Robust Decision Support System for a Closed-Loop Repair and Replenishment Network

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Abstract. A robust decision support system (DSS) is developed for a tactical planning problem of a closed-loop repair and replenishment network under the presence of demand uncertainties. The DSS involves the formulation of an optimization model that is intended to take on a mid to long term planning perspective and covers decisions that cannot be easily changed or undone. These decisions have lasting and binding impact on organizational performance. For instance, these decisions include facility location planning, repair capacity determination, and inventory acquisition planning.

The model aims to minimize capital expenditure (CAPEX) incurred with respect to these decisions. The problem is characterized by the need to satisfy uncertain network requirements that unfortunately lead to nonlinear relationships within the model. In this regard, a local search framework has also been developed as a solution approach for the optimization of the tactical planning model. Computational studies provide support for the effectiveness of the decision support system. It is shown that the use of the DSS significantly improves CAPEX performance across different problem instances. The solution is able to adapt to both favorable and unfavorable business scenarios.

Keywords: Closed-loop supply chain, optimization, uncertainty

1. INTRODUCTION

It is well-acknowledged in decision theory that real world agents rarely *optimize* their decisions. Doing so implies a need for a perfect model of a system from which the future behavior of variables may be deduced (Sterman, 2000). However, this can never be the case since reality by no means produces the exact conditions as initially planned. Thus, arriving at an optimal decision is virtually impossible even when faced with simple problems. Senge (1990) mentions that the complexities involved in decision making render organizations to fail to perform optimally even if they try to. These complexities lead them to ignore important aspects of a situation and underestimate the consequences of their decisions. Simon (1959) postulates that the need to achieve real, rather than ideal, representations of systems has imbued an attitude of *satisficing* in decision makers. They are often led to choose the first available actions which ensure that certain desired targets will be achieved. For instance, he illustrates that if business behavior is to be viewed in terms of this approach, it is to be expected that the firm's target would involve the attainment of a certain level of profit or holding a certain share of the market, as oppose to the maximization of profit.

This research proposes a target-oriented approach that is inspired by the decision analytic criterion of Brown and Sim (2010) and Brown et al. (2012). This approach is to be applied to a closed loop repair and replenishment network, which involves tactical repair, replenishment and logistics planning decisions. These decisions are to be evaluated based on management goals such as the achievement of target investment returns or CAPEX performance. A challenging issue in these decisions involves the presence of uncertainty. For example, because of the long implementation lead times of design decisions such as infrastructure development, many important system parameters may not be accurately known or projected before implementation of the decision. Hence, planning without explicitly accounting for these uncertainties can yield inferior performance in reality. In addition, data used in the evaluation and analysis of these systems inevitably contain errors and approximations. Results or actions obtained from these would therefore be subjected to uncertainties in the real system as well.

Ben-Tal and Nemirovski (1999) state that even a small degree of uncertainty can make the usual optimal solution completely meaningless. The reality of which creates the need to identify solutions that would be robust to the presence of uncertainty. Bertsimas and Sim (2004) equate this robustness to a solution's immunity to data uncertainty. Such that even if the underlying information deviate from their nominal values, the solution would still be able to achieve the targets of the system across all planning stages.

The motivation of this research is then based on addressing the research challenge of developing a target-oriented optimization approach that leads to the generation of robust solutions. The target-oriented approach preserves computational tractability and also allows for ambiguity in uncertainty information. Moreover, this research aims to show how traditional modeling paradigms can benefit from the use of a target-oriented optimization approach for applications in decision problems.

2. CLOSED-LOOP REPAIR AND REPLENISHMENT NETWORK

The closed-loop repair and replenishment network is diagramed in Figure 1. The products (or specifically fabrication boards) move both downstream and upstream involving the following: replenishment, use, collection, controlled disposal, recovery, repair and redistribution. The downstream movement of products begins with the repair hub and ends at the customers. Meanwhile, upstream movement begins with the customers and ends back at the repair hub.

"Good boards" coming from the repair hub are transferred to local stocking centers (LSC), which are then eventually distributed to the customers. After some time, these boards will fail and product recovery is triggered by the collection of defective boards, coming from customers. Boards that are returned to the LSCs are brought back to the repair hub where recovery options are performed. These boards are classified according to the appropriate recovery option they fall under. Their subsequent reintroduction to corresponding distribution channels depend upon the degree of recovery imposed on them. For instance, collected products may pass repair standards that would allow them to be included again to the world-wide pool. Meanwhile, controlled disposal occurs for collected boards that fail in any of the recovery options considered.

