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Emergency Logistics Scheduling Under Uncertain Transportation Time Using Online Optimization Methods

YUTONG ZHANG AND JING LIU, (Senior Member, IEEE)
School of Artificial Intelligence, Xidian University, Xi'an 710071, China

Corresponding author: Jing Liu (neouma@163.com)

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ABSTRACT In the immediate aftermath of large-scale disasters, emergency logistics services play important roles in saving lives and reducing losses. Efficient relief logistics scheduling depends on the accurate transport time information for available routes. However, this information cannot be obtained precisely until a vehicle uses the road. Considering the correlation between information acquisition and logistics operations, this paper focuses on a multiperiod online decision-making problem to simulate the information acquiring process. This problem can be referenced for emergency resource scheduling scenarios in which previous decisions impact knowledge for future logistics plans. A multi-trip cumulative capacitated vehicle routing problem with uncertain transportation time is investigated as the basic model. The tradeoff between transportation efficiency and the unknown transport time discovery rate is considered in a multiobjective evolutionary algorithm (MOEA). A memetic algorithm (MA) and a robust optimization (RO) -MA for single-period post-disaster emergency logistics are also proposed to solve the problem for comparison. In these algorithms, evolutionary operators that benefit solution fixing and variation are proposed. In the experiments, a real-world instance is employed. A simulative experimental environment is established. Dynamic information gained within the process of logistics scheduling is highlighted via multi-period online optimization. Different scenarios corresponding to estimates in emergency situations are provided to validate the performance of the algorithms. The experimental results show that the hybrid strategy, MOEA+MA, can obtain the best result in more than half of the considered cases which demonstrates the necessary balance between obtaining information and transportation efficiency.

INDEX TERMS Emergency service, uncertain environment, humanitarian logistics, Pareto optimization, robustness, multiphase scheduling.

I. INTRODUCTION

Natural and man-made disasters cause tremendous losses in lives and economies. Large scale disasters such as regional conflicts, earthquakes, hurricanes, and tsunamis also create victims who must be rescued and citizens who are evacuated from their homes. Organized by local governments or humanitarian organizations, emergency logistics for water, food or daily needs have a significant role in reducing the suffering of survivors over time. In the emergency logistics of post-disaster relief, the transportation infrastructure may be seriously damaged. The roads between local relief distribution centers (or local warehouses) and affected areas are full of uncertainties and hazard which makes the scheduling of emergency logistics different from traditional deterministic transportation planning [1].

Usually, teams of trucks are scheduled to provide relief commodity transportations. Multiple distribution centers [2] are considered in this scenario. Because of the flexible demand in affected areas and the limited capacity of each vehicle, some commodities cannot be unloaded in one place and some needs of any affected area cannot be satisfied with the arrival of a single truck. Considering this application backgrounds, a multi-trip cumulative capacitated vehicle

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routing problem (mt-CCVRP) [3], [4] is investigated in this paper. The scheduling of all available vehicles in logistics can be represented via route and action sequences. The final objective of emergency logistics is to reduce the suffering of the affected people by delivery commodities as quickly as possible.

Post-disaster emergency relief actions are usually conducted in an uncertain and unstable environment. Resource scheduling and planning are complicated by unknown situations that may interfere with well-organized planning by changing various parameters, e.g., demand amount, transportation time, and vehicle availability. In these environments, decision makers should react when the current situation differs from the previous situation. Unexecuted routes and task schedules can be changed at any time if necessary. Therefore, the optimal scheduling framework, which is based on a simple online optimization methodology with an ''optimal decision, implementation, and observation'' loop is proposed. A loop is a period in the following part of this paper. At the end of a period, the data related to the current situation, e.g., vehicle location, commodity storage, demand in affected areas, and transportation time, are collected. Subsequently, a new period is started when the optimizer and decision makers making routing plans or plan variations. Afterward, part of future routing will be changed. In some related research, similar frameworks are referred to as ''rolling horizons'' or ''multiphase frameworks'' [5]–[8].

Decision makers need accurate information as early as possible to issue appropriate command (or routing) changes. Time is one of the key types of information in the uncertain logistics of disaster relief. The transportation time costs around affected areas are the most uncertain factor after a disaster such as an earthquake striking a mountain area. The exact transportation time can be obtained only after a vehicle passes along a road. Vehicle routing is decided within the scheduling process; thus, plans made in previous scheduling periods can affect the knowledge in future scheduling processes. More specifically, updated information about the transportation time in a disaster region is collected by vehicles that are also scheduled for commodity transportation. Executed scheduling commands correspond to vehicle passing routes and acquiring transportation times, which also means more exact transportation times can be utilized in subsequent periods. This paper focuses on the problem of correlated vehicle routing and information updating.

Our work concentrates on how better or worse results could be obtained with existing solutions. Three optimization algorithms, i.e., memetic algorithm for single-period post-disaster emergency logistics (MA_SP_PDEL), multiobjective evolutionary algorithm (MOEA), and robust optimization based on memetic algorithm (RO_MA), are employed with different objective. MA_SP_PDEL and RO_MA are single-objective optimization methods that focus on the benefits of transportation on affected people in addition to RO plus the uncertainty about transportation time. By contrast, MOEA considers the mission based on two objective functions. The first is the objective function of MA_SP_PDEL. The second is the new road discovery rate based on vehicle routing to support scheduling in subsequent periods.

The situation considered in this paper is realistic: decisions must be made with limit knowledge of the model parameters, and scheduling must be adjusted when new information is obtained. A simulative online experimental environment is established. Initially, all transportation times are roughly estimated. Some come from historical information before a disaster or remote sensing from the air. The true transportation time collection procedure is embedded to simulate the real-world application in which the decision maker and scheduler must adjust the routing if a shorter option is discovered.

The performance of different algorithms in five different scenarios corresponding to estimations in emergency situations is studied to reveal some findings in this newly designed emergency logistics scheduling environment. MOEA+MA, a hybrid strategy that changes the optimization method from MOEA to MA_SP_PDEL in the last period of scheduling, outperforms single-objective optimization methods in realistic estimation scenarios. The balance between information gaining (IG) and transportation efficiency (TE) is shown to be unavoidable. Although the objective function value does not demonstrate the advantage of RO_MA, the indirect IG capability is still worth considering.

The contributions of this paper are listed as follows:

i A multiperiod online scheduling problem for post-disaster logistics with unknown transportation time is proposed. The framework for solving the problem with interactive IG is investigated.
ii Three optimization algorithms with different objective functions are employed to solve the problem. The objective function of road transportation time discovery is modeled and utilized in the MOEA.
iii Easy-to-implement simulative environments are designed such that single-period optimization methods can be tested impartially. A real-world instance that combines five different initial estimations of transportation time is considered in the numerical experiments to illustrate the performance of the algorithms.

The remainder of this paper is organized as follows. Section II reviews the related literature. In Section III, the mathematical models for single and multiple scheduling periods are provided. Optimization algorithms are introduced in detail in Section IV. A simulative experimental environment and test instances are constructed in Section V, and the corresponding experimental results are analyzed in Section VI. Section VII concludes the primary findings and present potential directions for future research.

II. RELATED WORK

Dynamic optimization, stochastic programming, and robust optimization are three widely used methods to address various challenges. The dynamic nature is a key characteristic of large-scale disasters [9], [10], Yi and Özdamar designed an integrated evacuation and logistics support model with multiperiod coordination approach that can adjust to information updating [11]. Sheu proposed a demand forecasting method to respond to demand dynamics over time. Data fusion has also been employed to address multiple sources of information acquisition [10]. Najafi *et al.* [12] emphasized the capability of re-routing vehicles at any moment if necessary in their dynamic dispatching and routing algorithm. Fang *et al.* [13] considered sliding time window services and group information updates for drug distribution with time-varying demands. Liu *et al.* [14] employed a robust model predictive control approach to address the challenge of adjusting distribution plan. A rolling horizon-based framework was also proposed to take advantage of the updated information. A common feature in these works is the information input or update during the vehicle dispatch process. Similarly, the problem investigated in this paper also accounts for knowledge that decision makers must consider to avoid suboptimal scheduling. However, in the problem solved in this paper, the information update is related to the executed scheduling which was not addressed in previous studies. Our work actively considers the problem. Information acquisition is accomplished by previous scheduling rather than prediction.

The second method for handling the uncertainty of model parameters is stochastic programming. Garrido *et al.* [15] proposed a spatiotemporal stochastic process model to simulate the impacts of floods in emergency logistics and considered the probability of uncertain demand in affected areas. Rennemo *et al.* [16] presented a three-stages location and routing problem that includes stochastic elements, such as demand, vehicle fleet capacity and infrastructure state. Alem *et al.* [17] employed stochastic mixed-integer programming to support planning in the prepositioning stage and post-disaster transportation stage. Additionally, different risk measures have been highlighted to show the reliability of solutions. A progressive hedging algorithm was applied by Hu *et al.* [6] to solve a multistage stochastic programming model that considered uncertain and dynamic road capacity. Wang *et al.* [18] investigated a time-dependent speed green vehicle routing problem. In these studies, the probability or distribution of a specific scenario or an uncertain parameter must be provided which renders these methods less popular than dynamic optimization approaches and robust optimization approaches. For this reason, stochastic programming is not considered in this paper.

