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Variable Reduction Strategy Integrated Variable Neighborhood Search and NSGA-II Hybrid Algorithm for Emergency Material Scheduling

Zhen Shu, Aijuan Song, Guohua Wu*, and Witold Pedrycz

Abstract: Developing a reasonable and efficient emergency material scheduling plan is of great significance to decreasing casualties and property losses. Real-world emergency material scheduling (EMS) problems are typically large-scale and possess complex constraints. An evolutionary algorithm (EA) is one of the effective methods for solving EMS problems. However, the existing EAs still face great challenges when dealing with large-scale EMS problems or EMS problems with equality constraints. To handle the above challenges, we apply the idea of a variable reduction strategy (VRS) to an EMS problem, which can accelerate the optimization process of the used EAs and obtain better solutions by simplifying the corresponding EMS problems. Firstly, we define an emergency material allocation and route scheduling model, and a variable neighborhood search and NSGA-II hybrid algorithm (VNS-NSGAII) is designed to solve the model. Secondly, we utilize VRS to simplify the proposed EMS model to enable a lower dimension and fewer equality constraints. Furthermore, we integrate VRS with VNS-NSGAII to solve the reduced EMS model. To prove the effectiveness of VRS on VNS-NSAGII, we construct two test cases, where one case is based on a multi-depot vehicle routing problem and the other case is combined with the initial 5·12 Wenchuan earthquake emergency material support situation. Experimental results show that VRS can improve the performance of the standard VNS-NSGAII, enabling better optimization efficiency and a higher-quality solution.

Key words: emergency material scheduling; evolutionary algorithm; variable reduction strategy

1 Introduction

Emergency logistics plays a crucial role in emergency disaster management[1]. As an important branch of emergency logistics, emergency material scheduling (EMS) is a special vehicle routing problem (VRP)[2]. EMS mainly focuses on making the best plan to deliver emergency materials from supply nodes to demand nodes in a timely, accurate, and effective manner, so as to minimize casualties and property losses[3].

Generally, EMS includes three phases: location, allocation, and route optimization[4]. Among them, location refers to finding some suitable supply nodes in an area to ensure that the demand nodes in the area can be reached within a certain period of time. The purpose of the allocation is to find the optimal allocation scheme of emergency material to minimize response time or costs. Route optimization is to find the best route from supply nodes to demand nodes considering road conditions.

In recent years, researchers have proposed plenty of

• Zhen Shu is with the College of Systems Engineering, National University of Defense Technology, Changsha 410073, China. E-mail: sz_1226@sina.com.
• Aijuan Song and Guohua Wu are with the School of Traffic and Transportation Engineering, Central South University, Changsha 410075, China. E-mail: aijuansong@csu.edu.cn; guohuawu@csu.edu.cn.
• Witold Pedrycz is with the Department of Electrical and Computer Engineering, University of Alberta, Edmonton, AB T6G 2V4, Canada, and also with the Systems Research Institute, Polish Academy of Sciences, Warsaw 01447, Poland. E-mail: wpedrycz@ualberta.ca.
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models that considered various constraints and designed various algorithms to solve these EMS problems from different perspectives and stages.

Regarding model construction, the EMS problems can be grouped into single-objective and multi-objective problems.

When it comes to EMS problems, the fastest response time is typically the main objective, which is essential to enhance emergency response capability. Many researchers have concentrated on the EMS optimization model with the objective of the fastest response time[5−9]. For example, Bodaghi et al.[8] defined a multi-resource scheduling model under uncertainty to minimize the weighted sum of completion time over all demand nodes, considering the sequencing and scheduling of both expendable and non-expendable resources. Lu et al.[9] established a relief distribution model with the objective of minimizing the total distribution time by considering uncertain data and the risk-averse attitude of the decision-maker. Besides, the shortest transportation route is also one of the most important goals of single-objective EMS. For example, Vidal et al.[10] established multi-depot scheduling models to obtain the shortest route, and they comprehensively considered possible situations in the material distribution process. Meanwhile, it is also crucial to improve demand satisfaction and ensure fairness in single-objective EMS. Demand satisfaction can be generally achieved by either minimizing unsatisfied demand nodes or maximizing demand coverage. For instance, Das[11] identified seven factors affecting demand and proposed a warehouse location model intending to maximize the demand coverage. Concerning fairness, Mishra et al.[12] proposed a greedy search algorithm for fair distribution of relief logistics. In Ref. [13], the distribution fairness was measured by considering the minimization of the absolute standard deviation between demand and supply in the demand regions and the number of disaster regions receiving the relief logistics. Furthermore, some research comprehensively considered various factors to construct a single-objective EMS model[13, 14] . For example, Ferrer et al.[14] built a compromise programming model for multi-criteria optimization in humanitarian last-mile distribution, where they considered time, cost, coverage, equity, and security.

The multi-objective EMS problems possess more than one objective function and are being extensively studied[15−20]. For instance, Zahedi et al.[19] developed a multi-objective resource and vehicle scheduling optimization model considering the heterogeneity and dynamics of demands. The goal of the model is to minimize unsupplied requests and costs. Wang et al.[15] constructed a bi-objective EMS model aiming at the lowest cost and the highest emergency response speed with limited transportation resources. Chang et al.[20] dynamically adjusted allocation schedules according to the requirements of demand nodes to minimize unsatisfied demand for resources, time to delivery, and transportation costs.

Concerning the solving algorithms, there have existed two alternative methods for solving EMS problems: exact algorithms and heuristic algorithms. When solving a small-scale and simple EMS problem, the exact algorithms[21] may have higher computational accuracy than the heuristic algorithms and even can find an optimal solution for the problem. However, due to the increasing scale and complexity of EMS problems and the limitation of exact algorithms, traditional exact algorithms can no longer meet the needs. Therefore, researchers have developed heuristic algorithms for solving EMS problems in recent years.

As a crucial branch of heuristic algorithms, evolutionary algorithms (EAs)[22−27] are competitive methods for solving a substantial number of EMS problems[22, 28−30] . For example, Liu and Xie[31] established an EMS model under the condition of material demand and vehicle amount continual alteration and proposed a dynamic programming and ant colony optimization (ACO) hybrid algorithm to solve it. To solve a grain EMS problem effectively, Zhang and Xiong[32] proposed an immune ACO algorithm, which makes use of the global convergence and randomness of the improved immune algorithm together with the distributed search ability and positive feedback of the ACO to enhance the performance of the algorithm. Zahedi et al.[19] used constraint method and NSGA-II algorithm to solve a constructed multi-objective EMS model, and the effectiveness of the proposed method was testified by the 2017 Kermanshah earthquake. Wang and Sun[22] presented an improved genetic algorithm (GA) to solve a multi-objective and multi-period EMS model. Zhou et al.[33] established a multi-objective, multi-period, and dynamic EMS problem model and designed an improved multi-objective evolutionary algorithm based on decomposition (MOEA/D)[34] to solve it. Wang et al.[28] proposed an adaptive weighted dynamic differential evolutionary algorithm to solve an EMS model, which is superior to the standard differential evolutionary algorithm and the chaos adaptive particle swarm algorithm.

In general, on one hand, EMS problems are usually NP-hard problems[2], which involve the constraints on demand nodes, supply nodes, vehicles, and so on. The size of the EMS problem increases with the number of supply nodes and demand nodes, and equality constraints widely exist in EMS problems, such as demand node constraints. On the other hand, most EAs can only find feasible solutions to an EMS problem, which is difficult to satisfy the actual need. Consequently, improving the performance of EAs in solving EMS problems with large-scale or complex equality constraints deserves further research.

To handle the challenge aroused by large-scale variables and equality constraints, we initially proposed a variable reduction strategy (VRS)[35] to obtain a lower dimension of solution space and eliminate partial equality constraints. VRS explores the relationships among variables by utilizing the general problem domain knowledge implied in an optimization problem, i.e., equality optimality condition. Based on relationships among variables, we always utilize a part of variables to represent and calculate the rest of the variables during the iteration process of an algorithm. Thereby, the optimization problem can possess a lower dimension of solution space and fewer variables. Some essential concepts are as follows.

(1) **Equality optimality condition:** It refers to the equality condition that an optimization problem must satisfy when obtaining optimal solutions, which is a necessary condition and is expressed in form of equations.

(2) **Core variable:** It is used to represent and calculate other variables.

(3) **Reduced variable:** It is represented and calculated by core variables via some functional relationships.

(4) **Eliminated equation:** It is the equation eliminated along with the reduction of variables due to being satisfied by all solutions in an equality optimality condition.

Currently, VRS has been applied to several optimization problems, like nonlinear equations systems and constraint optimization problems, and gained competitive performance[35–38]. Moreover, Ref. [39] realized the automatic reduction of VRS and simplified a continuous optimization problem automatically. Therefore, VRS has the potential to be applied in EMS. The main contributions of the paper are presented as follows.

(1) Construct an emergency material allocation and route optimization model and design a variable neighborhood search and NSGA-II hybrid algorithm (VNS-NSGAII) to solve the constructed model.

(2) Combined with problem domain knowledge, we utilize VRS to reduce the proposed EMS model, thereby enabling a lower dimension and fewer equality constraints. Furthermore, we integrate VRS with VNS-NSGAII (the integrated algorithm is called VRS-VNS-NSGAII) to solve the reduced EMS model.

(3) Two test cases are constructed to test the performance of the proposed method, where one case is based on a multi-depot vehicle routing problem and the other case is constructed by combining with the initial 5·12 Wenchuan earthquake emergency material support situation. Experimental results on the test cases verify that with the assistance of VRS, VNS-NSGAII enables a better optimization efficiency and a higher quality solution.

The paper proceeds as follows. Section 2 establishes the EMS model and Section 3 presents the detail of VNS-NSGAII to solve the proposed model. Section 4 applies VRS to reduce the EMS model and integrates VRS with VNS-NSGAII to solve the reduced EMS problem. Section 5 executes some experiments to test the effectiveness of VRS in solving the EMS model. Section 6 concludes the full paper and points out some future potential directions.

