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Cross-Training Design Strategies for Repair shops in Spare Part Supply Systems

Hasan Huseyin Turan, Maryam Al-Khatib, *Shaligram Pokharel, Andrei Sleptchenko, Tarek El Mekkawy
Department of Mechanical and Industrial Engineering
Qatar University, Doha, Qatar
*Corresponding Email: shaligram@qu.edu.qa

ABSTRACT

We propose a decision support framework to design a single repair shop in a single echelon repairable spare part supply system. The framework integrates heuristics or meta-heuristic techniques to solve the joint problem of skill-server assignment (cross-training), inventory and capacity level designation of the repair shop.

KEYWORDS: Decision Support System, Spare Part Logistics, Cross-Training, Pooling, Heuristics, Simulation Optimization

INTRODUCTION

Degradation and long-term usage of equipment, materials, and resources cause a reduction in their lifespan. Consequently, the performance of the system that uses the degrading items lowers. As a result, maintenance processes ensure the availability and productivity of systems (cf. Alrabghi and Tiwari, 2015). Also, the availability of the required parts plays a vital role in process sustainability. Specifically, maintenance logistics and efficient supply of spare parts are mandatory in modern society. However, keeping stock units requires proper planning as it affects the capital intensively. For example, it is estimated that about $40 billion of spare parts are owned by commercial airlines. At the same time, tens of million dollars of spare parts are being held by a single company in semiconductor manufacturing (cf. Basten and Van Houtum, 2014). In general, maintenance costs can reach up to 15% - 70% of the total production cost (cf. Bevilacquaa and Bragliab, 2000). Besides, around 10% - 15% of the total expenditure is accounted for spare part inventories in the modern world (cf. Muh-Cherng Wu, 2011).

In this research, we study a repairable spare part supply system that receives malfunctioned parts, while sending back maintained as-good-as-new parts in replacement. The system consists of a repair shop with several parallel multi-skilled servers, and storage facilities for the repaired items. Once a failed part received, it is queued to be served by a suitable server (server with the required skills). The repair shop serves the items based on first-come-first-served (FCFS) principle without any priority rules. In the same time, a repaired (as-good-as-new) item is sent from the storage as an exchange to the malfunctioned part. However, if the required item is not available, the request is backordered.

The effectiveness of repair shops; as the one discussed in this paper; and the total cost of a system depends highly on the design of repair facility and the management of inventory levels of the spare parts. In other words, it depends on the decisions of how many servers to install, which skills to assign for each server, and how many spare parts to keep in the inventory. In this paper, we develop a decision support system (DSS) to analyze several different strategies in order to optimize repair shop designs together with the spare parts inventories. The contribution of this work includes:

1. developing a flexible DSS enabling the decision maker to choose both solution algorithm and repair shop design strategy, and
2. conducting extensive numerical analysis by using different scenarios where the suggested repair shop designs via DSS compared to other design options.

The next sections are as follows. In Section 2, we discuss and present the relevant literature review. The problem description is presented in Section 3. In Section 4, details of the DSS are discussed. Results of the computational study are presented in Section 5. Finally, conclusion and plans for future research are summarized in Section 6.

LITERATURE REVIEW

The current research combines the study of inventory levels with capacity optimization of repair shops and flexibility of maintenance servers' skills. These areas have been studied extensively in the last decades. Therefore, the literature review outlines the related studies that are done in each area and any combination research done in these fields.

Several factors affect the capability of a repair shop. However, the decision of the proper design configuration is very crucial. In other words, flexibility plays a vital role in the system performance by reducing the amount of waiting items in the queues, and the spare parts get processed faster. The first study about design and usefulness of flexibility was done by Jordan and Graves (1995). This study shows that the benefits of full flexible systems can be already provided by a less flexible system. Consequently, many studies were built upon the finding that system's functionality could be performed optimally with restricted resources including Jordan et al. (2004); Tsitsiklis et al. (2012); Bassamboo et al. (2012). The flexibility of resources; in maintenance systems as the one presented this case; is controlled by assigning tasks to the workforce so that each malfunctioned part can be maintained by multiple resources. In other words, one method of controlling the flexibility of workforce and resources in complex systems is by cross-training. These systems include call centers, job shops productions, medical corporations and manufacturing systems are covered under the study of cross-training policies (Qin et al., 2015). In addition, applying cross-training can benefit the system from various aspects such as minimizing labor cost, reducing lead time, increasing the quality (Hopp and Oyen, 2004). However, applying cross-training includes making decisions among specific configurations that specify which servers should be trained on what tasks.

