MITIGATING REVENUE LOSS AND CONGESTION SURCHARGE BY RAIL FREIGHT SUBSIDY IN A MULTIMODAL MULTICOMMODITY FREIGHT TRANSPORTATION MARKET

Rusi Wang
Urban Mobility Institute
Tongji University
4800 Cao'an Hwy., Shanghai 201804, China
Email: rusiwang@tongji.edu.cn

Chi Xie, Ph.D., Corresponding Author
School of Transportation
Urban Mobility Institute
Tongji University
4800 Cao'an Hwy., Shanghai 201804, China
Email: chi.xie@tongji.edu.cn

Bo Zou, Ph.D.
Department of Civil, Materials and Environmental Engineering
University of Illinois at Chicago
842 West Taylor St., Chicago, Illinois 60607, United States
Email: bzou@uic.edu

Xiaowen Fu, Ph.D.
Department of Industrial and Systems Engineering
Hong Kong Polytechnic University
11 Yuk Choi Rd., Hung Hom, Hong Kong
Email: xiaowen.fu@polyu.edu.hk

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ABSTRACT

This study discusses a bilevel optimization problem for allocating rail freight subsidies in a multimodal multicommodity freight transportation market so as to simultaneously mitigate the revenue loss of the rail carrier and the congestion cost of cargo shippers choosing rail freight services. The lower-level part poses a freight transportation network equilibrium model that explicitly considers transportation capacity and bottleneck congestion. The upper-level part sets line-specific subsidies under a subsidy budget, minimizing a weighted sum of the total revenue loss and total congestion surcharge. Revenue loss reflects the potential loss of the rail carrier due to unused capacity, while congestion surcharge quantifies individual shippers' waiting delay for the limited transportation capacity of rail lines. The solution procedure relies on a tabu search metaheuristic, in which the lower-level equilibrium problem is solved by the iterative balancing algorithm in the Lagrangian relaxation framework. The proposed optimization model and solution method are applied to the China-Europe freight transportation market. The results show that the optimized subsidy scheme significantly outperforms the current subsidy scheme by reducing both the total revenue loss and total congestion surcharge in all months of the year of 2019. Specifically, the optimized subsidy scheme reduces the total revenue loss by 27.3% and the total congestion surcharge by 64.2%. The weighting coefficient can effectively adjust the relative importance of the carrier and shippers in the freight subsidy design: minimizing only the total revenue loss reduces it by up to 16.3% but increases the total congestion surcharge by up to 540%; minimizing only the total congestion surcharge reduces it by up to 44.2% but increases the total revenue loss by up to 30.1%.

Keywords: China Railway Express, Freight subsidy optimization, Network equilibrium, Revenue loss, Congestion surcharge, Tabu search

INTRODUCTION

Increasing the market share of rail freight services is often of positive significance for reducing carbon emissions and enhancing operational efficiency in the freight transportation sector. In the China-Europe freight transportation market, for example, China Railway Express (CRE) offers average transit times only one-third of those of China-Europe liner shipping lines (*1*). To increase the attractiveness of the CRE service, the Chinese government has taken proactive measures such as offering subsidies to reduce the CRE freight rates in the hope of attracting more demand. However, the current CRE subsidies own some shortcomings. First, all existing subsidy schemes are city-specific, typically providing a uniform subsidy amount to all CRE lines starting from the jurisdiction of a city. Such a simple subsidy policy overlooks the distinct operational features and competitive characteristics of different CRE lines in the market. Second, the China-Europe freight transportation market is a highly sophisticated and highly competitive economic system that involves multiple transportation modes and freight service lines, compounding the complexity of subsidy implementation. Without carefully considering the interaction between different CRE lines and between the CRE service and other freight transportation services in the market, the efficacy of subsidies will fall short of the optimal level. The still relatively low market share and competence of the CRE service under existing CRE subsidies reflect these challenges (*2*).

Freight transportation network models serve as fundamental tools for evaluating and optimizing subsidies, mathematically capturing spatiotemporal supply-demand interactions such as capacity constraints and congestion effects. Existing subsidy optimization models based on freight transportation models have various objectives, such as promoting infrastructure use, increasing carriers' profits, reducing greenhouse gas emissions, mitigating congestion, or alleviating geopolitical risks (*3–5*). However, in such models, the implicit waiting delays incurred by individual cargo shippers due to competition for limited transportation capacity are less frequently considered. Although Zhang et al. (*6*) impose an upper limit on the queueing delay of shippers, the dynamic traffic assignment models they introduce add significant complexity. Economically, the dual variables associated with the transportation capacity constraints of the optimization problem, termed congestion-induced waiting delay, represent the implicit waiting delay incurred by shippers to access their desired service links. However, the explicit incorporation of congestion-induced waiting delay into the objective function of subsidy optimization models is less common in the existing literature.

To this end, this paper discusses a bilevel subsidy optimization model for designing rail freight subsidies, with its application to the China-Europe freight transportation market. The lower-level model poses a multimodal multicommodity freight transportation network equilibrium model with explicit link capacity constraints. The upper-level model sets line-specific subsidies under a subsidy budget constraint, minimizing the weighted sum of the total revenue loss of the carrier and the total congestion surcharge of shippers using a weighting coefficient ranging from 0 to 1 to adjust the relative importance of the carrier and shippers. We apply this model to the China-Europe freight transportation network with CRE, China-Europe liner shipping, and the highway networks in China and Europe, with categorized monthly O-D freight demand rates for the year of 2019 serving as the demand input. Unlike existing models, our approach not only commits to increasing the utilization of rail freight transportation, but also considers protecting shippers from excessively concentrating on a small number of rail lines by explicitly introducing congestion surcharge as a cost term into the objective function, which monetizes the dual variables associated with transportation capacity constraints. This form of the objective function, which simultaneously incorporates primal variables (i.e., revenue loss of the rail carrier) and dual variables (i.e., congestion surcharge of cargo shippers) of the optimization problem, poses a new modeling approach that is less commonly adopted in the literature on freight subsidy design.

The remainder of the paper is organized as follows. The next section proposes the bilevel freight subsidy optimization model and develops the solution procedure for this model. The numerical analysis section applies the proposed model to the multimodal multicommodity China-Europe freight transportation network. The results are analyzed in two key aspects: A comparison between the optimized subsidy scheme and the current subsidy scheme, and a comparison among optimized subsidy schemes with different weighting coefficients in the objective function to evaluate policy trade-offs between the interests of the carrier and shippers. Finally, the last section summarizes our modeling work and reveals solution behaviors and advantages of the proposed model.

METHODOLOGY

Network Representation

The multimodal multicommodity freight transportation network is represented by a directed graph $G(\mathcal{N},\mathcal{A})$. The set of nodes $\mathcal{N}$, indexed by n, includes product origin cities $\mathcal{O}$, product destination cities $\mathcal{D}$, and intermediate transfer nodes $\mathcal{I}$. The set of origin-destination pairs is defined by $\mathcal{W} \subseteq \mathcal{O} \times \mathcal{D}$. The set of commodity categories $\mathcal{M}$, indexed by m, groups commodities based on the HS codes. The set of directed links $\mathcal{A}$, indexed by a, includes four distinct types: railway service links $\mathcal{A}_r$, liner shipping links $\mathcal{A}_s$, bottleneck facility links $\mathcal{A}_b$ (e.g., seaports, water channels, and break-of-gauge stations), and highway network links $\mathcal{A}_h$. Air transportation is not considered in the model, as it is attractive only for commodities with extremely high time sensitivity and does not directly compete with other modes.

