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A New Multi-Echelon Repair Network Model with Multiple Upstream Locations for Level of Repair Analysis Problem

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ABSTRACT

Level of repair analysis (LORA) determines (1) the best decision during a malfunction of each product component; (2) the location in the repair network to perform the decision and (3) the quantity of required resources in each facility. Capital goods have long life cycles and their total life cycle costs are extremely high. LORA, which can be done repeatedly during the life cycle of the product, both at design and product support phase, plays an important role in minimising the total life cycle costs of capital goods. It is mostly applied to systems that operate in different geographical areas and deployed in different regions, which include different subsystems with special technology and expertise, and have a complex product structure. In this study, we propose a new mathematical model to the LORA problem, which is more comprehensive and flexible than the other pure LORA models in the literature. The proposed model uses the multiple upstream approach that allows the transfer of the components from a location in the lower echelon to the predefined locations in the upper echelon and determines the material movement paths between each facility, defining the facilities' locations in the repair network. The performance of the proposed model is tested on benchmark instances and the results are compared with the single upstream model. Computational experiments show that the proposed model is more effective than the single upstream model and reduces the total life cycle costs by 4.85% on average, which is an enormous cost saving when total life cycle costs of capital goods are considered.

Keywords: Level of repair analysis; Maintenance; Life cycle cost; Capital goods; Mathematical model

1. INTRODUCTION

When a product fails, it cannot perform its task since it becomes out of service until the repair is done. Although there are varying measures to be taken, when capital goods having a complex product structure such as aircrafts, ships, or missile systems fail, immediate action is to be taken to remedy the malfunction. Since repair actions have a cost, a product's life cycle cost raises as the number of failures increases[1].

Due to budgetary limitations experienced in the last decades, the life cycle costs of products have gained much more importance, customers prefer products with lower life cycle costs, and companies aim to gain a competitive advantage by producing products with low life cycle costs. Therefore, the optimisation of the life cycle cost is one of the most desired objectives for the parties.

The capital goods are manufactured with an average life cycle of 20–30 years, and during this period, they go through various phases such as design, production, usage, and retirement. Logistics support activities, mainly occurring during the usage phase, play the most important role in a life cycle of a product in terms of time and cost[2]. Thus, optimising logistics support costs is of great importance to reduce the life cycle costs of the products.

Situations that cause capital goods to become out of service are usually caused by unexpected failures. When a component fails, it needs to be discarded or repaired. If a discard decision is made for a component, it must be replaced with a new one in the stock. If there is not enough stock, a new component must be produced or purchased. When a repair decision is made for the component, the component or faulty subcomponent must be repaired at the relevant repair level. Since each of these decisions generates various fixed and variable costs, an optimum decision must be made to reduce logistics costs and thus to reduce the life cycle cost.

Level of repair analysis (LORA) is an analytical methodology to decide on the discard or repair of a failed component. LORA makes such decisions to ensure that the product has the lowest potential life cycle cost throughout its life cycle[3]. In addition to the decision to repair or discard, LORA decide where to take this action within the repair network and determine the necessary resources at the respective locations. LORA can be performed repeatedly, both during the design phase of the product as part of Logistics Support Activities, and throughout the lifecycle of the product as its design matures.

LORA is mostly applied to systems that operate in different geographical areas and deployed in different regions, such as aircraft, ships, and land systems, which include different subsystems with special technologies and expertise, and have

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a complex product structure. For example, in the F35 Joint Strike Fighter program, there are three levels of international participation by countries from different continents, and companies in these countries have different contributions and work shares in the production phase[4]. The same companies also play an important role in the logistic support process of the products.

Capital goods consist of many components that are modelled as a family tree structure. These structures include many levels known as indenture levels. Indenture levels are determined by the father-son relation of the components. Depending on the resources used in the locations, each component can be removed from its higher assembly and replaced with a functioning one. According to the indenture levels, the components in this study are named as follows: System (Level 1), Line Replaceable Unit – LRU (Level 2), Shop Replaceable Unit – SRU (Level 3), Parts (Level 4). In the product family tree, the system contains LRUs, LRUs contain SRUs and SRUs contain parts. In this paper, we consider a multi-indenture system (Fig. 1(a)).

The network through which component movements are made between repair facilities is called a multi-echelon repair network (Fig. 1(b)). Repair facilities at depot, intermediate and organisational levels are in different echelons within the network.

In this paper, we propose a new multiple upstream approach to the LORA problem that considers multiple predefined locations in the upper echelon for material movements from a location in the lower echelon. The difference between single upstream and multiple upstream approach in a repair network is illustrated in Figs. 1(c) and 1(d).

The proposed approach provides significant advantages in terms of fixed costs as the facilities in a repair network have similar characteristics. Sometimes the same fixed cost occurs in different facilities due to the single upstream approach, although these facilities do not have any capacity shortages. However, if multiple upstream approach is used, a particular special test equipment can be sufficient to be deployed in a facility rather than having it in multiple factories. For example, suppose a special test equipment is required for a certain intermediate level maintenance task and the test equipment has a usage capacity of 1000 hours. In the single upstream approach, this test equipment must be purchased for each intermediate level repair facility, even if the total demand in the network is less than 1000 h. However, in the multiple upstream approach, it will be sufficient to install the test equipment in only one facility, and the defective components from lower echelon can be transferred to this location.

