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CARRIER SELECTION OPTIMIZATION BASED ON MULTI-COMMODITY RELIABILITY CRITERION FOR A STOCHASTIC LOGISTICS NETWORK UNDER A BUDGET CONSTRAINT

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Abstract. *In logistics management, selecting the carriers to deliver freight is a critical process for global enterprises. This paper determines the optimal carrier selection based on a multi-commodity reliability criterion for a logistics network subject to budget. Traditionally, a logistics network includes nodes and routes connecting the supplier and customer. Along each route, several carriers are available to deliver freight, which consists of multiple types of commodities. Since a carrier's capacity for service may be reserved by other requests, every carrier will exhibit numerous possible capacities following a distinct probability distribution. Carrier selection must choose exactly one carrier for each route. Thus, any logistics network associated with a carrier selection is characterized as a multi-commodity stochastic flow network. We evaluate the probability that a network can satisfy the customer's multi-commodity demand subject to a budget. This probability of multi-commodity reliability serves as a performance indicator for successful freight delivery. A genetic algorithm integrating minimal paths and Recursive Sum of Disjoint Products is developed to identify an optimal carrier selection strategy. A practical logistics network illustrates the computational efficiency of the proposed algorithm, comparing its performance with several algorithms.*
Keywords: Optimal carrier selection, Multi-commodity reliability, Multi-commodity stochastic logistics network, Budget constraint, Genetic algorithm, Recursive sum of disjoint products

1. Introduction.

Freight delivery has become increasingly more critical in planning logistics activities due to the globalization of competitive markets. Numerous global enterprises outsource the freight delivery activity to external carriers to strengthen their core competitiveness. In logistics management, selecting the carriers to deliver freight is a critical process for global enterprises. Liao and Rittscher [1] discussed the optimal carrier selection problem based on three criteria – total cost of logistics, total quality rejected items, and late delivery. Bolduc et al. [2] focused on minimizing the sum of external carrier cost, fixed and variable cost of internal fleet by selecting optimal carriers for customers and routing a heterogeneous internal fleet. In addition, many criteria of carrier selection, such as quality service, cost, physical financial stability, have been discussed in several studies [3-5]. According to the above literature, many criteria have been proposed to determine the carrier selection but no criterion is related to multi-commodity reliability.

A logistics network is constructed with nodes and routes (or called arcs) connecting the supplier (source s) and customer (sink t), where each node represents a transfer station or a city, and each route connecting a pair of nodes is an air route, a land route, or an ocean route. Since a carrier's capacity for service may be reserved by other requests, every carrier will exhibit numerous possible capacities (such as containers) following a distinct probability distribution. Carrier selection means the selection of exactly one carrier to deliver freight on each route herein. Any logistics network associated with a specified carrier selection is thus a typical stochastic-flow network [6-18]. Actually, the order from a customer may consist of multiple types of commodities (called multi-commodity throughout this paper). For instance, the customer orders several LCD televisions with various sizes, such as 42", 47", and 55", and then the products are delivered by the selected carriers through the logistics network. The consumed capacities vary with the type of commodity. Moreover, the freight delivery involves transportation cost (i.e., the cost per unit of the consumed capacity), and thus the manufacturer should take its budget into consideration. Associated with a carrier selection, any logistics network involving multi-commodity delivery is thus regarded as a multi-commodity stochastic logistics network (MSLN) herein. Multi-commodity reliability associated with a specified carrier selection is defined as the probability that an MSLN can satisfy the customer's multi-commodity demand subject to a budget, and is thus an important performance indicator for successful freight delivery. Such a probability is mainly evaluated in terms of minimal paths (MP) [14,15]. An MP is a sequence of routes from a source node to a sink node, which contains no cycle.

In quality management, multi-commodity reliability optimization is an important issue for many enterprises. Several references [7-10] have studied the optimal commodity assignment to source nodes for maximizing multi-commodity reliability. Liu et al. [17] focused on determining the optimal flow assignment with maximal multi-commodity reliability and minimal cost. Nevertheless, they did not involve carrier selection. Synthesizing the above discussion, this focused problem to find the optimal carrier selection based on the multi-commodity reliability criterion subject to a budget was never discussed. For instance, when the customer orders several LCD televisions with various sizes, the forwarder must plan the optimal carrier selection for the manufacturer such that the freight can be successfully delivered.

Genetic algorithm (GA) is applied to various optimization problems such as the assignment problems [20,21], the transportation problem [22], the scheduling problem [23]. A GA-based algorithm which integrates MP and Recursive Sum of Disjoint Products (RSDP [24]), namely GA-MPRSDP, is therefore proposed to solve this problem. The remainder of this paper is organized as follows. Section 2 addresses the notations and the assumptions. Section 3 introduces the MSLN model and the problem formulation. GA-MPRSDP is developed in Section 4. A simple example and a practical example of the LCD television delivery are displayed in Section 5 to demonstrate the solution procedure. The conclusion and discussion are drawn in the final section.

2. Notations and Assumptions.

Let ($\mathbf{N}$, $\mathbf{R}$) be an MSLN where $\mathbf{N}$ denotes the set of nodes, $\mathbf{R} = \{r_i | 1 \leq i \leq n\}$ denotes the set of n routes connecting two nodes. The MP of ($\mathbf{N}$, $\mathbf{R}$) are designated as p_1, p_2, $\ldots$, p_m and the demand of u commodities at sink t is designated as $D = (d_1, d_2, \ldots, d_u)$ where d_k is the demand of commodity k. Let $\mathbf{W}_i = \{w_{ie} | 1 \leq e \leq z_i\}$ be the set of z_i carriers on route r_i for $i = 1, 2, \ldots, n$, in which w_{ie} is the eth carrier on route r_i. Each carrier w_{ie} has multiple states, $1, 2, \ldots, M_{ie}$, with corresponding available capacities, $0 = h_{ie}(1) < h_{ie}(2) < \ldots < h_{ie}(M_{ie})$ for $e = 1, 2, \ldots, z_i$, in which $h_{ie}(l)$ is the lth capacity of w_{ie} for $l = 1, 2, \ldots, M_{ie}$. The cost c_{ie} means the cost per unit of capacity provided by carrier w_{ie} on route r_i. A carrier selection is designated as $B = (b_1, b_2, \ldots, b_n)$ where $b_i = e$ if carrier w_{ie} is selected to deliver freight on route r_i for $i = 1, 2, \ldots, n$. The logistic network associated with carrier selection B is an MSLN.

Several necessary assumptions for MSLN for are listed as follows:
I. Flow in $(\mathbf{N}, \mathbf{R})$ must satisfy the flow-conservation principle [25]. That is, no flow will be decreased or be increased during the delivery.
II. The capacities of different carriers are statistically independent.
III. Different commodities should not be loaded in the same container.

Definition 2.1. $\lceil x \rceil$ *is the smallest integer such that* $\lceil x \rceil \geq x$.

Definition 2.2. $\lfloor x \rfloor$ *is the greatest integer such that* $\lfloor x \rfloor \leq x$.

