Emergency Resource Allocation for Multi-Period Post-Disaster Using Multi-Objective Cellular Genetic Algorithm

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ABSTRACT As an important part of emergency response, the post-disaster emergency resource allocation is essential for mitigating disaster losses. To realize the effective allocation of relief materials and the reasonable selection of transportation routes, a multi-objective resource allocation model is proposed, considering the characteristics of uncertainty and persistence during rescue process. Furthermore, the multi-objective cellular genetic algorithm (MOCGA) is developed to solve the model by introducing the auxiliary population and neighborhood structure in the cellular automata. Finally, the comparison experiment proves that the overall performance of MOCGA is satisfactory compared with non-dominated multi-objective whale optimization algorithm (NSMOWOA), non-dominated multi-objective grey wolf optimizer (NSMOGWO) and non-dominated sorting genetic algorithm (NSGA-II) in the pareto front (PF), the hypervolume, the average value of objective function, and the PF ratio. Results show that MOCGA can solve the multi-objective dynamic emergency resource allocation model well, and can provide decision-makers with more excellent and diverse candidate rescue schemes than other algorithms. Besides, by analyzing the rescue schemes, this paper also provides a theoretical rescue scheme for decision-makers' scientific decisions.

INDEX TERMS Cellular genetic algorithm, emergency resource allocation, multi-objective optimization, disaster relief, emergency logistics.

I. INTRODUCTION

In recent years, natural and man-made disasters, such as earthquake, typhoons, and flood, mine collapse, and landslides have occurred more frequently [1]–[7], threatening lives and property. According to the Ministry of Emergency Management of the People's Republic of China, there are 130 million people in China affected by natural disasters in 2018, resulting in a direct economic loss of 264.46 billion yuan. Most disaster losses are due to lack of timely and reasonable emergency resource allocation. In the Haiti earthquake, most of emergency resources were stranded in the logistics web, and rescue operation remained stagnant, resulting the worsening disaster situation [8]. Thus, as an important part of emergency response [9], the post-disaster emergency resource allocation is significant for mitigating disaster losses.

Through the development of emergency resource allocation, we can provide relevant rescue decision models and algorithms to help decision-makers optimize emergency facility location and formulate reasonable emergency material reserve plans. It can also ensure the requirement of emergency rescue supplies in an emergency situation, and formulate rescue schemes with minimal time and disaster losses. Besides, the current research on emergency resource allocation is still in the early stages. By studying the problem of multi-objective and multi-period emergency resource allocation problem, it can not only provide theoretical basis for decision-makers to make scientific rescue schemes, but also promote the related research about emergency management.

Different from general commercial logistics, the emergency resource allocation is aimed to realize the efficient

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rescue material allocation and minimize casualties and losses [10]–[12]. However, due to uncertainties and dynamic changes in the rescue process [13], [14], how to provide a timely and appropriate rescue scheme is critical for the emergency resource allocation [15]–[17]. Moreover, to avoid tardiness from road damage, the uncertainty in the roadway availability cannot be ignored [18]. Therefore, our focus is to realize the effective allocation of relief materials and the reasonable selection of transportation routes.

The emergency resource allocation becomes a popular research topic recently and the research content has developed from maritime disasters to large-scale emergencies [8], [19], [20]. Zhou *et al.* [21] proposed an emergency resource allocation model for dynamic emergency resource scheduling (ERS) problem. Su *et al.* [22] established an emergency resource allocation model and allocated multiple resources to different concurrent events. Aalami and Kattan [23] established a resource allocation model in the process of evacuation based on traffic emergencies. Though according to the planning horizon, most researches can be divided into single-period [24], [25] and multi-period. However, due to the impacts of dynamic changes and uncertainties that accrue over subsequent time periods, single-period models cannot account for the inter-temporal effects. Therefore, lots of multi-period models have also been proposed [12], [26]–[29]. Gendreau *et al.* [30] proposed a dynamic rescue vehicle allocation system for redeployment of rescue vehicles. Yi and Özdamar [31] proposed a multi-period dynamic model of evacuation and resources for post-disaster response. Thus, to solve the characteristics of uncertainty and persistence during rescue process, the multi-period emergency resource allocation model is proposed in this paper.

For reflecting the principle of humanitarian logistics, multi-objective models are contemplated in the majority of emergency resource allocation research. However, to solve models more easily, most researches developed single objective or summed up objectives with weights [32]–[35]. There are only a few researches optimizing different objectives simultaneously. For example, to improve the rescue efficiency, Tzeng *et al.* [36] proposed a multi-objective resource allocation model including cost and transportation time, and allocation satisfaction. Huang *et al.* [37] proposed a multi-objective optimization model based on rescue efficiency, delay cost, and fairness to combine resource allocation with emergency management. Therefore, to realize the effective emergency resource allocation and the reasonable transportation road choice simultaneously, a multi-objective model is established in this paper.

Because of the NP-hardness of emergency resource allocation models, many algorithms have been developed to solve the models [18], [38], [39]. However, most research only consider the single-objective model. There are only a few researches optimizing the conflict objectives simultaneously. For example, Wang applied NSGA-II to solve the location-route multi-objective model [40]. Mohammadia applied a multi-objective particle swarm optimization

algorithm (MOPSO) to solve the location of emergency warehouses [41]. To solve the proposed model and optimize objectives simultaneously, considering the superior performance of MOCGA in finding distributed PFs [42], [43], MOCGA is employed in this paper.