Links are grouped based on two key characteristics: whether they have fixed transit times and whether they have fixed physical transportation capacity. Railway service links $\mathcal{A}_r$, liner shipping links $\mathcal{A}_s$, and highway network links $\mathcal{A}_h$ all have fixed transit times, denoted by $\bar{t}_a$ for each link a. Bottleneck links $\mathcal{A}_b$ have flow-dependent transfer delays $t_a(x_a) = t_a^0\left(1+\alpha(x_a/u_a^{\text{nom}})^\beta\right)$, where t_a^0 is the free-flow transit time, u_a^{nom} is a nominal capacity parameter, and α, β are model parameters. Railway service links $\mathcal{A}_r$ and liner shipping links $\mathcal{A}_s$ have limited physical transportation capacities u_a that enforce $x_a \le u_a$. Highway network links $\mathcal{A}_h$ are not modeled with transportation capacities. Moreover, only railway service links $\mathcal{A}_r$ are assumed to be eligible for government subsidies, which is consistent with policy practice in the China-Europe freight transportation market.

The set of scheduled service lines $\mathcal{L}$ includes railway service lines $\mathcal{L}_r$ and liner shipping lines $\mathcal{L}_s$. Each path $k \in \mathcal{K}_w$ for O-D pair w uses exactly one service line l, satisfying $\sum_l \lambda_{k,l} = 1$ where $\lambda_{k,l}$ is the path-line incidence indicator. Each railway service link or liner shipping link $a \in \mathcal{A}_r \cup \mathcal{A}_s$ belongs exactly to one service line l, satisfying $\sum_l \delta_{l,a} = 1$ where $\delta_{l,a}$ is the line-link incidence indicator.

Subsidy Optimization Model

The government-shipper interaction is modeled as a bilevel program. The lower-level model is a stochastic user equilibrium (SUE) problem with capacity side constraints:

$$\min_{\mathbf{f}} Z(\mathbf{f};\mathbf{s}) = \sum_{a\in\mathcal{A}_b} \int_0^{x_a} t_a(w)dw$$
$$+ \sum_{m,w,k} f_{k,w}^m \left(\frac{\sum_a \gamma_{k,a} c_a - \sum_l \lambda_{k,l} s_l}{v^m} + \sum_{a\in\mathcal{A}_r\cup\mathcal{A}_s\cup\mathcal{A}_h} \gamma_{k,a} \bar{t}_a \right)$$
$$+ \sum_{m,w,k} \frac{f_{k,w}^m \ln f_{k,w}^m}{\sigma_m v^m} \quad (1)$$

subject to:

$$\sum_k f_{k,w}^m = q_w^m \quad \forall w, m \quad (2)$$
$$x_a \le u_a \quad \forall a \in \mathcal{A}_r \cup \mathcal{A}_s \quad (3)$$
$$f_{k,w}^m \ge 0 \quad \forall k, w, m \quad (4)$$

where:

$$x_a = \sum_{m,w,k} \gamma_{k,a} f_{k,w}^m \quad \forall a \quad (5)$$

where x_a is the link flow rate, $f_{k,w}^m$ is the path flow rate of commodity category m, $\gamma_{k,a}$ is the path-link incidence indicator, c_a is the freight rate of link a, v^m is the value of time of commodity category m, σ_m denotes the scale parameter of the variance of perceived transportation costs in the multinomial logit model, and q_w^m denotes the demand for commodity category m in O-D pair w.

The upper level optimizes line-specific rail subsidies $\mathbf{s} = \{s_l\}_{l\in\mathcal{L}_r}$ to minimize the weighted sum of the total revenue loss and total congestion surcharge:

$$\min_{\mathbf{s}} Y(\mathbf{s}) = \theta \underbrace{\sum_{a\in\mathcal{A}_r} c_a(u_a - x_a^*)}_{\text{Total revenue loss } L(\mathbf{s})} + (1-\theta) \underbrace{\sum_{a\in\mathcal{A}_r\cup\mathcal{A}_s} \mu_a^* x_a^* v^m}_{\text{Total congestion surcharge } C(\mathbf{s})} \quad (6)$$

subject to:

$$\sum_{l\in\mathcal{L}_r} s_l f_l^* \le B \quad (7)$$
$$s_l \in \{0, \eta, 2\eta, \ldots, \lfloor \bar{c}_l/\eta \rfloor \eta\} \cup \{\bar{c}_l\} \quad \forall l \in \mathcal{L}_r \quad (8)$$
$$(\mathbf{f}^*, \boldsymbol{\mu}^*) \in \arg\min_{\mathbf{f}} \{Z(\mathbf{f};\mathbf{s}) \mid (2)\text{–}(4)\} \quad (9)$$

where:

$$f_l^* = \sum_{m,w,k} \lambda_{k,l} f_{k,w}^{m*} \quad \forall l \in \mathcal{L}_r \quad (10)$$

where $\theta \in [0,1]$ is the weighting coefficient that adjusts the trade-off between mitigating the total revenue loss and total congestion surcharge, B is the subsidy budget, η is the subsidy increment unit, $\bar{c}_l = \sum_a \delta_{l,a} c_a$ is the full freight rate of line l, f_l is the line flow rate, and μ_a is the congestion-induced waiting delay of link a. The objective function in (6) incorporates two terms: the total revenue loss $L(\mathbf{s})$, which quantifies the potential loss of the rail carrier due to the unused capacity of railway service lines; and the total congestion surcharge $C(\mathbf{s})$, which aggregates the monetized congestion-induced waiting delay over all links, and quantifies the additional cost that shippers incur to secure immediate access to their desired service links beyond regular freight rates.

Solution Algorithm

The upper-level subsidy optimization model is solved using a tabu search metaheuristic (Algorithm 1). The lower-level SUE problem is solved using an iterative balancing algorithm within the Lagrangian relaxation framework embedding a disaggregate simplicial decomposition (DSD) algorithm (Algorithm 2).

TABLE 1 Tabu Search Algorithm for the Subsidy Optimization Model

Algorithm 1: Tabu Search Algorithm for the Subsidy Optimization Model

Initialization: Use a feasible initial solution $\mathbf{s}_0^{(0)}$ satisfying the subsidy budget constraint in (7) and the discrete constraint in (8). Initialize short-term tabu list $\mathcal{T} = \emptyset$, long-term tabu list $\mathcal{F} = \{\mathbf{s}_0^{(0)}\}$, historical best solution $\mathbf{s}^* = \mathbf{s}_0^{(0)}$, and the corresponding objective function value $y^* = Y(\mathbf{s}_0^{(0)})$.