There are four common configurations architectures for cross-training that are pooling, chaining, full cross-training and dedicated (Qin et al., 2015). The dedicated and full cross-training designs are the extreme cases where either no cross-training of the skills is presented and each server is assigned to a specific skill or all the servers are capable of all the skills, respectively. Yet, cross-training all servers in many realistic situations is not beneficial/practical due to rising costs, quality penalties or scarcity of capable servers that are able to handle all required skills (cf. Turan et al., 2017). As a result, the choice of a suitable configuration such as pooling or chaining should be done. For more details on flexibility classification and cross-training applications, we refer to the recent review articles by De Bruecker et al. (2015); Tsitsiklis and Xu (2015); Qin et al. (2015).

Clustering the resources or pooling them in groups is a design strategy where servers are grouped and assigned to a particular set of task, though no intersection happens between the assigned skills of different servers groups (Qin et al., 2015). However, the critical part in pooling is to determine which tasks should be grouped together. Hence, the study of Aksin et al. (2007) analyzes the pooling policies for a call center with the aid of cross-training. In addition, pooling policies for call centers were presented by Tekin et al. (2009), where the department with the highest service time coefficient of variation minimizes the expected waiting times more when mean service times are similar among departments. similarly, Mandelbaum and Reiman (1998), Tsitsiklis et al. (2012), Van Dijk and van der Sluis (2009), Andrad´ottir et al. (2017) and Dijk and Sluis (2008) contributed to the research of different methodologies of pooling as well as resulted limitations of pooling.

On the other hand, chaining is a limited cross-training method where each server is connected to performing tasks in an indirect or direct way, by assigning a unique set of skills to each server (Qin et al., 2015). Inman et al. (2004) presented that prioritizing cross-training in an effective and reasonable way is by chaining to compensate for absenteeism on assembly lines. For further study of chaining, we refer to Hopp et al. (2004); Inman et al. (2004); Iravani et al. (2005); Parvin et al. (2012). However, even when cross training was covered broadly in the research studies, only a few recent effort about cross-training in spare part logistics were done that is presented in Sleptchenko et al. (2017), Turan et al. (2016) and (Turan et al., 2017).

Another important decision in the maintenance spare part supply systems is to optimize the capacity and inventory levels. The seminal paper Sherbrooke (1968) was the first to introduce the analysis of spare parts supply systems. In details, Sherbrooke (1968) approach used the assumption of infinite capacities to determine how many ready for use spares needs to be stored in each warehouse. Many researchers extended their work in the same region by developing new models that can be found in the review papers Sherbrooke (2006) and Muckstadt (2005). However, ample capacity is not considered to be accurate as it results in imprecise allocations of resources in systems that includes highly utilized repair shops as given in Sleptchenko et al. (2002); Van Harten and Sleptchenko (2003). Thus, the first extension to Sherbrooke (1968) but with limited capacity was done by Diaz and Fu (1997). Subsequently, restricted inventory capacity was introduced in Sleptchenko et al. (2002, 2003); Lau and Song (2008); Yoon et al. (2015).

The combination of these two areas can be optimized using optimization algorithms and technique. Various researchers have solved the cross-training problems or the capacity optimization problems similar to the one presented in this case using different algorithms and techniques. For example, in order to get a successful solution for the complex stochastic problem regarding cross-training architecture in call centers, a WS-APL methodology was introduced by Iravani et al. (2007). Ertay and Ruan (2005) applied data envelopment analysis for optimization of worker allocation in manufacturing cell. Samarghandi and ElMekkawy (2012) applied Genetic algorithm and particle swarm optimization to deal with no-wait flow shop scheduling. The review of De Bruecker et al. (2015) includes the application of different algorithms in the workforce planning.

Although an extensive research was done in these two research areas, to the best of our knowledge, there are no studies for joint optimization regarding flexibility in cross training schemes in parallel with optimization in policies of spare parts inventory systems. In addition, no studies were found that applies and compares the results of using the Genetic algorithm, Particle Swarm Optimization, K-median heuristics or packing heuristics on a problem like the one presented above.

