Proactive Resilience Strategies in Logistics Disruption Management

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Abstract:

International express is a most time-sensitive industry, whose members may need to develop proactive resilience strategies to mitigate severe impacts of disruptions, to respond disruptions in a timely manner, and to maintain their competitiveness with other logistics service providers. This paper contributes a method for quantifying and optimizing reliable proactive planning resilience strategies based on integrated resource assignment concepts. In order to examine the reliability of primary hubs, links, and mode operations within the existing logistics networks, a robust optimization approach is utilized to account for potential disruptions. Decisions are made by jointly minimizing the products of total time-dependent cargo value loss and the corresponding throughput, while considering a set of resilient actions such as investing in freight terminal expansions, selecting alternative routes, switching shipping modes, developing long-term and short-term contracts for renting other carriers' capacities, and prioritizing and sequencing shipments due to limited capacities.

Keywords: Proactive resilience planning; Robust optimization; International express; Multiple objectives mixed integer nonlinear programming problem.

1. INTRODUCTION AND BACKGROUND RESEARCH

Increasing awareness that climate change affect the patterns of logistic activities has increased the interest of enterprises in rapid but reliable transportation services. Freight transportation systems are key contributors to complete supply chains while providing strong linkages among production operations through the efficient movement and timely availability of raw materials and finished products. Murray et al. (2008) also addressed that societal functions are highly dependent on freight transportation systems, which significantly support the globalized market and foster international trade.

Although international logistics have grown in popularity over the past decade, it has been noted that supply chain systems are also increasingly threatened by natural and man-made disasters (e.g. the Iceland volcano eruption in 2011, the Fukushima nuclear disaster in Japan in 2012, the German air traffic controllers strike in 2013, catastrophic rainfall, floods, and landslides in Japan on 2018, and earthquake in Indonesia in 2018) as recorded in the Emergency Events Database (EM-DAT.) Many enterprises are motivated to prepare different resilience strategies to relieve catastrophic impacts caused by natural and man-made disruptions.

The subject of this research, international express logistics, is one of the fastest growing sectors in the global economy. Express logistics operators can provide reliable, fast,

on-demand, world-wide, integrated, and door-to-door services of shipments. In general, the core business of the express industry is the provision of value-added transport and highly time-sensitive delivery. Thus, members of international express logistics may need to respond disruptions quickly in order to insure service quality and avoid losing their competitiveness with other service providers.

Managing disruptions is a significant issue in operating international express logistics networks. Nowadays the international express companies rarely respond to severe disruptions through systematic measures to determine how to transport cargos in a timely manner. In addition, most decisions are usually made through discussions and influenced by the experience of customer service personnel after disruptions. To improve such decisions, our initial reactive- based model (Chen et al., 2013) focuses on decisions made in response to disruptions during the phases of post-disruptions. Since the resilience performance of such reactive-based model is highly restricted by remaining resource for reallocations, a proactive-based model is further developed in this study to quantify and optimize the resilience strategies during the logistics network planning and design stages, while also increasing the potential resilience capability during the severe disruptions.

Many previous studies focused on the mitigation strategies during the post-disaster phases, especially dealing with the effectiveness and efficiency of measures to reduce the environmental burden of transport (e.g. Hensher and Button, 2003; Suarez et al., 2005; Intergovernmental panel on climate change report, 2007.) Since certain disruptions resulting from climate changes may be preventable, few studies have started to explore potential proactive resilience strategies. The term "resilience" was first defined by Holling (1973) in ecological system. Perrings (1994) further defined resilience as the 'capacity of a system to retain its organizational structure following perturbation of some state variable from a given value.' This concept has been investigated, adopted, and applied in different research fields (e.g. Gibson et al., 2000; Reggiani et al., 2002; Fiksel, 2006.) Moreover, Bruneau et al. (2003) classified resilience activities in four categories of robustness, redundancy, resourcefulness, and rapidity. Godschalk (2003) and Murray-Tuite (2006) further defined a resilient transportation system in terms of ten properties, namely: redundancy, diversity, efficiency, autonomous components, strength, adaptability, collaboration, mobility, safety, and the ability to recover quickly. Christopher and Peck (2004) defined resilience as the ability of a system to quickly react to undesired events and then return to its original state or move to a new, more desirable state after being disturbed. It should be noted that increasing adaptation opportunities imply decreasing urgency to implement mitigation measures, and vice versa.

Several previous studies focused on evaluating resilience in different transportation fields. Ta, Goodchild, and Pitera (2009) considered the resilience of a freight transportation system as the ability to absorb the consequences of disruptions, reduce the impacts of disruptions, and maintain freight mobility. Paul and Maloni (2010) developed a simulation model to evaluate system performance of the studied ports under disruptions. Ip and Wang (2011) evaluated the system resilience and vulnerability of railway networks in China while countering earthquakes. Faturechi et al. (2014) examined the system resilience under different disaster scenarios of the studied airport pavement network. Ali et al. (2017) developed an integrative approach to cold chain logistics risks and resilience in perishable product supply chains.

Although a growing number of studies investigate the network failure problems due to disruptions, most of these works start from uni-modal transportation networks with risk of link failures (e.g. Rios et al., 2000; Viswanath and Peeta, 2003; Garg and Smith, 2008; Liu et

al., 2009; Desai and Sen, 2010; Peeta et al., 2010) and node failures (e.g. Snyder and Daskin, 2005; Peng et al., 2011; Hatefi and Jolai, 2014). Few studies incorporated resilience concepts into intermodal freight transportation network flow problems (e.g. Nair et al., 2010; Chen and Miller-Hooks, 2012; Miller-Hooks et al., 2012). Moreover, many studies above focused on reaction activities during the post-disruption phase, but seldom investigated the pre-planned strategies under multiple uncertainties. Miller-Hooks et al (2012.) considered a stochastic two- stage model to allocate limited budget to improve the resiliency of an intermodal network by choosing from a set of pre-disaster and recovery activities. The probabilities of severe disruption events in reality are somewhat difficult to estimate and hamper the usefulness of the proposed stochastic models.

