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Research on Train Dispatch Optimization and Scheduling Strategy for Railway Freight Network

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Abstract: With the continuous and rapid growth of China's railway freight volume, alongside the increasing complexity of modern transportation organization, traditional single-objective-oriented transportation planning methods are becoming increasingly inadequate. Specifically, these conventional approaches can hardly balance the critical trade-offs between minimizing overall transportation costs and maintaining a high service level for customers. To address this pressing industry challenge, this paper constructs a comprehensive bi-objective optimization model tailored for a typical railway freight network. The proposed framework explicitly considers both the minimization of operational transportation costs and the maximization of overall demand satisfaction. Furthermore, the mathematical model fully takes into account a variety of strict operational constraints, such as the total number of available trains, dynamic line capacity limitations, the marshalling capacity of intermediate stations and freight yards, specific operation time windows, and the required minimum service level thresholds. Aiming at the inherent nonlinear and multi-objective characteristics of the formulated model, an advanced genetic algorithm based on the weighted sum strategy is adopted for efficient solving. The fundamental effectiveness of the proposed model and the robust convergence of the applied heuristic algorithm are rigorously verified through extensive numerical simulation experiments. The comprehensive computational results clearly demonstrate that the developed model can effectively reduce daily operation costs while significantly improving the overall demand satisfaction rate. Ultimately, this research provides a highly useful and practical reference for the optimal scheduling and strategic management of complex railway freight systems.

Keywords: railway freight; multi-objective optimization; genetic algorithm; pareto optimality; transportation scheduling

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1. Introduction

As an integral component of the national comprehensive transportation system, the railway freight system plays a pivotal role in ensuring the transportation of bulk materials and supporting economic operations. In recent years, with shifts in transportation demand structure and the increasing challenge of limited transport capacity, achieving efficient and coordinated transportation organization under such constraints has become a significant research focus [1].

In recent years, addressing the challenges of limited capacity in railway corridors in the northwest region, uncoordinated hub layouts, and inefficiencies in transportation organization, numerous studies have been conducted on line capacity expansion, hub connectivity, and transportation organization optimization. For instance, research has explored connection and line station layout schemes by analyzing hub conditions and forecasting passenger and freight volumes, aiming to improve hub functionality. Other studies have focused on resolving bottlenecks in uncoordinated point-line capacity, proposing solutions such as station yard capacity expansion, operational division optimization, and combined station yard layouts to enhance transportation efficiency. Regarding corridor capacity improvement, analyses have been conducted on traffic flow structures, key nodes, and challenging sections, leading to recommendations such as passenger-freight separation, reduced tracking intervals, and capacity expansion at critical stations, which have proven effective in boosting coal transportation capacity [1]. For single-track railways, engineering-capacity comparisons of capacity expansion schemes have demonstrated the advantages of adding passing loops in terms of investment and construction interference. Additionally, evaluations of corridor selection and planning for cross-regional energy transportation demand have identified optimal routes with higher value coefficients. From a strategic perspective, studies have highlighted the necessity of constructing additional double-track freight railways to enhance the capacity of the western railway network, providing strategic recommendations for long-term development. Quantitative analyses of transportation demand for new railway lines have further clarified their roles and capacity requirements within high-speed and conventional passenger transport systems.

In summary, existing research predominantly focuses on corridor capacity expansion, station reconstruction, and transport capacity improvement, often employing single-objective optimization methods such as cost minimization, capacity maximization, or shortest travel time. However, real-world railway freight scheduling scenarios frequently involve dual constraints of cost control and service quality assurance, making single-objective approaches insufficient to address the decision-making needs of operating units [2]. To address this, from a systematic perspective, this paper develops a bi-objective train dispatch optimization model for railway freight networks. By balancing cost and service levels, and comprehensively considering multiple transportation routes, diverse freight demands, and station capacity constraints, the proposed systematic optimization method is designed to support medium- and long-term planning and scheduling decisions, offering practical and applicable strategic guidance for railway freight organization.

2. Problem Description

This study examines a small-scale railway freight planning problem. Within a specified planning period, such as one or several days, there are multiple origin-destination (OD) freight demands (measured in tons) and several optional transportation routes. Each route can provide transportation capacity by dispatching a certain number of freight trains [3]. Trains are treated as discrete resources, with each trip on a route offering a fixed transport capacity (tons per train), a fixed running time, and a unit running cost. The objective is to allocate trains to each route while adhering to constraints such as limited fleet size and station capacity, aiming to minimize operating costs and fulfill demands as effectively as possible. Key constraints include the total number of trains available for the entire network, the maximum allowable departures for a single route, operational time window restrictions, and the minimum or maximum departure frequency of routes to ensure the train scheduling scheme remains executable and operationally safe.