Alternatively, multiple upstream approach may increase the total transportation cost but significantly reduce the fixed costs, which are much more important than the variable costs, especially in defense industry. Thus, the proposed novel approach avoids insufficient use of resources and provides more cost-effective solutions.

2. LITERATURE REVIEW AND CONTRIBUTION

LORA was originally proposed by the US Department of Defense in MILSTD-1390 (1993) to develop maintenance concepts and to determine the location in the repair network where the components will be discarded, replaced, or repaired. It has been used extensively in the military industry since its introduction and has attracted an increasing number of researchers in the literature. As it has been discussed in studies conducted by Blanchard[5,6], *et al.* and Dinesh Kumar[7], *et al.*, LORA has a significant role in minimising the life cycle cost of a product.

In the extant literature, research focusing on LORA can be categorised into two groups. The first group covers studies discussing key aspects of the LORA problem. They mainly focus on the mathematical models and real-life applications

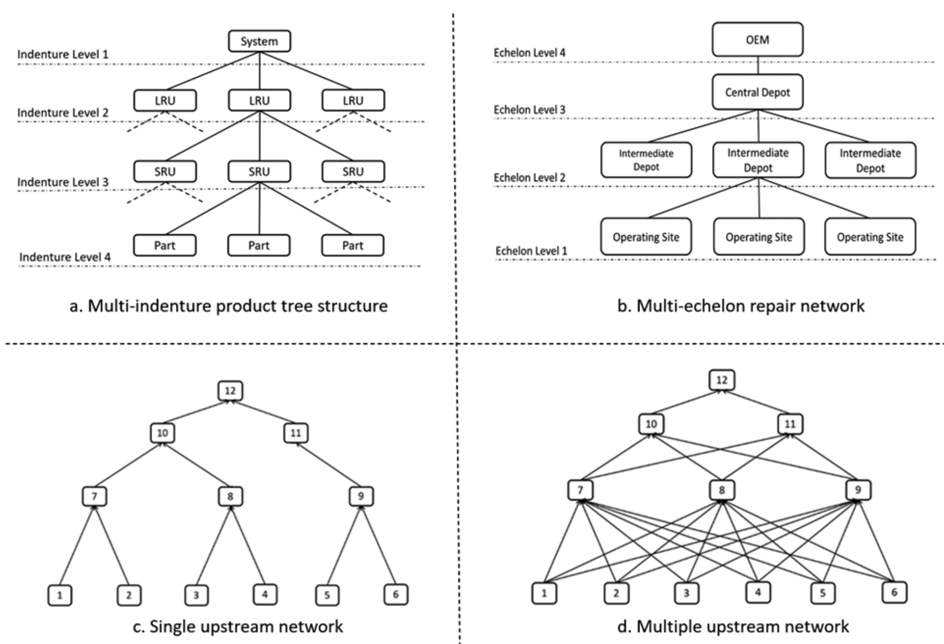

Figure 1. Illustration of multi-indenture product tree structure, multi-echelon repair network, single upstream repair network and multiple upstream repair network.

for the LORA problem. The second group includes research on the LORA and spares parts stock joint optimisation, and other aspects of the LORA problem such as optimisation under uncertainty.

There are few studies in the literature focusing on the key issues of the LORA problem. Each of these studies uses a (mixed) integer-programming model. Barros[8] first proposed a pure integer programming formulation for the LORA and assumed that all components at one indenture level share the same resources. Barros & Riley[9] developed a combinatorial approach for LORA based on heuristics to obtain tight bounds for a branch-and-bound algorithm. Saranga & Kumar[10] developed a mathematical model for LORA and proposed a solution methodology based on genetic algorithms. Brick & Uchoa[11] presented a mixed integer programming formulation for the LORA problem and applied their model to real-life problems. Basten[12], *et al.* proposed an integer programming formulation, which generalises the existing ones, and they solved realistic-size instances in seconds. In their study, they also proved that the LORA problem is NP-Hard. Bouachera[13], *et al.* presented a hybrid heuristic method based on Genetic Algorithm and Tabu Search Algorithm. Basten[4], *et al.* modelled the LORA problem as a minimum cost network flow problem, and Basten[14], *et al.* studied practical extensions of the minimum cost network flow model according to different repair strategies.