In order to clearly describe the concept of resilience, we first introduce Bruneau et al.'s (2003) resilience triangle to represent a measure of both the loss of functionality of a system during the post-disaster phases and the amount of time required for system recover to normal performance levels. Bruneau et al. assumed that resilience R can be measured by the size of the expected degradation of quality (i.e. probability of failure) over time. R can be expressed as the following Equation 1, where Q(t) denotes the quality of a system at a given time t.

$$\int_{t_0}^{t_n} \left[100 - Q(t)\right] dt \tag{1}$$

Similar to Bruneau et al.'s resilience triangle, Sheffi (2005) characterized the nature of the disruption and the dynamics of the company's response into eight phases. Furthermore, Dorbritz (2011) improved the resilience triangle for assessing the disaster resilience in public transportation systems. He considered prevention, intervention and recovery phases and revised the calculation methods of the system reduction area, as shown in Figure 1.

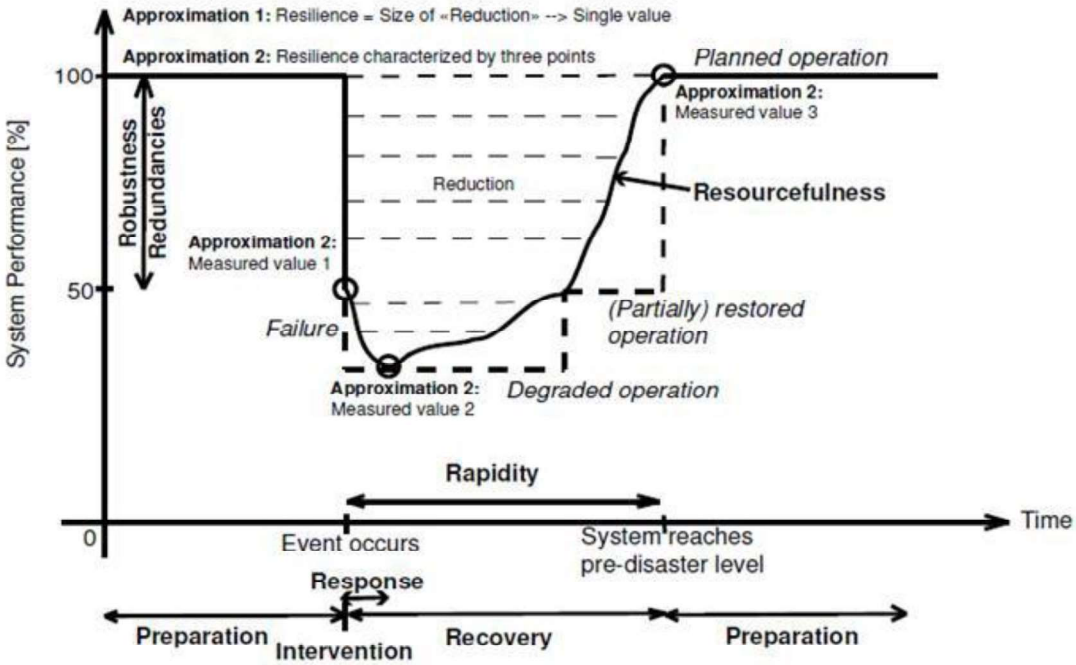

Figure 1. A Conceptual Illustration of Resilience Triangle (Source: Dorbritz, 2011)

It should be noted that many existing freight transport systems are running at capacity and have limited buffer to handle severe disruptions. Tierney and Bruneau (2007) mentioned that industries are reluctant to invest in proactive resilience strategies because the benefit and cost associated with different levels of flexibility are difficult to obtain. In addition, most disruptive events are fairly minor and many logistics companies blindly continue to eliminate buffer and backup, without considering the increasing potential for disruptions. However, lack of available resources would yield the poor resilience performance and extend the system reaction and recovery time, when serious disruptions really occur. In this study, we define resilience R as a function of Q(t) on the basis of above concepts, and further introduce a resilience index to evaluate the system performance by adopting different resilience strategies.

This paper develops a robust optimization model devoted to managing proactive resilience strategies in intermodal logistics networks, from potential disruptions under changing environment. Using nonlinear time-dependent cargo value functions, we consider a set of resilient actions such as investing in freight terminal expansions, selecting alternative routes, switching shipping modes, renting other carriers' capacities, and prioritizing and sequencing shipments due to limited capacities. Renting capacities (e.g. extra containers or spare transportation modes) from other carriers is one major action taken by the international express companies in practice, which can be further divided into two types: renting from non-contractual carriers (i.e. in the short-term) and contractual carriers (i.e. the long-run operations).

Several research gaps and the contribution of this study are listed below:

1. Many previous studies focused on the intermodal logistics network design and freight routing problems, but seldom deal with the disruption management in intermodal logistics fields. In this study, we formulate the studied problem as a mixed integer nonlinear programming robust optimization problem to assist intermodal freight service providers in developing reliable proactive planning resilience strategies within the studied international express networks.
2. Instead of estimating the cargo values as a fixed amount in each shipment, our study incorporates different time-dependent cargo value settings to capture the dynamic characteristics of certain time-sensitive shipments (i.e. express cargos.) Those time-dependent functions also increase the problem's nonlinear nature.
3. Most studies are purely theoretical, focus on reaction activities during the post-disruption phase, and rarely investigate the pre-planned strategies under multiple uncertainties. In addition, some stochastic-based models are somewhat difficult to estimate the actual probabilities in reality. In this study, we develop a new Min-Max regret function (see following Equation 8) based on Fatemeh and Tarokh's (2010) normalization technique, to integrate multiple objectives with various network uncertainties.