Robust optimization approaches have received considerable attention in this decade as an increasing number of researchers have concentrated on the uncertain nature of disaster scenarios. Zokaee *et al.* [19] proposed a robust counterpart of the relief chain for interval data uncertainty. Najafi. *et al.* [20] investigated a multiobjective robust optimization model for logistics in various situations. Bozorgi-Amiri *et al.* [21] combined robust optimization and stochastic programming to address challenges caused by three sources of uncertainty in disaster relief logistics. Ben-Tal *et al.* [5] initially applied an affinely adjustable robust counterpart approach to overcome demand uncertainty in traffic assignment problems. Dynamic adjustments to the realizations of uncertainty are considered in the proposed framework. This paper inspired us to consider the multistage perspective of logistics scheduling under uncertainty and to employ adjustable decisions when part of the uncertain data is realized. Recently transportation time uncertainty [7], [22] has attracted attention as a fundamental factor after a disaster. In [22], a tractable robust optimization formulation and a coaxial box uncertainty set were proposed. A recent review paper from Govindan *et al.* [23] provided a survey on the uncertainty of supply chain network design, which is helpful for a better understanding of these studies. Unknown transportation time can be considered an uncertainty; so, the robust optimization method is attempted in this research as a comparison.

"Online (or real-time) optimization" is a more appropriate term that describe the methodology employed in this paper. Wilson *et al.* [24] investigated a real-time scheduling problem for mass casualty instance response operations and considered the communication between optimization and the environment. Two types of dynamics affecting the solution space and the value of the objective function were discussed. A rolling-horizon approach was employed in relief distribution scheduling by Lu. *et al.* [8]. State estimation and prediction mechanics were applied in each horizon to mitigate the drawbacks of a lack of information. Jagtenberg *et al.* [25] has benchmarked the problem of ambulance dispatching in the scenario of continuously arriving emergency calls, and an offline model in which all the events that may occur in the future are known in advance was utilized as the lower bound of scheduling performance. In all the above studies, decisions are made within the IG procedure, and schedule fixing is also investigated. Intuitive but efficient, the rolling-horizon method is referenced in this paper and is referred to as multiperiods decision making. The affections of nonoptimal decisions that are based on imperfect information in future scheduling are highlighted in this paper.

The time linkage feature, which was proposed by Bosman [26], describes the aforementioned concerns from the perspective of optimization and is one of the typical features of the problems investigated in this paper. As discussed in the literature, previous decisions that have an influence on future optimizations are the focus of this feature, and some related studies show that a large number of "scheduling and resource allocation" optimizations in dynamic environments have these features [27], [28]. The unknown transportation time is the core factor that influences the implementation of emergency logistics scheduling. The collection of information about transportation time is controlled by the previous scheduling decisions. Nonetheless, the problems in this paper do not fully belong to dynamic time-linkage problems because: (1) although the problem is solved online by collecting real data, it is basically an uncertain optimization problem that is converted to a static optimization problem when all the unknown transportation times are discovered; (2) no prediction technology is involved, but the discovery of unknown information is highly affected by the previous decisions which can be considered a kind of estimation; and (3) the risk of inability to authentically evaluate the performance of any solution when optimizing is high because all the evaluations are based on estimations and current knowledge about the environment.

III. PROBLEM DESCRIPTION AND MODELLING

This section provides mathematical details about emergency logistics situations and objectives. Since real-time simulations are time-consuming, a multiperiod online optimization structure with an information obtaining process is presented for computational research and experiments.

In the single-period model, the mt-CCVRP is investigated in the situation of post-disaster relief in the scenario of uncertain transportation time. For simplicity, homogeneous vehicles are available and only one type of commodity remains to be transported from local warehouses to affected areas. Two initial vehicle statuses are considered, free and traveling, corresponding to the vehicle staying at its final visited location in the previous scheduling window and the vehicle moving from one location to another. When free, a vehicle can execute new commands immediately, while when traveling, the vehicle must first reach the target location before executing the new schedule. The objective of the proposed model is to reduce the accumulative loss of affected areas so that people can receive supplies as quickly as possible. This objective is referred to as the transportation effectiveness in the reminder of this paper. The model is based on the following assumptions:

- i Vehicles can only load the commodity from warehouses, and unload the commodity in an affected area;
- ii Each warehouse has a commodity storage capacity, and no additional commodity will be transported from outside areas during the emergency logistics process;
- iii Each vehicle can visit any location adjacent to its current location;
- iv The connection between any two locations is known in advance, but the transportation times are unknown;
- v The punishments of the losses caused by unsatisfactory commodity shortages in affected areas are based on the shortage and waiting times.

The indices, parameters, and decision variables considered in this paper are presented in TABLE 1.

The mt-CCVRP for post-disaster logistics is formulated as follows:

$$\min f = \sum_{j=1}^{m} Loss_j \tag{1}$$

Subject to:

$$Loss_j = loss_j(e) + loss_j(l) \tag{2}$$

$$loss_j(e) = \int_0^{mom_j} Rem\_dem_j(t) \cdot \left(\frac{Rem\_dem_j(t)}{dem_j}\right)^2 \cdot d(t) \tag{3}$$

TABLE 1. Notations and descriptions.

Notations	Descriptions
i; j	Singular warehouse and singular affected area
I; J	Warehouse set and affected area set
P	Location set ($P = I \cup J$)
V_f; V_t	Set of vehicles with *free* and *traveling* initial status
t_{ab}; t'_{ab}	Real and estimated transportation time from location a to b. ($a, b \in P$)
T	The terminal time of logistics scheduling.
$stor_i$	The initial commodity storage amount in warehouse i
dem_j	The initial demand amount of the commodity in affected area j
mom_j	The urgency moment and unit costs of affected area j
urg_j	The urgency unit costs of affected area j
$Loss_j$	The accumulative loss of affected area j
$Rec\_amo_{j,q}$	The amount of q-th earliest arriving commodity at affected area j
$Rec\_mom_{j,q}$	The q-th earliest moment of the commodity arriving at affected area j
$Rem\_dem_j(t)$	The remaining demand amount of the commodity of affected area j at t ($t \in [0, T]$)

$$loss_j(l) = \int_{mom_j}^{T} urg_j \cdot Rem\_dem_j(t) \cdot \left(\frac{Rem\_dem_j(t)}{dem_j}\right)^2 \cdot d(t) \tag{4}$$

$$Rem\_dem_j(t) = \begin{cases} dem_j & t = 0 \\ \max\left\{\left(dem_j - \sum_{Rec\_mom_{j,q} \le t} Rec\_amo_{j,q}\right), 0\right\} & t > 0 \end{cases} \tag{5}$$

The objective function aims to minimize the accumulative loss for all the affected areas caused by the shortage and latency of the commodity. The loss of each affected area can be calculated by constraints (2) to (5). Each affected area has an urgency coefficient ($urg_j > 1$) and the corresponding moment ($T > mom_j > 0$). These two parameters are determined according to the situation of the affected areas in advance. Commodity shortages lead to more serious consequences if beyond that moment. The fairness of supply is considered by multiplying the square of the ratio of remaining demand quantity to initial demand quantity.

Fairness is a key factor in the evaluation of commodity distribution in almost all aspects of resource scheduling in disaster relief and humanitarian aid. Tzeng *et al.* [29] proposed a tri-objective optimization model for relief delivery and set the minimization of unfair distribution as the third objective function. Bayram *et al.* [30] performed shelter location and evacuation planning in consideration of fairness among evacuees. Hung *et al*. [31] comprehensively modeled the humanitarian objectives in disaster response, and fairness received equal concentration as lifesaving effectiveness and human suffering.

As shown in (3) and (4), the unsatisfied demands are multiplied by the square of the fraction of unsatisfied demands vs. total demands in an area which can be viewed as the degree of dissatisfaction. The higher the degree is, the higher the objective value gaining it would contribute. The nonlinear influence measurement (quadratic) reduces the tolerance of the minority of affected areas to a much higher degree.

