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A HYBRID CODE GENETIC ALGORITHM FOR VRP IN PUBLIC-PRIVATE EMERGENCY COLLABORATIONS

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Abstract
To minimize the total time for the distribution of relief commodities participated by both private companies and the government, a vehicle routing problem (VRP) model in emergencies was proposed. Considering the differences in the starting points of vehicles, the VRP of general logistics, and departments of vehicles, constraints, such as vehicle capacity limitation and time windows, were introduced into the model, which was close to meeting the practical demands of emergency relief. A hybrid code genetic algorithm (HCGA) was proposed, and it used dynamic mutations to avoid early traps in local optimization and to accelerate convergence. This algorithm was programmed by MATLAB. Furthermore, the vehicle routing optimization plans in an emergency was calculated by a simple genetic algorithm (SGA) and the HCGA, respectively. Results demonstrate that the total time for relief distribution in the HCGA is 11.62 % lower and the calculation time is 14.24 % shorter than that of the SGA. The HCGA is not only convenient in processing the constraints of the model and the natural description of problem solutions, but it is also effective in improving the complexity.
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Key Words: Emergency Logistics, Vehicle Routing Problem, Genetic Algorithm, Health Emergencies

1. INTRODUCTION

Recently, emergencies, such as earthquakes, tsunamis, and epidemics, occur frequently worldwide, and thus private enterprises can play a vital role in humanitarian relief area [1]. In 2013, the H7N9 epidemic caused panic among the public. Then, in 2018, an earthquake and a tsunami caused 10,733 deaths in total. In particular, the 2019-nCoV epidemic led to severe shortages of medical materials. As the 2019-nCoV epidemic caused a huge demand for relief goods in the affected areas, emergency logistics has been facing serious situations. In rescue practices, repeated delivery in some disaster areas occur when civil society organizations and enterprises participate in the management of health emergencies, therefore, resulting in oversupply. In contrast, some disaster areas receive no relief supplies, thus leading to highly chaotic emergency relief operations. This observation is an important reflection of the lack of a scientific and reasonable logistics resource integration and optimization plan.

The vehicle routing problem (VRP) has been widely applied in logistics distribution management and transportation management since it was proposed by Dantzig and Ramser [2] in 1959. It has been a research hotspot in management science. Recently, theoretical studies on the VRP in the logistics system start from constraints (e.g., vehicle capacity limitation and service time). However, these studies are all biased toward a general (business) logistics system with various types of constraints and improvement of the solving algorithm. A vehicle routing problem in emergency (VRPE) is an important topic that needs to be further discussed. Although the cooperation of emergency logistics is significantly beneficial to the government's practices of rescuing behaviours, few studies have been conducted on public-private emergency collaborations in emergency logistics compared with those in business logistics [3]. For major health emergencies, the relief distribution routes in which both public and private vehicles participate were selected as the research object. In addition, a VRPE optimization model was built with considerations of disorder, repetition, and waste of social logistics resources in the rescuing process and integration of logistics resources, aiming at achieving the minimum total time for relief commodities distribution organized and implemented by both private companies and the government. Moreover, this study proposed the corresponding algorithm and attempted to provide a VRP optimization scheme for the emergency management department in relief distribution. Therefore, this study made the following contributions on the basis of similar studies. First, a vehicle routing problem with time windows in emergency (VRPTWE) optimization model was constructed from the perspective of logistics resource integration. With considerations to time windows, vehicle capacity limitation, and different starting points of vehicles stationed at emergency distribution centres to load disaster-relief materials and distribute to disaster demand points, this model was close to the practical demands of relief distribution to the maximum extent. Second, a hybrid code genetic algorithm (HCGA) was proposed. This algorithm is not only in favour of the natural expression of problem solutions and the processing of complicated constraints of the model, but it is also convenient for dynamic mutation operation without decoding. This process simplifies the calculation of the objective function, improves the calculation complexity, and verifies the feasibility and validity of the algorithm.

2. STATE OF THE ART

Numerous theoretical studies on VRP optimization have been reported. Theoretical discussions on various types of VRP optimization models and their improved algorithms in business logistics system are expanded continuously to discussions on VRP optimization for relief distribution in an emergency logistics system.

