

with $\varsigma_{prof}$ equal to 1 if operation $o$ for part $p$ in routing $r$ requires facility $f$ and 0 otherwise.

### 4.4. Capacity sub-model

To set appropriate capacity levels at each remanufacturing facility, we derive the utilization level at each facility in function of the volume and the number of operators. Secondly, the resulting lead times across the network are key if we want to satisfy given SLA's. Whereas service contracts for a refurbishment strategy specify a maximum waiting time for a customer to receive back its part, an exchange strategy imposes a minimal percentage of parts to be delivered directly from stock. To derive the required interrelationships, we use the rapid modeling technique of transforming the network into a queueing system that consists of arrival and remanufacturing processes.

#### 4.4.1. Arrival processes

From Section 4.2, we know that the system is characterized by an expected periodic demand rate of $D_p$ for each part $p$ with $p$ a combination of an SKU and a customer region. This is equivalent to an expected time between arrivals of $IA_p=1/D_p$. Based on the assumption of Poisson distributed demand, the arrival pattern at the remanufacturing facilities is Markovian with a squared coefficient of variation (SCV) of ${c_{IA_p}}^2=1$. As a result, assigning fractions $\tau_{pr}$ to routes $r$ does not change the SCV of the interarrival times at the entry point of these individual routes, referred to as ${c_{IA_{pr}}}^2$ [32]. Consequently, the remanufacturing facilities can be modeled as M/G/m queues. Since higher echelon facilities in the AirGen case (i.e. DC and the production facility) have infinite capacity, no queues are observed at these facilities. For a more general network structure the interarrival characteristics must be based on the variability and utilization of already conducted operations (see Lambrecht et al. [12]). After characterizing the arrivals of parts $p$, we need to aggregate these arrival rates in an average aggregate arrival rate $\lambda_f$ and a SCV of the interarrival times ${c_{IA_f}}^2$ at a facility $f$. When we define the aggregate arrival rate of part $p$ at facility $f$ as $\lambda_{pf}=\sum_{r=1}^{2R_p}\sum_{o=1}^{O_{pr}}\lambda_{pro}\varsigma_{prof}$, we have $\lambda_f=\sum_{p=1}^{P}\lambda_{pf}$.

### 4.4.2. Remanufacturing processes

In this section we elaborate on the relationship between capacity levels and lead times of the operations. In Section 4.4.3 these lead times will be aggregated to routing and SKU specific lead times. For each part $p$ that requires an operation $o$ along route $r$, we have the following operation characteristics: expected effective unit processing time $PR_{pro}$ with SCV $c^2_{PR_{pro}}$ and variance $\sigma^2_{PR_{pro}}$. Since we assume single unit batch sizes, set-up times in case of different SKUs can be incorporated into the processing time and the corresponding SCV and variance. We allow the processing time characteristics to be part $p$ dependent: not only different SKUs ($c$) differ in remanufacturing process times due to e.g. size or complexity of the part, but also the customer region has an impact on the required remanufacturing times. Depending on the customer region, parts may have been exposed to different working conditions such as heat and moisture and may have followed different preventive maintenance treatments. In our stochastic model, we use effective measures for expected processing time and associated variability by taking into account any disruption that reduces available capacity, e.g. the mean-time-to-repair, the number of working time units, the number of time units for preventive maintenance and other efficiency losses.

In order to aggregate these processing characteristics of parts $p$ to the processing characteristics at facility $f$, we express the average process time at facility $f$ as a weighted average of all the parts $p$ across all the routings and all the operations performed at facility $f$: $f: PR_f=1/\mu_f=\sum_{p=1}^{P}\sum_{r=1}^{R_p}\sum_{o=1}^{O_{pr}}\pi_{pro}PR_{pro}$, while its SCV becomes

$$c_f^2=\left[\sum_{p=1}^{P}\sum_{r=1}^{R_p}\sum_{o=1}^{O_{pr}}\pi_{pro}\left(PR_{pro}\right)^2\right]\mu_f^2-1+\sum_{p=1}^{P}\sum_{r=1}^{R_p}\sum_{o=1}^{O_{pr}}\pi_{pro}\frac{\sigma^2_{PR_{pro}}}{\left(PR_{pro}\right)^2} \quad (8)$$

with $\pi_{pro}=(\lambda_{pro}\varsigma_{prof}+\lambda_{p(r+R_p)o}\varsigma_{p(r+R_p)of})/\lambda_f$. The facility utilization becomes

$$\rho_f=\lambda_f/\mu_f s_f\leq 1. \quad (9)$$

The capacity level ($s_f$) and the resulting utilization level (Eq. (9)) influence the expected lead time of an operation $o$ for part $p$ along route $r$. We use the approximation from Whitt [33]

$$EW_{pro}\approx\sum_f EWQ_f\varsigma_{prof}+PR_{pro} \quad (10)$$

with

$$EWQ_f\approx\phi\left(\rho_f,c^2_{IA_f},c_f^2,s_f\right)\left(\frac{c^2_{IA_f}+c_f^2}{2}\right)\left(\frac{\rho_f^{\sqrt{2(s_f+1)}-1}}{s_f\left(1-\rho_f\right)}\right)PR_f. \quad (11)$$

It is an accurate GI/G/m-model with a correction factor $\phi$ that applies to a system under heavy traffic conditions with multiple parallel servers [11]. We refer to Whitt [33] for more details about this factor $\phi$. For the AirGen case with no queues at the production plant and DC, Eq. (11) applies to facilities $f\in\{1,\dots,5\}$ with $c^2_{IA_f}=1$. Since lead times clearly depend on capacities, the capacity decision can be linked with customer service and inventory levels.