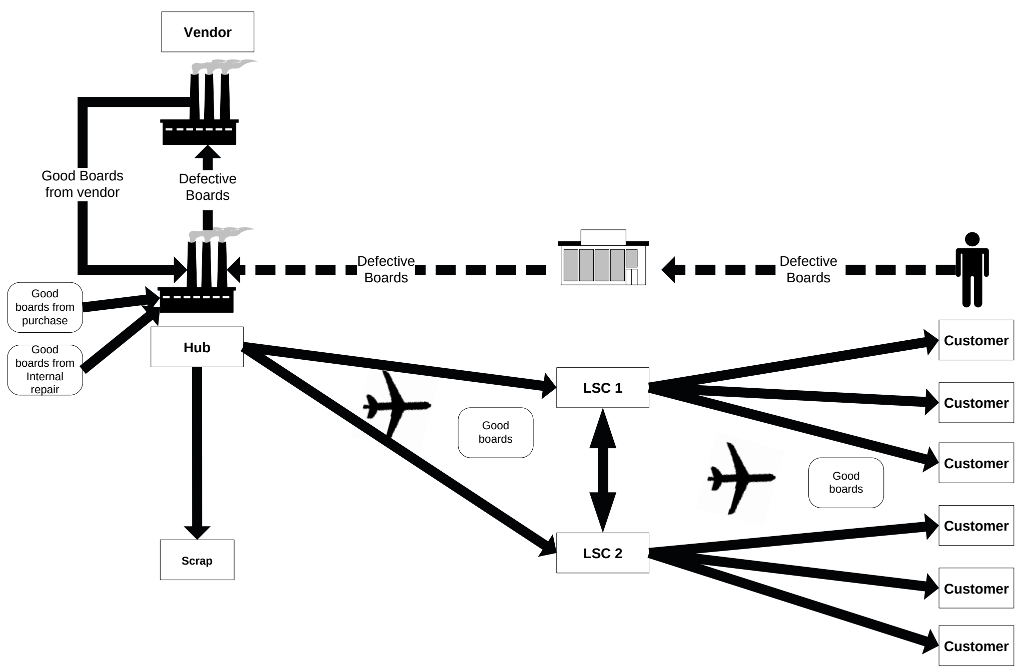

Figure 1: closed-loop repair and replenishment network

3. THEORETICAL FRAMEWORK

As shown in Figure 2, the model covers tactical decisions such as facility location siting, repair capacity determination, repair site-local stocking center (LSC)-customer linkages, worldwide pool (WWP) and planned level (PL) determination for inventory acquisition decisions. This model is intended to take on a mid to long term planning perspective (one year or more). It also aims to minimize capital expenditure (CAPEX) on repair location, repair capacity, LSC siting, logistical costs of repair site and LSC operation, shipping costs related to repair site-LSC and LSC-customer assignments, inventory purchase costs and inventory disposal costs. The decision output of the model includes the size of the repair capacity and expansion for each part in the repair facilities, the amount of inventory that would be shipped between the repair sites, LSCs and customer regions, and the PL for each LSC. The model will also decide on the network structure for repair and replenishment. Hence, another set of decisions includes binary decisions describing whether candidate repair facilities and LSCs would be installed. Furthermore, linkages between repair sites, LSCs and customer regions would also be determined. The model is also capable of monitoring system variables such as the total turnaround time of a spare part and the WWP in the network. The WWP can be further broken down into the following: defective inventory, work-in-process (WIP) inventory, in-transit inventory and serviceable inventory.

