Modeling Resilience Enhancement Strategies for International Express Logistics

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International express is a most time-sensitive industry, and members of this industry must be able to respond to disruptions quickly to ensure service quality and to avoid a loss of their competitiveness with other logistics service providers. Instead of a method that arbitrarily makes rushed decisions during the postdisruption phase, this paper describes a method for quantifying and optimizing resilience strategies based on concepts of integrated resource assignment, regardless of where the available resources are located in the logistics network studied or how much capacity can be rented from others. The study started with the use of a typical transportation network modeling approach and then incorporated nonlinear time-dependent cargo value functions into a multiobjective mixed-integer nonlinear programming problem. A set of optimal actions from resilience strategies, such as the selection of alternative routes, switching of shipping modes, rental of other carriers' capacities, reallocation of local trucks, and prioritization of the order of shipments because of limited capacities, was considered. Decisions should be based on overall trade-off considerations and, at the same time, joint maximization of the product of the total time-dependent cargo value and the corresponding throughput and minimization of the costs incurred with resilience enhancement strategies.

Supply chain systems are increasingly threatened by natural and human-made disasters, as shown in Figure 1. Sheffi found that the impacts of a disaster on a supply chain are heightened under current conditions in which product life cycles are ever shrinking and markets are unpredictable (*1*). When major disruptions occur, such as the volcano in Iceland in 2010 and the earthquake and tsunami in Japan in 2011, entire logistics systems are severely affected, and these effects can generate huge economic losses. Thus, many enterprises are motivated to draw up different resilience strategies to relieve the catastrophic impacts caused by disasters.

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The subject of this research, the international express industry, is one of the fastest-growing sectors in the global economy. Express logistics operators can provide reliable, fast, on-demand, worldwide, integrated, and door-to-door shipping services. In general, the core business of the express industry is the provision of value-added, door-to-door transport and a highly time-sensitive delivery service. When any disruption occurs, these shipments may require the implementation of resilience strategies to mitigate the adverse influences of the disruption.

The concept of supply chain resilience emerged in 2004 and has become widely recognized. Resilience is first defined as the ability of a system to react quickly to undesired events and then return to its original state or move to a new, more desirable state after it is disturbed (*2*). Ta et al. then defined the resilience of a freight transportation system to be "the ability for the system to absorb the consequences of disruptions to reduce the impacts of disruptions and maintain freight mobility" (*3*).

Several previous studies incorporated resilience concepts into transportation network flow problems (*4, 5*), but previous studies have seldom dealt with the time-dependent values of shipments (*6, 7*). To reflect the time-sensitive characteristics of express deliveries, four nonlinear time-dependent cargo value functions revised in this study from the work of Chen and Schonfeld (*7*), were considered, as shown in Figure 2.

Figure 2*a* illustrates the value for commodities that do not significantly change over time, such as some economic goods. Here, $\mu(t)$ represents the market value of a commodity at time t, and μ^b specifically denotes the cargo value function of shipment *b.* Figure 2*b* illustrates the value for some perishable commodities (e.g., flowers and seafood), and the corresponding time-varying value function is expressed in Equation 1:

$$\mu(t) = \frac{1}{\sqrt{2\pi z}} \exp\left(-\frac{1}{2}\left(\frac{t}{v}\right)^2\right) \tag{1}$$

where v is the time period adjustment factor, and z is the time value adjustment factor. Here it is assumed that the value of v will be a smaller number for products with shorter lifetimes. In addition, the value of z is smaller when the corresponding product has a higher market price.

Technological products, such as smartphones and tablet computers, are classified as products with short life cycles, the value for these products is shown in Figure 2*c.* The life cycle is considered short because the price may drop every week because new versions are frequently launched on the market. Certain clothing fashions also have this feature because of the possibility that they may go out of