2 Mathematical Model

We consider two phases of EMS: allocation and route optimization. The allocation phase needs to determine the amount of materials provided from each supply point to each demand node, which will directly affect the route optimization scheme. In the route optimization phase, we need to send a fleet of vehicles from each supply node to perform transportation tasks according to the material allocation results in the allocation phase.

To further understand the above phases, assume that there are 3 supply nodes $\{B_1, B_2, B_3\}$ and the amounts of material deposited are $\{10, 9, 11\}$. Moreover, there are 8 demand nodes $\{A_1, A_2, \ldots, A_8\}$ and the amounts of material needed are $\{2, 4, 3, 4, 3, 2, 5, 4\}$. One of the material allocation schemes is shown in Fig. 1.

According to the material allocation scheme in Fig. 1, assume that the capacity of a vehicle is 8. Then, when only considering the capacity of vehicles, a feasible route scheduling scheme is presented in Fig. 2.

The notion to be used in the proposed EMS model is exhibited in Table 1.

The objective functions of the EMS model are shown in Eqs. (1) and (2). The total time is mainly composed of transportation and handling loading time. The total cost includes transportation and vehicle operating costs.

$$\min f_1 = \sum_{i\in F}\sum_{j\in F}\sum_{k\in S} T_{ij}u_{ijk} + 2\sum_{i\in A}\sum_{j\in B} t x_{ij} \tag{1}$$

$$\min f_2 = \sum_{i\in F}\sum_{j\in F}\sum_{k\in S} C_1 D_{ij}u_{ijk} + KC_2 \tag{2}$$

where T_{ij} denotes the transportation time from node i to j $(i, j \in F)$ and can be expressed as

$$T_{ij} = (D_{ij}/\beta_{ij})/(v(1+\sigma_{ij})) \tag{3}$$

where $0 \leqslant \beta_{ij}$ and $\sigma_{ij} \leqslant 1$.

The constraints of the model are as follows:

$$\sum_{j\in B} x_{ij} = P_i,\ \forall i \in A \tag{4}$$

$$\sum_{i\in A} x_{ij} \leqslant V_j,\ \forall j \in B \tag{5}$$

$$c x_{ij} \leqslant Q,\ \forall i \in A, \forall j \in B \tag{6}$$

$$\sum_{i\in F}\sum_{k\in S} u_{ijk} \geqslant 1,\ \forall j \in A, j \neq i \tag{7}$$

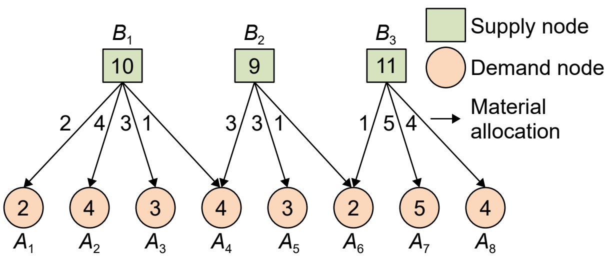

Fig. 1 Diagram of material allocation.

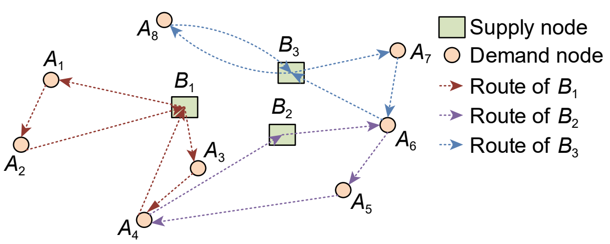

Fig. 2 Diagram of route scheduling.

Table 1 Notation used in the EMS mathematical model.

Type	Notation
Set	A: demand nodes set, $A=\{A_1, A_2, \ldots, A_m\}$; B: supply nodes set, $B=\{B_1, B_2, \ldots, B_n\}$; F: vertex set, $F = A \cup B$; S: vehicle set, $S=\{1, 2, \ldots, K\}$;
Parameter	P_i: an integer amount of materials needed at A_i; V_j: an integer amount of materials deposited at B_j; Q: capacity of a vehicle; c: weight per unit material; D_{ij}: distance from node i to j, $i, j \in F$; v: average speed of a vehicle; t: unit time of handling load (loading or unloading) of a vehicle; C_1: transportation cost per unit distance; C_2: operation cost for a vehicle; L: maximum allowed transportation time for a vehicle; β_{ij}: road access rate from node i to j, $i, j \in F$; σ_{ij}: road congestion factor from node i to j, $i, j \in F$; K: number of vehicles; m: number of demand nodes; n: number of supply nodes;
Decision variable	x_{ij}: an integer amount of resource delivered from node B_j to A_i; u_{ijk}: 0 or 1 decision variable. If vehicle k travels from node i to j, $i, j \in F$, then $u_{ijk} = 1$; otherwise, $u_{ijk} = 0$; U_{ik}: auxiliary variable for sub-tour elimination in node i.

$$\sum_{j\in F}\sum_{k\in S} u_{ijk} \geqslant 1,\ \forall i \in A, i \neq j \tag{8}$$

$$\sum_{j\in A} u_{ijk} = \sum_{j\in A} u_{jik},\ \forall i \in B, \forall k \in S \tag{9}$$

$$\sum_{j\in B}\sum_{i\in B} u_{ijk} = 0,\ \forall k \in S \tag{10}$$

$$U_{ik} - U_{jk} + (m+n)u_{ijk} \leqslant (m+n) - 1,\\ \forall i, j \in F, i \neq j, \forall k \in S \tag{11}$$

$$U_{ik} = 0,\ \forall i \in B, \forall k \in S \tag{12}$$

$$U_{ik} \geqslant 0,\ \forall i \in A, \forall k \in S \tag{13}$$

$$\sum_{j\in A} u_{ijk} \leqslant 1,\ \forall k \in S, \forall i \in B \tag{14}$$

$$\sum_{j\in B} u_{ijk} \leqslant 1,\ \forall k \in S, \forall i \in A \tag{15}$$

$$\sum_{j\in F}\sum_{i\in A} c u_{ijk} x_{ij} \leqslant Q,\ \forall k \in S \tag{16}$$

$$\sum_{j\in F}\sum_{i\in F} T_{ij}u_{ijk} \leqslant L,\ \forall k\in S \tag{17}$$

$$x_{ij} \in [0, \min(V_j, Q/c)],\ \forall i\in A, \forall j\in B,\quad x_{ij} \text{ is an integer} \tag{18}$$

$$u_{ijk} \in 0,1,\ \forall i\in F, \forall j\in F, \forall k\in S \tag{19}$$

Material demand constraint (4) requires that the amount of materials allocated to a demand node should be equal to the amount of materials needed at the demand node, which can ensure satisfaction and fairness without wasting resources. Material supply constraint (5) ensures that the total allocation amount of materials at a supply node cannot exceed the amount of materials deposited at the supply node, which can avoid allocation conflicts. Constraint (6) restricts that the number of materials allocated to a demand node from a supply node should not exceed the capacity of a vehicle. Constraints (7) and (8) guarantee that each demand node needs to be traveled at least once. Constraint (9) restricts that each vehicle should return to the original supply node after completing the transportation task. Constraint (10) limits that no path exists between any supply nodes. Constraints (11)−(13) are sub-tour elimination constraints. Constraints (14) and (15) are the vehicle availability constraints, i.e., at most one vehicle is allowed to travel from a supply node to a demand node, and at most one vehicle is allowed to return from one demand node to one supply node. Capacity constraint (16) guarantees that the materials carried by each vehicle cannot exceed its capacity. Vehicle transportation time constraint (17) ensures that the transportation time of each vehicle does not exceed its longest allowed transportation time (excluding loading and unloading time). Constraints (18) and (19) are variable constraints.

Compared with classical material scheduling problems, the constructed model in the paper possesses the characteristic of considering timeliness and economy, road factors, as well as multiple demand and supply nodes. Furthermore, in comparison with the majority of EMS problems, the EMS problem presented in this paper requires a balance of the amount of supply and demand materials (i.e., constraint (4)) to ensure satisfaction and fairness. Whereas most EMS problems allow the amount of materials allocated to a demand node to be less than the amount of materials needed at the demand node.

3 VNS-NSGAII Hybrid Algorithm

3.1 Main procedure of VNS-NSGAII

To solve the model presented in Eqs. (1)−(4), (9), (10), and (12) and Formulas (5)−(8), (11), and (13)−(19), we design a VNS-NSGAII hybrid algorithm to solve the model herein. NSGA-II is mainly responsible for optimizing the material allocation scheme and the VNS is used to optimize the route scheduling scheme. The two algorithms combine and promote each other to approximate the optimal solutions to the EMS problem. The main pseudocode of VNS-NSGAII is displayed in Algorithm 1, where VNS-NSGAII works as follows.

(1) Lines 1 and 2 generate the material allocation and route scheduling schemes of the initial population.

(2) In Line 3, we conduct the crossover and mutation operation for the initial population.

(3) Lines 4 and 5 initialize the relevant parameters.

(4) Line 7 generates the offspring population by crossover and mutation.

Algorithm 1 Main pseudocode of VNS-NSGAII

Input: Algorithm parameters; vertices parameters; vehicle parameters; material parameters; road parameters.

Output: Best-so-far material allocation scheme D_{best} and route scheduling scheme R_{best}.

