Optimization of short-haul cargo volume prediction and scheduling based on XGBoost and robust optimization

Zhaokun Li *

School of Transportation, Beijing Jiaotong University, Beijing, China, 100044

* Corresponding Author Email: 23241032@bjtu.edu.cn

Abstract. Short-distance transportation plays an important role in modern logistics network, especially in the end distribution, which directly affects the customer experience and logistics efficiency. This paper focuses on the issues of cargo volume prediction and vehicle scheduling in short-distance transportation. It proposes corresponding solutions to three main problems and optimizes transportation efficiency and cost by integrating XGBoost and robust optimization techniques. First, for the cargo volume prediction problem, this paper constructs a prediction model based on time series features using XGBoost algorithm to predict the cargo volume of each route in the next 24 hours, and further refines the results to a 10-minute granularity, which provides a fine-grained data support for the subsequent scheduling optimization. Secondly, based on the prediction results, this paper establishes a vehicle scheduling model, which determines the transportation demand and shipping time under the premise of shipping node constraints; meanwhile, through the preferential use of owned vehicles and the design of string-point scheme, it realizes the improvement of transportation efficiency and total cost. Finally, to address the uncertainty caused by prediction deviation, this paper introduces robust optimization and scenario analysis methods to evaluate the scheduling effect under different deviations, ensuring that the stability and low cost of the system can be maintained in the most unfavorable scenarios. By combining XGBoost and robust optimization methods, this study proposes a comprehensive solution that can effectively improve the efficiency of the short-haul transportation system, external carrier dependence, and ensure the robust operation of the scheduling system under the deviation of the cargo volume forecast. This research not only has important theoretical value, but also has strong practical application prospects.

Keywords: Short-haul Transportation, Cargo Volume Prediction, XGBoost, Robust Optimization, Scheduling Optimization.

1. Introduction

As an important part of modern logistics system, short-distance transportation plays a key role in the end distribution, and its efficiency and stability directly affect the logistics service level and operating costs. With the high speed of e-commerce, short-distance transportation presents the characteristics of high, small batch and fast response, which puts forward higher requirements on the flexibility and robustness of the transportation system. However, most of the existing researches focus on a single link of cargo volume prediction or vehicle scheduling optimization, lacking systematic and integrated solutions. At the same time, the uncertainty of cargo volume prediction is often not fully taken into account, which makes the scheduling scheme susceptible to prediction deviation in actual operation, leading to the decline of transportation efficiency and cost.

Therefore, there is an urgent need for a comprehensive research framework that can balance accurate forecasting and robust scheduling. In terms of transportation demand prediction, machine learning methods have gradually become mainstream. The XGBoost-based highway travel time prediction model proposed by Chen and Fan significantly outperforms the method in terms of accuracy [1]; Gutmann et al. fused XGBoost with LSTM for truck parking occupancy prediction, and the effect of the prediction is further improved [2]. Domestic research is also deepening, for example, Guo Dan uses NSGWO algorithm for short-haul transportation scheduling optimization [3], Wang Fang et al. use the improved LSTM model to improve the accuracy of urban distribution demand prediction [4], Wang Kai et al. propose a parcel volume prediction method based on deep learning [5], and Li Ming et al. put forward the optimization model of short-haul transportation vehicle scheduling for e-commerce logistics [6]. These studies have enriched the demand forecasting and scheduling methods, but generally assume that the forecasting results are more accurate, ignoring the impact of forecasting errors on subsequent scheduling. In terms of scheduling optimization, Polinder et al. proposed an adjustable robust railroad operating map optimization method, which effectively improves the applicability of the system under uncertainty [7]; Liu et al. constructed a robust optimization model of public transport dynamic scheduling with high robustness under multiple passenger flow scenarios [8]; Ghanbari et al. introduced a risk-responsive mechanism to optimize the train scheduling, which improves the ability to cope with uncertainty [9]. 9]. Domestic scholars Wang Lei and Zhang Hong, on the other hand, studied the application of robust optimization in urban bus scheduling [10], which provides a reference for short-distance transportation scheduling. At the theoretical level, Distributed Robust Optimization (DRO) has received extensive attention in recent years. Shehadeh proposed a DRO framework for fleet size, path and scheduling problems, which significantly enhances the robustness of the system [11]; Agra et al. explored the application of robust optimization in the maritime inventory path problem [12]; and Lin Feng provided a systematic review on the theory and application of DRO, which provides theoretical support to complex transportation systems [13]. transportation systems [13]. In addition, Zhang et al [14], Li and Bai [15], and Gupta et al [16] verified the effectiveness of the gradient boosting method in traffic time prediction, and Kunichetty [17] proposed a cargo volume prediction model for cross-country transportation, which also provides insights for the study of short-distance transportation.