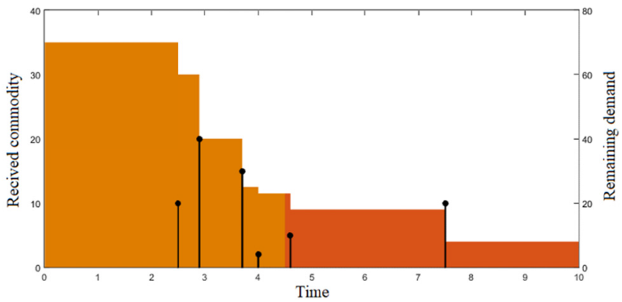

FIGURE 1. Graphical illustration of the calculation of accumulative loss based on an example affected area. The left Y-axis represents the vehicle unloading amount (black stick), and the right Y-axis corresponds to unsatisfied demands (line chart). The shadow divided by the two colors corresponds to the difference in the unit cost of a shortage.

Moments and quantities of commodities that affect areas receiving supply are determined by the vehicle routes and unloading amounts in these areas. For example, Figure 1 reveals the change in the remaining demand in an affected area. In this figure, vehicles arrive in the affected area with moments that do not need to be the same. The shadow area below the curve can be viewed as the accumulative effect of the shortage of the emergency commodity.

The calculation of $Rec\_mom_{j,q}$ and $Rec\_amo_{j,q}$ depends on detailed vehicle scheduling. Scheduling commands can be formulated as target location visiting and loading sequences for each vehicle, i.e., $\{(visit_{v,1}, load_{v,1}), (visit_{v,2}, load_{v,2})\ldots(visit_{v,p}, load_{v,p})\}$, where $load_{v,p}$ is the amount of commodity loaded or unloaded during its p – th mission, and $visit_{v,p}$ is the location of the p – th mission. For example, vehicle V_a is assigned to load γ units of the commodity at its initial location (warehouse i) and unload half of the γ units of the commodity at location j after passing through location m and unload the remaining commodity at location k after passing through location v. The scheduling of V_a can be formulated as: $\{(i, \gamma), (m, 0), (j, -0.5 \times \gamma), (v, 0)$, and $(k, -0.5 \times \gamma)\}$. The tuple of {location, amount} is referred to as a mission.

The transportation time is considered the only factor in the vehicle arrival time, and loading (unloading) time is omitted in this problem. Due to the uncertainty of transportation time in the optimization processes, t_{ab} cannot be used before any implementation of scheduling but can be applied when used in the previous logistics process. In practice, both t_{ab} and its estimation, t'_{ab}, should be employed.

To calculate the changing moment of remaining demand in Figure 1, the action time of missions based on scheduling can be obtained by (6) and (7), corresponding to vehicles with *free* and *traveling* initial status. The variable is labeled $time_{v,p}$, which means the occurrence time of the p – th mission of vehicle v.

$$time_{v,p} = \begin{cases} 0 & p = 1 \\ time_{v,(p-1)} + t_{ab} & p > 1 \end{cases} \quad \forall v \in V_f \tag{6}$$

$$time_{v,p} = \begin{cases} t_{Ori,Tar} - d_v & p = 1 \\ time_{v,(p-1)} + t_{ab} & p > 1 \end{cases} \quad \forall v \in V_t \tag{7}$$

where a is the location that the vehicle visited at its (p - 1) - th target location and b corresponds to the p – th location. *Ori* and *Tar* are the original location and target location, respectively, of the traveling vehicle; and d_v is the duration of traveling from *Ori* to *Tar* in the previous scheduling period. The remaining time from *Ori* to *Tar* cannot be obtained if $t_{Ori,Tar}$ is not revealed by previous scheduling. The difference in arrival time at the first location of the two types of vehicles can be obtained and will affect the following arrival time.

After collecting all the arrival times of vehicles, Rec_mom_j, the sequence of commodity arrival times, can be obtained after sorting all the missions located at j.

The loading of each mission is constrained by the remaining capacity of the vehicle and the remaining storage of the warehouse. The remaining storage of warehouses is calculated by (8).

$$Rem\_sto_i(t) = \begin{cases} stor_i - \sum\limits_{v \in V_f, visit_{v,1} = i} load_{v,1} & t = 0 \\ Rem\_sto_i(0) - \sum\limits_{visit_{v,p} = i, time_{v,p} \le t} load_{v,p} & t \ge 0 \end{cases} \tag{8}$$

Free vehicles starting from a warehouse can collect commodities in the first time step. In equation (8), the change in the remaining storage occurs after a vehicle is loaded at the warehouse. $Rem\_sto_i(T)$ is $stor_i$ in the next period.

$load_{v,p}$ is one of the decision variables. In the following sections, its representation and decision processes are provided in detail. Three natural constraints are considered: 1) the vehicle cannot overload at the warehouse; 2) the warehouse cannot provide a quantity of the commodity that exceeds its capacity, so $Rem\_sto_i(t) > 0$ for any $t > 0$; and 3) the amount unloaded at an affected area cannot exceed the current commodity carrying capacity.

The traditional optimization framework is unsatisfactory because the whole plan is generated before implementation since new information about the environment is not taken into account. The optimal plan might be shown to be unreachable as expected, or suboptimal. Scheduling modifications commonly occur in disaster relief; therefore, a new optimization framework for multiperiod scheduling is proposed for the post-disaster emergency logistics problem. First, four basic assumptions are presented:

i Any scheduling commands can be changed or canceled before execution;

ii The real transportation time of a road between two connected locations will be discovered when any vehicle passes it;

iii Any affected area that receives a surplus commodity will be changed to temporary relief distribution centers with properties that are identical to those of a warehouse;

iv Any vehicle whose schedule is stopped before the end of the last routing will have a *traveling* initial status in the next period.

The above four assumptions guarantee the connection, reasonability and necessity of the following interactive optimization process. Figure 2 shows the operation of the optimal scheduling process:

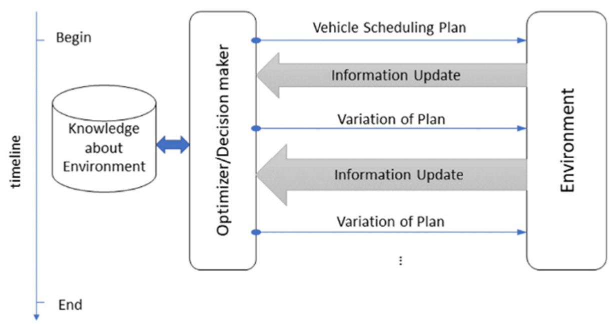

FIGURE 2. **Multiperiod online optimization structure with information obtaining.**

In this process, the initial knowledge of the optimal scheduling method is equivalent to the estimation of the problem parameters, i.e., transportation time. The terminal criteria can be time related such as the terminal moment reached, or progress related such as all commodities being transported to the affected area.

Decision making in the setup of logistics scheduling planning and plans variation is the core of optimization. As the insights of uncertain transportation time become comprehensive, more accurate decisions can be made and involve scheduling by plan variation.

IV. OPTIMIZATION ALGORITHMS

Three optimization algorithms are introduced in this section. Two single-objective optimization algorithms focus on improving TE, while the multiobjective algorithm also considers the promotion of IG when constructing plans. The multi-objective method benefits future scheduling for less uncertainty in each round of scheduling. In a solution (or a scheduling plan), it is expected that more information can be found without considerable loss in TE. The multi-objective evolutionary algorithm is designed to address this trade-off, which can simultaneously optimize these two objective functions. The two single-objective methods are single-period methods in which new plans are made based on the current situation and knowledge. The memetic algorithm addresses the transportation efficiency maximization only and the unknown transportation time is not considered when generating the optimal solution. The robust optimization shares the same objective function with the memetic algorithm, but the transportation time uncertainty is considered in the optimizing process. A solution that achieves better performance in average cases is expected.

In this section, solution representation, decoding method, solution evaluation, and evolutionary operators are commonly used in these three algorithms. Therefore, they are presented independently first. The objective function of IG and bicriteria decisions is explained in subsection *E* within MOEA. The frameworks of these algorithms are not the main contribution of this paper, so we only briefly present them.

A. SOLUTION REPRESENTATION

The scheduling commands of all the vehicles available are employed directly as the solution representation. A two-dimensional array is used. The array consists of a fixed number of vehicle mission lists; for each list, the number of locations assigned to visit is decided by the algorithm. There is a limitation of this direct representation: it is difficult to obtain valid loading and unloading amounts as mentioned in Section III. Therefore, when constructing a chromosome of a solution, varied coding is used to obtain a feasible solution while sacrificing the preciseness of commodity amount control. The chromosome does not directly represent the amount but code the behavior of vehicles at each location. The values $\{-1, 0, \text{and } 1\}$ represent the discrete coding of the behavior that corresponds to {unloading, passing, and loading}, respectively. The amount control at each location is realized by the repetition of successive missions belonging to the same vehicle. Figure 3 shows an example of chromosomes. In this example, Vehicle A loads as much of the commodity as it can at a_1, unloads the entire amount at a_3 and then reload at a_4. Vehicle B unload the commodity at b_2 and b_3. The amount that is unloaded at b_2 is two times that unloaded at b_3. Vehicle N loads at n_1 and n_2 if n_1 does not have sufficient commodity to fulfil N.

