Optimization of Multistage Logistic Network under Disruption Risk Considering Continuity Rate

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Abstract

This study is concerned with multistage logistic network optimization under disruption risk. In its development, we have examined an effect of continuity rate to make a final decision after defining a metric to stand for a certain operational level during the required time objective in business continuity plan/management. For this purpose, we deploy the foregoing three types of logistic network models, i.e., the multi-multi allocation, multi-single allocation and single-single allocation model. The resulting logistic models are formulated as respective mixed-integer programming models with the expected cost function. Through a numerical experiment, we compared new models to the previous ones and carried out a parametric study on the continuity rate. Finally, we show that the proposed idea is more useful to design a resilient logistic network from a practical view point.

Keywords
Disruption risk, Continuity rate, Mixed-integer programming, Multistage logistic network, Resiliency

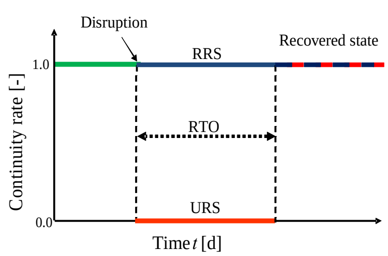
1. Introduction
Supply chains are subject to a wide range of risks such as demand uncertainty, natural disasters, terrorist attacks and intentional or unintentional human actions. A recent disruption caused by the Tohoku earthquake and tsunami in Japan in March, 2011 and flooding in Thailand in October, 2011 had a dramatic impact on the supply chains and logistic distribution of many companies. The resulting slowdown and cessation of operations seriously affected some companies due to the shortage of materials from the disrupted companies. We can anticipate disruptions by considering preventive action. If the preventive action takes into account against the disruptions, such actions are amenable to mitigation planning. Under such mitigation plans, the supply chain must build a resilient system that can minimize the impact of disruption in the future. One of such mitigation mechanism would be to have backup facilities that make it possible to continue supply if the primary facility would be disrupted. Schmitt (2011) recommended that one of the best protections can be achieved through backup capabilities that will protect the supply chain until the disruption’s end and prevent long or permanent interruptions to customer. In this study, we focus on the issue related to facility disruption risk for multistage logistic networks. The rest of the paper is organized as follows. The associated studies that form the background and the prospects of this study are reviewed in Section 2. Descriptions and formulations of the models are presented in Section 3. Then, numerical experiments are presented in Section 4. Finally, we give conclusions.

2. Literature Review
Definition of disruption in term of the supply chain context is unplanned and unanticipated events that disrupt the normal flow of products and materials within a supply chain (Craighead et al. 2007). Accordingly, robust and flexible supply chain designs have become a significant consideration to the decision maker. Moreover, real-world supply chain environment is becoming more dynamic in nature since they are subject to disruptions that can disrupt the system performance (Gholani and Zandieh 2009). There are some previous studies on supply chains considering disruption risk. For instance, the research of Tomlin (2006) investigates the impact of considering unreliable

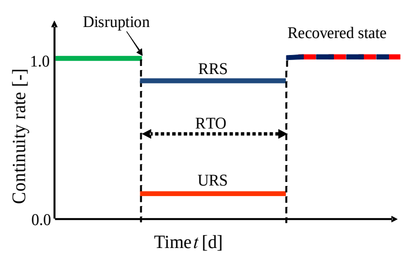
facilities for facility location problems. Snyder and Daskin (2005) introduced several reliability models based on traditional facility location problems, in which some facilities may fail with a given probability. They assumed that in normal circumstances, customers are assigned to primary facilities and other facilities will serve the customers if the primary facility fails. Snyder et al. (2006) presented a formal review of reliability considerations in facility location models. Berman et al. (2007) concerned with a reliable model based on different failure probabilities for various facilities. Lim et al. (2009) studied the facility reliability problem (FRP) which is an extension of the uncapacitated facility location problem (UFLP). They studied the FRP from the aspect of how to design a reliable supply chain network in the presence of random facility disruption. Chopra and Sodhi (2004) and Kleindorfer and Saad (2005) considered supply chain disruption from a risk management perspective. Parvaresh et al. (2012) noted a fail probability of the hub facilities due to some disruptions which can lead to excessive costs. The authors claimed that one of the most effective ways to hedge against disruptions especially for intentional disruptions is to design more reliable hub networks. Considering the risk associated with demand fluctuation, Shimizu et al. (2008) applied a flexibility analysis for a three-echelon logistic problem. A scenario-based approach was taken to provide a solution procedure via the recourse model (Shimizu et al. 2011). Moreover, Rusman and Shimizu (2011) compared some properties among the network configurations characterized by delivery manners. A general review on the logistic networks design is discussed in the literature (Melo et al. 2009).