### 4.4.3. Lead time aggregation

In order to integrate the SLA of both delivery strategies, i.e. enough safety stock to avoid stockouts for exchange and enough capacity to limit the lead time for refurbishment, we first aggregate the operation lead times to routing lead times and then to SKU lead times. The total expected lead time along a routing $r$ for each part $p$ is determined as $LT_{pr}\approx\sum_{o=1}^{O_{pr}}\left(TR_{pro}+EW_{pro}\right)$ and its variance as $\sigma^2_{LT_{pr}}\approx\sum_{o=1}^{O_{pr}}\left(\sigma^2_{T\ R_{pro}}+\sum_f\sigma^2_{WQ_f}\varsigma_{prof}+\sigma^2_{P\ R_{pro}}\right)$, where $\sigma^2_{T\ R_{pro}}=c^2_{T\ R_{pro}}TR^2_{pro}$. Furthermore, the transportation process related to each operation $o$ is characterized by an expected transportation time $TR_{pro}$ and an associated SCV $c^2_{TR_{pro}}$. From these two parameters, its variance $\sigma^2_{TR_{pro}}$ can be derived. For the variance of the facility waiting time $\sigma^2_{WQ_f}$, we opt for the approximation from Whitt [33].

Next, we aggregate the routing lead times for both service strategies into an aggregated total expected lead time of an SKU $c$. This is based on the total expected lead time of all parts $p$ that belong to SKU $c$, indicated by parameter $\upsilon_{cp}=1$. When part $p$ does not belong to SKU $c$, we have $\upsilon_{cp}=0$. Remember that we have defined a part $p$ as a unique combination of an SKU $c$ and customer region. In the exchange strategy, inventory is held for each SKU, but irrespectively of the demand origin. For example, if demand for a specific part type exists in two regions that are both supplied by the same facility, both regions will obtain parts from the same inventory at that facility. The lead time experienced by an SKU $c$ along an exchange routing ($es$) up to the facility $f$ where the last operation $O_{pr}$ takes place equals

$$LT_{cf}^{(es)}\approx\sum_{p=1}^{P}\upsilon_{cfp}\sum_{r=R_p+1}^{2R_p}\frac{\lambda_{prO_{pr}}\left(1-\omega_{prO_{pr}}\right)\varsigma_{prO_{pr}f}}{\lambda_{cf}^{(es)}}LT_{pr} \quad (12)$$

and its variance $\sigma^2_{LT_{cf}^{(es)}}$ is approximated by

$$\sum_{p=1}^{P}\upsilon_{cfp}\sum_{r=R_p+1}^{2R_p}\frac{\lambda_{prO_{pr}}\left(1-\omega_{prO_{pr}}\right)\varsigma_{prO_{pr}f}}{\lambda_{cf}^{(es)}}\left[LT_{pr}^2+\sigma^2_{LT_{pr}}\left(\frac{LT_{cf}^{(es)}}{LT_{pr}}\right)^2\right]-\left(LT_{cf}^{(es)}\right)^2$$

where $\lambda_{cf}^{(es)}=\sum_{p=1}^{P}\upsilon_{cfp}\sum_{r=R_p+1}^{2R_p}\lambda_{prO_{pr}}\left(1-\omega_{prO_{pr}}\right)\varsigma_{prO_{pr}f}$. We refer to Eq. (8) to explain the derivation of this aggregate variance, knowing that $(c_{cf}^{(es)})^2=\sigma^2_{LT_{cf}^{(es)}}/(LT_{cf}^{(es)})^2$. For each SKU $c$ with a refurbishment strategy ($rs$), we have an aggregation into $LT_{cf}^{(rs)}$ with $r$ in the equations above replaced by $r=1,\dots,R_p$. For this strategy, we impose an SLA on the maximum lead time $\overline{LT_{cf}^{(rs)}}$ that is still acceptable from a customer point of view. Assuming a lognormal distribution of the lead time, we determine its $x_{cf}^{(rs)}\%$ quantile $qlnorm(x_{cf}^{(rs)}\%,\beta_{cf}^{(rs)},\gamma_{cf}^{(rs)})$ as described in Lambrecht et al. [12]. As a result we have the following constraint

$$qlnorm\left(x_{cf}^{(rs)}\%,\beta_{cf}^{(rs)},\gamma_{cf}^{(rs)}\right)\leq\overline{LT_{cf}^{(rs)}}. \quad (13)$$

An SLA for the exchange strategy ($es$) is outlined in the next section.

## 4.5. Inventory sub-model

At this point, the relationships between the facility location and the corresponding costs on the one hand and the capacity decisions and lead times on the other hand have been explained. The next step is setting appropriate inventory levels including the stock required to meet the exchange SLA. We first determine the inventory level for the exchange strategy. Based on this expression, we derive the inventory level for the refurbishment strategy.