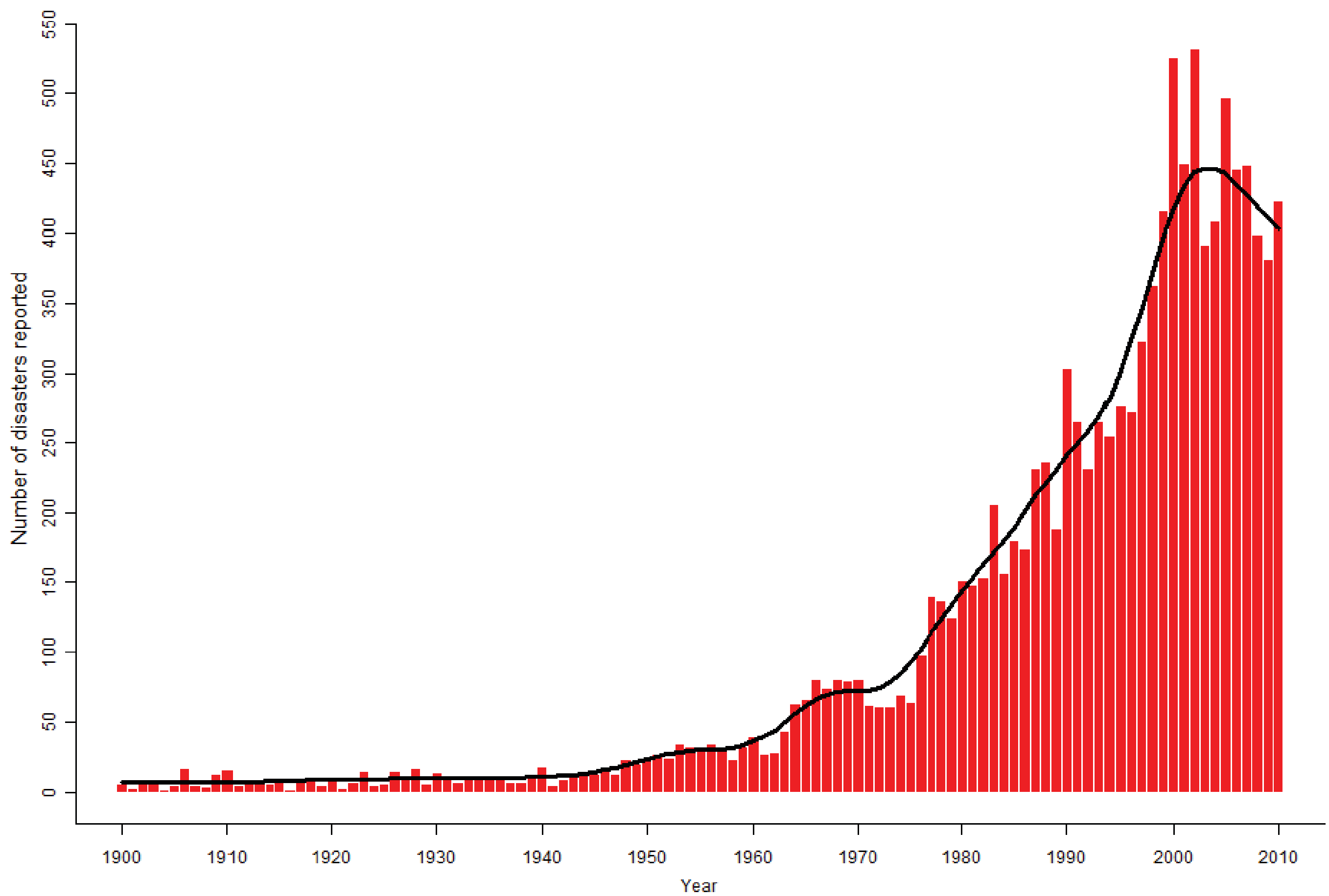

FIGURE 1 Natural disasters reported from 1900 to 2010. (Source: EM-DAT emergency events database, 2010.)