Overall, domestic and international research has made positive progress in the two directions of prediction and scheduling, but the deep integration of prediction and robust scheduling is still insufficient. Aiming at the above problems, this paper proposes a research framework for short-haul transportation that integrates XGBoost prediction and robust scheduling optimization. First, a cargo volume prediction model based on historical transportation data and external features is constructed, and the XGBoost algorithm is used to realize the refined prediction of cargo volume in the next 24 hours, with a time granularity of 10 minutes. Secondly, a scheduling optimization model considering the deployment of own vehicles and external vehicles, and standardized container configuration is established, with the goal of minimizing transportation costs and delays. Finally, a robust optimization method is introduced into the scheduling optimization, and the prediction error is handled by scenario analysis and distributed robust optimization techniques to ensure the stability and adaptability of the model under uncertainty. The framework forms a closed loop from demand forecasting to scheduling optimization to robust control, providing a systematic solution for the efficient and robust operation of short-distance transportation systems.

2. Modeling of cargo volume forecasts

An XGBoost (Extreme Gradient Boosting) method is used to build a volume prediction model to predict the volume of each line in the next 24 hours (from 14:00 on December 15th to 14:00 on December 16th), and the prediction is disaggregated to a 10-minute granularity.

2.1. Problem analysis

(1) Background to the mandate

The goal of this task is to predict the volume of shipments on each route for the coming day (December 15, 14:00 to December 16, 14:00) based on historical data, and to refine the prediction to a 10-minute granularity. The predicted time window covers 24 hours, and the challenge is to infer future changes in parcel volumes based on historical data and temporal characteristics and break them down into finer time intervals. The data input required for the task is historical parcel volume data, which is analyzed to complete the forecast of future time periods.

(2) Data characteristic

The data used comes from https://www.saikr.com/c/nd/30321, which contains the actual daily parcel volume of each route, and these data will be used as a training set to help the model learn the relationship between historical parcel volume and time characteristics. At the same time, the data have obvious time series characteristics, which are manifested in the peak and trough hours of each day and the demand changes in different seasons, with strong seasonality and trend.

2.2. Mathematical model

XGBoost is a regression model based on Gradient Boosted Trees (GBDT). It makes predictions by constructing multiple trees and combining their outputs (i.e., predicted values). The core formula of XGBoost is as follows:

$$y_t = \sum_{k=1}^{K} f_k\,(x_t) \tag{1}$$

(1) y_t is the predicted value at time t, the predicted parcel volume.
(2) f(x) is the predicted value of the kth tree, based on the input features.
(3) K is the number of trees.
(4) $x_t$is the input feature at time t, which can be the historical parcel volume, date, hour, weekday, etc.

Loss function: XGBoost trains the model by minimizing the loss function, with the goal of making predictions as close to the true value as possible. The loss function typically uses the mean square error (MSE) as a measure of the model's prediction error:

$$\text{Loss} = \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \tag{2}$$

(1) y_i is the true parcel volume.
(2) y_i is the parcel volume predicted by the model.

2.3. Solution process

In this step, we will explain in detail how to apply the XGBoost model for cargo volume prediction. The process is divided into the following steps.

(1) Data preprocessing (Python)

Data loading and feature extraction, firstly, we need to load the historical data from the CSV file and generate some new features, such as time period (hour), day of the week, date, and so on, from the date. These features are useful for capturing seasonal and intra-day patterns. Generate lagged features based on historical data, i.e., the number of packages in the last few days. xGBoost needs historical data to learn future predictions.

(2) Segmentation of training and test sets

Divide the data into training set and test set. The time series data requires a chronological order that cannot be randomly disrupted. The first 80% of the data is used for training, and the remaining 20% is used for testing.

(3) Build and train the XGBoost model

Use XGBRegressor to build a regression model with selected hyperparameters (e.g., learning rate, tree depth, etc.) to train the model. objective='reg: squared error': set as a regression problem, using squared error as the loss function. Col sample bytree=0.3: randomly sample 30% of the features of each tree during training to prevent overfitting. learning rate=0.1: learning rate, control the step size of each iteration, the smaller the value, the slower the model learns but the more stable it is. max depth=5: maximum depth of the tree, limit the complexity of each tree to prevent overfitting. alpha= 10: L1 regularization term weight, used to enhance the generalization ability of the model. n estimators=100: number of trees to iterate on, i.e., the number of base learners in the model.

