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Entire-process scheduling optimization strategy for railway emergency logistics based on two-stage multi-objective programming

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A B S T R A C T

Conventional railway emergency logistics frameworks are typically characterized by transport capacity adjustments to prioritize emergency material transportation. However, this paradigm frequently results in extended emergency response times and substantial delays in conventional freight operations. To address these limitations, an entire-process optimization strategy encompassing the Emergency Recovery Phase (ERP) and Post-Emergency Recovery Phase (PERP) was formulated, accompanied by a two-stage multi-objective optimization model. Diverging from conventional frameworks that necessitate operation plan reconfiguration for emergency train deployment, the proposed strategy streamlined operation plan replanning in the ERP through formation and loading plan optimization, while concurrently incorporating transportation cost-effectiveness in the PERP into the holistic optimization framework. The ERP submodel was designed to ensure the balanced allocation of limited emergency materials while achieving significant reductions in emergency response time. Subsequently, the PERP submodel incorporated dual considerations of transportation cost-effectiveness for railway carriers and cargo owners, while mitigating delay losses in conventional freight operations. To resolve this multi-objective optimization model, the Adaptive Variable Neighborhood Non-dominated Sorting Genetic Algorithm-II (AVNNSGA-II) was developed. The following results were obtained by this empirical study. (1) The ERP submodel attained emergency material satisfaction rates exceeding 51.28% across multiple disaster-affected areas while achieving emergency response time reductions of 6.16–19.22% relative to conventional railway emergency logistics frameworks. Notably, it demonstrated superior performance relative to road-based emergency logistics under different speed scenarios, with 55.9–69.4% response time reductions. (2) The PERP submodel effectively reduced delay losses in non-emergency freight operations by 50.49% through the implementation of differentiated transport prioritization mechanisms. (3) The superiority of this algorithm was confirmed with 97% of Pareto front solutions of AVNNSGA-II exceeding those of conventional NSGA-II. In conclusion, the proposed strategy is demonstrated to synergistically balance emergency response efficiency and transportation cost-effectiveness, thereby significantly enhancing railway emergency logistics performance. Furthermore, the integration of AVNNSGA-II with the multi-objective optimization model provides innovative perspectives for addressing large-scale rail freight allocation and scheduling challenges.

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1. Introduction

The rapid deployment of transportation resources during emergencies (e.g., natural disasters, public health crises, and major safety incidents) remains a critical challenge in emergency logistics systems. As a primary mode for emergency logistics, rail transportation continually faces operational constraints including delayed emergency response initiation and complex scheduling procedures. Previous studies have developed rescue train scheduling models (Bababeik et al., 2018; Tang, Li, et

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al., 2023) and relief material allocation strategies (K. Zhao et al., 2022; Zheng et al., 2015) under conventional railway emergency logistics frameworks; however, these systems typically require temporary capacity reallocations to prioritize emergency transportation, leading to two inherent drawbacks: (1) time-consuming scheduling replanning during critical emergency windows; and (2) cascading delays to prescheduled non-emergency freight operations. To address the inherent limitations of the current model, systematic optimizations should be implemented across critical stages of the railway emergency response process.

The railway emergency response process encompasses three interconnected stages: formulation of emergency train operation plans, development and implementation of emergency material train formation and loading plans, and emergency material transportation. Previous research has improved emergency train operation plans through emergency train insertion (Zheng, 2018) and enhanced the efficiency of emergency material transportation via route optimization (Liu & Yang, 2021); however, emergency material train formation and loading plans, a pivotal intermediate phase, remain understudied. To bridge this gap, this study proposes a comprehensive optimization strategy for the entire emergency logistics process, specifically targeting the coordinated optimization of emergency material train formation and loading plans. This approach enhances emergency response efficiency, while significantly reducing delay losses in conventional freight transportation.

The entire process of railway emergency logistics can be categorized into two sequential phases: the Emergency Recovery Phase (ERP) and the Post-Emergency Recovery Phase (PERP) (Li et al., 2019). Based on this classification framework, a strategic two-stage multi-objective optimization model was constructed. The ERP submodel employs an innovative emergency response strategy to develop integrated plans for emergency material transport train formation, loading, and scheduling. Through the optimization of allocation equity across disaster-affected areas, this submodel was designed to minimize emergency response times while maintaining a balanced distribution of limited emergency materials. In contrast, the PERP submodel addresses operational recovery through a dual mechanism: higher transportation priority was assigned to delayed non-emergency shipments from the ERP, and economic performance metrics for both railway carriers and cargo owners were systematically incorporated. Transportation schemes were formulated through this submodel to optimally mitigate operational disruptions caused by emergency logistics for non-emergency material transportation, thereby achieving global economic optimization. To effectively solve this complex multi-objective problem, an enhanced algorithm – AVNNSGA-II – was developed through systematic improvements to the traditional NSGA-II framework.

The principal contributions of this study are as follows:

(1) The proposition of a novel optimization strategy for the entire railway emergency logistics process, from which a two-stage multi-objective optimization model is constructed.

(2) The development of the ERP submodel to optimize formation, loading, and scheduling schemes during the ERP. Empirical analysis demonstrates that, relative to conventional railway emergency logistics frameworks and road-based emergency logistics, this submodel significantly reduces emergency response times while achieving a balanced allocation of emergency materials.

(3) The formulation of the PERP submodel to mitigate delay losses in non-emergency material transportation and ensure globally optimal economic performance of transport plans. Empirical analysis reveals that this submodel substantially reduces delay losses compared to traditional railway emergency logistics frameworks.

(4) The design of an enhanced algorithm – AVNNSGA-II – for efficient resolution of the proposed optimization model. Experimental results confirm the superiority of this algorithm over conventional NSGA-II in terms of solution performance, global search capability, and computational stability.

(5) The engineering of an emergency response strategy specifically for the optimization of railway emergency logistics. This innovation theoretically advances emergency logistics research while providing practical guidance for improving the efficiency of railway emergency logistics in real-world scenarios.

2. Literature review

Research concerning railway emergency logistics encompasses multiple critical dimensions ranging from resource scheduling and system resilience to multimodal transportation coordination, with the objective of enhancing operational responsiveness and recovery efficiency under emergency scenarios. Fundamentally, this involves the optimization of material transportation, emergency response mechanisms, infrastructure restoration, and strategic coordination between routine logistics operations and emergency contingencies. Scholarly investigations predominantly focus on three pivotal aspects: effective resource allocation during emergencies, minimization of response timeframes, and enhancement of system recovery capabilities, collectively spanning a spectrum of research challenges from single-material distribution to sophisticated multi-stage optimization frameworks. In terms of emergency material scheduling optimization, equity in railway emergency material allocation is recognized as a critical factor. Cumulative prospect theory has been applied to construct multi-stage scheduling

decision models, achieving psychological perception optimization of scheduling time and resource allocation equilibrium by considering the risk preferences of decision-makers (Yuan et al., 2018). Furthermore, fuzzy multi-objective programming models have been developed to integrate urban emergency medical resources with railway rescue capabilities while balancing cost-effectiveness and equity, thereby providing critical insights for achieving rapid emergency logistic responses under resource constraints (Cheng & Liang, 2014; Tang et al., 2021). Additionally, the modified artificial bee colony algorithm was designed to solve multi-objective optimization models in emergency logistics, offering innovative approaches for balancing equity and efficiency in complex accident scenarios (Zhao et al., 2022). Notably, the Shapley value allocation principle was introduced into the emergency logistics scheduling research, with a particular emphasis on the significance of equity in resource distribution across multiple disaster-affected areas (Tang, Zou, et al., 2023). In addition to equity considerations, research attention has been directed towards uncertainty management in emergency material scheduling. To address this challenge, fuzzy optimization and robust optimization methods were applied, establishing theoretical foundations for scheduling problems under uncertain conditions (Meng & Cui, 2014; Tang et al., 2021; Tang, Li, et al., 2023; W. Wang et al., 2022; Y. Wang et al., 2023; Yang et al., 2014). Collectively, the aforementioned studies demonstrate that equity in emergency material distribution constitutes an essential element and requires prioritized attention in resource scheduling optimization research; however, most existing investigations have been conducted within the conventional railway emergency logistics framework, such that response delays caused by the temporary insertion of emergency transport trains remain inadequately addressed.

Research on railway system resilience and failure recovery constitutes another major direction in the field of railway emergency logistics. Investigations in this domain are primarily conducted by constructing bilevel networks and distributionally robust optimization models to analyze system recovery speed and critical node stability under disaster scenarios. Several studies have investigated strategies for the efficient allocation of rescue resources through simulations of various failure scenarios, thereby reducing emergency response times (Tang et al., 2022; Zhang et al., 2023). These studies provide the quantitative foundations for enhancing railway emergency response capabilities. Regarding high-speed railway emergency scheduling, studies have demonstrated the feasibility of inserting emergency trains without disrupting conventional operations (Zhao et al., 2022; Zheng, 2018). This approach offers valuable insights for addressing response delays caused by the temporary insertion of emergency transport trains in conventional railway emergency logistics frameworks; however, such investigations also reveal an inherent conflict: non-emergency logistics operations frequently experience significant delays when prioritizing emergency material transportation (Gong & Zhang, 2017; E. Liu et al., 2022; Zheng, 2018). This fundamental contradiction between scheduling optimization and operational recovery further underscores the necessity for holistic optimization throughout the entire railway emergency logistics process.

In railway emergency logistics research, beyond emergency material scheduling and system resilience, studies concerning multimodal transportation and evacuation, infrastructure and logistics optimization, and safety and risk assessment have provided critical support for the efficient operation of integrated emergency logistics systems. Several researchers have employed mixed-integer programming and bilevel optimization models to investigate how railway, bus, and air transportation modes may be coordinated to reduce passenger waiting times during emergency evacuations (Liu et al., 2022), with concurrent optimization proposals for capacity allocation (Long et al., 2021). Although these methods primarily focus on enhancing evacuation efficiency under passenger-oriented emergency conditions, a distinct context from emergency logistics optimization, they also offer transferable methodological insights. Furthermore, the strategic positioning of emergency facilities was determined through location optimization and robust optimization methods (Wang & Zhou, 2023; Wang et al., 2022; Wang et al., 2023), while network layout optimization was demonstrated to further improve transportation efficiency (Yin et al., 2022). However, these findings are predominantly limited to improvements in isolated components of emergency logistics. Therefore, this study proposes the development of a coordination framework encompassing the entire process from the emergency response stage to the post-disaster recovery stage. For the safety and risk assessment, investigations utilizing Safety Integrity Level allocation and risk assessment cloud models provide data support for stable system operation during disasters (Ebrahimi et al., 2022; Ouedraogo et al., 2018; Wang et al., 2024). Additionally, Geographic Information System (GIS) and remote sensing technologies have been shown to be instrumental in multihazard early warning systems (Joshi et al., 2024); however, existing studies contain limited discussion of the balance between emergency logistics and non-emergency freight transportation during scheduling processes.

In summary, significant progress has been achieved in the field of railway emergency logistics across multiple dimensions, including multi-objective optimization, resource scheduling, system resilience, multimodal coordination, and safety risk assessment. These advancements provide diverse theoretical methodologies and practical case studies for enhancing emergency response capabilities and post-disaster recovery efficiency. However, several critical challenges remain unresolved:

(1) The emergency logistics response speed dilemma, whereby emergency transportation train insertion and priority scheduling paradigms inevitably prolong response times;

(2) The systemic optimization gap, because previous studies have predominantly focused on isolated transportation segments rather than holistic coordination from emergency responses during post-recovery phases;

(3) The coordination conflict between emergency and non-emergency logistics operations, such that prioritized emergency material scheduling frequently compromises non-emergency logistics operations.

Collectively, despite significant achievements within individual research domains, a unified framework integrating emergency response, systematic optimization, and non-emergency logistics coordination has yet to be attained. This critical knowledge gap provides the research motivation for this study.