B. DECODING AND SOLUTION IMPROVEMENTS

Although it is easy to address volume constraints and no continuous variables are involved, we should still consider other constraints. Four rules are applied to satisfy such constraints when decoding a chromosome: (i) repetition of missions should be performed after unloading; (ii) vehicles shall load as much of the commodity as possible at warehouses with loading assignment and shall not take any commodity from the warehouse when all the stored commodity has been collected by other earlier arriving vehicles; (iii) the repetition of missions should not be separated by the passing mission at the same location; and (iv) the unloading missions between any two successive loading missions will share the commodity taken by the vehicle with the ratio of repetition

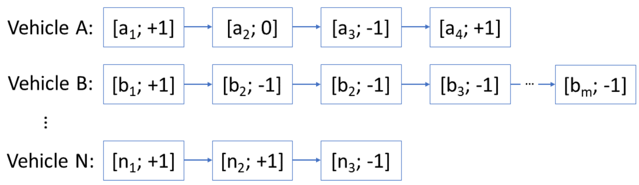

FIGURE 3. **Chromosome representation.**

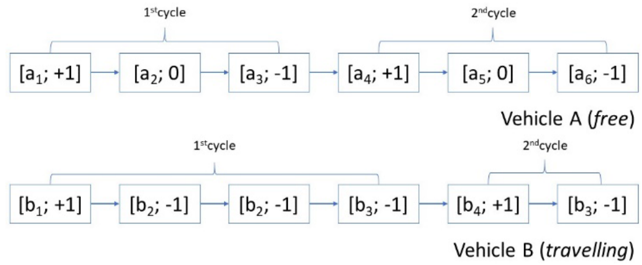

FIGURE 4. **Mission cycle separation of two example vehicles in chromosome.**

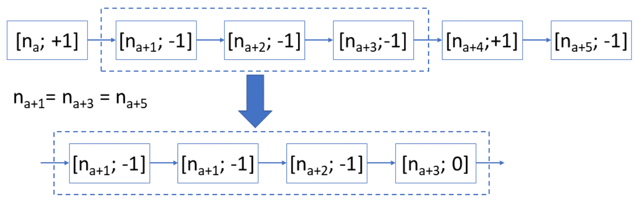

FIGURE 5. **Heuristic adjustment based on common sense.**

counts. However, if only one location is associated with unloading, the repetition will become meaningless and should be replaced by a single unloading mission. When calculating the objective function value, a newly designed operator is employed to fix the chromosome to satisfy the constraints. Algorithm 1 defines the process of this fixing operator, which is named *Rule_based_decoding*.

Line 1 initializes the solution with the problem parameters. The initial status of each vehicle is considered. **Line** 3 adjusts the order of unloading to generate a better chromosome without evaluation. **Line** 4 removes the inappropriate location repetition using the above rules. **Line** 5 generates the solution directly and returns a modified chromosome in which some loading missions with amounts approaching zero are removed. If there is no chromosome change in the process of solution generation, the solution and the fixed chromosome are outputted. Otherwise, the next iteration is conducted to further modify the chromosome.

Algorithm 1 *Rule_Based_Decoding*

```
Begin
1.  Sln.initialize(Par);
2.  Ch_fixed:= Ch_original;
3.  Ch_fixed.unloading_migration();
4.  Ch_fixed.remove_illegal_location_repetition();
5.  Ch_fixed2 = Sln.solution_generation(Ch_fixed, Par);
6.  if (Ch_fixed2 != Ch_fixed) then
7.      Ch_fixed:= Ch_fixed2;
8.      Goto Line 3;
9.  end if
10.   returnCh_fixed, Sln;
End
```

For each vehicle, all the missions can be separated into numbers of transportation cycles that contain one and only one loading mission for vehicles with free initial status (for vehicles with traveling initial status, the unloading missions before the first loading mission form the first transportation cycle). Figure 4 illustrates the mission separation results for two vehicles. As a vehicle with free initial status, vehicle A has two transportation cycles. The first cycle loads from a_1 and unloads all the commodity at a_3. The second cycle loads from a_4 which is adjacent to a_3 and unloads at a_6. The other vehicle must visit b_1 with its load to finish the previous routing, and unloads at b_2 and b_3 as its first cycle.

The earlier the commodity arrives in the affected areas the better the results that rescue can achieve. Within each cycle, the unloading behaviors at the same location should be assigned successively when the vehicle first reaches the location because the time cost of unloading is omitted and the adjustment has no influence on other affected areas. Thus, the commodity or vehicles' route planning is obtained. This adjustment is realized by **Line** 3 in *Rule_based_decoding* and is shown in Figure 5. A vehicle visits n_{a+1} n_{a+2} n_{a+3} sequentially. The unloading at the same place, n_{a+1} and n_{a+3}, should occur at the first visit. Therefore, the adjustment makes the routing more efficient. The revisit of n_{a+5} belongs to the next mission cycle, so the adjustments do not affect it.

At **Line** 5 in *Rule_based_decoding*, the feasible loading and unloading amounts of each mission are decided to construct a feasible solution. According to the estimation and current knowledge of transportation time ($TT_{E\&CK}$), the moment that each vehicle arrives at a warehouse to load the commodity can be calculated. Sorted by the arrival time, vehicles are filled if the remaining amount of commodity in the warehouse is larger than the remaining capacity of the vehicle upon arrival. However, not all loading missions can be satisfied due to the limited supply of warehouses. Hence, there is a moment corresponding to the last vehicle taking all the remaining commodity from a warehouse (usually the vehicle is not full), and a vehicle arriving at this warehouse later than the moment will not receive any commodity. If more than one vehicle simultaneously arrives at the warehouse, a sharing strategy is employed and the vehicles obtain the same amount of commodity if they are not overloaded. After loading, the unloading amount of each unloading mission can be calculated based on the commodity carried by the vehicle in each transportation cycle. The carried commodity will be unloaded within the cycle, and the amount follows the fourth rule.

These amount control operations will be revealed as the amount elements of the solution, so there is no possibility that a warehouse will supply an amount of the commodity that exceeds its storage capacity or that any vehicle will unload an excessive amount of the commodity at an affected area. Meanwhile, the amount control of this decoding process will make some loading and unloading missions invalid because the amount is zero. These "Zero missions" will be transformed to passing missions in which the chromosome will change in behavior. Ch_fix2 corresponds to this changed chromosome.

C. SOLUTION EVALUATION

When calculating the objective function value, the arrival time of each mission should be obtained with $TT_{E\&CK}$. The mission will be omitted if the arrival time exceeds the reference terminal time (RTT) which is one of the problem parameters. Then, the commodity receiving moment and amount can be obtained and the loss at each affected area can be calculated. RTT is used to replace T when applying this optimization algorithm to solve multiperiod scheduling problems with predefined time intervals, such as the concept of horizons in [8].

The value of the objective function can be easily obtained for a feasible solution. The number of missions for each vehicle cannot be limited because the motiveless mission at the end of some vehicles does not influence the calculation of the objective function. The uncontrolled length of mission lists is harmful to the optimal solution searching in evolutionary computation methods. Therefore, transportation costs are employed in the evaluation of chromosomes. The following equation is employed to calculate the fitness value of a chromosome.

$$Fit = \sum_{j=1}^{m} Loss_j + \alpha \times \sum_{v=1}^{|V|} mission\_count_v \tag{9}$$

where the *mission_count* of each vehicle is the number of locations assigned to be visited according to the solution. The coefficient α is a parameter that controls the tolerance of the number of missions and must be determined by decision makers in advance. The fitness evaluation of a chromosome (labeled fitness_evaluation) involves three major steps: (i) rule based decoding; (ii) objective function calculation; and (iii) fitness function value calculation.

D. EVOLUTIONARY OPERATORS

The random walk method is applied to randomly initialize a chromosome, which is labeled *initialization*. The mission count of each vehicle is randomly determined according to a uniform distribution in the range from 8 to 13. Along with the problem parameters, the start location of each vehicle is known and is set to be the current location of the first mission. The next location to visit is randomly selected from the neighbors of the current location with equal probability. To allow repetition, each location includes itself as a virtual neighbor. At warehouse locations, the probability of loading is 0.8 and at affected areas, the probability of unloading is 0.5. If locations in the mission list are repeated in affected areas, the behaviors in both missions are assigned to be unloading.

A set of chromosomes is selected randomly from the population to conduct *crossover*. Child chromosomes are generated via single-point crossover until the number of child chromosomes is the same as the population size. The operator takes two parents and generates two children for each single point crossover. A crossover point is randomly generated, and the vehicles whose ID is larger than the crossover point exchange mission lists. The feasibility of vehicle route connections can be guaranteed by the set of feasible chromosomes.