(4) Predicting future shipments

Once training is complete, the trained model is used to make predictions for the next 24 hours (or test set). Mean square error is one of the most commonly used performance metrics in regression problems, and is used to measure the degree of deviation between the predicted value and the true value. It reflects the overall prediction accuracy of the model by calculating the square of the prediction error and averaging it. Mathematical definition: Let the true value be y_i , the predicted value be $\hat{y}_i$, the sample size is n, then the formula for the mean square error is:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{3}$$

MSE = 0 when the predicted value is exactly the same as the true value. The smaller the MSE value, the closer the model's prediction is to the true value and the better the fit. Due to the squaring operation, the MSE is more for larger prediction errors and therefore can highlight the impact of anomalies on the overall model performance. Advantages are simple and intuitive, easy to calculate; good mathematical properties in convex optimization problems, easy to implement optimization algorithms such as gradient descent. The disadvantages of MSE are that it is more sensitive to outliers, and a single large error may cause the overall MSE to be too large; the size of the value is related to the size of the data, so it is difficult to directly compare between different data sets. MSE is widely used in the evaluation and optimization of regression problems, such as XGBoost, linear regression, neural networks, and other models of the training objective function or evaluation index.

(5) Visualization of results

By plotting the predicted results against the actual values, it is possible to compare the predicted values with the actual values, thus providing a more intuitive understanding of the effectiveness of the model.

(6) Split Prediction Results to 10-Minute Granularity

By disaggregating the prediction results into 10-minute granularity, the prediction can be refined to better support subsequent dispatch decisions.

(7) Showing forecasts for routes coded "Site 3 - Site 83 - 0600" and "Site 3 - Site 83 - 1400". 83 - 1400".

For specific route codes (e.g., "Site 3 - Site 83 - 0600" and "Site 3 - Site 83 - 1400"), the Python script can be used to extract and visualize the prediction results of the specified route codes. Firstly, the data of the target lines are filtered out from the prediction result table, such as "Site 3 - Site 83-0600" and "Site 3 - Site 83 -1400"; then, using the Matplotlib plotting tool, the extracted prediction results are plotted as a curve according to the time series, where the horizontal coordinate indicates the time and the vertical coordinate indicates the number of predicted parcels. Finally, by setting the title, legend and axis labels, the prediction results of different routes are displayed visually and comparatively, which makes it easy to analyze the trend of parcel volume change of each route in the future time period.

2.4. Results

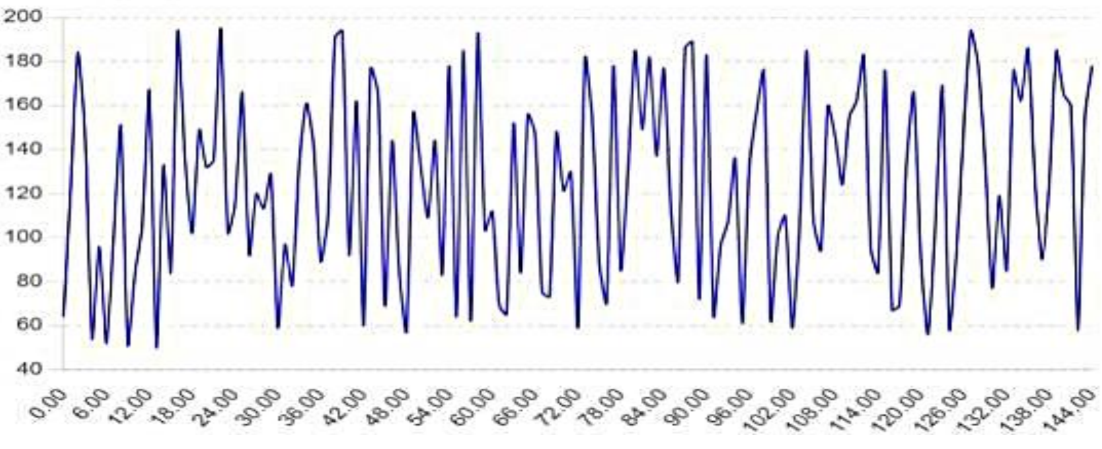

Figure 1. Predicted parcel volume (10-minute granularity)

Figure 1 shows the predicted parcel volume every 10 minutes from December 15, 2025 at 14:00 to December 16, 2025 at 14:00. x-axis represents the time (every 10 minutes on a scale) and y-axis represents the predicted parcel volume. The x-axis shows the time (every 10 minutes on a scale) and the y-axis shows the predicted parcel volume. As can be seen from Figure 1, the predicted parcel volume in the next 24 hours shows significant volatility, with an overall distribution between 60 and 180 pieces, with local peaks approaching 200 pieces and troughs dropping to around 60 pieces. The curve trend shows that the demand for parcels rises and falls on a short time scale, forming a cycle of multiple peaks alternating with troughs. This pattern of change suggests that parcel volumes are characterized by distinct time periods, with peaks of concentrated demand bursts likely to exist at certain times of the year, while at other times of the year relatively low levels of demand are demonstrated. In addition, the forecast results show that demand fluctuations are not a single trend, but are accompanied by strong short-term stochasticity, suggesting that the demand for cargo volume in short-haul transportation is not only influenced by the intraday cycle, but may also be driven by temporary external factors. Therefore, when modeling and scheduling optimization of this kind of data, it is necessary to consider both its cyclical pattern and uncertainty characteristics to enhance the robustness of the forecasting and scheduling model.