3. Model Construction

3.1. Model Assumptions

3.1.1. Known line transportation parameters

It is assumed that the single-trip transport capacity, transportation cost, and working hours required for the operation of each transportation route are known and input into the model as deterministic parameters. These parameters reflect the stable performance of the line under fixed equipment conditions, organizational methods, and operational rules, and can be used to calculate transport capacity allocation and cost optimization.

3.1.2. Trains as reusable resources

Trains are considered reusable resources that can be scheduled in a circular manner. Upon completing a task, they can immediately return to the resource pool to undertake the next transportation task [4]. The model does not impose limitations on the train life cycle or differentiate between individual trains, focusing solely on the constraint of the total number of trains in relation to overall transport capacity.

3.1.3. Return trips and track occupancy are integrated into time window constraints

Operational details such as return trips, passing, and section occupancy on the route are comprehensively reflected in a single time window constraint [5]. The model incorporates practical factors, including return trips, line occupancy capacity, and scheduling conflicts, into a unified "available operation period," thereby simplifying the representation of the railway operation process. All task arrangements must be completed within a feasible time window.

3.1.4. Demand can be partially unsatisfied with a penalty mechanism introduced

The model permits partial transportation demand to remain unmet, reflecting real-world scenarios such as limited transport capacity or scheduling conflicts. A penalty cost is applied to quantify the economic impact of unmet demand, ensuring the optimization objective effectively balances capacity allocation and demand fulfillment [6].

3.2. Symbols and Decision Variables

The decision variables and corresponding parameters developed in this paper are presented in Tables 1, 2, and 3.

Table 1. Sets and Indexes

Symbol	Meaning
R	Set of Lines
O	Set of all OD pairs
$R(o) \subseteq R$	Set of routes serving OD pairs, i.e., optional transportation paths for the OD
o	OD pair index, $o \in O$
r	Route index, $r \in R$

Table 2. Decision Variables

Symbol	Definition
x_r	Number of trains allocated to the r- route $x_r \in Z \geq 0$
u_0	Unsatisfied demand volume of OD pair (tons), $u_0 \geq 0$

Table 3. Parameter Definitions

Parameter	Definition
C_r	Single-trip transportation cost of the r-route (yuan per train)
Q_r	Single-trip transport capacity of the r-route (tons per train)
T_r	Single-trip running time of the r-route (hours)
D_o	Total transportation demand of OD pair (tons)
m_o	Minimum service ratio of OD pair, indicating the minimum demand ratio to be satisfied
Y_r	Upper limit of marshalling capacity of the station corresponding to the route, i.e., the maximum number of dispatchable trains
N_{max}	Total number of available trains
T_{max}	Upper limit of total running time, i.e., total vehicle hours allowed in the planning period (hours)

X_r^{max}	Maximum number of dispatchable trains for a single route
P_u	Penalty coefficient for unsatisfied demand (yuan per ton)
P_t	Penalty coefficient for overtime (yuan per hour)
P_y	Penalty coefficient for station overload (yuan per train)
P_j	Penalty coefficient for excess trains (yuan per train)

3.3. Objective Function

3.3.1. Minimization of transportation cost

$$Z_1 = \sum_{r\in R} C_r x_r + P_y V_y + P_t V_t + P_f V_f \quad (1)$$

$$V_y = \max(0, x_r - Y_r) \quad (2)$$

$$V_z = \max(0, \sum_r T_\mathrm{r} x_\mathrm{r} - T_{max}) \quad (3)$$

$$V_f = \max(0, \sum_r x_\mathrm{r} - \bar{N}_{max}) \quad (4)$$

Formula (2) represents the penalty for station overload, indicating that if the number of allocated trains on a route exceeds the marshalling capacity of the corresponding station, the excess number of trains is included in the overload volume. Formula (3) represents the penalty for time overrun, indicating that the total vehicle hours consumed by the arranged trains exceed the available total vehicle hours in the planning period, and the excess hours are considered time overrun [7]. Formula (4) represents the penalty for excess trains, where exceeding the number of vehicles implies borrowing trains or infeasible scheduling. A very large penalty coefficient is applied to enforce feasibility or make the solution prohibitively costly.