To address these deficiencies, this paper proposed a novel two-stage operational optimization framework dividing the entirety of the railway emergency logistics process into the ERP and PERP and a two-stage multi-objective optimization model was developed. The ERP submodel introduces an innovative emergency response strategy that references existing multi-objective and dynamic scheduling research. This strategy is specifically designed to reduce response times during both the formulation and implementation phases of formation and loading plans, while simultaneously achieving a balanced allocation of emergency materials. Complementarily, the PERP submodel mitigates operational interferences on conventional logistics by elevating the priority of non-emergency material transportation. This methodology is partially inspired by high-speed railway emergency scheduling and failure recovery studies. To solve the resulting multi-objective optimization problem, an enhanced AVNNSGA-II was developed through modifications to the NSGA-II framework, significantly improving both the solution quality and global search capability. Theoretically, this research advances railway emergency logistics optimization knowledge; practically, it proposes a pioneering two-stage strategy that simultaneously accelerates emergency responses while safeguarding non-emergency logistics operations, ultimately delivering a more efficient and scientifically grounded solution for emergency logistics.

3. Problem description

This study focuses on the optimization of railway emergency logistics for multiple disaster-affected areas. The scope of optimization covers both the ERP and PERP. The optimization aspects include the formation, loading, and scheduling planning of railway emergency logistics.

This study is based on the following key assumptions:

(1) All trains are capable of loading and transporting emergency materials.
(2) The stopping scheme, travel speed, and technical operation parameters of the trains are known.
(3) Due to limitations in locomotive traction capacity and economic factors, each train has a predefined maximum and minimum number of formation wagons.
(4) Each train can transport multiple types of emergency materials simultaneously, but individual wagons within the train are restricted to carrying only one type of emergency material.

The Entire Process of Railway Emergency Logistics

Recovery processes following severe disasters typically consist of two distinct phases: ERP and PERP. The characteristics of emergency materials in affected areas during these two phases are shown in Fig. 1.

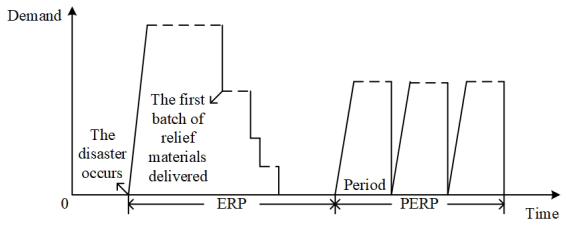


Fig. 1. The characteristics of emergency materials during two phases.

The ERP is defined as the preliminary phase of rescue operations subsequent to a disaster (Ling et al., 2021). The supply and demand characteristics of emergency materials during this phase are as follows:

(1) Surging demand for emergency materials. At the onset of this phase, the demand for emergency materials increases sharply. Subsequently, as emergency materials are continuously delivered to the affected areas, the demand gradually diminishes.

(2) High marginal cost of supply shortages. Resources allocated during the ERP are primarily designated for emergency rescue operations, and shortages of supplies may result in severe loss of life and property. Consequently, the core strategic objective of emergency logistics in this phase is to ensure that all areas affected by the disaster areas receive adequate emergency materials while minimizing the response time.

(3) Insufficient total available supplies: The sudden surge in demand for emergency materials may result in the supply of emergency materials being insufficient to meet all demands. To prevent excessive shortages of emergency supplies in any affected area, emergency logistics must focus on achieving a balanced allocation of limited resources.

The PERP is defined as the stage of survivor resettlement and post-disaster restoration following stabilization (Cheng & Liang, 2014). The supply and demand characteristics of emergency materials during this phase are as follows:

(1) Periodic fluctuations in demand for emergency materials. During the PERP, transportation demand primarily consists of essential living supplies for disaster survivors and materials required for post-disaster recovery. The demand for emergency materials exhibits periodic characteristics and tends to stabilize over time.

(2) Low marginal cost of supply shortages. During the PERP, affected areas are no longer under direct threat from the disaster. As a result, temporary shortages of certain resources do not pose significant risks to lives and property. Consequently, emergency logistics during the PERP should focus on transportation cost-effectiveness.

(3) Sufficiency in total available supplies. During the PERP, emergency material supply areas have sufficient time to produce or mobilize resources, ensuring that the total supply can meet all the demands of the affected areas. Therefore, emergency logistics during this phase should focus on enhancing transportation cost-effectiveness and efficiency.

Railway Emergency Logistics Strategy

Emergency logistics strategy for the ERP

During the ERP, enhancing the speed of the emergency response is critically important to alleviate material shortages in disaster-affected areas. Specifically, the formulation and implementation of formation and loading plans for emergency material transport trains is recognized as a critical component within the emergency response process. Through systematic optimization of these formation and loading plans, response durations can be effectively reduced while resource allocation can be optimized across all affected areas. To address this, the present study developed a novel emergency transport strategy through a comprehensive analysis of formation and loading plan development for emergency material trains during ERP. The proposed strategy is designed to ensure balanced resource distribution among all disaster-affected areas while simultaneously improving the efficiency of the emergency response. By utilizing the scenario of a large-scale epidemic outbreak across multiple locations as an illustrative example, the emergency formation and transportation strategy during the ERP is outlined in Fig. 2.

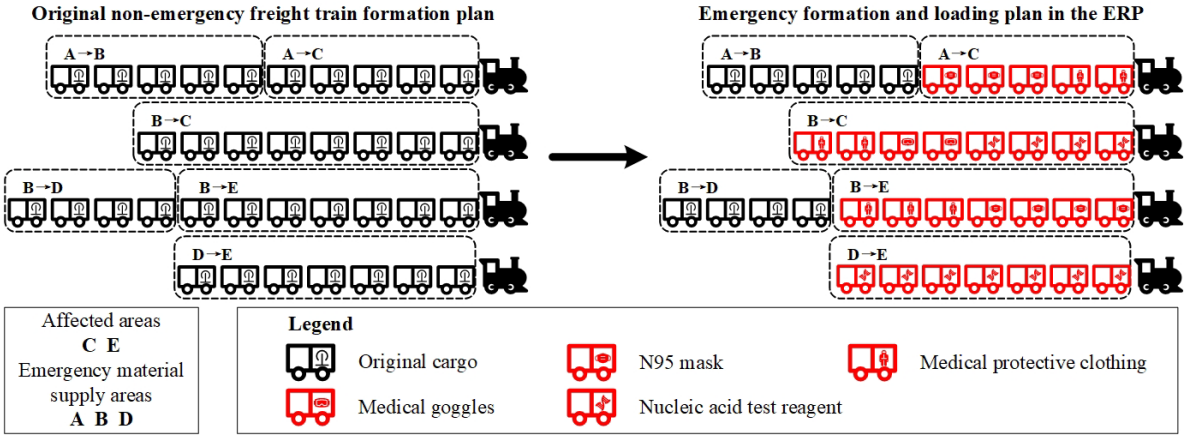


Fig. 2. Emergency logistics strategy for the ERP.

This strategy implements tactical adjustments by converting trains originally scheduled to transport non-emergency materials to disaster-affected areas into emergency material transporters. Notably, the departure stations, destinations, and departure timetables of these trains remain unaltered. This minimizes the complexity of formation planning. Furthermore, the loading plans for emergency logistics operations require meticulous coordination, such that both the categories and quantities of emergency materials per wagon must be determined through systematic analysis of actual demand in disaster-affected areas and real-time inventory status at emergency material supply areas.

Emergency logistics strategy for the PERP

During the PERP, emergency logistics should focus on the transportation economy. This includes mitigating the transportation delay losses of non-emergency goods caused by emergency logistics operations during the ERP and meeting the newly

generated transportation demands during the PERP. Utilizing the scenario of a large-scale epidemic outbreak across multiple locations as an illustrative example, the emergency formation and transportation strategy during the PERP is outlined in Fig.3.

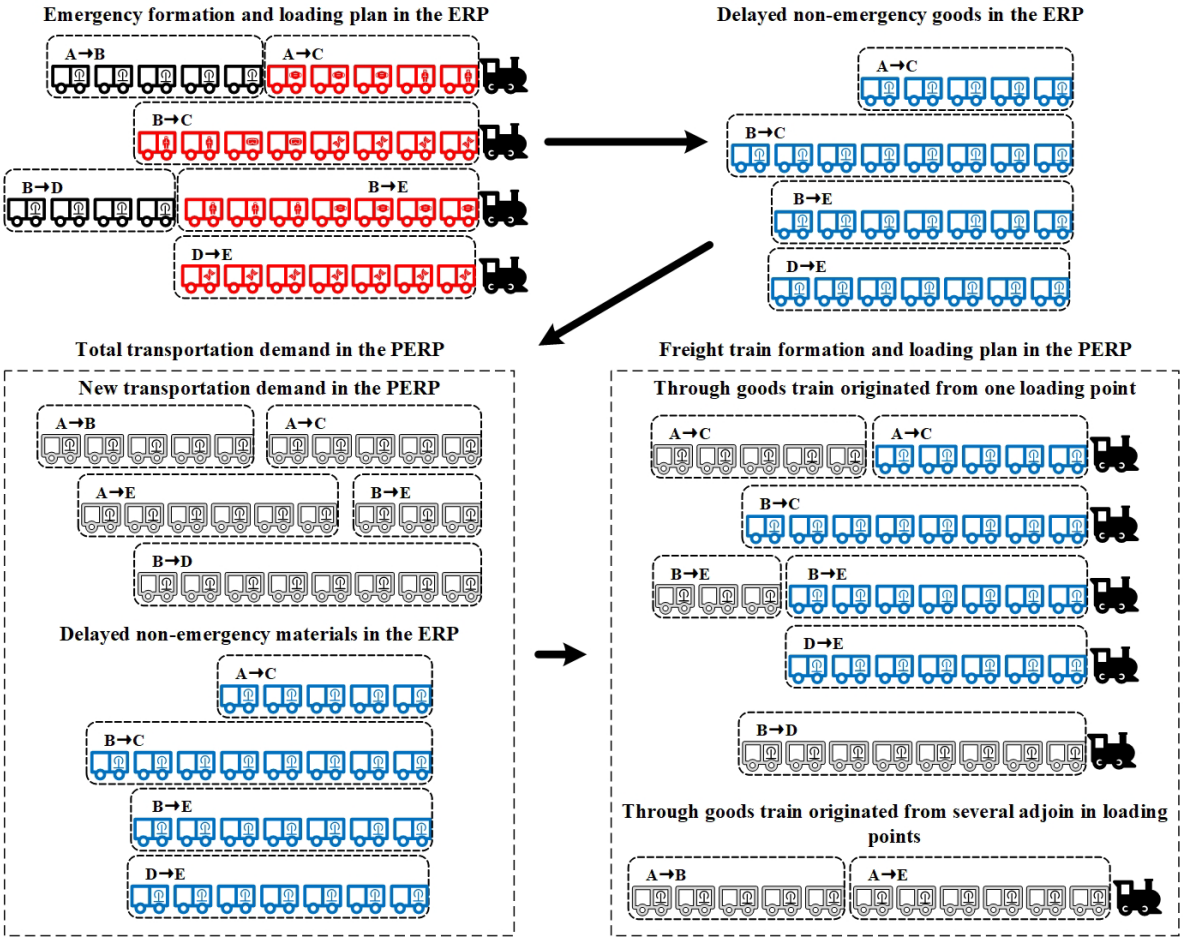


Fig. 3. Emergency logistics strategy for the PERP.

Transportation demands during the PERP require the integration of both delayed non-emergency materials from the ERP and newly generated requirements within the PERP. To achieve this objective, the proposed strategy prioritizes minimizing delay-related losses by assigning elevated transportation priority to affected non-emergency goods. This operational priority is enforced through the dedicated operation of "through goods trains originated from one loading point". Concurrently, the remaining freight demands are determined based on their corresponding number of formation wagons and railway scheduling rules to decide whether to operate "through goods trains originated from one loading point" or "through goods trains originated from several adjoin in loading points". The "through goods trains originated from one loading point" mode can be enacted if the freight demand meets at least one of the following conditions:

(1) The freight demand consists of non-emergency goods delayed during the ERP;
(2) The number of wagons required for a demand exceeds the minimum formation threshold.