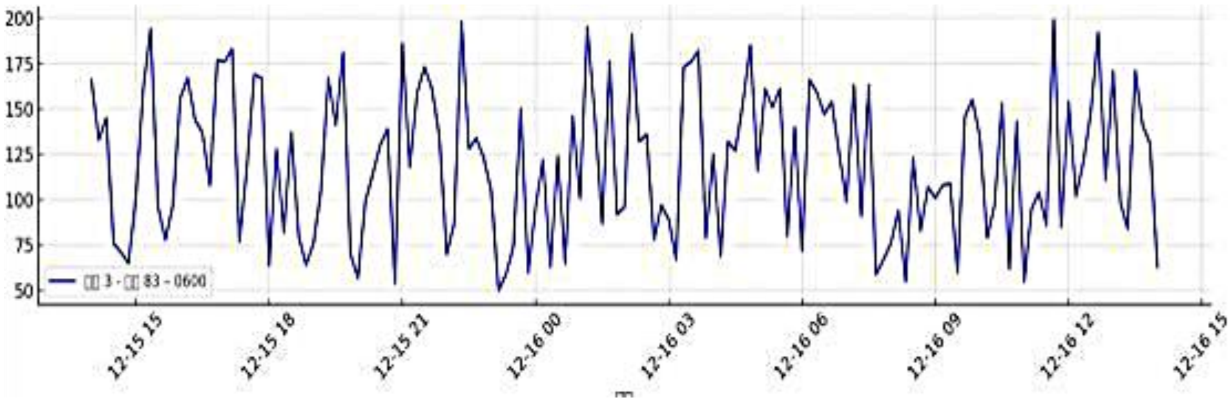

Figure 2. Projected parcel volumes for the "Site 3 - Site 83 - 0600" line

Figure 2 shows the predicted change in parcel volume for the route "Site 3-Site 83-0600" over the next 24 hours. As can be seen from the curve, the overall fluctuation range is between 60 and 180 pieces, with local peaks approaching 200 pieces and troughs dropping to about 60 pieces. The curve exhibits an undulating character, reflecting the stochastic volatility of parcel demand on shorter time scales for this route. Although the overall trend does not show a single stable trend, a certain cyclical pattern can still be observed from a macro perspective, i.e., alternating peaks and troughs, reflecting strong time-of-day differences in demand.

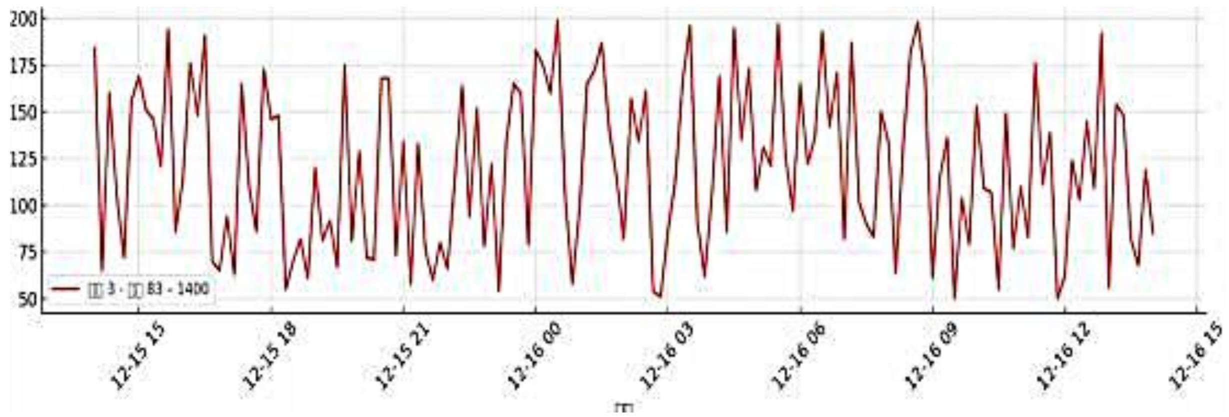

Figure 3. Projected parcel volumes for the "Site 3 - Site 83 - 1400" line

Figure 3 shows the forecast results for the "Site 3 - Site 83 - 1400" route for the same time window. Similar to Figure 2, the volume of packages for this route also fluctuates between 60 and 200 pieces, but the overall peak occurs slightly higher, and the volume of packages is above 120 pieces in some periods, indicating that the demand for this route is relatively concentrated during peak hours. The curve trend also shows high-frequency fluctuations and periodic substitution, indicating that demand is subject to the combined effect of time patterns and uncertainties. Comprehensive Fig. 2 and Fig. 3