In the present study, we first solve our proposed model by using given information and further compare the solution feasibility among different scenarios. The remainder of this paper is organized as follows: the mathematical formulations are provided, followed by robust optimization techniques to demonstrate the potential benefit of different disaster scenarios. Finally, some concluding remarks are offered.

2. RESILLIENCE ENHANCEMENT MODELLING FRAMEWORK

This paper develops a robust optimization model devoted to managing proactive resilience strategies in intermodal logistics networks, while considering the overall costs related to the resilience strategies and the trade-off between costs and expected system performance improvement (i.e. in terms of throughput.)

Here we consider a set of resilient actions such as investing in freight terminal expansions, selecting alternative routes, switching shipping modes, renting other carriers' capacities, and prioritizing and sequencing shipments due to limited capacities. This section presents the model formulations to address proactive resilience issues based on the predetermined express logistics networks, and given freight origin-destination information for a specific time period.

The study starts from a typical transportation network modeling approach and then incorporates nonlinear time-dependent cargo value functions into a multi-objective mixed integer nonlinear programming problem. Decisions should be based on overall trade-off considerations, while jointly minimizing the product of total time-dependent cargo value loss and the corresponding throughput, as well as minimizing the costs incurred with resilience enhancement strategies. All parameters and decision variables used in the formulation are listed below:

<u>Sets</u>

A = a set of arcs, where A = $\{(i, j) | i, j \in N\}$;
B = a set of shipping orders;
D = a set of destinations;
E = a set of carriers;
M = a set of modes;
N = a set of nodes;
O = a set of origins;
S = a set of disrupted scenarios.

<u>Parameters</u>

$c_{(f,\omega)ij}^{me}$ = the fixed costs of renting long-term capacity from carrier e for mode m on arc (i, j);

$c_{(v,\omega)ij}^{me}$ = variable costs of renting long-term capacity from carrier e for mode m on arc (i, j);

$c_{(v,\pi)ij}^{me}$ = variable costs of renting short-term capacity from carrier e for mode m on arc (i, j);

$c_{(k)i}$ = the terminal expansion costs at freight terminal i;

λ = the maximum allowable budget implemented in resilience enhancement strategies;
K_i = the existing capacities at freight terminal i;

u_{ij}^{m} = the maximum allowable capacities of mode m on arc (i, j);

$\alpha_{(s)ij}^{m}$ = capacity reduction factor on arc (i, j) of mode m due to damage of links in scenario s;

$\beta_{(s)ij}^{m}$ = capacity reduction factor on arc (i, j) due to the failure of modes in scenario s;

$\gamma_{(s)i}$ = capacity reduction factor at node i due to the shutdown of terminals in scenario s;

$T_{(s)}^{b}$ = the total shipping time of the cargos with shipping code *b* in scenario *s*;

$\pi_{(s,r)ij}^{me}$ = available renting capacities in short-term on arc *(i, j)* via mode *m* from carrier *e;*

t_{ij}^{bm} = travel time of cargos with shipping code *b* from node *i* to node *j* via mode *m*;

$t_{(\theta)i}$ = the total service time including loading, unloading, sorting, cargo processing, and custom clear time at node *j*;

$t_{(r)i}^{me}$ = total renting process time of mode *m* from carrier *e* at node *i*;

$\mu(t_0)^b$ = unit time-dependent cargo value function of cargos with shipping code *b* in initial stage;

$\mu(t)^b$ = unit time-dependent cargo value function of cargos with shipping code *b*.

<u>Decision Variables</u>

$f_{(s)ij}^{bm}$ = the amount of cargos with shipping code *b* on arc *(i, j)* shipped by mode m in scenario *s*;

$\omega_{(s)ij}^{me}$ = the long-term renting capacities of mode *m* on arc *(i, j)* from partner *e* in scenario *s*;

$\pi_{(s)ij}^{me}$ = the short-term renting capacities of mode *m* on arc *(i, j)* from partner *e* in scenario *s*;

$k_{(s)i}$ = the expanding capacities at freight terminal *i* in scenario *s*;

$\delta_{(s)ij}^{bm}$ = a binary indicator if 1 represents that cargos with shipping code *b* are shipped through arc *(i, j)* by mode m in scenario *s* and 0 otherwise;

$Y_{(s,\omega)ij}^{me}$ = a binary indicator if 1 represents that renting long-term capacities of mode *m* on arc *(i, j)* from carrier *e* in scenario *s* and 0 otherwise;

$Y_{(s,\pi)ij}^{me}$ = a binary indicator if 1 represents that renting short-term capacities of mode *m* on arc *(i, j)* from carrier *e* in scenario *s* and 0 otherwise.