LORA and spare parts stock joint optimisation and other aspects of the LORA problem have attracted interest from researchers in the last decades. Alfredsson[15] proposed the first study on the joint problem of LORA and spare part stocking. In his study, he proposed a nonlinear programming model, but he had to make simplifying assumptions regarding the maximum number of echelon and indenture levels. Basten[16], *et al.* discussed an integrated algorithm for a two-echelon and single-indenture system by assuring a target availability with spare parts stocking constraints. Basten[17], *et al.* proposed an iterative algorithm for multi-indenture and multi-echelon instances, which is more suitable for real-life problems. Ghaddar[18], *et al.* proposed a new approach to solve joint problem of LORA and spare part stocking for repair networks with more than two echelons. Liu[19], *et al.* considered a mixed integer nonlinear model with chance constraints for joint optimisation of the LORA and spare parts stocking problem. Rawat[20], *et al.* proposed a joint optimisation approach that takes into account the impact of modularisation on LORA. They used genetic algorithm-based simulation to solve the joint problem. Rawat & Lad[21] focused on a joint optimisation of reliability design and LORA. In their study, they presented a genetic algorithm approach-based Monte Carlo simulation.

In this paper, we have specifically focused on the key aspects of the LORA problem, excluding the spare part-stocking problem. Therefore, we review only the studies dealing with the key issues of the LORA problem in detail.

Most of the studies in the literature focuses on the LORA problem with single upstream approach, which ensures that each location in the network has a single upstream location to transfer failed components. This approach does not create cost-effective solutions because it requires more resources than necessary. Brick & Uchoa[11] proposed a model where defective components can be sent to all locations in the repair network without adopting a specific hierarchical structure. Also, they assumed there are only two repair options, (1) disposal and (2) repair. Their approach may not be used for multi-echelon repair networks since the move option is implicitly included in their model. However, in real life problems, there is usually a multi-echelon repair network, which is determined by the capabilities of the repair facilities. Thus, the model developed by Brick & Uchoa[11] has shortcomings for real-life applications.

Our contribution to the literature is that we propose a new multiple upstream approach to the LORA problem, which is more comprehensive than the other pure LORA models in the literature. In addition to defining the locations of the facilities in the repair network, with the proposed methodology, the material movement paths between each facility can be determined in the repair network. In this way, real life problems can be modelled more flexibly. Computational experiments show that our model provides a significant cost reduction in life cycle cost of a product compared to the single upstream approach. Therefore, it is important to consider this novel approach in all LORA applications including the joint LORA and spare parts stocking optimisation and other aspects of the LORA problem such as optimisation under uncertainty.

3. CONVERSION OF THE MINIMUM COST FLOW MODEL FOR LORA TO COVER MULTIPLE UPSTREAM APPROACH

Among the studies in the literature, the most comprehensive model in the literature seems to be the one proposed by Basten[4,14], *et al.* since the model can consider the asymmetric repair network among other features and does not aggregate all data per echelon level. Thus, we first implemented the multiple upstream approach to the LORA problem as an extension to their model.

Due to the structure of the model proposed by Basten[4,14], *et al.* component movements to be made to a higher echelon level in the repair network can only be performed to a single location. However, in the multiple upstream repair network, defective components can be transferred to more than one location in the higher echelon level. For example, in the single upstream repair network given in Fig. 1(c), a component that fails at location 5 can only be transferred to the location 9, whereas in the multiple upstream repair network, the defective component can be transferred from location 5 to 7, 5 to 8, or 5 to 9.

To extend the model proposed by Basten[4,14], *et al*. for multi-upstream repair networks, we define a new option (node) and name it “Move”. This node allows location selection for the movement of defective components to the next upstream location. In this case, if the move option is selected in the decision node, an arc originating from the decision node is connected to the move node of the facility in the same echelon level. Figure 2 shows an example usage of move node over the multiple upstream repair network given in Fig. 1(d). In this example, the defective component can be transferred from the location 5 to 7, 5 to 8, or 5 to 9 through the move node.

In the model developed by Basten[4,14], *et al.*, variable, and fixed costs for the repair, discard and move decisions are

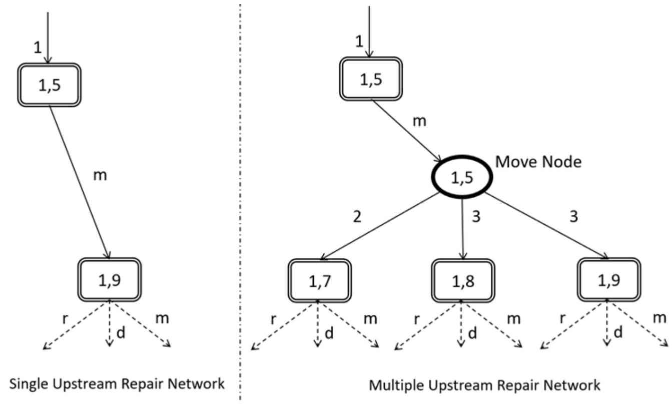

Figure 2. Illustration of move node.

attached to the arcs originating from the decision node. In this study, we keep the variable and fixed costs for the discard and repair decisions as they are, but we attach the variable and fixed costs for the move decisions to the arcs originating from the move node.

