# Data-Driven Empty Container Repositioning for Large Scale Railway Network With Fuzzy Demands

Minyi Cai, Haodong Li, Zhanqing Guo, and Shuisheng Lu

*Abstract*—**The Chinese rail network has a fast-growing number of containers in service to promote intermodal transport service and to attract more freight demand to the railway for a sustainable transport system. The repositioning of empty containers induces a significant problem for the large-scale rail network, due to the spatial imbalance between freight supply and demand. Traditionally, the empty container repositioning (ECR) problem is solved with the estimated parameters of a given demand distribution, which may difficult known to decision maker. This article develops a data-driven framework for the ECR problem based on the large datasets available. This framework employs machine-learning algorithms to forecast the supply/demand of empty containers, and to draw parameters identifying the factors that can be hardly integrated into optimization models. Based on those parameters, two optimization models for different ECR modes are then proposed to explore the optimal ECR plan. An integrated weight coefficient is introduced into the objective functions, which minimizes the total kilometers that empty containers transported. The models are solved by CPLEX after constraints conversion based on triangular fuzzy supply/demand. The numerical results based on a real-world case show that the proposed solution method can yield the optimal empty container repositioning plan. The total container-kilometer may increase after data-driven parameters are introduced, as some of the empty container repositioning may no longer follow the shortest path, while the final plan becomes more practicable and executable.**

*Index Terms*—**Data driven, empty container repositioning, fuzzy demands, machine learning, transportation problem.**

## I. Introduction

CONTAINER transportation, being the primary form of modern logistics, has many benefits for reducing transportation expenses, simplifying package, and improving transportation service. As the cleanest and greenest high-volume transport, rail has an essential role in creating sustainable lifestyles and economies. Railway container transport is the most environmentally sustainable mode of transporting cargo, and has developed rapidly in recent years in China driven by policies (transportation mode share adjustments for promoting freight demand shift from road to railway and water transport, developing sea-rail intermodal transport, and promoting sustainable development of green rail transport systems) and market (as fast-growing China Railway Express with the support of the Chinese initiative One Belt One Road). Some of the bulk cargos such as coal, metal ores and grain shift to container transportation for dust controlling. In the year of 2021, the volume of railway freight transport increased by 80 million tons in China. The rail container transportation takes up about 75% of more than 60 million tons. China now has more than 800 000 railway containers, including 20-ft, 40-ft, open-top containers, and various other types, enabling the tremendous growth of railway container traffic for a more sustainable rail system.

Trade imbalance results in a need of empty container repositioning. In trade activities of China, the container flow (takes 20 ft container as an example) between regions exhibits significant imbalance behavior. As larger number of full containers come to Chengdu Railway Bureau from Xi'an and Jinan Railway Bureau, smaller number of which are filled when sent back. For a five-day plan horizon, the average number of repositioned empty containers is about 13 000, with more than 5 000 000 km of empty transport. This motivated China State Railway Group Co., Ltd. (China Railway) to support this empty container repositioning (ECR) research. The context of container repositioning is becoming more and more important for large-scale railway system, facing the competition from other transport modes and need of costs reduction with fast-growing number of containers.

The principles and strategies of ECR are mainly based on the imbalance of the container flows among container stations of the rail network. Most of literature and practices developed models for empty container/railcars repositioning based on typical transportation problem. This approach simplifies the problem and allows for rapid iteration and updating of the repositioning result by using high-frequency calculations. CSX and other freight railroads in the United States used this method to solve their empty wagon repositioning problems [1], [2]. While, some of the features are difficult to be considered for large scale rail network in this traditional method. As indicated in Fig. 1, empty containers can transport from the supply station to the demand station directly, or transfer through the concentrate station. The decision maker should forecast the supply and demand of empty containers, and analyze the capacity of rail network

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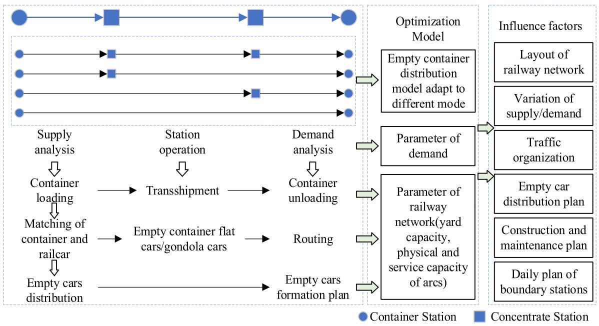


Fig. 1. Influencing factors of railway ECR process.

(yard capacity and physical and service capacity of network). First, forecasting the supply and demand of empty containers is a big challenge for over 2000 container stations. Traditionally, we estimate the demand with a specific distribution assumption, such as normal distribution. However, the distribution assumption is problematic in real-world applications, as the distribution is not known to the decision maker in reality. And the historical data shows that demand distribution even changes over time. Second, the capacity for ECR should be determined by the layout of rail network, daily traffic management plan, empty wagon repositioning plan, construction and maintenance plan, and so on. It costs too much to import all of those capacity parameters into the optimization model for a rail network with over 140 000 km of operating mileage (by the year of 2021). So, most researchers on empty container/wagon repositioning either ignore or set those parameters as fixed values, and the final plan may not be fully implemented.

The growing availability of large datasets for railway containers management can help overcome those issues and improve the performance of optimization models in real-world situations. According to an increasing number of researches and practices, the optimal utilization of large-scale data by machine learning (ML) and operational research (OR) can push existing optimization approaches to better adapt and address actual production challenges [3], [4]. China Railway has developed and implemented several information systems to aid in the organization of container operations. For example, the "Container Transportation Tracking System" allows for real-time tracking and statistical analysis of containers, and generates more than 200 million pieces of basic tracking data every month. Motivated by the growing availability of large datasets, this article moves forward to data-driven railway container repositioning with those real-world data. Machine learning methods can be used for the forecast analysis of empty container supply and demand, as well as the discovery of key capacity parameters that are related to ECR. The contributions of this study are 1) present a data-driven framework that integrates machine learning into the traditional optimization model sequentially for a more practicable and executable ECR plan. This is a generic framework that can be applied to optimization problems of transport and logistics using diverse data. 2) Daily dispatching insights based on machine learning methods and real-world data regarding the capacity and other parameters that are difficult to get manually.

The rest of this article is organized as follows. In Section II, an overview of related literature is provided. Section III describes the problem and introduces the data-driven framework of ECR. Section IV proposes the optimization models based on this framework. In Section V, the case study is presented for validating the methodology. Finally, Section VI concludes this article.

## II. Literature Review

The problem of ECR is similar to that of empty cars distribution and usually studied as a typical transportation problem. One of the first publications on this subject is the work of [5], where a linear programming model was developed to minimize the cost of empty vehicle distribution and solved it by using simplex method.

Empty containers/railcars generate only costs without revenue for they require the same time and expenditure on transportation. To reduce the cost of empty railcar transport, CSX and BNSF in USA developed a dynamic empty car distribution optimization system [1], [2]. Zhang and Li [6] incorporated customer satisfaction evaluation indicators into railway container distribution decisions. Reasonable empty container substitution helps to avoid convection transport and reduce costs. Chang et al. [7] used branch-and-bound method to solve empty container substitution problem. Shintani et al. [8] investigated the use of combi-containers as an alternative to multiple types of containers for cargo shipment.

In terms of maritime container distribution, a two-stage optimization method was proposed by Zheng et al. [9] to measure container leasing prices at different ports. Wong et al. [10] presented a yield-based container reallocation framework that uses constrained linear programming to optimize the reallocation of containers from surplus to deficit locations. Ko [11] proposed a model for intelligent ECR in the context of Industry 4.0 and used genetic algorithms to generate the best ECR solution. Lu et al. [12] studied joint decisions on pricing and empty container repositioning in two-depot shipping services with stochastic shipping demand. Luo et al. [13] introduced option contract into the empty container ordering problem. Chen et al. [14] developed a resource allocation approach for maritime empty containers, namely the largest-debt-first policy.

He et al. [15] proposed a simulation-based heuristic algorithm for multiechelon container supply chain network. Luo and Chang [16] studied a strategy for dealing with the empty container inventory repositioning problem based on revenue sharing contracts, which improves the coordination of ECR in intermodal transport. Cai et al. [17] proposed a multi-period mixed integer programming model to optimize the empty container repositioning between public hinterlands and ports.

More details on ECR may be found in the published works [18], [19]. There are few literature on ECR of railway transport in recent years, especially the application studies of new methods and technologies with rapid development and application of information technology in railway transportation, as shown in Table I.