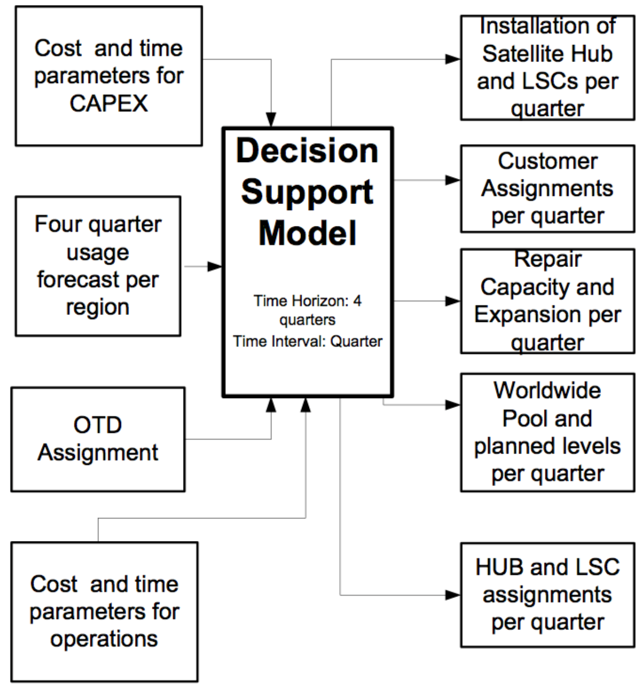

Figure 2: Theoretical framework of the optimization model

4. OPTIMIZATION MODEL

The network could handle multiple types of boards for a given product. The required input parameters of the model then include the repair cycle time and repair throughput time for each part, the required on-time-delivery (OTD) level for each part, the respective lead times involved in shipping spare parts between the repair site, LSCs and customer regions. These also include cost parameters found in logistics, investment and operating costs in the installation of repair sites and LSCs, purchase and disposal costs related to the inventory of each part. The respective notations used for these indices and parameters are shown in Table 1 and Table 2, respectively. Meanwhile, Table 3 identifies the system variables that are likewise considered in the model. These include the total turnaround time and the WWP in the network.

Table 1: Indices

Indices	Definition
$t = 1, \ldots, T$	Time period
$i = 1, \ldots, I$	Facilities with repair capabilities (Hub and Satellite Repair)
$j = 1, \ldots, J$	Local Stocking Centers (LSCs)
$k = 1, \ldots, K$	Customers
$p = 1, \ldots, P$	Parts

Table 2: Model Parameters

Parameters	Definition
r_p	Repair cycle time for part p
th_p	Repair throughput time for part p
$d_{k,t,p}$	Usage from customer region k in period \$t\$ for part p
$l_{i,j}^A$	In transit time between repair site i to LSC j
$l_{j,k}^B$	In transit time between LSC j to customer k
$l_{j,i}^C$	In transit time between LSC j to repair site i
$l_{k,j}^D$	Return time of defective boards from customer k to LSC j
$C_{i,j}^S$	Shipping cost from repair site i to LSC j per unit of

Parameters	Definition
	inventory
$C^{S}_{j,k}$	Shipping cost from LSC j to customer region k per unit of inventory
C^{dc}_{p}	Disposal cost per unit of inventory of part p
C^{pc}_{p}	Purchase cost per unit of inventory of part p
$C^{v}_{i,p}$	Variable cost attributed to repair capacity in repair site i for part p
$C^{v}_{j,p}$	Variable cost in LSC j
I^{A}_{i}	Investment cost for facility i installation
I^{B}_{j}	Investment cost for LSC j installation
I^{C}_{i}	Investment cost for repair capacity expansion in repair site i
f^{A}_{i}	Fixed cost for facility i installation
f^{B}_{j}	Fixed cost for LSC j installation
$f^{C}_{i,j}$	Fixed cost for linkage i to j
$f^{D}_{j,k}$	Fixed cost for linkage j to k
f^{E}_{i}	Incremental fixed cost per unit of capacity increase in repair site i
OTD_{p}	Required OTD level for part p