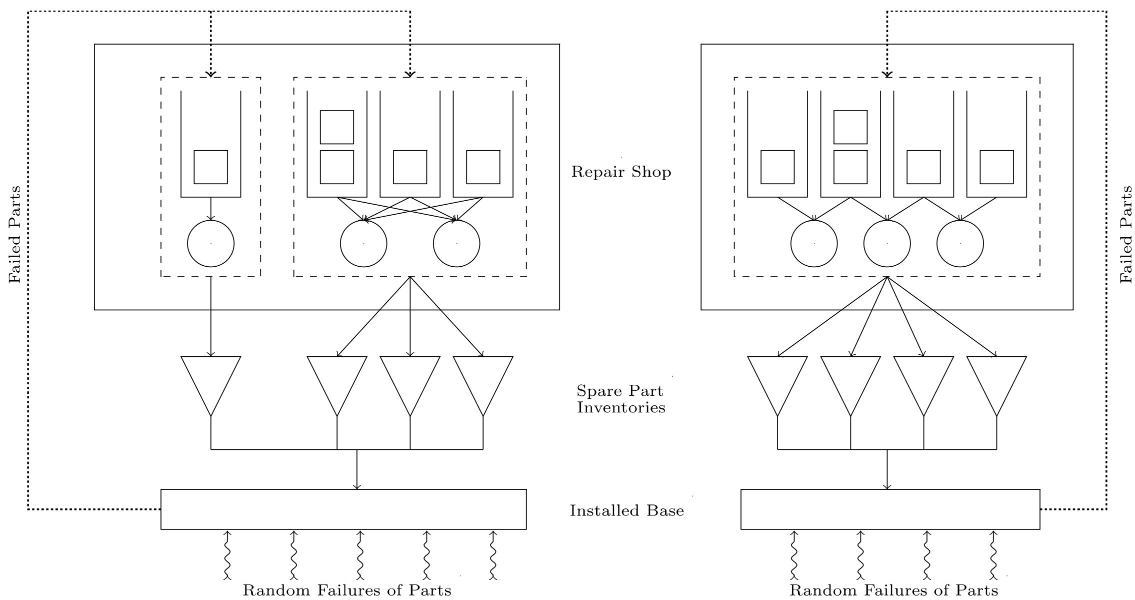
PROBLEM DESCRIPTION

The focus of this study is to design the repair facility in a single location spare part supply system. In addition to the repair facility, the studied spare part supply system has an inventory of repairable spare parts (multiple types) for critical technical systems (the installed base) in a certain region. When a part fails, a request is immediately placed at the stock point for a ready-for-use replacement of the same type, and the failed part is sent to the repair facility.

The repair shop may have pooled structure as in Figure 1(a) with one or more cells/clusters or an arbitrary structure such as ‘W’-type as depicted in Figure 1(b). Any particular design may include dedicated and/or cross-trained servers that can repair multiple types of spare parts.

The failed part is directed to its designated cluster in the repair shop, where it is repaired by either a dedicated or a cross-trained server. At the same time, if the demanded ready-for-use part is available, then the demand is immediately fulfilled. Otherwise, the demand is backordered and fulfilled as soon as a ready-for-use part of the necessary type becomes available from the repair shop. In the latter case, the technical system goes down, and downtime cost occurs till the requested ready-for-use part is delivered.

Figure 1: Different repair shop architectures in a single echelon spare part supply system.



(a) Pooled Design (b) W-Type Design

Figure 1 compares two feasible design for a system processing four different types of SKUs. In the pooled design (a), the repair shop consists of two clusters and three servers. The first cluster has a dedicated server with the ability to serve one type of SKU. The other cluster is obtained by pooling remaining three SKUs, and this cluster has two cross-trained servers to serve these three different types of repairables. In the ‘W’ -type design (b), the repair shop has only one cluster with three servers, in which all servers are cross-trained. However, the servers in the cluster do not have all skills to repair all SKUs in that cluster. In particular, for this example, every server can only repair only two types of SKUs.

Assumptions and Model

We present commonly used assumptions in the repairable spare part supply systems, and discuss details of decision support framework that tries to find best design settings (number of servers, the amount of spare inventories and level of cross-training for each server) under given design preference of decision maker in order to minimize total system cost.
The used assumptions are:

a) The failures of spares occur according to a Poisson process and mutually independent from each other with constant rates. This assumption is quite common and realistic for large installed bases where hazard rates are relatively stable.
b) The repair times are exponentially distributed and mutually independent. The expected repair times depend on the SKU type and are independent of the processing server.
c) First come first served (FCFS) queuing discipline is adopted inside of each cluster, and no priorities exist among failed spares. This discipline implies that whenever a server gets idle, it picks the failed part that has the longest waiting time in the queue, as long as the server has the needed skill.
d) The total holding costs for every SKU per time unit are linear in the initial inventory levels (initially acquired inventory).
e) Spare inventories are always replenished directly from the repair shop, i.e., there is no possibility of neither an emergency nor lateral shipments of spares from other locations and/or repairs shops at different echelons.
f) Penalty costs (or backorder costs) occur when the required part is not available and are paid per time unit per not available SKU. In many cases, the number of backorders directly reflect the number of the technical systems that are down at the installed base.
g) Positive cross-training (or flexibility) cost occurs whenever an additional skill is assigned to a server. In other words, cross-training cost is an increasing function of the number of skills per server.
h) For pooled designs, each cluster inside the repair shop is modeled as a multi-class multi-server M/M/k queuing system with dedicated queues, i.e., every server inside a cluster has the ability to repair all SKUs that are assigned to that cluster.
i) For pooled designs, the clusters inside the repair shop are mutually exclusive (disjoint) and collectively exhaustive, i.e., a particular failed SKU can be repaired at exactly one cluster and all SKUs are assigned to exactly one cluster.

The assumptions (a), (b), and (c) can be relaxed depending on chosen solution methodology and design type (see section 4). In particular, the simulation-based methodology is flexible to handle different types of failure/service processes and queuing disciplines. On the other hand, to utilize analytic solution methodologies (i.e., queue-theoretical) assumptions (a) and (b) together with (h) and (i) are needed. Besides, the last two assumptions not only enable using queue-theoretical approximations to find the steady-state probability distribution of items in the system but also limit the computational complexity of the system. Lastly, assumption (g) can be relaxed by adopting different cross-training cost structures, which would only lead to a slightly modified mathematical model without any computational burden.

Model Objective Function and Constraints

In order to solve the problem efficiently the objective function, constraints and the structure of the solution design must be defined. The main objective is to minimize the total cost by designing an appropriate structure of the repair shop. The minimization of the total cost is done by minimizing the objective function that includes four terms of costs: holding, backorder (downtime cost), the server (capacity) and cross-training cost terms where the decision-makers have to balance cost efficiency with effectiveness when designing a repair shop for spare parts. In fact, different designs will lead to different operating consequences in terms of cost and responsiveness.

There exist several trade-offs between cost terms such as the cost of holding excess inventory and the cost of downtime, and also the trade-off between the cost of having single or several clusters that include both/either dedicated and/or cross-trained servers. Where, the inventory holding cost represents the cost generated from the initial stock level, while the backorder cost is the cost generated from the penalty of not having enough stock items. The server cost is the operational cost of having a server and cross-training cost that is generated from each additional skill that a server must have. They can be represented as annual wages of the technicians and bonuses for their qualifications or annual operational costs of basic and upgraded equipment, respectively.

In addition to the cost minimization objective, regardless of design type, system constraints also have to be taken into account during the decision process. Firstly, in any design, there has to be a sufficient number of operational servers in the repair shop to prevent an overloaded system. Secondly, in the pooled designs, any SKU type must be repaired by exactly one cluster and clusters have to be mutually exclusive and total exhaustive.

SOLUTION FRAMEWORK

Figure 2 depicts the flow of the proposed decision support framework for the design of a repair shop in spare part logistics. In this framework, the first stage includes determination and estimation of the input parameters, such as the probability distribution parameters for service and inter-failure times and the related cost parameters, i.e., holding, backorder, cross-training, and server costs per a chosen time unit. Afterward, the decision maker has to choose the design type that will be analyzed.

The developed decision support system (DSS) has the ability to analyze two different design approaches; namely, the pooled designs (Figure 1a) and all other possible designs (Figure 1b) ranging from completely dedicated to fully flexible (including pooled designs).

The number of possible cross-training schemes, or, in other words, the size of the search space of the possible skill-server assignments, is considerably smaller in the pooled designs. Moreover, the special structure of the pooled designs enables analyzing each cluster separately using available queueing theory methods provided in Van Harten and Sleptchenko (2003). For the pooled design, two search algorithms, K-median and Packing Heuristics, are developed to generate feasible skill-server assignments with pooled structure. These two search heuristics try to pool SKUs that with similar service characteristics into the same cluster (cf. Turan et al., 2017).