4. Mathematical model

$G=(N,L)$ is defined to describe the railway freight network. The set of nodes $N=\{n_i\}=\{n_o,n_d,n_a\}$ contains all stations in the railway freight network, where n_o represents the departure stations, n_d represents the destination stations, and n_a represents other stations. In actual rescue operations, n_o typically represents emergency material supply areas, while n_d denotes areas affected by the disaster. $L=\{l_j\}$ contains all railway sections in the railway freight network.

C_i: receiving-departure capacity of station n_i, i.e., the maximum number of trains that station n_i can handle during a period (unit: train);

D_j: railway carrying capacity of railway section l_j (unit: train);

d_j: length of railway section l_j (unit: km);

$P=\left\{p_{o,d}^{k}\left|n_o,n_d\in N,k=1,2,3,\cdots\right.\right\}$ is the set of all paths from n_o to n_d and $p_{o,d}^{k}$ is the k^{th} path from n_o to n_d;

$\alpha_{o,d,k}^{i}$: binary variable equal to 1 if path $p_{o,d}^{k}$ passes through station n_i, otherwise zero; and

$\beta_{o,d,k}^{j}$: binary variable equal to 1 if path $p_{o,d}^{k}$ passes through railway section l_j, otherwise zero.

ERP Submodel

The ERP emergency logistics strategy involves the substitution of non-emergency cargoes into the original formation and loading plans with emergency materials, while retaining the existing railway operation scheme, encompassing OD pairs and dispatching times. The parameters governing this submodel are as follows:

A_o^g: supply capacity of the g^{th} type of emergency materials in emergency material supply area n_o (unit: wagon);

B_d^g: total demand of the g^{th} type of emergency materials in affected area n_d (unit: wagon);

$S_{ERS}=\left\{s_q\right\}$ is the set of available freight trains for emergency logistics in the original operation plan and s_q is the q^{th} freight train. Each s_q includes the information of travel speed, departure station, destination, path, and stop plan, among other characteristics.

$H_{o,d}^{q}$: binary variable equal to 1 if freight train s_q plans to transport cargo from n_o to n_d in the original operation plan, otherwise zero; and

$h_{o,d}^{q}$: quantity of cargo transported from n_o to n_d by s_q in the original operation plan (unit: wagon).

The decision variable of the ERP submodel is governed by the following:

$z_{o,d,g}^{q}$: quantity of the g^{th} type of emergency materials transported from n_o to n_d by freight train s_q (unit: wagon).

Emergency logistics plans may not fully satisfy the demands of disaster-affected areas due to constraints on transport capacity and temporary shortages of emergency materials at emergency material supply areas. However, considering the psychological conditions of humanitarian aid recipients and the high marginal costs associated with material shortages during the ERP, the allocation of emergency materials should be distributed as equitably as possible across all affected areas. Consequently, the objective function of this submodel is oriented towards minimizing the unmet quantity of all types of emergency materials in all affected areas. The objective of this submodel is outlined below:

$$\min\left[\max_{\forall n_d,g}\left(B_d^g-Z_d^g\right)\right] \tag{1}$$

$$Z_d^g=\sum_{s_q\in S_{ERS}}\sum_{n_o\in N}z_{o,d,g}^{q},\ \forall n_d\in N,\ \forall g \tag{2}$$

Objective (1) aims to minimize the maximum unmet quantity of emergency materials across all areas affected by the disaster. Z_d^g represents the total quantity of the g^{th} type of emergency materials transported to the affected area n_d. The constraints within this submodel are then delineated as follows:

$$\sum_{g}z_{o,d,g}^{q}=H_{o,d}^{q}h_{o,d}^{q},\ \forall s_q\in S_{ERS},\ \forall n_o,n_d\in N \tag{3}$$

$$\sum_{s_q\in S_{ERS}}\sum_{n_d\in N}z_{o,d,g}^{q}\le A_o^g,\ \forall g,\ n_o\in N \tag{4}$$

$$\sum_{s_q\in S_{ERS}}\sum_{n_o\in N}z_{o,d,g}^{q}\le B_d^g,\ \forall g,\ n_d\in N \tag{5}$$

$$z_{o,d,g}^{q}\ge 0,\ \forall s_q\in S_{ERS},\ \forall g,\ \forall n_o,n_d\in N \tag{6}$$

Constraint (Eq. 3) ensures that if s_q is selected to transport emergency materials, its freight capacity must be entirely allocated to this purpose. Constraint (Eq. 4) ensures that the total quantity of the g^{th} type of emergency materials transported from n_o does not exceed the supply capacity. Constraint (Eq. 5) ensures that the total quantity of the g^{th} type of emergency materials transported to n_d does not exceed the demand. Constraint (Eq. 6) ensures that the decision variables are non-negative.

PERP Submodel

The PERP submodel is established to formulate a new formation and operation scheme after the ERP. The parameters governing this submodel are as follows:

$R = \left\{ r_{o,d,g} \right\} = \left\{ r'_{o,d,g} \bigcup r''_{o,d,g} \middle| n_o, n_d \in N \right\}$: the set of total transport demands in the PERP;

$r'_{o,d,g}$: the g^{th} type of the original cargo from n_o to n_d delayed by transporting emergency materials in the ERP (unit: ton);

$r''_{o,d,g}$: the g^{th} type of the new transport demand from n_o to n_d generated in the PERP (unit: ton);

w_g: the maximum quantity of the g^{th} type of goods that can be loaded into a wagon (unit: ton);

$t_{o,d,g}$: the delivery time limit of demand $r_{o,d,g}$ (unit: hour);

$S_{CRS} = \left\{ s_q \right\}$ is the set of all available freight trains in the PERP;

s_q: the q^{th} freight train in the set S_{CRS}. Each s_q includes information about travel speed, departure station, destination, path, and stop plan, among other factors;

$\xi^q_{o,d,k}$: the binary variable equal to 1 if the freight train s_q runs on path $p^k_{o,d}$, otherwise zero;

γ^q_i: the binary variable equal to 1 if the freight train s_q stops at station n_i, otherwise zero;

μ_q: freight rate of freight train s_q (unit: Yuan/km•ton);

c_q: transportation cost of freight train s_q (unit: Yuan/km);

f_q: the fixed cost of the freight train s_q, including railway line usage fees and locomotive traction fees (unit: Yuan/train);

c^q_i: the cost of the freight train s_q required to execute a technical operation at station n_i (unit: Yuan/train);

v_q: travel speed of freight train s_q (unit: km/h);

δ_q: the maximum number of stop stations of the freight train s_q;

ϕ^q_i: the temporal duration essential for freight train s_q to execute a technical operation at station n_i, including receiving and departure operation and coupling and uncoupling operation (unit: hour);

$u^{\min}_q$: the minimum number of formation wagons of freight train s_q; and

$u^{\max}_q$: the maximum number of formation wagons of freight train s_q;

The decision variables of the PERP submodel are as follows:

$x^q_{o,d,g}$: binary variable equal to 1 if freight train s_q is chosen to transport demand $r_{o,d,g}$, otherwise zero; and

$\lambda^q_{o,d,g}$: operation frequency of freight train s_q corresponding to demand $r_{o,d,g}$;

The objectives encompassed in the PERP submodel are centered around economic benefits to both railway enterprises and shippers. The total freight profit is employed as a metric to gauge the economic benefits of railway enterprises, while the total freight costs for shippers serve as a measure of their economic gain. The specific objectives of this submodel are delineated as follows:

$$\max Z_1 = z_{\text{income}} - z_{\text{variable}} - z_{\text{fixed}} - z_{\text{technical}} \tag{7}$$

$$\min Z_2 = \sum_{s_q \in S_{CRS}} \mu_q \sum_{r_{o,d,g} \in R} r_{o,d,g} x^q_{o,d,g} \sum_{p^k_{o,d} \in P} \xi^q_{o,d,k} \sum_{l_j \in L} \beta^j_{o,d,k} d_j \tag{8}$$

$$z_{\text{income}} = \sum_{s_q \in S_{CRS}} \mu_q \sum_{r_{o,d,g} \in R} r_{o,d,g} x^q_{o,d,g} \sum_{p^k_{o,d} \in P} \xi^q_{o,d,k} \sum_{l_j \in L} \beta^j_{o,d,k} d_j \tag{9}$$

$$z_{\text{variable}} = \sum_{s_q \in S_{CRS}} c_q \sum_{r_{o,d,g} \in R} \lambda^q_{o,d,g} x^q_{o,d,g} \sum_{p^k_{o,d} \in P} \xi^q_{o,d,k} \sum_{l_j \in L} \beta^j_{o,d,k} d_j \tag{10}$$

$$z_{\text{fixed}} = \sum_{s_q \in S_{CRS}} f_q \sum_{r_{o,d,g} \in R} \lambda^q_{o,d,g} x^q_{o,d,g} \tag{11}$$

$$z_{\text{technical}} = \sum_{s_q \in S_{CRS}} \sum_{n_i \in N} c^q_i \gamma^q_i \sum_{r_{o,d,g} \in R} \lambda^q_{o,d,g} x^q_{o,d,g} \tag{12}$$

Objective (Eq. 7) is the economic benefit of railway enterprises. Objective (Eq. 8) is the total transportation cost of shippers. Objective (Eq. 9) is the income of railway freight transport. Objective (Eq. 10) is the variable cost of railway freight transport. Objective (Eq. 11) is the fixed cost of railway freight transport. Objective (Eq. 12) is the technical operation cost at the station.

The two objective functions in the PERP submodel exhibit inherent conflicts stemming from divergent stakeholder priorities. The railway carrier benefit (Z_1) emphasizes revenue maximization through high freight rate transportation schemes, favoring

strategies such as operating dedicated express trains and minimizing technical operations. Conversely, the cargo owner cost (Z_2) prioritizes minimizing total logistics expenditures, and is inclined toward economical routes and shared transportation modes. This conflict manifests in three dimensions: 1) resource allocation tradeoffs, whereby priority given to delayed shipments reduces capacity for new profitable demands; 2) technical operation contradictions, whereby fewer station stops lower carrier costs but increase cargo transit time; and 3) inverse frequency-scale relationships, whereby high-frequency small-batch shipments benefit cargo owners but escalate carrier fixed costs. These competing objectives create a Pareto-optimal frontier in which improvements in one metric necessitate results in compromises in others. Mathematical formulations reveal this tension through constraints on train formation (Eqs. 13–14), station capacity allocation (Eq. 17), and delivery time requirements (Eq. 21), fundamentally reflecting the zero-sum nature of resource utilization between transportation efficiency and economic optimality.