Table 3: System Variables

Variables	Definition
$u_{i,t,p}$	Repair capacity at repair site i in period t for part ${p}$
$e_{i,t,p}$	Repair capacity expansion at repair site i in period t for part ${p}$
$s^{A}_{i,j,t,p}$	Defective inventory returned to facility i by LSC j in period t for part p
$s^{B}_{j,k,t,p}$	Defective inventory returned to LSC j by customer k in period t for part p
$g^{A}_{i,t,p}$	1 if facility i is installed in period t for part p 0, otherwise
$g^{B}_{j,t,p}$	1 if LSC j is installed in period t for part p 0, otherwise
$g^{C}_{i,j,t,p}$	1 if facility i is assigned to LSC j in period t for part p 0, otherwise
$g^{D}_{j,k,t,p}$	1 if LSC j is assigned to customer k in period t for part p 0, otherwise
$b_{i,t,p}$	1 if facility i undergoes repair capacity expansion in period t for part p 0, otherwise
$ba_{i,j,t,p}$	Amount of backlogs from repair site i to facility j in period t for part p
$WWP_{t,p}$	Worldwide pool in period t for part $p
$PL_{j,t,p}$	Planned level for LSC j in period t for part p
$W_{j,t,p}$	Allocation of inventory for LSC j in period t for part p
$W'_{j,t,p}$	Inventory to be purchased for LSC j in period t for part p
$W''_{j,t,p}$	Inventory to be disposed for LSC j in period t for part p
$TT_{j,k,t,p}$	Turnaround time recorded at LSC j, originating from customer region k in period t for part p

Any feasible repair and replenishment plan must respect physical and logical requirements such as capacity and flow balance constraints. As stated in Figure 2, one of the considerations in creating the network involves the installation of repair facilities, LSCs and assignment of linkages. The aforementioned are defined in the following constraints

$$\sum_j g^{C}_{i,j,t,p} \leq J \sum_{t'=1}^{t} g^{A}_{i,t',p} \qquad \forall\, i,t,p \qquad (1)$$
$$\sum_k g^{D}_{j,k,t,p} \leq K \sum_{t'=1}^{t} g^{B}_{j,t',p} \qquad \forall\, j,t,p \qquad (2)$$
$$\sum_i g^{C}_{i,j,t,p} = \sum_{t'=1}^{t} g^{B}_{j,t'} \qquad \forall\, j,t,p \qquad (3)$$
$$\sum_j g^{D}_{j,k,t,p} = 1 \qquad \forall\, k,t,p \qquad (4)$$
$$\sum_t g^{A}_{i,t,p} \leq 1 \qquad \forall\, i,p \qquad (5)$$
$$\sum_t g^{B}_{j,t,p} \leq 1 \qquad \forall\, j,p \qquad (6)$$

Constraint (1) states that a linkage between a repair site and an LSC could only be assigned if that repair site has been installed. Similarly, (2) states that a linkage between an LSC and customer region could only be assigned if the LSC is designated to be active or operational. Constraint (3) requires that an active LSC must be assigned to a repair site while (4) ensures that a customer region is assigned to an LSC in each time period. Meanwhile, constraint (5) and (6) state that candidate repair sites and LSCs could only be respectively installed and activated once within the planning horizon.

$$u_{i,t,p} \leq M_1 g^{A}_{i,t,p} \qquad \forall\, i,t,p \qquad (7)$$
$$e_{i,t,p} \leq M_2 \sum_{t'=1}^{t} b_{i,t',p} \qquad \forall\, i,t,p \qquad (8)$$
$$b_{i,t,p} = \sum_{t'=1}^{t} g^{A}_{i,t',p} \qquad \forall\, i,t,p \qquad (9)$$

Repair capacities in each site can be increased through expansion as shown in (7) - (9). As in (7), an initial repair capacity could only be assigned to an installed repair site. The maximum initial repair capacity is denoted by M_1. Constraint (8) and (9) state that expansion in the succeeding periods could only be done on an existing repair site, in which the size of the expansion is capped to a maximum as denoted by M_2.

The succeeding constraints describe the usage fulfillment requirements in the network. Constraint (10) ensures that the amount of spare parts returned from a customer region equals the usage rate coming from that region. This implies that once a part fails, customers will have to return that part to the LSC it is assigned to. Constraint (11) and (12) state that shipments from a customer region to an LSC and an LSC to a repair site could only happen if a linkage has been assigned between each leg. Both type of shipments are assigned a cap as in M_3. Constraint (13) describes a flow balance requirement between repair sites and LSCs. Specifically, the amount of spare parts returned from a customer region to an LSC must equal the amount of boards to be returned from that LSC to the repair site.