3.3.2. Minimization of unsatisfied demand

$$Z_2 = \sum u_0 (5)$$

$$u_0 = D_0 - \sum_{r\in R(o)} Q_r x_r \geq 0 \quad (6)$$

Formula (6) demonstrates that the volume of unsatisfied demand must remain non-negative [8].

3.3.3. Weighted comprehensive objective function

$$\min Z = \omega_1 \frac{Z_1}{Z_1^*} + \omega_2 \frac{Z_2}{Z_2^*} \quad (7)$$

Where is the weighting coefficient of the bi-objective, and are normalization coefficients of the initial or ideal objectives, typically derived from the initial solution or single-objective optimal solution to prevent weight distortion caused by dimensional differences [9].

3.4. Constraints

3.4.1. Transportation volume constraints

$$\sum_{\mathrm{r}\in \mathrm{R(o)}} \mathrm{Q_r x_r} + \mathrm{u_o} = \mathrm{D_o}, \forall \mathrm{o} \in \mathrm{O} \quad (8)$$

Formula (8) represents the transportation balance constraint for each OD pair, indicating that the total transportation volume consists of both satisfied and unsatisfied transportation volumes.

$$\sum_{\mathrm{r}\in \mathrm{R(o)}} \mathrm{Q_r x_r} \geq \mathrm{m_o D_o}, \forall \mathrm{o} \in \mathrm{O} \quad (9)$$

3.4.2. Train resource constraints

$$\sum_{r\in R} x_r \leq N_{\max} \quad (10)$$

Formula (10) indicates that the total number of scheduled trains must not exceed the number of available trains [10].

3.4.3. Station capacity constraints

$$x_r \leq Y_r, \forall r \in R \quad (11)$$

Formula (11) indicates that the number of departures on each route must not exceed the capacity of the marshalling station.

3.4.4. Single-line scheduling upper limit constraint

$$x_r \le x_r^{\max}, \forall r \in R \tag{12}$$

Formula (12) represents the single-route scheduling upper limit constraint, designed to prevent excessive scheduling on a single line [9].

3.4.5. Time window constraints

$$\sum_{r \in r} \mathrm{T_r} x_r \le T_{\max} \tag{13}$$

Formula (13) represents the time window constraint, ensuring that the total running time of all trains does not exceed the available time limit within the scheduling cycle [11].

3.4.6. Non-negativity and integrality constraints

$$x_r \ge 0, u_o \ge 0, x_r \in Z \tag{14}$$

4. Solution Algorithm

Due to the large scale of the real problem and its bi-objective integer nonlinearity, such as time penalty and soft constraints, it is challenging to directly use an exact solver [12]. This paper adopts a weighted sum combined with a population-based heuristic algorithm process.

Weighted sum scalarization: Given weights for the bi-objective, a scalar objective is constructed.

$$Z = \lambda \cdot \tilde{Z}_1 + (1 - \lambda) \cdot \tilde{Z}_2 \tag{15}$$

Where $\tilde{Z}_1$ and $\tilde{Z}_2$, appropriate normalization is performed to eliminate order-of-magnitude differences.

1. Population initialization: Several feasible or near-feasible individual vectors are randomly generated, with large penalties imposed on individuals that clearly violate hard constraints to guide the algorithm toward the feasible region.
2. Selection, crossover, and mutation: Tournament selection or probability selection is adopted; single-point or uniform crossover is used for crossover; small-amplitude integer perturbation (±1, ±2) is applied for mutation to ensure variables remain within their upper and lower bounds.
3. Soft and hard constraint handling: Hard constraints are repaired as much as possible, such as trimming vectors exceeding the upper bound. For constraints that cannot be directly repaired, such as the total number of vehicles, a large penalty function is applied to reduce solution adaptability.
4. Multiple weights or multiple evolutions: An approximate Pareto frontier is obtained through repeated runs with different λ Pareto values.
5. Stopping criterion: The process terminates when a fixed number of generations is reached or when the objective shows no significant improvement.

This heuristic method is suitable for practical problems with large scale and discrete variables, providing a series of compromise solutions for scheduling decision-makers through different weights [13].

5. Case Verification

To verify the effectiveness of the model, this paper selects the Lanzhou-Xinjiang Railway as the research object and constructs a railway transportation network comprising seven transportation routes and five OD demand pairs. In the experiment, a genetic algorithm is employed for solving, and the changes in the optimal scalar objective and the average population scalar objective are recorded during each iteration. By analyzing iteration curves, this paper evaluates the convergence and stability of the algorithm, thereby assessing the application performance of the model within an actual railway network.