1 $\text{pop}_{\text{allocate}}$ ←InitialDistribution();
2 $\text{pop}_{\text{route}}$ ←IntialRoute();
3 $[\text{pop}_{\text{allocate}}, \text{pop}_{\text{route}}]$ ←LocalOptimization();
4 Initialize the iteration indicators iter ← 1 and $k \leftarrow 1$;
5 Initialize the best-so-far material allocation and route scheduling schemes: $D_{\text{best}} \leftarrow \text{pop}^{\text{best}}_{\text{allocate}}$, $R_{\text{best}} \leftarrow \text{pop}^{\text{best}}_{\text{route}}$;
6 **while** iter ⩽ $\text{iter}_{\max}$ **do**
7 $[\text{offspring}_{\text{allocate}}, \text{offspring}_{\text{route}}]$ ←Perform crossover and mutation operations for pop;
8 **if** iter = $k\times G$ **then**
9 $\text{offspring}_{\text{route}}$ ←RouteOptimization();
10 $k \leftarrow k+1$;
11 **end if**
12 $[\text{offspring}_{\text{allocate}}, \text{offspring}_{\text{route}}]$ ←LocalOptimization();
13 Combining pop and offspring forms the combined population cpop;
14 $[\text{spop}_{\text{allocate}}, \text{spop}_{\text{route}}]$ ←Perform the fast nondominated sorting and selection for cpop;
15 $[\text{pop}_{\text{allocate}}, \text{pop}_{\text{route}}]$ ←Perform the elitism and 2-tournament selection for spop;
16 Update the best-so-far material allocation scheme D_{best} and route scheduling scheme R_{best};
17 **end while**

(5) Lines 8−11 optimize the route scheduling schemes of the offspring population under a certain number of iterations.

(6) Line 12 performs the local optimization for the offspring population.

(7) In Lines 13−15, we combine the offspring and parent population and execute the fast nondominated sorting and selection for the combined population to select the population for the next iteration.

(8) Line 16 updates the best-so-far material allocation and route scheduling schemes.

3.2 Generation of initial population

3.2.1 Material allocation scheme of initial population

We sequentially encode n supply nodes as $1,2,\ldots,n$. And m demand nodes are denoted as $n+1, n+2,\ldots, n+m$. The material allocation scheme of the k-th individual is an $m\times n$ material allocation matrix, which can be represented as $\text{pop}^{m\times n}_{\text{allocate},k}$, $k\in\{1,2,\ldots,\text{NP}\}$, where $\text{pop}^{ij}_{\text{allocate},k}\geqslant 0$ denotes the amount of material allocated from supply node j to demand node $i+n$, and NP is population size.

Before generating an initial material allocation scheme, we should calculate the transportation distance matrix $M_{m\times n}$ between supply nodes and demand nodes as follows:

$$M_{ij}=D_{j,i+n},\ i=\{1,2,\ldots,m\}, j=\{1,2,\ldots,n\} \tag{20}$$

Moreover, we define a binary response matrix $R_{m\times n}$ that reflects whether a supply node responds to a demand node or not (i.e., there are materials allocated from the supply node to the demand node). The expression of $R_{m\times n}$ is

$$R_{ij}=\{0,1\},\ i=\{1,2,\ldots,m\}, j=\{1,2,\ldots,n\} \tag{21}$$

where if supply node j responds to demand node $i+n$, then $R_{ij}=1$; otherwise, $R_{ij}=0$.

The material allocation scheme $\text{pop}^{m\times n}_{\text{allocate},k}$ of the k-th individual in the initial population is constructed as follows:

(1) Initialize the matrix $\text{pop}^{m\times n}_{\text{allocate},k}$ to 0.

(2) Determine the response matrix $R_{m\times n}$ by Eq. (22).

$$R_{ij}=\begin{cases}1, \text{ if } p_{i,j-1}\leqslant\xi<p_{ij};\\ 0, \text{ otherwise}\end{cases} \tag{22}$$

where ξ is a random number between 0 and 1, $\xi\in U(0,1)$. p_{ij} is the response probability between supply node j and demand node $i+n$, which can be calculated by Eq. (23).

$$p_{ij}=(1/M_{ij})/(\sum_{j=1}^{n}1/M_{ij}) \tag{23}$$

where $i\in\{1,2,\ldots,m\}$ and $j\in\{1,2,\ldots,n\}$. The shorter the transportation distance, the greater the response probability.

(3) Allocate the material to the non-zero elements of matrix $R_{m\times n}$ and the amount of allocated material is a random integer in $(0,\min(V_i, Q/c)]$.

Accordingly, the pseudocode for generating the material allocation scheme of the initial population is shown in Algorithm 2.

In addition, to ensure the feasibility of the material allocation scheme for the initial population, we design a repair strategy to repair the infeasible material allocation scheme in the initial population. Repair strategy of the material allocation scheme $\text{pop}^{m\times n}_{\text{allocate},k}$ of the k-th individual in pop proceeds is as follows.

(1) Calculate the amount of materials remaining in each supply node by Eq. (24).

$$L_j=P_j-\sum_{i=1}^{m}\text{pop}^{ij}_{\text{allocate},k},\ j=\{1,2,\ldots,n\} \tag{24}$$

(2) Repair material supply constraints and make the total materials provided by a supply node less than or equal to the materials deposited in the supply node.

If $L_j<0$, $j\in\{1,2,\ldots,n\}$, we execute

$$\text{pop}^{i^*j}_{\text{allocate},k}=0 \tag{25}$$

Algorithm 2 Function InitialDistribution()

Input: Transportation distance matrix D; size of population NP; $P_{1\times n}$ and $V_{1\times m}$; number of supply nodes n; number of demand nodes m; capacity of a vehicle Q; weight per unit material c.

Output: Material allocation scheme of initial population $\text{pop}_{\text{allocate}}$.

```
Calculate the matrix M_{m×n} by Eq. (20).
for k = 1 → NP do
  Initialize pop_{allocate,k} ← 0;
  Calculate P_{m×n} via Eq. (23);
  Calculate R_{m×n} via Eq. (22);
  for i = 1 → m do
    for j = 1 → n do
      if R_{ij} = 1 then
        pop^{ij}_{allocate,k} ← randi(0, min{Q/c, V_i});
      end if
    end for
  end for
pop_{allocate,k} ← RepairStrategy();
end for
```

where $i^* = \arg\max(D_{ji^*}), \mathrm{pop}_{\mathrm{allocate},k}^{i^* j} > 0, j \in \{1,2,\ldots,n\}$. Repeat the operation in Eq. (25) until the material supply constraints are met, i.e., $L_j \geqslant 0,\ j=\{1,2,\ldots,n\}$.

(3) Repair material demand constraints and make the total materials provided by all supply nodes to a demand node equal to the total material needed of the demand node.

If $\sum_{j=1}^{n} \mathrm{pop}_{\mathrm{allocate},k}^{ij} > V_i, i \in \{1,2,\ldots,m\}$, then we perform

$$\mathrm{pop}_{\mathrm{allocate},k}^{ij^*} = \mathrm{pop}_{\mathrm{allocate},k}^{ij^*} - \min\{\mathrm{pop}_{\mathrm{allocate},k}^{ij^*}, \sum_{j=1}^{n} \mathrm{pop}_{\mathrm{allocate},k}^{ij} - V_i\} \tag{26}$$

where $j^* = \arg\max(D_{j^*i}),\ \mathrm{pop}_{\mathrm{allocate},k}^{ij^*} > 0,\ i \in \{1,2,\ldots,m\}$. Repeat the operation in Eq. (26) until the demand constraints are met, i.e., $\sum_{j=1}^{n} \mathrm{pop}_{\mathrm{allocate},k}^{ij} = V_i, i \in \{1,2,\ldots,n\}$.

If $\sum_{j=1}^{n} \mathrm{pop}_{\mathrm{allocate},k}^{ij} < V_i, i \in \{1,2,\ldots,n\}$, we have

$$\mathrm{pop}_{\mathrm{allocate},k}^{ij^*} = \mathrm{pop}_{\mathrm{allocate},k}^{ij^*} + \min\{L_{j^*}, V_i - \sum_{j=1 \wedge j \neq j^*}^{n} \mathrm{pop}_{\mathrm{allocate},k}^{ij}\} \tag{27}$$

where $j^* = \arg\min(D_{j^*i}),\ \mathrm{pop}_{\mathrm{allocate},k}^{ij*} > 0,\ i \in \{1,2,\ldots,m\}$. Repeat the operation in Eq. (27) until the demand constraints are met, i.e., $\sum_{j=1}^{n} \mathrm{pop}_{\mathrm{allocate},k}^{ij} = V_i, i \in \{1,2,\ldots,n\}$.

The pseudocode of the repair strategy is presented in Algorithm 3.

3.2.2 Route scheduling scheme of initial population

We encode the route scheduling scheme of an individual with a 2-D array, where the j-th row denotes all vehicle routes from supply node j and different vehicle routes are separated by inserting the supply node to which the vehicles belong. Furthermore, the first and last codes are the corresponding supply nodes, indicating that all vehicles depart from the supply node and eventually return to the same supply node.

Taking the material allocation and route scheduling schemes in Figs. 1 and 2 as an example, the 3 supply nodes are represented as {1, 2, 3}, and the 8 demand nodes are represented as {4, 5, ..., 11}, then the encoding of the route scheduling scheme is shown in Fig. 3.

The route scheduling scheme of the k-th individual in pop can be represented as $\mathrm{pop}_{\mathrm{route},k}^{1\times n}, k \in \{1,2,\ldots,\mathrm{NP}\}$, where $\mathrm{pop}_{\mathrm{route},k}^{j}$ denotes the route of supply node j. The initial route for each supply node is generated by a greedy heuristic algorithm, which chooses the next traveled node by judging the minimum transportation distance between the current node and other unserved nodes.

Algorithm 3 Function RepairStrategy()

Input: Material allocation matrix $\mathrm{pop}_{\mathrm{allocate},k}$; $P_{1\times n}$ and $V_{1\times m}$; number of supply nodes n; number of demand nodes m; $M_{m\times n}$.