$$\sum_j s^B_{j,k,t,p} = d_{k,t,p} \qquad \forall\, k,t,p \qquad (10)$$
$$s^B_{j,k,t,p} \le M_3 g^D_{j,k,t,p} \qquad \forall\, j,k,t,p \qquad (11)$$
$$s^A_{i,j,t,p} = M_3 g^C_{i,j,t} \qquad \forall\, i,j,t,p \qquad (12)$$
$$\sum_i s^A_{i,j,t,p} = \sum_k s^B_{j,k,t,p} \qquad \forall\, j,t \qquad (13)$$

Constraints (14) and (15) relate repair capacity requirement to usage. (14) states that repair capacity should be able to accommodate the amount of spare parts being shipped by the LSC to the repair site. This is subject to the standard repair cycle time assigned to each part and the allowable amount of backorder. The latter is defined by the assigned OTD level for each part. OTD is defined to be the ratio between the amount of backorder per part and the usage for each part.

$$\sum_{t'=1}^{t} (u_{i,t'} + e_{i,t'}) \ge \frac{\sum_j s^A_{i,j,t,p} - \sum_j ba_{i,j,t,p}}{r_p} \qquad \forall\, i,t,p \qquad (14)$$
$$\frac{\sum_i \sum_j ba_{i,j,t,p}}{\sum_k d_{k,t,p}} \le (1 - OTD_p) \qquad \forall\, t,p \qquad (15)$$

In computing for the planned level, the lead time considered consists of the transit time between repair site and LSC. Given this, PL is defined as in the following:

$$PL_{j,t,p} = \sum_i \left(\sum_k (\bar{d}_{k,t,p} g^D_{j,k,t,p}) l^A_{i,j} + z_p * \sum_k ({d^S}_{k,t,p} g^D_{j,k,t,p}) \sqrt{l^A_{i,j}} \right) \qquad \forall\, j,t,p \quad (16)$$

where $\bar{d}_{k,t,p}$ and ${d^S}_{k,t,p}$ denote the mean and standard deviation of the usage from customer region k in period t for part p. z_p denotes the z-values obtained from the normal distribution with respect to the required OTD level of each part. On the other hand, the turnaround time is composed of the transit times from customer region to LSC and LSC to repair site, repair wait time and throughput time and transit time from repair site to LSC.

$$TT_{j,k,t,p} = \sum_i ((l^A_{i,j} + l^C_{j,i} + WT_{i,j,t,p})\; g^C_{i,j,t,p}) + \left(l^B_{j,k} + l^D_{k,j}\right) g^D_{j,k,t,p} + TH_p \qquad \forall\, j,k,t,p \qquad (17)$$

where, $WT_{i,j,t,p}$ denotes the repair wait time for boards to be shipped from site i to j in period t for part p. The allocation of boards to each LSC is given by (18) where the planned level is added to the product of the turnaround time and usage in customer region k, period t and part p. Given that the allocation may change from one period to the next, there is an option to purchase additional inventory or dispose excess inventory as shown in (19). From this, the WWP is calculated as the sum of allocated boards from each LSC as in (20). The domain for the decision and state variables are then defined in (21) and (22).

$$W_{j,t,p} = \sum_k \left(TT_{j,k,t,p} d_{k,t,p} \right) + PL_{j,t,p} \qquad \forall\, j,t,p \qquad (18)$$
$$W_{j,t+1,p} - W_{j,t,p} = {W'}_{j,t-l,p} - {W''}_{j,t,p} \qquad \forall\, j,t,p \qquad (19)$$
$$WWP_{t,p} = \sum_k W_{j,t,p} \qquad \forall\, i,j,t,p \qquad (20)$$
$$u_{i,t,p}, e_{i,t,p}, s^A_{i,j,t,p}, s^B_{j,k,t,p}, ba_{i,j,t,p}, WWP_{t,p}, PL_{j,t,p} \qquad (21)$$
$${W'}_{j,t,p}, {W''}_{j,t,p} \in \mathbb{Z}^+, TT_{j,k,t,p} \in \Re^+$$
$$g^A_{i,t,p}, g^B_{j,t,p}, g^C_{i,j,t,p}, g^D_{j,k,t,p}, b_{i,t,p} \quad \in \{0.1\} \qquad (22)$$

Finally, the objective of minimizing the CAPEX is defined as follows:

$$\min CAPEX = \sum_t \sum_p \tilde{C}^O_{t,p} \qquad (23)$$

The CAPEX decisions involve both capital investments and operational cost considerations that result in cash outflows defined as in (24).