3. Problem Formulation

Having proper backup facilities is an essential element to reduce the Recovery Time Objective (RTO) in Business Continuity Planning (BCP) and to create resiliency. We attempted to present a resilient network consisting of major distribution center (DC), sub-DC that takes over the local delivery or relay station (RS) and customer (RE). Generally speaking, since every RS is located nearer to customer site than DC, it is adequate to consider the decision problem at the RS level. Then, assuming that DCs are sound safe while RSs potentially affected by the disruption, we provided two kinds of RSs, i.e., reliable RSs (RRSs) and unreliable RSs (URSs). URS is no longer available at all for serving customers when it fails or a disruption occurs. This means alternative sources of supply become necessary to provide service to customers. On the other hand, an RRS is stronger and has additional capacity and/or an external alternative sourcing strategy, for example. An RRS can continue fully business even after an incident.



(a)



(b)

Figure 1: Comparison of continuity rates: (a) in case of conventional *w/o*-model, (b) in case of present *w*-model. RRS: reliable relay station, URS: unreliable relay station, RTO: recovery time objective

Since the above assumptions are too excessive and not realistic, this study tries to introduce a parameter called continuity rate. It can ease the solidness for RRS while strength the vulnerability for URS. In Figure 1, we compare the representative schemes of the continuity rate under the previous assumptions (without model or *w/o*-model, hereinafter) and the present ones (with model or *w*-model), respectively. After the disruption, the operational level decreases somewhat below the normal condition even for RRS while URS can keep it at a certain level. Thus, the continuity rate is viewed as the operational level during the RTO after the disruption. Generally speaking, building RS with the higher continuity rate needs the higher investment cost or fixed charge and ultimately an infinite cost for the perfect reliability. This means we can describe the fixed charge as an exponential function of the continuity rates. It is described as r^R and r^U for reliable and unreliable RS, respectively.

$$F = \alpha \exp(\beta r) \; + \; \gamma, \text{ for } F = \{F^U, F^R\} \text{ and } r = \{r^U, r^R\} \tag{1}$$

Where, F denotes the fixed cost both for unreliable facility (F^U) and reliable facility (F^R), and α, β and γ constants. Figure 2a illustrates the profile of Equation (1) for both rates. If we set the respective value that is able to locate within its own interval described by the double directed arrows, we can decide the respective specified fixed charge for each.

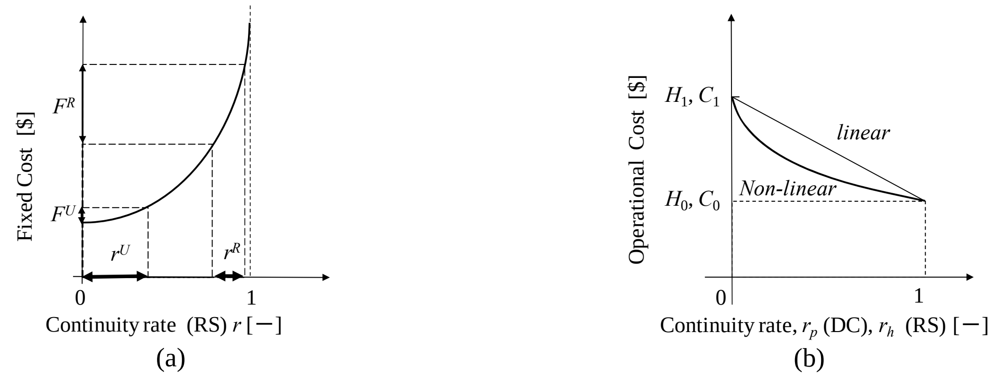


Figure 2: Scheme of fixed charge against continuity rate (a) and Operational costs against continuity rate (b)

On the other hand, the relation between the operational costs such as shipping or handling cost and the continuity rate has an opposite trend to such fixed charge. We describe the continuity rate of shipping and handling tasks as r_p, and r_h, respectively. These operational costs also changes with the continuity rate between upper and lower bounds. This change is possible to be described by either linear or nonlinear function as depicted in Figures 2b. For instance, when backup shipping cost linearly varies between the lower C_0 and the upper value C_1. It is given by the following equation.