The constraints of this submodel are as follows:

$$\sum_{r_{o,d,g}\in R}\frac{x^q_{o,d,g}r_{o,d,g}}{w_g\lambda^q_{o,d,g}}\geq u^{\min}_q,\ \forall s_q\in S_{CRS} \tag{13}$$

$$\sum_{r_{o,d,g}\in R}\frac{x^q_{o,d,g}r_{o,d,g}}{w_g\lambda^q_{o,d,g}}\leq u^{\max}_q,\ \forall s_q\in S_{CRS} \tag{14}$$

$$\lambda^q_{o,d,g}\begin{cases}=0 & x^q_{o,d,g}=0\\ >0 & x^q_{o,d,g}=1\end{cases} \tag{15}$$

$$\sum_{s_q\in S_{CRS}}\sum_{p^k_{o,d}\in P}x^q_{o,d,g}\xi^q_{o,d,k}=1,\ \forall r_{o,d,g}\in R \tag{16}$$

$$\sum_{s_q\in S_{CRS}}\left(\sum_{n_i=n_o\,r_{o,d,g}\in R}x^q_{o,d,g}\lambda^q_{o,d,g}+\sum_{n_i=n_d\,r_{o,d,g}\in R}x^q_{o,d,g}\lambda^q_{o,d,g}+\sum_{r_{o,d,g}\in R}x^q_{o,d,g}\lambda^q_{o,d,g}\gamma^q_i\right)\leq C_i,\ \forall n_i\in N \tag{17}$$

$$\sum_{r_{o,d,g}\in R}\sum_{s_q\in S_{CRS}}\sum_{p^k_{o,d}\in P}\lambda^q_{o,d,g}x^q_{o,d,g}\xi^q_{o,d,k}\beta^j_{o,d,k}\leq D_j,\ \forall l_j\in L \tag{18}$$

$$\begin{cases}\sum_{r_{o,d,g}\in R}\sum_{n_i\in N}x^q_{o,d,g}\gamma^q_i=0 & r_{o,d,g}=r'_{o,d,g}\quad or\quad \dfrac{r_{o,d,g}}{w_g}\geq u^{\min}_q\\ 0<\sum_{r_{o,d,g}\in R}\sum_{n_i\in N}x^q_{o,d,g}\gamma^q_i\leq\delta_q & else\end{cases},\ \forall s_q\in S_{CRS} \tag{19}$$

$$\delta_q=\begin{cases}0 & v_q=160\\ 1 & v_q=120\\ 2 & v_q=80\end{cases} \tag{20}$$

$$\sum_{s_q\in S_{CRS}}\sum_{p^k_{o,d}\in P}\left(x^q_{o,d,g}\xi^q_{o,d,k}\cdot\frac{\sum_{l_j\in L}\beta^j_{o,d,k}d_j}{v_q}+\sum_{n_i\in N}x^q_{o,d,g}\xi^q_{o,d,k}\alpha^i_{o,d,k}\gamma^q_i\phi^q_i\right)\leq t_{o,d,g},\ \forall r_{o,d,g}\in R \tag{21}$$

$$x^q_{o,d,g}\in\{0,1\},\ \forall r_{o,d,g}\in R,\ \forall s_q\in S_{CRS} \tag{22}$$

$$\lambda^q_{o,d,g}\in N,\ \forall r_{o,d,g}\in R,\ \forall s_q\in S_{CRS} \tag{23}$$

Constraints (Eq. 13) and (Eq. 14) ensure that the number of formation wagons satisfies the train operation requirements. Constraint (Eq. 15) ensures that if s_q is selected to transport goods, it must operate at least once. Constraint (Eq. 16) guarantees that a demand can choose only one s_q and that the train concerned can only choose one route. Constraint (Eq. 17) ensures that the railway freight plan must not exceed the receiving-departure capacity of the station. Constraint (Eq. 18) ensures that the railway freight plan does not exceed the railway carrying capacity of the railway section. Constraint (Eq. 19) ensures that if s_q is chosen to transport $r'_{o,d,g}$ or $r''_{o,d,g}$ but the wagon count adheres to $u^{\min}_q$, a "through goods train originated from one loading point" is operated. Alternatively, if the conditions are not met, a "through goods train originated from several adjoin in loading points" is operated, with the condition that the number of stops does not surpass δ_q. Constraint (Eq. 20) stipulates δ_q. Constraint (Eq. 21) ensures that the transportation time within the operation schedule must not exceed the temporal constraints. Constraints (Eq. 22) and (Eq. 23) ensure that the attributes of each decision variable are correct.

5. Algorithm design

The ERP submodel is characterized by linear objective functions and constraints, and the variable scale is within the solving capacity of commercial solvers because the total number of decision variables aligns with the total number of wagons in the original formation scheme. Consequently, Gurobi is selected as the solver for this submodel. In contrast, the PERP submodel

presents challenges due to its variable scale exceeding the computational capacity of solvers, together with multiple objective functions and complex constraints, making commercial solvers inadequate for meeting its solving requirements. NSGA-II has been proven to perform well in obtaining Pareto solutions for multi-objective optimization problems (K. Guo & Zhang, 2022); however, NSGA-II continues to suffer from limitations in global search capability and solution precision. Thus, an Adaptive Variable Neighborhood Non-Dominated Sorting Genetic Algorithm-II (AVNNSGA-II) was specifically devised to overcome these deficiencies. Fig. 4 illustrates the flowchart of AVNNSGA-II.

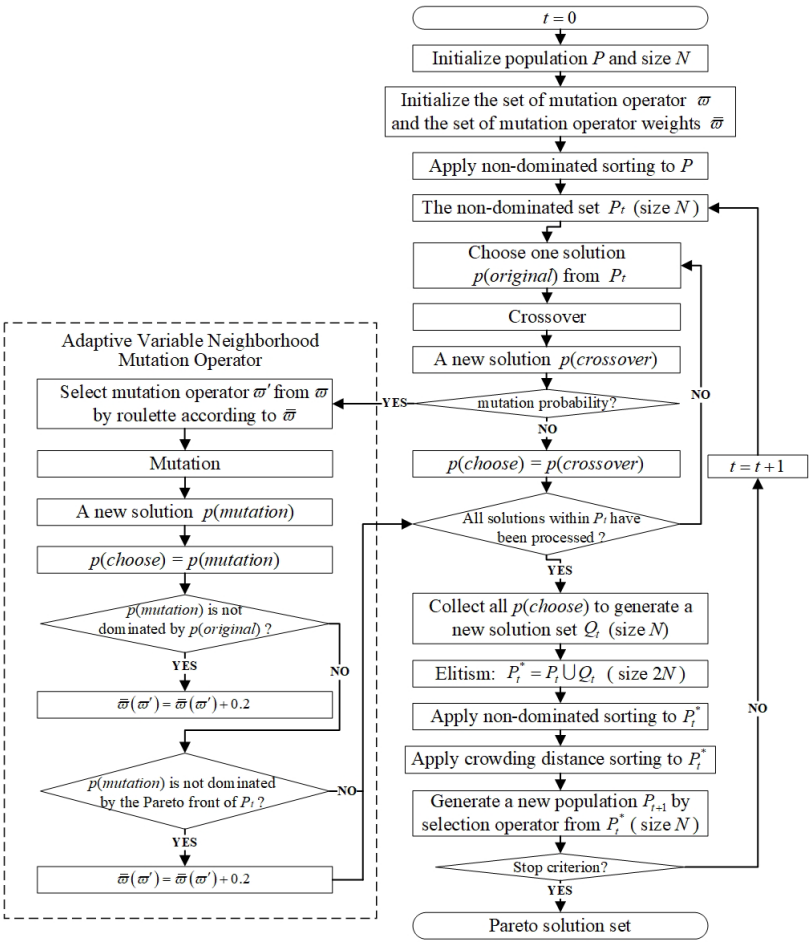


Fig. 4. Flowchart for AVNNSGA-II.

AVNNSGA-II improves the mutation operator of the traditional NSGA-II by introducing an adaptive variable neighborhood mutation operator (AVNMO), which enables the algorithm to adaptively select the mutation operator with the best solving performance during iterative processes. This adaptive mechanism consistently enhances the global search capability and solving performance of the algorithm.

Coding and Decoding

In this study, each chromosome of AVNNSGA-II represents a feasible formation and transportation plan in PERP. Since all plans are required to satisfy the same demand set R, set R is treated as an index for chromosome encoding. Each $r_{o,d,g} \in R$ requires selecting one train from multiple feasible s_q. Upon determining s_q, its optimal transportation frequency $\lambda_{o,d,g}^{q}$ can be calculated using the frequency calculation strategy (Eq. 24), thereby forming a complete gene in the chromosome.

$$\lambda_{o,d,g}^{q} = \left\lceil \left(\max_{l_j \in L} \sum_{r_{o,d,g} \in R} \sum_{p_{o,d}^{k} \in P} r_{o,d,g} x_{o,d,g}^{q} \xi_{o,d,k}^{q} \beta_{o,d,k}^{j} \right) \Big/ u_q^{\max} \right\rceil, \forall s_q \in S_{CRS}, r_{o,d,g} \in R \tag{24}$$

In summary, the chromosome-encoding steps for AVNNSGA-II designed for this model are as follows:

Step 1: Establish the encoding sequence indexed by freight demand $r_{o,d,g}$;

Step 2: Select a $r_{o,d,g}$ and identify the set of feasible s_q corresponding to this $r_{o,d,g}$;

Step 3: Choose one s_q from the feasible set and calculate the $\lambda_{o,d,g}^{q}$; and

Step 4: Generate the whole chromosome.

The process of chromosome encoding is described in Fig. 5.

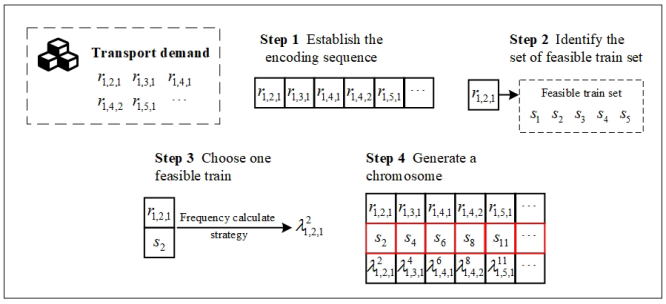


Fig. 5. The AVNNSGA-II encoding process.

5.2 Adaptive Variable Neighborhood Mutation Operator

AVNNSGA-II employs multiple distinct mutation operators simultaneously, each of which is assigned a variable weight coefficient. In each iteration, a mutation operator is probabilistically selected based on the probability distribution derived from the weight coefficients. Conversely, after each iteration, the algorithm dynamically adjusts the weight coefficients of the mutation operators according to their outcomes, forming a closed-loop optimization process.

Mutation operator 5.2.1

Four various mutation operators were designed for AVNNSGA-II in this study:

- Mutation operator 1: randomly alter the freight train s_q corresponding to a transportation demand $r_{o,d,g}$;
- Mutation operator 2: randomly alter the freight trains s_q corresponding to two different transportation demands $r_{o,d,g}$;
- Mutation operator 3: randomly alter the freight trains s_q corresponding to three different transportation demands $r_{o,d,g}$; and
- Mutation operator 4: randomly alter the freight trains s_q corresponding to four different transportation demands $r_{o,d,g}$.

The steps for randomly altering the s_q corresponding to the $r_{o,d,g}$ are as follows:

Step 1: randomly select a transportation demand $r_{o,d,g}$ within the transportation scheme (chromosome);

Step 2: generate a feasible set of freight trains s_q based on the $r_{o,d,g}$;

Step 3: remove the s_q corresponding to the selected $r_{o,d,g}$ from the feasible set of s_q;

Step 4: randomly select a new s_q from the current feasible set of s_q as the new freight train corresponding to $r_{o,d,g}$; and

Step 5: utilize the frequency calculation strategy (Eq. 24) to determine the new optimal operational frequency for this subplan, subsequently generating a new complete transportation scheme (the chromosome completing the mutation operation).

The schematic diagram of the alteration is shown in Fig. 6.

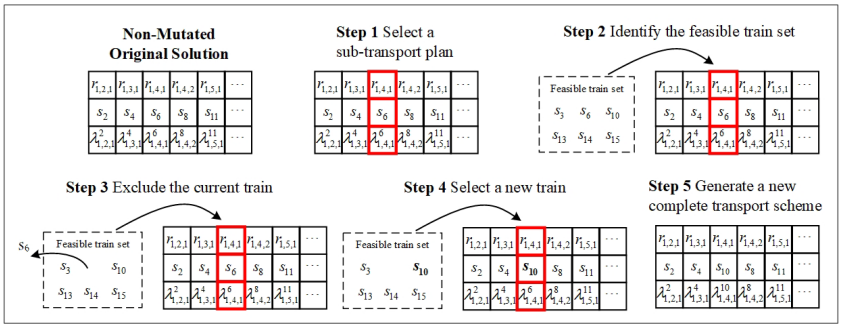


Fig. 6. Schematic diagram showing the alteration steps.