The initial model is expressed as follows:

$$\text{Minimize } Z_s^R = \sum_b \sum_i \sum_{j,i\neq j} \sum_m \left[\mu(t_0)^b - \mu(T_{(s)})^b\right] f_{(s)ij}^{bm} \tag{2}$$

$$\text{Minimize } Z_s^C = \sum_m \sum_e \sum_i \sum_j Y_{(s,\omega)ij}^{me} (c_{(f,\omega)ij}^{me} + c_{(v,\omega)ij}^{me} \omega_{(s)ij}^{me}) + \sum_m \sum_e \sum_i \sum_j Y_{(s,\pi)ij}^{me} c_{(v,\pi)ij}^{me} \pi_{(s)ij}^{me} + \sum_i c_{(k)i} k_{(s)i} \tag{3}$$

Subject to

$$\sum_j f_{(s)ji}^{bm} - \sum_i f_{(s)ij}^{bm} = \begin{cases} Q & if\ \ i \in O \\ -Q & if\ \ i \in D \\ 0 & otherwise \end{cases} \qquad \forall i, j \in N\ i \neq j, \forall m \in M, \forall b \in B \tag{4}$$

$$\sum_b f_{(s)ij}^{bm} \leq (1 - \alpha_{(s)ij}^{m}) u_{ij}^{m} \tag{5}$$

$$\sum_{j}\sum_{b}\sum_{m} f_{(s)ij}^{bm} \le (1-\gamma_{(s)ij}^{m})(K_i + k_{(s)i}) \tag{6}$$

$$\sum_{b} f_{(s)ij}^{bm} \le (1-\beta_{(s)ij}^{m})u_{ij}^{m} + Y_{(s,\omega)ij}^{me}\omega_{(s)ij}^{me} + Y_{(s,\pi)ij}^{me}\pi_{(s)ij}^{me} \tag{7}$$

$$\pi_{(s)ij}^{me} \le \sum_{e} \pi_{(s,r)ij}^{me} \tag{8}$$

$$\sum_{m}\sum_{e}\sum_{i}\sum_{j} Y_{(s,\omega)ij}^{me}(c_{(f,\omega)ij}^{me} + c_{(v,\omega)ij}^{me}\omega_{(s)ij}^{me}) + \sum_{m}\sum_{e}\sum_{i}\sum_{j} Y_{(s,\pi)ij}^{me} c_{(v,\pi)ij}^{me}\pi_{(s)ij}^{me} + \sum_{i} c_{(k)i}k_{(s)i} \le \lambda \tag{9}$$

$$T_{(s)}^{b} = \sum_{i}\sum_{j}\sum_{m} \delta_{(s)ij}^{bm}\left(f_{(s)ij}^{bm} t_{(\theta)i} + t_{ij}^{bm} + \sum_{e} Y_{(s,\pi)ij}^{me} t_{(r)i}^{me} \right) \tag{10}$$

$$\sum_{m}\sum_{j} \delta_{ij}^{bm} \le 1 \tag{11}$$

The first objective function (Equation 2) is derived from the minimization of the product of total time-dependent cargo value loss and the corresponding system throughputs. Here we further define a priority rule for those shipments with higher cargo time values. Thus, the shipments with higher priority will be shipped first if the capacities are insufficient. In addition, if the system operators want to implement resilience enhancement strategies, the incremental resilient costs will be considered, as shown in the second objective function (Equation 3.)

Equation 4 states the flow conservation constraints. Equation 5 expresses the link capacity constraints. Equation 6 expresses the terminal capacity constraints. Equations 7 and 8 ensure the sum of available capacities and rented capacities satisfy the requirements for different modes. Equation 9 states the budget constraints to implement resilience strategies. Equation 10 calculates the total shipping time. Equation 11 specifies that at most one path can be chosen by an identical shipment.

3. METHODOLOGY AND SOLUTION TECHNIQUES

Robust optimization is a technique applied by researchers to deal with uncertainties (Kouvelis and Yu, 1997). It addresses uncertainty by considering a finite set of scenarios and finds a solution which is near-optimal for all cases. There are several robust optimization techniques, including min-max cost, min-max regret, minimum expected regret, and p- robustness. The general concepts of different robust optimization techniques are addressed as follows.

Let S represent a set of s finite scenarios for the uncertain parameter (e.g. demand, link capacity) and x denote a feasible solution for the robust problem. $Z_s(x)$ is the objective function value of scenario s at feasible point x and Z_s^* is the deterministic-based optimal solution for scenario s (for all x in the set X). Kouvelis and Yu (1997) first proposed an absolute robust decision method, namely '*Min-Max Cost,*' which is developed for minimizing the worst scenario costs (see equation 12.)

$$\underset{x\in X}{Min}(\underset{s\in S}{Max}\, Z_s(x)) \tag{12}$$

They further considered the concepts of opportunity costs and developed a robust deviation decision method, namely '*Min-Max Regret.*' Regret is represented by the difference between $Z_s(x)$ and Z_s . Daskin et al. (1997) assumed that the probability of scenario occurrence (q_s) could be estimated and then revised the above Min-Max Regret model to solve the hub location problem. The min-max regret method can obtain a solution which minimizes the maximum regret over all scenarios and is formulated as:

$$\underset{x\in X}{Min}(\underset{s\in S}{Max}(Z_s(x)-Z_s^*)) \tag{13}$$

The third type of model objective function developed by Kouvelis and Yu is called the relative robust decision approach, namely '*Min-Max Relative Regret.*'. In equation 14 the overall objective value is expressed as a percentage, while removing the units.

$$\underset{x\in X}{Min}(\underset{s\in S}{Max}(\frac{Z_s(x)-Z_s^*}{Z_s^*})) \tag{14}$$

Snyder and Daskin (2006) incorporated q_s into the Min-Max Relative Regret model and formulated the following optimization model, namely '*p-Robustness*' with a pre-determined and positive threshold value *p*, as shown in equations 15 and 16. They assumed that p must be a positive number.

$$Min\sum_{s\in S} q_s Z_s(x) \tag{15}$$

$$\frac{Z_s(x)-Z_s^*}{Z_s^*} \le p \quad \forall s\in S,\ \forall x\in X \tag{16}$$