Four types of *mutation* operators are considered in this paper. In the first operator, two vehicles with more than one mission are randomly selected, and two cutting points are also randomly selected. The missions after the cutting points are exchanged and connected to the other vehicle's mission list. Concerning the location connectivity in the mission lists, the shortest paths found according to $TT_{E\&CK}$ are used in the connection, and in the missions of the connection path, the behaviors are set to be passing. In the second operator, the arrival time for each mission is calculated based on $TT_{E\&CK}$. The mission is removed if a previous location visit falls behind RTT, which has no influence on the vehicle routes before the terminal time. In the third operator, for each vehicle, a head address and tail address are randomly selected first. Missions within the two addresses are removed and the shortest path is used to connect the remaining missions similar to the operation in the first mutation operator. The fourth mutation operator changes the number of passing missions to be unloaded in affected areas to be unloadedwith the probability of 0.5 to increase the number of unloading missions.

Two different strategies are employed to improve chromosomes with limited fitness, which is labeled *local_search*. The first strategy removes passing missions between two operating missions, while the second strategy randomly adds missions for vehicles that can complete all their missions before the RTT.

The first strategy (which can be referred to as "*mission_simplify*") operates on a specific vehicle. All the loading and unloading missions besides the first mission are reserved, as with their original permutation. These missions are then connected by the shortest path as the connection operation in the first mutation operator. Useless traveling can be eliminated by this strategy, which makes the routes of vehicles concise. However, the variation of routes does not always lead to improvement in chromosomes because other vehicles can be affected. In contrast, the second strategy (which can be called "*mission_add*") adds missions to vehicles that have time to conduct more transportation. The random walk method, which is similar to the initialization operator, is employed to add a random number of missions in the range of [1, 5].

Some of the vehicles are not considered by *mission_simplify* to reduce computational costs. Only 10% of vehicles are randomly selected and tested to improve the original chromosomes. The best candidate solution is employed in each iteration to modify the chromosome. If no vehicle whose chromosome can be improved is identified, the *mission_add* strategy is applied 3 times to modify the chromosome without reducing the fitness.

E. MOEA FOR SINGLE-PERIOD POST-DISASTER EMERGENCY LOGISTICS

Discovering more information is a naive but effective idea that makes the subsequent optimization more reasonable due to better knowledge about the problem parameters. However, the task of transportation time discovery also depends on the scheduling of vehicles. The scheduling of vehicles will reduce the efficiency of commodity transportation in some cases. Therefore, evolutionary multi-objective optimization and bi-criterial decisions from the Pareto solution set address the trade-off between transportation efficiency and transportation time discovery so that a more practical scheduling plan can be obtained to improve the global performance in multiperiod post-disaster emergency logistics.

In this model, the number of roads first used by the vehicle can be viewed as a measure of discovery. Nevertheless, without knowledge of the transportation time, the measure of discovery cannot precisely reveal the IG in the following implementation, because the accomplishment of missions is not guaranteed, especially for missions located at the bottom of mission lists. The moment of discovering any transportation time is expected to be as early as possible. Hence, these moments should be included in the measure of discovery.

Road R_{ab} connecting locations a and b is discovered after the end of any pair of missions from a to b (or along the other direction). Consequently, the arrival time of the later mission can be saved and associated with R_{ab}. The earliest arrival time associated with the road is the moment of discovery and is labeled $Disco_{ab}$. For some roads without any mission pair, the moment is set to a large value. All $Disco_{ij}$ value smaller than RTT are accumulated by $score$ with the following equation.

$$score = \frac{\sum_{Disc_{ij}<RTT} e^{-\frac{Disco_{ij}}{RTT}}}{unknown} \tag{10}$$

The normalization of the discovery measure is divided by the maximum number of unknown roads (labeled *unknown*). Therefore, the *score* cannot exceed the range of [0, 1).

Considering the consistency of the objective functions, the two objective functions for logistics are defined as:

$$\begin{aligned} \min f_1 &= \sum_{j=1}^{m} Loss_j + \alpha \times \sum_{v=1}^{|v|} mission\_count_v \\ \min f_2 &= e - score \end{aligned} \tag{11}$$

where e is the base of the natural log. The conflict of these two objectives is shown in the Appendix A.

A multiobjective evolutionary algorithm that is based on NSGA-II [32] is employed to simultaneously minimize the loss in affected areas and maximize the transportation time discovery within the current period. NSGA-II is shown to be efficient for the multiobjective location-routing problem [33]. A dynamic solution selection strategy,in which the higher the unknown transportation time is, the higher the preference of selecting a solution is expected to discover more information. The ratio of discovered roads versus all the roads, i.e., R_{known}, is determined according to the current knowledge. The interval of [0, 1] is divided into three regions by two predefined bounds, i.e., upper bound, U_b, and lower bound, L_b. For case 1, in which R_{known} is higher than U_b, the solution with the minimum value of objective function 1 is selected; for case 2, in which R_{known} it is lower than L_b, the solution with minimum the value of objective function 2 is selected; for case 3 in which R_{known} falls between U_b and L_b, the solution whose cosine distance in the objective space between itself and the preference point is the smallest is selected. The calculation of the cosine distance follows the equations (12) and (13), as shown at the bottom of the page.

where $Extr\_point_1$ corresponds to the solution in the Pareto set with the minimum value of objective function 1, similar to $Extr\_point_2$. Both are 2-dimentional vectors in the objective space. $Ideal\_point = (z_1^*, z_2^*)$, and z_i^* is the minimum value of objective function i within all the solutions in the Pareto set. Figure 6 clearly illustrates the selection preference.

F. MEMETIC ALGORITHM FOR SINGLE-PERIOD POST-DISASTER EMERGENCY LOGISTICS

For each period of vehicle routing scheduling, the transportation time of some roads can change due to the difference between the estimated data and the real data. After the terminal moment set for single period optimization, the next round of optimization is initialized. Form the perspective of satisfying commodity shortages, routings are meaningful if they can be completed before the terminal moment or if they have no benefits to transportation, as they could not be executed. Each period of vehicle routing scheduling is performed to solve a ‘‘subproblem’’ divided by time.

MA_SP_PDEL is started by population *initialization*. In each iteration, chromosomes in the *Population* and *Offspring population*, chromosomes generated in the previous iteration and current iteration respectively, are mass selected by *Binary tournament selection*. A portion of chromosomes in the selected *Population* can be improved by the *local search* operator. Some randomly selected chromosomes are

$$Pref\_point = \frac{R_{known} - L\_b}{U\_b - L\_b} \times Extra\_point_1 + \frac{U\_b - R_{known}}{U\_b - L\_b} \times Extra\_point_2 \tag{12}$$

$$\cos_{solu} = \frac{(Pref\_point - Ideal\_point) \cdot (Solu\_point - Ideal\_point)}{\|Pref\_point - Ideal\_point\|_2 + \|Solu\_point - Ideal\_point\|_2} \tag{13}$$

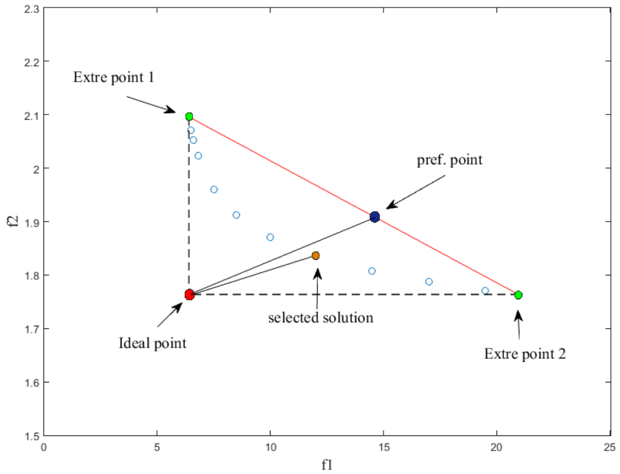

FIGURE 6. Dynamic solution selection with preference point.

used to generate offspring that will be stored in *Offspring population* and some of them will be modified by one of four *mutation* operators. When the iteration time limitation is reached, the best individual in the *Population* can be identified and will be decoded before outputting.

Some additional explanations of operations in MA_SP_PDEL are now considered. In the *Binary tournament selection* operator, two chromosome sets are first combined into a larger chromosome set named *MIX*. Then, in each iteration of tournament selection, two chromosomes with different indices are randomly selected from *MIX* to compare their fitness. The chromosome with a higher fitness value is removed until the number of chromosomes in *MIX* equals *P_size*. The best chromosome is reserved since none of the comparisons cause it to be discarded. The 1% of chromosomes with the best performance are selected in *Top_selection* to conduct the local search operator to minimize the evaluation times and maintain gene diversity in the populations. The candidate parent chromosomes for *crossover* are selected randomly from the population in *Random_selection* with the number being $Pc \times P\_size$.