TABLE I
PRIMARY LITERATURE ON ECR STUDIES

| Authors | Subject Focus | Model | Characteristics |
|---|---|---|---|
| Misra [5] | Railway railcar/container repositioning | Linear programming model and Simplex method | First study of empty vehicle distribution as a transport problem |
| Zhang and Li [6] | | Optimization model based on customer satisfaction | Incorporated customer satisfaction evaluation indicators into railway container distribution decisions |
| Gorman et al. [1] | | Transportation problem formulation | Developed dynamic empty cars distribution optimization systems |
| Gorman et al. [2] | | Transportation problem formulation | |
| Chang et al. [7] | Empty container substitution | Mixed integer programming models | Containers substitution between different types |
| Shintani et al. [8] | | Multicommodity network flow model | Combi-containers used as an alternative to multiple types of containers |
| Zheng et al. [9] | Maritime container repositioning | Two-stage optimization method | A two-stage optimization method to measure container leasing prices at different ports |
| Ko [11] | | An intelligent empty container dispatching system model | Fuzzy set theory for cost estimation and genetic algorithms to obtain the optimal solution. |
| Lu et al. [12] | | Stochastic dynamic programming model | Coordinating Pricing and Empty Container Repositioning |
| Luo et al. [13] | | Empty container ordering model with option trading | Introduced a one-period, two-echelon option contract into the empty container ordering problem from the forwarder's perspective |
| Chen et al. [14] | | Nonlinear stochastic programming model | A novel model for container inventory management is developed. |
| Luo and Chang [16] | | Contractual coordination theory | Contractual coordination theory has been Applied |
| He et al. [15] | Multimodal container repositioning | A mixed integer programming model | Modeling and optimizing the multi-echelon container supply chain networks |
| Cai et al. [17] | | A multi-period mixed integer programming model | Markov decision process combined with dynamic programming method |

TABLE II
PRIMARY LITERATURE ON DATA-DRIVEN RESEARCH

| Authors | Subject Focus | Model | Characteristics |
|---|---|---|---|
| Beutel and Minner [20] | Safety Stock Planning | Linear Programming | Incorporated linear regression function into the supplier model |
| Sachs and Minner [21] | Newsvendor problem | Distribution-free model | A data-driven approach to solve news providers problem with censored demand observations |
| Zhang and Gao [22] | | Machine learning | Proposed a machine learning method for optimizing product demand |
| Oroojlooyjadid et al. [23] | | Deep neural network | Applied a deep neural network to the newsvendor model and proved its superiority |
| Ban and Rudin [3] | | Machine learning | Solved the newsvendor problem with a single-step machine learning algorithm |
| Laan et al. [24] | | Sample-average approximation | Distributionally robust chance constrained optimization model |
| Neghab et al. [25] | | Deep neural networks | Proposed an integrated estimation and optimization approach using a deep learning network |
| Prak and Teunter [26] | Inventory management | Bayesian methods | Proposed a framework of demand distribution-free into an inventory decision model |
| Mamani et al. [27] | | Robust optimization models | Proposed a robust model for inventory management problem |
| Zhi et al. [28] | | GARCH-EVT-Copula approach | Proposed an innovative data-driven approach to include the risk of market volatility in determining the loan-to-value ratio and interest rate for different collateral units |
| Kamandanipour et al. [29] | | Simulated annealing algorithm | Solved the problem of dynamic multi-class pricing and capacity allocation for passenger rail transport |
| Shu et al. [30] | Transportation and logistics | Density-based spatial clustering of applications with noise | Used a data-driven approach to design shuttle transport routes and schedules |
| Chen et al. [31] | | Machine learning algorithms | Proposed a data-driven framework to investigate the multiperiod anticipatory shipping problem |
| Tufano et al. [32] | | Kalman filter | Introduced data driven logistic platforms merging data from vehicle operators |

Data science has been growing rapidly in recent years. Decision-making driven by data has attracted the attention of researchers. For example, Beutel and Minner [20] set safety stock levels by incorporating a linear regression function into the supplier model within a data-driven framework. Lots of researches focus on the newsvendor problem, Sachs and Minner [21] used a distribution-free model based on a data-driven approach to address the problem of news providers with censored demand observations. Zhang and Gao [22] used ML algorithms to train demand forecasting models. Oroojlooyjadid et al. [23] integrated a deep neural network into the newsboy model and integrated data forecasting and inventory optimization to optimize product order quantities based on the characteristics of the demand data, and demonstrated the superiority of the strategy. Ban and Rudin [3] proposed an algorithm based on the empirical risk minimization principle, and an algorithm based on kernel-weights optimization to solve the "big data" newsvendor problem. Laan et al. [24] studied data driven newsvendor problem with a service-level constraint. Neghab et al. [25] integrated ML and optimization problem for optimizing a newsvendor's strategy.

Prak and Teunter [26] proposed a framework for substituting the demand distribution of lead time into the inventory decision model, thereby reducing the uncertainty in the parameter estimates. Mamani et al. [27] proposed robust optimization models for inventory management problem. Zhi et al. [28] used a data-driven model to determine both of loan-to-value ratio and interest rate.

Kamandanipour et al. [29] proposed an optimization model to divide the number of seats into different classes and determine the selling price in railway passenger transport. Shu et al. [30] applied a data-driven approach to design shuttle transport routes and schedules to improve the efficiency and convenience of last-mile transport. To minimize costs for e-retailers and maximize the saved time that customers wait to receive their goods, Chen et al. [31] proposed a multistage forward shipping data-driven decision framework to address the question of when to deliver the right amount of goods before the customer places an order to reduce customer receipt time. Tufano et al. [32] introduced data-driven logistic platforms for barge transportation network under incomplete data. Representative researches are shown in Table II. Those studies inspired us to use a data-driven strategy for ECR based on the large datasets of railway containers management.

A brief comparison of the literature on ECR and this article is shown in Table III. For the supply/demand of empty containers, [6] and [33] set it as a fixed value, while the works in [15] and [16] generated it by uniform distribution and normal distribution respectively for ECR problem. Based on machine learning, this article will generate supply/demand of empty containers in a distribution-free way, and introduce an integrated weight coefficient to regard the capacity and other parameters that are difficult to get manually.

## III. DATA-DRIVEN FRAMEWORK FOR ECR

### A. Problem Analysis

Fig. 1 depicts the transportation organization of empty containers between stations. It is required to forecast and analyze the

TABLE III
COMPARISON OF LITERATURE ON ECR AND THIS ARTICLE

| Researchers | Supply/demand | Parameters |
|---|---|---|
| Choong et al. [33] | Fixed value | Fixed capacity parameters |
| He et al. [15] | Uniform distribution | Some inconstant parameters are randomly generated based on some distributions (i.e. the uniform distribution, normal distribution). And fixed value for the other parameters. |
| Luo and Chang [16] | Normal distribution | The other parameters are set to constant values. |
| Zhang and Li [6] | Fixed value | Assume that the line capacity meets the transportation need. |
| This article | Distribution-free with machine learning | An integrated weight coefficient is introduced to deal with the parameters that are difficult to be imported into the models directly. |

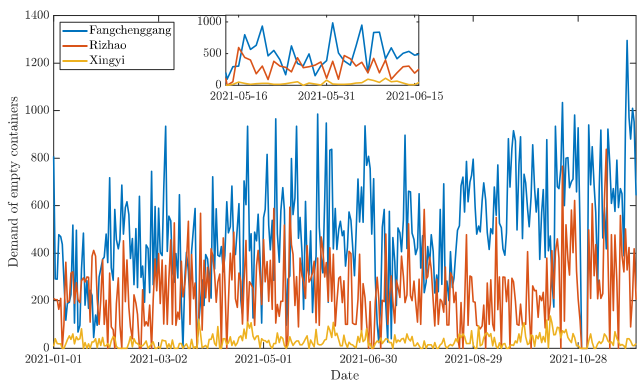


Fig. 2. Change of empty containers demand.

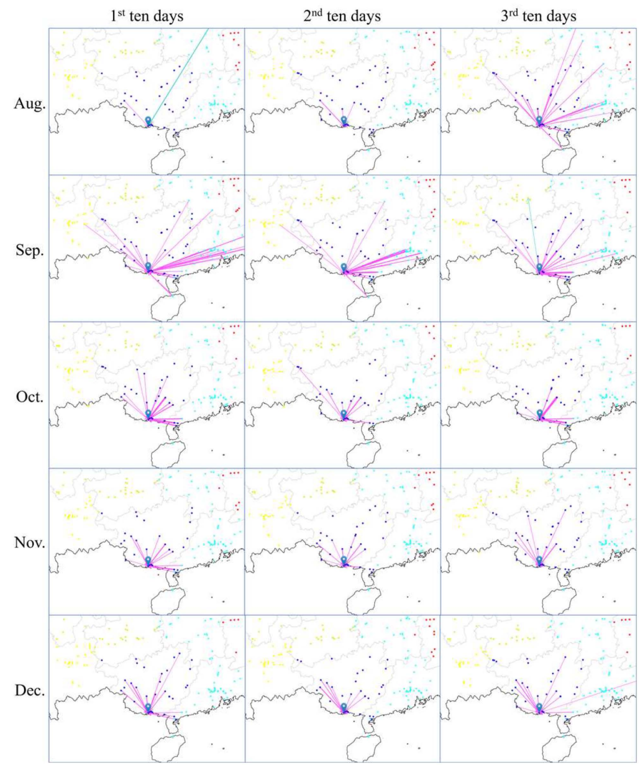


Fig. 3. Empty containers to Fangchenggang station.

supply and demand of empty containers accurately for an ECR plan. At the same time, it is necessary to analyze the transport capacity, such as the supply of empty wagons for loading empty containers, the capacity of container stations and concentrate stations for storage, capacity of rail lines, and so on. Those parameters are difficult to get precisely or to consider in the model, which are crucial to determine whether the ECR plan can be implemented or not.