$$\tilde{C}^O_{t,p} = \underbrace{\sum_i I^A_i g^A_{i,t,p} + \sum_j I^B_j g^B_{j,t,p} + \sum_i I^C_i b_{i,t,p}}_{\text{Investment costs}} + \underbrace{\sum_i \sum_j c^s_{i,j}\, s_{i,j,t,p} + \sum_j \sum_k c^s_{j,k} s_{j,k,t,p}}_{\text{Logistics costs}} + \underbrace{\sum_i f^A_i \sum_{t'}^{t} g^A_{i,t'} + \sum_j f^B_j \sum_{t'}^{t} g^B_{j,t'} + \sum_i \sum_j f^C_{i,j} g^C_{i,j,t,p}}_{\text{Fixed costs}}$$
$$+ \underbrace{\sum_j \sum_k f^D_{j,k} g^D_{j,k,t,p}}_{\text{Fixed costs}} + \underbrace{\sum_j c^v_{j,p} \left(\sum_k s_{j,k,t,p}\right) + \sum_i c^v_{i,p} \left(\sum_j s_{i,j,t,p}\right)}_{\text{Variable costs}} + \underbrace{\sum_i (c^{pc}_p {W'}_{j,t,p} + c^{dc}_p {W''}_{j,t,p})}_{\text{Purchase and disposal cost of boards}} + \underbrace{\sum_i f^E_i \left(u_{i,t,p} + e_{i,t,p}\right)}_{\text{Repair costs}} \qquad \forall\, t,p \qquad (24)$$

5. TARGET-ORIENTED ROBUST OPTIMIZATION MODEL

In this network, the demands of the respective boards are subject to uncertainty. This uncertainty affects the objective function and the demand constraints in the formulation. For the purpose of exposition, let us summarize the decision variables as $\boldsymbol{x}$, objective function as $\max \boldsymbol{c}'\boldsymbol{x}$, and constraints as: $A\boldsymbol{x} \leq \boldsymbol{d}$. Once the uncertainties on demand are considered, the revised formulation is given by:

$$\max_{\boldsymbol{x}\geq\boldsymbol{0}} \boldsymbol{c}'\boldsymbol{x} \tag{25}$$

$$A\boldsymbol{x} \leq \widetilde{\boldsymbol{d}} \tag{26}$$

where, $\widetilde{\boldsymbol{d}}$ denote the vector of uncertain demand. We attempt to integrate this uncertainty through the TORO methodology proposed by Ng and Sy (2014). TORO facilitates process synthesis through the achievement of targets derived under uncertainty. The primary objective is to identify appropriate settings for the decision variables so that system constraints are feasible for as large a range of uncertain parameters as possible. In line with this, the uncertain vector $\widetilde{\boldsymbol{d}}$ could then be defined as follows:

$$\widetilde{\boldsymbol{d}} = \overline{\boldsymbol{d}} - \boldsymbol{d} \tag{27}$$

where $\overline{\boldsymbol{d}}$ represents the nominal values of demand and the perturbations $\boldsymbol{y}$ are such that

$$D_\theta = \{\boldsymbol{d} \in \Re^N \mid 0 \leq d_i \leq \hat{d}_i(\theta), \forall\, i = 1, \ldots, N\}. \tag{28}$$

The largest perturbations would take on the values $d_i = \hat{d}_i$, for all $i = 1, \ldots, N$. This also assumes that under the most favorable case, $\widetilde{\boldsymbol{d}}$ would be at the maximum $(\boldsymbol{d} = 0)$. This follows since profit is directly proportional to the number of units sold in the system. It can also be seen that these perturbations are parameterized by the robustness index, $\theta \in [0,1]$. A higher value of θ implies a larger degree of perturbations for the demand. This has practical implications in describing the attitude of a decision maker. A more uncertainty averse attitude would prefer a higher θ, while a risk seeking attitude would lean towards a lower θ.

TORO hinges on the integration of the robust optimization framework and target-oriented decision making. As mentioned, we want to ensure that process synthesis remains feasible for as large a range of uncertain parameters as possible. Meanwhile, target-oriented decision making is reflected in the model by transforming the original objective function into a constraint through its assignment as a system target. Using this perspective primarily allows us to solve our uncertain problem in an efficient and effective manner, which would be discussed below.