Output: Material allocation matrix $\mathrm{pop}_{\mathrm{allocate},k}$.

```
Calculate L_{1×n} by Eq. (24);
for j = 1 → n do
  while L_j < 0 do
    Execute the operation in Eq. (25);
    Update L_j by Eq. (24);
  end while
end for
for i = 1 → m do
  while Σ_{j=1}^{n} pop_{allocate,k}^{ij} > V_i do
    Execute the operation in Eq. (26);
    Update L_j by Eq. (24);
  end while
  while Σ_{j=1}^{n} pop_{allocate,k}^{ij} < V_i do
    Execute the operation in Eq. (27);
    Update L_j by Eq. (24);
  end while
end for
```

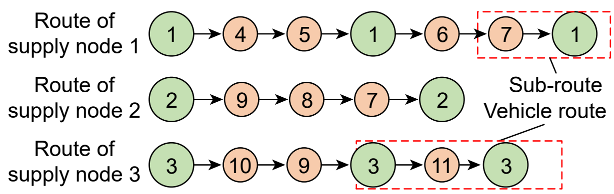

Fig. 3 Diagram of the encoding of a route scheduling scheme.

3.3 Local search strategy

To ensure a sufficient exploration of solution space, a local search strategy is designed herein. The main idea of the local search strategy is to transfer demand nodes in sub-routes with long transportation time and distances to other supply nodes.

Assume that demand node A_3 in the route of supply node B_1 should be transferred in Fig. 4. Then, the

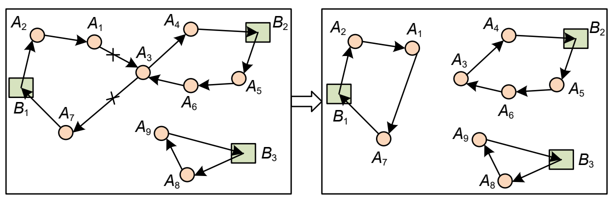

Fig. 4 Diagram of demand node merge.

materials allocated to demand node A_3 from supply node B_1 should first be transferred to other supply nodes. Then we delete demand node A_3 from the route of supply node B_1 and put A_3 to the route of another supply node. There are two situations for transferring a demand node to the route of another supply node.

The first situation is that the route of the supply node to be transferred has already involved the transferred demand node. As presented in Fig. 4, if we should transfer A_3 to the route of B_2, we should delete the route $A_1 \rightarrow A_3 \rightarrow A_7$ and add the route $A_1 \rightarrow A_7$. The situation can be regarded as transforming the situation that two supply nodes provide materials to a demand node into a single supply node providing materials to the demand node, which is called a demand node merge herein.

The second situation is that the route of the supply node to be transferred does not contain the transferred demand node. As shown in Fig. 5, if demand node A_3 needs to be transferred to the route of B_3, then we should delete the route $A_1 \rightarrow A_3 \rightarrow A_7$ and $A_9 \rightarrow B_3$, and add the route $A_1 \rightarrow A_7$ and $A_9 \rightarrow A_3 \rightarrow B_3$. The situation is known as a demand node shift.

The demand nodes that need to be transferred are determined by the sub-route transportation distance and time. To eliminate the dimensional difference between time and distance, we first normalize the transportation time matrix T and the transportation distance matrix D:

$$\overline{T} = \frac{T - T_{\min}}{T_{\max} - T_{\min}},\ \overline{D} = \frac{D - D_{\min}}{D_{\max} - D_{\min}} \tag{28}$$

Subsequently, the normalized transportation time and distance matrices are linearly weighted:

$$\overline{TD} = \alpha_1 \overline{T} + \alpha_2 \overline{D} \tag{29}$$

where $\alpha_1 = \alpha_2 = 0.5$.

The pseudocode of local optimization is displayed in Algorithm 4.

3.4 Route optimization

Since the demand nodes and the allocation amount that each supply node needs to respond to have been determined in the allocation phase, we adapt the

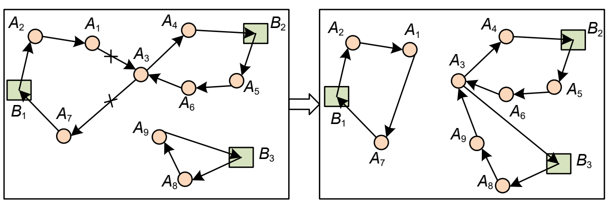

Fig. 5 Diagram of demand node shift.

Algorithm 4 Function LocalOptimization()

Input: Size of population NP; number of supply nodes n; number of demand nodes m; capacity of a vehicle Q; maximum allowed transport time for a vehicle L; weight per unit material c; $\text{pop}_{\text{allocate}}$ and $\text{pop}_{\text{route}}$.

Output: $\text{pop}_{\text{allocate}}$ and $\text{pop}_{\text{route}}$.

Calculate $\overline{TD}$ by Eqs. (28) and (29);
for $k = 1 \rightarrow \text{NP}$ **do**
  Sort all sub-routes in $\text{pop}_{\text{route},k}$ in descending order according to $\overline{TD}$;
  Select the demand nodes and supply nodes corresponding to the sub-routes in the first half of the order and put them into the set C^M;
  for $i = 1 \rightarrow |C^M|$ **do**
    $\text{new\_pop}_k \leftarrow \text{pop}_k$;
    Record the demand node as i^* and supply node as j^* in C_i^M;
    if $\exists \text{pop}_{\text{allocate},k}^{i^*-n,j} \neq 0, j \in \{1,2,\ldots,n\}, j \neq j^*$ **then**
      Put other supply nodes that respond to demand node i^* except for j^* into Candi;
      Select the supply node j' in Candi with the shortest transport distance with demand node i^* and the remain materials in j' are more than $\text{pop}_{\text{allocate},k}^{i^*-n,j^*}$;
      $\text{new\_pop}_{\text{allocate},k}^{i^*-n,j'} \leftarrow \text{new\_pop}_{\text{allocate},k}^{i^*-n,j'} + \text{new\_pop}_{\text{allocate},k}^{i^*-n,j^*}$, $\text{new\_pop}_{\text{allocate},k}^{i^*-n,j^*} \leftarrow 0$;
      $\text{new\_pop}_{\text{route},k}^{j^*} \leftarrow \text{new\_pop}_{\text{route},k}^{j^*} / i^*$;
    else
      Select the supply node $j' \in \{1,2,\ldots,n\}$, $j' \neq j^*$ with the shortest distance from i^*;
      if $P_{j'} - \sum_{i=1}^{m} \text{new\_pop}_{\text{allocate},k}^{i,j'} \geqslant \text{new\_pop}_{\text{allocate},k}^{i^*-n,j^*}$ **then**
        $\text{new\_pop}_{\text{allocate},k}^{i^*-n,j'} \leftarrow \text{new\_pop}_{\text{allocate},k}^{i^*-n,j'} + \text{new\_pop}_{\text{allocate},k}^{i^*-n,j^*}$, $\text{new\_pop}_{\text{allocate},k}^{i^*-n,j^*} \leftarrow 0$;
        $\text{new\_pop}_{\text{route},k}^{j^*} \leftarrow \text{new\_pop}_{\text{route},k}^{j^*} / i^*$, $\text{new\_pop}_{\text{route},k}^{j'} \leftarrow \text{new\_pop}_{\text{route},k}^{j'} \cup i^*$;
      end if
    end if
    if $\text{new\_pop}_{\text{route},k}^{j'}$ violates constraints **then**
      Reallocate vehicles for $\text{new\_pop}_{\text{route},k}^{j'}$
    end if
    if new_pop_k is better than pop_k **then**
      $\text{pop}_k \leftarrow \text{new\_pop}_k$;
    end if
  end for
end for

adaptive neighborhood selection mechanism embedded VNS (ANS-VNS) for solving multi-depots VRP[40] to optimize the vehicle route scheme herein, where the pseudocode is presented in Algorithm 5.

In terms of the characteristics of the designed model, we design the following 5 neighborhood operators.

(1) **Segment reverse:** Select a segment of a supply node route and reverse it. For instance, in Fig. 6, we choose the route $4 \rightarrow 5 \rightarrow 6$ as the reverse segment and reverse it, and we can obtain $6 \rightarrow 5 \rightarrow 4$. Reallocate the vehicles, and the changed route is $1 \rightarrow 6 \rightarrow 5 \rightarrow 1 \rightarrow 4 \rightarrow 7 \rightarrow 1$.

(2) **Or-opt:** Select a vehicle route in the route of a supply node. Then randomly choose 1−3 sequential demand nodes in the vehicle route and insert them to other positions of the vehicle route. For example, we have chosen demand node 6 as the changed node in Fig. 7. If the insert position is after demand node 7, then the changed vehicle route is $1 \rightarrow 7 \rightarrow 6 \rightarrow 1$.

Algorithm 5 Function RouteOptimization()

Input: Population size NP; number of supply nodes n; number of demand nodes m; pop_k.
Output: Route planning scheme $\text{pop}_{\text{route}}$.
for $k = 1 \rightarrow \text{NP}$ **do**
  Initialize the best-so-far route $B_{\text{route},k} \leftarrow \text{pop}_{\text{route},k}$ and the current route $C_{\text{route},k} \leftarrow \text{pop}_{\text{route},k}$;
  Initialize $g = 0$ and $\text{kk} = 1$;
  while $g < G_{\max}$ **do**
    for $j = 1 \rightarrow n$ **do**
      Select a neighborhood operator by the adaptive neighborhood selection mechanism;
      $N^j_{\text{route}} \leftarrow$Change $C^j_{\text{route},k}$ by the selected neighborhood operator;
      if N^j_{route} satisfies the acceptance criterion **then**
        $C^j_{\text{route},k} \leftarrow N^j_{\text{route}}$;
      end if
      Update the used times and successful times for all neighborhood operators;
    end for
    if $C_{\text{route},k}$ is better than $B_{\text{route},k}$ **then**
      $B_{\text{route},k} \leftarrow C_{\text{route},k}$;
    end if
    if $g = \text{kk} \times G^*$ **then**
      $\text{kk} \leftarrow \text{kk} + 1$;
      Update the weight of each neighborhood operator;
      for $j = 1 \rightarrow n$ **do**
        if $C^j_{\text{route},k}$ is unchanged at G^* iterations **then**
          Perturb $C^j_{\text{route},k}$ by greedy insertion heuristic;
        end if
      end for
    end if
    $g \leftarrow g + 1$;
  end while
end for

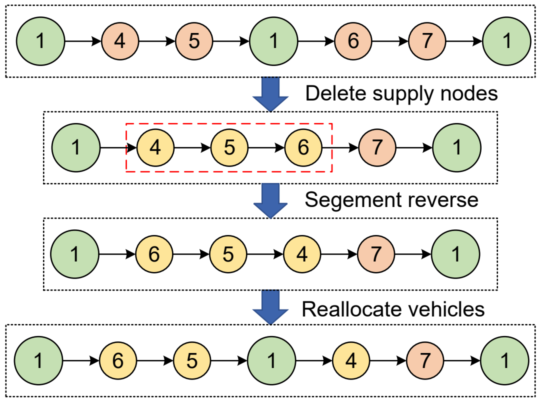

Fig. 6 Example of segment reverse.