3. Multi-commodity Stochastic Logistics Network Model.

3.1. **Flow model.** The maximal capacity on route r_i denoted by $h_{ib_i}(M_{ib_i})$ is equal to $h_{i\varepsilon}(M_{i\varepsilon})$ if $b_i = \varepsilon$ where $\varepsilon \in \{1, 2, \ldots, z_i\}$ for $i = 1, 2, \ldots, n$. Let $M_B = (h_{1b_1}(M_{1b_1}), h_{2b_2}(M_{2b_2}), \ldots, h_{nb_n}(M_{nb_n}))$ be the maximal capacity vector associated with carrier selection B. Let $X = (x_1, x_2, \ldots, x_n)$ be a current capacity vector of $(\mathbf{N}, \mathbf{R})$ where x_i is the current capacity on route r_i. Any capacity vector X which is feasible associated with B meets the following constraint:

$$X \leq M_B \tag{1}$$

Constraint (1) means the current capacity x_i should not exceed the maximal capacity on route r_i for $i = 1, 2, \ldots, n$. For the convenience, let $\mathbf{U}_B = \{X | X \leq M_B\}$ be the set of all feasible X associated with B.

Let $F = (f_{11}, f_{12}, \ldots, f_{1m}, f_{21}, f_{22}, \ldots, f_{2m}, \ldots, f_{u1}, f_{u2}, \ldots, f_{um})$ be a flow vector where f_{kj} is the flow of commodity k through p_j. The consumed capacity per commodity k denoted by q_k for $k = 1, 2, \ldots, u$ is a real number. Under capacity vector M_B, the amount of commodity k through route r_i is bounded by $\lfloor h_{ib_i}(M_{ib_i})/q_k \rfloor$. Thus, any F satisfying the following constraints is said to be feasible under capacity vector M_B.

$$\sum\nolimits_{k=1}^{u} \left(\left\lceil q_k \sum_{j:r_i \in p_j} f_{kj} \right\rceil \right) \leq h_{ib_i}(M_{ib_i}) \quad \text{for } i = 1, 2, \ldots, n, \text{ and} \tag{2}$$

$$\lceil q_k f_{kj} \rceil \leq \min_{i:r_i \in p_j} \{h_{ib_i}(M_{ib_i})\} \quad \text{for } j = 1, 2, \ldots, m, \text{ and } k = 1, 2, \ldots, u, \tag{3}$$

where $\sum\limits_{j:r_i \in p_j} f_{kj}$ is the flow of commodity k traveling through route r_i, $\left\lceil q_k \sum\limits_{j:r_i \in p_j} f_{kj} \right\rceil$ is the consumed capacity on r_i by commodity k, $\sum\nolimits_{k=1}^{u} \left(\left\lceil q_k \sum\limits_{j:r_i \in p_j} f_{kj} \right\rceil \right)$ is the total consumed capacity on r_i by all commodities, and $\min\limits_{i:r_i \in p_j} \{h_{ib_i}(M_{ib_i})\}$ is the maximal capacity of p_j. Constraint (2) means the consumed capacity on route r_i should not exceed the maximal capacity of route r_i for $i = 1, 2, \ldots, n$. Constraint (3) means the consumed capacity of the flow f_{kj} should not exceed the maximal capacity of p_j. The following corollary shows that constraint (3) is redundant.

Corollary 3.1. *Any F satisfying constraint (2) satisfies constraint (3).*

Proof: Since $\left\lceil q_k \sum\limits_{j:r_i \in p_j} f_{kj} \right\rceil = \left\lceil \sum\limits_{j:r_i \in p_j} q_k f_{kj} \right\rceil$, constraint (2) infers $\lceil q_k f_{kj} \rceil \leq h_{ib_i}(M_{ib_i})$ for each i: $r_i \in p_j$. That is, $\lceil q_k f_{kj} \rceil \leq \min\{h_{ib_i}(M_{ib_i}) \,|\, i : r_i \in p_j\}$. The proof is completed.

For the convenience, let $\mathbf{F}_{M_B}$ denote the set of all feasible F under M_B. Similarly, let $\mathbf{F}_X$ denote the set of all F satisfying the following constraint:

$$\sum\nolimits_{k=1}^{u}\left(\left\lceil q_k \sum_{j:r_i\in p_j} f_{kj}\right\rceil\right) \leq x_i \quad \text{for } i=1,2,\ldots,n \tag{4}$$

3.2. **Multi-commodity reliability measurement.** Any capacity vector X is said to meet the demand D and the budget C if and only if there exists a flow vector $F \in \mathbf{F}_X$ satisfying the following constraints:

$$\sum_{j}^{m} f_{kj} \geq d_k \quad \text{for } k=1,2,\ldots,u, \text{ and} \tag{5}$$

$$\sum\nolimits_{i=1}^{n}\left(c_{ib_i}\sum\nolimits_{k=1}^{u}\left\lceil q_k \sum_{j:r_i\in p_j} f_{kj}\right\rceil\right) \leq C \tag{6}$$

where $c_{ib_i}\sum_{k=1}^{u}\left\lceil q_k \sum\limits_{j:r_i\in p_j} f_{kj}\right\rceil$ is the cost of the total flow traveling through route r_i. For the convenience, let $\mathbf{X}_B = \{X|X \in \mathbf{U}_B$ satisfies the demand D and the budget $C\}$. The multi-commodity reliability associated with carrier selection B denoted by $R_{D,C}(B)$ is a probability that the demand D can be successfully delivered from s to t through the logistics network associated with B subject to budget C. That is, $R_{D,C}(B) = \sum_{X\in\, \mathbf{X}_B} \Pr(X)$.

However, it is inefficient to enumerate all $X \in \mathbf{X}_B$ and add their probabilities [12,13]. Instead, a (B,D,C)-MP is defined to improve the computational efficiency of multi-commodity reliability measurement.

Definition 3.1. *A (B,D,C)-MP is a capacity vector $X \in \boldsymbol{X}_B$ such that $Y \notin \boldsymbol{X}_B$ for any $Y < X$ (where $Y \leq X : (y_1, y_2, \ldots, y_n) \leq (x_1, x_2, \ldots, x_n)$ if and only if $y_i \leq x_i$ for each i; $Y < X$ if and only if $Y \leq X$ and $y_i < x_i$ for at least one i).*

Equivalently, any (B,D,C)-MP X is the maximal capacity vector in $\mathbf{X}_B$. Suppose there are totally $v(B,D,C)$-MP: $X_1, X_2, \ldots, X_v$. Then, $\mathbf{X}_B = \left\{\bigcup\limits_{i=1}^{v}\{X|X \geq X_i, X \in \mathbf{U}_B\}\right\}$. Thus,

$$\begin{aligned} R_{D,C}(B) &= \sum\nolimits_{X\in\mathbf{X}_B} \Pr(X) \\ &= \Pr\left\{\bigcup_{i=1}^{v}\{X|X \geq X_i, X \in \mathbf{U}_B\}\right\} \end{aligned} \tag{7}$$

Such a probability can be calculated by inclusion-exclusion principle [13,18,26], state-space decomposition [6,12], or RSDP [24]. The inclusion-exclusion method easily results in memory overloaded for larger networks. Additionally, RSDP has better computational efficiency than the state-space decomposition, especially for larger networks [24]. Hence, RSDP is utilized in this study.