$$C^B = r_p C_0 + (1 - r_P) C_1 \tag{2}$$

Similarly, the backup handling cost is given as follows.

$$H^B = r_p H_0 + (1 - r_P) H_1 \tag{3}$$

Where, H_0 and H_1 are the lower and upper values of the handling cost, respectively. Apparently, the primary costs of those (at normal state, r_p=1) corresponds to the lower values. Generally, these continuity rates of operational costs are closely related with the fixed charge since the vulnerable RSs need higher cost and vice versa. For simplicity, we assume that it refers to the following linear model to represent this situation.

$$r = f_n(r^U, r^R) = (1-w) r^U + w r^R, \quad r \in \{r_h, r_p\} \tag{4}$$

Where, w denotes a weighting coefficient. Finally, we also assume that the customer demands decrease after the disruption. We describe its rate as r_d (<1). We take three configurations of network that were used in the previous studies (Rusman and Shimizu 2011) and shown in Figure 4. In MMA model, each RS will receive the product from multiple DCs and each customer also from multiple RSs. In MSA model, each RS can receive the product from multiple DCs while customer only from single RS. Finally, in SSA model, each RS receives just from single DC and customer also receives from single RS. We can formulate each problem more realistically compared with the previous one by applying these additional parameters like r^U, r^R, r_h and r_p.

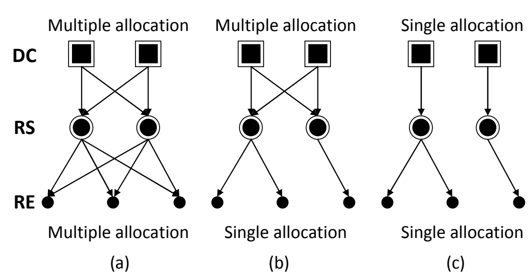


Figure 4. Allocation model: (a) multi-multi allocation model, (b) multi-single allocation model, and (c) single-single allocation model. DC: distribution center, RS: relay station, RE: customer.

In these models, we commonly assume the following conditions. Each customer $k \in K$ has a demand d_k. The product will be distributed from DC i to RS j and RS j to RE k, respectively. At each RS j, we may locate either RRS with opening cost F_j^R or URS with opening cost F_j^U. The fixed cost for opening an RRS is higher than for a URS (F_j^R > F_j^U) due to disruption related reasons. Nomenclature that is used in this paper is presented in Table 1.

Table 1: Nomenclature

Index	Description
Sets	
I	set of Distribution Center (DC)
J	set of Relay Station (RS)
K	set of Customer (RE)
Parameters	
F_j^U	Fixed cost for opening URS j
F_j^R	Fixed cost for opening RRS j
C_i^P	Shipping cost at DC i as primary assignment
C_i^B	Shipping cost at DC i as backup assignment
H_j^P	Handling cost at RS j as primary assignment
H_j^B	Handling cost at RS j as backup assignment
$T1_{ij}^P$	Transport cost from DC i to RS j as primary assignment
$T1_{ij}^B$	Transport cost from DC i to RS j as backup assignment
$T2_{jk}^P$	Transport cost from RS j to customer k as primary assignment
$T2_{jk}^B$	Transport cost from RS j to customer k as backup assignment
U_j	Capacity of RS j
PU_i	Maximum supply ability of DC i
PL_i	Minimum supply ability of DC i
d_k	Demand of customer k
q_j	Probability of disruption ($0<q_j<1$)
r^R	Continuity rate of reliable facility ($0 < r^R < 1$)
r^U	Continuity rate of unreliable facility ($0 < r^U < 1$)
r_p	Continuity rate of production ($0 < r_p \le 1$)
r_h	Continuity rate of handling ($0 < r_h \le 1$)
r_d	decrease rate in demand ($0 < r_d \le 1$)
Decision variables	
a_{ij}^P	Shipped amount from DC i to RS j as primary assignment
a_{ij}^B	Shipped amount from DC i to RS j as backup assignment
b_{jk}^P	Shipped amount from RS j to customer k as primary assignment
b_{jk}^B	Shipped amount from RS j to customer k as backup assignment
x_j^U	1 if RS j is opened as unreliable one and 0 otherwise
x_j^R	1 if RS j is opened as reliable one and 0 otherwise
y_{jk}^P	1 if RS j distributes customer k as primary assignment and 0 otherwise
y_{jk}^B	1 if RS j distributes customer k as backup assignment and 0 otherwise
z_{ij}^P	1 if DC i distributes RS j as primary assignment and 0 otherwise
z_{ij}^B	1 if DC i distributes RS j as backup assignment and 0 otherwise