can be found that the parcel volume forecasts of both routes show the characteristics of alternating peaks and troughs with large fluctuations, indicating that the demand for short-haul transportation has a significant temporal pattern and uncertainty within the day. This pattern suggests that subsequent scheduling optimization not only needs to consider the overall cyclical trend, but also needs to pay attention to the concentrated demand during local peak hours to improve the responsiveness and robustness of the transportation system.

3. Transportation demand determination and dispatch optimization

3.1. Problem analysis

This study aims to determine the transportation demand for each route based on the parcel volume forecast given in Problem 1, which mainly includes calculating the number of shipping vehicles required for each route, determining the expected shipping time to ensure that it is not later than the shipping node, and designing a multi-route crosstalk scheme where possible. In terms of optimization objectives, the model pursues high turnover and utilization of owned vehicles to external vehicle dependence; it also seeks to enhance the loading capacity of a single vehicle, and thus the total number of vehicles and transportation costs, and ultimately aims to minimize the overall cost. Constraints are mainly reflected in the shipping time cannot be later than the specified nodes of each line, the number of parcels per vehicle cannot exceed the capacity limit, and give priority to ensure that the use of their own vehicles, in the case of insufficient number of external vehicles will be considered. In order to simplify the problem, the model makes the following assumptions: the capacity of each vehicle is fixed at 100 parcels; in the vehicle selection priority is given to the use of their own vehicles, if insufficient to supplement the external vehicles; the shipping time is determined by the ratio of the parcel volume and the vehicle capacity; the transportation cost of each vehicle is uniformly set at 50, and does not take into account the additional costs of fuel, maintenance, etc.; finally, the number of vehicles required to calculate the shipping needs of each line, and ensure that the shipping time meets the requirements of the node. and ensure that the shipping time meets the node requirements.

3.2. Mathematical model

(1) Objective function

The total cost needs to be minimized. The total cost is calculated as:

$$\text{Total Cost}=\sum\nolimits_{\text{routes}}(\text{Number of Vehicles}\times\text{Vehicle Cost}) \tag{4}$$

The number of vehicles to be shipped on each route and the cost of vehicles are decision variables that need to be calculated based on projected parcel volumes and vehicle capacity.

(2) Restrictive condition

Shipping time constraint: each route cannot be shipped later than its shipping node. The shipping time is proportional to the volume of packages, and is calculated as follows:

$$T_{dispatch}=\frac{\text{forecasted volume}}{\text{vehicle capacity}\times\text{vehicle cost}} \tag{5}$$

Vehicle capacity constraint: the volume of parcels per vehicle cannot exceed the maximum capacity of the vehicle, so the volume of parcels per vehicle Required:

$$\text{vehicles needed}=\left\lfloor\frac{\text{forecasted volume}}{\text{vehicle capacity}}\right\rfloor \tag{6}$$

Owned vehicle constraints: Try to optimize the turnover of owned vehicles. Vehicle scheduling needs to be optimized based on the number of owned vehicles and the cost of external vehicles.

3.3. Solution process

(1) Initializing the population

The first step of the genetic algorithm is to initialize the population, where each individual represents a possible scheduling scheme. The gene of each individual consists of the number of vehicles shipped on each route and the type of vehicle (owned or external vehicle allocation). For this purpose, the population size is set to 10, i.e., 10 candidate solutions are included in each iteration. The number and type of vehicles for each route are represented through genetic coding, which enables different scheduling options to be explored and optimize the problem solution during the iterations of the algorithm.

(2) Fitness function

The fitness function evaluates the advantages and disadvantages of each individual (scheduling scheme). Define fitness as the total cost:

$$\text{Fitness} = \text{Total Cost} \tag{7}$$

The objective of each individual is to maximize the total cost while maximizing the turnover of owned vehicles. The smaller the value of the fitness function, the better the solution is.