(3) **1-0 shift:** Randomly select a demand node in the route of a supply node and transfer it to another vehicle route. For example, in Fig. 8, we select demand node 7 and transfer it to the first vehicle route.

(4) **1-1 swap:** Randomly select two demand nodes located in two different vehicle routes and swap them. In Fig. 9, we choose demand nodes 5 and 6 to swap and

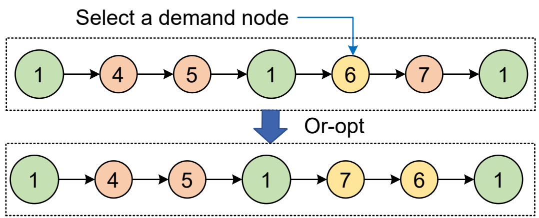

Fig. 7 Example of or-opt.

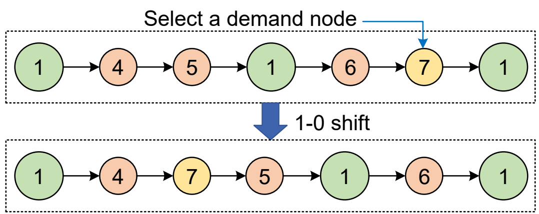

Fig. 8 Example of 1-0 shift.

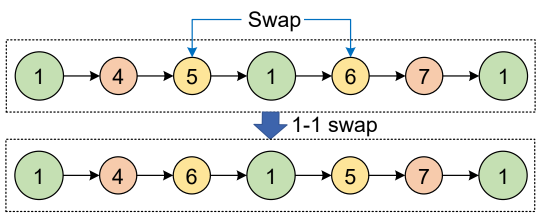

Fig. 9 Example of 1-1 swap.

obtain the changed route $1 \rightarrow 4 \rightarrow 6 \rightarrow 1 \rightarrow 5 \rightarrow 7 \rightarrow 1$.

(5) **2-opt***[41]: Remove two vehicle routes in the route of a supply node and bring in two new vehicle routes. For instance, in Fig. 10, we execute the 2-opt* operator and can obtain the changed route $1 \rightarrow 4 \rightarrow 7 \rightarrow 1 \rightarrow 6 \rightarrow 5 \rightarrow 1$.

3.5 Crossover and mutation

The encoding of an individual in a population consists of a material allocation scheme and a route scheduling scheme.

(1) The first part represents the material allocation scheme and is an $m \times n$ matrix, where the j-th gene in the i-th row denotes the material amount allocated by the supply node j to the demand node $i+n$;

(2) The second part represents the route scheduling scheme, where the j-th row denotes the route of supply node j.

Take material allocation and route scheduling schemes in Figs. 1 and 2 as an example, and the encoding of the individual is shown in Fig. 11, where the material allocation scheme is inverted as an $n \times m$ matrix.

We sequentially select an individual in the parent population as P1, and P2 is randomly selected from the remaining parent population. During the crossover, an offspring inherits most of the genes from the material allocation scheme of P1, and P2 provides several genes to the offspring. Hence, we call P2 a donor. The route scheduling scheme of offspring is changed along with the material allocation scheme. For example, in Fig. 12, the offspring inherits the most genes from the material allocation scheme of P1 and the genes of demand nodes 5 and 7 from the material allocation scheme of P2.

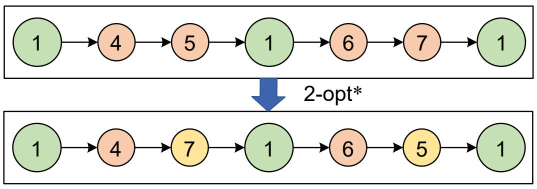

Fig. 10 Example of 2-opt*.

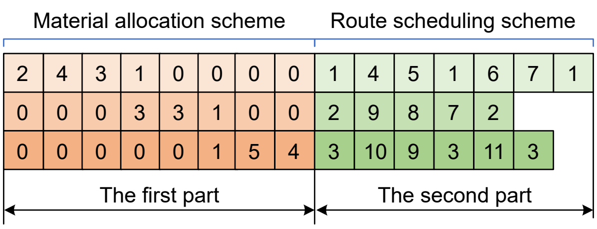

Fig. 11 Illustration of an individual.

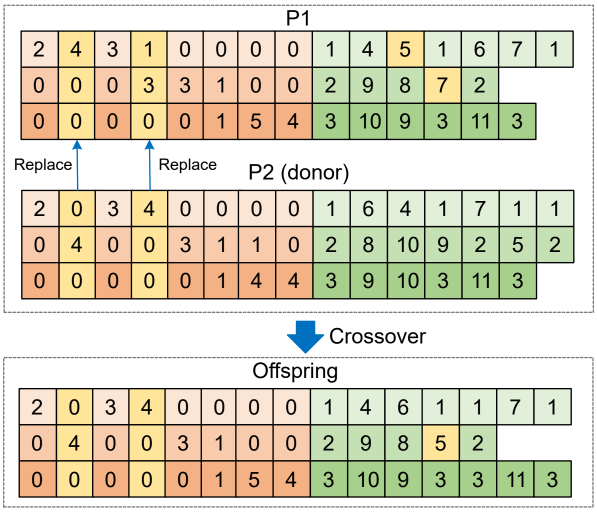

Fig. 12 Illustration of crossover.

As depicted in Fig. 13, the mutation is operated by swapping the amounts of material allocated by two different supply nodes to a demand node (1-1 inter-swap).

3.6 Nondominated sorting and selection strategy

In the nondominated sorting, we consider the influence of model constraints on sorting results. Considering a multi-objective constraint optimization problem with n decision variables and m objective functions:

$$\min f(x) = (f_1(x), f_2(x), \ldots, f_m(x)) \tag{30}$$

We redefine the dominant relationship between individuals x_u and x_v:

$$x_u \prec x_v \Leftrightarrow \begin{cases} f_i(x_u) \leqslant f_i(x_v) \text{ and } f_j(x_u) < f_j(x_v), \text{ if } \bar{v}(x_u),\ \bar{v}(x_v) = 0; \\ \bar{v}(x_u) < \bar{v}(x_v), \text{otherwise} \end{cases} \tag{31}$$

where $\forall i \in \{1, 2, \ldots, m\}$, $\exists j \in \{1, 2, \ldots, m\}$. $\bar{v}$ is the violation degree value.

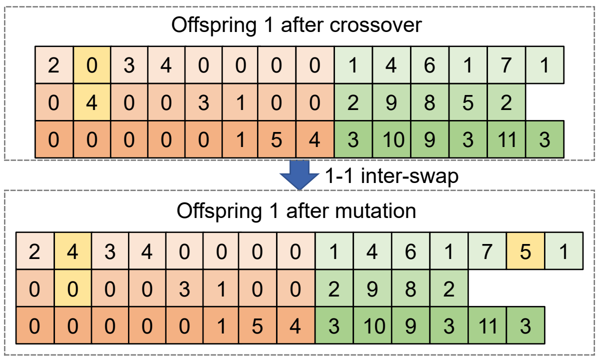

Fig. 13 Illustration of mutation.

In the selection, we first select the top NP individuals according to the nondominated sorting results. Subsequently, we select the top 10% of individuals into the next generation in terms of the elitism strategy and the remaining individuals into the next generation by the 2-tournament selection strategy until the population size into the next generation reaches NP.

4 Integrate Variable Reduction Strategy with VNS-NSGAII

4.1 Problem complexity reduction by variable reduction strategy

The proposed emergency material allocation and route scheduling model involves the equality constraint (4), which will be regarded as the equality optimality condition. Expand Eq. (4) and we obtain

$$\begin{aligned}\varphi_1(x) &= x_{11}+x_{12}+\cdots+x_{1n}=V_1,\\ \varphi_2(x) &= x_{21}+x_{22}+\cdots+x_{2n}=V_2,\\ &\vdots\\ \varphi_m(x) &= x_{m1}+x_{m2}+\cdots+x_{mn}=V_m\end{aligned} \tag{32}$$

In Eq. (32), each equation possesses totally different variables and the variables whose coefficients are not equal to 0 in equation φ_i can be denoted as $\Omega_i=\{x_{i1},x_{i2},\ldots,x_{in}\}$. If we can obtain the following variable relationship by equation φ_i,

$$x_{ik}=R_{ik,i}(\{x_l|l\in\Omega_i,l\neq ik\}) \tag{33}$$

then variable x_{ik} can be reduced by equation φ_i. Among them, x_{ik} is a reduced variable and $\{x_l|l\in\Omega_i,l\neq ik\}$ is a subset of core variables. $R_{ik,i}$ indicates the function expression of x_{ik} derived from equation φ_i. Meanwhile, equation φ_j can be reduced due to being satisfied when calculating variable x_{ik} and is deemed an eliminated equation.