For Iteration n:

1. **Candidate generation**: For each railway service line $l_j \in \mathcal{L}_r$:
   If $s^*_{n-1,l_j} = 0$: generate candidate with $s_{n,l_j} = \min(\eta, \lfloor \bar{c}_{l_j}/\eta \rfloor \eta)$
   If $\eta \leq s^*_{n-1,l_j} \leq \lfloor \bar{c}_{l_j}/\eta \rfloor \eta$: generate candidates with $s_{n,l_j} = \min(s^*_{n-1,l_j} + \eta, \bar{c}_{l_j})$ and $s_{n,l_j} = s^*_{n-1,l_j} - \eta$
   If $s^*_{n-1,l_j} = \bar{c}_{l_j}$: generate candidate with $s_{n,l_j} = \lfloor \bar{c}_{l_j}/\eta \rfloor \eta$
   Remove solutions in $\mathcal{F}$ to form candidate set $\Gamma_{n,\mathrm{nl}}$.
2. **Candidate evaluation and feasibility check**: Evaluate each candidate solution $\mathbf{s}_n^{(k)} \in \Gamma_{n,\mathrm{nl}}$ through parallel computing:
   a. Solve lower-level equilibrium (Algorithm 2)
   b. Compute f_l^*, x_a^*
   c. If $\sum_{l \in \mathcal{L}_r} s_{n,l}^{(k)} f_l^* \leq B$, accept the solution and add to the feasible set $\Gamma_{n,\mathrm{f}}$
3. **Selection**:
   If $\min_{\mathbf{s}_n^{(k)} \in \Gamma_{n,\mathrm{f}}} Y(\mathbf{s}_n^{(k)}) < y^*$ (aspiration criteria), select best $\mathbf{s}_n^*$ and update $\mathbf{s}^*, y^*$
   Else, select best candidate $\mathbf{s}_n^*$ with $(l_k, \delta_k) \notin \mathcal{T}$
4. **Tabu list update**:
   Add reverse move $(l^*, -\delta^*)$ to $\mathcal{T}$
   Remove oldest entry if $|\mathcal{T}| > T_{\max}$, where $T_{\max}$ denotes the short-term tabu tenure
   Add $\mathbf{s}_n^*$ to $\mathcal{F}$
5. **Termination check**: Terminate after $N_{\max}$ iterations or $K_{\max}$ consecutive non-improving iterations.

TABLE 2 Iterative Balancing Algorithm for the SUE Problem

Algorithm 2: Iterative Balancing Algorithm for the SUE Problem
Initialization: $n := 0$; $\mu_a^0 := 0\ \forall a \in \mathcal{A}_r \cup \mathcal{A}_s$; $f_{k,w}^{m,0} := q_w^m / \lvert \mathcal{K}_w \rvert\ \forall k, w, m$; $x_a^0 := \sum_{m,w,k} \gamma_{k,a} f_{k,w}^{m,0}$ $\forall a$; $LB := -\infty$; $UB := +\infty$. Preset the convergence tolerance parameters $\varepsilon_1, \varepsilon_2, \varepsilon_3$. *Outer loop*: 1. **Path generalized costs**: $g_{k,w}^{m,n} = \frac{1}{v^m}\left(\sum_a \gamma_{k,a} c_a - \sum_{l \in \mathcal{L}_r} \lambda_{k,l} s_l\right) + \sum_{a \in \mathcal{A}_r \cup \mathcal{A}_s} \gamma_{k,a} \bar{t}_a + \sum_{a \in \mathcal{A}_b} \gamma_{k,a} t_a(x_a^n) + \sum_{a \in \mathcal{A}_r \cup \mathcal{A}_s} \gamma_{k,a} \mu_a^n$ 2. **DSD inner loop**: a. Compute auxiliary path flows $\tilde{f}_{k,w}^{m,n}$ using the multinomial logit model b. Find optimal step size $\lambda^* = \arg\min_{\lambda \in [0,1]} L((1-\lambda)\mathbf{f}^n + \lambda \tilde{\mathbf{f}}^n; \boldsymbol{\mu}^n)$ c. Update flows: $f_{k,w}^{m,n} := (1-\lambda^*) f_{k,w}^{m,n} + \lambda^* \tilde{f}_{k,w}^{m,n}$ d. Update aggregate link flows $x_a^n := \sum_{m,w,k} \gamma_{k,a} f_{k,w}^{m,n}$ e. Repeat until $\frac{\lVert \mathbf{x}^n - \tilde{\mathbf{x}}^n \rVert^2}{\sum_a x_a^n} \leq \varepsilon_1$ 3. **Feasibility test**: If $x_a^{n+1} \leq (1+\varepsilon_2) u_a\ \forall a \in \mathcal{A}_r \cup \mathcal{A}_s$: $UB := Z(\mathbf{f}^{n+1})$ Else: $LB := Z(\mathbf{f}^{n+1})$ 4. **Convergence test**: If $(UB - LB)/LB < \varepsilon_3$: terminate and return $\mathbf{f}^*, \boldsymbol{\mu}^n$ 5. **Multiplier update**: $\mu_a^{n+1} := \max\left\{0, \mu_a^n + \omega\left[\ln x_a^{n+1} - \ln u_a\right]\right\}\ \forall a \in \mathcal{A}_r \cup \mathcal{A}_s$; $n := n+1$

NUMERICAL ANALYSIS

Experimental Setup

The multimodal multicommodity China-Europe freight transportation network used in this study has 50 Chinese origins, 51 European destinations, 55 CRE lines, and 27 liner shipping lines. The network specifications and categorized monthly O-D freight demand rates for the year of 2019 are from (*1*). The parameters include: the subsidy increment unit $\eta = \$500/\text{TEU}$, tabu search termination criteria $N_{\max} = 500$ and $K_{\max} = 150$, convergence tolerance parameters $\varepsilon_1 = \varepsilon_2 = \varepsilon_3 = 10^{-4}$, and the subsidy budget B of each month equal to the total subsidy expenditure under the current subsidy scheme.

We calibrate the short-term tabu tenure through evaluating tenure efficacy across tenure values from 7 to 30 with $\theta = 0.5$, primarily based on the quality of the solution measured by the objective function value of the optimized solution, and secondarily based on the convergence efficiency measured by iteration count. The experimental results indicate that a tenure value of 25 achieves the best overall performance and therefore this tenure value is adopted for all subsequent experiments. For each month, we run the tabu search algorithm multiple times with random feasible initial solutions with $\theta = 0.5$, selecting the best solution as the initial solution for all subsequent experiments in this month. The subsidy optimization problem is solved repeatedly with a discrete set of weighting coefficient values ranging from 0 to 1 for all 12 months of the year of 2019.

The solution algorithm is implemented in C++ and executed on a desktop computer equipped with an Intel Core i9-12900KF processor and 32 GB of RAM.