The succeeding model reflects the modification to the original uncertain model such that the objective function now maximizes the robustness index subject to achieving the profit target (τ). This is in conjunction to the other functional constraints of the system such as the set of demand constraints defined earlier.

$$\max_{\boldsymbol{\theta\epsilon[0,1]}} \theta \tag{29}$$

$$\boldsymbol{c}'\boldsymbol{x} \geq \tau \tag{30}$$

$$A\boldsymbol{x} \leq \widetilde{\boldsymbol{d}} \qquad \forall\, \widetilde{\boldsymbol{d}} \in D_\theta \tag{31}$$

$$\boldsymbol{x} \geq 0 \tag{32}$$

As discussed by Ng and Sy (2014), the robust model as it is formulated above would require evaluating an infinitely large number of constraints. This is because the uncertain constraints would lead us to create individual constraints for each possible realization of the uncertain demand. Hence, there is a need to convert this into an equivalent formulation, which would be amenable to solve using traditional linear programming techniques. Using the property of duality, an equivalent formulation is obtained below:

$$\max_{\boldsymbol{\theta\epsilon[0,1]}} \theta \tag{33}$$

$$\boldsymbol{c}'\boldsymbol{x} \geq \tau \tag{34}$$

$$A\boldsymbol{x} \leq \left(\overline{\boldsymbol{d}} - \theta\hat{\boldsymbol{d}}\boldsymbol{z}\right) \tag{35}$$

$$\boldsymbol{z} \geq \boldsymbol{1} \tag{36}$$

$$\boldsymbol{x}, \boldsymbol{z} \geq 0 \tag{37}$$

where $\boldsymbol{z}$ is a vector of the dual variables obtained during the translation of the constraints. We refer the readers to for a more thorough discussion on the translation to the robust model.

Furthermore, we see that $D_{\theta'} \subseteq D_\theta$ whenever $\theta \geq \theta'$. If a process synthesis is feasible for an uncertainty set defined by θ, then it will be feasible for all perturbations that would fall within this range. In addition, given a fixed value of θ, the model is linear with respect to the decision variables. The model could thus be solved for the maximum robustness index by performing a line search on $\theta \in [0,1]$. We could utilize well-known search algorithms like the bisection or golden search methods in this regard. The following case study demonstrates how the bisection search could be used in identifying the best value of θ that would satisfy a profit target set for the system.

6. COMPUTATIONAL STUDIES

In this section, we present some computational studies on the spare parts CLSC. The objective of the computational studies is to be able to compare the performance of TORO models under different robustness levels with respect to the total supply chain costs. The computational studies are facilitated through a hypothetical case study of a spare part CLSC. The CLSC is for a single product that contains four types of spare parts. Specifically, four different spare parts were considered in the computational studies. There is also one existing repair hub with the option of opening an additional 10 repair satellites. There are also nine candidate LSCs that could be assigned to customer regions and 10 customer regions that need to be served by the network. As mentioned, the planning horizon is set at four quarters, which implies that four quarterly usage quantities have also been identified to serve as spare parts demand from customers.

Figure 3 shows the decision support framework developed for the problem. This presents how the model is solved and deployed. Microsoft Excel is initially used for encoding the input parameters of the model. These parameters are then fed into MATLAB, wherein the optimization is solved through the CPLEX solver engine versions 12.6.1. After which, the results of the model are again written into the Excel solver in a spreadsheet format. The solution time of the model is recorded to be 31.6 seconds using a Macbook Pro 3 GHz Intel Core i7, 8 GB 1600 MHz DDR3.