*1) Empty Container Supply and Demand:* There are over 2000 railway container stations in China, and the supply and demand of empty containers vary dramatically. Fig. 2 shows the daily empty container demand at Fangchenggang Station (large-sized), Rizhao Station (medium-sized), and Xingyi Station(small-sized) in 2021. It does not show obvious fluctuation patterns of empty container supply/demand throughout time. Data analysis shows that it is difficult to get the supply and demand distribution, especially for medium-sized and small-sized stations. So, the traditional demand forecasting approaches are difficult to apply to large-scale ECR problem.

*2) Relevant Capacity Parameters:* The influencing factors of capacity parameters (e.g., capacity of stations and paths) include the layout of the railway network, railcar flow organization scheme, empty car distribution plan, construction and maintenance plan, other monthly organization plans, as well as the impact of daily operation plan in stations. It is difficult to collect all of those information even though many information systems have been applied. On the other hand, the model may be too complicated to solve if all those information are integrated. While the historical trajectory of ECR can indicate the influence of those capacity parameters.

1) Railway passenger and freight transportation capacity fluctuates seasonally. For example, August is the traditional peak period of railway passenger transport, and a large amount of coal is transported from October to December for the demand during the Spring Festival. The railway capacity of large-scale of those two months are arranged for passenger and coal transportation, respectively. As shown in Fig. 3, the flow of 20 ft empty containers reflects the impact of the railcar flow organization plan on ECR.
2) Seasonality of construction and maintenance plan. As shown in Fig. 4, the Chengxiang station supply empty containers to the Xiangyang station (Wuhan Bureau) consistently in recent months (lines to the right in Fig. 4). However, due to the construction and maintenance of the Xiangyu line and other related lines during September and October, the number of empty containers to the south increases (downward lines) to ensure the demand for empty containers within the Nanning Bureau. The demand for empty containers around the Xiangyang Station is supplied by the Guangzhou Bureau (originally distributed westward to the Nanning Bureau).

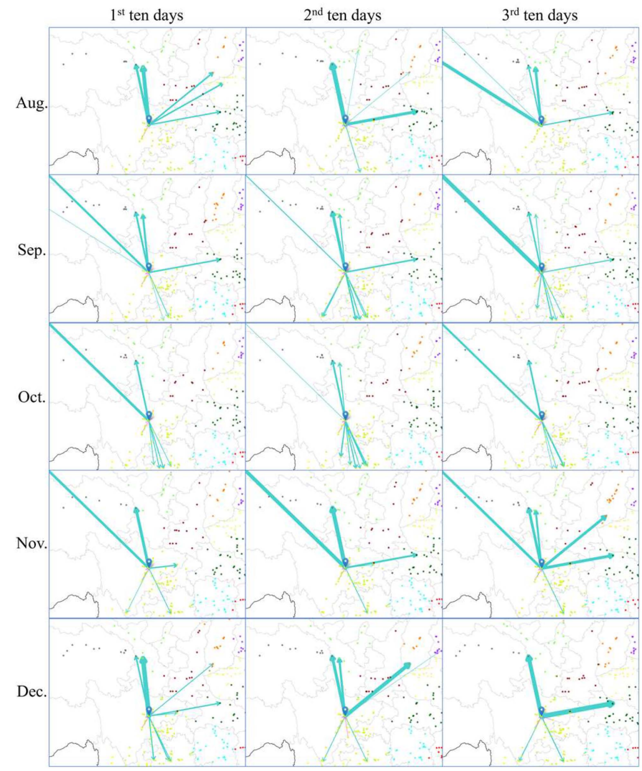


Fig. 4. Empty containers from Chengxiang station.

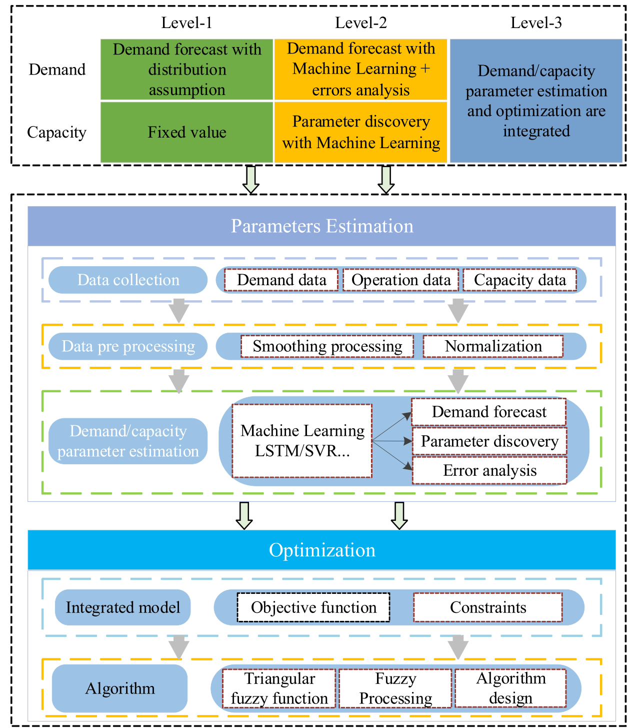


Fig. 5. Data-driven framework for ECR decisions.

3) The directivity of empty container repositioning. Similar to empty railcar repositioning flow, the flow of empty containers moves from south to north, and from east to west in China. As most of the lines of empty containers from Chengxiang Station point to north and northwest in Fig. 4, which roughly show the impact of the empty railcar repositioning plan on ECR.

## B. Technical Framework

With the continuous development and application of information systems, the increasing size of container transportation data such as real-time status, location, and other information are available. Those information systems lay a foundation for data-driven optimization of ECR. Huber et al. [4] distinguished three levels on which data can be used to revise the traditional decision process. Based on this study, this article proposes a data-driven ECR optimization framework, as shown in Fig. 5. The first level is to forecast empty container demand using the determined demand distribution, with the relevant capacity parameters set as fixed value. The second level is that demand forecast, error analysis, and parameter discovery are generated based on machine learning. For the third level, the machine learning and optimization model are integrated.

In this article, the machine learning method is combined with operation optimization as follows.

1) Parameters estimation, including forecasted supply and demand of container, forecasting errors and capacity-related parameters. We need preprocessing (such as noise processing and dimensionless) of the collected data, and then select the right forecast methods according to the features of data.
2) *Modeling*. Determine the objectives and constraints of ECR optimization models. The obtained parameters then can be integrated into the models.
3) *Algorithm design*. Process the forecast value of empty container supply and demand and errors as fuzzy supply and demand. An algorithm is designed to solve the model, and finally, get the optimal ECR plan.

## C. Demand Forecast

The forecast of empty container supply and demand is achieved by using ML based on the empty container tracking data. The initial data is smoothed using the central moving average method over a five-day plan horizon, and normalized by the min–max data normalization method.

Several forecasting methods are examined and compared with the commonly used indexes [such as root-mean-square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE)], including the autoregressive integrated moving average model (ARIMA), gray forecast (GM, 11), long Short-term memory (LSTM), back propagation neural network (BP), support vector regression (SVR) model, and integrated forecasting model of LSTM-SVR. The forecast results of Fangchenggang Station are presented in Fig. 6, and the error analysis are shown in Table IV. The combined model of LSTM-SVR has the best performance, as shown in Table IV.

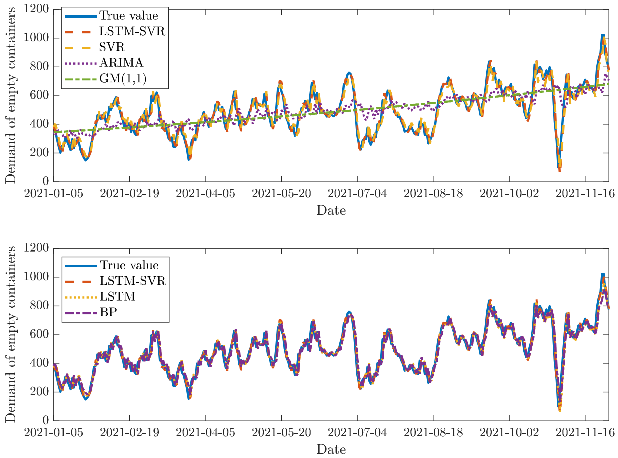


Fig. 6. Forecast results of empty container demand at Fangchenggang station.