We also define a new set denoted by V^m for all move nodes in the repair network and add constraint (1) to ensure that the inflow into the move node is equal to the outflow.

$$\sum_{u|(u,v)\in A} X_{uv} = \sum_{w|(v,w)\in A} X_{vw} \quad \forall v \in V^m \tag{1}$$

After this extension, we randomly generated 10 problems, which are solved with the model. As obtained from the results, with this extension, relatively small problems with multiple upstream repair networks can be solved in a short period. However, adding the move node to the model with the existing source, decision, transformation, and end nodes have made the model even more complex. Therefore, this drawback significantly reduces the usability of the extended model in real-life applications.

On the other hand, the X_{vm} decision variable used in the model proposed by Basten[4,14], *et al.* determines the flow through the arc (v,m) and does not consider the information as to "which system the defective component originally belonged to", which is particularly important to determine the component-based logistics data, such as repair time or cost. This suggests that the model proposed by Basten[4,14], *et al.* will be insufficient for further studies on component-based logistics data analysis.

4. PROBLEM DEFINITION AND PROPOSED MODEL

To overcome the shortcomings mentioned in the previous section, we propose a mixed integer programming model for LORA considering a multi-indenture system structure and a multi-echelon repair network. Let be N the set of locations in the repair network where the systems are initially deployed along with all their sub-components. The systems deployed in location $n \in N$ have a multi-indenture product structure. Let S be the set of components subject to a decision. Let $Q_{(s)}$ be the set of components at the lower indenture level of the component $s \in S$. The system has the indenture level 1.

Each location in the repair network can have multiple upstream locations (see multiple upstream repair network in Fig. 1(d). In other words, it is possible to access from the location in the lower echelon to the predefined locations in the upper echelon. Let I be the set of locations where the facilities are in the repair network. Let I_L be the set of locations except the top echelon in the repair network. Let D be the set of decisions, (1) discard (the component is discarded, and new component is acquired), (2) repair (the component is repaired and assembled) and (3) move (the component is moved to a location in the upper echelon for a new decision). The locations are defined by nodes and the decisions are defined by arcs in the network. Let J_i be the set of the locations associated with location $i \in I$ by an arc. Let D_{ij} be the set of potential decisions from location $i \in I$ to location $j \in J_i$ which is shown by the arc (i, j). The arcs corresponding to (1) discard and (2) repair decisions are represented by a self-loop arc. Figure 3 illustrates the nodes and arcs. In the example, the location i is associated with two locations, i.e. location i itself and location j in the upper echelon. Therefore, the set of locations associated with location i are location i and location j $(J_i = \{i, j\})$. Consequently, the decisions are defined as $D_{ii} = \{1,2\}$ and $D_{ij} = \{3\}$.

Let be R the set of required resources for repair option. A variable cost $c_{nijd}(s)$ is incurred for the component $s \in S$ of the system deployed in location $n \in N$ for the repair option $d \in D$ which is defined with the arc directed from $i \in I$ to $j \in J_i$. The decision may appear in three ways, which are (1) if the component $s \in S$ is discarded in location i; (2) if the component $s \in S$ is repaired in location i; (3) if the component $s \in S$ is moved from location i to location j (see, e.g., Fig. 3). The variable cost includes labor costs, spare parts, transportation costs, etc. A fixed cost f_{rid} is incurred if resource $r \in R$ is used for repair option $d \in D$ in location i $(i \in I)$. The fixed cost comprises inventory costs, special tools, and test equipment costs, etc. The total number of malfunctions in life cycle of component $s \in S$ is defined by λ_s. The capacity of resource $r \in R$ in location i $(i \in I)$ is defined by C_{ri}. The amount of resources $u_{rid}(s)$ is used for the component $s \in S$ in location i to perform the repair option $d \in D$. It is assumed that all these parameters are known at time zero. The objective is to minimise the total fixed and variable costs resulting from the decisions within the repair network.

We define two sets of decision variables. Let the binary variables $X_{nijd}(s)$ be *1*, if the decision d from location i to location j is chosen for the component s of the system deployed in location n, and *0* otherwise. Let the decision variables Y_{rid} define the amount of resources r for the decision d in location i. For further clarification, the illustration of the

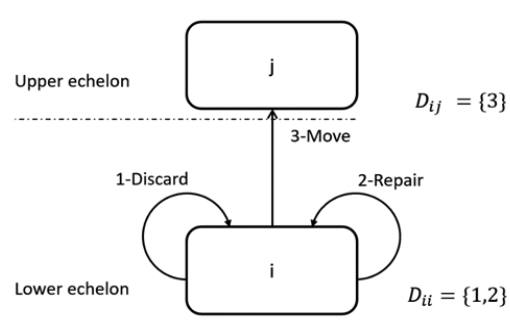

Figure 3. Illustration of the nodes and arcs.

$X_{nijd}(s)$ is given in Fig. 4.