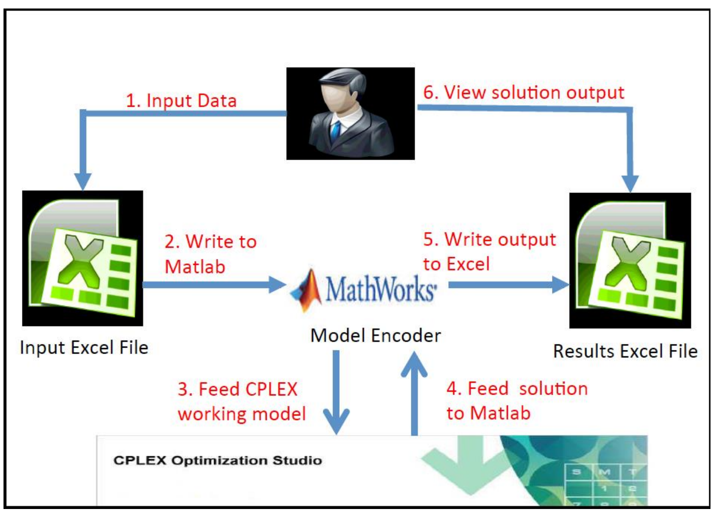

Figure 3. Deployment of optimization model

In the succeeding computational experiments, we considered five cost budget levels. We obtained a corresponding design solution for each of these targets through a bisection search on θ to identify the best robustness index for each profit target. Out-of-sample testing has also been performed using 1000 realizations of the usage under a uniform distribution. This was done in order to gauge the performance of each design solution under different scenarios. Table 4 presents the performance of the TORO model in terms of expected total cost and the corresponding breakdown of these costs.

In the computational experiments, one could observe that the expected cost decreases until the robustness index of 0.65 and then subsequently increases thereafter. These observations imply that too conservative or too risky cost budgets would not necessarily equate to the bestcost performance. One might actually be better off with considering a mid-range target, rather than be too extreme in setting a cost budget for the system.

A robustness level of 0.0 is equivalent to stating that one would not consider any degree of uncertainty. As a result, the corresponding design solution performed worse than the other design solutions. However, it should be noted that for this particular case study, the aforementioned led to a better set of results than the design solution under a robustness level of 1.00. Hence, it should give the decision maker an inkling that he would be better off to be more risky in this case. This could be attributed to the required investment costs associated with being too conservative. Because one would want to service all of the defective parts flowing back into the system, he would be led to purchase more equipment or new inventory. This therefore leads to incurring additional costs for the supply chain.

Table 4 Results ('000)

	1.00	0.85	0.65	0.45	0.00
Total Cost	**$11,791**	**$11,622**	**$10,895**	**$11,036**	**$11,206**
Repair Facility Cost	**$4,678**	**$4,678**	**$4,678**	**$4,678**	**$4,678**
Operations (Variable + Fixed)	$4,247	$4,247	$4,247	$4,247	$4,247
Shipping (Hub to LSC)	$430	$430	$430	$430	$430
LSC	**$827**	**$827**	**$827**	**$827**	**$827**
Operations (Variable + Fixed)	$723	$723	$723	$723	$723
Shipping (LSC to Customer)	$104	$104	$104	$104	$104
Inventory Cost	**$6,285**	**$6,116**	**$5,389**	**$5,530**	**$5,700**

7. CONCLUSIONS AND RECOMMENDATIONS

This work develops a decision support model for spare parts CLSC. The model helps facilitate mid to long term planning decisions that cover the areas of investment, customer assignments, and inventory. It is able to consider different areas of a CLSC, which is necessary when a strategic perspective is desired. The computational studies demonstrate that the model has the ability to evaluate different business scenarios. This in turn allows a decision maker to gain managerial insights and develop policies with respect to the aforementioned scenarios.

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REFERENCE

Ben-Tal, A. and Nemirovski, A. (1999) Robust solutions to uncertain programs. *Operations Research Letters*, **25**, 1-13.

Bertsimas D. and Sim, M. (2004) The price of robustness. *Operations Research*, **52**, 35-53.

Brown, D. and Sim, M. (2010) Satisficing measures for analysis of risky positions. *Management Science*, **55**, 71-84.

Brown, D., De Giorgi, E. and Sim, M. (2012) Aspirational Preferences and their Representation by Risk Measures. *Management Science*, 58, 2095-2113.

Senge P. (1990) *The Fifth Discipline: The Art and Practice of the Learning Organization*, Doubleday Currency, New York.

Simon, H.A. (1959) Theories of decision-making in economics and behavioral science, *The American Economic Review*, **49**, 253-283.

Sterman J. (2000) *Business Dynamics: Systems Thinking and Modeling for a Complex World*, Irwin/McGraw-Hill, Boston, MA.

Ng T.S. and Sy C. (2014) A resilience optimization approach for workforce-inventory control dynamics under uncertainty. *Journal of Scheduling*, **17**, 427-444.