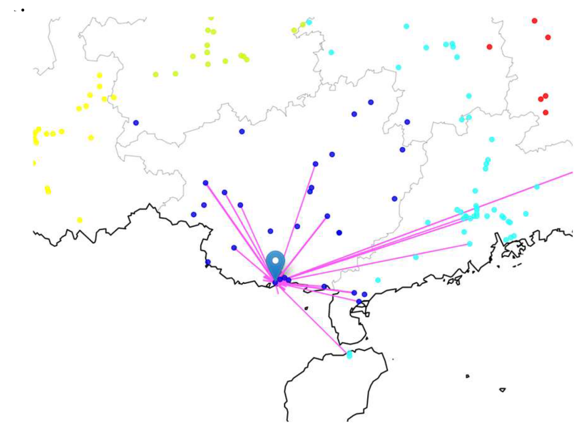

Fig. 7. Forecasted empty containers transported to Fangchenggang Station.

TABLE IV
FORECASTING ERROR OF DIFFERENT METHODS

| | RMSE | MAE | MAPE |
|---|---|---|---|
| LSTM-SVR | 43.10 | 33.84 | 7.83% |
| LSTM | 52.52 | 41.16 | 9.70% |
| SVR | 53.98 | 43.25 | 10.25% |
| BP | 54.26 | 43.03 | 10.16% |
| ARIMA | 123.13 | 94.23 | 24.26% |
| GM (1,1) | 127.62 | 99.33 | 26.64% |

TABLE V
INTEGRATED WEIGHT COEFFICIENTS OF FANGCHENGGANG STATION

| Supply Station | Demand Station | Forecast Quantity | RMSE | $\varepsilon_{ij}$ |
|---|---|---|---|---|
| Haikounan | | 1 | 0.187 | 0.994 |
| Xiaotang | | 1 | 0.476 | 0.994 |
| Zhanjiang | | 1 | 0.884 | 0.994 |
| Jiangmen | | 3 | 0.077 | 0.981 |
| Liujiang | | 3 | 0.349 | 0.981 |
| Nali | | 3 | 0.836 | 0.981 |
| Tieshangang | | 6 | 0.934 | 0.961 |
| Chongzuo | Fangcheng-gang | 13 | 0.245 | 0.916 |
| Jiebian | | 15 | 0.153 | 0.903 |
| Tiandong | | 15 | 1.758 | 0.903 |
| Xingningxi | | 25 | 1.148 | 0.839 |
| Guigang | | 42 | 2.311 | 0.729 |
| Suixi | | 44 | 2.871 | 0.716 |
| Baisedong | | 60 | 1.981 | 0.613 |
| Huangchengao | | 155 | 2.276 | 0.000 |

### *D. Key Parameters Discovery*

This article uses a machine learning approach to convert the capacity elements into an integrated weight coefficient based on the analysis in Section III-A. This coefficient can be introduced into the objective function, to make sure that the relevant capacity parameters can be considered in the models indirectly.

The specific convert process is as follows.

1) Analyze the origin and destination (OD) of ECR based on the historical empty container tracking data.
2) Get the OD of empty containers for all of the container stations, as shown as the lines in Figs. 3 and 4. The width of line means the volume of empty containers. And the purple (green) line shows the empty containers that arrive at (depart from) the station.
3) Use the procedure in Section III-C to forecast and analyze the OD of empty containers in each station. Then, we can get the number of empty containers that from/to a station to/from any other stations.
4) The weight of each OD pair is measured and calculated as (1) based on the OD volume.
5) The parameter is multiplied in the objective function of the ECR models

$$\varepsilon_{ij} = \frac{\left| e_{ij} - \max\limits_{k \in I_j} e_{kj} \right|}{\max\limits_{k \in I_j} e_{kj}}. \quad (1)$$

In (1), $\varepsilon_{ij}$ denotes the integrated weight coefficient between container handling station $i$ and $j$, $e_{ij}$ means the forecast volume of ECR between container station $i$ and $j$, and $\max\limits_{k \in I_j} e_{kj}$ denotes the maximum value of the forecast value of ECR among all the other stations associated with container station $j$.

Taking Fangchenggang Station as an example, the LSTM-SVR method is used to get its OD (five-day plan horizon) of empty container with the associated stations, and then the integrated weight coefficient $\varepsilon_{ij}$ is calculated, where $i$ is the stations that supply empty containers to Fangchenggang Station, and $j$ is Fangchenggang Station. The results are shown in Fig. 7 and Table V. For the other container stations, the value of the integrated weight coefficient to Fangchenggang Station is set to 1.

TABLE VI
NOTATIONS OF MODEL 1

| Notations | Definition |
|---|---|
| $B$ | Set of railway bureaus, $b$ and $b'$ are the indices. |
| $I$ | Set of container stations. Define $I_b$ as the set of container stations belong to Railway Bureau $b$, so $I = \cup_{b\in B} I_b$. |
| $I_{bd}$ | Set of demand nodes of containers belonging to the Railway Bureau $b$, $i$ is the index. Define $\bar{I}_d$ as the set of demand nodes of rail network, so $\bar{I}_d = \cup_{b\in B} I_{bd}$. |
| $I_{bs}$ | Set of supply nodes of containers belonging to the Railway Bureau $b$, $j$ is the index. Define $\bar{I}_s$ as the set of supply nodes of rail network, so $\bar{I}_s = \cup_{b\in B} I_{bs}$. |
| $\varepsilon_{ij}$ | Coefficient of integrated weight, which can be calculated by the method proposed in Section III-D. |
| $l_{ij}$ | Transport distance between container stations $i$ and $j$. |
| $c_{bb'}$ | Capacity between Railway Bureau $b$ and $b'$ for ECR, determined by empty railcars repositioning plan and capacity of boundary stations between $b$ and $b'$. |
| $\tilde{s}_i$ | The fuzzy supply of station $i$. |
| $\tilde{d}_j$ | The fuzzy demand of station $j$. |
| $x_{ij}$ | Decision variable, the number of empty containers transported from station $i$ to $j$. |

## IV. OPTIMIZATION OF ECR

Based on the forecasted demand of containers and integrated weight coefficient, two different data-driven models for ECR based on transportation problem are proposed in this Section IV-A basic model based on transportation problem, and a two-level model adapt to ECR mode of China. We introduce triangular fuzzy demand that transforms forecasting results and errors into fuzzy demand, which are brought into the optimization models. The objective of two models are to minimize the total empty container kilometers.

### A. Model 1: Basic Model of ECR

The basic model of ECR is built based on transportation problem, with the objective of minimizing the total empty container kilometers. Table VI presents the notations and their definitions in the model.

The ECR problem can be formulated by the following model:

$$\min C = \sum_{i\in\bar{I}_d}\sum_{j\in\bar{I}_s} \varepsilon_{ij} l_{ij} x_{ij} \quad (2)$$

$$\sum_{j\in\bar{I}_s} x_{ij} = \tilde{s}_i \;\; \forall i \in \bar{I}_d \quad (3)$$

$$\sum_{i\in\bar{I}_d} x_{ij} = \tilde{d}_j \;\; \forall j \in \bar{I}_s \quad (4)$$

$$\sum_{i\in I_{bd}}\sum_{j\in I_{b's}} x_{ij} \leq c_{bb'} \;\forall b, b' \in B, b \neq b'$$

$$x_{ij} \in \mathbb{N}. \quad (5)$$

The objective function (2) of the ECR model minimizes the total kilometers that empty container transported. Constraint sets (3) and (4) bring supply and demand into balance. Two dummy stations for empty supply and demand, respectively, are introduced to ensure that demand equals supply for the whole railway network. Constraint set (5) ensures that the total number of empty containers transported between two railway bureaus cannot exceed the capacity.

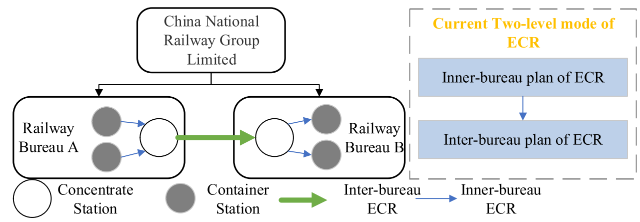


Fig. 8. Two-level mode of ECR.