The transportation cost per unit demand from DC i to RS j is given by $T1_{ij}^P$ and $T1_{ij}^B$ for the primary assignment and backup assignment, respectively. We also assume that $T1_{ij}^P < T1_{ij}^B$ due to the consequence of using the backup resources. Similarly, the transportation cost per unit demand from RS j to RE k is given by $T2_{jk}^P$ and $T2_{jk}^B$ for the primary assignment and backup assignment, respectively. We also assume that $T2_{jk}^P < T2_{jk}^B$ due to the same reason given above. Moreover, the shipping cost at DC i and the handling cost at RS j are denoted as C_i^P and C_i^B, H_j^P and H_j^B for the primary and backup conditions, respectively. We also assume that $C_i^P < C_i^B$ and $H_j^P < H_j^B$.

We assume that each RS has a certain disruption probability denoted by q_j. The primary event occurs with probability 1-q_j under the normal costs while the backup event occurs with probability q_j under the abnormal costs. Finally, we formulate each model as the mixed-integer programming problem described below. The objective function is expected costs that consist of shipping cost at the DC, the transportation cost between each facility and the handling cost at each RS besides the fixed cost for opening each RS. Among the decision variables, the binary variables are closely related to the structure of the network (design) while the integer variables closely relate to the operations under the prescribed structure. In other words, the resulting different structures will return the corresponding different operations.

3.1 Multi-Multi Allocation Model (MMA Model)

The model for MMA is described as follows.

Minimize

$$\sum_{j\in J} F_j^U x_j^U + \sum_{j\in J} F_j^R x_j^R + \sum_{j\in J}(1-q_j)\left(\sum_{i\in I}(C_i^P + T1_{ij}^P)a_{ij}^P + \sum_{k\in K}(H_j^P + T2_{jk}^P)b_{jk}^P\right)$$
$$+\sum_{j\in J} q_j \left(\sum_{i\in I} C_i^B + T1_{ij}^B)a_{ij}^B + \sum_{k\in K}(H_j^B + T2_{jk}^B)b_{jk}^B\right) \tag{5}$$

subject to

$$x_j^U + x_j^R \le 1 \qquad \forall j\in J \tag{6}$$
$$\sum_{j\in J} x_j^R \ge 1 \tag{7}$$
$$\sum_{i\in I} a_{ij}^P \le U_j(x_j^U + x_j^R) \qquad \forall j\in J \tag{8}$$
$$\sum_{i\in I} a_{ij}^B \le U_j\left(r^R x_j^R + r^U x_j^U\right) \qquad \forall j\in J \tag{9}$$
$$\sum_{j\in J} a_{ij}^P \le PU_i \qquad \forall i\in I \tag{10}$$
$$\sum_{j\in J} a_{ij}^B \le r_p PU_i, (0 < r_p \le 1) \qquad \forall i\in I \tag{11}$$
$$\sum_{j\in J} a_{ij}^P \ge PL_i \qquad \forall i\in I \tag{12}$$
$$\sum_{j\in J} a_{ij}^B \ge PL_i \qquad \forall i\in I \tag{13}$$
$$\sum_{i\in I} a_{ij}^P - \sum_{k\in K} b_{jk}^P = 0 \qquad \forall j\in J \tag{14}$$
$$\sum_{i\in I} a_{ij}^B - \sum_{k\in K} b_{jk}^B = 0 \qquad \forall j\in J \tag{15}$$
$$\sum_{j\in J} b_{jk}^P = d_k \qquad \forall k\in K \tag{16}$$
$$\sum_{j\in J} b_{jk}^B = r_d d_k, (0 < r_d \le 1) \qquad \forall k\in K \tag{17}$$
$$x_j^R \in \{0,1\},\ x_j^U \in \{0,1\} \qquad \forall j\in J \tag{18}$$

$$a_{ij}^{P} \geq 0,\ a_{ij}^{P} \geq 0 \qquad \forall i \in I, \forall j \in J \tag{19}$$

$$b_{jk}^{P} \geq 0, b_{jk}^{B} \geq 0 \qquad \forall j \in J, \forall k \in K \tag{21}$$