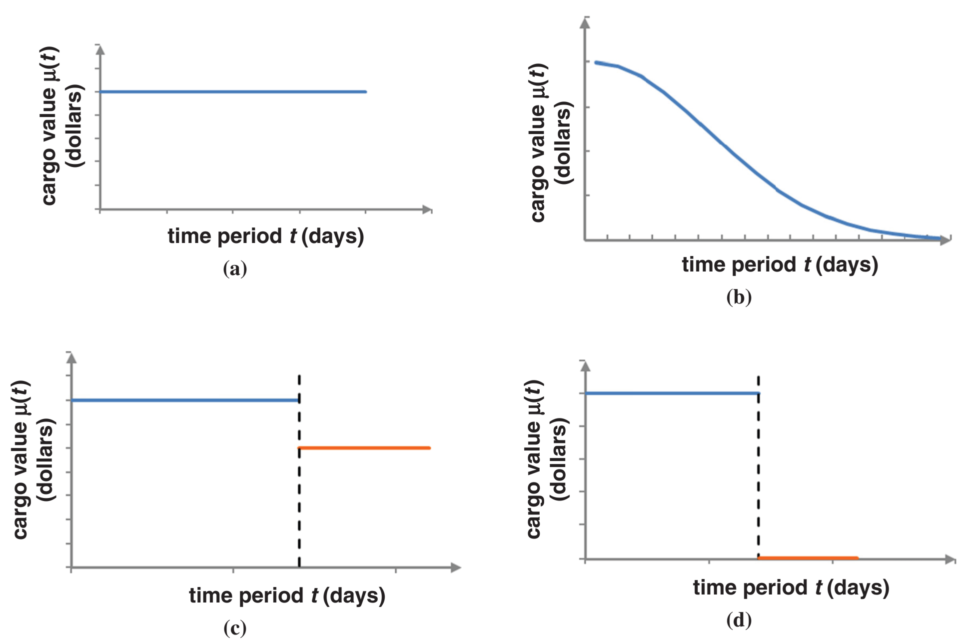

FIGURE 2 Time-dependent cargo value functions: (*a*) products with constant values over time, (*b*) perishable products, (*c*) commodities with short life cycles, and (*d*) holiday gifts.

style. This kind of time-dependent cargo value function is formulated in the following equations, where u is a price decay factor:

$$\mu(t) = \begin{cases} \text{market price} & 0 < t \leq \text{time threshold} \\ (1-u)\text{market price} & t > \text{time threshold} \end{cases} \tag{2}$$

Figure 2*d* illustrates the value for the most time-sensitive commodities (e.g., holiday gifts). Equation 3 indicates that the total cargo value approaches 0 if the total shipping time exceeds the specific time windows:

$$\mu(t) = \begin{cases} \text{market value} & 0 < t \leq \text{time threshold} \\ 0 & t > \text{time threshold} \end{cases} \tag{3}$$

When any nonrecurrent event occurs, the model seeks to optimize all available transportation resources to facilitate recovery of the system in a timely manner. A set of resilience enhancement strategies identified from a literature review and interviews with practitioners is considered in the model described here. These strategies include selection of alternative routes, switching of shipping modes, rental of other carriers' capacities (if applicable), reallocation of local trucks, and prioritization of the order of shipments because of limited capacities.

The capacity to rent (e.g., extra containers or spare transportation modes) from other carriers is one major action that international express companies take in practice. Such an action can be further divided into two types: rental from noncontractual carriers and rental from contractual partners.

Because noncontractual carriers may not be able to provide sufficient and efficient capacities, some logistics service providers tend to develop strategic alliances to achieve economies of scale and increase the use of unfilled space. Oum et al. described a strategic alliance as a medium- to long-term partnership formed by two or more firms with a common goal of improving competitiveness (*8*). For example, DHL Express and Polar Air Cargo Worldwide have a long-term contractual service agreement. The partnership transaction includes a commercial arrangement that gives DHL Express guaranteed access to the aircraft capacity of Polar Air Cargo Worldwide in key global markets. The transit times are reduced, and the reliability of delivery is increased. In general, contractual partners can provide a better level of service and satisfy contingent or emergent requirements in a timely manner. However, the total costs of maintenance of these contracts are higher than the cost to rent from noncontractual carriers.

During normal operations, international express companies tend to ship cargo by use of the fastest path and mode combinations (e.g., truck–air–truck). Trucks for inland transport need to deliver cargo by the departure times of scheduled flights at airports; otherwise, the cargo is delayed until the next available flight. However, rail and maritime modes of transport are considered only if the preplanned routes and modes are no longer available because of disruptions. These slow shipping modes are chosen for short-term transfers to other fast modes. For example, because airports in Shanghai, China, are usually overwhelmed during Japan's Golden Week in April, some shipments are shipped through other intermodal logistics operations (i.e., truck–port–truck–air) from the Port of Shanghai to the Port of Keelung in Taiwan and then transferred to the Taiwan Taoyuan International Airport. Airports in the United States are also overwhelmed during the Thanksgiving holiday in November of each year. This study also considers different intermodal operations to enhance the resilience capability of the system when severe disruptions occur.

Through interviews with practitioners, the authors observed that certain international express operators are using strategies to improve system resilience and robustness by allocating buffers (e.g., slack times) or additional resources (e.g., spare capacities) to absorb disturbances. Although adequate buffers can help operators reduce the queuing pressure caused by disruptions, the high costs required to maintain spare capacities still limit the effects of systems used to create resilience.