The mixed integer programming model is given below.

$$Min \sum_{n\in N}\sum_{s\in S}\sum_{i\in I}\sum_{j\in J_i}\sum_{d\in D_{ij}} c_{nijd}(s)X_{nijd}(s)\lambda_s + \sum_{r\in R}\sum_{i\in I}\sum_{d\in D} f_{rid}Y_{rid} \quad (2)$$

s.t.

$$\sum_{j\in J_i}\sum_{d\in D_{ij}} X_{nijd}(s)=1 \quad \forall i\in I, \forall n\in N, (i=n), \forall s\in S \quad (3)$$

$$X_{nij,move}(s)\leq \sum_{k\in J_i}\sum_{d\in D_{jk}} X_{njkd}(s)$$
$$\forall i\in I_L, \forall j\in J_i, (i\neq j), \forall n\in N, \forall s\in S \quad (4)$$

$$X_{nii,repair}(s)\leq \sum_{j\in J_i}\sum_{d\in D_{ij}} X_{nijd}(q)$$
$$\forall i\in I, \forall n\in N, \forall s\in S, \forall q\in Q_{(s)} \quad (5)$$

$$X_{nii,discard}(s)\leq X_{nii,discard}(q)$$
$$\forall i\in I, \forall n\in N, \forall s\in S, \forall q\in Q_{(s)} \quad (6)$$

$$X_{nij,move}(s)\leq X_{nij,move}(q)$$
$$\forall i\in I_L, \forall j\in J_i, (i\neq j), \forall n\in N, \forall s\in S, \forall q\in Q_{(s)} \quad (7)$$

$$\sum_{d\in D} Y_{rid}\leq C_{ri} \quad \forall i\in I, \forall d\in D_{ii} \quad (8)$$

$$\sum u_{rid}(s)X_{niid}(s)\leq Y_{rid}$$
$$\forall r\in R, \forall i\in I, \forall d\in D_{ii}, \forall n\in N, \forall s\in S \quad (9)$$

$$Y_{rid}\geq 0 \quad \forall r\in R, \forall i\in I, \forall d\in D \quad (10)$$

$$X_{nijd}(s)\in\{0,1\} \quad \forall n\in N, \forall i\in I, \forall j\in J_i, \forall d\in D_{ij}, \forall s\in S \quad (11)$$

Objective function (2) minimises the total fixed and variable costs resulting from the decisions within the repair network. Constraint set (3) ensures that only one repair option is chosen for the first echelon of the repair network.

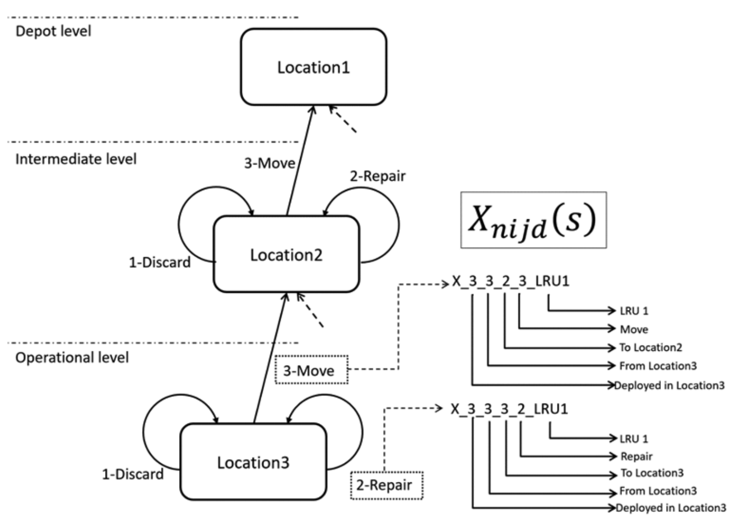

Figure 4. Illustration of the $X_{nijd}(s)$.

Constraint set (4) guarantees that a decision is made in the upper echelon when component $s\in S$ is moved to the upper echelon. Constraint set (5) enforces that an action is performed for the lower indenture parts in the same echelon when a repair decision is made for the component $s\in S$. Constraint set (6) ensures that discard action is performed for the lower indenture parts in the same echelon when a discard decision is made for the component $s\in S$. Constraint set (7) provides that move action is performed for the lower indenture parts in the same echelon when a move decision is made for the component $s\in S$. Constraint set (8) guarantees that the amount of resources in location i does not exceed the predefined capacity for this location. Constraint set (9) enforces that the required amount of resources is available in the location for the determined decision. Constraints (10) are the non-zero constraints and constraints (11) are the binary constraints.

5. ILLUSTRATIVE EXAMPLE – POWER PACK OF AN ARMORED VEHICLE

An illustrative example is given by considering the power pack of an armored vehicle for the application of the proposed model. The power pack system of the vehicle consists of two LRUs, i.e., the engine and transmission. Each LRU includes two SRUs.

The repair network of the vehicles consists of three echelons. The armored vehicles are deployed in city-1 and city-2, which constitute the echelon level 1 (operating sites). The facilities in city-3 and city-4 form the echelon level 2 (intermediate depots) and the facility in city-5 is the echelon level 3 (central depot). Capacity constraint of the facilities in the repair network is not considered in the calculations.

Parameters used for generating the costs are given in Table 1. Uniformly generated fixed and variable costs, which are presented in Table 2, occur according to the decisions made within the scope of LORA.