G. ROBUST OPTIMIZATION FOR SINGLE-PERIOD POST-DISASTER EMERGENCY LOGISTICS

Robust optimization is a commonly used method to address optimization problems with uncertain parameters. In this paper, RO based on scenarios is introduced as a competitor to evaluate the performance of the other algorithms. The methodology of RO is embedded in a memetic algorithm labeled RO_MA.

Scenarios are randomly generated based on $TT_{E\&CK}$. Noise following a normal distribution, i.e., $\mathcal{N}(0, 0.2)$, is added to $TT_{E\&CK}$,which is still unknown, to form different scenarios. The transportation times are set as the lower bound if they are smaller than the lower bound. To ensure a fair comparison, the evaluation times of different algorithms should be similar. As a result, the product of the number of scenarios and the maximum number of iterations in RO_MA should approximate the maximum number of iterations in other algorithms.

The fitness evaluation in RO_MA is the average objective function value of accumulative loss under different scenarios with a penalty for the number of missions. In the rule based decoding process, only $TT_{E\&CK}$ is used to generate a feasible solution and the performance of this solution is evaluated based on all the scenarios. Except for the objective function evaluation, all the operations are the same as those in MA_SP_PDEL and are based on $TT_{E\&CK}$.

V. SIMULATIVE EXPERIMENTAL ENVIRONMENTS

Simulative experiments are necessary to verify the performance of an optimization method before real-world applications, especially for emergency logistics scheduling. The interaction between scheduling, real-world implementation, and uncertain transportation time confirmation is modeled by a simulative experimental environment proposed in this paper. The mechanics of the information update are the major difference between the experiments in this paper and other existing studies [4], [14], [24], [25].

In terms of post-disaster emergency logistics, situations related to infrastructures are reported on time. We compress the simulation of implementations to be momentary, which means that given a pause condition, the circumstances of warehouses, affected areas, vehicles, and transportation times of part of newly utilized roads, in addition to the timeline, are provided instantaneously. The implementation of optimal scheduling plans can be completed within seconds, but the generation of the optimal scheduling plan takes several tens of minutes. Hence, the interactive optimization process is formulated as a loop of {*optimization*, *implementation*, and *information update*}, and the loop represents one period of multiperiod scheduling. The following procedures describe the simplified interactive experimental environment:

Step 1 : Initialize the knowledge for the optimal scheduling method;
Step 2 : Generate an optimal scheduling plan based on the current knowledge;
Step 3 : Implement the optimal scheduling plan and collect the unknown information based on pause conditions;
Step 4 : Update the vehicle status, knowledge of transportation time, and demand & supply quantity;
Step 5 : If the terminal condition is satisfied, then stop this process; otherwise, go to **Step 2**;
Step 6 : Calculate the objective function value according to all the executed schedules.

Step 3 is critical for the continuation of multiperiod optimization. In real applications, the pause conditions can be decided by the optimal scheduling methods or decision makers after observing the implementation of the current plan. However, real-time observations cannot be realized in these experiments and the pause condition must be decided by the optimization algorithms or set in advance. A time break is an intuitive pause condition that assigns the operation duration of the current optimal scheduling plan. The statuses of vehicles in the next period of optimization are also decided. The vehicles can remain at their terminal location according to the plan or travel on their route to the next location. If any vehicle passes a road during this time, the transportation time of the road is known for the next period of optimization. Moreover, the demand and supply quantities are updated to avoid infeasible solutions being generated because of parameter inconformity.

At the end of the experiment, in **Step 6**, all the executed logistics scheduling commands are saved as log data and the defined quantity of the commodity is received in the affected areas. The objective function value is calculated based on these log data for the model in a single scheduling period.

RTT is a significant parameter in the optimizations. A simple strategy is used to automatically decide RTT in each period of optimization. RTT is set to the remaining time of the logistics process when the proportion of the number of current unknown roads versus the number of all the roads is lower than a threshold, which means that the amount of unknown information is sufficiently small that the complete schedule should be made; otherwise, RTT equals RTT_def, a predefined parameter whose influence is discussed in the following experiments. Concerning the different tested instances, a fixed threshold in RTT decisions is unrealistic because not all unknown roads must be visited. The threshold cannot be reached for some algorithms that do not aim to discover information. Thus, a fuzzy threshold is employed to replace the fixed threshold such that the probability of deciding that the next period of optimization is the terminal optimization is linearly related to the proportion. The relation of the probability and the proportion is represented by the following function.

$$Prob. = \begin{cases} 1 & Prop. < L\_bound \\ 1-\frac{Prop.-L\_bound}{U\_bound-L\_bound} & L\_bound \leq Prob. \leq U\_bound \\ 0 & Prop. < U\_bound \end{cases} \tag{14}$$

where *U_bound* and *L_bound* are two parameters that reveal the tolerance of decision makers and are set to 0.2 and 0.05, respectively, in the following experiments.

VI. EXPERIMENTS

A. TEST INSTANCES

The CHICHI earthquake that occurred on Sep. 21, 1999 in Taiwan, China, was employed as a practical case to verify the performance of the algorithms and the proposed optimization model. Such real-world cases are widely used in research on humanitarian logistics and disaster relief operations research [8], [10], [34]–[39]. Specifically, most of the data stem from numerical experiments in [34]. The demanded commodity was a homogeneous necessity of life stored at 4 local warehouses for emergency response. Twenty-nine school campuses in different counties were used as shelters to provide the emergency supply for victims and were regarded as affected areas that demanded the commodity. In this paper, the demand amount of these affected areas is estimated according to the number of people serviced at each location. The urgency degree and corresponding moment are generated randomly within the range of [1, 11] and [5, 25] and both obey a uniform distribution. The amount of storage at each warehouse is set to 99999 units. Ninety-two homogeneous trucks, each with a capacity of 2000 units, are applied to transport the commodity. The real transportation time between two connected locations is estimated based on the direct distance calculated according to the longitude and latitude data. The terminal time of emergency logistics is set to 150 time units.

Moreover, the initial estimation of transportation time is generated based on 5 different considerations. The first 3 types of estimated data are generated with knowledge of TT_R. Disturbance is randomly added to TT_R in different ways: in the first scenario, noisy data obeying the standard normal distribution, i.e., $\mathcal{N}(0, 1)$, are added to simulate a precise estimation. If any transportation time is shorter than the lower bound, i.e., 0.1 unit, it will be regenerated until it is higher than the lower bound. In the second scenario, the absolute value of $\mathcal{N}(0, 1)$ is added to simulate a conservative estimation; in the third scenario, the negative absolute value of $\mathcal{N}(0, 1)$ is added to simulate the usage of transportation time before the disaster, which evidently has better conditions. Similar to the first scenario, none of the transportation times can be lower than the lower bound. As the TT_Rs of different scenarios are the same, the lower bounds of the objective function values are the same, and the results can be contrasted to analyze the different algorithms in different scenarios.

The last two types of estimation are not based on any information about TT_R so that the behaviors of different algorithms can be investigated. The first is the same value estimation, in which all the connected roads are given the same value higher than the lower bound. The second is random estimation, in which all the transportation times are generated according to a uniform distribution within the range of [2, 8].

An example solution is partly represented in Appendix B, complete instance related data is demonstrated in supplementary data.

B. SETTINGS OF TESTED ALGORITHMS

According to primary experiments, population size is set to 100 and the terminal iteration time is 1000, which is practical for real-worlds applications. In RO_MA, the terminal iteration time is reduced to 20 since the number of randomly generated scenarios is 50.

MOEA + MA, is a hybrid strategy that selects an algorithm in the current scheduling period according to the proportion of unknown roads as previously described. If the proportion is smaller than 20%, MA_SP_PDEL is employed; otherwise, MOEA is applied to discover more information. The reason the hybrid strategy is used is that the performance of MOEA