3.3. **Generate all $(\boldsymbol{B},\boldsymbol{D},\boldsymbol{C})$-MP.** Any flow vector $F \in \mathbf{F}_{M_B}$ is said to meet exactly demand D and budget C if it satisfies constraints (6) and (8):

$$\sum_{j}^{m} f_{kj} = d_k \quad \text{for } k=1,2,\ldots,u \tag{8}$$

Let $\mathbf{\Phi}_B = \{F|F \in\ \mathbf{F}_{M_B}$ meets constraints (6) and (8)$\}$ be the set of F satisfying exactly D subject to C under M_B. A necessary condition for any (B,D,C)-MP is illustrated in the following theorem.

Theorem 3.1. *If $X \in \boldsymbol{U}_B$ is a (B, D, C)-MP, then there exists a feasible $F \in \boldsymbol{\Phi}_B$ such that*

$$x_i = h_{ib_i}(l) \text{ where } l \in \{1, 2, \ldots, M_{ib_i}\} \text{ and } h_{ib_i}(l-1) < \sum\nolimits_{k=1}^{u} \left(\left\lceil q_k \sum_{j: r_i \in p_j} f_{kj} \right\rceil \right) \leq h_{ib_i}(l) \quad \text{for } i = 1, 2, \ldots, n \tag{9}$$

Proof: Let X be a (B, D, C)-MP and an F. $\boldsymbol{\Phi}_B \cap \mathbf{F}_X$. Suppose to the contrary that there exists a route r_π with $x_\pi > h_{\pi b_\pi}(l) \geq \sum_{k=1}^{u} \left(\left\lceil q_k \sum_{j: r_\pi \in p_j} f_{kj} \right\rceil \right)$ and $x_i = h_{ib_i}(l) \geq \sum_{k=1}^{u} \left(\left\lceil q_k \sum_{j: r_i \in p_j} f_{kj} \right\rceil \right) \forall i \neq \pi$. Set $Y = (y_1, y_2, \ldots, y_n)$ with $y_\pi = h_{\pi b_\pi}(l)$ and $y_i = x_i \ \forall i \neq \pi$. Thus, $Y < X$ and F is feasible under Y due to $\sum_{k=1}^{u} \left(\left\lceil q_k \sum_{j: r_i \in p_j} f_{kj} \right\rceil \right) \leq y_i$ for $i = 1, 2, \ldots, n$. It infers $Y \in \mathbf{X}_B$ and contradicts that X is a (B, D, C)-MP. The proof is completed.

Based on Theorem 3.1, we transform each flow vector $F \in \boldsymbol{\Phi}_B$ into a capacity vector X through Equation (9). Such a capacity vector X is treated as a (B, D, C)-MP candidate. Let $\boldsymbol{\Gamma}_B = \{X | X \text{ is transformed from } F \in \boldsymbol{\Phi}_B \text{ via Equation (9)}\}$ be the set of such (B, D, C)-MP candidates, and $\boldsymbol{\Gamma}_{B,\min}$ be the set of minimal vectors in $\boldsymbol{\Gamma}_B$. The following theorem shows that $\boldsymbol{\Gamma}_{B,\min}$ is equivalent to the set of (B, D, C)-MP.

Theorem 3.2. *$\boldsymbol{\Gamma}_{B,\min}$ is equivalent to the set of (B, D, C)-MP.*

Proof: Suppose $X \in \boldsymbol{\Gamma}_{B,\min}$ that means $X \in \mathbf{X}_B$ but it is not a (B, D, C)-MP. Hence, there exists a (B, D, C)-MP Y such that $Y < X$. That is, $Y \in \boldsymbol{\Gamma}_B$ which contradicts $X \in \boldsymbol{\Gamma}_{B,\min}$. Conversely, suppose X is a (B, D, C)-MP but $X \notin \boldsymbol{\Gamma}_{B,\min}$. It is known $X \in \boldsymbol{\Gamma}_B$ based on Theorem 3.1. There exists a $Y \in \boldsymbol{\Gamma}_B$ such that $Y < X$. It is given that $Y \in \mathbf{X}_B$ which contradicts that X is a (B, D, C)-MP. We therefore conclude $\boldsymbol{\Gamma}_{B,\min}$ is the set of (B, D, C)-MP. The proof is completed.

Based on Theorem 3.2, whether (B, D, C)-MP candidates are (B, D, C)-MP is identified by the following algorithm.

The *(B, D, C)*-MP generation algorithm. //Check which capacity vectors in $\boldsymbol{\Gamma}_B$ are (B, D, C)-MP.

Step 1. $I = \varnothing$ (I is the stack which stores the indexes of the capacity vectors in $\boldsymbol{\Gamma}_B$ which are not a (B, D, C)-MP. Initially, I is empty.)

Step 2. For $i = 1$ to $|\boldsymbol{\Gamma}_B|$ & $i \notin I$. //$|\boldsymbol{\Gamma}_B|$ means the number of capacity vectors in $\boldsymbol{\Gamma}_B$.

Step 3. For $j = i+ 1$ to $|\boldsymbol{\Gamma}_B|$, & $j \notin I$.

Step 4. If $X_j < X_i$, then X_i is not a (B, D, C)-MP, $I = I \cup \{i\}$, and go to Step 7. Else X_j is not a (B, D, C)-MP, $I = I \cup \{j\}$.

Step 5. Next j.

Step 6. X_i is a (B, D, C)-MP.

Step 7. Next i.

4. GA-based Algorithm Development.

4.1. Problem formulation.

The mathematical program of this problem is thus given by

$$Maximize\ R_{D,C}(B) = \Pr\left\{ \bigcup_{i=1}^{v} \{X | X \geq X_i, X \in \mathbf{U}_B\} \right\} \tag{10}$$

$$\textit{Subject to } b_i = e \quad e \in \{1, 2, \ldots, z_i\} \quad \text{for } i = 1, 2, \ldots, n. \tag{11}$$

constraint (11) says route r_i must be assigned exactly one carrier from set $\mathbf{W}_i$ for $i = 1, 2, \ldots, n$. All feasible carrier selections are found subject to constraint (11). Note that $R_{D,C}(B) = 0$ if $\mathbf{X}_B = \left\{ \bigcup_{i=1}^{v} \{X | X \geq X_i, X \in \mathbf{U}_B\} \right\} = \varnothing$. The optimal carrier selection with maximal multi-commodity reliability subject to budget C is obtained by maximizing objective Function (10).