Computational Results

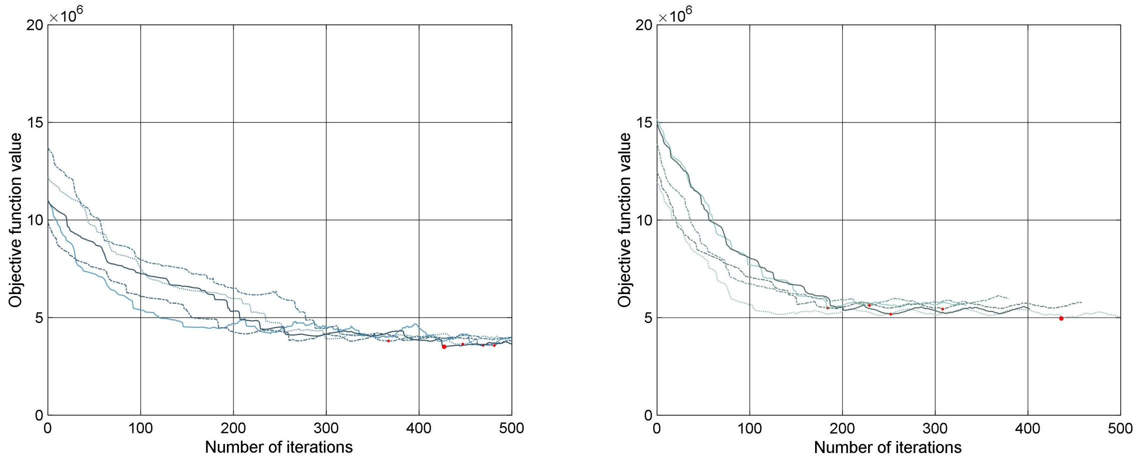
In the China-Europe freight transportation demand dataset, the freight demand rates and the composition exhibit a significant fluctuation across months. In July 2019, the month with the highest demand rate, the demand rate is 53% higher than that in February 2019, the month with the lowest demand rate. Therefore, we elaborate the computational results and the optimization results for February and July 2019 as two representative months, although the results for all other months are also obtained.

The convergence curves of all tabu search processes initialized with random feasible subsidy solutions for February and July 2019 are shown in Figure 1. For the same month, the objective function value of the worst optimized solution is up to 13% higher than that of the best optimized solution. This underscores the necessity to select the best initial solution for each month prior to conducting further experiments.

Table 3 shows that the average computation time across all weighting coefficient values is 8.7 h and 12.5 h for February and July 2019, respectively. The computation time is heavily dependent on many factors, especially the termination criteria in the tabu search algorithm, and the convergence tolerance parameters in the iterative balancing algorithm and the DSD algorithm. Therefore, these metrics presented in the table should only be considered as references that indicate that the tabu search algorithm can provide high-quality solutions in a reasonable computation time.

Optimization Results

For simplicity, we compare only the performance of the optimized subsidy scheme with $\theta = 0.5$ with that of the current subsidy scheme for each month. The weighting coefficient



(a) February 2019 (b) July 2019

FIGURE 1 Example convergence curves of the tabu search procedure

TABLE 3 Example Computation Performance of the Tabu Search Procedure

Month		Weighting Coefficient						
		0	0.1	0.2	0.5	0.8	0.9	1
February 2019	Iterations	380	435	466	500	500	394	425
	Time (h)	7.05	8.05	10.39	11.04	10.44	7.16	6.90
July 2019	Iterations	352	338	300	500	375	286	313
	Time (h)	10.77	8.89	9.57	17.18	9.91	13.73	17.77

of 0.5 indicates an equal treatment of the concerns of the carrier and shippers.

In terms of total revenue loss and total congestion surcharge, which are directly impacted by subsidies and the main concerns of the CRE carrier and individual cargo shippers, the economic advantage of the optimized subsidy scheme is evident, as shown in Figure 2. It clearly shows that the optimized subsidy scheme realizes a significantly lower level of the two performance measures than that under the current subsidy scheme for all months of the year of 2019, indicating that it benefits both the CRE carrier and shippers as expected and performs substantially better than the current subsidy scheme. Specifically, the total revenue loss under the optimized subsidy scheme is reduced by 27.3% on average over 12 months, equivalent to $1.74 million per week, from that under the current subsidy scheme. Similarly, the total congestion surcharge under the optimized subsidy scheme is reduced by 64.2% on average over 12 months from that under the current subsidy scheme.

Figure 3 compares the containerized freight flow rates and compositions of all CRE service lines under the current subsidy scheme and the optimized subsidy scheme. The volume of high-value goods (e.g., food and electronics) carried by a line remains stable unless

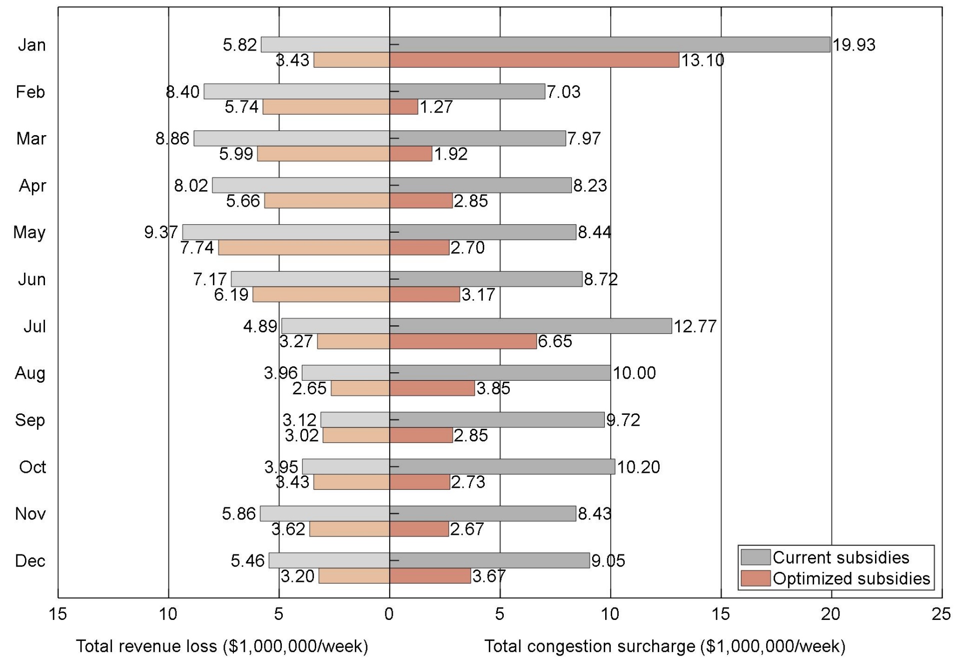
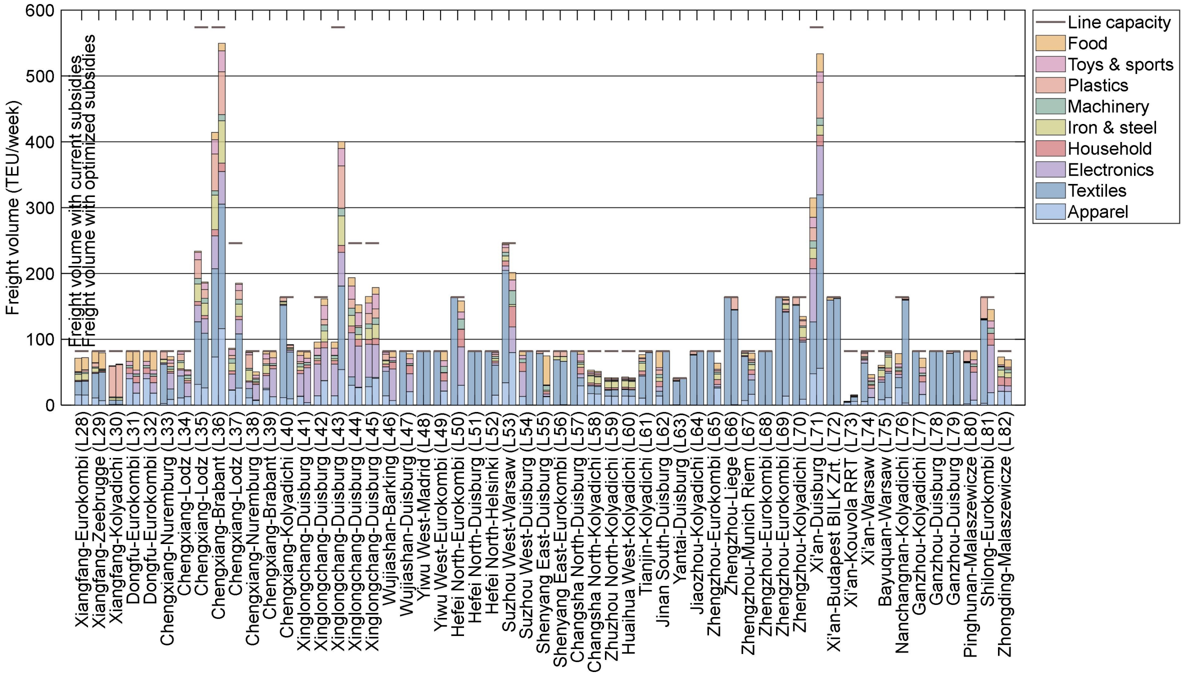