When executing an exchange strategy, an inventory of parts that can be shipped directly to the customers is required. At AirGen, all inventories of as-good-as-new parts are held at the last facility in the selected routing, i.e. the DC or the remanufacturing facility. If a refurbishment with exchange is ordered, the part is supplied from this stocking location. The shipment of the part is coordinated with the arrival of a field technician, who disassembles the machine at the customer site and replaces the used part. When this used part completes the remanufacturing cycle, it replenishes the inventory of as-good-as-new parts (exchange strategy). In case of scrap, new parts are added. So each time a unit is taken from stock, it is automatically replenished by either a used or a new part. Consequently, the inventory is managed according to a continuous review, one-for-one replenishment policy, i.e. an $(S-1,S)$ inventory system where $S$ is the order-up-to level. Fig. 2 gives a graphical representation of the inventory in the remanufacturing network for both delivery strategies. With the exchange strategy, two types of inventory can be identified. On the one hand, work-in-process inventory resides in the network as it is being transported, remanufactured or in queue. On the other hand, the exchange strategy requires an inventory of as-good-as-new parts ready to be shipped to customer regions. We refer to this inventory as safety stock.

Similar to Nozick and Turnquist [20], we derive the appropriate order-up-to levels $S_{cf}^{(es)}$ based on a target stock-out probability (SLA). The superscript '*es*' indicates that we determine the order-up-to-level only for the exchange strategy and this for each inventory of an SKU $c$ at facility $f$. An order-up-to level exists of two components: inventory to satisfy the expected demand during total lead time, further referred to as $\hat{\mu}_{DDLT}$, and additional inventory to guarantee a specific SLA, i.e. safety stock $\hat{S}S$. So we have $S=\hat{\mu}_{DDLT}+\hat{S}S$.

Based on the aggregated lead time of SKU $c$ at a facility $f$ (Eq. (12)), we determine the order-up-to level $S_{cf}^{(es)}$ in order to satisfy, with an SLA of $x_{cf}^{(es)}$%, the demand for parts of SKU $c$ with an exchange contract. To determine the order-up-to levels, we need the distribution of the demand during the lead time. Nozick and Turnquist [20] use Palm's Theorem to justify their choice for a Poisson distributed demand during lead time. However, Palm's Theorem relies on the assumption of ample (infinite) capacity. As we take capacity decisions explicitly into account, the use of a Poisson distributed demand during lead time is in disagreement with the queueing relationships in our model. The distribution of the demand during lead time is a convolution of the demand distribution, which we assume to be Poisson, and the lead time distribution, which we assume to be lognormal. These assumptions are confirmed by Diaz and Fu [7] for the Poisson arrivals and Lambrecht et al. [12] for the lognormality of the lead times. In order to identify a parametric distribution for the demand during lead time, we follow the approach of Tadikamalla [30]. When the demand distribution and the lead time distribution are not known, they propose the lognormal, the gamma and the Weibull as adequate distributions for the demand during lead time. When both distributions are known, which is the case here (Poisson and lognormal respectively), they suggest a mathematical expression followed by the selection of the best approximate distribution. Since a closed form for this mathematical expression is not guaranteed, we have conducted a simulation study to find the general, best fit parametric distribution under our modeling assumptions. First, observations are sampled from both a Poisson and a lognormal distribution with different parameters, i.e. Poisson arrivals with parameters {0.25, 0.5, 0.75, 1, 2, 4, 6, 8} for the daily rates in combination with a lognormal lead time with a fixed mean of 10 days and standard deviation levels of {1, 5, 10, 15} (32 scenarios). Next, the observations are convoluted to calculate the demand during the lead time and a set of parametric distributions is fitted to the demand data. Fig. 3 summarizes the results for different fitted distributions. We observe that the Beta distribution has the strongest and most stable performance. Consequently, we opt to use the Beta distribution to approximate the distribution of the demand during lead time.

The standard Beta distribution is defined in the interval $[0,1]$ while the demand during lead time belongs to the interval $[0,b_{cf}]$. Therefore, we need to rescale the mean $\hat{\mu}_{DDLT_{cf}}$ and the variance $\hat{\sigma}^2_{DDLT_{cf}}$ in order to derive the two parameters $\alpha_{cf}^{(es)}$ and $\beta_{cf}^{(es)}$ that describe the standard Beta distribution. So we have

$$\frac{\hat{\mu}_{DDLT_{cf}}}{b_{cf}} = \frac{\alpha_{cf}^{(es)}}{\alpha_{cf}^{(es)}+\beta_{cf}^{(es)}}$$
$$\frac{\hat{\sigma}^2_{DDLT_{cf}}}{b^2_{cf}} = \frac{\alpha_{cf}^{(es)}\beta_{cf}^{(es)}}{\left(\alpha_{cf}^{(es)}+\beta_{cf}^{(es)}\right)^2\left(\alpha_{cf}^{(es)}+\beta_{cf}^{(es)}+1\right)}$$