In each equation, we choose a variable as a reduced variable, then m reduced variables can be denoted as

$$X^R=\{x_{1,r1},x_{2,r2},\ldots,x_{m,rm}\} \tag{34}$$

where $x_{i,ri}$, $i\in\{1,2,\ldots,m\}$ indicates the variable reduced by equation φ_i. The set of $m(n-1)$ core variables can be represented as

$$X^C=\{x_{1,c1},\ldots,x_{1,c(n-1)},\ldots,x_{m,c1},\ldots,x_{m,c(n-1)}\} \tag{35}$$

Consequently, the variable relationship between reduced variable $x_{i,ri}$ and core variables $x_{i,cj}$, $j=\{1,2,\ldots,n-1\}$ obtained by equation φ_i is denoted as

$$x_{i,ri}=V_i-\sum_{j=1}^{n-1}x_{i,cj},\ ri\neq cj,i\in\{1,2,\ldots,m\} \tag{36}$$

Meanwhile, the reduction will add the following constraints related to reduced variable x_{ri}.

$$0\leqslant x_{i,ri}=V_i-\sum_{j=1}^{n-1}x_{i,cj}\leqslant\min(Q,V_i) \tag{37}$$

where $x_{i,cj}\in[0,\min(Q,V_i)]$.

Accordingly, the relationship between reduced variables X^R and core variables X^C can be further expressed as

$$\begin{aligned}x_{1,r1}&=V_1-\sum_{j=1}^{n-1}x_{1,cj},\\ x_{2,r2}&=V_2-\sum_{j=1}^{n-1}x_{2,cj},\\ &\vdots\\ x_{m,rm}&=V_m-\sum_{j=1}^{n-1}x_{m,cj}\end{aligned} \tag{38}$$

With the assistance of VRS, the value of reduced variables $\{x_{1,r1},x_{2,r2},\ldots,x_{m,rm}\}$ can be calculated by variable relationships shown in Eq. (38) and the value of core variables. Hence, there are m variables and equations that can be reduced.

In the EMS model, variable x_{ij} denotes the amount of material allocated from supply node B_j to demand node A_i. Hence, regarding demand node A_i, we only need to determine the amount of material allocated from $n-1$ supply nodes to it (i.e., determine $n-1$ core variables in equation φ_i), and the whole allocation scheme of demand node A_i can be acquired by variable relationship in Eq. (36).

In terms of the objective functions in Eqs. (1) and (2), there is a positive correlation between total time and transportation time or total cost and transportation distance. For a demand node, it will take less time and cost to choose a supply node with a shorter transportation distance and time to respond to it. Therefore, to minimize the two objective functions, a supply node with a shorter transportation distance and time to a demand node is more likely to respond to the demand node.

In addition, the application of VRS brings the constraint (37). To gain the lowest constraint violation degree, reduced variable $x_{i,ri}$ and core variables $\{x_{i,c1},x_{i,c2},\ldots,x_{i,c(n-1)}\}$ in equation φ_i can be determined by the following steps.

(1) Record the transportation time from n supply nodes to demand node A_i as $T^d=\{t_{1i},t_{2i},\ldots,t_{ni}\}$ and the transportation distance can be denoted as

$D^d = \{d_{1i}, d_{2i}, \ldots, d_{ni}\}$. Normalize the above transportation time and distance:

$$\overline{T}^d = \frac{T^d - T^d_{\min}}{T^d_{\max} - T^d_{\min}},\ \overline{D}^d = \frac{D^d - D^d_{\min}}{D^d_{\max} - D^d_{\min}} \tag{39}$$

(2) Linearly weight of the normalized transportation time and distance can be obtained

$$\overline{TD}^d = (\overline{T}^d + \overline{D}^d)/2 \tag{40}$$

(3) Record the corresponding supply node with $\min(\overline{TD}^d)$ as B_{ri} and the core variable is denoted as $x_{i,ri}$ in equation φ_i. The remaining variables in equation φ_i are represented as $\{x_{i,cj} | cj \neq ri, j = \{1,2,\ldots,n-1\}\}$, which are regarded as core variables. The relationship of $x_{i,ri}$ and core variables can be indicated as

$$(x_{i,j^*} \cup \{x_{i,cj} | cj \neq j^*, j = \{1,2,\ldots,n-1\}\}) = \Omega_i \tag{41}$$

and

$$(x_{i,j^*} \cap \{x_{i,cj} | cj \neq j^*, j = \{1,2,\ldots,n-1\}\}) = \varnothing \tag{42}$$

The pseudocode of grouping reduced variables and core variables for the proposed EMS model is presented in Algorithm 6.

4.2 Integrate variable reduction strategy with VNS-NSGAII algorithm

Considering the characteristics of the reduced problem and the VNS-NSGAII algorithm, the reduced EMS problem should be solved by the algorithm that integrates VRS and VNS-NSGAII (abbreviated as VRS-VNS-NSGAII). The flowchart of VRS-VNS-NSGAII is exhibited in Fig. 14, where the implementation of VRS-VNS-NSGAII is consistent with that of VNS-NSGAII other than the generation of initial population and offspring population.

For the generation of an initial population, the main difference between VRS-VNS-NSGAII and VNS-NSGAII is the generation of material allocation scheme. VNS-NSGAII randomly generates $m \times n$ variables for material allocation, which cannot ensure the satisfaction of the material demand constraint (4). Nevertheless, VRS-VNS-NSGAII only needs to generate $m \times (n-1)$ core variables. And the value of reduced variables is calculated by the value of core variables and variable relationships. The whole initial material allocation scheme can be acquired by integrating reduced variables and core variables.

In VRS-VNS-NSGAII, the process of generating the material allocation scheme for individual is as follows.

(1) Determine whether a core variable is responded by Eqs. (22) and (43), where the response probability shown in Eq. (23) should be shrunk by the coefficient δ in [0,1) to have a lower constraint violation degree

$$p_{ij} = \delta \frac{1/M_{ij}}{\sum\limits_{j=1}^{n} 1/M_{ij}} \tag{43}$$

where $\delta = 0.5$ and $i \in \{1,2,\ldots,m\}, j \in \{1,2,\ldots,n\}$ herein.

(2) Calculate

$$L_i^d = V_i - \sum_{j=1}^{n-1} x_{i,cj} \tag{44}$$

where $x_{i,cj}, j = \{1,2,\ldots,n-1\}$ are the core variables in equation φ_i.

(3) If $R_{i,cj} = 1$, then core variable $x_{i,cj}$ is calculated by Eq. (45).

$$x_{i,cj} = \max\{0, \mathrm{floor}(\min\{L_i^d, Q/c\} - \sum_{j=1}^{n-1} x_{i,cj}) \times \mathrm{rand}\} \tag{45}$$

where rand denotes a random number between 0 and 1.

(4) Calculate the value of reduced variables by the value of core variables and variable relationship in Eq. (38).

(5) Integrate the value of core variables and reduced variables and obtain the material allocation scheme of pop_k.

(6) Repair the variables that violate material supply

Algorithm 6 Pseudocode of grouping reduced variables and core variables

Input: Equality optimality condition φ; transportation time matrix T; transportation distance matrix D.

Output: Set of reduced variables X^R; set of core variables X^C; set of variable relationships R.

Initialize the set of reduced variables $X^R \leftarrow \varnothing$, set of core variables $X^C \leftarrow \varnothing$, and set of function expressions of variable relationships $R \leftarrow \varnothing$;
for $i = 1 \rightarrow m$ **do**
  $T^d \leftarrow \varnothing$ and $D^d \leftarrow \varnothing$;
  for $j = 1 \rightarrow n$ **do**
    $T^d \leftarrow T^d \cup T_{j,i+n}$, $D^d \leftarrow D^d \cup D_{j,i+n}$;
  end for
  Calculate $\overline{TD}^d$ by Eqs. (39) and (40);
  Record the corresponding supply node with the minimum value in $\overline{TD}^d$ as ri;
  $X^R \leftarrow X^R \cup x_{i,ri}$;
  Put the variables in equation φ_i into set Ω_i;
  $X^C \leftarrow X^C \cup \Omega_i \backslash x_{i,ri}$;
  $R \leftarrow R \cup \mathrm{solve}(\varphi_i, x_{i,ri})$;
end for