The research objectives of this paper are to realize the efficient emergency resource allocation and the reasonable selection of transportation routes. Besides, by solving the multi-period and multi-period emergency resource allocation problem, we can provide a theoretical rescue scheme for decision-makers' scientific decisions.

Although there has been some emergency resource allocation research, most of which focuses on single-period or single-objective problems. And the main contributions of this are summarized as follows:

(1) A multi-objective dynamic emergency resource allocation model is proposed. For the effective emergency resource allocation and the reasonable transportation road choice, we propose a multi-objective post-disaster emergency resource allocation model and the characteristics of uncertainty and persistence during rescue process are considered.

(2) A multi-objective cellular genetic algorithm (MOCGA) is devised to optimize the proposed model simultaneously. The MOCGA combines the domain structure and evolution operations, and realizes the balance between global and local optimization.

(3) A real case study based on the Wenchuan earthquake is applied to validate the performance of MOCGA in solving the proposed model, and a series of comparison experiments with other multi-objective algorithms, non-dominated multi-objective whale optimization algorithm (NSMOWOA), non-dominated multi-objective grey wolf optimizer (NSMOGWO) and non-dominated sorting genetic algorithm (NSGA-II), are carried out.

The rest parts of this paper are organized as follows. Section 2 is the formulation of the proposed model. Section 3 is about the introduction of MOCGA. Section 4 is about the experiments. Section 5 is about the conclusions.

II. PROBLEM FORMULATION

An efficient and timely emergency resource allocation scheme is essential to mitigate disaster losses. However, due to the uncertainties and dynamic changes in the rescue process, it is hard to satisfy different demands at different periods. Therefore, to obtain effective and timely schemes, a multi-objective resource allocation model is proposed, and the characteristics of uncertainty and persistence during rescue process are considered. The model consists of supply points (SPs), affected points (APs) and the road network, and the resources from SPs are transported to APs through the road network.

A. PRESUMPTION

1. The number and the type of relief supplies storage in SPs and demanded from APs are known at the beginning of each period.

2. The emergency resources from SPs to APs are one-way and cannot exceed the inventory of SPs.

3. The transportation risks between SPs and APs are known before each period.

4. The single transportation mode is adopted and the transportation time is proportional to the distance.

5. There are no transportation between SPs and between APs during the rescue process.

B. LIST OF SYMBOLS
The following are some parameters and symbols in the model.

I	Set of SPs, indexed by i
J	Set of DPs, indexed by j
H	Set of resource types, indexed by h
T	Set of time periods, indexed by t
$p_{j,m}$	The SP with the distance ranked mth from j
$G_{i,h,t}$	The quantity of emergency resources h SP i supplies in time period t
$D_{j,h,t}$	The quantity of emergency resources h AP j demands in time period t
$r_{i,j}$	The transportation risk between SP i and AP j
$dis_{i,j}$	The distance between SP i and AP j
dis_{max}	The maximum allocation distance
$x_{i,j,h,t}$	The quantity of emergency resources h from SP i and AP j in time period t

C. MULTI-OBJECTIVE EMERGENCY RESOURCE ALLOCATION MODEL

There are two objective function proposed in the model. The first objective function is to minimize the disaster losses in the rescue process with the purpose of the effective allocation. And the effective allocation is represented that the demands are satisfied as soon as possible during the rescue process. Thus, the disaster losses are related to the quantity and arrival time of emergency resources, and expressed as the parts surrounded by axis and emergency resource demand function. As the damage losses decrease, it indicates the more efficient and timely emergency resource allocation. The second objective function is to minimize the total risks of the selected routes during the rescue process, and aims at a reasonable choice of transportation routes.

Disaster losses and transportation risks are both important factors in evaluating emergency resource allocation schemes. However, as transportation risks decrease, disaster losses may increase. Thus, in order to realize the optimization of disaster losses and transportation risks simultaneously, the following multi-objective emergency resource allocation model is proposed.

$$\text{Min} \sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{h=1}^{H}\left(g_{j,h,t}^{1}\, dis_{p_{j,1},j} + \sum_{m=1}^{I-1} g_{j,h,t}^{m+1}\left(dis_{p_{j,m+1},j} \right.\right.$$
$$\left.\left. - dis_{p_{j,m},j}\right) + g_{j,h,t}^{I+1}\left(dis_{\max} - dis_{p_{j,I},j}\right)\right) \quad (1)$$

$$\text{Min} \sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{h=1}^{H} x_{i,j,h,t} dis_{i,j}\left(1 - r_{i,j}\right) \quad (2)$$