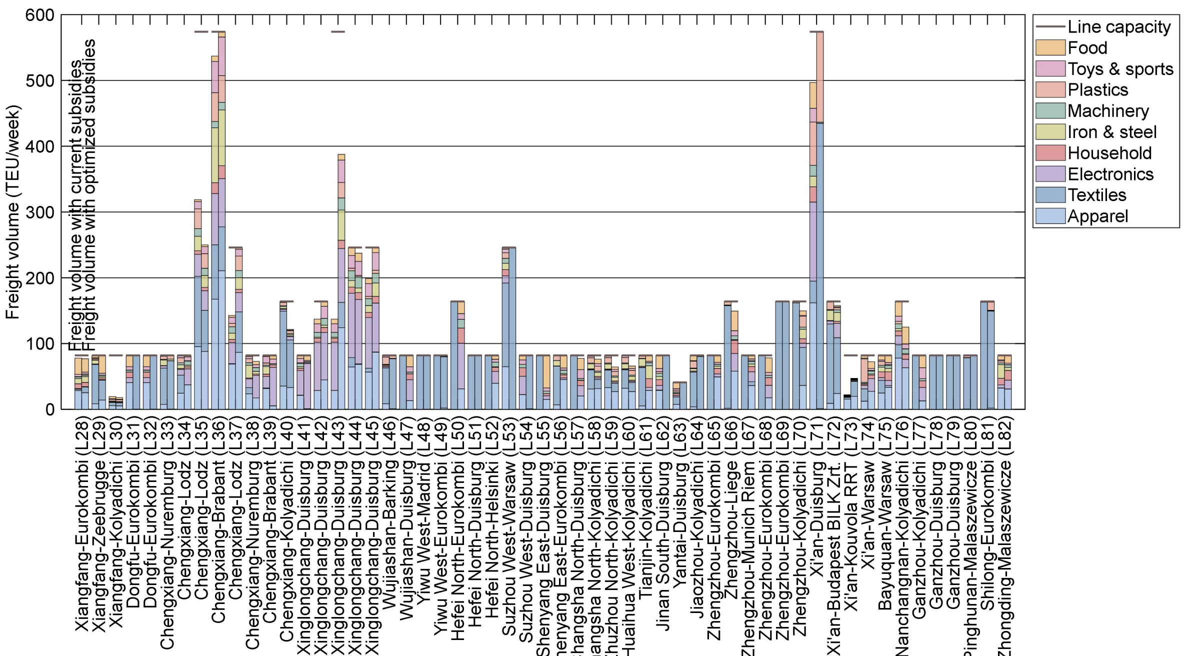
FIGURE 2 Comparison of total revenue loss and total congestion surcharge under the current subsidy and optimized subsidy scenarios

the line reaches saturation under the optimized subsidy scheme. On the other hand, those saturated lines under the current subsidy scheme observed the optimized subsidy scheme's success in enabling a larger proportion of high-value goods to use these lines (e.g., Line 50, Line 67 and Line 77 in February and July 2019), except for a few cases where lines remain dominated by textiles under the optimized subsidy scheme due to their relatively low subsidy values under the current subsidy scheme (e.g., Line 54 and Line 62 in February and July 2019). Moreover, a small number of saturated lines under the current subsidy scheme are now carrying goods below their capacity under the optimized subsidy scheme (e.g., Line 40 and Line 74 in February and July 2019).

We perform a comparative evaluation on the economic effectiveness of the optimized subsidy scenario compared to the current subsidy scenario, as shown in Table 4. In July 2019, for example, with a total subsidy expenditure of $19,710,206, the optimized subsidy scheme reduces the total revenue loss of the CRE carrier and the total congestion surcharge of shippers by 33% and 48%, respectively, compared to the current subsidy scenario, although the subsidy expenditure paid by the government is only 97% of that under the current subsidy scheme. We define the *benefit-cost ratio* (BCR) as the total cost reduction divided by total subsidy expenditure, where the total cost reduction is the sum of the total revenue loss reduction and the total congestion surcharge reduction made by subsidies. A higher BCR indicates greater efficiency in producing system benefits through subsidies. Again, using February and July 2019 as two example months, we found that the BCR is only 0.63 in February and 0.72 in July under the current subsidy scheme; however, the BCR reaches 1.11 and 1.14 in the two months under the optimized subsidy scheme. The results of other months of the year of 2019 demonstrate that the government's subsidy expenditure is reduced



(a) February 2019



(b) July 2019

FIGURE 3 Comparison of freight flow redistribution under the current and optimized subsidy scenarios

by 8.3% on average under the optimized subsidy scheme. A subsidy expenditure of $1 would reduce system loss by $1.08 to $1.39, with an average of $1.20, compared to $0.63 to $0.73 under the current subsidy scheme, which averages $0.69. As we know, a BCR value greater than 1 indicates that the benefit produced outweighs the investment cost. The above result shows that the current subsidy scheme is unfortunately not a financially worthy option in that it produces a net social loss, but the optimized subsidy scheme successfully overcomes the deficiency. In summary, the optimized subsidy scheme achieves a desirable tripartite situation, in which the government, CRE carrier, and individual shippers all benefit from it.