First, the problem is solved as single upstream. The illustration of the solution is given in Fig. 5. In this illustration, the components of the system deployed in city-1 are shown in an orange dotted frame, and the components of the system deployed in city-2 are displayed in a blue double frame. In each frame, the name of the component, the decision given and the location where the decision is conducted (D:Discard and R:Repair) are indicated. For example, the notation "SRU1 (D,5)" means that the discarded decision of the component SRU1 will be executed the facility in city-5.

Table 1. Parameters used for generating the illustrative example

Total number of components	12
Subsystem malfunction rate	[0.01;1]
Component Price	[500;5000]
Repair Cost (rate by component price)	[0.3;0.5]
Discard Cost (rate by component price)	[0.5;1]
Move Cost (rate by component price and the distance between facilities)	0.01*km
Resource Cost	[5;2500]

Table 2. Fixed and variable costs of the illustrative example

		Variable Costs ($)											Fixed Costs ($)							
		Discard (1)				Repair (2)				Move (3)			Discard (1)				Repair (2)			
		E1	E2		E3	E1	E2		E3	E2		E3	E1	E2		E3	E1	E2		E3
	Components		3	4	5		3	4	5	3	4	5		3	4	5		3	4	5
1	LRU1	3500	3325	3430	3150	1750	1400	1400	1225	107	82		350	280	35	245	1523	1348	1348	2146
	SRU1	1200	1140	1176	600	600	480	480	420	37	28		120	96	12	84	784	904	904	884
	SRU2	1500	1425	1470	1350	750	600	600	525	46	35		150	120	15	105	1135	738	738	904
	LRU2	4300	4085	4214	2580	2150	1290	1720	1505	132	101		430	258	516	301	1822	80	878	60
	SRU3	800	760	784	480	400	240	320	280	25	19		80	48	96	56	274	21	175	43
	SRU4	550	523	539	330	275	165	220	193	17	13		55	33	66	39	188	15	205	8
2	LRU1	3500	3325	3430	3150	1750	1400	1400	1225	116	96		350	280	35	245	1523	1348	1348	2146
	SRU1	1200	1140	1176	600	600	480	480	420	40	33		120	96	12	84	933	904	904	884
	SRU2	1500	1425	1470	1350	750	600	600	525	50	41		150	120	15	105	932	738	738	904
	LRU2	4300	4085	4214	2580	2150	1290	1720	1505	142	117		430	258	516	301	1858	80	878	60
	SRU3	800	760	784	480	400	240	320	280	26	22		80	48	96	56	384	21	175	43
	SRU4	550	523	539	330	275	165	220	193	18	15		55	33	66	39	216	15	205	8
3	LRU1											244								
	SRU1											84								
	SRU2											105								
	LRU2											300								
	SRU3											56								
	SRU4											38								
4	LRU1											168								
	SRU1											58								
	SRU2											72								
	LRU2											206								
	SRU3											38								
	SRU4											26								

In the single upstream solution, LRU1, LRU2, SRU2, SRU3, and SRU4 of the system located in city-1 are moved to the facility located in city-3 (echelon level 2) for a repair decision while SRU1 is moved to the facility located in city-5 (echelon level 3) for a discard decision. On the other hand, regarding components of the system deployed in city-2, LRU1, and SRU2 are moved to the facility located in city-4 (echelon level 2) for a repair decision while LRU2, SRU3, and SRU4 are moved to the facility located in city-5 (echelon level 3) for a repair decision. SRU1 is also discarded in the same facility. Total fixed and variable costs are $14,450.

As can be seen, the components of the system deployed in city-1 are moved to the facilities located in city-3 or city-5; the components of the system deployed in 2 are dispatched to the facilities located in city-4 or city-5. Due to the differences in fixed and variable costs of the decisions in city-3 and city-4, the components are processed in different echelon levels. For instance, LRU2, SRU3, and SRU4 of the system located in city-1 are repaired in the facility located in city-3 (echelon level 2) while LRU2, SRU3, and SRU4 of the system located in city-2 are repaired in the facility located in city-5 (echelon level 3). Different costs related to these components in echelon level 2 and echelon level 3 occur.

As the next step, the problem is solved as multiple upstream by using the same parameter set. The solution is shown in Fig. 6. In this solution, LRU2, SRU3, and SRU4 of the system deployed in city-1 are repaired in the facility located in city-3 (echelon level 2), LRU1, and SRU2 can be repaired in the facility located in city-4 (echelon level 2). SRU1 is discarded in the facility located in city-5 (echelon level 3). Exactly the same decisions are made for the system deployed in city-2. Total fixed and variable costs incur as $13,953 which is 4% less than the solution obtained from single upstream.

When the problem is solved as multiple upstream, it is clear that the components of the system in city-1 can be dispatched to the facility in city-4, and the components of the system in city-2 can be dispatched to the facility in city-3. Table 3 gives the comparison of the costs based on the components for the optimal solution. The cells corresponding to the cost improvements are highlighted by grey colour.