Equation 16 can be re-written as equation 17. If the probability of scenario occurrence (q_s) is relatively low, a large *p* value is suggested to relax the constraint.

$$Z_s(x) \le Z_s^*(1+p) \quad \forall s\in S,\ \forall x\in X \tag{17}$$

Since the probability of scenario occurrence (q_s) is somewhat difficult to estimate in practice, we mainly apply the min-max regret method developed by Kouvelis and Yu (*31*). It should be noted that the percentage and normalization are in different. In order to integrate multiple objective values, we revise the Min-Max regret function based on Fatemeh and Tarokh's normalization technique (2010), into the following new Min-Max regret function:

$$\underset{x\in X}{Min}(\sum_{i=1}^{k} w_i^p\ \underset{s\in S}{Max}\left|\frac{Z_{s,i}(x)-Z_{s,i}^*}{Z_{s,i}^{\max}-Z_{s,i}^*}\right|)^{\frac{1}{P}} \tag{18}$$

The optimization of the studied MMINLP model is typically difficult due to their combinatorial nature and potential existence of multiple local minima. Meng and Wang (2011) proved that MINLP is a NP-Hard problem. Since nonlinear programming problems are usually much harder to solve than linear programming problems, some previous studies tend to transform the nonlinear functions into piece-wise linear functions, which can reduce nonlinear problems to linear ones. Those transformations might reduce the problem's complexity but sometimes could only offer a reasonable bound.

Many previous studies apply genetic algorithms (GAs) to solve MINLP applications (e.g.

Cheung et al., 1997; Ponsich et al., 2007.) The application of GAs to a specific problem includes several steps. A proper encoding method should be devised first. A fitness function is required for selecting individuals and evaluating produced offspring, which is derived through some problem-specific genetic operators. Thus the main aspects of GAs should include solution encoding, initial population, fitness function, selection, genetic operators, and population replacement.

Since GAs are well suited for solving such nonlinear programming problems with complex and nonlinear formulations, the numerical examples in this study are solved by Matlab GA toolbox to examine the model feasibility. A potential solution to the problem is encoded into a binary string, called a chromosome, of a given length which depends on the required precision. Here the initial population is randomly generated. In most cases where GAs are applied, the fitness function is the objective function to be optimized (i.e. the minimization of the product of total time-dependent cargo value loss and the corresponding system throughputs in this study.) The individuals in the population are selected to reproduce offspring according to their fitness value. A crossover operator generates the offspring by swapping parents' genes at some randomly chosen locus of the chromosomes. In this study, a scattered crossover function creates a random binary vector. A probabilistic distribution adds a random number to each vector entry of an individual. This random number is taken from a Gaussian distribution centered on zero. Finally, the stopping criteria has been set as either reach the maximum 500 generations, and/or no more improvement during the consecutive 100 iterations.

4. MODLE APPLICATIONS AND COMPUTATIONAL RESULTS

This study develops a robust optimization model devoted to managing proactive resilience strategies in intermodal logistics networks, from potential disruptions under changing environment. Most input parameters are generated through literature review, information gathered from websites, and extensive consultation with our industrial partners, to closely replicate real world data.

Case 1: Small Network Configurations with Multiple Source Disruptions

In Case 1, the studied network contains 10 nodes and 32 links, as shown in Figure 2. Four different modes are considered, namely: truck (m = 1), aircraft (m = 2), rail (m = 3), and ship (m = 4). Here we assume that each mode only support by one carrier. There are four shipments (b=1, 2, 3, 4) with two kinds of commodities. The time- dependent cargo value functions and demand information are shown in Table 1.

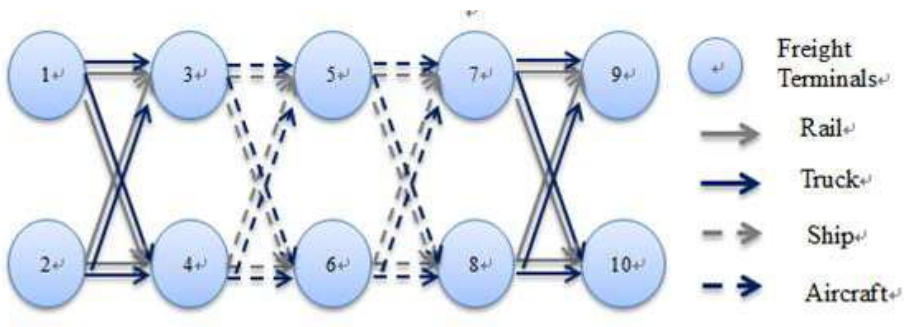

Figure 2 An illustration of Small Network Configuration

Table 1 Demand and Time-Dependent Cargo Value Loss Functions

b	(Origin, Destination)	Shipment Demand (Unit: lbs)	Time-Dependent Value Functions
1	(1,10)	30,000	$\mu^b = \begin{cases} 50, & 0 < t \leq 240\ hrs \\ 30, & t > 240\ hrs \end{cases}$
2	(2,9)	30,000	$\mu^b = \begin{cases} 50, & 0 < t \leq 240\ hrs \\ 30, & t > 240\ hrs \end{cases}$
3	(2,10)	40,000	$\mu^b = \begin{cases} 100, & 0 < t \leq 240\ hrs \\ 10, & t > 240\ hrs \end{cases}$
4	(1,9)	40,000	$\mu^b = \begin{cases} 100, & 0 < t \leq 240\ hrs \\ 10, & t > 240\ hrs \end{cases}$

Seven scenarios are listed in Table 2, from single source delay perturbations to multiple disruptions resilience. The capacity reduction factors due to disruptions are as follows: γ_5 = 0.9 (i.e. represents that 90% of capacity remains unused at node 5,) α_{36} = 0.8 (i.e. means that the capacity at link (3, 6) is 80% of the original capacity), and β_{35} = 0.9. For example, link disruptions represent that corridors damage resulted from the disasters. For example, the highway might be blocked and partially destroyed by typhoons. Difference disasters might incur various damage within the studied network. All optimized results are listed in Table 3.