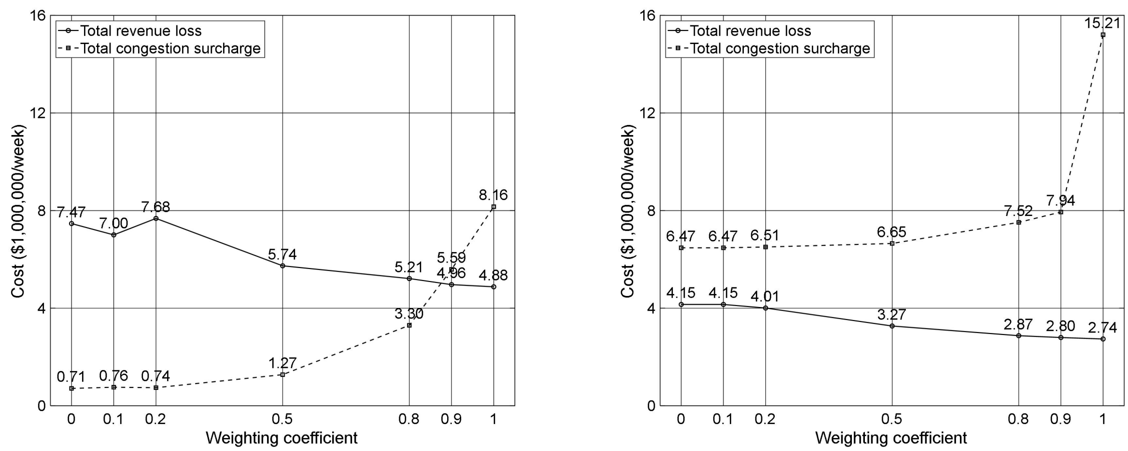
TABLE 4 Economic Performance Results of CRE with Different Subsidy Schemes

Performance Measure	Current Subsidy Scheme		Optimized Subsidy Scheme	
	Feb. 2019	Jul. 2019	Feb. 2019	Jul. 2019
Total freight flow rate (TEU/week)	5,894.80	6,721.00	6,439.05	7,024.85
Total revenue loss ($/week)	8,399,960	4,885,089	5,735,600	3,268,242
Total congestion surcharge ($/week)	7,030,585	12,769,490	1,274,926	6,651,558
Total cost reduction ($/week)	11,340,334	14,766,759	19,760,352	22,501,539
Total subsidy expenditure ($/week)	17,915,269	20,403,471	17,784,562	19,710,206
Benefit-cost ratio	0.63	0.72	1.11	1.14

Impact of Weighting Coefficient in the Objective Function

The weighting coefficient in the subsidy optimization model, θ, directly controls how the government prioritizes the interest of the carrier versus the interest of shippers in the context of specific policy objectives. From an optimization perspective, a higher weighting coefficient value would yield a solution with a lower total revenue loss but a higher total congestion surcharge. The total revenue loss and total congestion surcharge with the discrete set of weighting coefficient values in February and July 2019 are shown in Figure 4.

Notably, the observed variations in total revenue loss and total congestion surcharge with respect to the weighting coefficient values are in line with our expectations. As demonstrated in the figure, when θ increases from 0.5 to 1, the total revenue loss decreases by 15.0% and 16.3% in February and July 2019, respectively; when θ decreases from 0.5 to 0, the total congestion surcharge decreases by 44.2% and 2.7% in the two months, respectively. This result demonstrates that changing the weighting coefficient can effectively adjust the relative importance of the carrier and shippers in the optimization of subsidies. In addition, high-demand months like July 2019 have greater potential to reduce the total revenue loss of the carrier, while lower-demand months like February 2019 have greater potential to reduce the total congestion surcharge of shippers. However, reducing either the total revenue loss or total congestion surcharge comes at the expense of the other stakeholder. Specifically, when θ decreases from 0.5 to 0, the total revenue loss increases by 30.1% and 27.0% in February and July 2019, respectively; when θ increases from 0.5 to 1, the total congestion surcharge



(a) February 2019 (b) July 2019

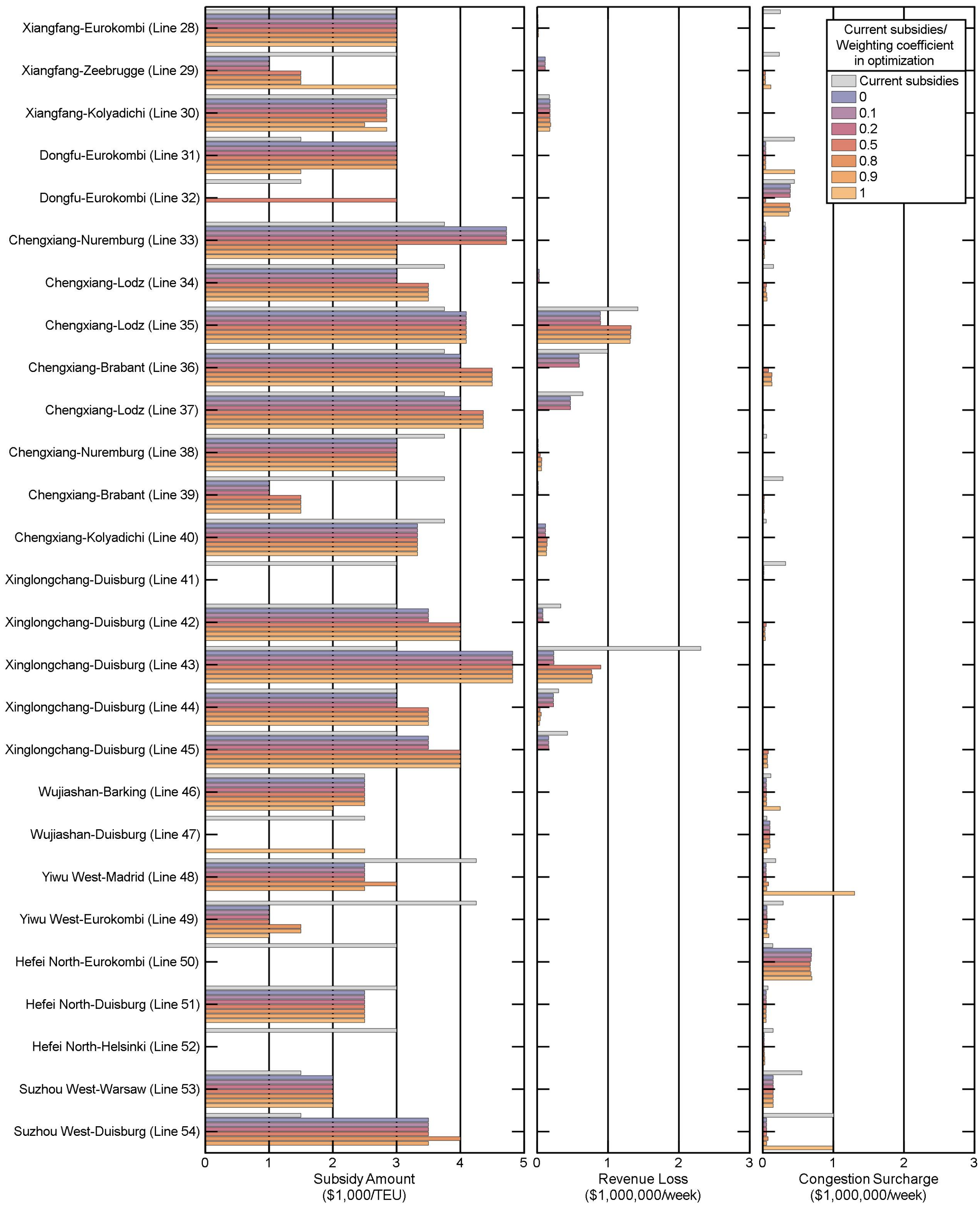
FIGURE 4 Total revenue loss and total congestion surcharge under the optimized subsidy schemes with different weighting coefficient values

becomes 540% and 129% higher in the two months, respectively. This observation indicates that overly prioritizing mitigating the total revenue loss of the carrier while ignoring shippers' fierce competition for limited transportation capacity may lead to an unacceptable situation.