4.2. **Definition of parameters and chromosome representation.** Several parameters - population size (θ), crossover rate (α), mutation rate (β) and number of generations (λ) must be set before executing GA-MPRSDP. The population size means the number of chromosomes in the population. Grefensette [27] and Mitchell [28] suggested setting θ to be in the intervals of [10, 60] and [30, 100], respectively. The crossover rate handles the probability of crossover execution. Schaffer et al. [29] and Man et al. [30] suggested setting α to be in the intervals of [0.75, 0.95] and [0.6, 1.0], respectively. The mutation rate handles the probability of mutation execution. Schaffer et al. [29] recommend setting β to be in the interval of [0.005, 0.01], and Man et al. [30] recommend setting it not to exceed 0.1. The number of generations is GA-MPRSDP terminal condition. If GA-MPRSDP runs for λ generations, it stops and returns the solution in the last generation; otherwise it continues.

A chromosome (solution) represents a carrier selection. In GA-MPRSDP, the integer representation is employed to represent a chromosome such that the chromosome is identical with a carrier selection. A chromosome is thus denoted by $G = (g_1, g_2, \ldots, g_n)$, where $g_i = e$, $w_{ie} \in \mathbf{W}_i$ if carrier w_{ie} is assigned to route r_i. That is, chromosome G is equivalent to carrier selection B.

4.3. **Fitness function.** GA-MPRSDP starts with a random initial population, $\{G_1, G_2, \ldots, G_\theta\}$, and then the fitness function focuses on evaluating multi-commodity reliability for the corresponding chromosome. That is, the fitness value of any chromosome is its multi-commodity reliability. To be worthy of attention, $R_{D,C}(G) = 0$ due to $\mathbf{X}_G = \varnothing$. The following algorithm illustrates the process of multi-commodity reliability measurement for a chromosome, namely MCRM.

Algorithm MCRM //Evaluate multi-commodity reliability for a specified chromosome

Step 1. Find all F satisfying the following constraints:

$$\sum\nolimits_{k=1}^{u} \left(\left\lceil q_k \sum_{j: r_i \in p_j} f_{kj} \right\rceil \right) \leq h_{ig_i}(M_{ig_i}) \quad \text{for } i = 1, 2, \ldots, n, \tag{12}$$

$$\sum\nolimits_{i=1}^{n} \left(c_{ig_i} \sum\nolimits_{k=1}^{u} \left\lceil q_k \sum_{j: r_i \in p_j} f_{kj} \right\rceil \right) \leq C, \text{ and} \tag{13}$$

$$\sum_{j}^{m} f_{kj} = d_k \quad \text{for } k = 1, 2, \ldots, u. \tag{14}$$

If there is no F satisfying constraints (12)-(14), set $R_{D,C}(G) = 0$ and then evaluate the next chromosome.

Step 2. Transform each F into (G, D, C)-MP candidate X via the following equation:

$$x_i = h_{ig_i}(l) \text{ where } l \in \{1, 2, \ldots, M_{ig_i}\} \text{ and } h_{ig_i}(l-1) < \sum\nolimits_{k=1}^{u} \left(\left\lceil q_k \sum_{j:r_i \in p_j} f_{kj} \right\rceil \right) \le h_{ig_i}(l) \quad \text{for } i = 1, 2, \ldots, n. \tag{15}$$

Step 3. Utilize the (G, D, C)-MP generation algorithm to identify which (G, D, C)-MP candidates are (G, D, C)-MP. //(G, D, C)-MP is (B, D, C)-MP since G is equivalent to B.

Step 4. Suppose there are v (G, D, C)-MP. Evaluate $R_{D,C}(G) = \Pr\left\{ \bigcup_{i=1}^{v} \{X | X \ge X_i, X \in \mathbf{U}_G\} \right\}$ using RSDP.

4.4. **Evolution process – selection, crossover and mutation.** A chromosome with a higher multi-commodity reliability has a higher possibility to be preserved and propagate the offspring. This study employs roulette wheel selection due to its common-use and simplicity, in which this selection operator is regarded as playing a game of roulette, where the size of each slot in wheel is proportional to the fitness value [31]. The selection operator is implemented twice to select two chromosomes from the population for the following crossover and mutation.

Suppose the two selected chromosomes are $(2, 3, 4, 3, 1)$ and $(1, 1, 3, 4, 2)$. The crossover operator searches for approximately optimal solutions and provides a direction of convergence. In GA-MPRSDP, the uniform crossover is employed to pair the two selected chromosome. The execution of crossover is handled by crossover rate α. A crossover vector denoted by $\mathbf{\Omega} = (\Omega_1, \Omega_2, \ldots, \Omega_n)$ is a random binary vector. Gene g_ρ of the first chromosome switch with gene g_ρ of the second chromosome as $\Omega_\rho = 1$, $\rho \in \{1, 2, \ldots, n\}$. Suppose $\mathbf{\Omega} = (1, 1, 0, 0, 1)$. Then, the two selected chromosomes, $(2, 3, 4, 3, 1)$ and $(1, 1, 3, 4, 2)$, switch with each other to be $(1, 1, 4, 3, 2)$ and $(2, 3, 3, 4, 1)$.

The mutation operator is a momentum variable which holds the diversity of the population and prevents premature convergence. In GA-MPRSDP, the uniform mutation is employed to mutate the two selected chromosomes. The execution of mutation is controlled by mutation rate β. A mutation vector denoted by $\mathbf{\Psi} = (\Psi_1, \Psi_2, \ldots, \Psi_n)$ is a random binary vector. The τth gene of the chromosome must become another element in the set $\{1, 2, \ldots, z_i\}$ as $\Psi_\tau = 1$, $\tau \in \{1, 2, \ldots, n\}$. For example, the two chromosomes, $(1, 1, 4, 3, 2)$ and $(2, 3, 3, 4, 1)$, from the uniform crossover, $\mathbf{\Psi}$ is supposed to be $(1, 0, 0, 0, 1)$, and then the two chromosomes become $(\underline{3}, 1, 4, 3, \underline{3})$ and $(\underline{1}, 3, 3, 4, \underline{4})$ where $g_1 \in \{1, 2, \ldots, z_1\}$ but $g_1 \ne 1$ and $g_5 \in \{1, 2, \ldots, z_5\}$ but $g_5 \ne 2$ in the first chromosome, and $g_1 \in \{1, 2, \ldots, z_1\}$ but $g_1 \ne 2$ and $g_5 \in \{1, 2, \ldots, z_5\}$ but $g_5 \ne 1$ in the second chromosome.

The following steps describe the procedure of implementing GA-MPRSDP to solve the discussed problem.

Algorithm GA-MPRSDP //Search for the approximately optimal carrier selection with maximal multi-commodity reliability subject to budget

1) Initially, set θ, α, β, and λ and let $\Xi = 1$. //Ξ is utilized to count how many generations GA-MPRSDP runs.
2) Generate initial population with θ chromosomes by using the integer representation.
3) Compute $R_{D,C}(G)$ for each chromosome by algorithm MCRM.
4) If $\Xi = \lambda$, return the optimal solution of the λth generation and GA-MPRSDP stops. Else if $\Xi < \lambda$, $\Xi = \Xi + 1$ and go to Step 5.
5) Execute the evolution process
   5.1) Employ the roulette wheel selection.