Adaptive weight coefficient 5.2.2

ϖ represents the set of weight coefficients for the four mutation operators. The selection of the mutation operator in each iteration is determined by a roulette mechanism based on ϖ. Initially, the weight coefficients for all four mutation operators are set to 1. The rules governing the adjustment of weight coefficients are as follows. Firstly, the newly generated solution through the mutation operator is compared with the original solution before mutation. If the new solution is not entirely dominated by the original solution, the weight coefficient of the corresponding mutation operator is increased by 0.2. Then, the new solution is compared with all solutions in the current Pareto front. If the new solution is not entirely dominated by the current Pareto front, the weight coefficient of the corresponding mutation operator is further increased by 0.2.

6. Case study

6.1 Case Background

To illustrate the applicability of the proposed model, this study focuses on the scenario of a large-scale COVID-19 outbreak that transpired in China in 2022 (Wang & Qin, 2022). Drawing data from the 2022 epidemic situation report available on the website of the National Health Commission of the People's Republic of China (http://www.nhc.gov.cn/), a railway express freight network comprising ten cities was chosen for investigation (Sun, 2019). Among these cities, Jilin, Shanghai, Xi'an, and Wuhan were identified as areas affected by COVID-19, while Nanjing, Hangzhou, Hefei, Zhengzhou, Jinan, and Shijiazhuang were designated as supply points for epidemic prevention materials. The necessary epidemic prevention materials for the ERP encompass five categories: N95 masks, medical protective clothing, medical goggles, medical surgical masks, and nucleic acid test reagents. The railway express freight network is illustrated in Fig. 7 and technical characteristics of railway stations and sections are summarized in Table 1 and Table 2.

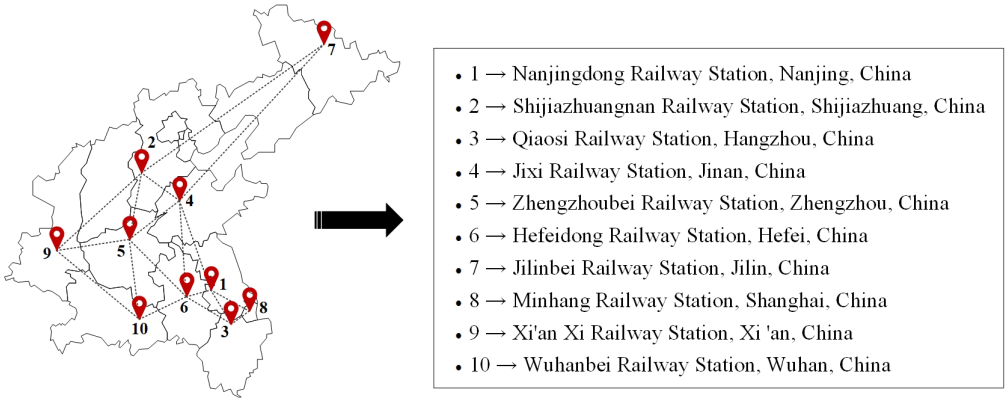


Fig. 7. Railway express freight network.

Table 1
Technical characteristics of railway stations

Station *i*	Receiving and departure	Railway technical	Railway technical operation time / hour		
			Express	Fast	Ordinary
1	30	450	0	1	3
2	24	400	0	2	2
3	30	430	0	2	3
4	30	460	0	2	2
5	30	500	0	2	2
6	24	520	0	1	2
7	30	480	0	1	2
8	24	500	0	1	2
9	30	450	0	2	3
10	24	480	0	1	3

Table 2
Technical characteristics of railway sections

Section *j*	Distance / km	Carrying capacity / train	Section *j*	Distance / km	Carrying capacity / train
1→3	284	36	3→8	150	36
1→4	619	30	4→5	427	24
1→6	176	36	4→6	607	36
1→8	306	30	4→7	1437	24
2→4	291	36	5→6	579	30
2→5	416	24	5→9	475	36
2→7	1397	30	5→10	500	36
2→9	825	36	6→10	370	24
3→6	424	24	9→10	726	24

The determination of epidemic prevention material requirements follows a calculation based on urban population, the number of medical personnel, epidemic severity, daily consumption rates, and existing inventory (X. Guo & Liu, 2022; X. Wang, 2022; Wikipedia, 2024). Detailed information regarding the inventory and demand status of epidemic prevention materials is presented in Table 3 and Table 4.

Table 3
Inventory of epidemic prevention materials in supply areas (unit: wagon)

Station	N95 mask	Medical protective clothing	Medical goggles	Medical surgical mask	Nucleic acid test reagent
1	24	55	53	13	3
2	63	145	140	36	9
3	31	71	68	17	4
4	23	54	52	13	3
5	32	74	71	18	4
6	24	55	53	13	3

Table 4
Demands of epidemic prevention materials in affected areas (unit: wagon)

Station	N95 mask	Medical protective clothing	Medical goggles	Medical surgical mask	Nucleic acid test reagent
7	29	17	17	16	0
8	36	10	11	13	3
9	50	46	37	29	29
10	54	39	39	40	16

The original formation and operation plan for non-disaster scenarios is shown in Table 5. The subplans highlighted meet the requirements of the emergency logistics strategy proposed in this paper and are capable of implementing the strategy required for the ERP.

Table 5
Original freight formation and operation plan

No.	Demand	Stopping plan	Route	Speed / (km/h)	Formation wagon number	Operation frequency
				…		
7	**1→6**	**[1, 6]**	**1→2→3→6**	**160**	**25**	**1**
8	**1→7**	**[1, 7]**	**1→2→5→4→7**	**120**	**28**	**1**
9	**1→7**	**[1, 7]**	**1→4→7**	**160**	**15**	**1**
10	**1→8**	**[1, 8]**	**1→4→8**	**120**	**10**	**1**
11	**1→9**	**[1, 9]**	**1→2→5→9**	**160**	**15**	**1**
				…		
19	**2→9**	**[2, 9]**	**2→5→9**	**160**	**25**	**1**
20	**2→9**	**[2, 9]**	**2→5→9**	**120**	**10**	**1**
				…		
25	**3→10**	**[3, 10]**	**3→2→5→9→10**	**160**	**25**	**1**
26	**3→10**	**[3, 10]**	**3→6→10**	**160**	**20**	**1**
				…		
31	**4→7**	**[4, 7]**	**4→7**	**160**	**15**	**1**
32	**4→8**	**[4, 8]**	**4→8**	**120**	**14**	**1**
33	**4→8**	**[4, 8]**	**4→8**	**160**	**17**	**1**
34	**4→9**	**[4, 9]**	**4→8→9**	**120**	**30**	**1**
35	**4→9**	**[4, 9]**	**4→8→9**	**160**	**15**	**1**
				…		
40	**5→9**	**[5, 9]**	**5→9**	**160**	**20**	**1**
41	**5→9**	**[5, 9]**	**5→9**	**160**	**18**	**1**
42	**5→10**	**[5, 10]**	**5→9→10**	**80**	**40**	**1**
43	**5→10**	**[5, 10]**	**5→9→10**	**120**	**20**	**1**
44	**6→10**	**[6, 10]**	**6→10**	**120**	**14**	**1**
45	**6→10**	**[3, 6, 10]**	**3→6→10**	**80**	**10**	**1**
46	**7→8**	**[7, 8]**	**7→8**	**120**	**8**	**1**
				…		

6.2 Results of the ERP Submodel

The optimal emergency formation and loading plan for epidemic prevention materials in the ERP is shown in Table 6. An outline of the satisfaction rate of each kind of emergency materials in affected areas is provided in Table 7.

Table 6
Optimal emergency formation and loading plan for epidemic prevention materials in the ERP (unit: wagon)

No.	N95 mask	Medical protective clothing	Medical goggles	Medical surgical mask	Nucleic acid test reagent	Transport time / hour
8	16	4	6	2	0	13.21
9	5	4	1	5	0	4.44
10	2	2	3	2	1	7.13
11	1	4	5	3	2	6.75
19	7	5	5	1	7	4.13
20	5	2	1	0	2	5.50
25	5	3	3	12	2	8.50
26	7	6	3	2	2	4.06
31	2	7	3	3	0	2.22
32	7	2	3	1	1	4.17
33	10	2	1	4	0	3.13
34	4	14	10	1	1	7.50
35	0	5	5	4	1	5.63
40	7	7	2	3	1	2.25
41	9	2	2	4	1	2.25
42	12	8	9	10	1	8.25
43	4	1	13	1	1	5.50
44	3	1	2	6	2	2.50
45	3	1	1	4	1	5.75

Table 7
Satisfaction rate of each kind of emergency materials in affected areas.

Station	N95 mask	Medical protective clothing	Medical goggles	Medical surgical mask	Nucleic acid test reagent
7	79.31%	88.24%	58.82%	62.50%	100.00%
8	52.78%	60.00%	63.64%	53.85%	66.67%
9	66.00%	84.78%	81.08%	55.17%	51.72%
10	62.96%	51.28%	79.49%	87.50%	56.25%

As shown in Table 7, by employing the emergency logistics optimization strategy proposed in this paper, the satisfaction rate of various emergency materials in the affected areas during the ERP can reach 51.28% or higher. This ensures a balanced distribution of materials while reducing the risk of extreme shortages.

6.3 Results of the PERP Submodel

Freight demand during the PERP consists of two components. The first is the transportation demand for non-emergency materials that were replaced during the ERP. Since these demands have already been delayed, no specific transportation time constraint is set, but priority is given to transportation. The second component comprises new freight demands generated during the PERP, including emergency materials and non-emergency materials. Details of some freight demands in the PERP are shown in Table 8.

Table 8
Transportation demands in the PERP

Priority transportation demands				New freight demands			
Origin station	Destination station	Demand / wagon	Time limit / hour	Origin station	Destination station	Demand / wagon	Time limit / hour
1	**7**	**28**	**-**	1	2	10	18
1	**7**	**15**	**-**	1	3	19	20
1	**8**	**10**	**-**	1	4	22	24
1	**9**	**15**	**-**	1	4	20	24
2	**9**	**25**	**-**	1	5	18	12
2	**9**	**10**	**-**	1	5	20	36
3	**10**	**25**	**-**	1	6	25	24
3	**10**	**20**	**-**	1	7	28	18
4	**7**	**15**	**-**	1	7	15	24
4	**8**	**14**	**-**	1	8	10	20
4	**8**	**17**	**-**	1	9	15	36
4	**9**	**30**	**-**	2	3	20	30
4	**9**	**15**	**-**	2	3	7	18
5	**9**	**20**	**-**	2	4	11	24
5	**9**	**18**	**-**	2	4	35	24
5	**10**	**40**	**-**	2	5	20	18
5	**10**	**20**	**-**	2	5	15	20
6	**10**	**14**	**-**	2	6	16	28
6	**10**	**10**	**-**	2	9	25	20

Using AVNNSGA-II, the results obtained after 500 iterations are shown in Fig. 8.

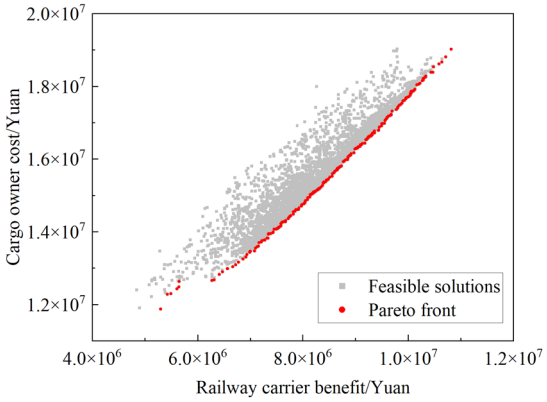


Fig. 8. Solutions of the PERP submodel calculated using AVNNSGA-II.