The aim of the research described here is to study which resilience strategies international express companies should choose when disruptions occur and affect their delivery activities. The core concepts for integration of the resilience treatments are built into the proposed model and are illustrated in Figure 3.

The remainder of this paper is organized as follows: several resilience strategies are developed from literature reviews and interviews with experts and practitioners. The relevant optimization problems are described in detail. Through a case study solved with commercial software, the optimal strategies and decisions needed to relieve the impacts of disruptions are determined. Finally, some concluding remarks are offered.

MODEL ASSUMPTIONS AND FORMULATIONS

The intermodal logistics network studied includes multiple hubs, multiple modes, multiple carriers, and multiple commodities. The network is given by $G = (N, L)$, where G represents the directed network graph; N, which is equal to $\{1, \ldots, n\}$, is the set of nodes; and L, which is equal to $\{(i, j) \mid i, j \in N\}$ (where i and j are nodes), is the set of links. Cargos are denoted as a set of shipping orders, $b \in B$. Each order records a pair of origin and destination nodes with the corresponding time-dependent cargo value function. A path is defined as an acyclic chain of arcs.

Three failure types caused by disruptions are defined in this study, namely, link, node, and mode failures. Three adjustment factors (α_{ij}^m, β_i, and γ_i, where m is the mode) describe the capacity reductions after disruptions. Other basic assumptions are listed below:

- All attributes within the studied network, such as link travel costs, times, and capacities by different transportation modes, are given;
- The information about available routes and terminals is already known during the predisruption phase;
- Each order is detachable, which means that vehicles can transport partial amounts of cargos based on optimized results; and
- The rental time includes the time to dispatch the rented capacity from the carriers (if renting activities become applicable).

The model is expressed as follows:

$$\max \sum_{b,j \in d} \left[\mu^b \left(A^b\right) \left(\sum_{m,i} f_{ij}^{bm} \right) \right] \tag{4}$$

$$\min \sum_{m,e,i,j} \left(\mathrm{KR}_{ij}^{me}\right)\left(\mathrm{RC}_{ij}^{me}\right) + \left(\sum_{i,j} \frac{\left|\mathrm{WL}_{ij} - W_{ij}\right|}{2} \right) C^* \tag{5}$$

subject to

$$\sum_b f_{ij}^{bm} \leq \alpha_{ij}^m K_{ij}^m \qquad \forall m \in M, i, j \in N, i \neq j \tag{6}$$

$$\sum_b f_{ij}^{bm} \leq \gamma_i K_{ij}^m \qquad \forall m \in M, i, j \in N, i \neq j \tag{7}$$