With respect to studies on VRP optimization and algorithm solving in the business logistics system, VRP was proposed in 1959. Subsequently, Solomon and Desrosiers [4] were the first ones to discuss the heuristic solving algorithm of VRP with time windows. Montero et al. [5] investigated VRP with pick-up and delivery (VRPPD) and developed a local search procedure based on integer linear programming (ILP). Through case study results, the promising potentials of ILP was proven in solving VRPPD. Leggieri and Haouari [6] discussed a new asymmetric capacitated vehicle routing problem (ACVRP) and solved standard cases by the three sequential stages of a matheuristic of mixed integer linear programming. The results proved that these three sequential stages could provide high-quality solutions. Eshragh et al. [7] proposed VRP with quantity limitation and solved it with a dynamic programming algorithm. In addition, Bianchessi and Irnich [8] proposed the split delivery vehicle routing problem with time windows (SDVRPTW) and a new and tailored branch-and-cut algorithm to solve the SDVRPTW. It was based on a new, relaxed compact model, in which some integer solutions were infeasible for the SDVRPTW. As VRP is a NP-hard problem, it is difficult to be solved by using accurate algorithms, such as integer linear programming and dynamic programming, when the problem scale is large. Hence, Brandão [9] studied the multi-depot open VRP and analysed its two differences from the classical VRP. Moreover, a memory-based iterated local search algorithm was proposed. Its performance was tested using a large set of benchmark problems and compared with other algorithms; the results proved that it had very strong competitiveness. Martins et al. [10] built a VRP model in the omni-channel distribution system for the new models of commerce and a savings heuristic algorithm was proposed, as VRP was a NP-hard problem. The research results demonstrated that the proposed heuristic algorithm could find competitive solutions in a very short computational time. Pankratz [11] proposed a grouping genetic algorithm, which adopted unique coding and decoding techniques. This algorithm realized genetic coding and the crossing and mutation of vehicles, thus achieving some effects. Liu et al. [12] established a VRP model and proposed an improved genetic algorithm. Nazif and Lee [13] put forward a capacitated vehicle routing problem (CVRP) and designed a genetic algorithm that contained an optimization crossover operator to solve it. Some researchers have also built various types of VRP models from constraints and designed the corresponding optimization solving algorithm. For example, Sabar et al. [14] constructed a dynamic vehicle routing problem (DVRP), in which the objective of the problem was to maximize the total distribution cost with considerations to different traffic congestion in various periods; they also proposed a self-adaptive evolutionary algorithm that used variable parameters to solve it. Klodawski et al. [15] generated a simulation model of VRP with dynamic information in the FlexSim. Yahyaoui et al. [16] proposed a GA based on partially matched crossover to solve the multi-compartment vehicle routing problem in oil delivery and found that solutions generated by the proposed algorithm on all involved standard cases were optimal. On the basis of the above research results, several types of VRP optimization models have been built. Some designs have corresponding accurate algorithm, such as integer linear programming, dynamic programming, and branch-and-bound, to adapt to small-scale VRP. However, most researchers have solved various VRPs by heuristic algorithms, such as a savings heuristic algorithm, and GA. On the one hand, existing studies have mainly focused on the superiority of various types of VRP and relevant algorithms in a business logistics system but have sparsely involved the VRP optimization model and a high-efficiency algorithm in emergency logistics. On the other hand, Jayanthi and Balasubramanian [17] pointed out that traditional GA and particle swarm optimization algorithm reduced the efficiency. Therefore, the computational efficiency of the heuristic algorithm has to be improved. For example, the used coding method increases the strong length of chromosome when the simple genetic algorithm (SGA) is used, which needs decoding. This approach fails to simplify the calculation and occupies a lot of space in the memory, thus being disadvantageous in improving the algorithm complexity and prolonging the computation time of algorithms. Moreover, problems against processing of constraint and execution of genetic operations are present. Early-maturing problem of SGA is also not handled effectively.