Subject to

$$x_{i,j,h,t} \geq 0, \quad i \in I,\ j \in J,\ h \in H,\ t \in T \quad (3)$$

$$G_{i,h,1}^{*} = G_{i,h,1}, \quad i \in I,\ h \in H \quad (4)$$

$$G_{i,h,t}^{*} = G_{i,h,t} + \left(G_{i,h,t-1}^{*} - \sum_{j=1}^{J} x_{i,j,h,t-1}\right),$$
$$i \in I, h \in H, t \in T, t \geq 2 \quad (5)$$

$$\sum_{j=1}^{J} x_{i,j,h,t} \leq G_{i,h,t}^{*}, \quad i \in I,\ h \in H,\ t \in T \quad (6)$$

$$\sum_{i=1}^{I} x_{i,j,h,t} \leq D_{j,h,t}, \quad j \in J,\ h \in H,\ t \in T \quad (7)$$

$$g_{j,h,t}^{1} = D_{j,h,t}, \quad j \in J,\ h \in H,\ t \in T \quad (8)$$

$$g_{j,h,t}^{m+1} = g_{j,h,t}^{1} - \sum_{l=1}^{m} x_{p_{j,l},j,h,t}, \quad m \in I,\ j \in J,\ h \in H,\ t \in T \quad (9)$$

Eq. (1), labeled as F1, aims at minimizing disaster losses, and is related to transported emergency resources and arrival time. Eq. (2), labeled as F2, aims at minimizing transportation risks, and is related to transported emergency resources, the distance and risks of selected routes. Eq. (3)-(9) are the constraints. Constraint (3) ensures the transport quantity is non-negative. Constraints (4)-(5) determine the quantity of resources SPs supply at each period. Constraint (6) ensures the transport quantity from SPs at each period does not exceed the quantity of resources SPs supply. Constraints (7) ensures the quantity of resources to APs does not exceed their demands at each period. Constraints (8)-(9) represent the recursive formula of dynamic emergency demand function.

III. MOCGA

Although there are many multi-objective algorithms [44]–[51], some of them are difficult to maintain a good balance between solution quality and diversity. However, the multi-objective cellular genetic algorithm can effectively adjust the balance between global search and local optimization by combing domain structure and evolutionary operation. And the quality and diversity of the optimal solution set are taken into account during the optimization. Due to its excellent optimization performance, MOCGA has been applied in many fields, such as the Transportation Field, but it is rare for emergency resource allocation problems [52]. Therefore, in order to verify the effectiveness of MOCGA for solving the multi-objective emergency resource allocation problems and provide decision makers with more excellent and diverse rescue schemes, this paper employs and modifies the MOCGA.

In order to solve the proposed multi-objective emergency resource allocation model, MOCGA is adopted and adjusted. MOCGA sets a single cell as an individual, enables it

self-learning capabilities, and implements the evolutionary operation in the neighborhood structure of the cellular automaton model. Besides, in order to prevent the superior individuals from being destroyed, MOCGA employs the contemporary superior individuals as the auxiliary population to generate offspring with parents. And the pseudocode of MOCGA is introduced below.

A. CHROMOSOME CODING AND FITNESS EVALUATION

The decision variable in the proposed model $x_{i,j,h,t}$ is real numbers, and indicates the transport quantity of emergency resource h from SP i and AP j in time period t. Therefore, it is intuitive to adopt real coding to represent the resource flows during the rescue process. And each individual represents a rescue scheme, including the transport quantity of different type resources from SPs to APs at different period. Thus, each individual in MOCGA is represented as $Chrom = \{Er_1^1, Er_2^1 \cdots Er_h^t \cdots Er_H^T\}$, divided into $H \times T$ parts according resource types and time periods, and each part is represented as $Er_h^t = \{x_{1,1,h,t}, x_{1,2,h,t} \cdots x_{I,J,h,t}\}$.

To optimize objectives simultaneously, the generated population is subjected to rapid non-dominated sorting [53] and then the fitness is evaluated according the layers individuals are in. Since the individuals in lower layer dominate those in higher layer, they are valuated larger fitness value *Fitness* (*Chrom*) and considered as superior individuals.

B. SELECTION

To conduct the evolutionary operation, individuals are selected separately from the parents and the auxiliary population. In the selection operation on parents, individuals are divided into two-dimensional grids and the selection operation is conducted within the set Ω composed by central cell $Chrom_{i,j}$ and its neighborhood structure. Thus, the selected probability is represented as $P_{i,j}$, $P_{i,j} = \frac{Fitness(Chrom_{i,j})}{\sum_{x,y \in \Omega} Fitness(Chrom_{x,y})}$. Like traditional GA, the roulette wheel method is adopted, but the difference is that individuals involved in roulette are limited the set Ω, and the neighborhood structure in the two-dimensional spatial structure ensures the diversity of the population.

C. SORTING

In order to keep the population size invariant and screen superior individuals in subsequent iteration, it is necessary to conduct sorting on the new population composed by parents and offspring. The sorting operation is based on the fitness and the crowding distance. Therefore, the new population firstly is conducted the fitness evaluation operation, and the individuals with the largest fitness, noted as PFs, and represent the contemporary optimal emergency resource allocation schemes. Then, since individuals in the same layer are valuated the same fitness, the crowding distance is carried to eliminate similar ones and maintain a diverse population. Therefore, the crowding distance is conducted on each layer of individuals, wherein the crowding distance of PFs is 0,

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Algorithm 1 MOCGA

Input:
 NIND: the size of parents or offspring in the iterative procedure, $NIND = I \times J$;
 nind: the size of auxiliary population in the iterative procedure;
 MAXGEN: the maximum iteration number;
 P_c: the probability of cross operation;
 P_m: the probability of mutation operation;
 N: the number of objectives proposed in the model;