(3) Selection, crossover and mutation

Selection, crossover and mutation are important operational steps in genetic algorithm. In the selection stage, the individual's strengths and weaknesses are evaluated according to the fitness, and the individual with higher fitness is selected as the parent for reproduction by roulette selection or tournament selection. In the crossover stage, recombination of genes is simulated by randomly selecting some of the genes of the parents for combination to generate new individuals to expand the solution space. The mutation operation, on the other hand, randomly changes the genes of individuals (e.g., changes in the number of vehicles) to enhance the diversity of the population and avoid falling into local optimal solutions, thus improving the global search capability of the algorithm.

(4) Iterative evolution

Genetic algorithm searches for the optimal solution through multi-generation iterative evolution, and each generation selects better individuals for crossover and mutation based on the fitness to get a better scheduling scheme.

(5) Output optimal solution

The final output includes the number of vehicles to be shipped on each route, the estimated time of shipment, and the type of vehicles to be carried, etc.

3.4. Key parameters

In the implementation of the genetic algorithm, the core code includes the following key parameters: Population Size In the initialization phase, the population size is set to 10, which means that 10 candidate solutions will be evaluated in each iteration. This parameter affects the breadth of the search space; the larger the population, the more solutions are possible, but also the computational cost. Fitness Function The fitness function is used to evaluate the strengths and weaknesses of each individual, usually taking into account several factors such as transportation costs, number of vehicles, shipping time, and so on. Through this function, the strengths and weaknesses of an individual are quantified and provide the basis for subsequent selection operations. Selection In the selection phase, individuals with a high degree of fitness are selected by means of roulette selection or tournament selection. Roulette selection is a random selection of individuals based on their fitness ratios, while tournament selection compares the fitness of a group of randomly selected individuals and selects the superior one. Crossover A crossover operation simulates the process of genetic recombination by randomly selecting a combination of genes from a parent to create a new individual. The Crossover Rate is set to 0.8, which means that 80% of the parents will participate in crossover to generate new individuals in each iteration. Mutation A mutation enhances the diversity of a population by randomly changing the value of a portion of an individual's gene, such as the number of vehicles or changing route assignments. The Mutation Rate is set to 0.1, which means that each individual has a 10% chance of having a mutation. Termination Condition The algorithm terminates when the maximum number of iterations is reached or when the change in population fitness is less than a set threshold.

The maximum number of iterations is set to 1000, and the threshold of change in fitness is 0.001, i.e., the algorithm terminates when the improvement in fitness falls below this value.

3.5. Results Showcase

Table 1. "Site 3 -- Site 83-0600" and "Site 3 -- Site 83-1400" transportation scheduling program

Line code	Estimated Time of Shipment (hours)	Own car	Exterior Vehicles	Total Vehicles Number of vehicles	Crosstalk program
Site 3 - Site 83 - 0600	12.0	10	0	10	Site 3 - Site 83 - 0600 / Site 3 - Site 83 - 1400 / Site 3 - Site 83 - 1400
Site 3 - Site 83 - 1400	15.0	13	0	13	Site 3 - Site 83 - 0600 / Site 3 - Site 83 - 1400 / Site 3 - Site 83 - 1400

Table 1 shows the transportation scheduling schemes and their corresponding results based on the genetic algorithm optimization, with an optimal cost of 1350. The table lists the predicted departure time, vehicle requirements and corresponding crosstown schemes for each route-by-route code. Taking "Site 3-Site 83-0600" as an example, the projected delivery time of this route is 12 hours, and a total of 10 vehicles are required, all of which are owned by the vehicles and do not require external vehicle support; another route "Site 3-Site 83-1400" requires 13 vehicles, of which the same number of vehicles are required for the same route. The other route, "Site 3 - Site 83 - 1400", requires 13 vehicles, all of which are also owned. The Crosstown Scenario section shows the consolidation of different routes, e.g., multiple identical or similar routes are combined into a single crosstown to maximize vehicle utilization. The reference value of this table is that it not only gives the departure time and vehicle configuration of each route, but also visualizes the optimized resource allocation and string point strategy. By comparing the number of owned vehicles and external vehicles used, it can reflect the effectiveness of the scheme in terms of transportation cost and improving the turnover rate of owned vehicles. Meanwhile, the design of the crosstown scheme provides practical guidance for scheduling optimization, showing that the model is not only capable of time constraints, but also of achieving overall efficiency improvement through route consolidation.

4. Impact of cargo forecast bias on scheduling optimization results

4.1. Problem analysis

In real transportation and logistics scheduling, cargo volume prediction is crucial, but the prediction results often have deviations, for example, the predicted cargo volume may be high or low. To address this problem, this study simulates different cargo volume prediction error scenarios and optimizes vehicle allocation through a robust optimization approach combined with scenario analysis. The objective is to ensure that the system is able to demand and minimize the total number of vehicles under all possible cargo volume deviation scenarios. In addition, it is assumed that the deviation range of the cargo volume prediction error is known, e.g., ±10%, ±20%; and three vehicle types - owned, external, and standard containers - are considered, each with different capacities. Meanwhile, multiple cargo scenarios are generated for each route, e.g., predicted cargo, predicted cargo ±10%, which are used to simulate the impact of different cargo errors on scheduling. Ultimately, the optimization goal is to minimize the total number of vehicles and ensure that the demand is transported under all scenarios.