With respect to studies on the VRP optimization model and algorithm solution in emergency logistics, some researchers have focused on the location-allocation problem (LAP) [18-20] and relief distribution scheduling problem [21, 22] in emergency logistics system optimization. Some researchers have discussed VRP in an emergency from different perspectives and designed corresponding accurate algorithms and heuristic algorithms. For instance, Akbari and Salman [23] built an accurate mixed integer programming VRP model for relief distribution with considerations to impassable route caused by the blocking of post-disaster debris and designed a local searching algorithm according to the characteristics of the model, thus enabling the connectivity of the network and the trafficability of roads to be regained. Oruc and Kara [24] built a bi-objective VRP mathematical model that could search the rescuing route effectively. These researchers studied VRPE under the hypothesis that vehicles start from the emergency distribution centre and return to the centre. This claim differs significantly from practical rescuing situations. In real rescue operations, vehicles start from different points to the emergency distribution centre to load disaster-relief goods. Then, they deliver to different rescue demand points, and finally return to the starting point after finishing the delivery task. Moreover, the supply of emergency logistics resources involves multiple aspects when a major health emergency occurs. Relying only on public logistics resources of government departments leads to the delay of rescue. Hence, it is suggested that social rescue organizations, third-party logistics and other private transportation facilities should be brought into play, and the whole society should be mobilized to participate in the relief distribution team. Few studies have concentrated on VRPTWE from the perspective of public-private emergency collaborations. Some relief goods (e.g., drugs and blood) must be delivered to the rescue demand points at first time, and these goods require strong timeliness. Therefore, the constraints of time windows and the efficiency of the algorithm must be considered. Designing high-efficiency algorithms is crucial to studies on VRPE. As a result, the situations that vehicles from different departments and at different starting points participate in rescuing in emergency logistics system were considered in this study. Vehicle routes for health emergency relief distribution involving public-private collaborations were selected as the research object. A VRPTWE optimization model in a large-scaled health emergency logistics system was formulated, and a hybrid code genetic algorithm was proposed. Moreover, the validity of this model and algorithm was proven by case studies.

The remainder of this study is organized as follows. Section 3 builds a VRPTWE optimization model with public-private collaborations in emergency logistics system and designs an improved GA. Moreover, the rules of this improved GA regarding VRPTWE optimization are set up. The improved GA is compared with the traditional classical SGA in terms of coding and process. Section 4 presents the numerical simulation study on solving the VRPTWE model with traditional classical SGA and the improved GA, respectively. Section 5 summarizes the conclusions and proposes future research directions.

3. METHODOLOGY

3.1 Definition of symbols

Definition of parameters: C is the set of rescue demand points in disasters. W is the set of relief distribution centres. V is the set of vehicle types, including K' vehicles from the public department and K vehicles from the private department. $k(m)$ reflects that k vehicles start from their original locations m. $VQ_{k(m)}$ is the maximum capacity vehicle k at m point. T_{kj} is the unit cargo loading or unloading time of vehicle k at node j. $T_{kj} = 0$ when $j = m$. VT_{kj} is the time of vehicle k arriving at node j. $VT_{kj} = 0$ when $j = m$. N is the set of all nodes. $d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$ refers to the plan distance from node i to node j, x_i and y_i ($i \in N$) are the x-axis and y-axis coordinates of node i. $v_{k(m)}$ is the mean velocity of vehicle k at m point. q_j ($j \in C$) is the amount of demand of rescue point j in disasters. t_j ($j \in C$) is the time constraint of rescue point j in disasters.

Decision variables: $x_{ij}^{k(m)}$: If vehicle k ($k \in V$) at m point travels from node i to node j ($i, j \in N$), it is 1; otherwise, it is 0. Q_{kj}: The amount of cargo loading or unloading of vehicle k at node j ($j \in N$). $Q_{kj} = 0$, when $j = m$.

3.2 VRPTWE model and solution

Therefore, a VRPTWE optimization model under public-private collaborations was built:

$$\min \quad Z=\sum_{k(m)\in V}\sum_{i\in N}\sum_{j\in N} T_{kj} Q_{kj} x_{ij}^{k(m)} + \sum_{k(m)\in V}\sum_{i\in N}\sum_{j\in N}\frac{d_{ij}}{v_{k(m)}} x_{ij}^{k(m)} \tag{1}$$

$$s.t. \sum_{j\in C} q_j \sum_{i\in N} x_{ij}^{k(m)} <= VQ_{k(m)}, \forall k(m)\in V \tag{2}$$

$$\sum_{i\in N} x_{ij}^{k(m)} - \sum_{i\in N} x_{ji}^{k(m)} = 0, \forall k(m)\in V, j\in N \tag{3}$$