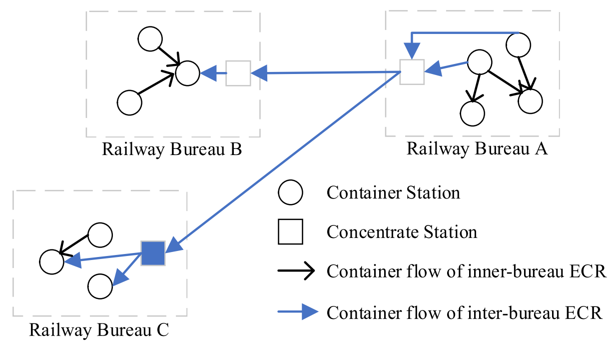


Fig. 9. Flow of empty containers of two-level of ECR.

TABLE VII
NOTATIONS OF MODEL 2

| Notations | Definition |
|---|---|
| $K$ | Set of concentrate stations, $K_b$ is the set of concentrate stations of Railway Bureau $b$, $k \in K_b$. |
| $c_{bb'}$ | Capacity between Railway Bureau $b$ and $b'$ for ECR, determined by empty railcars repositioning plan and capacity of boundary stations between $b$ and $b'$. |
| $n_b$ | The number of concentrate stations within Railway Bureau $b$. |
| $z_{kk'}$ | Decision variable, the number of empty containers that transported from concentrate station $k$ to $k'$. |
| $y_k$ | Decision variable, =1 if station $k$ is select as concentrate station, =0 otherwise. |
| $y_{kk'}$ | Decision variable for model linearization. |

### B. Model 2: Two-Level of ECR

Right now, ECR of China Railway follows a two-level mode, as shown in Fig. 8. Each railway bureau selects two or more stations as concentrate stations, and the interbureau ECR should go through those corresponding concentrate stations. The empty containers flow of two-level mode of ECR is shown in Fig. 9. The surplus empty containers are transported to concentrate stations of the Railway Bureau A, and then repositioned to the Railway Bureaus B and C that need empty containers. Except for the decision variable $x$ of ECR between container stations, model 2 makes the major decisions of concentrate stations selection, and the container flow distribution among those concentrate stations. Table VII presents the notations and their definitions for Model 2.

The two-level ECR can be formulated as follows:

$$\mathrm{Min}Z = \sum_{b\in B}\left(\sum_{i\in I_{bd}}\sum_{j\in I_{bs}}\varepsilon_{ij}x_{ij}l_{ij} + \sum_{i\in I_{bd}}\sum_{k\in K_b}x_{ik}l_{ik} + \sum_{k\in K_b}\sum_{k'\in K/K_b}z_{kk'}l_{kk'} + \sum_{j\in I_{bs}}\sum_{k'\in K_b}x_{k'j}l_{k'j}\right) \quad (6)$$

$$\sum_{j\in I_{db}}x_{ij} + \sum_{k\in K_b}x_{ik} = \tilde{s}_i \quad \forall i\in I_{sb}, b\in B \quad (7)$$

$$\sum_{i\in I_{sb}}x_{ij} + \sum_{k\in K_b}x_{kj} = \tilde{d}_j \quad \forall j\in I_{db}, b\in B \quad (8)$$

$$\sum_{i\in I_{sb}}x_{ik} \le My_k \quad \forall k\in K_b, b\in B \quad (9)$$

$$\sum_{j\in I_{db}}x_{kj} \le My_k \quad \forall k\in K_b, b\in B \quad (10)$$

$$\sum_{k\in K_b}y_k \le n_b \quad \forall b\in B \quad (11)$$

$$\sum_{i\in I_{sb}}x_{ik} = \sum_{k'\in K}z_{kk'} \quad \forall k\in K_b, b\in B \quad (12)$$

$$\sum_{j\in I_{db}}x_{kj} = \sum_{k'\in K}z_{k'k} \quad \forall k\in K_b, b\in B \quad (13)$$

$$z_{kk'} \le My_{kk'} \quad \forall k\in K_b, k'\in K_{b'}, b\ne b'\in B \quad (14)$$

$$y_{kk'} \le y_k \quad \forall k\in K_b, k'\in K_{b'}, b\ne b'\in B \quad (15)$$

$$y_{kk'} \le y_{k'} \quad \forall k\in K_b, k'\in K_{b'}, b\ne b'\in B \quad (16)$$

$$y_{kk'} \ge y_k + y_{k'} - 1 \quad \forall k\in K_b, k'\in K_{b'}, b\ne b'\in B \quad (17)$$

$$\sum_{k\in K_b}\sum_{k'\in K_{b'}}z_{kk'} \le c_{bb'} \quad \forall b, b'\in B, b\ne b'$$

$$y_k, y_{kk'} \in \{01\}, x_{ij}, x_{ik}, x_{k'j}, z_{kk'} \in \mathbb{Z}. \quad (18)$$

The objective function (6) aims to minimize the total kilometers that empty containers transported. Constraints (7) and (8) ensure the flow conservation of empty containers with each railway bureau. Constraints (9) to (11) represent the selection of concentrate stations, where (11) indicates the number of concentrate stations of each railway bureau. Constraints (12) and (13) ensure the flow conservation of empty containers for interbureau ECR. Constraints (14) to (17) are used to linearize the expression of $z_{kk'} \le y_k y_{k'}$. Constraint (18) ensures that the total number of empty containers transported between two railway bureaus cannot exceed the capacity.

### C. Model Solution

Constraint sets (3), (4), (7), and (8) are fuzzy constraints in the models, which can be converted into auxiliary crisp constraints by the procedures presented in [34] and [31]. The fuzzy demand constraint of Model 1 in the ECR is taken as an example to explain the specific conversion process. Suppose $\tilde{d}$ is a triangular fuzzy demand set, which is represented by a three-tuple $(a, b, c)$,

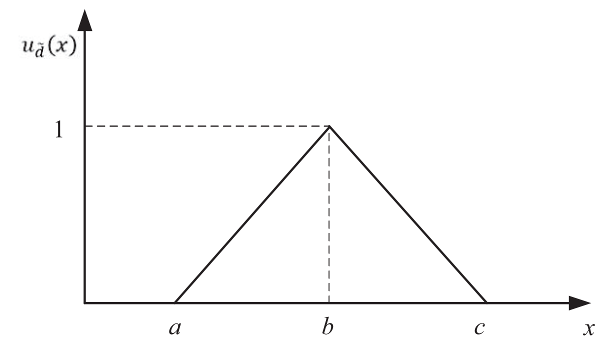


Fig. 10. The membership function of the fuzzy demand $\tilde{d}$.

where b is the most likely value of demand, a is the most pessimistic value of demand, c is the most optimistic value of demand, and $a \le b \le c$. Then, the membership function of the fuzzy demand $\tilde{d}$ is shown in Fig. 10. The expression is shown in

$$u_{\tilde{d}}(x) = \begin{cases} \frac{x-a}{b-a}, & a \le x \le b \\ \frac{c-x}{c-b}, & b \le x \le c \\ 0, & \text{other.} \end{cases} \quad (19)$$

$u_{\tilde{d}}(x)$ is the membership function, which reflects the degree to which any number x belongs to the fuzzy demand set $\tilde{d}$. The greater the value of $u_{\tilde{d}}(x)$ the higher the degree to which element x belongs to $\tilde{d}$. In this article, the forecasted empty container demand $d_j$ is set to be the most likely value of demand d. Considering the possible forecasting error RMSE, The $d_j - \mathrm{RMSE}_j$ is set to be the most pessimistic value of demand a and $d_j + \mathrm{RMSE}_j$ is set to be the most optimistic value of demand c. $\mathrm{RMSE}_j$ stands for the root-mean-square error of demand forecast of container handling station j. Combined with the prediction error, the predicted empty container demand $d_j$ is transformed into a fuzzy demand $\tilde{d}_j$ taking value in interval $[d_j - \mathrm{RMSE}_j,\ d_j + \mathrm{RMSE}_j]$.

Since $\tilde{d}$ is a fuzzy number satisfying the membership function $u_{\tilde{d}}$, for any real number x, a chance-constraint is shown as

$$Ch\left\{\tilde{d} \circledast x\right\} \ge \alpha \quad (20)$$

where abbreviation *Ch* represents the chance and $\alpha$ represents the confidence level selected by the decision maker, which means a fuzzy constraint has to be satisfied not always but with a predefined confidence level, $\alpha \in [01]$. $\circledast$ is any one of the relations $>$, $\ge$, $<$, $\le$, or $=$ .