5.1. Parameter Settings

The population size and algorithm parameters are set as follows: To balance search diversity and computational efficiency, the genetic algorithm in this study adopts a population size of 80 and takes 120 iterations as the termination criterion. The selection operator employs tournament or roulette selection, while the crossover and mutation strategies utilize single-point crossover and small-amplitude integer mutation, respectively, with a mutation probability of 0.28 to balance local search and global exploration. Regarding the setting of objective scalarization and penalty function, this study adopts the weighted sum method for the bi-objective, with weight coefficients $\omega_2 = 0.72$, $\omega_2 = 0.28$, to obtain an engineering-acceptable solution with a slight bias toward cost minimization. To strictly constrain feasible solutions and quantify the violation of soft constraints into the objective function, penalty factors are set as follows: P_t=40 (yuan/h), P_y=15000 (yuan per train), P_f=20000 (yuan per train), P_u=12 (yuan/t). This parameter combination is calibrated through small-scale sensitivity testing before the experiment, effectively penalizing seriously infeasible solutions without excessively suppressing reasonable compromise solutions in the solution space, thus ensuring a good balance between the convergence speed and solution feasibility of the algorithm [14].

5.2. Optimization Results

Based on the bi-objective programming model and genetic algorithm solver constructed in this paper, the feasible optimal solution obtained is as follows:

Optimal allocation result (x_r):

$x = [3,2,2,1,1,3,0]$

The solution uses a total of 12 trains, accounting for about 30% of the 40 available trains, with a total transportation cost of 52,400 yuan and zero tons of unsatisfied demand.

Table 4 shows the allocation, contributed capacity, and cost of each line.

Table 4. Example Solution Results

No.	Route	Number of Allocated Trains	Transport Capacity (t)	Cost (yuan)
1	A-B (Lanzhou-Wuwei)	3	3600	14400
2	A-C(Lanzhou-Zhangye)	2	2000	8400
3	B-D(Wuwei-Jiayuguan)	2	1800	7800
4	C-D(Zhangye-Jiayuguan)	1	1500	6000
5	A-D(Lanzhou-Jiayuguan)	1	2000	9200
6	E-F(Hami-Wulumuqi)	3	1800	6600
7	B-E(Wuwei-Hami)	0	0	0
Total	-	12	12700	52400

It can be concluded from Table 4:

The model preferentially allocates high-cost-performance routes. For example, Route 1 (A-C) and Route 0 (A-B) have the characteristics of "medium capacity + medium cost + multi-OD coverage," so they are allocated more trips.

Long-distance, high-cost routes are used the least. For example, Route 4 (A-D) has a high cost of 9,200 yuan per trip and low overall cost performance, so it is only used to meet part of the necessary OD traffic.

Low-demand OD (such as E-F) is accurately met without excess. The E-F route only needs 1,800 tons to meet the demand, and three trains are allocated to meet the demand exactly without extra waste.

The above solution results demonstrate that the model and algorithm can effectively identify the cost-capacity-OD matching structure and automatically find the optimal transportation combination.

5.3. Convergence Curve

The horizontal axis represents the iteration generation, while the vertical axis denotes the normalized value of the objective function. It can be observed from Figure 1 that the genetic algorithm achieves rapid convergence within the first 15-20 generations, with the objective value showing a clear downward trend. This indicates that a significant number of poor-quality schemes with numerous constraint violations in the initial random population are quickly eliminated. The crossover and selection operations effectively combine better train allocation structures, significantly improving costs and addressing unsatisfied demand. Between 20-60 generations, the curve's descent rate slows, and the algorithm transitions from a global rough search to detailed local adjustments, gradually refining the resource allocation structure of high-cost routes and enhancing overall feasibility and transportation matching. The average population fitness progressively approaches the optimal value, reflecting continuous improvement in overall quality. After approximately 60 generations, the optimal value curve stabilizes and aligns closely with the average fitness, indicating that the population has concentrated in a high-quality feasible region, making further significant improvements difficult. At this stage, the algorithm enters a stable convergence phase. Overall, the curve demonstrates the typical "rapid decline-steady improvement-stable convergence" search characteristics of the genetic algorithm, ultimately forming a train scheduling scheme that satisfies all hard constraints, eliminates unsatisfied demand, and achieves a better cost level, thereby verifying the effectiveness and stability of the model solution method.