5.2) Implement the uniform crossover based on α.
5.3) Implement the uniform mutation based on β.
6) Utilize the new chromosomes from Step 5 to produce the new population.

Evaluate $R_{D,C}(G)$ for the chromosomes in the new population using the MCRM algorithm and then go to step 4.

5. **Numerical Experiments.** In this section, GA-MPRSDP is applied to a simple logistics network and a practical logistics network and we compare it with Implicit Enumeration Approach (IEA), Random Solution Generation (RSG), Simulated Annealing (SA), and Particle Swarm Optimization (PSO), where RSG keeps searching for a better solution by randomly generating solutions without adopting the evolution process [32]. In the simple example, we observe maximal multi-commodity reliability and CPU time. In the other example, we explore the multi-size LCD television delivery from Asia to Europe. In both examples, the experiments are implemented on a personal computer with Intel Core 2 Quad CPU 2.4G and 2G RAM. GA-MPRSDP, IEA, RSG, SA and PSO are programmed in MATLAB language.

5.1. **Simple logistic network.** The simple logistics network with 6 routes and 4 MP is shown in Figure 1, in which each route consists of four carriers, and the MP are $p_1 = \{r_1, r_2\}$, $p_2 = \{r_1, r_3, r_6\}$, $p_3 = \{r_2, r_4, r_5\}$ and $p_4 = \{r_5, r_6\}$. The available capacity data of carriers are listed in Table 1, where the unit of capacity is counted in terms of TEU (Twenty-feet Equivalent Unit). One unit of commodity 1 consumes 1.5 TEU and one unit of commodity 2 consumes 2.2 TEU. That is, $q_1 = 1.5$ and $q_2 = 2.2$. First, we acquire the optimal solutions according to various demands and budgets by IEA. Subsequently, GA-MPRSDP with $\theta = 30$, $\alpha = 0.9$ and $\beta = 0.01$ is executed for the same constraints. In particular, we utilize the terminal constraint that GA-MPRSDP stops while its maximal multi-commodity reliability equals the maximal one from IEA. The experimental results are listed in Table 2 and Figure 2. We observe that GA-MPRSDP not only obtains the solutions which are the same with IEA's, but also displays better computational efficiency than IEA. Furthermore, GA-MPRSDP obtains the optimal solutions within 120 generations in these experiments.

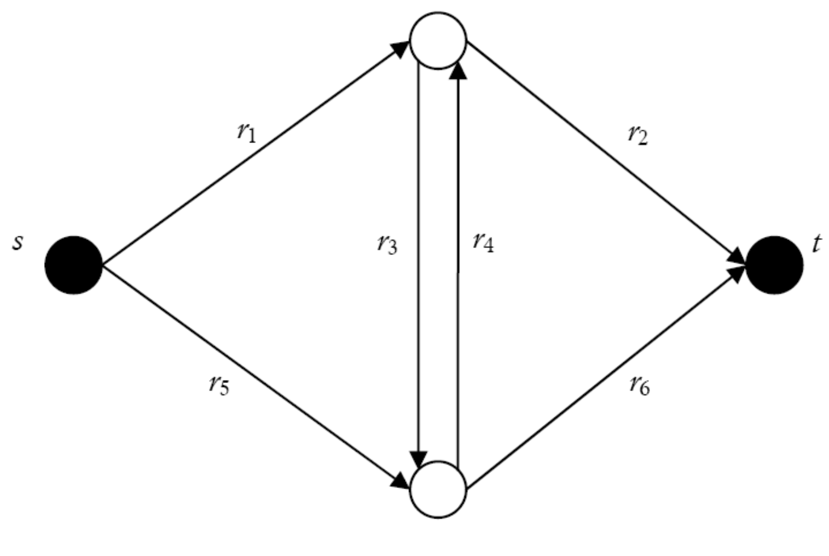

FIGURE 1. Simple logistics network

Table 1. Capacities of the carriers on routes in Figure 1

Route (r_i)	Carrier (w_{ie})	Cost (c_{ie}, unit: USD/TEU)	Capacity (unit: TEU)						
			0	10	20	30	40	50	60
r_1	w_{11}	250	0.005	0.01	0.05	0.935	0^a	0	0
	w_{12}	225	0.01	0.015	0.025	0.05	0.06	0.84	0
	w_{13}	200	0.01	0.02	0.03	0.05	0.06	0.1	0.73
	w_{14}	210	0.1	0.15	0.1	0.1	0.5	0	0
r_2	w_{21}	320	0.01	0.02	0.03	0.04	0.9	0	0
	w_{22}	250	0.02	0.04	0.06	0.08	0.1	0.7	0
	w_{23}	380	0.005	0.005	0.005	0.01	0.01	0.03	0.935
	w_{24}	280	0.05	0.05	0.05	0.05	0.05	0.75	0
r_3	w_{31}	250	0.005	0.005	0.01	0.01	0.01	0.01	0.95
	w_{32}	260	0.01	0.05	0.05	0.01	0.88	0	0
	w_{33}	300	0.1	0.1	0.05	0.1	0.65	0	0
	w_{34}	280	0.01	0.02	0.03	0.04	0.5	0.85	0
r_4	w_{41}	330	0.01	0.01	0.05	0.1	0.83	0	0
	w_{42}	300	0.1	0.15	0.1	0.05	0.6	0	0
	w_{43}	350	0.01	0.05	0.01	0.01	0.01	0.01	0.9
	w_{44}	290	0.01	0.05	0.05	0.01	0.18	0.7	0
r_5	w_{51}	265	0.05	0.01	0.05	0.89	0	0	0
	w_{52}	200	0.10	0.15	0.1	0.05	0.6	0	0
	w_{53}	250	0.01	0.05	0.01	0.01	0.01	0.01	0.9
	w_{54}	230	0.005	0.005	0.01	0.01	0.01	0.16	0.8
r_6	w_{61}	235	0.03	0.04	0.05	0.1	0.1	0.68	0
	w_{62}	290	0.05	0.05	0.05	0.05	0.8	0	0
	w_{63}	270	0.02	0.02	0.02	0.02	0.02	0.9	0
	w_{64}	250	0.01	0.015	0.025	0.05	0.1	0.8	0

a. The carrier does not provide the capacity.