Fig. 8 shows all feasible solutions obtained during the 500 iterations, indicating that the feasible solutions of the PERP submodel gradually approach the optimal Pareto front with an increasing number of iterations, eventually forming a distinct Pareto front consisting of 209 Pareto solutions. In conclusion, the AVNNSGA-II designed in this study exhibits excellent convergence performance and an ability to find optimal Pareto solutions.

6.4 Analysis of Results

6.4.1 Comparison of emergency response time

The emergency response phase of railway emergency logistics comprises five key stages: emergency train scheduling, formulation of operating plans, development of formation and loading schemes, loading of emergency materials onto wagons, and emergency material transportation. To evaluate the optimization effect of the ERP submodel on emergency response time, this study systematically compares the time required for each of these five stages under conventional strategies and those formulated by the ERP submodel. The results of this comparison are shown in Table 9.

Table 9
Comparison of response time between conventional strategy and the ERP submodel

Stage	Emergency response time / hour		Response time reduction
	Conventional strategy	ERP submodel	
Emergency train scheduling	1–2	0	-
Formulation of operating plans	0.5–1	0	-
Development of formation and loading schemes	0.5–1	0.5–1	-
Loading of emergency materials onto wagons	1	1	-
Emergency material transportation	13.2	13.21	-
Total emergency response time	16.2–118.21	14.71–15.21	6.16–9.22%

Table 9 shows that the ERP submodel can reduce the emergency response time of railway emergency logistics by 6.16–19.22%, thereby validating the effectiveness of the proposed emergency logistics optimization strategy.

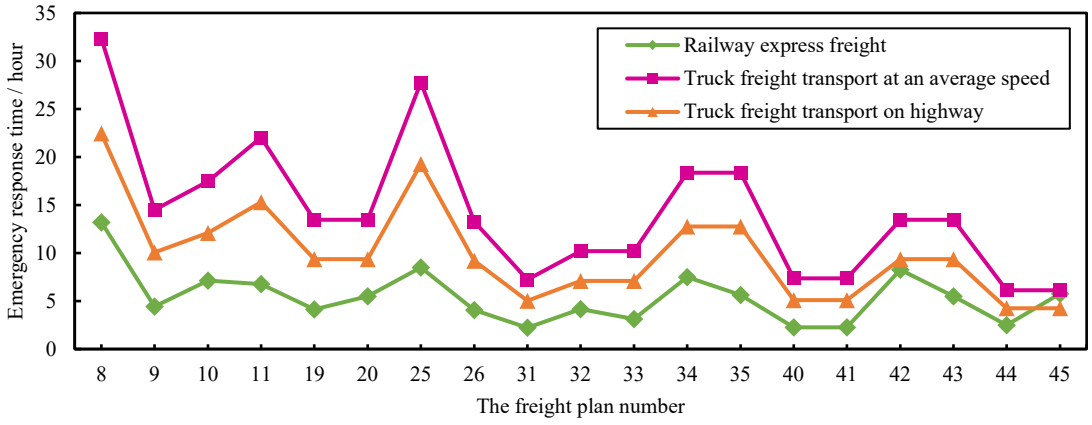


Fig. 9. Comparison of response time between road emergency logistics and the ERP submodel

Road transportation remains a primary mode of emergency logistics in current practices. To evaluate the differences in emergency response time between the proposed strategy and conventional road-based emergency logistics approaches, this study conducted a comparative analysis between railway emergency logistics schemes derived from the ERP submodel and equivalent road logistics schemes under identical operational conditions. According to "Analysis of China's Road Freight Industry Operation Based on Big Data (2020)" published by the Research Institute of Highway Ministry of Transport (https://www.transformcn.com/Topics/2021-10/18/content_267895.htm), the average annual speed of freight wagons in China during 2020 was 49.0 km/h, and the average speed of trucks on highways reached 70.6 km/h. Fig. 9 summarizes the emergency transportation time utilizing railway express freight, truck freight at the average speed, and truck freight on highways under equivalent conditions.

As shown in Fig. 9, the emergency response time of the proposed strategy is consistently shorter than that of conventional truck freight, regardless of whether trucks operate at average or high speeds. When compared to conventional truck freight at average speeds, the proposed strategy reduces emergency response times by up to 69.40%. Furthermore, when compared with conventional truck freight at high speeds, the strategy achieves a reduction of 55.90% in emergency response time.

6.4.2 Comparison of delay losses

In the PERP submodel, the transportation priority of delayed non-emergency cargo is elevated, and delay losses are mitigated through the operation of "through goods trains originated from one loading point". Compared to conventional strategies, the reduction in delay losses achieved by the PERP submodel may be quantified as shown in Table 10.

Table 10
Comparison of delay loss reduction between the traditional strategy and the PERP submodel

No.	Demand	Total transportation time under conventional strategy / hour	Total transportation time under PERP submodel / hour	Delay losses reduction
8	1→7	28.08	12.85	54.24%
9	1→7	13.35	12.85	3.75%
10	1→8	13.37	1.91	85.71%
11	1→9	12.26	7.69	37.28%
19	2→9	6.07	5.16	14.99%
20	2→9	7.93	5.16	34.93%
25	3→10	19.07	4.96	73.99%
26	3→10	5.46	4.96	9.16%
31	4→7	8.98	8.98	0.00%
32	4→8	7.71	5.78	25.03%
33	4→8	5.78	5.78	0.00%
34	4→9	21.01	5.64	73.16%
35	4→9	15.88	5.64	64.48%
40	5→9	2.97	2.97	0.00%
41	5→9	2.97	2.97	0.00%
42	5→10	15.51	3.13	79.82%
43	5→10	10.51	3.13	70.22%
44	6→10	3.08	2.31	25.00%
45	6→10	10.43	2.31	77.85%
Total	-	210.42	104.18	50.49%

As shown in Table 10, the PERP submodel achieves an overall reduction of 50.49% in the delay losses of non-emergency cargo, demonstrating its effectiveness in addressing the transportation delays of non-emergency cargo caused by emergency logistics.

6.4.3 Effectiveness of the algorithm

The AVNNSGA-II algorithm developed in this study incorporates four distinct mutation operators. Fig. 10 illustrates the adaptive weight coefficient variations of each operator during the iterative process.

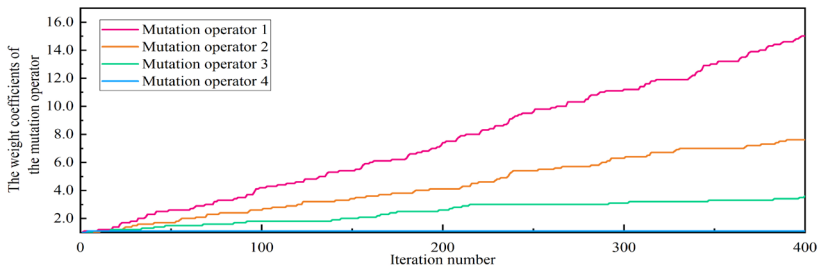
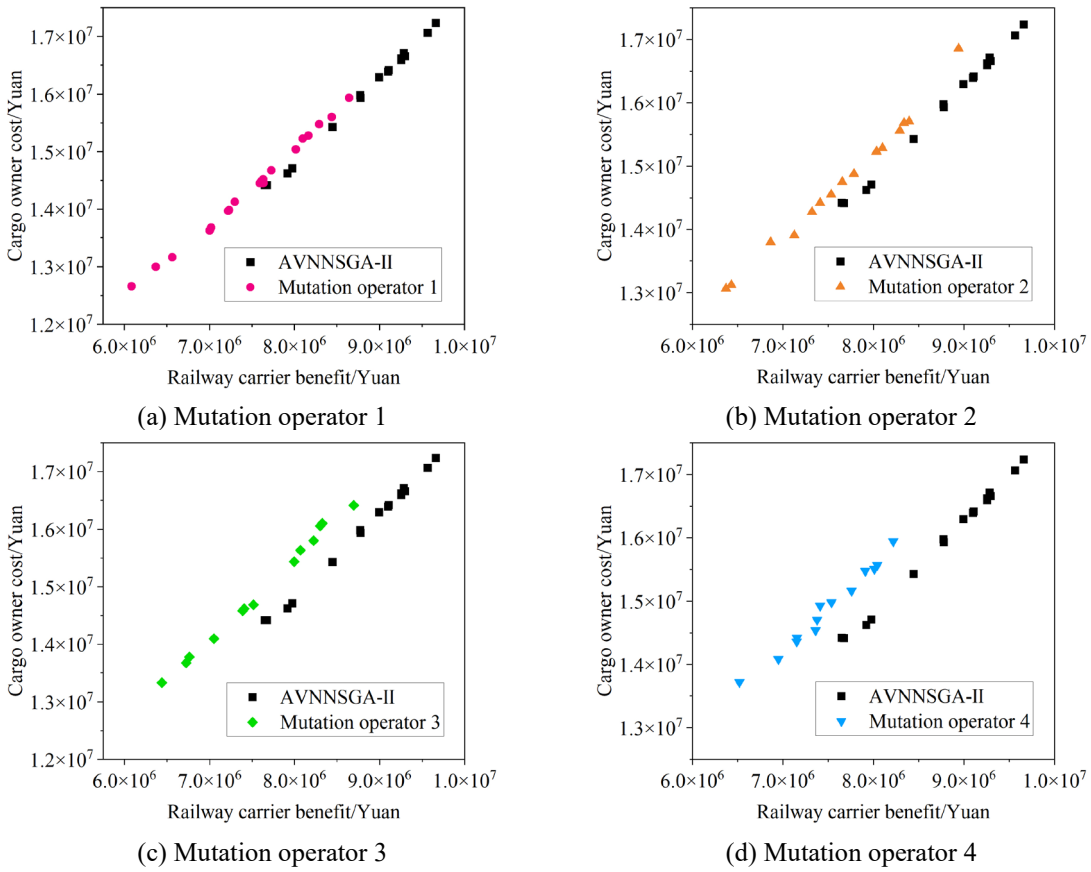


Fig. 10. Weight coefficients of the mutation operators.

Analysis of Fig. 10 reveals that the weight coefficients of mutation operator 1 exhibit the fastest growth rate among all operators and are higher than those of other operators. This indicates its superior capability in escaping local optima and identifying better feasible solutions. To validate this finding, each of the four mutation operators was individually applied to solve the problem, and the resulting Pareto solutions were compared with those of AVNNSGA-II. Comparative results are presented in Fig. 11.



(a) Mutation operator 1 (b) Mutation operator 2

(c) Mutation operator 3 (d) Mutation operator 4

Fig. 11. The final Pareto solution set of the PERP submodel using different mutation operators.

Analysis of Fig. 11 demonstrates that the Pareto solutions obtained using mutation operator 1 alone are the optimal solution among solutions of all four operators and closely approximate those of AVNNSGA-II (Fig. 11(a)). This aligns with the observation in Figure 10 indicating that mutation operator 1 consistently exhibits the highest adaptive weight coefficients, thereby confirming the capability of AVNNSGA-II to accurately identify the most effective mutation operator. Furthermore, all four subplots in Fig. 11 reveal that the Pareto solutions derived from individual mutation operators are universally inferior to those obtained by AVNNSGA-II. This underscores the conclusion that AVNNSGA-II, enhanced with the AVNMO, outperforms all NSGA-II variants that employ single mutation operators in terms of solution performance.

6.4.4 Comparison of algorithm performance

NSGA-II is a classical multi-objective optimization algorithm that has demonstrated superior performance relative to genetic algorithm (GA) in addressing multi-objective programming problems (Chen et al., 2022; Y. Wang et al., 2021).