Initialization:
 For $(i = 1, 2, \cdots I)$
  For $(j = 1, 2, \cdots J)$
   Initialize the individual $Cell_{i,j}$ according the chromosome coding and the constraints in the model and place it at the two-dimensional grid respectively;
  End for
 End for
 Set the initial population as parents, P;

Iteration:
While $(gen = 1 : MAXGEN)$
 (1) Fitness evaluation:
  Calculate the objective function values of each individuals, $f_n (Cell_{i,j})$, $n \in N$;
  $a = 1$;
  While $(P = \emptyset)$
   Obtain the PFs and note them as $layer_a$, $P = P - layer_a$, $a = a + 1$;
  End while;
  The fitness of each individual *Fitness* $(Cell_{i,j})$ is valued according the layer it is;
 (2) Select the auxiliary population randomly from parents;
 (3) Update the population:
 For $(i = 1, 2, \cdots I)$
  For $(j = 1, 2, \cdots J)$
   If $(P_c > rand)$
    Select two individuals randomly from the $Cell_{i,j}$ and its neighborhood structure Ω and from the auxiliary respectively;
    Conduct the cross operation and if the generated individual $Cell_{i,j}^*$ satisfies the constraints, it replaces the $Cell_{i,j}$;
   End if;
   If $(P_m > rand)$
    Conduct the mutation operation and if the generated individual $Cell_{i,j}^*$ satisfies the constraints, it replaces the $Cell_{i,j}$;
   End if;
  End for;
 End for;
 Set the generated population as offspring, C;
 (4) Sorting:
  $B = [parents; offspring]$;
  Evaluate the fitness and the crowding distance;
  Select *NIND* individuals from B according the fitness and the crowding distance;
  Set the individuals as parents, P;
End while;

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and the crowding distance of individuals at the two ends of the same floor is infinite since their maximum or minimum function value. For those between the ends of the same floor, the crowding distance is valued $C_i = \sum_{n=1}^{N} \left(\left| f_n^{i+1} - f_n^{i-1} \right| \right)$, where N represents the number of objective functions, and f_n^i represents the *nth* objective function value of i. The sorting ensures superior and different individuals as the next generation parents, and improves the average fitness of population.

D. CONSTRAINT OPTIMIZATION

In order to improve the efficiency of generating feasible solution, we restrict the search range in population initialization so that it can generate an initial population that satisfies constraints. And then we write a judgment function about constraints. If the generated individuals meet the constraints, they are returned as new individuals, otherwise they are replaced by previous ones. And the pseudocode of judgment function is introduced below.

Judgment Function

Input:
  $NIND$: the size of parents or offspring in the iterative procedure;
  M: the number of constraint function;
  $Cell^P$: the parents;
  $Cell^C$: the offspring;
Iteration:
  For ($nind = 1, 2, \cdots NIND$)
    For (m$= 1, 2, \cdots M$)
      If $Cell_{nind}^C$ does not satisfy the constraint m
        $Cell_{nind}^C = Cell_{nind}^P$;
        Break;
      End if;
    End for;
  End for;
Output:
  $Cell^C$: the offspring;

IV. EXPERIMENTS

In this section, a series of experiments are conducted to compare the performance of MOCGA with other multi-objective algorithms, such as NSMOWOA, NSMOGWO and NSGA-II in solving the proposed model and to demonstrate application in the rescue process. The instance used in experiments is based on the Wenchuan earthquake, and the location of SPs and APs is shown in Fig.1. The rescue process is divided into two periods and the first period is only for the heavy disaster area. And the predicted supplies and demands at each period, distances and transportation risks in the network are shown in Table 2-4 in Appendix A, which are all simulated based on the population and generated for illustration purpose only.

In order to evaluate the performance, the hypervolume (HV), the PF ratio and the average value of objective function are adopted in the following experiments. The HV and the

PF ratio are to evaluate the quality of PFs, where the PF ratio represents the proportion of superior individuals in the contemporary population. And the average value of objective function is measure to the average performance of the population on the objective function.

A. PARAMETER SETTING

Considering NSMOWOA and NSMOGWO adopt the self-adaptive parameters, the parameter setting is conducted in MOCGA and NSGA-II. As the evolutionary parameters of MOCGA and NSGA-II, P_c and P_m determine the probability of crossover and mutation in the population. Therefore, it is necessary to select suitable parameters in the following experiments. In the parameter setting, the area of cell space is set to 12×10, the size of population is set to 120, the number of iterations is set to 100, and P_c and P_m are increased from 0.1 to 0.9 respectively. The average hypervolume ($ave.HV$) of each parameter is obtained from 6 independent runs.

The simulation results are shown in Fig.2, and indicate the $ave.HV$ of MOCGA and NSGA-II in each combination of parameters. As shown in Fig.2, when $P_c = 0.6$ and $P_m = 0.9$, both MOCGA and NSGA-II have the best performance. Thus, P_c and P_m set to 0.6 and 0.9 in the following experiments.

B. COMPARISON EXPERIMENT

In order to validate the performance of MOCGA compared with other multi-objective algorithms in obtaining rescue schemes, a series experiments are conducted in this section, and the best solution is selected for demonstration. The area of cell space is set to 12×10, the size of population is set to 120, the number of iterations is set to 250, 5 independent runs are conducted.