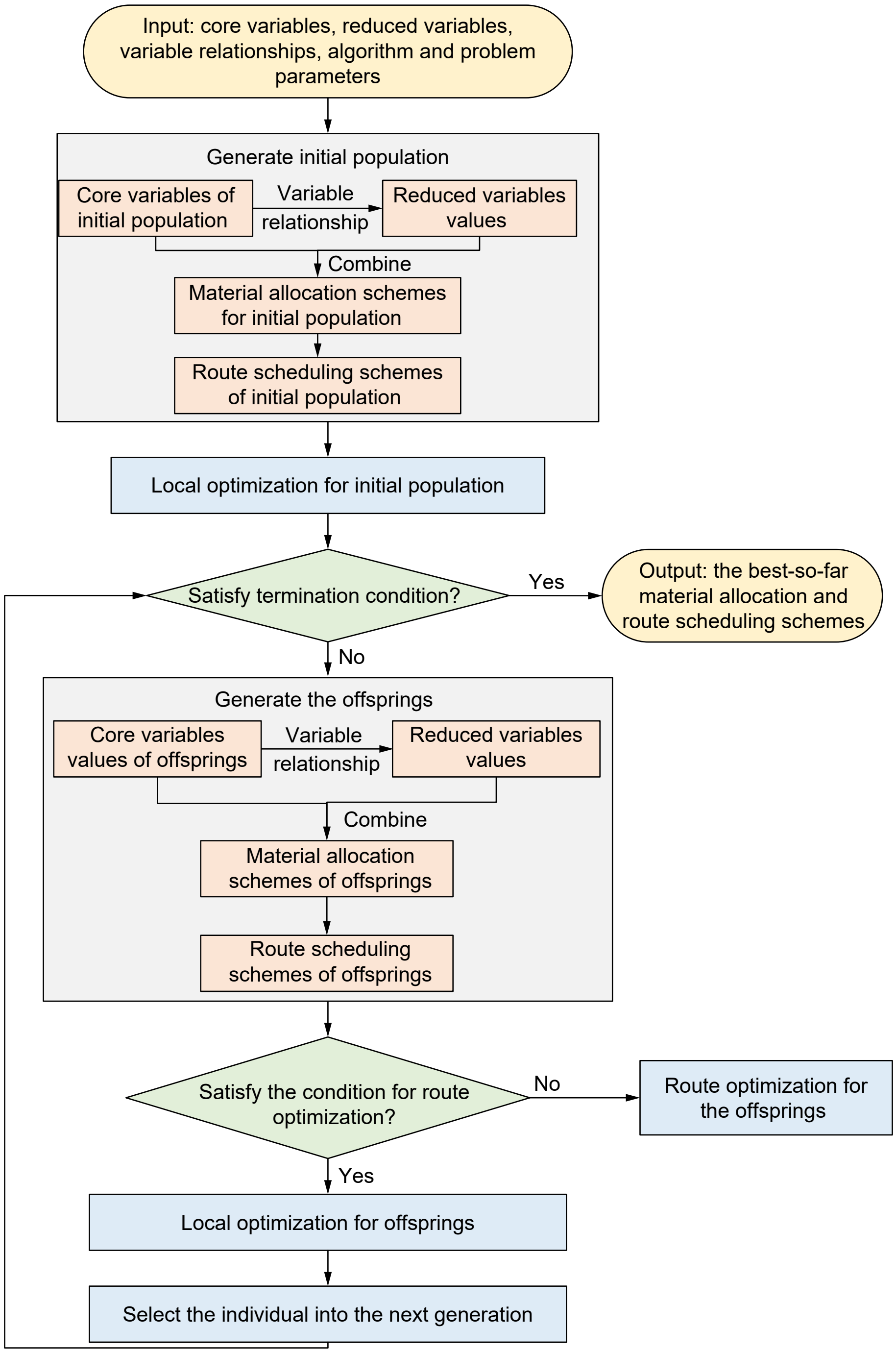

Fig. 14 Flowchart of VRS-VNS-NSGAII.

constraint (5) by the repair strategy proposed in Algorithm 3.

The pseudocode of VRS-VNS-NSGAII for generating the material allocation scheme $pop_{allocate}$ of initial population is presented in Algorithm 7.

Regarding the generation of the offspring, VRS-VNS-NSGAII only executes the crossover and mutation operations for core variables. The value of reduced variables is calculated by core variables.

5 Experimental Study

5.1 Test case

Two test cases are constructed for experimental study. The first case is adapted by multi-depot VRP. The second case combines the initial situation of emergency material support for the 5·12 Wenchuan earthquake.

(1) Test case 1

Test case 1 possesses 5 supply nodes and 50 demand

Algorithm 7 Generation of material allocation scheme of initial population for VRS-VNS-NSGAII

Input: Transport distance matrix D; population size NP; $V_{1\times m}$; number of supply nodes n; number of demand nodes m; capacity of a vehicle Q; weight per unit material c; set of reduced variables X^R; set of core variables X^C; set of variable relationships R.

Output: Material allocation scheme of initial population $\text{pop}_{\text{allocate}}$.

$M_{m\times n} \leftarrow 0$;
for $i = 1 \rightarrow m$ **do**
  for $j = 1 \rightarrow n$ **do**
    $M_{ij} \leftarrow D_{i,j+n}$;
  end for
end for
for $k = 1 \rightarrow \text{NP}$ **do**
  Initialize $R_{m\times n} \leftarrow 0$, $\text{pop}_{\text{allocate},k} \leftarrow 0$, and $P_{m\times n} \leftarrow 0$;
  Determine $R_{m\times n}$ by Eqs. (22) and (43);
for $i = 1 \rightarrow m$ **do**
    $L_i^d \leftarrow V_i$;
    for $j = 1 \rightarrow n$ **do**
      if $R_{ij} = 1$ **then**
        Calculate $\text{pop}_{\text{allocate},k}^{ij}$ by Eq. (45);
        $L_i^d \leftarrow L_i^d - \text{pop}_{\text{allocate},k}^{ij}$;
      end if
    end for
    $\text{pop}_{\text{allocate},k}^{i,ri} \leftarrow V_i - \sum\limits_{j=1}^{n-1} \text{pop}_{\text{allocate},k}^{i,cj}$;
  end for
  $\text{pop}_{\text{allocate},k} \leftarrow$RepairStrategy();
end for

nodes. The location and encoding of each node and the demand amount of each demand node are shown in Fig. 15. Among them, the supply nodes are encoded as 1–5, and the corresponding materials deposited at these

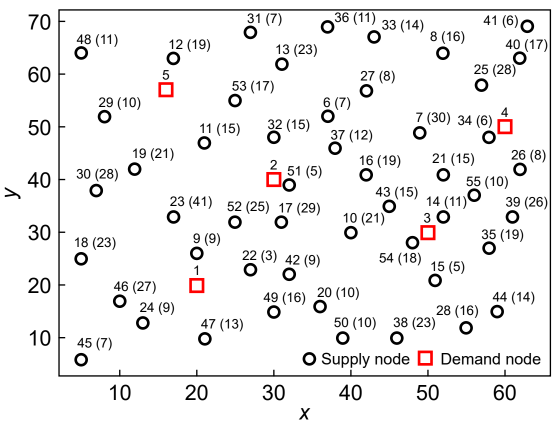

Fig. 15 Illustration of vertexes for test case 1.

supply nodes are {200, 170, 190, 200, 160} in sequence. 50 demand nodes are encoded as 6−55. In Fig. 15, the value in parentheses after a demand node number indicates the amount of material demanded at the demand point. The transportation distance between any two nodes is simply regarded as the Euclidean distance between the two nodes.

(2) Test case 2

We construct test case 2 under the background of the 5·12 Wenchuan earthquake[42]: Dujiangyan, Maoxian, Mianzhu, Mianyang, and Guangyuan are selected as the supply nodes, numbered 1−5. Moreover, 50 places like Guankou Town, Qingchengshan Town, and Xiaojin are the demand nodes, numbered 6−55. The latitude and longitude coordinates of the demand and supply nodes, as well as the transportation distance between any two nodes, are obtained by crawling the API of Amap. The brief information on supply and demand nodes are presented in Tables 2 and 3.

In addition, Table 4 shows the other parameter settings for the two test cases.

5.2 Performance metrics and parameter settings of algorithms

To evaluate the solution obtained by an algorithm, the objective functions and the number of vehicles are firstly selected as the performance metrics. Moreover, we also adopt the hypervolume (HV) to assess the convergence and diversity of an algorithm.

To ensure a fair comparison, the parameter settings of VRS-VNS-NSGAII are consistent with those of VNS-NSGAII, which are exhibited in Table 5. In addition, to enable a reliable comparison, 10 independent runs are executed on each case.

5.3 Experimental results and discussion

The experimental results for VRS-VNS-NSGAII and VNS-NSGAII over 10 independent runs are presented in Tables 6 and 7, including the best, worst, mean, and standard deviation (std.) values of total time, total cost, number of vehicles, and HV.

As shown in Tables 6 and 7, compared with VNS-

Table 2 Brief information on supply nodes for test case 2.

Supply node	No.	Amount of deposited resources
Dujiangyan	1	5800
Maoxian	2	5865
Mianzhu	3	5905
Mianyang	4	5600
Guangyuan	5	5805

Table 3 Brief information on demand nodes for test case 2.

Demand node	No.	Amount of needed resources	Demand node	No.	Amount of needed resources	Demand node	No.	Amount of needed resources
Guankou Town	6	530	Xiaojin	23	340	Luojiang County	40	470
Qingcheng Mountain	7	486	Heishui	24	420	Zhongjiang County	41	530
Hongkou	8	480	Songpan	25	230	Santai County	42	580
Fushun	9	360	An County	26	800	Yanting County	43	630
Feihong	10	380	Xiushui	27	356	Zitong County	44	565
Heihu	11	400	Baolin	28	420	Deyang	45	639
Taiping	12	320	Gaochuan	29	228	Qingchuan	46	705
Li County	13	490	Shifang	30	400	Rubble Township	47	412
Putou Township	14	320	Luoshui Town	31	380	Banqiao Township	48	488
Muka Township	15	200	Shuangsheng Town	32	520	Qima Township	49	450
Tonghua Township	16	480	Yinghua Town	33	480	Yingpan Township	50	410
Wenchuan	17	940	Qingping Town	34	312	Chaotian District	51	802
Yingxiu Town	18	400	Hanwang Town	35	272	Cangxi	52	865
Shuimozhen	19	360	Beichuan	36	720	Jiange	53	775
Wolong Town	20	340	Yongan	37	388	Yuanba Town	54	890
Yanmen Town	21	348	Yongchang	38	400	Xiangyan Town	55	440
Sanjiang	22	308	Kaiping	39	380	–	–	–

Table 4 Parameter settings for the test cases.

Parameter	Value	
	Test case 1	Test case 2
Capacity of a vehicle Q	6 t	20 t
Weight per unit material c	0.1 kg	0.01 kg
Average speed of a vehicle v	60 km/h	70 km/h
Unit time of handling load of a vehicle t	0.01 h/t	0.01 h/t
Transportation cost of per unit distance C_1	10 RMB/km	20 RMB/km
Operation cost for a vehicle C_2	500 RMB	1000 RMB
Maximum allowed transport time for a vehicle L	12 h	18 h
Road access rate β and congestion factor σ	Generate randomly	Generate randomly

Table 5 Parameter settings of the algorithm.