with $\hat{\mu}_{DDLT_{cf}}\approx\lambda_{cf}^{(es)}LT_{cf}^{(es)}$ (Little's law) and $\hat{\sigma}^2_{DDLT_{cf}}\approx\sigma^2_{D_{cf}^{(es)}}LT_{cf}^{(es)}+\sigma^2_{LT_{cf}^{(es)}}\left(\lambda_{cf}^{(es)}\right)^2$, and where $\sigma^2_{D_{cf}^{(es)}}$ is the variance of the exchange demand for SKU $c$ for which the last operation is conducted at facility $f$, i.e. part delivered from stock located at facility $f$. For the Poisson distributed demand, we have $\sigma^2_{D_{cf}^{(es)}}=\lambda_{cf}^{(es)}$. By solving both equations for $\alpha_{cf}^{(es)}$ and $\beta_{cf}^{(es)}$ we obtain

$$\alpha_{cf}^{(es)} = \frac{\hat{\mu}_{DDLT_{cf}}}{b_{cf}}\left(\frac{\hat{\mu}_{DDLT_{cf}}\left(b_{cf}-\hat{\mu}_{DDLT_{cf}}\right)}{\hat{\sigma}^2_{DDLT_{cf}}}-1\right)$$
$$\beta_{cf}^{(es)} = \left(1-\frac{\hat{\mu}_{DDLT_{cf}}}{b_{cf}}\right)\left(\frac{\hat{\mu}_{DDLT_{cf}}\left(b_{cf}-\hat{\mu}_{DDLT_{cf}}\right)}{\hat{\sigma}^2_{DDLT_{cf}}}-1\right).$$

The $x_{cf}^{(es)}$% quantile of the beta distribution $qbeta(x_{cf}^{(es)}\%,\alpha_{cf}^{(es)},\beta_{cf}^{(es)})$ multiplied by $b_{cf}$ determines the level of $S_{cf}$. Note that $S_{cf}$ is also equal to $\hat{\mu}_{DDLT_{cf}}+\hat{S}S_{cf}$, so we have $\hat{S}S_{cf}=b_{cf}qbeta\left(x_{cf}^{(es)}\%,\alpha_{cf}^{(es)},\beta_{cf}^{(es)}\right)-\hat{\mu}_{DDLT_{cf}}$. This $S$-level ensures that exchange parts can be delivered from stock with an SLA of $x_{cf}^{(es)}$%. Note that the average inventory of as-good-as-new parts equals $\hat{S}S_f$. The work-in-process inventory is at least equal to $\hat{\mu}_{DDLT_{cf}}$ as each part delivery coincides with a part return. If there would be no scrap in the remanufacturing process, work-in-process equals $\hat{\mu}_{DDLT_{cf}}$. However, as scrap does occur in the remanufacturing

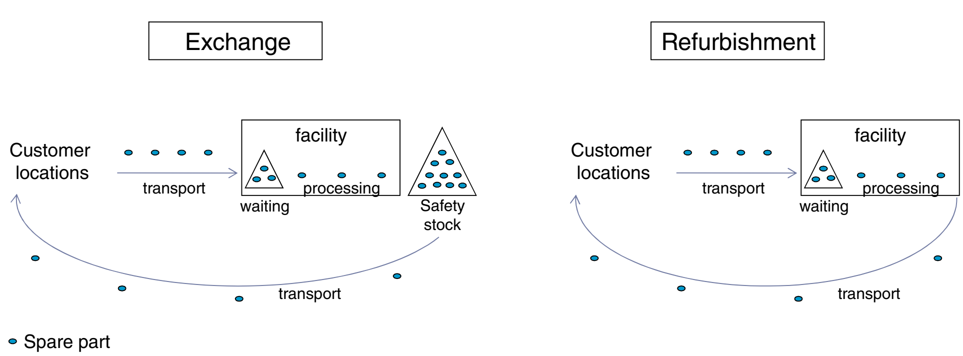


**Fig. 2.** Representation of inventory across the remanufacturing network.

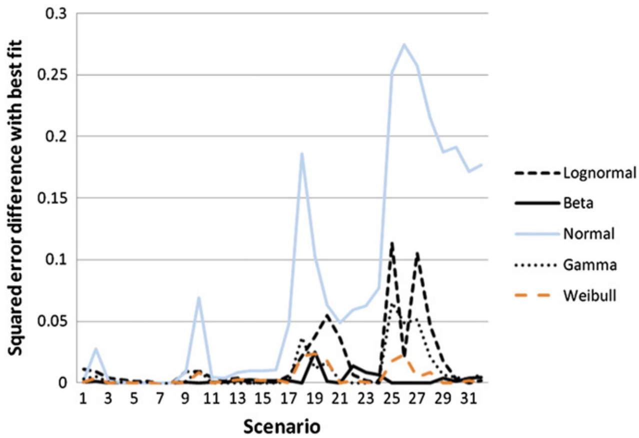


**Fig. 3.** Experimental results for the demand during lead time distribution.

process, more inventory arise due to additional units that enter the system from new production to compensate for these rejections. If we define $EN_{pro}$ as the total expected number of parts $p$ at each operation $o$ in the 'exchange' routings $r$, we can determine their value by applying their total expected arrival rates to the total expected lead times in the system (Little's Law). Time in the system equals transportation time $TR_{pro}$ and lead time at the facilities (Eq. (10)):

$$EN_{pro} \approx \lambda_{pro}\left(TR_{pro} + EW_{pro}\right). \tag{14}$$

Finally, total inventory costs in the network with an exchange strategy is the sum of work-in-process and safety inventory multiplied by the unit holding costs

$$IC1 \approx \sum_{p=1}^{P}\sum_{r=R_p+1}^{2R_p}\sum_{o=1}^{O_{pr}} HC_{pro}EN_{pro} + \sum_{c=1}^{C}\sum_{f=1}^{F} HC_{cf}\hat{S}S_{cf} \tag{15}$$

where $HC_{pro}$ and $HC_{cf}$ are defined as the cost to keep one unit in stock for exchange during planning period $T$.