The PFs of MOCGA, NSMOWOA, NSMOGWO and NSGA-II are shown in Fig.3 (a). It can be seen that the PFs of MOCGA dominate the PFs of other multi-objective algorithms and the number of PFs obtained by MOCGA is also more than others. From the Fig.3 (b), as the iterations (gen) increase, the HV increases, and MOCGA has the better performance compared with others. It indicates that MOCGA can obtain the more excellent and diverse solutions in solving the proposed emergency resource allocation model. The fig.3 (c) shows the PFs ratio in the optimization process. The PF ratio of MOCGA increase as the gen increase, and reach stability faster than NSGA-II. The fig.3 (d)-(e) demonstrate the optimization of conflict objectives in the mode. The objective values are all decreasing with the increasing of iterations, and compared with other algorithms, the MOCGA shows the better performance in dealing with conflict objectives.

From the above results, it shows that the MOCGA has an overall better performance in solving the multi-objective model well and obtains the more excellent and diverse solutions. Thus, compared with other algorithms, MOCGA can not only solve the multi-objective emergency resource allocation well but also provide the decision makers with a set
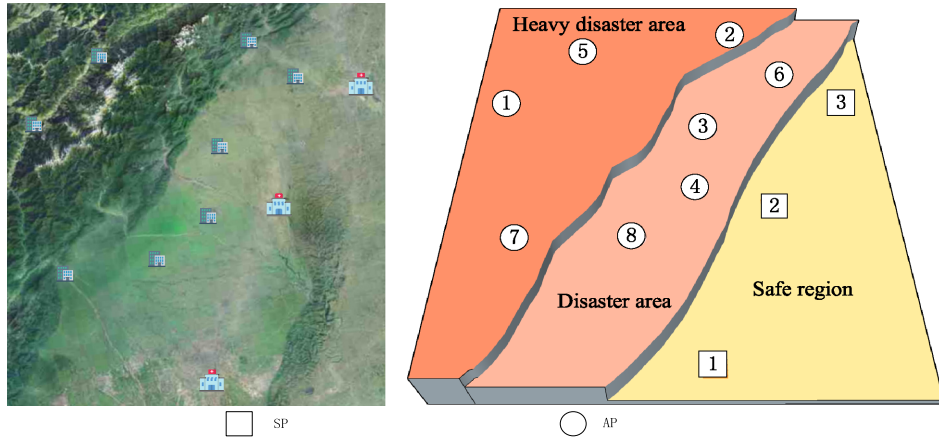
FIGURE 1. Upper graph shows the location of SPs and APs in the instance, where there are three supply points in the safe region and four affected points in the heavy disaster area and the disaster area respectively.
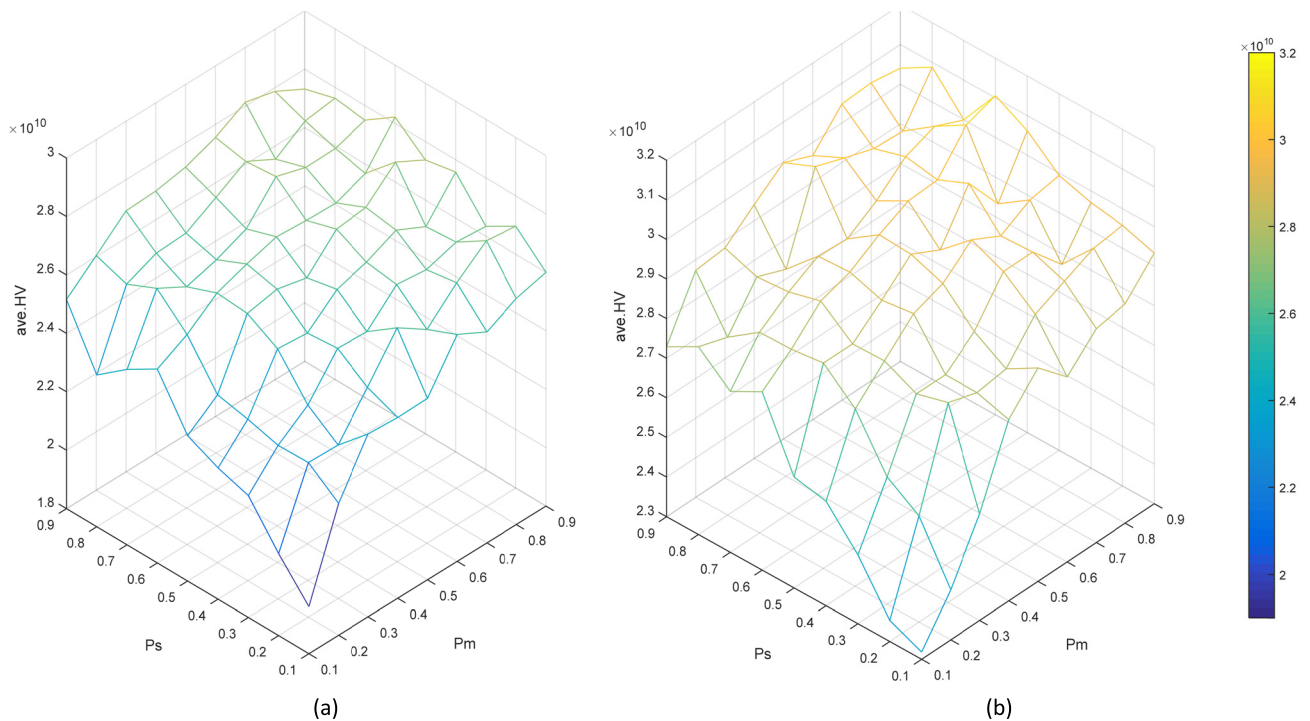

FIGURE 2. Upper graphs show the *ave.HV* with different P_s and P_m, where graph (a) shows the *ave.HV* of NSGA-II and graph (b) shows the *ave.HV* of MOCGA.

of better rescue schemes rather than a single rescue scheme, which empowers the room for discussion and decision.