Following the method proposed in [34], we know that the transformation of fuzzy constraints needs to meet a certain confidence level (i.e., possibility). A likelihood function in (21) represents the chance of fuzzy constraints to calculate this probability. When the fuzzy empty container demand $\tilde{d}_j$ equals any real number *x* [such as fuzzy constraint (4)], the likelihood can

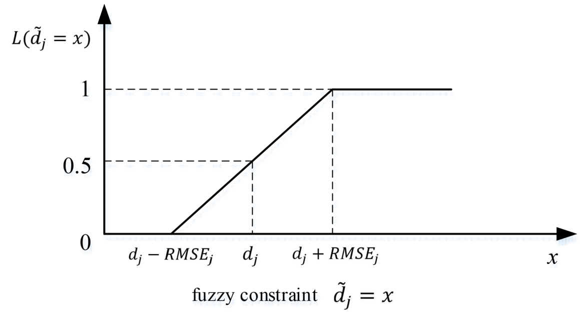


Fig. 11. Likelihood of fuzzy constraint.

be defined as

$$L\left(\tilde{d}_j = x\right)\begin{cases} 0, & x \le a \\ \dfrac{x-a}{2(b-a)}, & a \le x \le b \\ \dfrac{c-2b+x}{2(c-b)}, & b \le x \le c \\ 1, & x \ge c. \end{cases} \tag{21}$$

Substituting $b = d_j, a = d_j - \mathrm{RMSE}_j$ and $c = d_j + \mathrm{RMSE}_j$ into (21), which can be simplified as (22) (the corresponding function relationship is shown in Fig. 11)

$$L\left(\tilde{d}_j = x\right)\begin{cases} 0, & x \le d_j - \mathrm{RMSE}_j \\ \dfrac{x-d_j+\mathrm{RMSE}_j}{2\mathrm{RMSE}_j}, & d_j - \mathrm{RMSE}_j \le x \\ & \le d_j + \mathrm{RMSE}_j \\ 1, & x \ge d_j + \mathrm{RMSE}_j \end{cases}. \tag{22}$$

For a given confidence level, the fuzzy constraint set (4) in the first ECR model can be converted in (23) as follows:

$$L\left\{\sum_{i=1}^{m} x_{ij} = \tilde{d}_j\right\} \ge \alpha_j, \quad \forall j. \tag{23}$$

Since the likelihood function [i.e., (22)] is monotonic in the interval $[d_j - \mathrm{RMSE}_j,\ d_j + \mathrm{RMSE}_j]$, its inverse function exists. Similarly, fuzzy supply constraints can also be transformed accordingly. Then, at a given confidence level $\alpha$, the fuzzy constraint sets (3) and (4) can be converted to the following clear constraint sets

$$\sum_{j=1}^{n} x_{ij} = L^{-1}_{\tilde{s}_i}\left(\alpha_i\right), \quad \forall i \tag{24}$$

$$\sum_{i=1}^{m} x_{ij} = L^{-1}_{\tilde{d}_j}\left(\alpha_j\right), \quad \forall j. \tag{25}$$

Therefore, the objective function of Model 1 is (2), and the fuzzy supply and demand constraint sets are (24) and (25). The same procedure can be used on (7) and (8) in Model 2. Then the models can be solved by CPLEX.

TABLE VIII
FORECASTING RESULTS OF SUPPLY/DEMAND OF EMPTY CONTAINERS

| Forecast method | Supply | Demand | Deviation |
|---|---|---|---|
| GM(1.1) | 8653 | 12 690 | 21.8% |
| LSTM | 8019 | 9392 | 27.6% |
| SVR | 8494 | 7119 | 35.7% |
| LSTM-SVR | 12 294 | 12 354 | 11.1% |
| Approximate real-life value | 12 567 | 11 070 | / |

## V. CASE STUDY

This section presents a case study based on the data of container transport of China Railway. The proposed models are solved using Cplex 12.4 on a laptop with 2.70 GHz Intel Core i7-8550U processor and 16-GB RAM. The results of the proposed models are discussed and compared.

### A. Data

There are 500 container stations in this case, handling more than 80% of the total workload of the rail network. Take 20 ft container as an example, the history data including the number of loading and unloading of empty containers in each station, and the tracking of containers in the year of 2021. The LSTM-SVR is used to forecast empty container supply and demand, and the integrated weight coefficients for a five-day plan horizon from January 1–5, 2022. The interbureau ECR capacity parameters are calculated based on the empty railcar repositioning plan over the rail network boundaries.

The forecasted empty container supply and demand are shown in Table VIII. We get the number of empty containers that arrived at/departed from each station, and then multiply by 0.8 as the approximate value of real-life ECR data. As those stations handle about 80% of the total workload of the rail system. We calculated the difference-value of the minimum value of forecasted supply/demand and that of approximate real-life data, and then divided it by 11 070 to get the index of deviation. Comparison of this index shows that LSTM-SVR has the best performance. Please note that the calculated values do not mean a significant deviation between forecasted results and practical supply/demand, which may exist a gap from approximate real-life value subject to the imbalance phenomenon between supply and demand. For example, when supply is greater than demand, we should reposition empty containers to the railway bureau group companies with storage capacity even though they have enough empty containers.

Five scenarios are designed for measurement and analysis. Scenarios 1 to 4 are based on Model 1, and Scenario 5 is based on Model 2. Scenario 1 is calculated based on the empty container forecast value of supply and demand, the integrated weight coefficients are set as 1, without considering (5); Scenario 2 takes the empty container forecast and forecast error into account, and transforms the supply and demand as fuzzy values; Scenario 3 further introduces the integrated weight coefficient; Scenario 4 adds the constraint set (5) based on Scenario 3. Then, Scenario 5

TABLE IX
RESULTS OF MODEL 1 IN DIFFERENT SCENARIOS

| Scenario | Supply | Demand | CPU time/s | Objective Function Value |
|---|---|---|---|---|
| 1 | 12 294 | 12 354 | 3.12 | 4 472 062 |
| 2 | 13 067 | 11 391 | 3.65 | 3 451 904 |
| 3 | 13 067 | 11 391 | 3.18 | 3 464 703 |
| 4 | 13 067 | 11 391 | 3.24 | 3 608 536 |

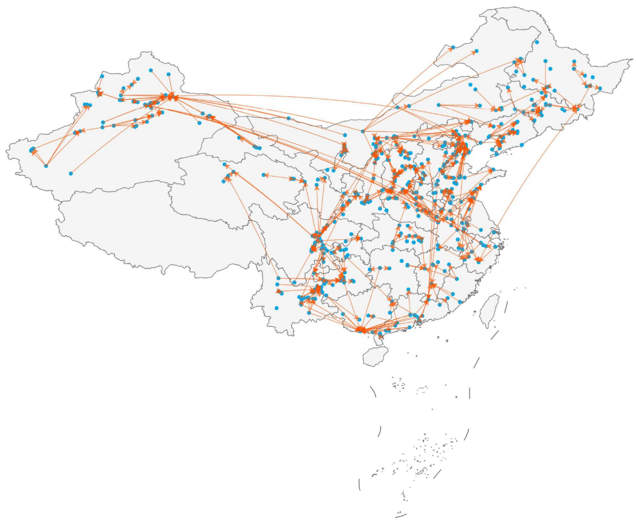

Fig. 12. Scenario 1, based on supply and demand forecasts.

is for Model 2, which takes fuzzy supply and demand, integrated weight coefficient and the transport capacity between railway bureaus into consideration.

### B. Impact of Data-Driven Parameters

Table IX shows the results of model 1 under different scenarios. For Scenario 2 to Scenario 4, both confidence levels $\alpha_i$ and $\alpha_j$ are set to 0.8, and the final supply and demand are 13 067 and 11 391 containers after fuzzy transformation.

*1) Scenario 1:* The result of Scenario 1 is shown in Fig. 12, the total empty container kilometers are 4 472 062 km. The long-distance empty container repositioning is mostly from Shanghai Bureau to Harbin Bureau, Lanzhou Bureau, and Urumqi Bureau, from Chengdu Bureau to Lanzhou Bureau, and from Kunming Bureau to Lanzhou Bureau, and so on.

*2) Scenario 2:* Fig. 13 shows the results, with the empty container transport distance of 3 451 904 km. The demand for empty containers drops by 7.80% at the specified confidence level, while the distance traveled by empty containers decreases by 22.81%. The reason is that sufficient supply resulting in fewer long-distance empty container repositioning. Compared to Fig. 12, the empty container repositioning of long distance from Shanghai to Harbin and Urumqi Railway Bureau Group Corporation, and from Kunming to Lanzhou Bureau Group Corporation are reduced in Scenario 2.

Fig. 13. Scenario 2, considering forecast errors.

Fig. 14. Scenario 3, adding the integrated weight coefficient.

*3) Scenario 3:* In Scenario 3, the integrated weight coefficient is imported into the objective function, and the result is shown in Fig. 14. Comparing to Fig. 13, the transport path of empty containers has small changes for some of the OD (i.e., ECR from Harbin to Qiqihaer, from Tongliao to Sanjianfang of Railways Bureau of Harbin and Shenyang), as the historical pattern of ECR has some effect on the result. The large-scale construction and maintenance are always scheduled from March (after the Spring Festival) to June, September and October. In January, there is sufficient freight transport capacity before the traffic peak of the Spring Festival travel season. That is why most of the ECR in Scenario 3 can follow the shortest path, and resulting in an increase of 0.37% in the distance traveled by empty containers compared with Scenario 2.