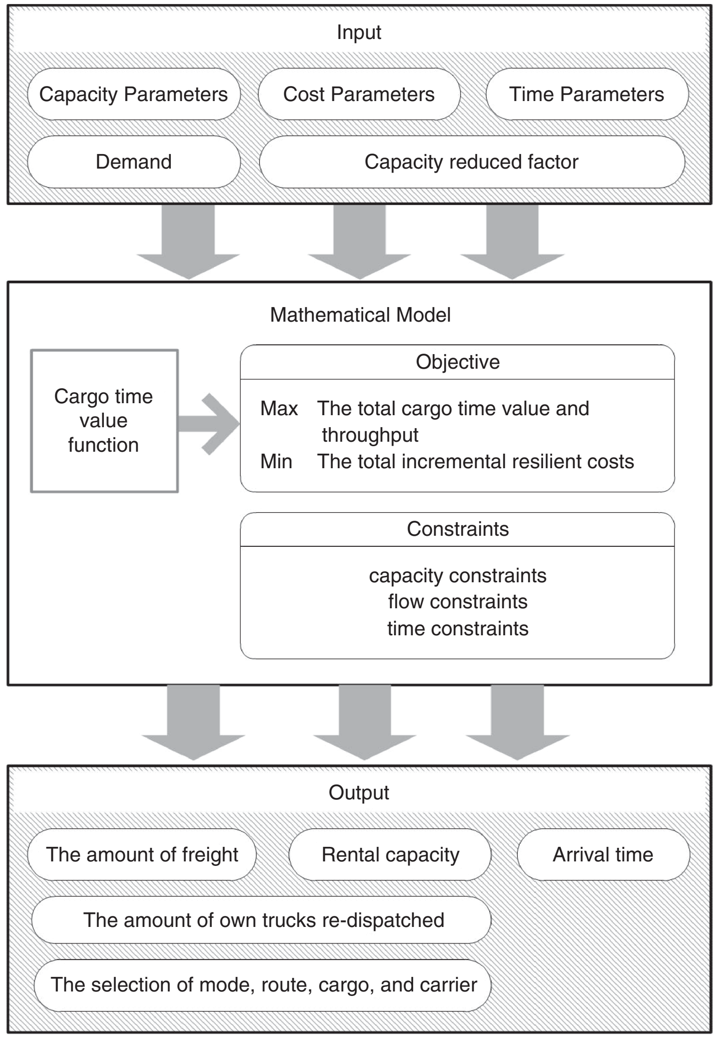

FIGURE 3 Conceptual model for integration of resilience treatments (max = maximum; min = minimum).

$$\sum_{b} f_{ij}^{bm} \leq \gamma_j K_{ij}^{m} \qquad \forall m \in M, i, j \in N, i \neq j \tag{8}$$

$$\sum_{b}\sum_{m\in \mathrm{Tr}} f_{ij}^{bm} \leq \mathrm{WL}_{ij} + \sum_{m\in \mathrm{Tr}}\sum_{e} \mathrm{KR}_{ij}^{me} \tag{9}$$

$$\sum_{b} f_{ij}^{bm} \leq \sum_{e} \mathrm{KR}_{ij}^{me} \qquad \forall m \in \mathrm{Ra}, i \in \mathrm{OS} \cup \mathrm{DP}, j \in \mathrm{OP} \cup \mathrm{DS}, i \neq j \tag{10}$$

$$\sum_{b}\sum_{m\in \mathrm{Ai}} f_{ij}^{bm} \leq \beta_i \mathrm{WA}_{ij} + \sum_{m\in \mathrm{Ai}}\sum_{e} \mathrm{KR}_{ij}^{me} \tag{11}$$

$$\sum_{b} f_{ij}^{bm} \leq \sum_{e} \mathrm{KR}_{ij}^{me} \qquad \forall m \in \mathrm{Sh}, i \in \mathrm{OP} \cup \mathrm{TP}, j \in \mathrm{TP} \cup \mathrm{DP}, i \neq j \tag{12}$$

$$\sum_{j\in \mathrm{OP}\cup \mathrm{DS}} \mathrm{WL}_{ij} \leq \beta_i\ \mathrm{KL}_i \qquad \forall i \in \mathrm{OS} \cup \mathrm{DP}, i \neq j \tag{13}$$

$$\mathrm{KR}_{ij}^{me} \leq \mathrm{AK}_{ij}^{me} \qquad \forall m \in M, e \in E, i, j \in N, i \neq j \tag{14}$$

$$\sum_{j}\sum_{b,m} f_{ji}^{bm} = \sum_{j}\sum_{b,m} f_{ij}^{bm} \qquad \forall i \in N, i \neq j \tag{15}$$

$$\sum_{j}\sum_{m} f_{ji}^{bm} = \sum_{j}\sum_{m} f_{ij}^{bm} \qquad \forall b \in B, i \in N, i \neq j \tag{16}$$

$$\sum_{m}\sum_{i\in \mathrm{DP}} f_{ij}^{bm} \leq \sum_{o} \mathrm{DM}_{od}^{b} \qquad \forall j = d, b \in B \tag{17}$$

$$\sum_{m,j}\sum_{j\in \mathrm{OP}} f_{ij}^{bm} \leq \sum_{d} \mathrm{DM}_{od}^{b} \qquad \forall i = o, b \in B \tag{18}$$

$$\sum_{m,j} \delta_{ij}^{bm} \leq 1 \qquad \forall i \in N, b \in B \tag{19}$$

$$\delta_{ij}^{bm} = \begin{cases} 0 & \text{if } f_{ij}^{bm} = o \\ 1 & \text{if } f_{ij}^{bm} > o \end{cases} \tag{20}$$

$$y_{ij}^{me} = \begin{cases} 0 & \text{if } \mathrm{KR}_{ij}^{me} = o \\ 1 & \text{if } \mathrm{KR}_{ij}^{me} > o \end{cases} \tag{21}$$