$$\sum_{l\in W} x_{il}^{k(m)} = 1, \forall k(m)\in V', \quad V'\subset V, i\in N \tag{4}$$

$$\sum_{j\in C} x_{ij}^{k(m)} \ge x_{il}^{k(m)}, \forall k(m)\in V, i\in N, l\in W \tag{5}$$

$$\sum_{k(m)\in V}\sum_{i\in N} x_{ij}^{k(m)} = 1, \forall j\in C \tag{6}$$

$$\sum_{r\in W} x_{ir}^{k(m)} - \sum_{j\in C} x_{ji}^{k(m)} = 0, \forall k(m)\in V, i=1,2,...,M'+M \tag{7}$$

$$VT_{kj} = VT_{ki} + T_{ki} + \frac{d_{ij}}{v_{k(m)}}, \forall i,j\in N, k(m)\in V \tag{8}$$

$$VT_{kj} \le t_j - T_{kj}, \forall j\in C \tag{9}$$

$$Q_{kj} = \begin{cases} q_j, \forall j\in C \\ 0, \forall j = m & \forall k(m)\in V \\ \sum_{j'\in C} q_{j'} \sum_{i\in N} x_{ij'}^{k(m)}, \forall j\in W \end{cases} \tag{10}$$

$$x_{ij}^{k(m)} \in \{0,1\}, \forall i,j\in N, k(m)\in V \tag{11}$$

In this model, the objective function (1) shows the minimum total time of relief commodities distribution in emergency logistics system. Constraints (2) are the constraint of vehicle capacity. Constraints (3) oblige that each vehicle enters a rescue point to leave the same rescue point. Constraints (4) are subtour elimination constraints, which guarantee that each tour must station at an emergency distribution centre to load disaster-relief goods. Constraints (5) mean that vehicles assigned to the emergency distribution centre to load disaster-relief goods must serve rescue demand points. Constraints (6) reflect that every rescue demand point in the disaster area is served. Constraints (7) reflect that every vehicle has to return to the starting point. Constraints (8) are the mathematical expression of VT_{kj}. Constraints (9) are the time constraints of rescue demand points j. Constraints (10) are the mathematical expression of Q_{kj}. Constraints (11) are decision variables of 0-1.

According to the above model characteristics, a hybrid code genetic algorithm was designed. It has evident advantages in solving VRP compared with the GA proposed by Pankratz [11] and Nazif and Lee [13]. The specific steps are given as follows.

Step 1: Setting of algorithm parameters: Let *Po*, *GGAP*, *Maxgen*, *Pc*, and *Pm* be the number of individuals in the population (the population size), generation gap, maximum number of generations, crossover rate, and mutation rate, respectively.

Step 2: Chromosome coding and construction of initial population: Generally speaking, most researchers use the binary string chromosome representation in a simple genetic algorithm (SGA). Binary-coded chromosome is the most important coding technique in GA, and the set of the used coded identifications is the binary symbol set {0, 1}, which is composed of binary symbols 0 and 1. The individual genotype composed by the binary symbol set is a binary coding symbol string. The decision variables of the parameter set are encoded as a binary, and they form a chromosome (genotype) through connection in a series. The decision variable (phenotype) is gained from mapping chromosomes in the decision variable space. For a VRP with J rescue demand points and $K' + K$ vehicles, the parameter set is $\{x_1, x_2, x_3, ..., x_J, x_1', x_2', x_3', ..., x_J'\}$. If the required accuracy is Z decimal places, each variable is divided into at least $(K' + K - 1) \times 10^Z$ part. The binary string number of a variable x_j ($j = 1, 2, 3, ..., J$) (expressed by u) is calculated according to the formula of $2^{u-1} < (K' + K - 1) \times 10^Z \le 2^u - 1$. In this way, one chromosome string is $2 \times J \times u$ places. One variable x_j is encoded as $b_u b_{u-1} b_{u-2} ... b_2 b_1$, and the value of variable x_j is gained from the decoding formula of $\sum_{i=1}^{u} 2^{i-1} b_i (K' + K - 1) / (2^u - 1)$. As vehicles and rescue demand points are numbered by natural numbers, rounded-off numbers are needed after decoding. For example, when three vehicles ($K' + K = 3$) are available and five rescue demand points ($J = 5$) exists and the accurate requires two digit places ($Z = 2$), $u = 8$ can be calculated. Then, each variable has 8 bits of binary code and 2^8 binary strings. On this basis, decision parameters are encoded (Fig. 1). Although binary code is a common coding method in GA, it can't reflect the structural characteristics of the problem for solving, so decoding is needed. Moreover, under the condition of high precision, the searching space of GA is significantly expanded.