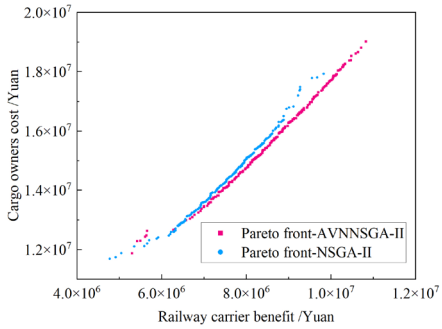
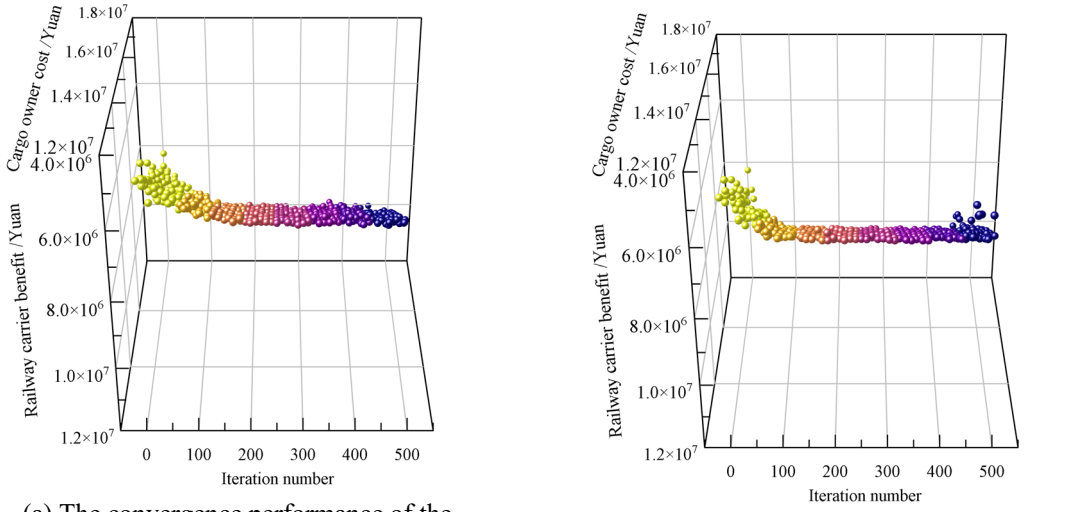


Fig. 12. Comparison of Pareto front in AVNNSGA-II and NSGA-II

By enhancing the classical NSGA-II framework, this study designed AVNNSGA-II. To evaluate its performance relative to NSGA-II, both algorithms were applied to solve the PERP submodel, and their Pareto fronts and convergence characteristics were compared. The results of this comparison are shown in Fig. 12 and Fig. 13.

The Pareto fronts of AVNNSGA-II and NSGA-II after 500 iterations are shown in Fig. 12, leading to the following conclusions:

(1) 97% of AVNNSGA-II's Pareto front solutions are entirely superior to those of NSGA-II, indicating its ability to identify higher quality Pareto solutions and demonstrating an overall superior performance in determining optimal solutions.
(2) The Pareto front of AVNNSGA-II exhibits a wider distribution range than that of NSGA-II, highlighting its enhanced global search capability.
(3) Solutions at the extremes of AVNNSGA-II's Pareto front display smaller fluctuations and more uniform distributions than those of NSGA-II, indicating its improved search stability.



(a) The convergence performance of the AVNNSGA-II

(b) The convergence performance of NSGA-II

Fig. 13. Comparison of convergence performance in AVNNSGA-II and NSGA-II

Fig. 13 presents the convergence characteristics of AVNNSGA-II and NSGA-II after 500 iterations. Analysis of this figure reveals that AVNNSGA-II converges after approximately 200 iterations, whereas NSGA-II converges after approximately 100 iterations. Combined with the observation in Figure 12 that the Pareto front of NSGA-II is inferior to that of AVNNSGA-II, this demonstrates that NSGA-II exhibits a trend of premature convergence. This is primarily attributed to the incorporation of the AVNMO in AVNNSGA-II, enabling it to escape local optima more effectively than NSGA-II. Furthermore, Fig. 13(b) shows that NSGA-II solutions exhibit fluctuations after approximately 400 iterations, whereas the results obtained using AVNNSGA-II remain comparatively smoother. This underscores the superior stability of AVNNSGA-II relative to NSGA-II during the search process.

6.5 Parameter Sensitivity Analysis

The key parameters of AVNNSGA-II include population size, mutation rate, and weight adjustment steps. To investigate the impacts of these critical parameters on the ability of AVNNSGA-II to solve multi-objective scheduling problems, this study conducted a multivariate analysis of variance (MANOVA) on Pareto solution sets and performed a visual analysis of Pareto fronts under different parameter configurations.

6.5.1 Population size

A systematic evaluation of population size effects on solution quality was conducted through multi-objective optimizations using population sizes of 25, 50, and 75. Initially, MANOVA was performed on the Pareto solution sets under different population sizes, the results of which are summarized in Table 11.

Table 11
MANOVA analysis results for population size

Statistic	Value	Num DF	Den DF	F Value	Pr > F
Wilks' lambda	0.7544	4.0000	1316.0000	49.7827	0.0000
Pillai's trace	0.2456	4.0000	1318.0000	46.1236	0.0000
Hotelling-Lawley trace	0.3255	4.0000	788.5612	53.5218	0.0000
Roy's greatest root	0.3255	2.0000	659.0000	107.2585	0.0000

MANOVA results (Table 11) revealed statistically significant impacts of population size on the bi-objective Pareto solution sets (Wilks' $\Lambda = 0.754$, $p < 0.001$). To further clarify the independent effects of population size on individual objectives, univariate ANOVA and Tukey HSD *post-hoc* tests were performed.

Table 12
Between-group variations across different population sizes (Tukey HSD test)

Dependent variable	Group1 vs Group2	Mean difference (Δ)	95% confidence interval	p-adj
Railway carrier benefit	25 vs 50	191,509.97	[110,687.51, 272,332.42]	<0.001
	25 vs 75	332,438.32	[254,362.82, 410,513.83]	<0.001
	50 vs 75	140,928.36	[76,921.81, 204,934.90]	<0.001
Cargo owner cost	25 vs 50	193,627.28	[94,828.06, 292,426.50]	<0.001
	25 vs 75	336,861.25	[241,419.97, 432,302.53]	<0.001
	50 vs 75	143,233.97	[64,990.90, 221,477.03]	0.0001

As shown in Table 12, population size exerted significant influences on both railway carrier benefits and cargo owner costs. The Tukey HSD tests demonstrated that increasing population size (from 25 to 75) significantly enhanced railway carrier benefit but concurrently elevated cargo owner costs. Notably, a balanced trade-off between benefit and cost was achieved at a moderate population size (50). To analyze parameter impacts on Pareto front characteristics, Fig. 14 shows the Pareto fronts generated across different population sizes.

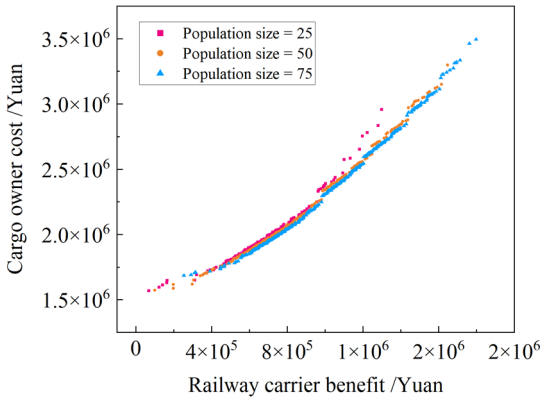


Fig. 14. Pareto fronts generated for different population sizes.

Fig. 14 reveals that the Pareto fronts for population sizes of 50 and 75 exhibit superior objective attribute values, broader distribution ranges, and more uniform dispersions relative to those for a population size of 25. Furthermore, the Pareto fronts for population sizes of 50 and 75 are shown to almost overlap.

Table 13
Solving time for different population sizes

	Population size = 25	Population size = 50	Population size = 75
Solving time /s	112.65	332.19	1624.37

However, as shown in Table 13, the solving time for a population size of 75 was nearly five-fold longer than that for a population size of 50. Consequently, the visualization results suggest that although population size critically affects Pareto front quality, an excessively large population size (75) yields negligible improvements in Pareto front quality while substantially increasing computational burden.

6.5.2 Mutation rate

The MANOVA results for different mutation rates and their corresponding Pareto solution sets are shown in Table 14.

As shown in Table 14, the mutation rate exerted statistically significant effects on the bi-objective Pareto solution sets (Wilks' $\Lambda = 0.887$, $p < 0.001$). To further investigate the independent impacts of mutation rate on individual objectives, univariate ANOVA and Tukey HSD *post-hoc* tests were conducted.

Table 14
MANOVA analysis results for mutation rate

Statistic	Value	Num DF	Den DF	F Value	Pr > F
Wilks' lambda	0.8872	4.0000	954.0000	14.7075	0.0000
Pillai's trace	0.1145	4.0000	956.0000	14.5092	0.0000
Hotelling-Lawley trace	0.1253	4.0000	571.3616	14.9260	0.0000
Roy's greatest root	0.1078	2.0000	478.0000	25.7579	0.0000

Table 15
Between-group variations across different mutation rates (Tukey HSD test)

Dependent variable	Group1 vs Group2	Mean difference (Δ)	95% confidence interval	p-adj
Railway carrier benefit	0.05 vs 0.10	+178,816.67	[103,258.07, 254,375.27]	<0.001
	0.05 vs 0.15	+146,714.47	[72,746.57, 220,682.36]	<0.001
	0.10 vs 0.15	-32,102.20	[-100,496.50, 36,292.10]	0.512
Cargo owner cost	0.05 vs 0.10	+188,316.13	[98,369.70, 278,262.56]	<0.001
	0.05 vs 0.15	+130,190.54	[42,137.72, 218,243.36]	0.002
	0.10 vs 0.15	-58,125.59	[-139,543.50, 23,292.32]	0.214

Table 15 demonstrates nonsignificant differences ($p > 0.001$) in both railway carrier benefit and cargo owner cost between the moderate (0.10) and high (0.15) mutation rate groups, indicating inherent limitations when optimizing benefit-cost trade-offs solely through mutation rate adjustments. Specifically, low mutation rates (0.05) favored local exploitation, resulting in a suboptimal performance for both objectives. Moderate mutation rates (0.10) enhanced global exploration capabilities, expanding the solution set toward higher benefit values at the expense of elevated costs. High mutation rates (0.15) diminished returns due to the potential disruption of elite solution preservation, stabilizing the cost-benefit gains. To analyze the parameter impacts on Pareto front characteristics, the generated Pareto fronts for different mutation rates were plotted as shown in Fig. 15.

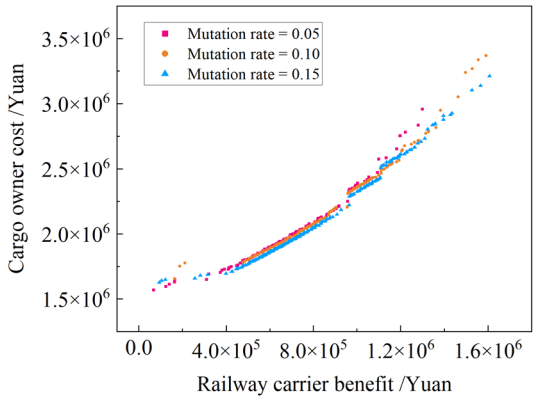


Fig. 15. Pareto fronts for different mutation rates

This analysis reveals that increasing the mutation rate from 0.05 to 0.10 significantly expanded the Pareto front's coverage (i.e., a statistically significant enhancement in benefits), while further increases to 0.15 stabilized the frontier morphology (i.e., statistically non-significant between-group variations), suggesting declining algorithmic convergence efficiency with excessive mutation rates. To balance diversity and convergence, we propose a dynamic adjustment strategy involving the use of higher mutation rates (0.15) during initial iterations to enhance solution diversity, followed by a reduction to 0.10 in later stages to refine solution quality.

6.5.3 Weight adjustment step

The MANOVA results for different mutation rates and their corresponding Pareto solution sets are shown in Table 16.