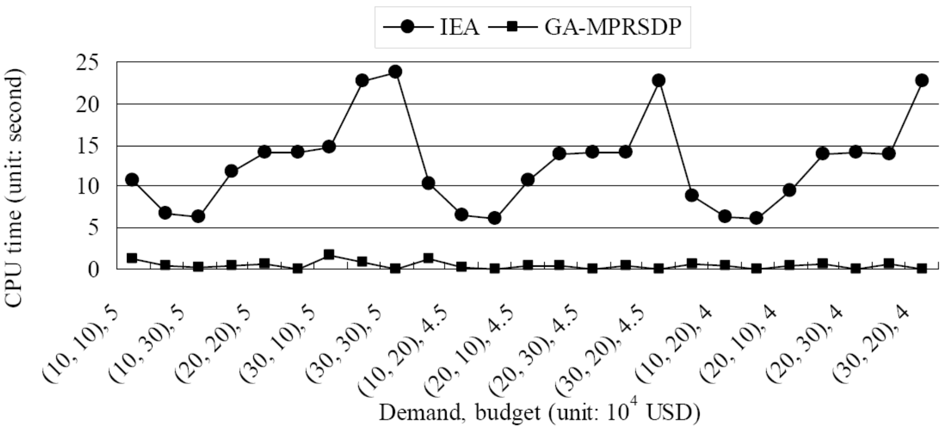

Figure 2. Comparison of GA-MPRSDP and IEA based on CPU time

5.2. **Practical logistic network for multi-size LCD television delivery.** A LCD television manufacturer in Taiwan has an assembly plant at Xiamen in China and produces the three types of LCD televisions including 42" LCD television, 47" LCD television, and 55" LCD television. The freight delivery from Xiamen to Berlin in Germany is through the logistics network with 18 routes and 10 MP (see Figure 3). The available capacity

Table 2. Comparison results of GA-MPRSDP and IEA

			IEA		GA-MPRSDP ($\theta = 30, \alpha = 0.9$) and $\beta = 0.01$)		
Demand $D = (d_1, d_2)$	Budget (unit: USD[a])	Maximal multi-commodity reliability	Optimal solution/# optimal solutions	CPU time (s)	Optimal solution	CPU time (s)	No. generations
(10, 10)	50,000	0.99642742	(2, 3, 1, 3, 4, 4)/1	10.625	(2, 3, 1, 3, 4, 4)	1.359	113
(10, 20)	50,000	0.91830399	(2, 3, 1, 1, 4, 4)/4	6.797	(2, 3, 1, 4, 4, 4)	0.406	55
(10, 30)	50,000	0.6387792	(2, 2, 1, 1, 4, 3)/16	6.218	(2, 2, 1, 2, 4, 3)	0.219	27
(20, 10)	50,000	0.97458223	(3, 3, 1, 1, 4, 4)/1	11.688	(3, 3, 1, 1, 4, 4)	0.375	30
(20, 20)	50,000	0.85485432	(2, 3, 1, 1, 4, 3)/16	14.063	(2, 3, 2, 3, 4, 3)	0.703	51
(20, 30)	50,000	0	$\varnothing$[b]	14.156	Infeasible solution	0.066	1
(30, 10)	50,000	0.88464045	(3, 3, 1, 4, 4, 4)/1	14.656	(3, 3, 1, 4, 4, 4)	1.594	116
(30, 20)	50,000	0.53784	(3, 4, 1, 1, 4, 3)/16	22.75	(3, 4, 1, 4, 4, 3)	0.765	23
(30, 30)	50,000	0	$\varnothing$	23.766	Infeasible solution	0.098	1
(10, 10)	45,000	0.99633187	(2, 3, 1, 4, 4, 4)/1	10.328	(2, 3, 1, 4, 4, 4)	1.156	107
(10, 20)	45,000	0.9182238	(2, 3, 1, 1, 4, 4)/16	6.469	(2, 3, 1, 2, 4, 4)	0.266	39
(10, 30)	45,000	0	$\varnothing$	6.172	Infeasible solution	0.051	1
(20, 10)	45,000	0.97272672	(3, 3, 1, 4, 4, 4)/1	10.703	(3, 3, 1, 4, 4, 4)	0.484	52
(20, 20)	45,000	0.8507838	(2, 3, 1, 1, 4, 4)/16	13.891	(2, 3, 1, 2, 4, 4)	0.453	28
(20, 30)	45,000	0	$\varnothing$	14.14	Infeasible solution	0.072	1
(30, 10)	45,000	0.8820175374999998	(3, 3, 1, 1, 4, 4)/16	14.125	(3, 3, 1, 1, 4, 4)	0.391	23
(30, 20)	45,000	0	$\varnothing$	22.688	Infeasible solution	0.076	1
(10, 10)	40,000	0.99581166	(2, 3, 1, 4, 4, 4)/1	8.797	(2, 3, 1, 4, 4, 4)	0.641	83
(1, 2)	40,000	0.90120285	(2, 3, 1, 1, 4, 4)/16	6.25	(2, 3, 1, 3, 4, 4)	0.468	79
(10, 30)	40,000	0	$\varnothing$	6.188	Infeasible solution	0.049	1
(20, 10)	40,000	0.94593281	(3, 3, 1, 1, 4, 4)/4	9.5	(3, 3, 1, 3, 4, 4)	0.328	41
(20, 20)	40,000	0.7559376	(2, 2, 1, 1, 4, 3)/16	13.828	(2, 2, 3, 1, 4, 3)	0.719	55
(20, 30)	40,000	0	$\varnothing$	14.157	Infeasible solution	0.074	1
(30, 10)	40,000	0.771588	(2, 2, 1, 1, 4, 4)/16	13.797	(2, 2, 1, 2, 4, 4)	0.547	42
(30, 20)	40,000	0	$\varnothing$	22.734	Infeasible solution	0.081	1

a. United States dollar.
b. No solution.

data of carriers are listed in Table 3. Each carrier has multiple capacities, 0, 10 TEU, ..., 40 TEU with a probability distribution. The dimensions of 42", 47", and 55" LCD televisions are $108.1 \times 76.8 \times 20$, $125.5 \times 83.6 \times 24.3$, and $138.3 \times 94.5 \times 25.5$ (unit: cm), respectively. A TEU with the size of $589.8 \times 235.2 \times 238.5$ can approximately load 200 (resp. 130 and 100) pieces of 42" (resp. 47" and 55") LCD televisions. Generally, one unit of LCD television is calculated in terms of 100 pieces. Hence, one unit of 42" (resp. 47" and 55") LCD television approximately consumes 0.5 (resp. 0.8 and 1) TEU, i.e., $q_1 = 0.5$ (resp. $q_2 = 0.8$ and $q_3 = 1$).