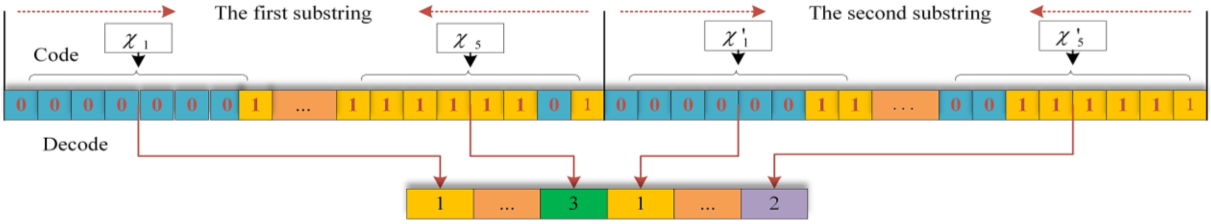

Figure 1: Diagram of GA with 0-1 codes.

For a specific application problem, designing a perfect coding scheme is one of difficulties in the application of GA, and it is also an important research direction of GA. To overcome shortages of binary coding in SGA, an improved GA was proposed for VRP in emergencies, which is called a hybrid code genetic algorithm. The solving process of hybrid code genetic algorithm is shown in Fig. 2.

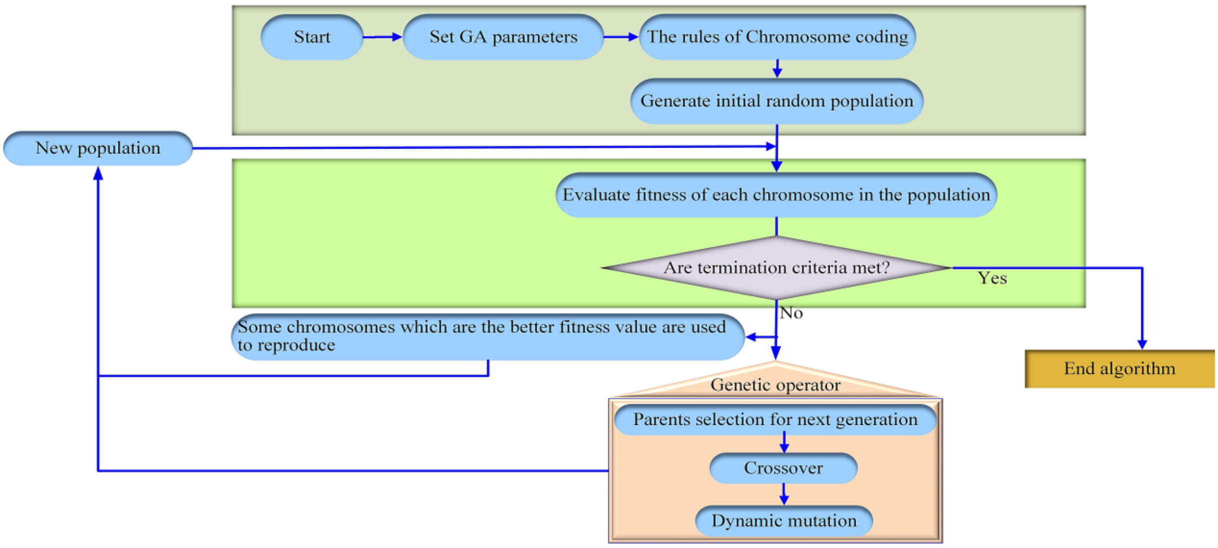

Figure 2: Flowchart of a hybrid code genetic algorithm for VRP.