Table 16
MANOVA analysis results for the weight adjustment step

Statistic	Value	Num DF	Den DF	F Value	Pr > F
Wilks' Lambda	0.8354	4	804	18.9158	<0.001
Pillai's Trace	0.1676	4	806	18.4304	<0.001
Hotelling-Lawley Trace	0.1935	4	481.3619	19.4322	<0.001
Roy's Greatest Root	0.1729	2	403	34.8465	<0.001

As shown in Table 16, the weight adjustment step exerted statistically significant effects on the bi-objective Pareto solution sets (Wilks' $\Lambda = 0.835$, $p < 0.001$). To further investigate the independent impacts of weight adjustment steps on individual objectives, univariate ANOVA and Tukey HSD *post-hoc* tests were conducted.

Table 17
Between-group variations across different weight adjustment steps (Tukey HSD test)

Dependent variable	Group1 vs Group2	Mean difference (Δ)	95% confidence interval	p-adj
Railway carrier benefit	0.1 vs 0.2	+182,832.54	[107,787.86, 257,877.22]	<0.001
	0.1 vs 0.5	+205,417.40	[124,567.65, 286,267.14]	<0.001
	0.2 vs 0.5	+22,584.86	[-54,042.99, 99,212.71]	0.767
Cargo owner cost	0.1 vs 0.2	+202,012.26	[112,238.32, 291,786.21]	<0.001
	0.1 vs 0.5	+200,720.10	[104,001.71, 297,438.49]	<0.001
	0.2 vs 0.5	-1,292.16	[-92,960.01, 90,375.69]	0.999

Table 17 reveals nonsignificant differences ($p > 0.001$) between moderate (0.2) and large (0.5) weight adjustment steps, indicating that increasing the step magnitude does not accelerate the identification of optimal mutation operators. Specifically, the use of a small step (0.1) prioritized refined screening but resulted in suboptimal benefit-cost tradeoffs. A moderate step (0.2) was shown to enhance screening efficiency, expanding the solution set toward higher benefit values while incurring elevated costs. Using a large step (0.5) failed to improve the screening speed relative to the moderate step (0.2) and introduced instability in benefit-cost gains. To analyze parameter impacts on Pareto front characteristics, the generated Pareto fronts for different weight adjustment steps were plotted as shown in Fig. 16.

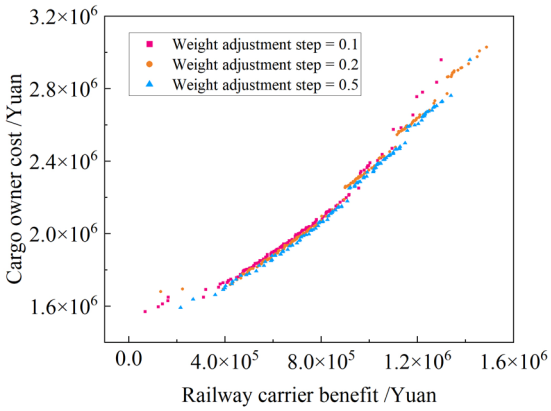


Fig. 16. Pareto fronts for different weight adjustment steps.

As indicated in Fig. 16, the Pareto front analysis reveals consistent cost-benefit tradeoff patterns across the examined weight adjustment steps (0.1, 0.2, 0.5), with all solutions forming characteristic convex frontiers. Although macroscopic morphology shows comparable trends of increasing cargo owner costs with railway carrier benefits, step=0.2 solutions dominate the high-benefit region (0.8-1.6×10⁶ Yuan) with tighter clustering, aligning with its statistical superiority in MANOVA (Roy's root=0.173, p<0.001). Step=0.1 solutions exhibit a scattered distribution in high-cost areas (>2.8×10⁶ Yuan), consistent with inferior *post-hoc* performance. The visual-statistical concordance confirms that using a step of 0.2 achieves an optimal balance between screening efficiency and convergence efficiency.

In summary, population size, mutation rate, and weight adjustment step collectively exhibited significant impacts on the Pareto front of the multi-objective railway emergency scheduling model; however, the degree of influence of each of these factors varied across parameter values. Based on the empirical findings, this study recommends: (1) setting the population size to 50 for computational efficiency; (2) adopting a dynamic adjustment strategy for mutation rate to balance exploration and exploitation; and (3) selecting a weight adjustment step of 0.2 to optimize the stability and quality of Pareto-optimal solutions.

7. Discussion

This study aims to comprehensively enhance the response efficiency of railway emergency logistics while mitigating its adverse impacts on the conventional logistics system. To achieve this, an entire-process optimization strategy encompassing ERP and PERP was proposed, and a two-stage multi-objective optimization model was formulated based on this framework. Empirical results demonstrate that this strategy achieves an emergency material satisfaction rate exceeding 51.28% in the ERP, accompanied by a response time reduction ranging from 6.16% to 19.22%. In the PERP, it reduces the overall delay losses for non-emergency materials by 50.49%. Furthermore, the AVNNSGA-II designed in this study outperforms the traditional NSGA-II in 97% of Pareto fronts under identical conditions, denoting its superiority in solving performance.

The effectiveness of the proposed strategy is empirically validated in this study and is also supported by multi-perspective discussions from existing literature. Multi-stage dynamic scheduling concepts for emergency logistics have already gained recognition (Cheng & Liang, 2014; Zheng, Mu, et al., 2015). Through the organic integration of ERP, which prioritizes urgent rescue operations, and PERP, which balances economic considerations with conventional freight transportation, this study further demonstrates the feasibility of multi-stage emergency logistics optimization. In scenarios with initial resource shortages, allocation equity has been widely regarded as a crucial criterion for emergency material distribution (Tang et al., 2021). In the ERP, an equity-oriented objective has been established to ensure the balanced allocation of limited emergency materials among multiple disaster-affected areas. In contrast, during the PERP, impacts on conventional freight transportation are minimized, reflecting the consensus that emergency logistics should not excessively disrupt conventional freight transportation. Finally, through empirical analysis, it has been demonstrated that the optimization strategy can effectively balance both material allocation and transport capacity distribution equity.

Considering the framework of multi-stage scheduling, researchers are required to comprehensively consider the different characteristics of demands when confronted with large-scale demands and complex scenarios (Tang, Li, et al., 2023). Building upon this conceptual foundation, the present study is extended to synchronously manage emergency material transportation demands and transport capacity resources during the ERP, together with newly generated demands and delayed demands during the PERP, while enhancing response efficiency and maintaining economic objectives. Both heuristic and evolutionary algorithmic strategies have been shown to exhibit superior efficiency in railway scheduling and emergency logistics operations (Zheng et al., 2014; Zheng, Zhang, et al., 2015). Concurrently, modifications to NSGA-II have been shown to enhance algorithmic performance in multi-objective optimization (Cheng & Liang, 2014). The AVNNSGA-II proposed in this study, which integrates multiple mutation operators with an adaptive weight mechanism, has significantly improved global search capabilities and Pareto front quality. This further confirms the applicability of the proposed AVNNSGA-II in addressing large-scale railway emergency logistics challenges.

Although this study proposes an effective two-stage emergency logistics optimization strategy, several unresolved challenges persist in its practical implementation, particularly regarding the application and integration of multimodal transportation. Recent studies have identified that multimodal transportation demonstrates significant potential in emergency logistics under complex scenarios. For example, the integration of road, air, and water transportation modes with railway systems has been verified to substantially enhance collaborative efficiency while strengthening network resilience (E. Liu et al., 2022, 2023). Although a two-stage model has been constructed in this research, further exploration is still required to achieve deep coupling between railway systems and other transportation modes. Particularly in the ERP, systematic methodologies for effectively connecting railway emergency logistics with multimodal transportation are lacking, as are those for leveraging the comparative advantages of different transportation modes under resource constraints and temporal conflicts. Future research should address multimodal coordination management and global scheduling strategies. Through the integration of multimodal transportation network configurations with transport capacity allocation, dynamic distribution mechanisms of multimodal transportation can be explored, thereby providing novel insights for extending railway emergency logistics applications.

In conclusion, this study integrated railway emergency material transportation during both ERP and PERP into a unified optimization framework, through which a novel railway emergency logistics optimization strategy was developed. Significant enhancements have been achieved in both the theoretical foundation and practical implementation of railway emergency logistics systems. Moreover, the coupling mechanism between the two-stage multi-objective optimization model and AVNNSGA-II has been shown to provide innovative solutions for large-scale railway freight allocation and scheduling challenges, while simultaneously offering technical support for the practical implementation of railway emergency logistics systems in complex operational scenarios. However, in the integrated context of diversified transportation resources and dynamic scenario evolution, the coordination between railway emergency logistics and multimodal transportation systems remains to be systematically investigated.

8. Conclusion

To address the issue that traditional railway emergency logistics modes compromise emergency response efficiency, resulting in severe delays and losses to prescheduled conventional freight operations, an entire-process optimization strategy coordinating ERP and PERP is proposed. A two-stage multi-objective optimization model for railway emergency logistics has been constructed to holistically optimize plans for wagon formation, emergency material loading, and operations. The proposed strategy has been applied to practical railway emergency logistics scenarios for empirical validation. The research outcomes and contributions are as follows:

(1) The developed ERP submodel ensures the balanced allocation of emergency materials while achieving significant reductions in emergency response time during railway emergency logistics operations. Empirical results reveal that a minimum satisfaction rate of 51.28% for emergency material supply has been observed across all disaster-affected areas in the ERP. This capability effectively mitigates the risks associated with critical shortages of emergency materials while improving their equitable distribution. Furthermore, comparative analyses with road-based emergency logistics demonstrate that the emergency response duration is reduced by 69.40% relative to average-speed truck transportation,

whereas a 55.90% reduction is achieved relative to high-speed truck transportation. Collectively, these quantitative comparisons validate the operational effectiveness of the proposed strategy in railway emergency logistics scenarios.

(2) The developed PERP submodel can mitigate operational impacts on conventional freight operations while maintaining transportation cost-efficiency during emergency material distribution. Empirical validation confirms that multi-objective optimization in the PERP achieves a balanced consideration of transport economic benefits for all stakeholders, including railway carriers and cargo owners. Furthermore, the implementation of differentiated transport prioritization mechanisms results in a 50.49% reduction in total delay losses for the affected conventional freight demand during the ERP. These operational improvements collectively demonstrate the effectiveness of the proposed strategy in coordinating emergency logistics and conventional transport systems.

(3) An AVNNSGA-II has been designed for the multi-objective optimization model, demonstrating significant advantages over traditional NSGA-II. Empirical analyses reveal that AVNNSGA-II achieves superior performance in solution quality, Pareto front distribution breadth, and convergence stability relative to NSGA-II. Specifically, 97% of AVNNSGA-II-generated Pareto front solutions are superior to those from NSGA-II. Furthermore, the proposed algorithm is equipped with an enhanced global search capability that effectively prevents premature convergence while maintaining more stable convergence behavior throughout the optimization process.

The results have significant practical implications for emergency logistics management, as they enable faster disaster response, improve resource allocation, and minimize economic disruptions. This optimization approach provides a robust decision-making framework for transportation planners, improving the efficiency of emergency response and recovery strategies while maintaining the resilience and regularity of logistical operations.

Nevertheless, this research acknowledges several limitations that require further exploration. One significant challenge lies in effectively integrating multimodal transportation. Although multimodal logistics incorporating road, air, water, and railway modes has demonstrated substantial potential to improve operational efficiency and resilience during emergencies, this research primarily focused on railway logistics. Thus, future work should extend the model proposed by systematically incorporating multimodal transportation networks, enhancing multimodal coordination strategies, and developing dynamic allocation mechanisms. Such enhancements could effectively balance logistical costs and efficiencies, providing broader practical insights for comprehensive emergency logistics optimization and its real-world applications.

Data Availability Statement

Some or all data, models, or codes that support the findings of this study are available from the corresponding author upon reasonable request.

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