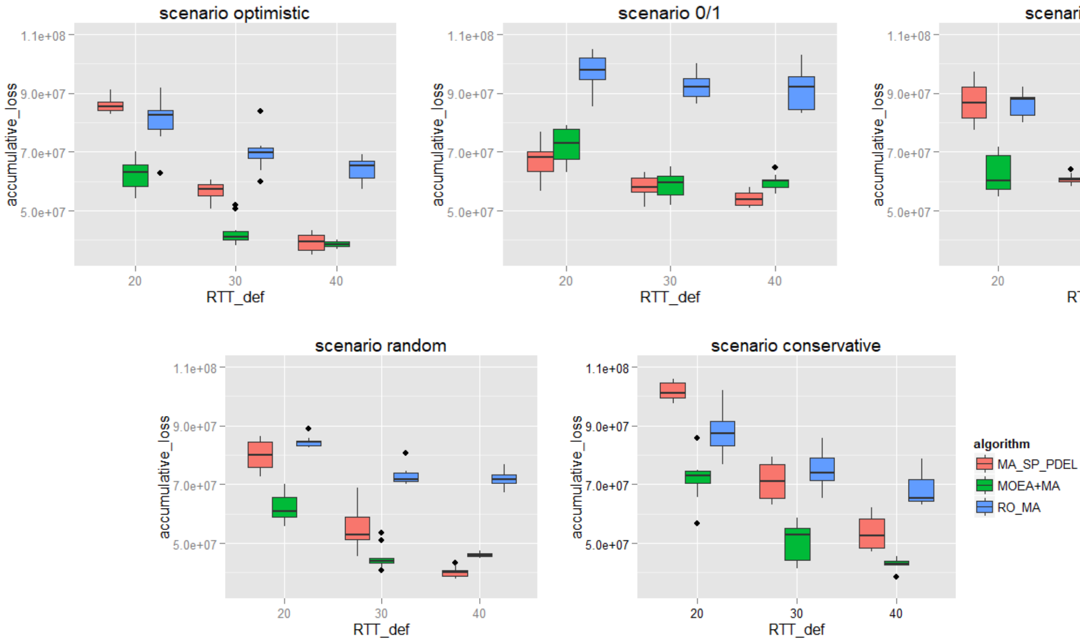

FIGURE 7. **Boxplots of three algorithms' performance in five scenarios.**

declines sharply with the decrease in the proportion and information discovery is less valuable compared to the efficiency of logistics in this situation. Hence, a single-objective optimization method is more suitable for the following logistics scheduling. In MOEA, the population size and terminal iteration time are the same as those in MA_SP_PDEL. *U_b* and *L_b* are set to 0.9 and 0.1, respectively, in multicriteria decision-making.

The three other parameters are the same for all the algorithms. Pm $= 0.25$, Pc $= 0.9$ and $\alpha = 100$. The above algorithm parameters are selected by test experiments. On different synthetic instances, RTT_def varies within $\{20, 30, 40\}$ and the influence is revealed by the variance of the global objective function values.

The algorithms are coded by C++ in Visual Studio 2019. The experiments are conducted using a computer with OS = Windows 10 professional, CPU = Intel Core i7-8550U @ 3.8 GHz, and RAM = 16 GB.

C. EXPERIMENTAL RESULTS AND DISCUSSIONS

Each algorithm is tested 10 times in each scenario with different RTT_def values to observe the stability of results of the algorithms with random mechanics.

Figure 7, consisting of 5 subfigures corresponding to the different scenarios, shows a boxplot of objective values (accumulative_loss). Each subfigure shares the same legend in the subfigure of scenario conservative. Table 2 reports the numerical results of these experiments, including the average objective value and its standard derivation. Average computational times for the first period of each algorithm is also included.

For most cases, the higher the value of RTT_def is, the better the results are. However, the sensitivity of the algorithms is vary. RO_MA shows less sensitivity, while MA_SP_PDEL does not. The stability does not appear to be influenced by RTT_def.

The realistic scenarios lead to better results while the results of scenario 0/1 are worse than random. Compared with the conservative scenario, the optimistic scenario achieves better performance. The random scenario does not result in worse performance than scenarios with more information about real transportation time which exceeds our expectations.

Figure 8 provides more information about the transportation time discovering and the progress of logistics. The subfigures on the left side show the fraction of transportation time discovered at each decision moment, and the subfigures on the right side show the fraction of commodity satisfaction among all affected areas. Discovery stops when the algorithm has sufficient knowledge to complete the remaining logistics scheduling. Not all independent runs result in the same number of decision periods because random factors are considered. Figure 8 (a) and (b) correspond to the accurate scenario and that with RTT_def = 30, while the remaining two subfigures correspond to the random scenario and that with RTT_def = 40.

The boxplots in Figure 7 indicate that MOEA+MA outperforms the other two algorithms in realistic cases, which have transportation times estimated based on real data, but in other cases, it does not. In the realistic case, MOEA finds a better trade-off and guarantees a better result.

TABLE 2. Statistics of the objective values corresponding to Figure 7.

Scenarios	Algorithms	CPU time for the first period	20		30		40	
			Average	SD	Average	SD	Average	SD
0/1	MA_SP_PDEL	639.238s	**6.7492E+07**	6.1146E+06	**5.8175E+07**	3.8424E+06	**5.4054E+07**	2.4744E+06
	MOEA+MA	532.430s	7.2269E+07	5.9566E+06	5.8845E+07	4.2274E+06	5.9667E+07	2.6018E+06
	RO_MA	24.261s	9.8644E+07	7.6167E+06	9.2217E+07	4.4147E+06	9.1248E+07	6.7584E+06
Accurate	MA_SP_PDEL	672.550s	8.7080E+07	6.8604E+06	6.0783E+07	1.7244E+06	4.5971E+07	5.8919E+06
	MOEA+MA	515.671s	**6.2388E+07**	6.4479E+06	**4.6060E+07**	5.7818E+06	**4.2254E+07**	2.1430E+06
	RO_MA	25.372s	8.6513E+07	3.9715E+06	7.4217E+07	2.7520E+06	6.5071E+07	6.2393E+06
Optimistic	MA_SP_PDEL	621.323s	8.5959E+07	2.7046E+06	5.6760E+07	2.9906E+06	**3.7997E+07**	3.6840E+06
	MOEA+MA	525.022s	**6.2354E+07**	5.0273E+06	**4.2768E+07**	4.7243E+06	3.8594E+07	9.5867E+05
	RO_MA	25.180s	8.0635E+07	7.5691E+06	6.9731E+07	6.1572E+06	6.4186E+07	3.7727E+06
Random	MA_SP_PDEL	656.293s	7.9723E+07	5.1479E+06	5.5693E+07	7.9523E+06	**4.0187E+07**	1.7697E+06
	MOEA+MA	536.213s	**6.2009E+07**	4.7064E+06	**4.5084E+07**	4.0277E+06	4.6122E+07	8.4505E+05
	RO_MA	24.372s	8.4510E+07	1.8374E+06	7.3494E+07	4.0573E+06	7.1412E+07	3.1396E+06
Conservative	MA_SP_PDEL	657.190s	1.0177E+08	2.9682E+06	7.1324E+07	6.7290E+06	5.3367E+07	5.7676E+06
	MOEA+MA	566.010s	**7.1913E+07**	7.3904E+06	**5.0703E+07**	6.4209E+06	**4.3143E+07**	1.8637E+06
	RO_MA	24.821s	8.7513E+07	7.2461E+06	7.5278E+07	6.3300E+06	6.8664E+07	5.7038E+06

TABLE 3. Demonstration of a partial solution.

Vehicle ID	Initial Status	Target Location Visiting and Loading Sequences										
1	Free	Location	0	12	13	18	29	30	31	32		
		Loading	2000	0	0	0	0	0	-666.7	-1333.3		
2	Free	Location	0	8	7	6	5	6	7	1	8	…
		Loading	2000	0	-1000	-666.7	-333.3	0	0	2000	-800	…
3	Free	Location	0	12	13	18	28	27	24			
		Loading	2000	-857.1	-285.7	0	0	-571.4	-285.7			
86	Traveling	Location	14	15	14							
		Loading	-1000	-1000	0							
87	Traveling	Location	1	11	12	13	12	11	1	7	8	…
		Loading	0	0	0	-2000	0	0	2000	-1333.3	-6667	…
91	Traveling	Location	21	9	1	7	6					
		Loading	-2000	0	2000	-666.7	-1333.3					

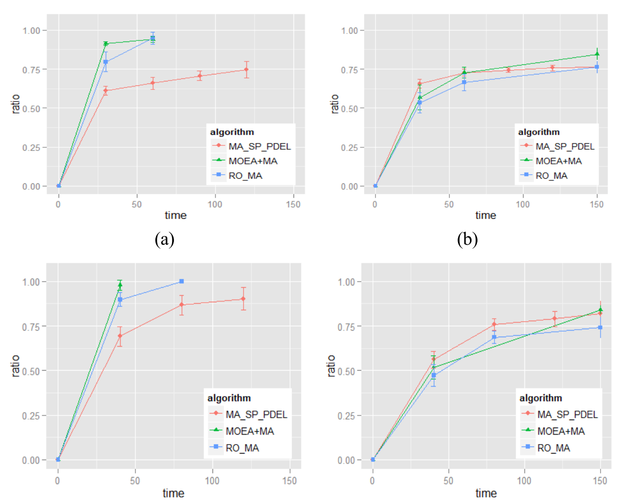

FIGURE 8. Progress of information discovery and commodity delivery.

However, in the unrealistic case, MOEA focuses excessively on information discovery, and the critical transportation at the beginning is omitted. In Figure 8, MOEA and RO_MA show similar progress in information discovery. The best performance in all cases indicates a strong capability of discovery, which is worth investigating and improving in the future.