$$A^b = \sum_{m\in M, i\in N, j\in N} \delta_{ij}^{bm}\left[f_{ij}^{bm} S_j + T_{ij}^m + \sum_e \left(y_{ij}^{me}\mathrm{RT}_i^{me}\right) + \frac{\left|\mathrm{WL}_{ij} - W_{ij}\right|}{2}(T^*)\right] \tag{22}$$

where

M = set of modes,
Tr = set of trucks,
Ai = set of aircraft,
Sh = set of ships,
Ra = set of trains,
E = set of multicarrier recovery activities,
o = set of origins,
d = set of destinations,
OS = set of service centers in origin country,
OP = set of seaports or airports in origin country,
DS = set of service centers in destination country,
DP = seaports or airports in destination country,
TP = seaports or airports in transshipment country,
f_{ij}^{bm} = amount of cargo with shipping code b on arc (i, j) shipped by mode m,
WL_{ij} = capacity of private trucks reallocated to arc (i, j),
KR_{ij}^{me} = rental capacity of mode m on arc (i, j) from partner e,
A^b = total shipping time of cargo with shipping code b,
K_{ij}^m = maximum allowable capacity of arc (i, j) for mode m,
KL_i = capacity of available trucks at node i,
W_{ij} = capacity of original truck allocation on arc (i, j) before disruption occurs,
WA_{ij} = available flight capacity on arc (i, j),
AK_{ij}^{me} = available rental capacity on arc (i, j) of mode m by carrier e,
RC_{ij}^{me} = cost of rental capacity from carrier e for mode m on arc (i, j),
C^* = truck reallocation costs,
S_j = service time and cargo sorting time at node i,
T_{ij}^m = travel time from node i to node j via mode m,
RT_i^{me} = total rental process time of mode m from carrier e at node i,
T^* = extra time spent on reallocation of trucks,
DM_{od}^b = total demand with shipping code b from origin o to destination d,
$\mu(t)^b$ = time-dependent cargo value function of cargos with shipping code b, and
y_{ij}^{me} and δ_{ij}^{bm} = indicator variables.

To satisfy customers' delivery requests as much as possible, the first objective function (Equation 4) is derived from the maximization of total system throughputs. A priority rule for those shipments with higher cargo time values is further defined here. That is, shipments with higher priority will be shipped first if capacities are insufficient. If the system operators want to implement resilience enhancement strategies, all incremental resilience costs will be considered, as shown in the second objective function (Equation 5.) Both objective functions are optimized on the basis of overall tradeoff considerations, and the express company must simultaneously balance customer satisfaction and the recovery costs.

Equations 6 to 8 express the link capacity constraints. Equations 9 and 10 represent the mode capacity constraints for ground transportation. Equations 11 and 12 indicate the mode capacity constraints for transnational transportation. Equations 13 and 14 ensure that the sum of truck capacities and rental capacities satisfy the requirements. Equations 15 and 16 state the flow conservation constraints. Equations 17 and 18 express the demand constraints. Equation 19 specifies that at most one path can be chosen for an identical shipment, and Equations 20 and 21 define the binary indicator variables δ_{ij}^{bm} and y_{ij}^{me}. The variable δ_{ij}^{bm} is equal to 1 if cargo flow with shipment b passes through arc (i, j) by mode m and 0 otherwise. The variable y_{ij}^{me} is equal to 1 if the recovery capacity (KR_{ij}^{me}) is not 0 and 0 otherwise. Equation 22 calculates the total shipping time.

MODEL APPLICATIONS AND ANALYTICAL RESULTS

The purpose of this work is to optimize the resilience decisions on the basis of the consideration of two objectives. Fatemeh and Tarokh developed a compromise programming approach for k objectives to minimize the distance between some reference point and the feasible objective region (*9*). This approach was also adopted in this study. When k objective functions of $\{f_1(x), f_2(x), \ldots, f_k(x)\}$ [where $f(x)$ represents function f corresponding to input x] are considered to be optimized simultaneously, some corresponding design references of $\{f_1^*, f_2^*, \ldots, f_k^*\}$ are assigned on the basis of the lower bound of each objective function $\{f_{1,\max}, f_{2,\max}, \ldots, f_{k,\max}\}$ (for the minimization problems). Thus, the problem is reformulated as shown in Equation 23:

$$\min\left(\sum_{i=1}^{k} w_i^p \left|\frac{f_i(x) - f_i^*}{f_{i,\max} - f_i^*}\right|^p\right)^{1/p} \tag{23}$$

where w is the weight of each objective function and p is a specified exponent.