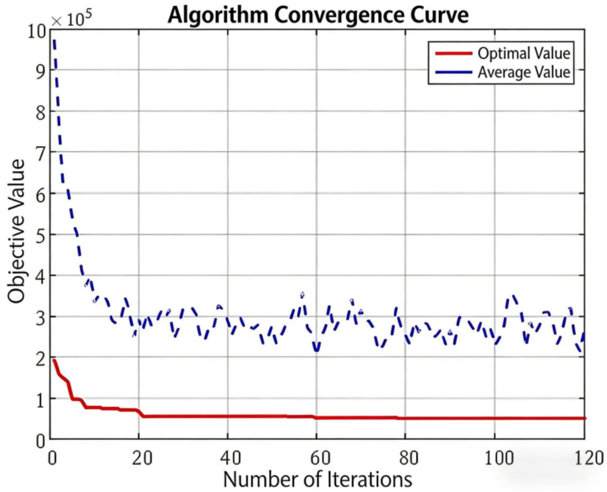

Figure 1. Iteration Curve.

As shown in Figure 2, the train allocation for each main trunk line exhibits a clear pattern of "main trunk line concentration, branch line moderate supplement." Train investment on routes such as A-B, A-C, and E-F is significantly higher than on other routes, indicating that under the optimization model, train resources are preferentially allocated to key corridors with high demand density, moderate transportation distances, and strong network connectivity. These routes handle the primary OD traffic within the network, and higher capacity allocation effectively reduces unsatisfied demand and enhances overall transportation efficiency. For branch lines with lower demand and greater path substitutability, train allocation is kept minimal to avoid inefficient resource usage [2]. Overall, the optimization results demonstrate that the model can autonomously achieve rational train resource allocation based on OD demand, line capacity, and cost structure, resulting in a robust capacity layout scheme.

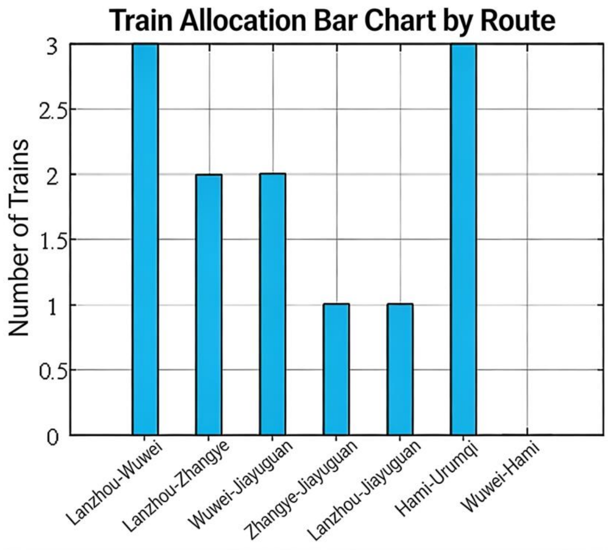

Figure 2. Histogram of Train Allocation for Each Route.

Figure 3 illustrates the demand satisfaction rate for each OD pair. All ODs achieve a 100% satisfaction rate, with no unsatisfied volume. This indicates that under the current demand scale, the optimized railway network capacity is sufficient to fully meet freight demand, with no supply-demand gaps caused by bottleneck routes. Both high-demand ODs, such as A→F and C→E, and low to medium-demand ODs are fully satisfied, demonstrating that the model maintains stable service capacity in high-load sections while avoiding neglect of low-demand ODs due to optimization bias. The consistently high satisfaction rate also reflects a relatively balanced network structure layout and an effective capacity redistribution strategy.

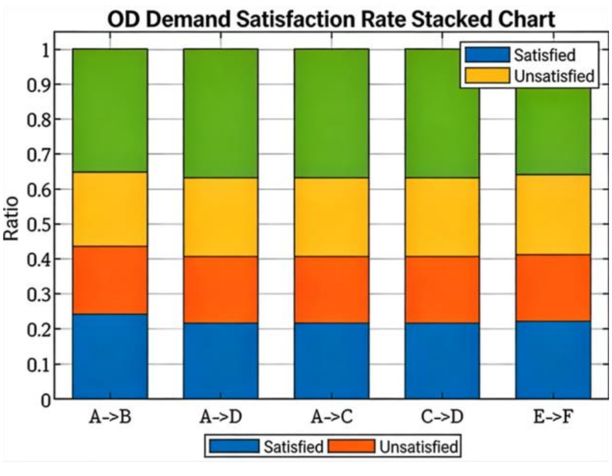

Figure 3. Stacked Chart of Demand Satisfaction Rate for Each OD.