VII. CONCLUSION AND FUTURE WORK

In this paper, an emergency logistics scheduling problem with transportation time uncertainty is modeled and the issue of dynamic IG controlled by vehicle routing is explicitly considered. An interactive online optimization experimental environment inspired by real-world operations in disaster relief is established. Three population-based evolutionary algorithms concentrating on transportation efficiency, information discovery, and average performance are developed. The experimental results for 5 synthetic scenarios, indicate that MOEA+MA obtained the best results in more than half of the cases based on consideration of both delivery efficiency and information discovery. The effects of information discovery are demonstrated. Meanwhile, RTT_def has a strong influence on the final objective value, and a higher RTT_def is expected. Concerning information discovery efficiency, we should not ignore the performance of RO_MA.

The practical value of this paper is the significance of information gained in scheduling for the scenario of post-disaster relief. In addition, the experimental simulation environment represents an interactive research direction for transportation scheduling with uncertain or unknown components.

The investigation of the relationship between logistics operations and unknown information discovery is the core contribution of this paper. However, this is just the beginning of research on such features in scheduling under uncertainties in which only two conflicting objectives and few optimization methodologies are involved. More real-world applications are believed to contain such features. For these two reasons, our future research will focus on the following two aspects: (1) theoretical analysis based on easy-to-implement problems and (2) application in other scopes such as emergency medication services dispatching.

APPENDIX A
OBJECTIVE FUNCTION CONFLICT ANALYSIS

The conflict of the two objectives proposed in Section VI *E* can be understood by means of an intuitive small instance, as shown in Figure 9. A vehicle full of commodity tends to support affected area D1 from local warehouse S. Two path ways connect these two locations. One is the direct connection and the other passes a location with no demand. According to the estimation of uncertainty TT, reaching D1 directly and returning in the same way is the best choice for logistics efficiency if all the TTs are currently unknown. If we select the other path in the first return, the TT of D1-D2-S will be discovered while the supply arriving in the second cycle of transportation will be extended, which will yield a higher accumulative loss.

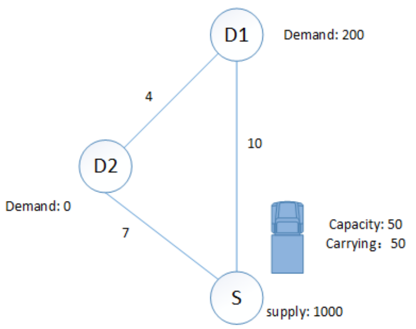

FIGURE 9. A small instance illustrates the existence of conflicts between objectives.

For more complicated cases, we cannot easily find this relationship. Thus, a specially designed MA_SP_PDEL is employed in its first period to demonstrate the trajectory of the best chromosome in each generation. Notably, this implementation is not involved in the following experiments. The experiments are divided into two phases. In the first phase, f_1 is the objective function for the optimization started from a set of random initialized chromosomes. In the second phase, the objective function is changed to f_2 with the best chromosome starting from its final position in optimization phase one. The chromosome with the lowest objective value is marked in the objective space. In the first phase, the population is randomly generated as described in Section VI *D*. However, in the second phase, the population is generated by the mutation operator based on the best chromosome in the last generation of phase one. Figure 10 contains the trajectory of the best chromosome in these two phases and the Pareto front obtained by MOEA. The conflicting relationship can be observed in the objective space, where pursuing the optimal solution in one objective will sacrifice the other. MOEA can find a chromosome with better performance in both objectives, but the diversity of chromosomes in the Pareto front is unsatisfactory.

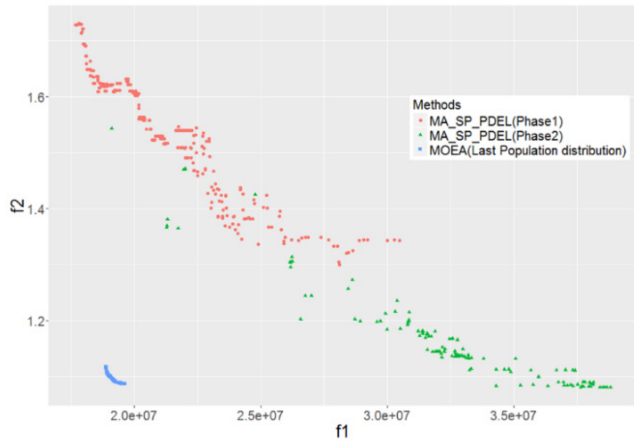

FIGURE 10. Conflict relationship illustration of accurate scenario with RTT_def = 30.

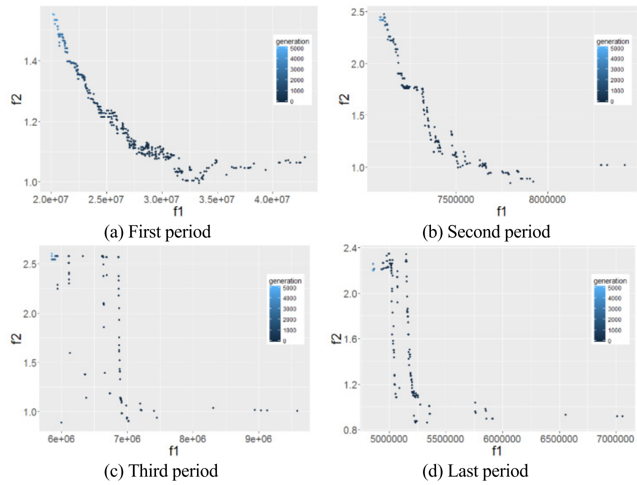

FIGURE 11. Trajectories of the best chromosome generated by MA_SP_PDEL in each scheduling period.

The conflict is not clear in the following periods. In the accurate scenario with RTT_def = 40, MA_SP_PDEL is observed in its conventional experiments in Section VI. The best chromosome is selected to generate scheduling commands. In Figure. 11, as the period count increases, the trajectory shows less correlation between objectives. Therefore, the multiobjective optimization method is affected, and the Pareto front cannot be constructed.

APPENDIX B
SOLUTION REPRESENTATION EXAMPLE

TABLE 3 provides a partial solution outputted by optimizer. Since the number of vehicles is too many, only 6 vehicle routes are contained. Each period of scheduling will generate a solution for optimal vehicle scheduling.

First 3 vehicles are with free initial status, and the last 3 vehicles are with traveling initial status. The vehicle 86 is traveling from #12 to #14 with 2000 unit commodity and the duration of this travel is 5.0 time unit. The vehicle 87 is traveling from #9 to #1 with 2000 unit commodity and the duration of this travel is 7.7 time unit. The vehicle 91 is traveling from #9 to #21 with 2000 unit commodity and the duration of this travel is 6.8 time unit.

The chromosome of these 6 vehicles is:

Vehicle 1: [0, 1]; [12, 0]; [13, 0]; [18, 0]; [29, 0]; [30, 0]; [31, −1]; [32, −1]; [32, −1]

Vehicle 2: [0, 1]; [8, 0]; [7, −1]; [7, −1]; [7, −1]; [6, −1]; [6, −1]; [5, −1]; [6, 0]; [7, 0]; [1, 1]; [8, −1]…

Vehicle 3: [0, 1]; [12, −1]; [12, −1]; [12, −1]; [13, −1]; [18, 0]; [28, 0]; [27, −1]; [27, −1]; [24, −1];

Vehicle 86: [14, −1]; [15, −1]; [14, 0];

Vehicle 87: [1, 0]; [11, 0]; [12, 0]; [13, −1]; [12, 0]; [11, 0]; [1, 1]; [7, −1]; [7, −1]; [8, −1] …

Vehicle 91: [21, −1]; [9, 0]; [1, 1]; [7, −1]; [6, −1]; [6, −1];

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YUTONG ZHANG received the B.S. degree in intelligence science and technology from Xidian University, Xi'an, China, in 2014, where he is currently pursuing the Ph.D. degree in circuits and systems with the School of Artificial Intelligence.

His current research interests include complex scheduling, operations research, and evolutionary algorithms.

JING LIU (Senior Member, IEEE) received the B.S. degree in computer science and technology, and the Ph.D. degree in circuits and systems from Xidian University, Xi'an, China, in 2000 and 2004, respectively.

She joined Xidian University, as a Lecturer, in 2005, where she was promoted to a Full Professor, in 2009. From 2007 to 2008, she was a Postdoctoral Research Fellow with the University of Queensland, Brisbane, QLD, Australia. From 2009 to 2011, she was a Research Associate with the University of New South Wales, Australian Defense Force Academy, Canberra, ACT, Australia. She is currently a Full Professor with the School of Artificial Intelligence, Xidian University. Her current research interests include evolutionary computation, complex networks, fuzzy cognitive maps, multiagent systems, and data mining.

Dr. Liu was the Chair of the Emerging Technologies Technical Committee of IEEE Computational Intelligence Society, from 2017 to 2018. She is an Associate Editor of the IEEE Transactions on Evolutionary Computation.