*4) Scenario 4:* The interbureau empty railcar repositioning plan and the capacity of boundary stations between railway bureaus are transformed into parameter $c_{bb'}$. The results as shown

Fig. 15. Scenario 4, adding the interbureau distribution capacity constraint.

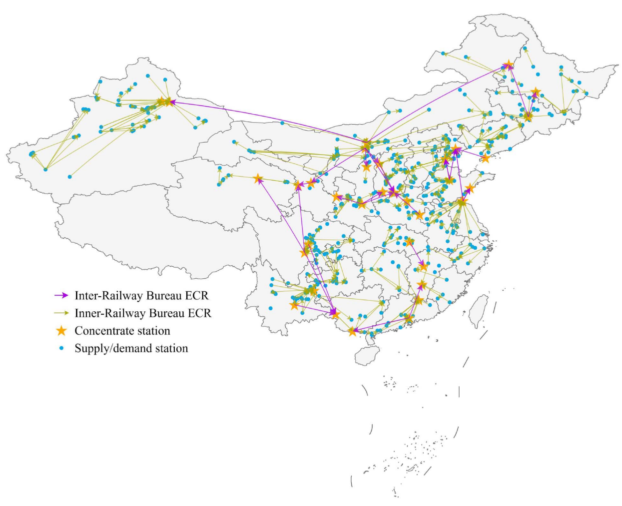


Fig. 16. Scenario 5, Model 2 with integrated weight coefficient.

in Fig. 15. Constraint set (5) reduces the number of empty containers across railway bureaus, as the lines of interbureau ECR with short distance in the figure are reduced. At the same time, this constraint changes some of the long-distance interbureau ECR, for example, the lines from the Railway Bureaus of Shanghai to Urumqi, as Shanghai Railway Bureau has no extra empty railcars repositioning to the west. And the deletion of the line from Xiangyang station in Wuhan Railway Bureaus to Fangchenggang station in Nanning Railway Bureaus, as the flow of empty railcars always from south to north. That is why the total transport distance of empty containers increases by 4.15% compared to Scenario 3.

### C. Models Comparison and Analyses

In this section, we compare the results of two models and the possible ECR plan in real-life.

*1) Results of Model 2 and Comparison:* The confidence levels $\alpha_i$ and $\alpha_j$ are also set to 0.8 in Model 2. The results are shown in Fig. 16. The value of objective function value is

TABLE X
COMPARISON OF THE RESULTS WITH REAL-LIFE ECR PLAN

| | CPU time/s | TKECT /km | RECR within Railway Bureaus |
|---|---|---|---|
| Scenario 4 | 3.24 | 3 608 536 | 69.4% |
| Scenario 5 | 8.83 | 4 939 980 | 77.0% |
| Real-life ECR Plan | / | 5 180 891 | 76.9% |

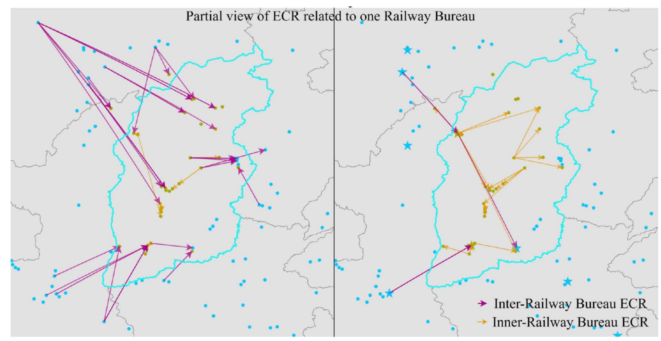


Fig. 17. Comparison of ECR plan between model 1 and model 2.

4 939 980 km, increased by 36.90% compared with that of Scenario 4, because the empty container repositioning between railway bureaus must transfer through concentrate stations.

At the same time, 77.0% of the empty containers in the plan are transported within the bureau, which is 7.6% higher than that of the innerbureau ECR in Scenario 4. With the two-level mode of ECR, the empty containers are distributed within each Railway Bureau in priority. Many of the direct interbureau ECR with shorter transport distance are deducted. Compared with Fig. 15, the lines in Fig. 16 are reduced significantly, as the interbureau ECR must be carried out through concentrate stations, the number of lines between two Railway Bureau reduced to no more than 4. The bundling of empty containers flows between inter-concentrate stations results in lower total network costs and more individual travel kilometers, because most containers no longer follow direct transport.

*2) Comparison of the Results With Real-Life ECR Plan:* The results of those two models and real-life plan derived from container tracking data are compared in Table X as follows.

The total kilometers that empty containers are transported (TKECT) and the ratio of empty containers repositioned (RECR) within Railway Bureaus of Scenario 4 (Model 1) are 3 608 536 km and 69.4%, which are smaller than the other two cases. As there are lots of inter-Railway Bureau ECR for the stations close to the boundary line, as show as the left subfigure of Fig. 17. Driven by the objective function, some empty containers are transported to Railway Bureau B from A, even though the requirements of some stations within A cannot be fulfilled. Based on the two-level mode of ECR, the empty containers are allocated within Railway Bureau first, then carry out inter-Railway Bureau ECR. The RECR of Scenario 5 (Model 2) and real-life ECR plan are 77% and 76.9%, respectively. The number of inter-Railway Bureau ECR decreased, while TKECT

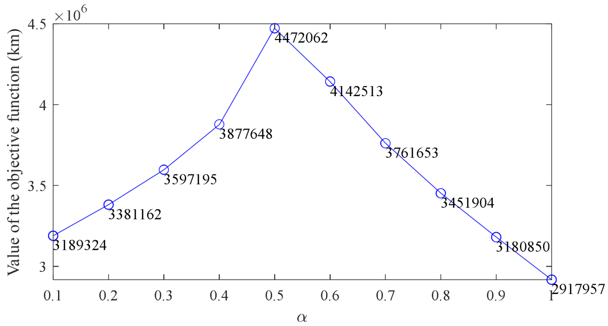


Fig. 18. Effect of confidence levels on the value of objective function.

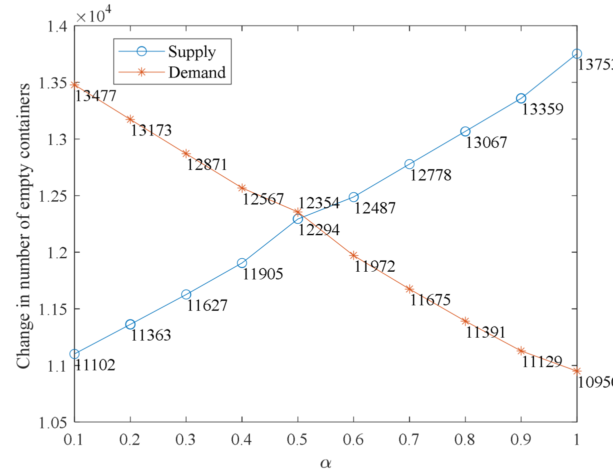


Fig. 19. Total supply and demand of empty containers with the change of confidence levels.

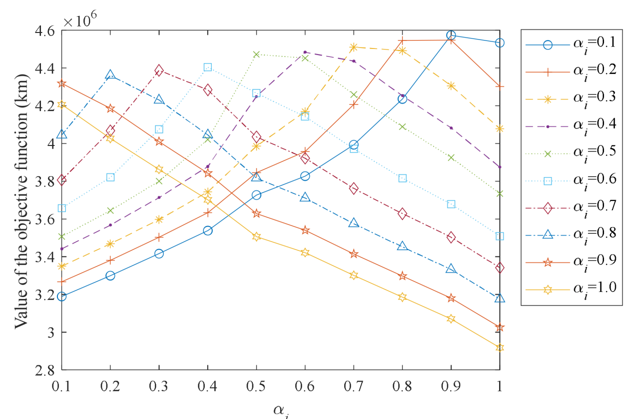


Fig. 20. Influence of confidence levels on the objective function value.

increased as the inter-Railway Bureau containers should move to concentrate stations, and then repositioned between concentrate stations of different Railway Bureaus, as shown in the right subfigure of Fig. 17.

Comparing the results of Model 2 and real-life ECR plan, we know that the TKECT is reduced by 4.65% by optimizing the ECR plan. That is 240 911 container-kilometer for a five-day plan horizon. Please note that the case study takes 20 ft container as an example, this type of container accounts for about 25% of the total container of China Railway.