In contrast to the exchange strategy, the refurbishment strategy does not require the service provider to maintain a safety stock of remanufactured or new parts (see also right hand side of Fig. 2). Consequently, the inventory in such a network is limited to work-in-process inventory, which is equal to $EN_{pro}$. Hence, the inventory costs can be written as

$$IC2 \approx \sum_{p=1}^{P}\sum_{r=1}^{R_p}\sum_{o=1}^{O_{pr}} HC_{pro}EN_{pro} \tag{16}$$

with $EN_{pro}$ similar to Eq. (14), but for routings $r \in \{1,\ldots,R_p\}$. Total inventory cost equals $IC \approx IC1 + IC2$.

### 4.6. Profit maximization model

All the relationships discussed so far can be combined into a profit objective function to characterize all the trade-offs in the problem description. To this end, we define the expected revenue as

$$REV = T\sum_{p=1}^{P}\sum_{r=1}^{2R_p}\left(1-\omega_{prO_{pr}}\right)\lambda_{prO_{pr}}SP_{pr}. \tag{17}$$

Revenue from part $p$ is generated in a routing $r$ by multiplying the part specific unit selling price $SP_{pr}$ by its volume sold. This volume equals the departure rate at the last operation in route $r$ multiplied by the number of time units $T$.

The selling price $SP_{pr}$ can differ between parts and even between routings. This is useful to distinguish between regional prices and to charge a price depending on the service delivery strategy which are characterized by different routings. We can argue that a customer's willingness to pay is higher for exchanged parts because of the faster response time (delivery from stock). The opposite is true when the customer requests to receive back its own part.

Finally, another cost component of the objective function still needs to be formulated to cover cost differences between the refurbishment strategies with and without the exchange option. On the one hand, the exchange strategy is characterized by higher inventory costs (Section 4.5), but on the other hand, it is characterized by a field technician process time that is only half the time of the other strategy. Whereas for an exchange the technician visits the customer only once, two interventions are required for a refurbishment strategy: one intervention to retrieve the part and another intervention to re-install the part. Since the difference in inventory costs is already taken into account, we formulate the transportation and labor costs of the technicians ($TeC$) here

$$TeC = T\sum_{p=1}^{P}\sum_{r=1}^{2R_p}\left(1-\omega_{prO_{pr}}\right)\lambda_{prO_{pr}}FTeC_{pr}. \tag{18}$$

The cost of field technicians equals the volume of remanufacturing services multiplied by a unit cost for field technician working hours. Since total volume to be uninstalled equals total volume to be installed, we distinguish between the different number of required field trips in both delivery strategies by defining a fixed unit cost $FTeC_{pr}$ for a strategy without exchange ($r=1,\ldots,R_p$) that is twice the value of $FTeC_{pr}$ for a strategy with exchange ($r=R_p+1,\ldots,2R_p$).

Eqs. (4)–(6) and (15)–(18) can be summarized in the profit objective function:

$$Profit \approx REV - FC - TC - PC - IC - TeC.$$

We maximize profit subject to constraints 2, 3, 7, 9, 13 and the constraints $0 \le \tau_{pr} \le 1\ \forall \tau_{pr}$.

### 4.7. Model optimization

The network optimization model described above consists of three difficult sub-problems that are simultaneously solved, subject to the goal of overall network profit maximization.

The model formulation consists of a non-linear objective function and non-linear constraints with mixed integer variables. The queueing formulas for the expected waiting times are not only non-linearly dependent on the utilization level $\rho_f$, which depends on the decision variables $s_f$ and $\tau_{pr}$, but also various conditional relationships in the correction factor $\phi(\rho_f, c_{IA_f}^2, c_f^2, s_f)$ make it difficult to solve. Clearly, finding a global optimum for our mixed integer non-linear programming (MINLP) problem is hard and requires a heuristic search approach. We have observed that optimizing this kind of problem in a traditional, sequential way leads to sub-optimal solutions because combinations of intermediate values for the decision variables (e.g. a mixed service delivery strategy) are not attainable during this solution approach. It is the power of the simultaneous consideration of the interrelated strategic questions (e.g. inventory investments depend on waiting times, which depend on network structure and capacity levels) that drives the search towards the global optimum. In the end, optimality can never be guaranteed with a heuristic approach.