Table 3 Detailed Parameter Settings in Different Scenarios

Scenario (s)	**Disruptions Type**	**Capacity Reduction Factors**
1	link disruptions	α_{36} = 0.8, α_{46} = 0.8, α_{67} = 0.8, and α_{68} = 0.8
2	mode failures	β_{35} = 0.9, β_{45} = 0.9, β_{57} = 0.9, and β_{58} = 0.9.
3	terminal closures	γ_5 = 0.9
4	link disruptions and mode failures	Both scenarios 1 and 2 occur simultaneously.
5	link disruptions and terminal closures	Both scenarios 1 and 3 occur simultaneously.
6	mode failures and terminal closures	Both scenarios 2 and 3 occur simultaneously.
7	link disruptions, mode failures, and terminal closures	All scenarios 1, 2, and 3 occur simultaneously.

Although we can determine the optimized resilience strategies for each scenario, it should be noted that decision makers may not be able to invest all due to limited budget during the pre- planning and design stage. A robust optimization technique can assist decision makers to determine the most reliable strategy via our new Min-Max regret method.

Detailed processes of the robust optimization technique are illustrated in Tables 3(a)-3(d). We first calculate the scenario-strategy matrix with optimized fitness values (after normalization), as shown in Table 3(a). After finding the smallest value of each row (see Table 3(b),) we then further compute the regret values, as listed in Table 3(c). The worst regret values can be found in Table 3(d). Finally, the lowest worst regret value is 0.105, which represents the fifth strategy.

Table 3. (a) The Optimized Fitness Values, (b) Finding the Smallest Value of Each Row, (c) Computing the Regret Values, and (d) Finding the Worst Regret Value of Each Column

		Proactive Resilience Strategies						
		1	2	3	4	5	6	7
S	1	0.086	0.150	0.168	0.132	0.132	0.150	0.132
	2	0.205	0.145	0.286	0.186	0.250	0.145	0.186
	3	0.191	0.132	0.082	0.186	0.045	0.132	0.186
	4	0.291	0.355	0.373	0.277	0.336	0.291	0.277
	5	0.277	0.341	0.168	0.259	0.132	0.277	0.259
	6	0.205	0.145	0.286	0.186	0.250	0.145	0.186
	7	0.293	0.355	0.373	0.273	0.336	0.291	0.273

		Proactive Resilience Strategies						
		1	2	3	4	5	6	7
S	1	0.086	0.150	0.168	0.132	0.132	0.150	0.132
	2	0.205	0.145	0.286	0.186	0.250	0.145	0.186
	3	0.191	0.132	0.082	0.186	0.045	0.132	0.186
	4	0.291	0.355	0.373	0.277	0.336	0.291	0.277
	5	0.277	0.341	0.168	0.259	0.132	0.277	0.259
	6	0.205	0.145	0.286	0.186	0.250	0.145	0.186
	7	0.293	0.355	0.373	0.273	0.336	0.291	0.273

		Proactive Resilience Strategies						
		1	2	3	4	5	6	7
S	1	0.000	0.064	0.082	0.045	0.045	0.064	0.045
	2	0.059	0.000	0.141	0.041	0.105	0.000	0.041
	3	0.145	0.086	0.036	0.141	0.000	0.086	0.141
	4	0.014	0.077	0.095	0.000	0.059	0.014	0.000
	5	0.145	0.209	0.036	0.127	0.000	0.145	0.127
	6	0.059	0.000	0.141	0.041	0.105	0.000	0.041
	7	0.020	0.082	0.100	0.000	0.064	0.018	0.000

		Proactive Resilience Strategies						
		1	2	3	4	5	6	7
S	1	0.000	0.064	0.082	0.045	0.045	0.064	0.045
	2	0.059	0.000	0.141	0.041	0.105	0.000	0.041
	3	0.145	0.086	0.036	0.141	0.000	0.086	0.141
	4	0.014	0.077	0.095	0.000	0.059	0.014	0.000
	5	0.145	0.209	0.036	0.127	0.000	0.145	0.127
	6	0.059	0.000	0.141	0.041	0.105	0.000	0.041
	7	0.020	0.082	0.100	0.000	0.064	0.018	0.000

It should be noted that short-term renting capacity is almost undesirable among scenarios, during the phase of pre-disruption planning. In addition, decision makers can also prioritize and sequence the candidate resilience strategies due to limited budget. Finally, all optimized results are recorded in Table 4.

Table 4. Optimized Resilience Strategies in Case 1

S	**Disruptions Type**	**Resilience Strategies**
1	Link	Selecting alternative routes
2	Mode	Long-term renting capacity: increasing 40,000 lbs capacity on arc (6, 8) shipped by air
3	Node	Terminal expansions: increasing 600,000 lbs capacity at node 5
4	Scenarios 1 and 2	Long-term renting capacity: increasing 24,000 lbs capacity on arc (6, 7) shipped by air
5	Scenarios 1 and 3	Terminal expansions: increasing 600,000 lbs capacity at node 5
6	Scenarios 2 and 3	Long-term renting capacity: increasing 40,000 lbs capacity on arc (6, 7) shipped by air
7	Scenarios 1, 2, and 3	Long-term renting capacity: increasing 24,000 lbs capacity on arc (6, 7) shipped by air

Case 2: Flood Disasters Disruption Resilience in Thailand

While flood disasters occurred every summer in Thailand, these disruptions usually cause severe transportation problems. Several candidate strategies are developed for alleviating these frequent disasters. The studied international logistics network contains 18 nodes and 38 links, as shown in Figure 3. Three scenarios are analyzed while considering different levels of flood events. All optimized results are listed in Table 5.