4.2. Mathematical model

There are n routes and m types of vehicles (owned, external, and standard containers), and the predicted volume for each route is qi. The predicted volume for each route is qi and the capacity of each vehicle is cj. It is assumed that the volume prediction may deviate by Δqi, i.e., the true value of the volume qi is in the interval [qi - Δqi, qi + Δqi].

(1) Decision variables

xij: denotes the number of vehicles of type j to be used on route i.

(2) Objective function

Minimize the total number of vehicles:

$$\min \sum_{i=1}^{n} \sum_{j=1}^{m} x_{ij} \tag{8}$$

(3) Restrictive condition

Demand constraint: for each line i, in each scenario, the actual demand should be:

$$\sum_{j=1}^{m} x_{ij} \times c_j \geqq_i^{(k)}, \forall k \tag{9}$$

Qi (k) is the cargo volume of the i-th route under the k-th scenario. Scenario k may be: qi (1) = qi: predicted cargo volume qi (2) = qi × (1 + Δ): high forecast cargo volume qi (3) = qi × (1 - Δ): under-forecasted cargo volume Δ is the volume deviation (e.g. 0.1 means ± 10% deviation)

The number of vehicles is non-negative constrained:

$$x_{ij} \geq 0, \forall i, j \; 1 \tag{10}$$

4.3. Solution process

(1) Scenario Generation

Multiple scenarios are generated for each route based on a given volume deviation (e.g., ±10%). The volume for each scenario may be ±10%, ±20% of the forecasted volume.

For example, assuming that the forecasted volume for a route is 1200 units, three scenarios can be generated: Predicted Volume (1200), Predicted Volume + 10% (1320), and Predicted Volume - 10% (1080).

(2) Robust Optimization Modeling

The optimization objective is to minimize the total number of vehicles.

It is required that the vehicles are dispatched to meet the actual demand in all cargo scenarios. This means that it needs to be ensured that the number of vehicles used in each scenario is realistic for the volume demand.

(3) Solution Modeling

Use linear programming (LP) or mixed integer linear programming (MILP) to solve the model for optimal vehicle allocation.

By calculating the optimal solution, the number of vehicles used for each route and the total number of vehicles can be obtained.

(4) Result Analysis

Evaluate the responsiveness of the robust optimization method to cargo deviation by comparing the vehicle configurations under different scenarios.

Check the robustness of the model by comparing the change in the total number of vehicles under different scenarios.

4.4. Important parameter

In the scenario analysis and robust optimization model based on the PuLP library, the main parameters include: (1) 10 transportation routes, each using three vehicle types (owned, external, and standard containers) with different capacities; (2) cargo volume forecasts and their error margins (e.g., ±10%, ±20%) for each route to simulate the actual cargo volume variations; (3) a decision variable indicating each vehicle configuration quantity; (4) constraints ensure demand under all scenarios; and (5) the optimization objective is to minimize the total number of vehicles. By combining robust optimization with scenario analysis, it is possible to ensure that the dispatch model can robustly cope with different cargo volume deviation scenarios and minimize the total number of vehicles when facing cargo volume forecast deviations. This approach improves the adaptability and robustness of the scheduling system to effectively cope with realistic uncertainties.