As shown in Figure 4, the utilization rates of key constraints, including line capacity, train number, transfer capacity, and node processing capacity, range between 0.3 and 0.8, with none reaching saturation (utilization rate of 1). This structural outcome indicates:

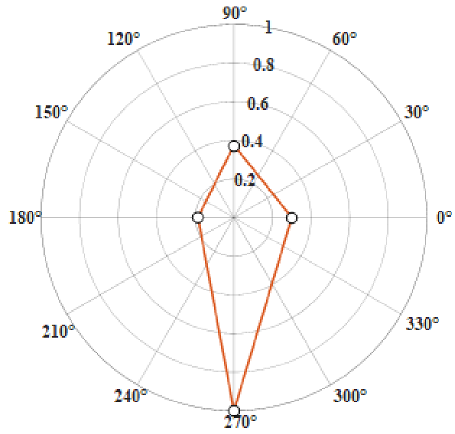

Figure 4. Radar Chart of Constraint Utilization.

1. There are no mandatory bottlenecks in the network, and all sections retain some redundant capacity, enhancing the network's adaptability to demand fluctuations or emergencies.
2. Train resources are not overutilized, as the model identifies more cost-effective route combinations through optimization rather than simply deploying all available trains to meet demand.
3. There is no resource congestion at transfer nodes, with node processing traffic and scheduling strategies remaining relatively balanced.

Overall, the constraint utilization is evenly distributed, with no single constraint nearing saturation [5]. This indicates that the model's optimization results provide a robust and implementable transportation scheduling configuration.

6. Conclusion and Prospect

This paper addresses the critical challenge of balancing economic efficiency and service levels within the constraints of limited transport capacity and multiple operational restrictions in railway freight transportation. A bi-objective programming model was developed to optimize transportation costs and demand satisfaction rates simultaneously, incorporating multiple resource constraints. By abstractly representing the freight network structure and demand characteristics, and employing a genetic algorithm based on the weighted sum strategy for problem-solving, the study verifies both the feasibility of the model and the effectiveness of the algorithm. The main findings are summarized as follows:

1. The bi-objective model effectively balances transportation costs and demand satisfaction levels, optimizing transportation organization. By introducing the dual objectives of cost minimization and unsatisfied demand minimization, the model captures the inherent conflict between economic efficiency and service quality in railway transportation planning. Experimental results demonstrate that the optimized scheme significantly reduces transportation costs while meeting all origin-destination demands, achieving a harmonious balance between transportation efficiency and quality.
2. The model's incorporation of various constraints accurately reflects the resource allocation characteristics of the railway freight system. Constraints such as train numbers, station marshalling capacity, line scheduling limits, minimum service levels, and operation time windows are included. Optimization results highlight the critical role of these constraints in preventing impractical solutions and guiding the rational allocation of train resources. Notably, the station capacity constraint effectively mitigates the risk of overloading marshalling stations, ensuring the feasibility of the proposed solutions.
3. The genetic algorithm demonstrates strong performance in solving complex multi-objective optimization problems. Experimental results indicate that the algorithm

rapidly reduces the objective function value within the initial 20 generations before stabilizing, showcasing its fast convergence capability. The final allocation scheme adheres to all constraints and outperforms random or greedy scheduling strategies, validating the algorithm's effectiveness in addressing nonlinear, non-convex, and discrete optimization challenges.

4. The calculation results provide valuable guidance for practical freight scheduling decisions. The optimal train allocation scheme leverages the capacity characteristics of different lines, minimizing the use of high-cost routes while meeting demand. This approach emphasizes resource concentration in high-efficiency areas and the automatic reduction of redundant capacity, aligning closely with the "spatio-temporal balanced allocation" concept in railway transportation planning. These findings underscore the model's potential for practical engineering applications.

In summary, the model developed in this study achieves lower transportation costs while ensuring demand satisfaction, offering a quantitative and scalable decision-making tool for optimizing railway freight systems. Future research could explore several directions, including the development of more complex multi-objective optimization frameworks and the application of advanced algorithms such as NSGA-II and MOEA/D to generate Pareto frontiers. Additionally, incorporating dynamic demand and uncertainty factors through robust optimization and stochastic programming could enhance resilience. Further improvements could involve integrating train operation periods and routing connections to enhance the practicality of the solutions, optimizing energy consumption and carbon emissions in line with sustainability goals, and developing a visual decision support system to advance the intelligence of railway transportation planning.

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