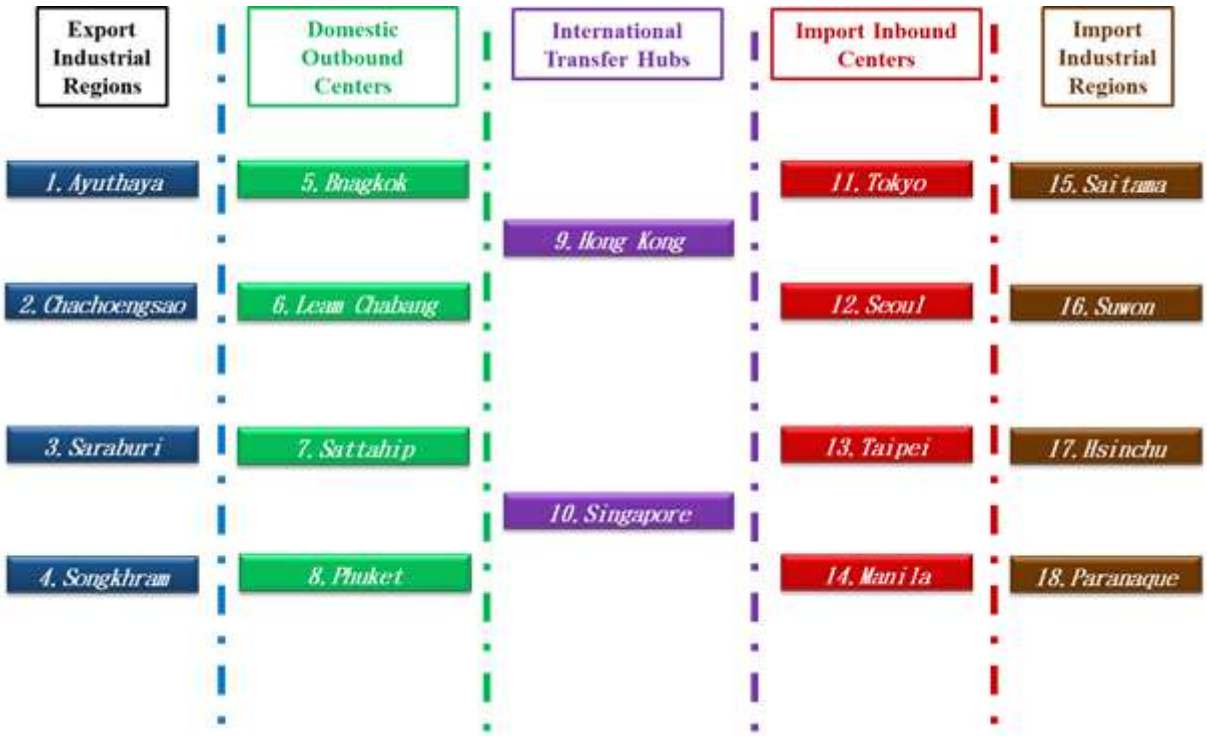

Figure 3 The Studied International Express Logistics Network System in Thailand

Table 6 Optimized Resilience Strategies in Case 2

s	Level of Flood Impact	Optimized Resilience Strategies
1	Minor	1. **Terminal expansions** Increasing 4,000/26,000/25,000/16,000/19,000/11,000 lbs capacity at nodes 1, 2, 3, 4, 7, and 8, respectively. 2. **Long-term renting contracts** increasing 50,000/49,000/41,000 lbs capacity on arcs (2, 5)/(3, 7)/(4, 8) shipped by rail, respectively. 3. **Short-term renting contracts** increasing 1,000 lbs capacity on the arc (6, 10) via ship.
2	Middle	1. **Terminal expansions** increasing 8,000/25,000/27,000/29,000/62,000 lbs capacity at nodes 1, 2, 3, 4, and 7, respectively. 2. **Long-term renting contracts** increasing 44,000/45,000 lbs capacity on arcs (2, 5) and (3,

			7) shipped by rail, and increasing 47,000 lbs capacity on the arc (4, 7) via ship.
		3.	**Short-term renting contracts** increasing 1,000 lbs capacity on the arc (6, 10) via ship.
3	Severe	1.	**Terminal expansions** increasing 42,000/28,000/35,000/29,000/20,000/55,000/11,000 lbs capacity at nodes 1, 2, 3, 4, 6, 7, and 8, respectively.
		2.	**Long-term renting contracts** Increasing 45,000/41,000 lbs capacity on arcs (3, 7) and (4, 8) via ship, and increasing 15,000 lbs capacity on the arc (1, 6) shipped by rail.

In accordance with different level of flood impact areas, the proactive resilience strategies for each scenario are optimized. But if decision makers cannot implement all strategies simultaneously due to limited budget, our robust min-max regret model can assist them to choose the most reliable resilience alternative. As shown in Table 6, the third strategy for severe flooding events should be planned and design in advance.