Equation (6) states that each RS can be open as either RRSs or URSs, but not as both. Equation (7) requires at least one RRS to be open. Equations (8) and (9) are capacity constraints for RSs as the primary and backup assignments, respectively. Equations (10) and (11) are the upper bounds for the available supply as primary and backup assignments, respectively. Equations (12) and (13) are the lower bounds for the available supply as the primary and backup assignments, respectively. Equations (14) and (15) are balances of product flow as the primary and backup assignments, respectively. Equations (16) and (17) mean that demand of every customer must be satisfied as the primary and backup assignments, respectively, Equations (18) are integer conditions on decision variables. Equations (19) - (21) are nonnegative conditions for the primary and backup amounts.

3.2 Multi-Single Allocation Model (MSA Model)

The model for MSA is described as follows.

Minimize

$$\sum_{j \in J} F_j^U x_j^U + \sum_{j \in J} F_j^R x_j^R + \sum_{j \in J} (1-q_j)\left(\sum_{i \in I} (C_i^P + T1_{ij}^P) a_{ij}^P + \sum_{k \in K} (H_j^P + T2_{jk}^P) d_k y_{jk}^P \right)$$

$$+ \sum_{j \in J} q_j \left(\sum_{i \in I} (C_i^B + T1_{ij}^B) a_{ij}^B + \sum_{k \in K} (H_j^B + T2_{jk}^B) d_k y_{jk}^B \right) \tag{22}$$

subject to

Equations (6) - (13) and (18) - (19)

$$\sum_{j \in J} y_{jk}^P = 1 \qquad \forall k \in K \tag{23}$$

$$\sum_{j \in J} y_{jk}^B = 1 \qquad \forall k \in K \tag{24}$$

$$y_{jk}^P \leq x_j^U + x_j^R \qquad \forall j \in J, \forall k \in K \tag{25}$$

$$y_{jk}^B \leq x_j^R \qquad \forall j \in J, \forall k \in K \tag{26}$$

$$\sum_{i \in I} a_{ij}^P - \sum_{k \in K} y_{jk}^P = 0 \qquad \forall j \in J \tag{27}$$

$$\sum_{i \in I} a_{ij}^B - \sum_{k \in K} r_d d_k y_{jk}^B = 0 \qquad \forall j \in J \tag{28}$$

$$y_{jk}^P \in \{0,1\},\ y_{jk}^B \in \{0,1\} \qquad \forall j \in J, \forall k \in K \tag{29}$$

In the MSA model, explanation of the objective function and constraints are all equivalent to that of the MMA model except for equations (25), (26), and (29). These equations express that each customer must be assigned to single RS for both the primary and backup assignment, respectively. The equations (25) - (28) are correspond to equations (14) - (17).

3.3 Single-Single Allocation Model (SSA Model)

The model for SSA is described as follows.

Minimize

$$\sum_{j \in J} F_j^U x_j^U + \sum_{j \in J} F_j^R x_j^R + \sum_{j \in J} (1-q_j)\left(\sum_{i \in I} (C_i^P + T1_{ij}^P) a_{ij}^P z_{ij}^P + \sum_{k \in K} (H_j^P + T2_{jk}^P) d_k y_{jk}^P \right)$$

$$+ \sum_{j \in J} q_j \left(\sum_{i \in I} (C_i^B + T1_{ij}^B) a_{ij}^B z_{ij}^B + \sum_{k \in K} (H_j^B + T2_{jk}^B) d_k y_{jk}^B \right) \tag{30}$$

subject to

Equations (6), (7), (18) - (19), (23) - (26), and (29)

$$\sum_{i \in I} z_{ij}^P = 1 \qquad \forall j \in J \tag{31}$$

$$\sum_{i\in I} z_{ij}^B = 1 \qquad \forall j \in J \tag{32}$$

$$\sum_{i\in I} a_{ij}^P z_{ij}^P \le U_j (x_j^U + x_j^R) \qquad \forall j \in J \tag{33}$$

$$\sum_{i\in I} a_{ij}^B z_{ij}^B \le U_j (r^R x_j^R + r^U x_j^U) \qquad \forall j \in J \tag{34}$$