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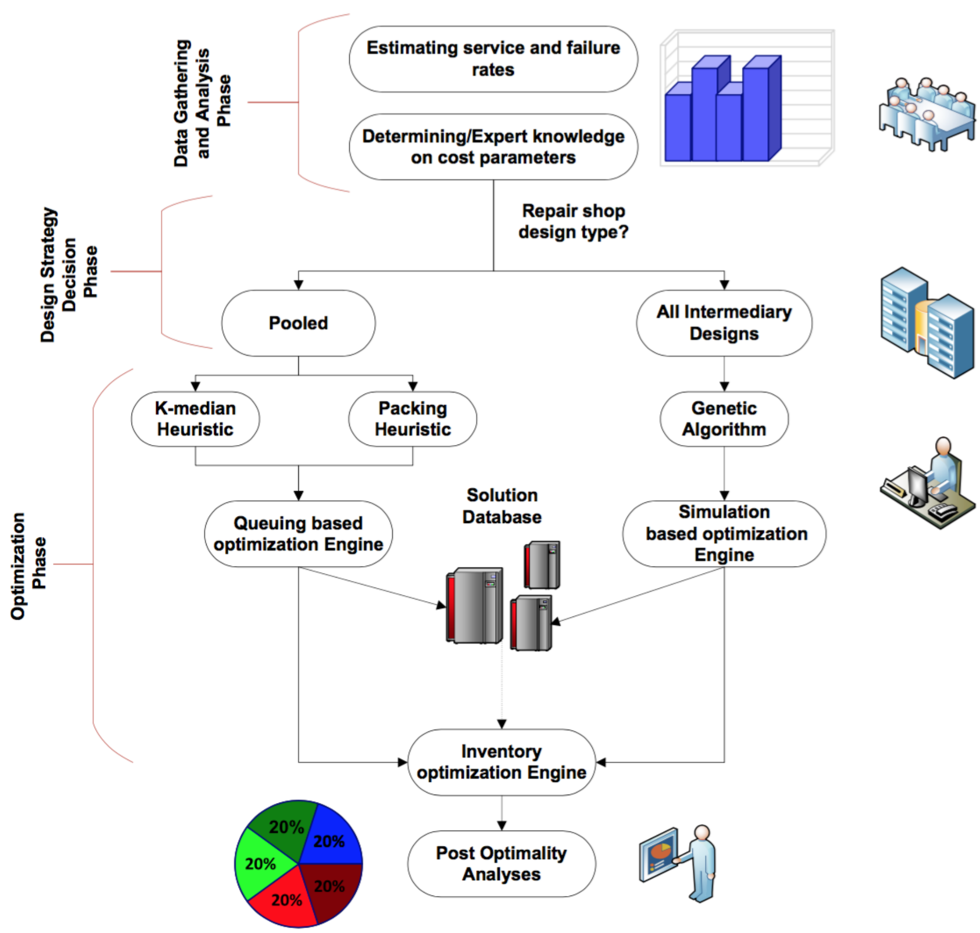
The search space of the possible skill-server assignments that allow any type of design is obviously much bigger. Furthermore, for most of such designs, there exists no analytical or numerical solution. Therefore, the simulation-based optimization algorithms based on evolutionary meta-heuristics are implemented for the presented DSS (cf. Sleptchenko et al., 2017; Turan et al., 2016; Sleptchenko et al., 2016b).

To sum up, both design strategies described above follow sequential solution procedures to solve the joint optimization problem of skill-server assignments, capacity level designation, and inventory allocation. In these procedures, the skill-server assignments and capacity levels are optimized by general meta-heuristics, and the inventory levels are optimized for given skill-server assignments by the separate subroutine, see Figure 2.

Figure 2: Decision support framework for repair shop design.