Because the unit of each objective function might be different, a normalization process is required. The multiobjective mixed-integer nonlinear programming problem studied is solved with the LINGO (Version 12.0) program, and all programs are executed on a PC with an Intel Core i7 processor and a central processing unit with a 2.93-GHz processor and 4 GB of RAM. Here it is assumed that the maximum allowable resilience duration is 6 days.

The network studied contains nine nodes and 12 links, as shown in Figure 4. Five shipments ($b = 1, 2, 3, 4, 5$) with two kinds of com-

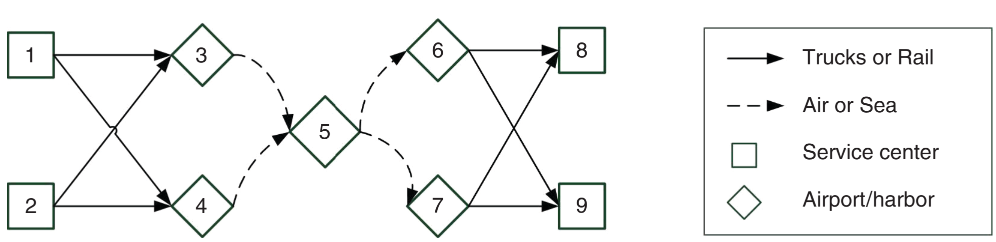

FIGURE 4 Network configuration in the case study.

TABLE 1 Demand and Time-Dependent Cargo Value Functions

b	Origin, Destination	Shipment Demand (lb thousands)	Time Value Function
1	1, 8	10	$\mu^b = 20$
2	2, 9	7	
3	1, 9	5	
4	2, 8	6	$\mu^b = \begin{cases} 100 & 0 < t \le 200 \\ 10 & t > 200 \end{cases}$
5	1, 9	3	

modities are studied. The time-dependent cargo value functions and demand information are shown in Table 1.

Four modes are considered, namely, truck ($m = 1$), aircraft ($m = 2$), rail ($m = 3$), and ship ($m = 4$). Link capacity and transportation time are listed in Table 2. The capacities of self-owned trucks and flights are recorded in Table 3. The capacities of the trucks and the cargo processing time at each node are given. Table 4 shows the parameter settings for rental activities. The capacity reduction factors caused by disruptions are as follows: γ_3 is equal to 0.1, α_{13}^1 is equal to 0.4, and α_{24}^1 is equal to 0.4. Here, γ_3 equal to 0.1 indicates that only 10% of the capacity at Node 3 remains unused. Similarly, α_{24}^1 equal to 0.4 means that the capacity at Link (2, 4) is 40% of the original capacity.

All optimized results are listed in Table 5. For example, cargo whose shipping code is 1 is transported from Node 1 to Node 4 by truck, from Node 4 to Node 5 by sea, from Node 5 to Node 7 by air, and from Node 7 to Node 8 by truck. All demands are satisfied, and the total shipping time is 274 h. Most cargo shipped over such a long period of time consists of commodities with a constant cargo time value setting. Most perishable commodities are delivered by air. Some shipments could not be completed (i.e., the shipping code is 2) because of limited link capacities during the postdisruption phase. Table 6 shows that some trucks were reallocated to Links (1, 4) and (2, 3). In addition, the system operators had to rent some capacity from other maritime carriers at Link (4, 5).

TABLE 2 Settings of Link Capacities and Corresponding Transport Times

Link (i, j)	K_{ij}^m	T_{ij}^m (h)	Link (i, j)	K_{ij}^m	T_{ij}^m (h)
$m = 1$			$m = 3$		
(1, 3)	22	3.3	(1, 3)	30	4.7
(1, 4)	23	20.6	(1, 4)	15	11.7
(2, 3)	24	23	(2, 3)	15	10
(2, 4)	18	7	(6, 8)	15	5
(6, 8)	26	13	(7, 8)	25	7.5
(6, 9)	25	2.5	(7, 9)	22	10.2
(7, 8)	27	17.2			
(7, 9)	18	19.2			
$m = 2$			$m = 4$		
(3, 5)	50	7	(4, 5)	120	96.2
(4, 5)	40	6	(5, 7)	120	96.2
(5, 6)	50	6.3			
(5, 7)	40	6			

TABLE 3 Capacities of Self-Owned Trucks and Aircraft

Link (i, j)	W_{ij} (no. of vehicles)	WA_{ij} (no. of vehicles)
(1, 3)	4	NA
(1, 4)	0	NA
(2, 3)	0	NA
(2, 4)	4	NA
(3, 5)	NA	20
(4, 5)	NA	20
(5, 6)	NA	20
(5, 7)	NA	20
(6, 8)	1	NA
(6, 9)	3	NA
(7, 8)	4	NA
(7, 9)	0	NA

NOTE: No. = number; NA = not available.