$$\sum_{j\in J} a_{ij}^P z_{ij}^P \le PU_i \qquad \forall i \in I \tag{35}$$

$$\sum_{j\in J} a_{ij}^B z_{ij}^B \le r_p PU_i, (0 < r_p \le 1) \qquad \forall i \in I \tag{36}$$

$$\sum_{j\in J} a_{ij}^P z_{ij}^P \ge PL_i \qquad \forall i \in I \tag{37}$$

$$\sum_{j\in J} a_{ij}^B z_{ij}^B \ge PL_i \qquad \forall i \in I \tag{38}$$

$$\sum_{i\in I} a_{ij}^P z_{ij}^P - \sum_{k\in K} d_k y_{jk}^P = 0 \qquad \forall j \in J \tag{39}$$

$$\sum_{i\in I} a_{ij}^B z_{ij}^B - \sum_{k\in K} r_d d_k y_{jk}^B = 0 \qquad \forall j \in J \tag{40}$$

$$z_{ij}^P \in \{0,1\},\ z_{ij}^B \in \{0,1\} \qquad \forall i \in I, \forall j \in J \tag{41}$$

Equations (32) and (41) are necessary for single allocation for DCs. Equations (33) - (40) correspond to equations (8) - (15). Since this model involves bi-linear terms like $a_{ij}^P z_{ij}^P$ and $a_{ij}^B z_{ij}^B$, we need to introduce new variables and the additional constraints to linearize them as follows:

$$Z_{ij}^P = a_{ij}^P z_{ij}^P \tag{42}$$

$$Z_{ij}^B = a_{ij}^B z_{ij}^B \tag{43}$$

$$a_{ij}^P - Z_{ij}^P \ge 0,\ a_{ij}^B - Z_{ij}^B \ge 0 \qquad \forall i \in I, \forall j \in J \tag{44}$$

$$a_{ij}^P - B \le Z_{ij}^P - Bz_{ij}^P,\ a_{ij}^B - B \le Z_{ij}^B - Bz_{ij}^B \qquad \forall i \in I, \forall j \in J \tag{45}$$

where B is a certain large value.

4. Numerical Experiments

In this section, we show the results of numerical experiments. The purpose of these numerical experiments is to compare the total cost between the *w/o*-model and *w*-model. We provided benchmark problems by randomly generating every system parameter within the respective prescribed extents. The probability of disruption q_j is assumed to be same for $\forall j \in J$ (hereinafter, denoted simply as q), and varied from 0.1 to 0.5. Every node denoting the members of the facilities is also generated randomly. Then, distances between them are calculated based on the Euclidian norm. We obtain the transportation cost by multiplying the unit factor 1.5 and 1.0 with the distance between DC to RS and RS to RE, respectively. Moreover, the same fixed cost that is derived from Equation (1) depending on the continuity rate is used both for *w/o* and *w*-models. We then solved the formulated problems using commercial software known as CPLEX 12.2 on a computer with 2.66GHz core 2 duo processor and 2 GB of RAM.

4.1 Result for small size problem

First, to reveal the effect of continuity rate, we took a small size problem with 2 distribution centers (DCs), 5 relay stations (RSs) and 50 customers (REs). Then, the parameters of continuity rate are changed as shown in Table 2. We examine the effect of the critical parameters such as the disruption probability will affect the relative difference (RD) between the *w/o* and *w*-model. RD is the percentage of the difference between the cost of *w/o* and *w*-model and defined by the following equation.

$$RD(\%) = \frac{\text{Expected Cost of } w/o - \text{model} - \text{Expected Cost of } w - \text{model}}{\text{Expected Cost of } w\text{-model}} \tag{52}$$

Table 2 Continuity rate of facility (r^U,r^R)

r^U \ r^R	0.8	0.9
0.1	(Low, Low)	(Low, High)
0.2	(High, Low)	(High, High)