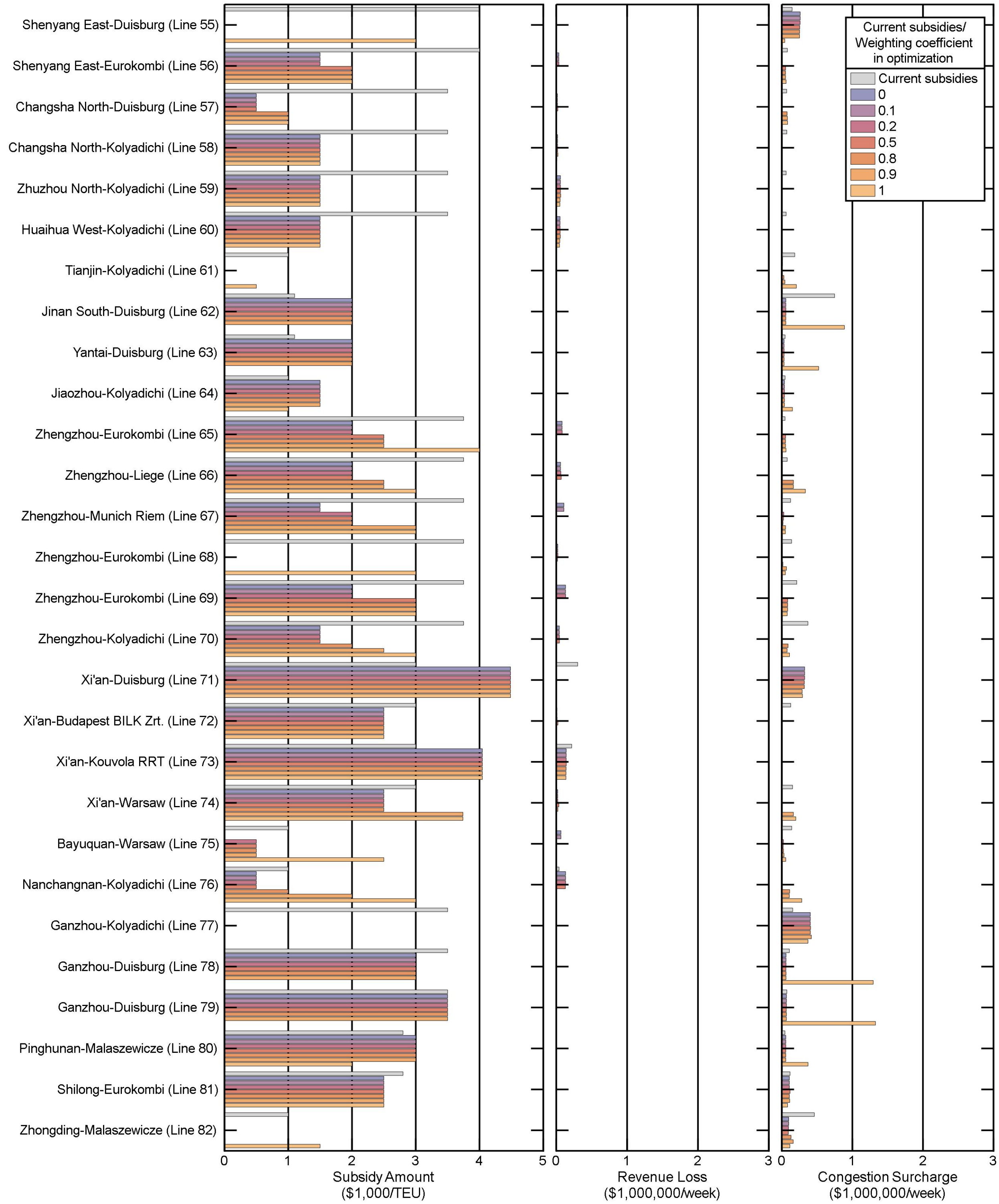
We then make an in-depth comparison of the subsidy amount, revenue loss, and congestion surcharge on the line level among the current subsidy scheme and optimized subsidy schemes with different weighting coefficient values, as shown in Figure 5. The revenue loss of a line is defined as the sum of the revenue loss over all its links (i.e., $L_l(\mathbf{s}) = \sum_{a\in\mathcal{A}_u}\delta_{l,a}\cdot c_a(u_a - x_a^*)$), and the congestion surcharge of a line is defined similarly as the sum of the congestion surcharge over all its links (i.e., $C_l(\mathbf{s}) = \sum_{a\in\mathcal{A}_c}\delta_{l,a}\cdot(\sum_{m\in\mathcal{M}}\mu_a^* x_a^{m,*} v^m)$). Overall, the optimized subsidy schemes generally reduce both revenue loss and congestion surcharge for most CRE lines compared to the current subsidy scheme, exhibiting good equity performance in enhancing individual lines' efficiency. Importantly, for most lines, the direction of change in subsidy amount, revenue loss, and congestion surcharge (i.e., increase or decrease relative to the current subsidy scheme) remains consistent across all weighting coefficient values in the optimized subsidy schemes. However, for a small number of lines (e.g., Line 76 and Line 80), the direction of change in these indicators is inconsistent across weighting coefficient values. All CRE lines may be grouped into three subsets: (1) lines with zero/low revenue loss and high congestion surcharge; (2) lines with zero/low revenue loss and zero/low congestion surcharge; (3) lines with high revenue loss and zero/low congestion surcharge. The high congestion surcharge or revenue loss phenomena with lines in the first and third subsets are typically due to demand shortage/surplus and geographical locations. It is interesting to find that for unsaturated CRE lines under the current subsidy scheme, the optimized subsidy schemes yield a subsidy level not lower than the current subsidy scheme for most weighting coefficient values. In contrast, for oversaturated lines under the current subsidy scheme, optimized subsidy schemes reduce subsidies for most weighting coefficient values. This reduction alleviates congestion surcharge significantly for most oversaturated lines, with some even transitioning to unsaturated status with minor revenue loss. This finding justifies that optimized subsidy schemes improve system performance simultaneously: increasing subsidies for unsaturated lines and reducing financial support for oversaturated ones. Under such intentionally optimized subsidy schemes, over 90% of the CRE lines are now either saturated with a short waiting delay or unsaturated with a small unused capacity.

Discernible differences emerge among the optimized subsidy schemes themselves depending on the weighting coefficient, though less pronounced than those observed between the optimized schemes collectively and the current scheme. Generally, higher weighting coefficient values lead to higher overall subsidy levels, as increased subsidies generally raise the probability that shippers use the CRE service. At the individual line level, the optimized subsidy amount increases or remains constant for most lines as θ increases, but decreases for a minority of lines. Notably, when minimizing the total revenue loss is the only optimization objective (i.e., $\theta = 1$), the resulting optimized subsidy scheme allocates significantly higher subsidies to specific lines than optimized subsidy schemes under other weighting coefficient values (e.g., Line 47, Line 66, and Line 76). Although an excessively high subsidy on a specific line does not necessarily increase the congestion surcharge on itself due to complex competition among modes and lines, a more expensive overall subsidy scheme can significantly increase the congestion surcharge on certain critical lines (e.g., Line 48, Line 78, and Line 79). This occurs because the enhanced attractiveness of the entire CRE service relative to liner shipping increases the overall demand for the CRE service. This increased demand then concentrates on certain critical lines, raising their congestion surcharge. Consequently, the total congestion surcharge for the shippers increases, consistent with Figure 4 where very high total congestion surcharge occurs with $\theta = 1$. This outcome clearly demonstrates the negative effects of focusing only on minimizing the total revenue loss in the subsidy optimization model, particularly given that the percentage increase in congestion surcharge for individual lines can be substantially higher than that for the total congestion surcharge.