Since it is shown in Lieckens and Vandaele [15] that Differential Evolution (DE) as a member of the broader family of genetic algorithms has a strong performance in solving MINLP models for stochastic network design problems, we opt for this heuristic search algorithm. This choice is also motivated by Babu and Angira [1], who have concluded after studying seven difficult design and control MINLP problems in chemical engineering that the technique of DE is the best evolutionary computation method. According to Lampinen and Zelinka [13], DE outperforms any of the competing methods like branch and bound using sequential quadratic programming, integer-discrete-continuous non-linear programming, simulated annealing, non-linear mixed-discrete programming, etc., also for hard non-linear objective functions with multiple non-trivial constraints. In addition, some DE characteristics defined by Storn and Price [29] are applicable in our problem formulation: DE has a superior global optimization ability, it is effective in non-linear optimization, it handles undifferentiable objective functions it operates on flat surfaces and it can provide multiple solutions in a single run.

Briefly summarized, the first step of DE is the creation of an initial population of different elements. Each element contains a value for each decision variable, randomly selected between their lower and upper bounds. Feasible solutions are initially not guaranteed, but it is the difference of randomly sampled population elements in combination with a constraint handling procedure that drives the mutation and recombination process towards better performing children in the population. Different mutation schemes can be selected, but they all reflect information of the objective function that is being optimized. Instead of using only local information for each population element, DE mutates all elements with the same universal distribution. In this way, the whole search space is covered and a global optimum can be found. Another advantage of DE for mixed integer problems is that discrete variables are treated as continuous values to create subsequent children (this maintains the diversity of the population), while they are rounded at the moment of objective function evaluation (this avoids sub-optimal results because only feasible solutions give feedback to the optimization process). We refer to Lieckens and Vandaele [14] for more details about this algorithm.

## 5. Case study results

In this section, we report on the results of the AirGen case study in which the following questions need to be answered:

- Should the exchange option be promoted?
- Where are the facilities located?
- What are the appropriate number of operators in these facilities?
- What is the level of safety stock for the exchange strategy?
- Is the network design different for fast and slow moving parts?

We conducted computational experiments in which we used realistic scenarios based on data from the marketing department and internal company surveys. The impact of increasing demand levels is studied by analyzing scenarios with six different demand levels, ranging from a minimal demand (level 1) up to the market potential (level 6). These demand levels are combined with different price levels. The selling price of a remanufacturing service with exchange option (exchange strategy) can either be lower, equal or higher than the price of a remanufacturing service without exchange (refurbishment strategy) (see Table 1). These eighteen scenarios can be solved for the fast and slow moving parts separately and combined for the two part types. Next, we also investigated the possibility to remanufacture in a low wage region and the impact of the SLA of the contracts.

Table 1 gives an overview of the results for the fast mover part category with varying demand and price levels. We remark that for each volume and price setting, it is optimal to implement a single echelon: the option of a centralized DC is never selected due to high transportation costs (and times) compared to inventory costs (not shown in Table 1). Next, volume plays an important role in the level of centralization: two remanufacturing facilities are opened at the lowest volume level, while up to five facilities are required at the highest volume level. Also, growing volume not only justifies the employment of more operators, their optimal utilization level increases too.

The optimal delivery service clearly depends on the relative selling price of the exchange strategy compared to the refurbishment strategy. Whereas the refurbishment strategy is to be preferred at low price levels for exchange, AirGen should offer more exchange services as their relative selling prices increase. At the high price level, all remanufacturing services are delivered by an exchange strategy (in all regions), while at the intermediate price level, the refurbishment strategy should only be implemented in one region. Customers in this particular region have a strong preference to recollect their own part, leading to a higher willingness to pay for refurbishment service contracts than customers in other regions. This characteristic, in combination with very low field technician costs that temper the negative cost impact of a second visit in the refurbishment strategy, explains the high attractiveness of this strategy in the involved region.

An even more interesting observation is that the optimal utilization rate of the operators decreases as the exchange strategy becomes more popular in case of an increasing selling price. Here the queueing dynamics are at play: lower utilization rates lead to shorter lead times. The model obtains lower utilization rates by increasing the number of operators and/or by diverting the part flow to other facilities. Due to the higher inventory requirements in an exchange policy, shorter lead times are especially advantageous as some inventory holding costs can be avoided. In summary, we can state that the potential inventory savings in the exchange strategy advocate a higher investment in capacity, where the lower utilization rates that result from this decision will reduce the lead time of the remanufacturing process.

Compared to fast moving parts, slow movers are typically more expensive, complex and either small or voluminous. Therefore, compared to the fast movers, slow moving parts are characterized not only by a significantly lower volume, but also by lower (fixed) transportation costs, higher inventory costs and higher remanufacturing process times and variabilities.

If we add the slow moving part category to the model, we observe strong differences between the optimal network structure of both part categories. Where the network for the fast moving parts is decentralized as volume increases, slow moving parts are fully centralized in one remanufacturing facility and this for all tested volume levels. The longer lead times and high holding costs for slow moving parts make holding inventory more expensive than for the fast moving parts. This is especially true for the exchange strategy where even more safety stock is required to protect the demand during this extended lead time. A centralized layout keeps the inventory costs under control due to pooling effects, leading to substantial savings in inventory costs. Furthermore, cheaper transportation is in favor of longer distance coverage. However, these positive pooling effects can be canceled out when queueing dynamics are involved in the model. Closing one facility and assigning its volume to the remaining open facilities can result in a reduction of the total number of operators. This management decision saves on labor costs but not on inventory costs due to higher utilization levels of the operators that are still active. In other words, centralizing in combination with fewer operators may be more profitable than centralizing without a capacity reduction because the cost savings from less labor can compensate the higher inventory costs. Clearly, additional operators should be employed at the facility that remanufactures all slow moving parts. The inventory savings are such that even the customer region where high trade barriers (cost and time) result in a stand-alone remanufacturing facility for fast moving parts, will send its slow moving parts to the centralized facility.