### *D. Sensitivity Analysis of the Confidence Level*

This section analyzes the influence of confidence levels on the value of the objective function for Model 1. First, set $\alpha_i = \alpha_j$, and the value of objective function changes with the confidence levels shown in Fig. 18. The results show that the total distance of ECR increases first and then decreases with the increase of confidence levels, and reaches the maximum value when $\alpha_i = \alpha_j = 0.5$. The main reason is that the total supply of empty containers increases with the increase of the confidence level value, while the total demand shows the opposite trend. If $\alpha_i = \alpha_j = 0.5$, there is the minimum difference between supply and demand of empty containers, leading to the largest number of repositioned empty containers, as shown in Fig. 19.

When $\alpha_i$ and $\alpha_j$ take different values, the influence of the confidence levels on the value of objective function is shown in Fig. 20. If $\alpha_i \leq 0.8$, the value of objective function shows a trend of increasing first and then decreasing with the increase of $\alpha_j$. The smaller of the $\alpha_i$, the earlier the turning point appears, as there is a positive correlation between transformed supply and $\alpha_i$. If $\alpha_i > 0.8$, the supply of empty containers is greater than demand after fuzzy transformation. And the total demand of empty containers decreases when $\alpha_j$ increases, resulting in a decreasing trend of the value of objective function. Similarly, if $\alpha_j \leq 0.8$, the value of objective function increases and then decreases with the increase of $\alpha_i$.

### *E. Sensitivity Analysis of Integrated Weight Coefficient*

Actually, each $\varepsilon_{ij}$ is different and it is inconvenient to present the sensitivity analysis. In order to show the impact of this coefficient on the ECR plan briefly, we replace $\varepsilon_{ij}$ with ${\varepsilon'}_{ij}$ in (26), where $0 < \theta \leq 1$. The significance of changing $\theta$ is that if there are any ECR between container stations $i$ and $j$ (i.e., $\varepsilon_{ij} < 1$), the value of the integrated weight coefficient is further reduced by multiplying $\theta$. While the ECR between the OD of other $\varepsilon_{ij}$ (i.e., $\varepsilon_{ij} = 1$) is no longer adjusted, and sets their values of ${\varepsilon'}_{ij}$ as 1. Confidence levels $\alpha_i$ and $\alpha_j$ are set as 0.8, the value of objective function for Scenario 3 and Scenario 4 with different $\theta$ can be calculated and is shown in Fig. 21. The value of objective function increases with the decrease of $\theta$, the maximum deviation of Scenario 3 and 4 reach 3.38% and 2.85%, respectively. The result shows that with the influence of various transport capacities, the repositioning of empty containers between container stations does not follow the shortest routing in the historical ECR plan. The introduction of integrated weight coefficients can reflect the influence factors such as transport capacities in the process of ECR

$$
{\varepsilon'}_{ij} = \begin{cases} \theta * \varepsilon_{ij}, & \text{if } \varepsilon_{ij} < 1 \\ 1, & \text{if } \varepsilon_{ij} = 1 \end{cases}. \tag{26}
$$

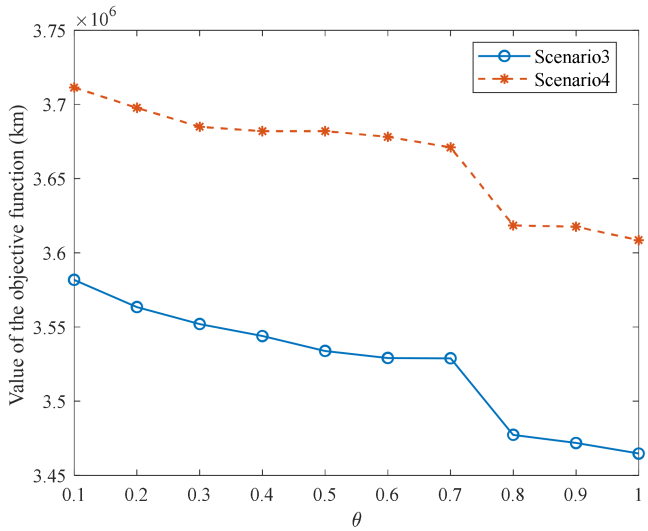


Fig. 21. Value of objective function changes with $\theta$.


| 路局 | 哈 | 沈 | 京 | 太 | 呼 | 郑 | 武 | 西 | 济 | 上 | 南 | 广 | 宁 | 成 | 昆 | 兰 | 乌 | 青 | 合计 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
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| 武 | | | | | | | | 1500 | | | | | | | | | | | 1500 |
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| 兰 | | | | 300 | | | | | | | | | | | | | | | 300 |
| 乌 | | | | | | | | | | | | | | | | | | | 0 |
| 青 | | | | | | | | | | | | | | | | | | | 0 |
| 合计 | | 400 | 200 | 2550 | | | | 1800 | | | | | | | | | | | 4950 |

Fig. 22. Interface of ECR in container transportation tracking system.

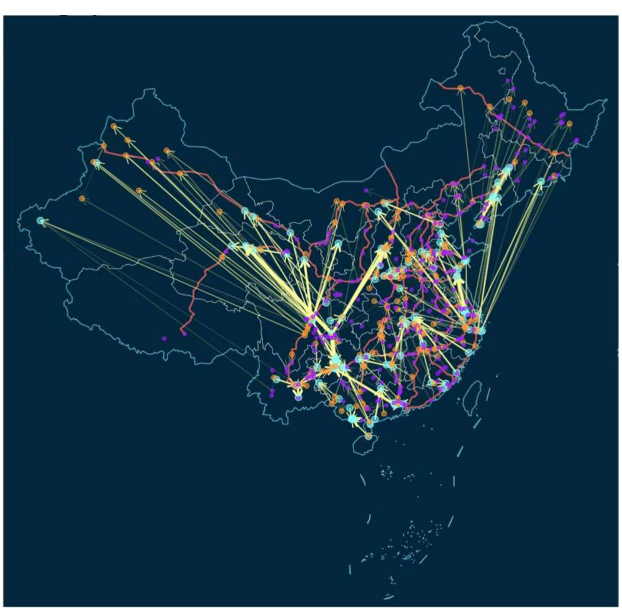

Fig. 23. Visualization of ECR results of model 1.

Fig. 24. Visualization of ECR results of model 2.

## VI. Conclusion

Empty container repositioning helps to reduce the total transport distance of empty containers. Motivated by the real-life research needs and growing availability of large datasets of empty container management, this article proposed a data-driven framework to solve the ECR problem. First, the supply/demand forecasting of empty containers, and parameters discovering by machine learning approaches are proposed. Then, integer programming models for two ECR modes in line with actual production process are presented to minimize the total kilometers that empty containers are transported. In those two models, the forecasting empty container supply/demand and forecasting error are transformed into triangular fuzzy values. Finally, we solved the models by CPLEX after fuzzy constraints are converted to auxiliary crisp constraints. The case study based on data from China Railway is conducted. The results show the following: 1) The data-driven framework may increase the value of the objective function, compared with the traditional approach. While the ECR plan of the new framework becomes more practicable and executable, as the forecasted demand becomes more reliable and the routing and transport capacity can be considered implicit in the new parameters introduced from the large history dataset. 2) Model 2 is more suitable for real case of China Railway, and model 1 can be used for inner-railway company (railway bureau) ECR problem. The results show that empty containers flow of model 2 is similar to the tracking of real-life ECR plan.

The implication of this article is empty containers repositioning. The supply/demand distribution of empty containers of different stations varies greatly, or the actual supply/demand distribution and its parameters are unknown to the decision maker. Some of the capacity parameters change day by day. The cost of determining the value of parameters accurately is too high for such a large railway network. The data from Information

Technology systems for containers management can support the application of the data-driven framework. This is a generic framework that can be applied to lots of medium-term and short-term optimization problems of transport and logistics. For example, the daily repositioning of empty car/railcar, the weekly service design of logistics network. The parameters of those problems (i.e., supply/demand, capacity parameters) should be more accurate for a better solution, while short-term fluctuations are more obvious (may change day by day) for a large-scale network.

ECR causes environmentally harmful emissions of carbon by handing equipment and vehicle transporting empty containers. It is an interesting topic to model the ECR problem from the perspective of collaborative reuse of empty containers, integrating the supply chain of full containers and empty containers since they function in the same transportation network using the same resources. In addition to the problem specific extensions, the forecasting of machine learning methods may be integrated into a single model, rather than integrate the forecasting value as parameters into the optimization model. Other machine learning approaches can be used for optimization, e.g., random forest or the other artificial neural networks.

## Appendix

The ECR problem was part of our project for computerizing daily dispatching for China Railway to improve their productivity. The method has been integrated as a functional module into the "Container Transportation Tracking System". The ECR plan can be calculated and visualized in this system. The interface of the computerized system is shown in Figs. 22–24.

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