The manufacturer has acquired such an order which is to deliver 1000 pieces of 42" LCD television, 2,000 pieces of 47" LCD television, and 2000 pieces of 55" LCD television to the customer at Berlin, i.e., $D = (10, 20, 20)$. Suppose the manufacturer pays the delivery expanse at most \$72,000 USD (United States dollar). Under this budget constraint, the forwarder devotes to planning the best carrier selection. In this example, we execute GA-MPRSDP with $\theta = 50$, $\alpha = 0.8$, $\beta = 0.05$ and $\lambda = 1000$ for 10 times to observe the largest maximal multi-commodity reliability, the average maximal multi-commodity reliability, the largest CPU time, and the average CPU time. The experimental result presents the largest maximal multi-commodity reliability is 0.86618217, the average maximal multi-commodity reliability is 0.84926714, the largest CPU time is 6813 seconds, and the average CPU time is 5906 seconds. Obviously, the maximal multi-commodity reliability is not high enough. Generally speaking, the manufacturer is suggested to increase the budget for improve the reliability of freight delivery. According to the average CPU time, the addressed problem can be solved by GA-MPRSDP in a reasonable time. Table 4 lists the

TABLE 3. Capacities of the carriers on routes in Figure 3

Route (r_i)	Carrier (w_{ie})	Cost (c_{ie}, unit: USD/TEU)	Capacity (unit: TEU)				
			0	10	20	30	40
r_1	w_{11}	110	0.01	0.01	0.98	0	0
	w_{12}	90	0.03	0.05	0.16	0.76	0
	w_{13}	125	0.05	0.05	0.05	0.85	0
	w_{14}	140	0.01	0.01	0.07	0.075	0.835
r_2	w_{21}	125	0.085	0.09	0.114	0.711	0
	w_{22}	105	0.01	0.05	0.94	0	0
	w_{23}	95	0.01	0.01	0.05	0.1	0.83
	w_{24}	100	0.01	0.034	0.058	0.11	0.788
r_3	w_{31}	100	0.003	0.006	0.014	0.977	0
	w_{32}	115	0.006	0.006	0.012	0.013	0.963
	w_{33}	105	0.1	0.1	0.8	0	0
	w_{34}	95	0.01	0.05	0.2	0.74	0
	w_{35}	90	0.02	0.03	0.95	0	0
	w_{36}	85	0.002	0.005	0.008	0.017	0.968
	w_{37}	105	0.025	0.03	0.945	0	0
r_4	w_{41}	300	0.02	0.02	0.1	0.86	0
	w_{42}	350	0.01	0.14	0.17	0.68	0
	w_{43}	350	0.09	0.11	0.14	0.66	0
	w_{44}	380	0.01	0.01	0.01	0.01	0.96
	w_{45}	320	0.01	0.02	0.03	0.04	0.9
r_5	w_{51}	300	0.012	0.012	0.14	0.836	0
	w_{52}	310	0.053	0.055	0.062	0.08	0.75
	w_{53}	250	0.028	0.032	0.94	0	0
	w_{54}	270	0.016	0.022	0.123	0.839	0
r_6	w_{61}	110	0.01	0.04	0.06	0.12	0.77
	w_{62}	125	0.003	0.011	0.011	0.975	0
	w_{63}	130	0.016	0.042	0.023	0.079	0.84
r_7	w_{71}	125	0.004	0.005	0.009	0.01	0.972
	w_{72}	120	0.001	0.005	0.02	0.15	0.824
	w_{73}	145	0.002	0.008	0.013	0.217	0.76
	w_{74}	120	0.03	0.06	0.1	0.81	0
r_8	w_{81}	140	0.01	0.01	0.98	0	0
	w_{82}	135	0.009	0.009	0.01	0.972	0
	w_{83}	115	0.001	0.002	0.09	0.1	0.807
r_9	w_{91}	195	0.012	0.017	0.041	0.93	0
	w_{92}	200	0.05	0.01	0.05	0.89	0
	w_{93}	180	0.01	0.05	0.01	0.01	0.92
	w_{94}	190	0.023	0.035	0.052	0.08	0.81
	w_{95}	210	0.1	0.1	0.12	0.13	0.55
r_{10}	w_{101}	370	0.01	0.01	0.01	0.02	0.95
	w_{102}	280	0.01	0.035	0.065	0.1	0.79
	w_{103}	340	0.024	0.033	0.14	0.803	0
	w_{104}	260	0.05	0.05	0.1	0.15	0.65
r_{11}	w_{111}	1300	0.005	0.008	0.016	0.971	0
	w_{112}	1240	0.053	0.055	0.062	0.08	0.75
	w_{113}	1180	0.03	0.03	0.2	0.74	0
	w_{114}	1340	0.02	0.02	0.03	0.05	0.88
r_{12}	w_{121}	800	0.002	0.022	0.043	0.05	0.883
	w_{122}	840	0.001	0.003	0.008	0.017	0.971
	w_{123}	980	0.001	0.001	0.005	0.005	0.988
r_{13}	w_{131}	70	0.012	0.012	0.14	0.17	0.666
	w_{132}	60	0.053	0.055	0.062	0.08	0.75
	w_{133}	85	0.028	0.032	0.94	0	0
	w_{134}	75	0.016	0.022	0.123	0.839	0
	w_{135}	80	0.004	0.008	0.009	0.979	0
	w_{136}	90	0.01	0.01	0.025	0.03	0.925
	w_{137}	100	0.001	0.006	0.007	0.009	0.977
r_{14}	w_{141}	350	0.001	0.001	0.005	0.01	0.983
	w_{142}	310	0.01	0.02	0.12	0.85	0
	w_{143}	270	0.002	0.998	0	0	0
	w_{144}	320	0.002	0.006	0.053	0.07	0.869
r_{15}	w_{151}	950	0.007	0.008	0.009	0.01	0.966
	w_{152}	900	0.001	0.006	0.08	0.01	0.903
	w_{153}	870	0.006	0.006	0.07	0.018	0.9
r_{16}	w_{161}	1040	0.085	0.09	0.114	0.711	0
	w_{162}	1160	0.01	0.01	0.05	0.1	0.83
	w_{163}	1080	0.01	0.034	0.058	0.11	0.788
r_{17}	w_{171}	100	0.01	0.011	0.014	0.115	0.85
	w_{172}	85	0.004	0.111	0.885	0	0
	w_{173}	105	0.007	0.009	0.01	0.974	0
	w_{174}	100	0.014	0.014	0.02	0.231	0.721
	w_{175}	95	0.003	0.007	0.01	0.02	0.96
r_{18}	w_{181}	125	0.001	0.001	0.06	0.08	0.858
	w_{182}	130	0.005	0.005	0.015	0.115	0.86
	w_{183}	120	0.003	0.005	0.01	0.982	0
	w_{184}	140	0.001	0.006	0.01	0.014	0.969
	w_{185}	100	0.01	0.01	0.02	0.04	0.92