However, due to the NP-hardness of the proposed model, it is hard to obtain the exact PFs for comparison. Therefore, to validate the effectiveness of MOCGA, the approximate exact PFs obtained from unlimited iterations are employed. As results shown in the Fig.3 (f), there are litter difference between the PFs of MOCGA and the exact PFs, and it indicates that the rescue schemes obtained from MOCGA is sufficiently close to the approximate exact rescue schemes and it can solve the proposed model effectively.

C. SENSITIVITY ANALYSIS
In order to validate the effect of the auxiliary population and the sorting in MOCGA, the sensitivity analysis is conducted in this section. The area of cell space is set to 12×10, the size of population is set to 120, the number of iterations is set to 250, 5 independent runs are conducted, and the best solution is selected for comparison. Fig.4 (a) shows the PFs of MOCGA, MOCGA without the auxiliary population (labeled as A) and MOCGA without the sorting (labeled as B). Results show that PFs of A and B are dominated by MOCGA, it indicates that the auxiliary population and the
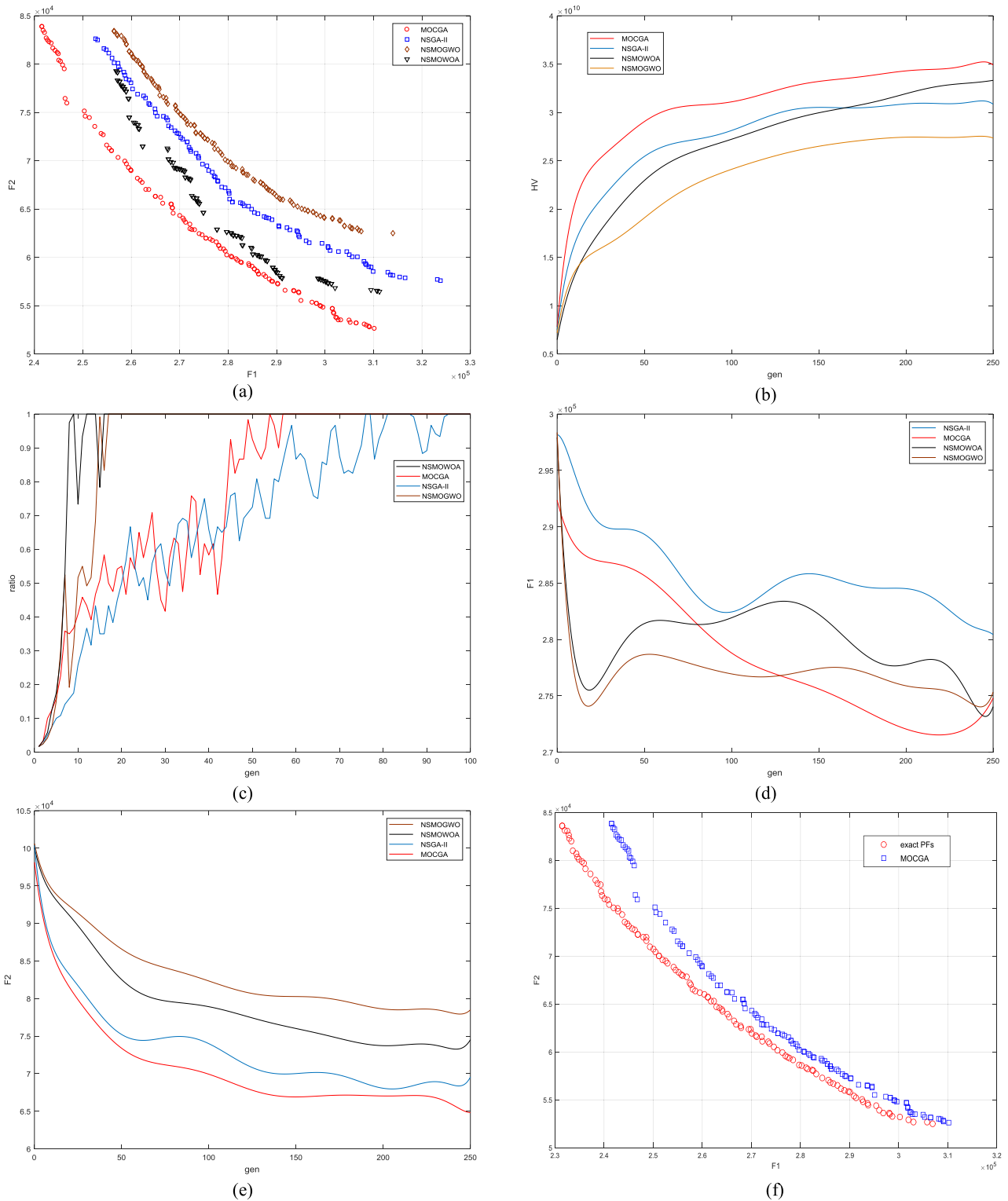
FIGURE 3. Upper graphs show the performance comparison, where graph (a) shows the PFs of MOCGA, NSGA-II, NSMOWOA and NSMOGWO; graph(b) shows the *HV* of MOCGA, NSGA-II, NSMOWOA and NSMOGWO; graph (c) shows the PF ratio of MOCGA, NSGA-II, NSMOWOA and NSMOGWO; graphs (d) and (e) show the average value of objection function of MOCGA, NSGA-II, NSMOWOA and NSMOGWO; graph (f) shows the exact PFs and the PFs of MOCGA.