In our subsidy optimization model, the subsidy budget constraint in (7) stipulates that the total subsidy expenditure of the government should not exceed a subsidy budget for each month. Figure 6 shows that the subsidy budget constraint effectively constrains the total subsidy expenditure of the government. The total subsidy expenditure generally increases as the weighting coefficient increases, until it is very close to the subsidy budget. Notably, since the subsidy amount is assumed to be discrete, the total subsidy expenditure generally cannot equal the subsidy budget (i.e., the subsidy budget constraint is binding), but the subsidy budget constraint takes effect for the optimization in specific months under certain weighting coefficient values. The subsidy budget constraint takes effect by excluding those solutions that violate them during the feasibility check in the tabu search algorithm. Examination of the solution process reveals that subsidy budget constraints take effect in the experiments with $\theta = 0.8$, 0.9, and 1 in February 2019, and with $\theta = 1$ in July 2019. Maximizing system benefits with a smaller total subsidy expenditure is worth considering, especially given that, at least partially, increasing the overall subsidy level may not always benefit the CRE system, particularly individual shippers. Thus, setting an appropriate subsidy budget is a critical step before changing the weighting coefficient to make a good trade-off between the interest of the carrier and the shippers. Yang et al. (7) directly minimizes the total subsidy expenditure when there is a lower limit on the system benefit, which is different from our model from a policy perspective. Incorporating the total subsidy expenditure as a term in the objective



(a) February 2019



(b) July 2019

FIGURE 5 Line-specific subsidy amount, revenue loss and congestion surcharge under the current subsidy scheme, and optimized subsidy schemes with different weighting coefficient values

function is also an alternative, but this would increase the complexity of the model.

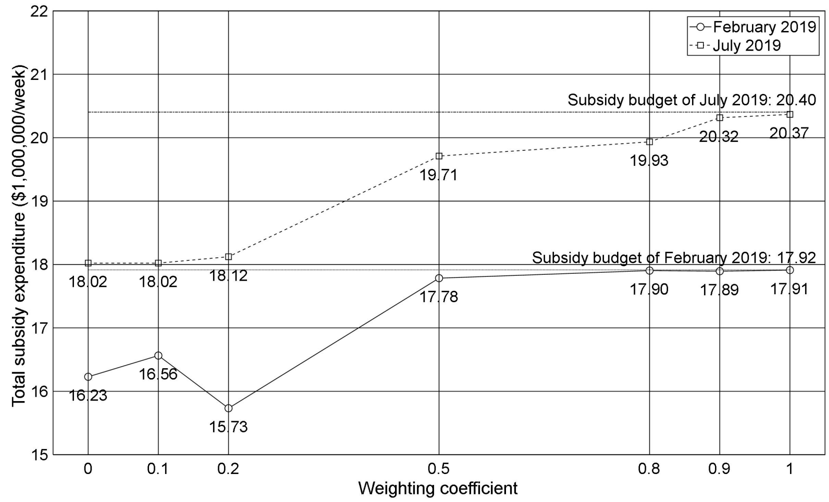


FIGURE 6 Total subsidy expenditure under the optimized subsidy schemes with different weighting coefficient values

CONCLUSION

This paper proposes a bilevel optimization model for designing CRE rail freight subsidies. The lower level formulates a multimodal multicommodity freight transportation network equilibrium model with explicit link transportation capacity constraints and flow-dependent transfer delays at bottleneck facilities. The upper level optimizes line-specific subsidies under a subsidy budget constraint, minimizing the weighted sum of the total revenue loss of the carrier and the total congestion surcharge of shippers. The key novelty with this modeling work lies in explicitly incorporating the total congestion surcharge into the upper-level objective function, where this term monetizes the dual variables associated with link transportation capacity constraints. This approach quantifies the implicit waiting delay incurred by shippers due to competition for limited transportation capacity, a consideration less commonly addressed in the existing literature on freight subsidy design. To solve this complex bilevel model, a specialized solution procedure is developed: the lower-level network equilibrium problem with capacity side constraints is solved using an iterative balancing method within the Lagrangian relaxation framework embedding a disaggregate simplicial decomposition algorithm; the upper-level subsidy optimization problem is solved using a tabu search metaheuristic.

The model is applied to the multimodal multicommodity China-Europe freight transportation network using categorized monthly O-D freight demand rates for the year of 2019. The analysis focused on two key aspects: Comparing the optimized subsidy scheme with the current subsidy scheme, and evaluating the impact of the weighting coefficient in the objective function. The following findings reveal some solution behaviors and advantages of the proposed model.

First, the optimized subsidy scheme substantially outperformed the current scheme. It achieves an average reduction of 27.3% in the total revenue loss of the rail carrier across all months, and simultaneously an average reduction of 64.2% in the total congestion surcharge of shippers. A subsidy expenditure of \$1 would reduce system loss by \$1.20, substantially higher than the \$0.69 reduction achieved under the current subsidy scheme. This demonstrates that optimized subsidies can economically benefit both the carrier and shippers more effectively than existing practices. At the individual line level, optimized schemes generally increase subsidies for unsaturated lines and reduce subsidies for oversaturated lines. This intentional reallocation alleviates congestion surcharge significantly on oversaturated lines while maintaining utilization. Consequently, over 90% of the rail lines under optimized schemes were found to be either saturated with short waiting delays or unsaturated with minimal unused capacity.

Second, the weighting coefficient in the subsidy optimization model proves to be a crucial parameter governing the trade-off between mitigating the revenue loss of the carrier and the congestion surcharge of shippers. As anticipated, increasing the weighting coefficient value reduces total revenue loss but increases total congestion surcharge, while decreasing the weighting coefficient value reduces total congestion surcharge but increases total revenue loss. Importantly, optimization schemes prioritizing the carrier's interest excessively may lead to an unacceptable situation where the total congestion surcharge increases dramatically, by hundreds of percent in some months. This outcome arises because such schemes allocate very high subsidies to specific lines, making the entire rail service significantly more attractive relative to liner shipping. This increased attractiveness concentrates demand and disproportionately penalizes shippers competing for capacity on critical railway service lines, leading to sharply increased congestion surcharges.

Third, the subsidy budget constraint plays an important role in the optimization. Total subsidy expenditure generally increases with the weighting coefficient value until it approaches the budget limit. While the discrete nature of subsidies often prevents the constraint from being strictly binding, it frequently takes effect during the tabu search process, especially for higher weighting coefficient values, by excluding infeasible solutions. This underscores the importance of setting an appropriate subsidy budget level to effectively balance stakeholder interests. An insufficient budget may restrict potentially beneficial schemes, while an excessively high budget could enable schemes that exacerbate congestion surcharge under high weighting coefficient values.

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