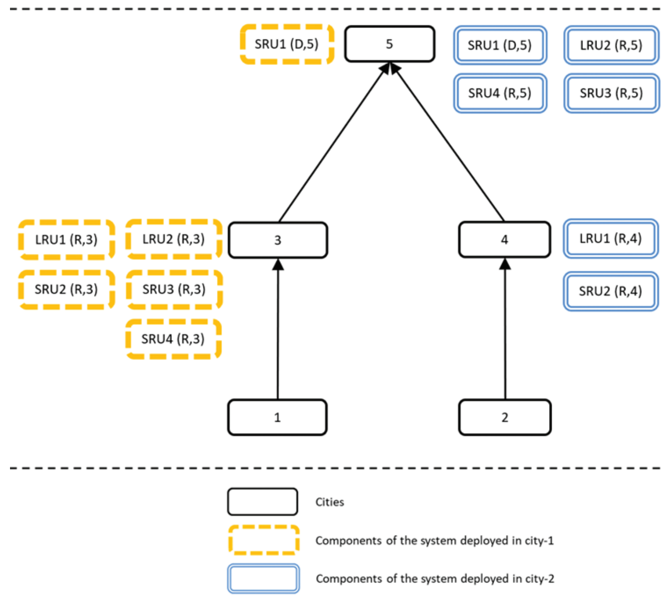

Figure 5. Illustration of solution as single upstream.

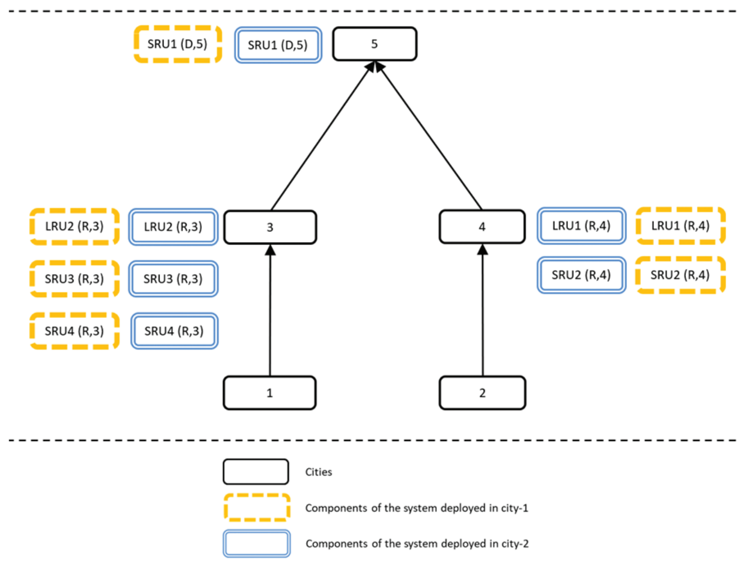

Figure 6. Illustration of solution as multiple upstream.

Table 3. Cost comparison of the components

		Single upstream ($)	Multiple upstream ($)
System located in city-1	LRU 1	2,855	2,830
	SRU1	805	770
	SRU2	1,384	1,373
	LRU2	1,502	1,502
	SRU3	286	286
	SRU4	197	197
System located in city-2	LRU 1	2,844	2,844
	SRU1	775	775
	SRU2	1,379	1,379
	LRU2	1,888	1,512
	SRU3	383	287
	SRU4	242	198
		14,540	13,953

6. COMPUTATIONAL EXPERIMENTS

In this section, we present the results of the computational analysis and analyse the performance of our proposed model. The proposed model was coded in *C++* and the experiments were performed in an *Intel Xeon Phi 7290 with 1.5 GHz and 384 GB of RAM.* We used *CPLEX 12.4* to solve the benchmark instances.

6.1 Benchmark Instances

In the extant literature, the most comprehensive computational studies are reported by Basten[4], *et al.* Therefore, a similar methodology to Basten[4], *et al.* is adopted in our study when generating benchmark instances for the LORA problem. Since Basten[4], *et al.* does not cover multiple upstream approach, we have used the same parameters for both single and multiple upstream cases to be able to compare the total costs between two approaches.

The assumptions and the structure of the benchmark instances are given below.

i. The system consists of LRUs, SRUs and parts.
ii. The total number of components is determined as 500, 1000, 1500, 1750, 2000, and 5000.
iii. The number of repair levels comprises three levels, which are operational, intermediate and depot.
iv. There is only one depot-level facility in the repair network.
v. The number of intermediate level facilities and the number of systems can take two values, which are 2 and 5 (at most 5 intermediate level facilities and 25 systems).
vi. Move costs are calculated in accordance with the distances between facilities.
vii. A single resource is used for each part.
viii. The resource capacity is unlimited.
ix. Total number of components, the number of intermediate level facilities and the system level are considered as experimental factors.
x. 50 benchmark instances are generated for each combination.
xi. Parameters used for generating benchmark instances are given in Table 4.