sorting both play a role in preventing the superior individuals in the population from being destroyed. Moreover, the number of PFs of B is also less than MOCGA and A, it proves

that the sorting ensures superior and different individuals as the next generation parents, and improves the average fitness of population.
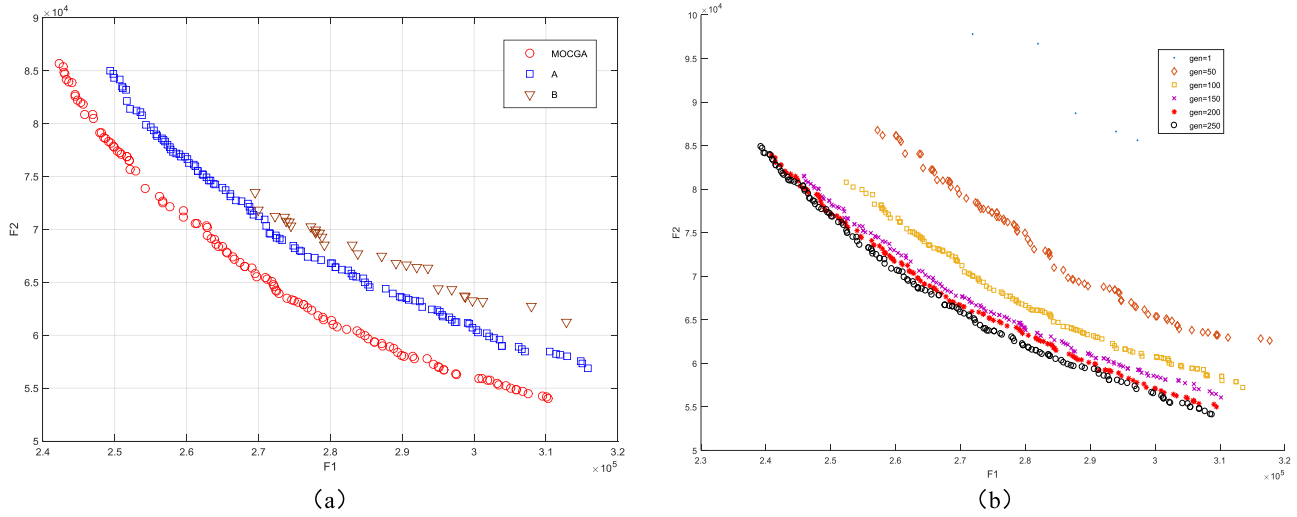
FIGURE 4. Upper graphs show the PFs of MOCGA, where graph (a) shows the PFs of MOCGA, MOCGA without the auxiliary population (labeled as A) and MOCGA without the sorting (labeled as B); graph (b) shows the PFs of MOCGA in different generations.
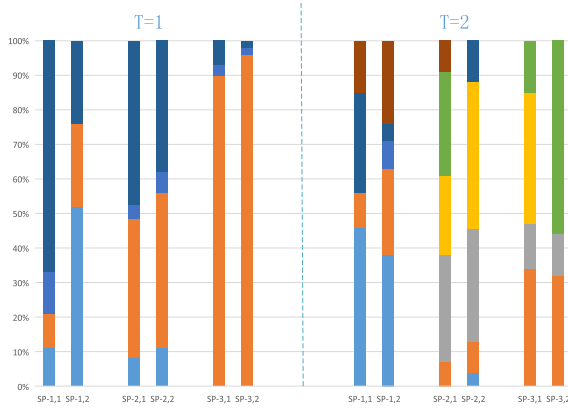

FIGURE 5. The proportion of resource flows in different periods.

TABLE 1. The performance comparison with different generations.

Gen	F1 (10^5)	F2 (10^4)	HV (10^{10})
1	2.97	9.88	1.03
50	2.85	7.33	2.72
100	2.81	6.76	3.14
150	2.75	6.75	3.25
200	2.69	6.90	3.34
250	2.68	6.85	3.40

where $SP - i, h$ represents the flow of resources h from SP i, and $AP - j$ represents AP j. Results show that since the first period is mainly for the heavy disaster area, the resource flows of SPs are limited to the heavy disaster area. However, the main rescue objects between SPs are also different, of which $SP - 1$ is mainly for $AP - 1$ and $AP - 5$, $SP - 2$ is mainly for $AP - 1$ and $AP - 5$, and $SP - 3$ is mainly for $AP - 2$. The second period is both for the heavy disaster area and the disaster area. Therefore, the resource flows from SPs are more complicated. The flows of different resource types from the same SP is different. For example, $SP - 3, 1$ is mainly for $AP - 2$ and $AP - 4$, and $SP - 3, 2$ is mainly for $AP - 2$ and $AP - 6$. It is because the types of emergency resources required for each AP are also different.