Next to the impact of demand, price and part characteristics on the optimal remanufacturing network, we have investigated the possibility of moving remanufacturing activities to a low wage country. Despite the lower operator and facility costs, the model never favors this option because of the high associated transportation costs and times. In addition, these longer delays also require more safety stock

**Table 1**
Summary results of case study for fast moving parts.

Service deliverystrategy: exchange +capacity ↑

Decentralization ↓

| Demand level | Price levelexchange | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Low | | | Intermediate | | | High | | |
| | # fac. | | ρ | # fac. | | ρ | # fac. | | ρ |
| 1 | 2 | 6 | 80% | 2 | 6 | 80% | 2 | 6 | 80% |
| 2 | 3 | 10 | 88% | 3 | 11 | 80% | 3 | 11 | 80% |
| 3 | 3 | 15 | 86% | 3 | 15 | 86% | 3 | 15 | 86% |
| 4 | 3 | 18 | 94% | 3 | 20 | 85% | 3 | 20 | 85% |
| 5 | 4 | 23 | 91% | 4 | 24 | 88% | 4 | 24 | 88% |
| 6 | 4 | 27 | 93% | 5 | 29 | 87% | 5 | 29 | 87% |
| | Refurbishment | | | Refurbishment and exchange | | | Exchange | | |

to protect against stock outs in an exchange strategy, which makes this option even less attractive.

If service levels specified in the service contracts would increase, the type of service delivery strategy will impact the effect on the network. If customer service is increased in the exchange strategy, inventory costs will increase. Higher inventory costs will create a tendency towards more centralization. Contrary, for a refurbishment strategy higher customer service results in a need to keep lead times short, either by investing in more capacity or in more local facilities. Therefore, intensifying competition (higher SLA) will have an opposite effect depending on the service delivery strategy: encouraging decentralization for refurbishment without exchange services but leading to more centralized facilities for refurbishment with exchange services.

Based on our computational experience with the AirGen case it is clear that solution space is characterized by an extensive number of local optima that are close to the global optimum. This indicates that the objective function is dish shaped and rather insensitive to the number of facilities, where an incremental increase in the number of facilities is less critical than making an error in the opposite direction. The DE characteristic of providing several near optimal solutions has a major value for top management when making strategic decisions. They can compare the different alternative solutions and judge whether or not other external factors compensate the small differences in profit. Less tangible, but important strategic variables that also influence the location of a business include economic, political and labor conditions, as well as the availability of an appropriate infrastructure concerning ICT, administration, etc.

## 6. Conclusions

In this paper we have taken a profit maximization perspective to optimize the remanufacturing network design and the delivery strategy for a global manufacturer of industrial equipment. The choice of the service delivery strategy, refurbishment either with or without an exchange option, has implications on costs and revenues of the network. Apart from this decision and the profit perspective in the developed model, our contribution lies in the simultaneous solution of three related network design problems, i.e. the facility location problem, the capacity and the inventory problem.

For this company's multi-echelon repairable network structure, we determine the optimal number and location of remanufacturing facilities. Taking into account the stochastic nature of both demand and processing times, a queueing model is integrated into the model to set proper capacity and inventory levels, while a specific customer service level is guaranteed. Due to the non-linearity of the rapid modeling formulation, we solve the model by applying a differential evolution search procedure.

The case study results emphasize the importance of volume as a driver for decentralization. As volume goes up, the number of remanufacturing facilities increases accordingly. Sales price is the main driver for the choice of the service delivery strategy. Next, the choice of the service delivery strategy influences the capacity levels in the optimal network structure. In addition, the impact of increased service levels will differ depending on which service delivery strategy is chosen. Therefore, we emphasize the need to simultaneously analyze the design of networks and the mix of service contracts. Slow moving parts should be remanufactured in a central facility, whereas fast moving parts tend to be more decentralized. Note that the recommendations resulting from this research have been fully implemented by the case study company.

The authors acknowledge that the insights derived from the case study need further support by more case study research and sensitivity analysis. Nevertheless, our research shows that a holistic approach in network optimization is necessary. Several extensions are possible e.g. taking into account transportation batching, investigating limited field technician capacity and allowing for non-Poisson distributed demand. However, by assuming general distributions for both transportation and remanufacturing times and by allowing multiple part classes, multiple resources and multiple network echelons in the model formulation, the decision support tool can be easily applied to any general case.