To name the benchmark instances, the structure of the upstream (single or multiple), the structure of the repair network and total number of components are used in the given order. For example, a problem with a multiple upstream approach, including 2000 components, 5 systems, 2 intermediate levels and 1 depot, is denoted by multiple_521_2000. There are 100 benchmark instances (50 single, 50 multiple) for each combination, which makes 2400 benchmark instances.

Table 4. Parameters used for generating benchmark instances

Total number of components	500, 1000, 1500, 1750, 2000, 5000
Subsystem malfunction rate	[0.01;1]
Component price	[1000;100,000]
Repair cost (rate by component price)	[0.1;0.4]
Discard cost (rate by component price)	[0.75;1.25]
Move cost (rate by component price and the distance between facilities)	0.01*km
Resource cost	[10,000;1,000,000]

6.2 Results

Since the LORA problem is a strategic level problem that is not solved daily, time limits may not be set in real-life applications. However, in this study time limit is determined as 14400 seconds to solve the instances. In the experiments, the more the number of facilities, the more difficult it was to solve the instances. Therefore, the instances having more than 13 facilities (repair network structure 251 and 551) could not be solved in the specified time limit, which suggests that a total of 1200 instances could only be solved.

Basten[12], *et al.* expressed that a reasonable system structure contains 1000 components. Since the benchmark instances including up to 13 facilities and 5000 components can be solved within the given time limit, it is seen that the size of the problems solved in this study is reasonable.

After multiple upstream solutions were made, the proposed model is modified for single upstream to compare the cost savings between two approaches. The results of the computational analysis are given in Table 5. As the LORA problem is modelled with multiple upstream approach, an average decrease in cost is 4.85% compared to single upstream approach.

Table 5 reports the percentages of average and maximum decrease in cost for each test combination set. The average decrease in cost is the average cost improvement for 50 benchmark instances in a test combination set, while the maximum decrease in cost is the highest cost improvement in that set. For example, the average decrease in cost is 6.04% and the maximum decrease in cost is 9.73% for the test combination set 521_500.

Additionally, as the structure of the repair network becomes more complex, it is observed that the solution time increases, but the cost savings get higher.

Note: Avg. CPU time-multiple (s): average solution time of multiple upstream in seconds; Avg. CPU time-single (s): average solution time of single upstream in seconds; Avg. imp. in cost %: average percentage improvement in cost; Std. dev. imp. in cost %: standard deviation of improvement in cost; Max. imp. in cost %: maximum percentage improvement in cost for the corresponding test combination set.

Table 5. Results of the computational analysis

The test combination	Avg. CPU time-multiple (s)	Avg. CPU time-single (s)	Avg. imp. in cost %	Std. dev. imp. in cost %	Max. imp. in cost %
221_500	124.7	3.9	3.65	0.90	5.48
221_1000	304.2	8.31	3.83	0.94	5.60
221_1500	596.62	11.94	4.01	0.63	5.96
221_1750	598.82	19.26	4.01	0.43	4.82
221_2000	676.84	19.48	3.69	0.49	4.61
221_5000	3210.37	55.87	3.30	1.60	4.11
521_500	922.54	7.34	6.04	1.54	9.73
521_1000	2126.85	16.87	6.06	1.29	8.99
521_1500	2387.37	28.17	6.09	0.93	8.45
521_1750	2288.02	33.28	6.03	0.79	8.27
521_2000	4959.67	39.58	6.01	0.85	7.60
521_5000	9352.41	41.05	5.50	0.53	6.46

7. CONCLUSION AND FUTURE RESEARCH

In this paper, we propose a new multiple upstream model to the LORA problem, which is considered more comprehensive than the other pure LORA models in the literature. The multiple upstream model is more flexible in terms of move operations compared to single upstream models. With multiple upstream methodology, we can model the material movement paths between each facility in the repair network as well as the locations of the facilities in the repair network. By this means, the proposed model can provide solutions for both single and multiple upstream repair networks. To the best of our knowledge, there is no study in the literature that considers multiple upstream approach for multi-echelon repair networks.

We tested our model on 2400 problems and 1200 of them could be solved to optimality in the specified time limit. Our model solved the benchmark instances, including up to 13 facilities and 5000 components, which indicates that it can provide solutions for the real-life sized problems.

It is observed that multiple upstream model yields more cost-efficient results than single upstream models, reducing the total life cycle costs by 4.85% on average. In some cases, cost savings can increase up to 9.73%, which equals to an annual saving of $2,017,985.43 for our test environment. We see that the cost savings increase as the structure of the repair network gets more complicated.

The average percentage of the cost improvements that our model makes is significant since the total life-cycle cost of capital goods is extremely high. Even a few percentages of cost reduction causes millions of savings in the life cycle of a capital good. For example, according to the figures announced by the US DoD, in the US military budget for fiscal year 2019, the total number of budget items regarding logistics services exceeds $20 billion. These figures further explain the importance of considering the multiple upstream model in all LORA applications, including the joint LORA and spare parts stocking optimisation and other aspects of the LORA problem such as optimisation under uncertainty.

As a future research, the capacity constraint and its impact on cost can be analysed. The proposed model in this study can be extended to consider multiple transportation modes.

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