The core of such hybrid code genetic algorithm is the combination of real-value codes and symbol codes. In other words, some gene values of a chromosome (individual) are expressed by real values within a range, and the rest are expressed by a sequence of symbols. Next, their codes are connected in a certain order according to the correlations between the genic value and the genic loci, which form individual chromosomes coding that express all parameters. Such a set of decision variables is expressed by a mixed coding scheme of individuals. Specifically, for a VRP involving J rescue demand points and $K' + K$ vehicles, the parameter set is $\{x_1, x_2, x_3, ..., x_J, x_1', x_2', x_3', ..., x_J'\}$. Thus, the codes are $\{x_1, x_2, x_3, ..., x_J, x_1', x_2', x_3', ..., x_J'\}$. In this way, the length of every chromosome string is $2 \times J$ digits. Specifically, every chromosome is composed of two substrings. The genic loci of the first substring is J, which correspond to every demand point that is numbered. The genic values are random numbers from 1 to $K' + K$. The numbers from 1 to K' are vehicles from the public department, and numbers from $K' + 1$ to $K' + K$ are vehicles from the private department. This substring reflects the distribution of rescue demand points to vehicles. The genic loci of the second substring is also J, which correspond to the locations of the first substring. Genic values are nonnegative random integers, thus indicating the service order of the rescue demand point by vehicles. All rescue demand points are served in a loop according to genic values. Fig. 3 demonstrates that Vehicle 1 serves the corresponding rescue points at the 2nd, 4th, 5th, and 8th genic loci in the first substring; Vehicle 2 serves the rescue points at the 1st, 6th, and 9th genic loci; Vehicle 4 serves the rescue points at the 3rd, 7th, and 10th genic loci. In the second substring, genic values at the 2nd, 4th, 5th, and 8th genic loci are 7, 9, 6, and 3, respectively, which are served in an ascending order. Therefore, the route of Vehicle 1 is 8-5-2-4. Similarly, the route of Vehicle 2 is 6-1-9, and the route of Vehicle 4 is 3-10-7.

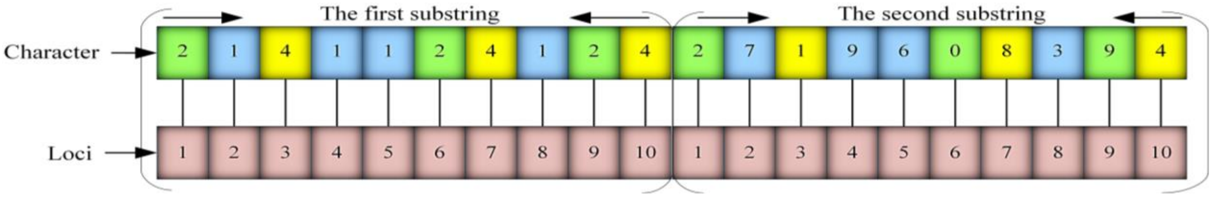

Figure 3: Diagram of a hybrid code genetic algorithm.

This hybrid code genetic algorithm has the following characteristics in solving VRP compared with SGA:

a) The complicated constraints in the model are highly convenient to process. The parallel symbol set of Substring 1 is the set of dispatched vehicles (Vehicles 1, 2, and 4 are dispatched in Fig. 3). The location of Substring 1 can reflect that all rescue demand points are served. Vehicle capacity constraint is convenient to use in the penalty function.

b) Comparison Fig. 1 and Fig. 3 shows that the transformation from chromosome's genotype to phenotype (decoding) is not required during the calculation of the objective function. Meanwhile, the design of fitness function is simple, which reduces the computational time and space complexity, thus improving the efficiency of genetic algorithm.

c) Relative to the binary codes of SGA to VRP, each chromosome string has $2 \times J \times u$ bits. However, each chromosome string has only $2 \times J$ in the proposed hybrid code genetic algorithm, which can decrease the demands of computer memory significantly.

The Genetic Algorithm Toolbox for MATLAB, which was developed by The University of Sheffield, is used to generate an initial random population. First, a vector is built using the crtbase function. The length is J, thus indicating that it is composed of J basic characters {0, 1, 2, ..., $K' + K - 1$} with a base number of $K' + K$. Next, the matrix Chrom1, which uses elements as the random number (basic characters are decided by corresponding vectors), is created by the crtbp function. The number of rows is Po. The number of dimension and the matrix ones, which use the same element of 1, are added to assure that none of the row and column sequences in the matrix processing is 0. Next, the matrix Chrom2, which has Po rows and J columns and uses elements as random numbers, is built by a function. The matrix Chrom = [Chrom1, Chrom2] is defined. So far, the initial population (Chrom) is gained.