Figure 4 shows the result of RD when r_d=0.8. This value tends to decline while fluctuating a bit as q grows. Since the w-model is considered to be more flexible than the w/o-model, the w-model outperforms the w/o-model for all disruption probability as a generic nature. It is likely the w-model opens more URSs than w/o-model. By opening more number of URS, w-model can reduce the operational cost by providing some products to customers in the abnormal situation. Though URSs in the w-model are failed partially in the abnormal situation, they might still be able to serve with a portion of their initial capacity as backups in the abnormal situation depend on the continuity rate (r^U). According to the increase in disruption probability, however, RD will decline as a whole due to the higher rate of RRSs in the opening RSs. This situation for q=0.1 is depicted in Figure 5 for (Low, High) continuity rate setting. Both w/o and w -model open the same types of RS, two URS and one RRS. In the w-model, DC#1 will distribute the product not only to RRS#2 but also to URS#1 and URS#4 in an abnormal situation. Moreover, URS#1 and URS#4 also supply some product to customers. On the other hand, w/o-model becomes more rigid in the abnormal situation. Thereat, URS#4 is completely stopped the operation and RRSs must supply all customer demands. Such decision is able to reduce the operational cost significantly in w-model.

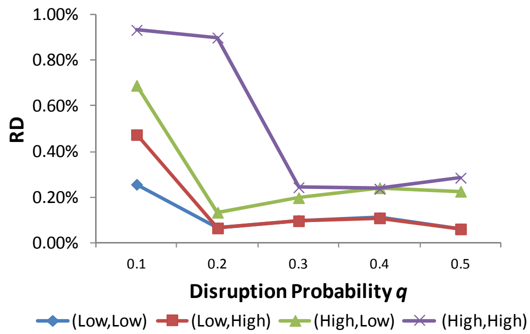
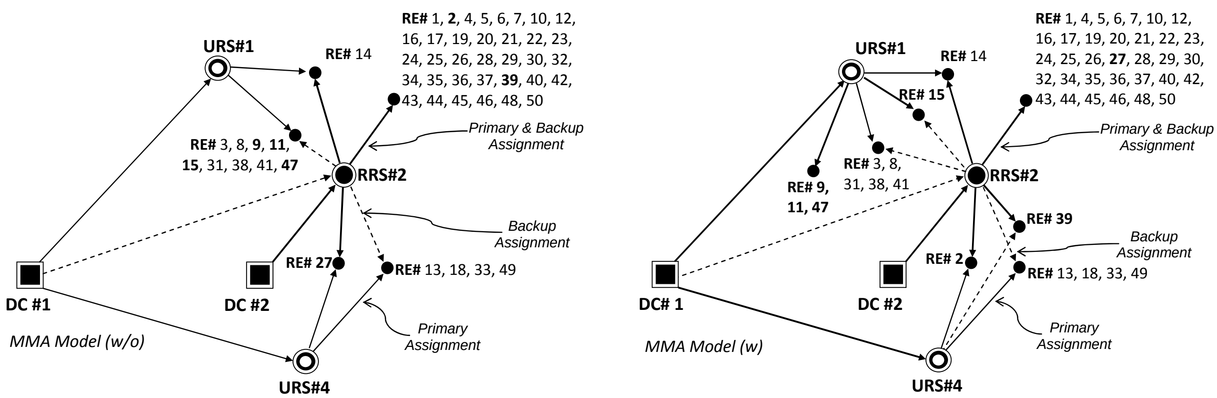


Figure 4: Relative difference (RD) against disruption probability (q).



(a) (b)

Figure 5: Allocation model comparison for multi-multi allocation model (MMA) between the w-model (a) and w/o-model (b) with q = 0.1, r^U =0.1, r^R =0.9, r_p = 0.8, r_h = 0.5 r_d = 0.8, DC: distribution center, RE: customer, RRS: reliable relay station, URS: unreliable relay station.

4.2 Result for larger size problems

The results for the larger problems like (|I|, |J|, |K|) = (4, 15, 150) are shown in Tables 3, 4 and 5. The parameters of continuity rate are given as r^U=0.2, r^R=0.9, r_p=0.8 and r_h=0.5, r_d=0.8. These tables show comparison between the w -

model and the *w/o*-model for three allocation models. Thereat, we summarize the results such as the number of opening facilities, the expected cost, CPU time (in seconds) and GAP as well as the relative difference (RD). Just similar to the small size problem, URS will shift to RRS along with the increase in the disruption probability and the similar profile of RD is observed after all.

We can also know from these tables that the *w*-model outperforms the *w/o*-model for the (4, 15, 150) problem sizes for MMA model. This is not the case of MSA and SSA models. Let note that in those models, customers must received the product only from single RS. So when a certain RRS will lose its backup ability, another URS must take for the backup even with higher transportation cost. This situation will lead the increase in the operational cost for the *w*-model in the abnormal situation.