INITIAL RESULTS AND COMPUTATIONAL STUDY

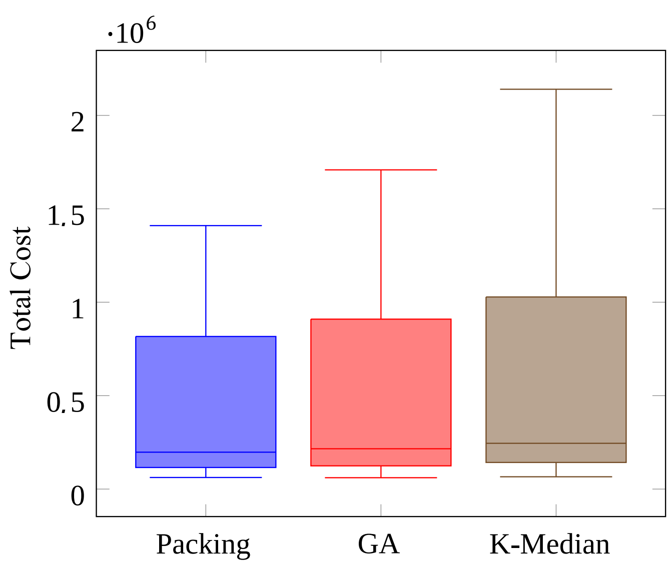
In the computational study, the performance of optimization heuristics is compared: two optimization heuristics based on the pooled design (Packing and K-median) and the one based on the general design (Genetic Algorithm or GA). General discussion on the results is also given.

The computational study of the proposed DSS framework and the discussed heuristics is based on the dataset presented in Sleptchenko et al. (2016b). In general, the testbed used for this study is generated by full factorial design (DoE) with seven factors and two levels per factor (128 test cases in total). Table 1 presents the used factors and levels. The holding costs and system workload in these experiments are either uncorrelated (factor IND) or inversely proportional (factor HPB). The basic comparison of the different optimization heuristics discussed above shows following results (Figure 3).

Table 1: Problem parameter variants for test bed.

FACTORS	LEVELS	
No. of skills (SKUs)(N)	10	20
No. of servers (M)	5	10
Utilization rate (ρ)	0.65	0.8
Server cost (f)	10000	100000
Cross training cost (c_i)	100	1000
Minimum holding cost (h^{min})	1	100
Holding cost/Workload relation	IND	HPB

Figure 3: Total cost comparison for different search algorithms.



The results show that the Sorted Packing heuristic performed best and obtained the minimum cost in 88 instances, whereas GA found the minimum cost in only 40 cases. The better performance of the Sorted Packing is mainly due to the computational efficiency of the queueing evaluation algorithms for the pooled designs. As indicated above, the GA based heuristic uses the simulation based optimization engine and therefore, it requires much more time to converge to good solutions. In general, the computation times of the proposed heuristics are as indicated in Table 2. All the experiments are implemented on a computer with 16 GB RAM and 2.8 GHz i7 CPU.

Table 2: Running time (CPU seconds) comparison for different search algorithms

Search Algorithm	minimum	mean	maximum
Sorted Packing	137.66	1779.00	17759.66
GA	37794.93	71480.22	97218.51
K-median	5.66	81.64	2811.61

The algorithms developed to find the skill-server assignments under pooled designs (Packing and K-Median) converge quite fast in most of the cases compared to the GA based heuristic. The efficiency pooled designs based heuristics is mainly due to the computational efficiency of the used queueing evaluation algorithms. At the same time, the GA based heuristic uses the simulation-based optimization method and requires multiple lengthy simulation calls for evaluation of the objective function.

Managerial Insights

The optimized skill assignments have much lower total system cost in comparison to the cases where each server can process all types of incoming failures (fully flexible servers). On an average, the optimization of the skill assignment can produce on average of 24% savings, and in some extreme cases, it reaches up to 85%. Table 3 summarizes all savings under different search algorithms.

Table 3: Average % decrease in total cost compared to dedicated and fully-flexible design

Search Algorithm	Dedicated design	Fully-flexible Design
Packing	44.85	24.33
GA	42.53	21.21
K-Median	35.08	12.22

CONCLUSION AND FURTHER RESEARCH

In this study, we presented a decision support framework for optimization of a spare part supply system for repairable spare parts with multi-server repair shop and cross-training. We compared three different heuristics that can be used for optimization of the repair shop architecture. The main results and conclusions include:

1. The pooling architecture of the repair shops is much easier for analysis and optimization.
2. The pooling architecture of the repair shops gives very good solutions that are also optimal in many cases.
3. The total system cost can be reduced by 31% in average. In some extreme cases, the cost reduction can reach 85%.

In our further research, we plan to investigate other routing and prioritization rules rather than FCFS, taking into account service rates and costs characteristics of the SKUs, as well as improve the optimization techniques by combining the best futures of the discussed heuristics.

In addition, we plan to apply the idea of skill assignment in more complex and detailed settings, for example, in a pool of service engineers (cf. Rahimi-Ghahroodi et al., 2017; Sleptchenko et al., 2016a). In such a problem, the skills are based not only on the SKU types but also on geographical locations of the failures and service engineers.

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