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## References

[1] B. Babu, R. Angira, A differential evolution approach for global optimization of MINLP problems, Proceedings of 4th Asia-Pacific Conference on Simulated Evolution And Learning, 2, 2002, pp. 880–884.
[2] J. Buzacott, J. Shanthikumar, Stochastic Models of Manufacturing Systems, Prentice Hall, Englewood Cliffs, NY, 1993.
[3] K.E. Caggiano, J.A. Muckstadt, J.A. Rappold, Integrated real-time capacity and inventory allocation for reparable service parts in a two-echelon supply system, M&Som-Manufacturing & Service Operations Management 8 (2006) 292–319.
[4] M.A. Cohen, N. Agrawal, V. Agrawal, Winning in the aftermarket, Harvard Business Review 84 (2006) 129–138.
[5] P.J. Colen, M.R. Lambrecht, Product service systems: exploring operational practices, The Service Industries Journal (2012), http://dx.doi.org/10.1080/02642069.2011.614344.
[6] M.S. Daskin, C.R. Coullard, Z.J.M. Shen, An inventory-location model: formulation, solution algorithm and computational results, Annals of Operations Research 110 (2002) 83–106.
[7] A. Diaz, M.C. Fu, Models for multi-echelon repairable item inventory systems with limited repair capacity, European Journal of Operational Research 97 (1997) 480–492.
[8] S.C. Graves, A multi-echelon inventory model for a repairable item with one-for-one replenishment, Management Science 31 (1985) 1247–1256.
[9] D. Gross, D.R. Miller, R.M. Soland, A closed queuing network model for multi-echelon repairable item provisioning, IIE Transactions 15 (1983) 344–352.
[10] V.D.R. Guide, G.C. Souza, L.N.V. Wassenhove, J.D. Blackburn, Time value of commercial product returns, Management Science 52 (2006) 1200–1214.
[11] W. Hopp, M. Spearman, Factory Physics, The McGraw-Hill Companies, New York, 2000.
[12] M. Lambrecht, P. Ivens, N. Vandaele, ACLIPS: a capacity and lead time integrated procedure for scheduling, Management Science 44 (1998) 1548–1561.
[13] J. Lampinen, I. Zelinka, Mechanical engineering design optimization by differential evolution, Mechanical Engineering Design Optimization by Differential Evolution, McGraw-Hill, London, 1999, pp. 127–146.
[14] K. Lieckens, N. Vandaele, Reverse logistics network design: the extension towards uncertainty, Computers and Operations Research 34 (2007) 395–416.
[15] K. Lieckens, N. Vandaele, Multi-Level reverse logistics network design under uncertainty, International Journal of Production Research 50 (2012) 23–40.
[16] H.Y. Mak, Z.J.M. Shen, A two-echelon inventory-location problem with service considerations, Naval Research Logistics 56 (2009) 730–744.

[17] M.T. Melo, S. Nickel, F. Saldanha-da Gama, Facility location and supply chain management — a review, European Journal of Operational Research 196 (2009) 401–412.
[18] J. Muckstadt, Model for a multi-item, multi-echelon, multi-indenture inventory system, Management Science Series B-Application 20 (1973) 472–481.
[19] A. Neely, Exploring the financial consequences of the servitization of manufacturing, Operations Management Review 1 (2008) 103–118.
[20] L.K. Nozick, M.A. Turnquist, A two-echelon inventory allocation and distribution center location analysis, Transportation Research Part E-Logistics and Transportation Review 37 (2001) 425–441.
[22] J.A. Rappold, B.D. Van Roo, Designing multi-echelon service parts networks with finite repair capacity, European Journal of Operational Research 199 (2009) 781–792.
[23] G. Reiner, Rapid Modelling for Increasing Competitiveness, Springer, London, 2009.
[24] G. Reiner, Rapid Modelling and Quick Response, Springer, London, 2010.
[25] Z.J.M. Shen, C. Coullard, M.S. Daskin, A joint location-inventory model, Transportation Science 37 (2003) 40–55.
[26] C.C. Sherbrooke, Metric: a multi-echelon technique for recoverable item control, Operations Research 16 (1968) 122–141.
[27] C.C. Sherbrooke, Vari-metric—improved approximations for multi-indenture, multiechelon availability models, Operations Research 34 (1986) 311–319.
[28] A. Sleptchenko, M.C. van der Heijden, A. van Harten, Trade-off between inventory and repair capacity in spare part networks, Journal of the Operational Research Society 54 (2003) 263–272.
[29] R. Storn, K. Price, Differential evolution—a simple end efficient heuristic for global optimization over continuous spaces, Journal of Global Optimization 11 (1997) 341–359.
[30] P. Tadikamalla, A comparison of several approximations to the lead time demand distribution, Omega International Journal of Management Science 12 (1984) 575–581.
[21] J.C.W. van Ommeren, A.F. Bumb, A.V. Sleptchenko, Locating repair shops in a stochastic environment, Computers and Operations Research 33 (2006) 1575–1594.
[31] F. Wang, X. Lai, N. Shi, A multi-objective optimization for green supply chain network design, Decision Support Systems 51 (2011) 262–269.
[32] W. Whitt, The queueing network analyzer, The Bell System Technical Journal 62 (1983) 2779–2815.
[33] W. Whitt, Approximations for the GI/G/m queue, Production and Operations Management 2 (1993) 114–161.
[34] K. Willis, D. Jones, Multi-objective simulation optimization through search heuristics and relational database analysis, Decision Support Systems 46 (2008) 277–286.
[35] S. Zuo-Jun Max, M.S. Daskin, Trade-offs between customer service and cost in integrated supply chain design, Manufacturing & Service Operations Management 7 (2005) 188–207.

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