Figure 6 shows the comparison of the relative difference (RD) in MMA model with the pair of occurrence of continuity rate already shown in Table 1. This figure shows how RD decreases as q grows. We also see from this figure that RD has the highest value at q=0.2 because the *w*-model opens more number URS than *w/o*-model at this disruption probability. By opening more number of URS that is able to backup within some portion, we can reduce the operational cost in the abnormal situation. Those facts imply allocation of investment highly depends on the disruption probability and relative locations of the logistics members.

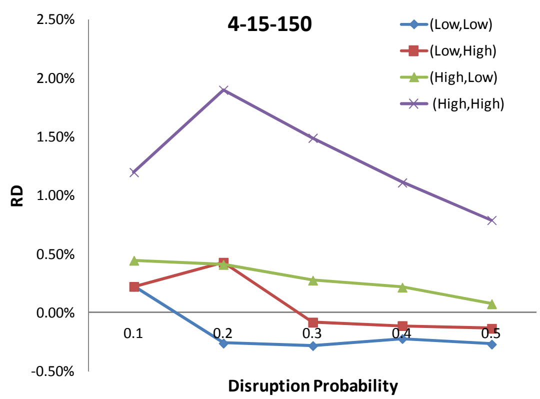


Figure 6: Related difference against disruption for large size problem

Table 3: Result of MMA for 4-15-150

q	*w/o* model					*w* model					RD [%]
	URS	RRS	Expected Cost	CPU time [s]	GAP [%]	URS	RRS	Expected Cost	CPU time [s]	GAP [%]	
0.1	3	2	6,975,890	0.48	0.41	4	1	6,893,214	0.58	0.43	1.20
0.2	3	2	7,273,330	0.59	0.48	4	1	7,137,642	0.53	0.29	1.90
0.3	1	4	7,492,164	0.45	0.38	4	1	7,382,071	0.56	0.00	1.49
0.4	0	4	7,697,519	0.45	0.24	3	2	7,612,965	0.41	0.24	1.11
0.5	0	4	7,893,849	0.31	0.00	3	2	7,831,917	0.42	0.35	0.79

Table 4: Result of MSA for 4-15-150

q	*w/o* model					*w*- model					RD [%]
	URS	RRS	Expected Cost	CPU time [s]	GAP [%]	URS	RRS	Expected Cost	CPU time [s]	GAP [%]	
0.1	3	2	7,064,103	6.69	0.01	3	2	7,062,914	10.30	0.01	0.02
0.2	2	3	7,448,267	12.64	0.01	3	2	7,447,648	11.64	0.01	0.01
0.3	0	4	7,761,643	13.72	0.01	0	4	7,767,986	17.28	0.01	-0.08
0.4	0	4	8,044,508	7.20	0.01	0	4	8,052,688	12.86	0.01	-0.10
0.5	0	4	8,326,829	6.77	0.01	0	4	8,337,364	4.17	0.01	-0.13

Table 5: Result of SSA for 4-15-150

q	*w/o* model					*w-* model					RD [%]
	URS	RRS	Expected Cost	CPU time [s]	GAP [%]	URS	RRS	Expected Cost	CPU time [s]	GAP [%]	
0.1	2	2	11,858,824	0.91	0.01	1	3	11,888,565	5.55	0.01	-0.25
0.2	0	5	12,349,457	4.05	0.03	0	5	12,367,278	4.20	0.44	-0.14
0.3	0	5	12,717,037	4.81	0.01	0	5	12,743,695	8.39	0.01	-0.21
0.4	0	5	13,081,549	3.69	0.01	0	5	13,117,093	4.34	0.12	-0.27
0.5	0	5	13,437,014	3.69	0.01	0	5	13,481,735	3.51	0.01	-0.33

5. Conclusion

In this paper, we presented three allocation models in multistage logistic network design considering disruption risk and continuity rate. The continuity rate is a new parameter to formulate the models more practically and make the analysis more comprehensively. Then, we formulated each model as mixed-integer programming problems and used commercial optimization software to solve the models. Through the numerical experiments, we have compared the behavior between the *w*-model and the *w/o*-model and shown the flexibility is endowed by introducing the continuity rate. Future studies will be devoted to applying the models for a certain real world case by considering DC is affected by disruption and evaluating the models for the distributed disruption probability instead of the deterministic one.

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