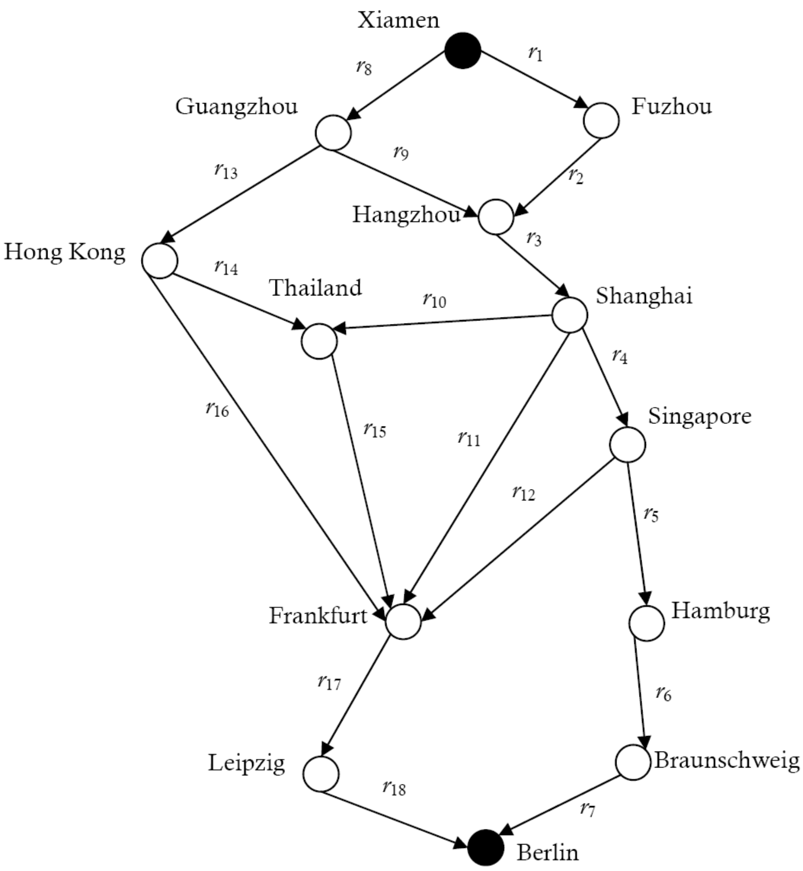

Figure 3. Logistics network connecting Xiamen and Berlin

Table 4. Carrier selection of Figure 3

Maximal multi-commodity reliability: 0.86618217			
i of r_i	Selected carrier: e of w_{ie}	i of r_i	Selected carrier: e of w_{ie}
1	4	10	2
2	3	11	3
3	6	12	1
4	5	13	7
5	1	14	2
6	2	15	3
7	2	16	3
8	3	17	5
9	3	18	3

best carrier selection with the reliability of 0.86618217, where the 4th carrier is selected to deliver the goods from the 4 carriers on the route r_1.

5.3. **Compare GA-MPRSDP, RSG, SA and PSO.** By utilizing the China-Germany example, GA-MPRSDP is subsequently compared with the three methods of RSG, SA and PSO, in which RSG, SA and PSO stop when they run for 1000 iterations. Moreover, SA and PSO are executed for 10 times to observe the largest maximal multi-commodity reliability, the average maximal multi-commodity reliability, the largest CPU time, and the average CPU time. Through PSO (resp. SA), the largest maximal multi-commodity reliability is 0.80466235 (resp. 0.83525133), the average maximal multi-commodity reliability is 0.78158063 (resp. 0.81454648), the largest CPU time is 8772 (resp. 8378) seconds, and the average CPU time is 8390 (resp. 7952) seconds. Figure 4 illustrates the comparison result of GA-MPRSDP, RSG, SA and PSO according to their largest maximal multi-commodity reliabilities, and shows that the proposed algorithm obtains the larger maximal multi-commodity reliability than RSG, SA and PSO. Table 5 summarizes the results of GA-MPRSDP, SA and PSO. Apparently, GA-MPRSDP has better computation efficiency than the others.

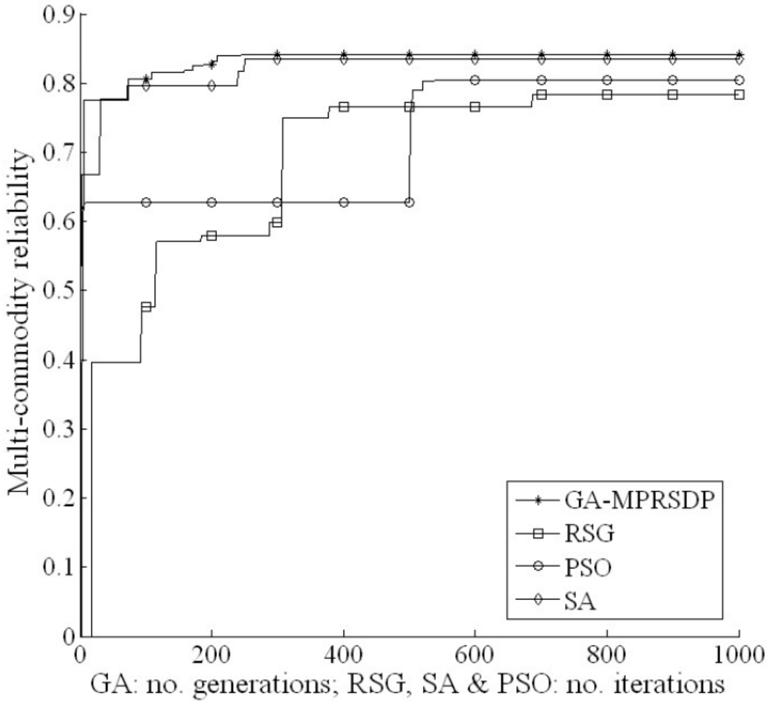

FIGURE 4. Comparison of GA-MPRSDP, RSG, PSO and SA

TABLE 5. Comparison results of GA-MPRSDP, SA and PSO for Figure 3

Algorithm	Largest maximal network reliability	Average maximal network reliability	Largest CPU time (s)	Average CPU time (s)
GA-MPRSDP	0.86618217	0.84926714	6813	5906
SA	0.83525133	0.81454648	8378	7952
PSO	0.80466235	0.78158063	8772	8390

6. **Discussion and Conclusion.** This study proposes a new measure of multi-commodity reliability for freight delivery and regards it as a criterion to determine the optimal carrier selection. By solving the addressed problem, the freight can be reliably delivered to the customer such that the customer's service level is maintained, and the enterprise strengthens the logistics operation accordingly.

Although the global logistics networks in the real world are not very complex, the number of possible carrier selections follows an exponential growth. For instance, the simple example has $\prod_{i=1}^{6} z_i = 4^6 = 4096$ possible carrier selections and the practical example has $\prod_{i=1}^{18} z_i = 121,927,680,000$ possible ones. That is, it is very time-consuming for using IEA to solve such a problem as the logistics network is rather complicated. The

GA-based algorithm integrating MP and RSDP is thus proposed to solve this problem. In particular, the major characteristic of the proposed algorithm is that the algorithm to evaluate fitness value (i.e., network reliability) is never proposed in previous genetic algorithms.

In the simple example, the proposed algorithm is shown to have better computational efficiency than IEA. In the practical example with $D = (10, 20, 20)$ and $C = 72,000$, the best carrier selection is found in 6813 seconds by the proposed algorithm. Furthermore, the proposed algorithm has higher multi-commodity reliability than RSG, SA and PSO under the same terminal constraint. In addition, the proposed algorithm is not only applied to the case of multi-commodity delivery but also applied to the case of single-commodity delivery. For instance, if $D = (0, 30)$ and $C = 50,000$ in the simple example, the optimal carrier selection (2, 3, 1, 1, 4, 3) with the maximal multi-commodity reliability of 0.85485432 is acquired by the proposed algorithm.

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