By solving the emergency resource allocation model, decision makers can not only obtain the feasible rescue schemes, but also obtain the guiding opinions and develop a rescue scheme based on the real rescue process.

D. INSTANCE ANALYSIS

The instance analysis is divided into two parts, and the first part is to compare the optimal rescues schemes with the initial rescue schemes and validate the effect in the rescue process. Fig.4 (b) shows the PFs of MOCGA in different generations, results demonstrate that the initial PFs are dominated by the optimal PFs. Furthermore, it can be seen from Table 1 that compared to the initial schemes, the average value of F1 is reduced by 10%, the average value of F2 is reduced by 31%, the *HV* of the optimized schemes is increased by 230%. In summary, the optimal schemes have significantly improved in solving the emergency resource allocation problem compared with the initial schemes, and it proves that the optimized resource allocation by MOCGA is of great significance for improving the emergency rescue capability and mitigating post-disaster losses.

The second part is to provide guiding opinions from the optimal rescue schemes. The rescue schemes with the F1 value in the range of $2.6 \sim 2.7 \times 10^5$ are selected for analysis. Therefore, Fig.5 shows statistic of the proportion of emergency resource flows from each SP at each period,

E. CONCLUDING REMARKS

Firstly, through a series of comparison experiments, it is proved that MOCGA can only handle the proposed emergency resource allocation model well, but also find excellent and diverse PFs. It shows that MOCGA provides a set of better rescue schemes for decision makers than other algorithms. Secondly, in order to validate the effect of the auxiliary population and the sorting in MOCGA, we conduct the sensitivity analysis. It proves that they can ensure superior and different individuals as the next generation parents, and

TABLE 2. The supply of SPs and the demand of APs in different periods.

H	T	SP_1	SP_2	SP_3	AP_1	AP_2	AP_3	AP_4	AP_5	AP_6	AP_7	AP_8
1	1	80	80	60	90	80	0	0	50	0	50	0
	2	200	120	80	80	60	60	70	30	60	50	40
2	1	160	100	80	150	130	0	0	80	0	50	0
	2	320	180	140	130	120	90	100	70	80	40	50

TABLE 3. The distance between SPs and DPs.

	AP_1	AP_2	AP_3	AP_4	AP_5	AP_6	AP_7	AP_8
SP_1	149	185	212	89	204	120	62	52
SP_2	186	127	57	34	240	63	99	62
SP_3	227	92	86	85	235	28	141	126

TABLE 4. The risks between SPs and DPs.

	AP_1	AP_2	AP_3	AP_4	AP_5	AP_6	AP_7	AP_8
SP_1	0.47	0.68	0.40	0.21	0.64	0.23	0.60	0.30
SP_2	0.67	0.56	0.25	0.28	0.67	0.45	0.60	0.49
SP_3	0.62	0.31	0.41	0.21	0.57	0.41	0.46	0.21

improve the average fitness of population. Thirdly, in the instance analysis, we develop a scientific rescue scheme to solve the multi-period and multi-objective emergency rescue problem, which provides guidance for the rescue process.

V. CONCLUSION
The efficient and reasonable emergency resource allocation schemes are of significance to the post-disaster rescue process. Based on the characteristics of uncertainty and persistence of natural rescue process, this paper establishes a multi-objective and multi-period emergency resource allocation model. The model is proposed to minimize the disaster losses and the transportation risks in the rescue process, and realizes the effective allocation of relief supplies and reasonable choice of transportation routes. To optimize the conflict multi-objective functions simultaneously, the multi-objective cellular genetic algorithm is developed. The MOCGA realizes the balance between global and local optimization and obtains a set of excellent diversity resource allocation schemes.

From the comparison experiments, it demonstrates that MOCGA has a better performance than NSMOWOA, NSMOGWO and NSGA-II in solving the multi-objective emergency resource allocation model, and has better superiority and stability in the searching process. Thus, MOCGA can provides decision makers with better rescue schemes. Furthermore, the sensitivity analysis shows that the auxiliary population and the sorting are essential to MOCGA. They not only ensure the superior individuals, but also preserve the diversity of the population in the searching process.

It proves that the optimization of rescue schemes is of great significance for improving emergency rescue capability, reducing post-disaster losses, and providing guiding opinions in the rescue process. However, there are still many limitations in this paper. Firstly, the constraints in the initialization

are satisfied by limiting the scope of the search rather than penalty functions. We will take other constraint optimization methods into account. Secondly, there are few researches referred to the multi-objective dynamic emergency resource allocation, which means it is hard to compare with other study. We will take this drawback into account, and develop methods to compare in different models. Thirdly, the disaster chain has been a hot topic, and it has not been considered in this paper. In the future, we will take the primary and secondary disaster into consideration.

APPENDIX
The date of the instance is shown in the Table 2, 3, 4.

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