Table 6 (a) The Optimized Fitness Values (b) The Worst Regret Values in Case 2

		Resilience Strategies		
		1	2	3
Scenarios	1	0.070	0.077	0.110
	2	0.127	0.077	0.110
	3	0.215	0.176	0.110

		Resilience Strategies		
		1	2	3
Scenarios	1	0.000	0.007	0.040
	2	0.050	0.000	0.033
	3	0.106	0.066	0.000

Here we also develop a resilience index to measure the system resilience performance, as expressed in equation 19. Herein, the resilience ε is derived from the product of total time-dependent cargo value loss and the corresponding throughput before and after the disruptions. For example, ε = 0.5 represents that 50% of system resilience remains unrecovered. In this study, the resilience index of scenario 1, 2, and 3 are 0.42, 0.405, and 0.255, respectively. It should be noted that system performance would be affected by budget constraint.

$$\varepsilon = E\left(\frac{\sum_{b}\sum_{i}\sum_{j,i\neq j}\sum_{m}\left[\mu(t_0)^b - \mu(T_{(s)})^b\right] f_{(s)ij}^{bm}}{\sum_{b}\sum_{i}\sum_{j,i\neq j}\sum_{m}\left[\mu(t_0)^b - \mu(T_{(s)})^b\right] F_{(s)ij}^{bm}}\right) \tag{19}$$

Figure 4 illustrates the trade-off between the product of total time-dependent cargo value loss and the corresponding throughput, as well as the costs incurred with resilience enhancement strategies, based on different budget levels. The optimal decisions are determined based on the overall trade-off results among resilience benefits and incremental costs to implement strategies. More budget amounts can increase the system performance but yield diminishing resilience effects.

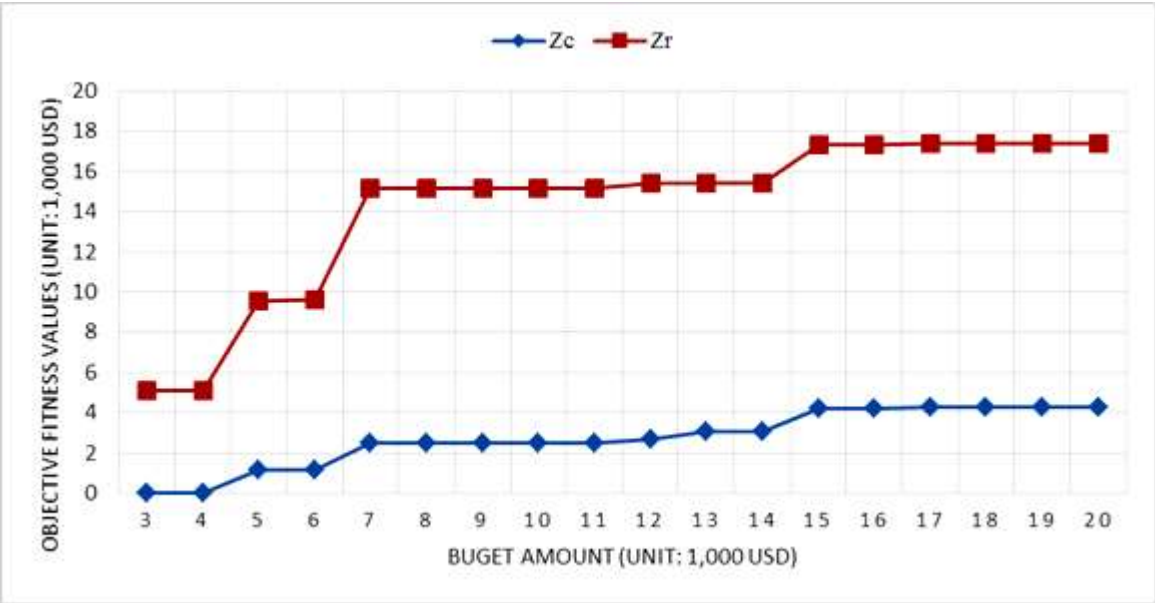

Figure 4 Costs and Benefits Analysis with Different Budget Levels

5. CONCLUSIONS

Nowadays the international express companies rarely respond to severe disruptions through systematic measures to determine how to transport cargos in a timely manner. Although the numerical examples seem relatively simple, the main purpose is to examine and demonstrate the ability of our proposed models and optimize the resilient strategies during the freight system pre-planning and design stages. Using nonlinear time-dependent cargo value functions, we consider a set of resilient actions such as investing in freight terminal expansions, selecting alternative routes, switching shipping modes, developing long-term and short-term contracts for renting other carriers' capacities, and prioritizing and sequencing shipments due to limited capacities. The results show that the resilient strategies decrease the total shipping time and increase the delivery rate before the customers' request deadlines.

For planning purposes, the models can provide an overview for decision makers in developing a robust regional freight transportation network system including the alignments of corridors, location choices of transfer terminals, and design of warehouses and storage facilities. From the operational viewpoint, the models can help carriers, forwarders, and terminal operators relieve disaster impacts during the phases of post-disruptions. These models might also be used by consortiums or alliances of private freight transportation companies.

In this study, we develop a robust MMINLP problem to quantify and optimize the proactive resilience strategies for different disruption scenarios. Optimized results of each

scenario are further jointly compared to distinguish the system performance among all situations, especially under limited budget and cannot implement all strategies simultaneously. In Case 1, we mainly seek to examine the model feasibility and observe the robust strategies from single source delay perturbations to multiple disruptions resilience. Our robust optimization technique can assist decision makers to determine the most reliable strategy under budget constraints.

In accordance with different level of flood impact areas in Case 2, the proactive resilience strategies for each scenario are optimized. Although the resilience index in Case 2 shows that the studied system only recover by 25% - 42%, decision makers could consider to lift budget constraint at the appropriate timing to improve system resilience. Moreover, it might be worth considering proactive resilient strategies in details, such as optimal reserved capacities at some hubs with high vulnerabilities.

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