Parameter	Value
Crossover rate P_c	0.9
Mutation rate P_m	0.2
Maximum number of generations of NSGA-II $\text{iter}_{\max}$	200
Indicator for route optimization G	40
Population size NP	20
Maximum number of generations of ANS-VNS $G_{\max}$	200
Indicator for perturbing the best-so-far solution in ANS-VNS G^*	25

NSGAII, VRS-VNS-NSGAII always can obtain a better scheduling scheme with less time and cost as well as fewer vehicles. In addition, the HV indicator values obtained by VRS-VNS-NSGAII are also better than those of VNS-NSGAII.

Regarding solving test case 1, in comparison with VNS-NSGAII, the mean total time and cost of VNS-NSGAII are reduced by 3.36% and 4.83%, respectively. In terms of the number of vehicles, the minimum number of vehicles required for the material scheduling schemes obtained by the VNS-NSGAII algorithm is 15, while the number of vehicles required for the best solution obtained by the VRS-VNS-NSGAII algorithm over 10 runs is 14. Moreover, the mean HV index value obtained by VRS-VNS-NSGAII is 40.94% higher than that of VNS-NSGAII.

For solving test case 2, compared with VNS-NSGAII, the mean total time and total cost of VRS-VNS-NSGAII are reduced by 9.33 h and 11 331.06 RMB. The mean number of vehicles obtained by VRS-VNS-NSGAII is 14.4, which is also lower than the 14.7

Table 6 Total time and total cost for compared algorithms.

Test case No.	Compared algorithm	Total time (h)				Total cost (RMB)			
		Best	Worst	Mean	Std.	Best	Worst	Mean	Std.
1	VRS-VNS-NSGAII	**27.08**	**28.56**	**27.57**	**0.43**	**13 910.55**	**14 389.24**	**14 092.26**	**296.09**
	VNS-NSGAII	27.38	30.05	28.53	1.14	14 023.63	15 720.64	14 808.10	534.34
2	VRS-VNS-NSGAII	**532.59**	**538.65**	**535.41**	**1.76**	**83 893.26**	**90 573.18**	**89 134.53**	**2277.14**
	VNS-NSGAII	533.98	552.00	544.74	5.60	92 425.98	107 950.40	100 465.59	5245.85

Table 7 Number of vehicles and HV indicator values for compared algorithms.

Test case No.	Compared algorithm	Number of vehicles				HV			
		Best	Worst	Mean	Std.	Best	Worst	Mean	Std.
1	VRS-VNS-NSGAII	**14.00**	**16.00**	**15**	0.67	**2.72×10^4**	**1.86×10^4**	**2.41×10^4**	**2.71×10^3**
	VNS-NSGAII	15.00	16.00	15.40	0.52	2.53×10^4	8.40×10^3	1.71×10^4	6.23×10^3
2	VRS-VNS-NSGAII	**14.00**	**16.00**	**14.4**	0.70	**1.65×10^6**	**1.17×10^6**	**1.35×10^6**	**1.40×10^5**
	VNS-NSGAII	14.00	16.00	14.7	0.67	1.30×10^6	3.60×10^5	7.24×10^5	2.91×10^5

obtained by VNS-NSGAII. Furthermore, in terms of the HV indicator, the mean HV value obtained by VRS-VNS-NSGAII is improved by 86.46% than that obtained by VNS-NSGAII over 10 independent runs.

Overall, we can conclude that VRS-VNS- NSGAII is able to obtain higher quality material allocation and route scheduling schemes than VNS-NSGAII, and VRS-VNS-NSGAII possesses better convergence and diversity.

To further study the performance of VRS-VNS-NSGAII and VNS-NSGAII, Fig. 16 shows the convergence process of the normalized weighted objective function value provided by the two algorithms over a single run. The normalized weighted objective function normalizes the two objective functions and weights them linearly, which can eliminate the influence of different dimensions.

It can be observed from Fig. 16 that VRS-VNS-NSGAII converges faster and can robustly obtain better solutions than VNS-NSGAII and that the integration of VRS can noticeably improve the search efficiency of the standard VNS-NSGAII. When solving test case 1, although both VNS-NSGAII and VRS-VNS-NSGAII can converge a solution at about 120 generations, VRS-VNS-NSGAII can converge to a better solution than VNS-NSGAII. For solving test case 2, VNS-NSGAII converges to a solution at about 160 generations, with the assistance of VRS, the algorithm can locate a better solution at about 120 generations.

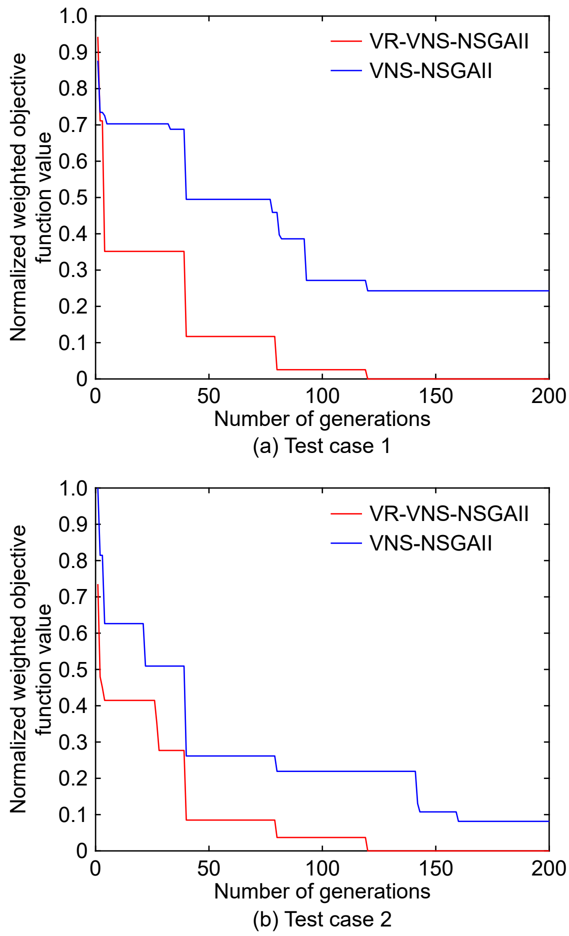

Fig. 16 Convergence curves for the test cases.

6 Conclusion and Future Work

This paper proposes an EMS model and designs a VNS-NSGAII hybrid algorithm to solve it. To improve the search efficiency of VNS-NSGAII, we employ the variable reduction strategy (VRS) to reduce the modeled EMS problem via utilizing the problem characteristics. VRS can reduce some variables, eliminate the demand equality constraint, and result in lower problem complexity. Based on the characteristics of the constructed model and the proposed VNS-NSGAII, we integrate VRS with VNS-NSGAII (which is called the VRS-VNS-NSGAII algorithm) to solve the reduced EMS problem. Based on the multi-depot VRP problem and combined with the initial 5·12 Wenchuan earthquake emergency material support situation, two test cases are constructed in the paper. The relevant experimental study has verified that the integration of VRS can improve the performance of VNS-NSGAII, enabling a better optimization efficiency and a higher quality solution.

It is noted that there are still limitations in this work. On one hand, the EMS model considered is slightly simple herein. On the other hand, we only use an EA to integrate with VRS. Therefore, for future work, we can consider applying VRS to a more complex EMS model with dynamic demands, multiple materials, different vehicle capacities, and so on. Additionally, it would be worthwhile to conduct more research into integrating another potential EA with VRS in order to assist the EA to perform better. Furthermore, the paper provides a reference for employing VRS to effectively solve real-world combinatorial optimization problems, and we can also focus on utilizing the idea of VRS to solve more complicated real-world optimization problems in the future.

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Zhen Shu received the BS degree in applied mathematics from National University of Defense Technology in 1999, the MS degree in management science and engineering from National University of Defense Technology in 2002, and the PhD degree in military command from National University of Defense and Technology in 2013. Currently, he is an associate researcher in the Key Laboratory of Information Systems and Engineering, the College of Systems Engineering, National University of Defense Technology. His research interests include top-level design of complex information systems, service computing, intelligent planning, and other aspects. In recent years, he has published more than 20 academic papers.

Guohua Wu received the BS degree in information systems and the PhD degree in operations research from National University of Defense Technology, China in 2008 and 2014, respectively. During 2012 and 2014, he was a visiting PhD student at University of Alberta, Edmonton, Canada. He is currently a professor at the School of Traffic and Transportation Engineering, Central South University, Changsha, China. His current research interests include planning and scheduling, computational intelligence, and machine learning. He has authored more than 100 referred papers including those published in *IEEE TCYB*, *IEEE TSMCA*, and *IEEE TEVC*. He serves as an associate editor of *Information Sciences* and *Swarm and Evolutionary Computation Journal*, an editorial board member of *International Journal of Bio-Inspired Computation*, and a guest editor of several journals.

Aijuan Song received the BEng and MEng degrees from Central South University, China in 2019 and 2022, respectively. Currently, she is pursuing the PhD degree at the School of Traffic and Transportation Engineering, Central South University. Her research interests include computational intelligence and planning and scheduling.

Witold Pedrycz received the MSc degree in computer science, the PhD degree in computer engineering, and the DSci degree in systems science from Silesian University of Technology, Gliwice, Poland in 1977, 1980, and 1984, respectively. He is a professor and the Canada Research Chair (CRC-Computational Intelligence) with the Department of Electrical and Computer Engineering, University of Alberta, Edmonton, Canada and also with the Department of Electrical and Computer Engineering, the Faculty of Engineering, King Abdulaziz University, Jeddah, Saudi Arabia. He is also with the Systems Research Institute, Polish Academy of Sciences, Warsaw, Poland. In 2012, he was elected a fellow of the Royal Society of Canada. His current research interests include computational intelligence, knowledge discovery and data mining, pattern recognition, knowledge-based neural networks, and software engineering. He has published numerous papers in the above areas. He is an editor-in-chief of *Information Sciences*. He currently serves as an associate editor of *IEEE Transactions on Fuzzy Systems* and *IEEE TSMCS* and a member of a number of editorial boards of other international journals.