TABLE 4 Parameter Settings for Rental Activities

Carrier	Link (i, j)	AK_{ij}^{me} (no. of vehicles)	RC_{ij}^{me} (\$ hundreds)	RT_i^{me} (h)
$m = 1$				
$e = 1$	(1, 3)	15	10	5
	(1, 4)	20	25	5
	(2, 3)	20	22	16
	(2, 4)	20	6	16
	(6, 8)	15	12	4
	(6, 9)	15	6	4
	(7, 8)	25	18	16
	(7, 9)	10	22	16
$e = 2$	(1, 3)	20	11	18
	(1, 4)	10	24	18
	(2, 3)	15	21	6
	(2, 4)	15	9	6
	(6, 8)	20	11	14
	(6, 9)	15	5	14
	(7, 8)	10	17	6
	(7, 9)	25	21	6
$m = 2$				
$e = 1$	(3, 5)	20	210	4
	(4, 5)	10	230	6
	(5, 6)	20	210	10
	(5, 7)	10	230	10
	(3, 5)	10	150	4
	(4, 5)	0	170	6
	(5, 6)	10	150	10
	(5, 7)	0	170	10
$m = 3$				
$e = 1$	(1, 3)	27	11	10
	(1, 4)	11	76	10
	(2, 3)	13	67	10
	(6, 8)	12	27	10
	(7, 8)	21	39	10
	(7, 9)	20	67	10
$m = 4$				
$e = 1$	(4, 5)	56	120	20
	(5, 7)	56	120	20
$e = 2$	(4, 5)	56	119.3	20
	(5, 7)	56	119.3	20

TABLE 5 Overall Optimized Results of the Case Study

b	Path: Normal Operation	Path: Postdisruption	Freight Quantity/ Demand (lb thousands)	Transportation Time Spent on Delivery (h)
1	1→3➔5➔7→8	1→4···5➔7→8	10/10	274
2	2→4➔5➔6→9	2→3➔5➔6→9	2/7	61.8
3	1→3➔5➔6→9	1→4➔5➔6→9	5/5	94.4
4	2→4➔5➔7→8	2→4➔5➔7→8	6/6	103.2
5	1→3➔5➔6→9	1→4➔5➔6→9	3/3	72.4

NOTE: → = truck; - - - = rail; ➔ = air; · · · = sea.

TABLE 6 Results of Truck Reallocations and Rental Capacities

Link	Original Truck Allocations (no. of vehicles)	No. of Truck Reallocations (no. of vehicles)	Rental Capacity (tons)
(1, 3)	4	0	NA
(1, 4)	0	4	NA
(2, 3)	0	1	NA
(2, 4)	4	3	NA
(4, 5)	NA	NA	28[a]

[a]Data are for shipment by sea.

CONCLUSIONS

Nowadays, international express companies rarely respond to severe disruptions through the use of systematic measures to determine how to transport cargo in a timely manner. In practice, the decisions are usually made through discussions and are influenced by the experiences of customer service personnel. To improve such decisions, a quantitative method for the optimization of resilience strategies during the postdisruption phase was developed.

Although the case studies tested seemed to be relatively simple, the main purpose was to test and demonstrate the ability of the proposed models and optimize the resilience strategies when disruptions occur. The results show that the resilience strategies decrease the total shipping time and increase the delivery rate before the customers' requested deadlines. The use of proactive resilience strategies might be worth considering, such as the use of optimal reserved capacities at some hubs with high vulnerabilities.

The problem studied was formulated as a multiobjective mixed-integer nonlinear programming problem. In this multivariable nonlinear optimization problem, it is somewhat difficult to guarantee a global minimum. The bound is not readily identifiable because (*a*) the mixed-integer programming problem uses linear programming or the Lagrangian relaxation method to find the bounds and (*b*) some nonlinear constraints do not satisfy the requirements of the Karush–Kuhn–Tucker conditions. In addition, some hybrid metaheuristic techniques will be tested to improve program run times in the future (*10*).

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