4.5. Results Showcase

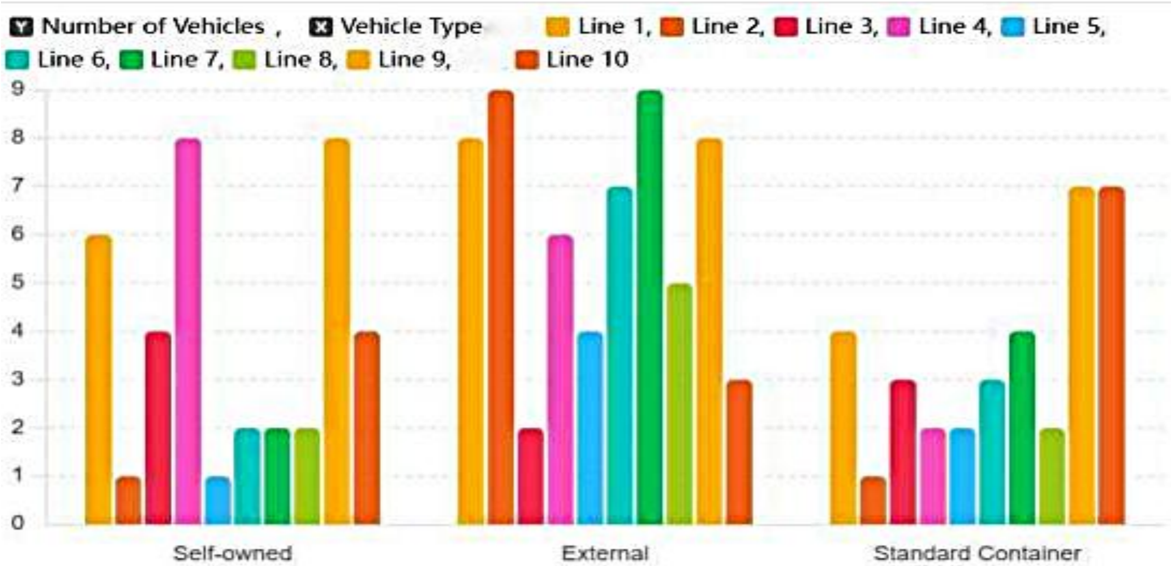

Figure 4. Optimal vehicle allocation per route

Figure 4 shows the optimal vehicle allocation for each route obtained based on the robust optimization and scenario analysis methods. From the results, it can be seen that there are obvious differences in the number of three types of vehicles (owned vehicles, external vehicles, and standard containers) used on different routes: some routes rely more on owned vehicles to complete transportation, such as Route 1 and Route 4; while some routes have a larger proportion of external vehicles or standard containers, such as Route 6 and Route 9 using more external vehicles, and Route 8 and Route 10 have an outstanding performance in the configuration of standard containers. The overall picture is that there is no single preference for vehicle configurations. Overall, there is not a single preference for vehicle allocation, but rather a flexible selection of different types of vehicles based on scenarios of volume demand and forecast deviation to achieve the optimization goal of minimizing the total number of vehicles. Such results show that the model is able to reasonably allocate various types of vehicle resources according to the transportation characteristics of different routes, which not only ensures the transportation demand, but also improves the robustness and adaptability of transportation scheduling. This is of reference value to the actual logistics system, which can provide scientific vehicle scheduling decision-making basis for enterprises in the face of demand uncertainty.

5. Conclusion

As an important part of the modern logistics system, short-distance transportation, in the context of rapid e-commerce, puts forward higher requirements for the accuracy of cargo forecasting and the robustness of scheduling optimization. However, existing studies often focus on a single link, and it is difficult to take into account the integrated optimization of forecasting and scheduling at the same time. To address this problem, this paper proposes a systematic research framework combining the XGBoost prediction model and robust optimization methods, forming a more complete solution from cargo volume prediction, vehicle scheduling optimization to robustness analysis under prediction deviation. The results show that: on the one hand, XGBoost can accurately portray the fluctuation pattern of cargo volume at 10-minute granularity, which provides data support for fine scheduling; on the other hand, through the scheduling optimization by genetic algorithm, the transportation cost can be significantly reduced and the utilization rate of the own vehicles can be improved under the premise of guaranteeing the constraint of transportation nodes; finally, the introduction of robust optimization and scenario analysis effectively improves the performance of the model under the prediction deviation, and the model is more efficiently optimized. Finally, the introduction of robust optimization and scenario analysis effectively improves the adaptability and stability of the model under prediction deviation, ensuring that the system is still able to provide feasible and efficient scheduling solutions under uncertain conditions. Despite the positive results achieved in this paper, there are still some shortcomings: first, the cargo volume prediction still mainly relies on historical data and time characteristics, and does not fully consider external influences such as weather, holidays, and emergencies; second, the vehicle types and constraints in the scheduling optimization are more simplified, and more realistic constraints (e.g., traffic conditions, driver scheduling, and vehicle maintenance costs, etc.) are not involved; and third, the robust optimization can improve the stability of the system, but it can be used in large-scale scenarios to improve the stability of the system. improve the stability of the system, but the computational complexity is high in large-scale scenarios, which may affect the efficiency of practical applications. Future research can be carried out in the following directions: first, introducing more multi-source data and deep learning methods to improve the accuracy and generalization ability of cargo volume prediction; second, further enriching the scheduling model, combining intelligent traffic information, real-time road conditions and multi-objective optimization methods to achieve more relevant decision support; third, exploring distributed robust optimization or approximation algorithms to model the computational overhead in large-scale instances; Fourth, considering carbon emission and green transportation goals, to provide support for enterprises to achieve cost reduction and efficiency at the same time.

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