Step 3: Calculate fitness: f_i = Fitness (Chrom$_i$ (gen)) indicates the fitness of chromosome i of Chrom at the gen. It is gained through the conversion of the objective function, that is, the fitness function $f_i = 1 / Z(i)$, $Z(i)$ is the objective functional value of chromosome i.

Step 4: Genetic operations: Selection: Stochastic universal sampling and a fitness-based reinsertion (an elitist strategy) method are combined. Crossover: Multi-points crossover operator (crossover operator with great destruction is used) can promote the algorithm to search the solving space. Mutation: Real-valued mutation is used, and the range of mutation is restricted after the field descriptor is added to assure that the boundaries of decision variables do not exceed after mutation.

Step 5: Termination conditions of algorithm: When gen $\leq$ *Maxgen*, repeat Steps 3-4, and the algorithm terminates until gen > *Maxgen*.

4. ANALYSIS AND DISCUSSION

4.1 Data acquisition

According to scenarios after the occurrence of a major health emergency, 40 rescue demand points are given randomly. The *x*-axis and *y*-axis coordinates of the emergency distribution centre are 100 km and 150 km, respectively. The vehicles of different types are deployed (1-5 are from the public department, and 6-10 are from the private department). Information on all 10 vehicles are listed in Table I. Relevant data of rescue demand points are shown in Table II.

Table I: Information on vehicles.

No.		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Maximum capacity (pc)		180	180	140	180	180	180	180	180	160	180
Loading (unloading) time (h/pc)		0.005	0.005	0.004	0.005	0.005	0.005	0.005	0.005	0.0045	0.005
Coordinates (km)	**x**	35	105	115	220	155	55	110	125	286	90
	y	85	245	248	100	136	255	87	90	122	55
Speed (km/h)		70	70	50	70	70	70	70	70	60	70

Table II: Information on rescue demand points.

No.		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Demands (pcs)		25	28	32	28	35	35	47	32	35	47
Time windows (h)		[0, 7]	[0, 6]	[0, 7]	[0, 8]	[0, 8]	[0, 7]	[0, 7]	[0, 8]	[0, 9]	[0, 8]
Coordinates (km)	**x**	35	105	115	76	85	66	126	40	148	112
	y	38	245	248	177	253	155	200	275	58	145
No.		**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
Demands (pcs)		43	35	27	37	37	33	34	45	36	25
Time windows (h)		[0, 7]	[0, 6]	[0, 9]	[0, 10]	[0, 9]	[0, 9]	[0, 9]	[0, 9]	[0, 7]	[0, 10]
Coordinates (km)	**x**	233	225	90	47	281	180	291	55	300	218
	y	180	158	85	86	95	293	114	153	189	181
No.		**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**
Demands (pcs)		35	40	45	32	31	46	32	33	37	45
Time windows (h)		[0, 11]	[0, 9]	[0, 9]	[0, 7]	[0, 9]	[0, 9]	[0, 9]	[0, 9]	[0, 8]	[0, 8]
Coordinates (km)	**x**	169	265	133	251	173	165	165	105	187	170
	y	107	263	235	144	250	172	152	75	80	251
No.		**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**	**40**
Demands (pcs)		25	30	20	30	22	35	28	23	25	30
Time windows (h)		[0, 9]	[0, 9]	[0, 10]	[0, 8]	[0, 9]	[0, 8]	[0, 7]	[0, 10]	[0, 9]	[0, 8]
Coordinates (km)	**x**	50	200	135	175	130	140	165	241	228	200
	y	65	110	185	75	260	95	120	270	200	135

4.2 Results analysis of case study

On the basis of the above-mentioned hybrid code genetic algorithm, the HCGA is implemented in MATLAB, and runs are taken on a PC (1.83 GHz CPU and 1 GB RAM). The parameters of the algorithm are set as follows: $Po = 500$, $GGAP = 0.9$, $Maxgen = 800$, $Pc = 0.7$, and $Pm = 0.08$ at the early stage and 0.02 at the late stage.

The vehicle routing optimization plan of relief distribution is gained from the traditional classical SGA (Fig. 4). Vk (k = 1, 2, ..., 10) is vehicle number in Fig. 4.

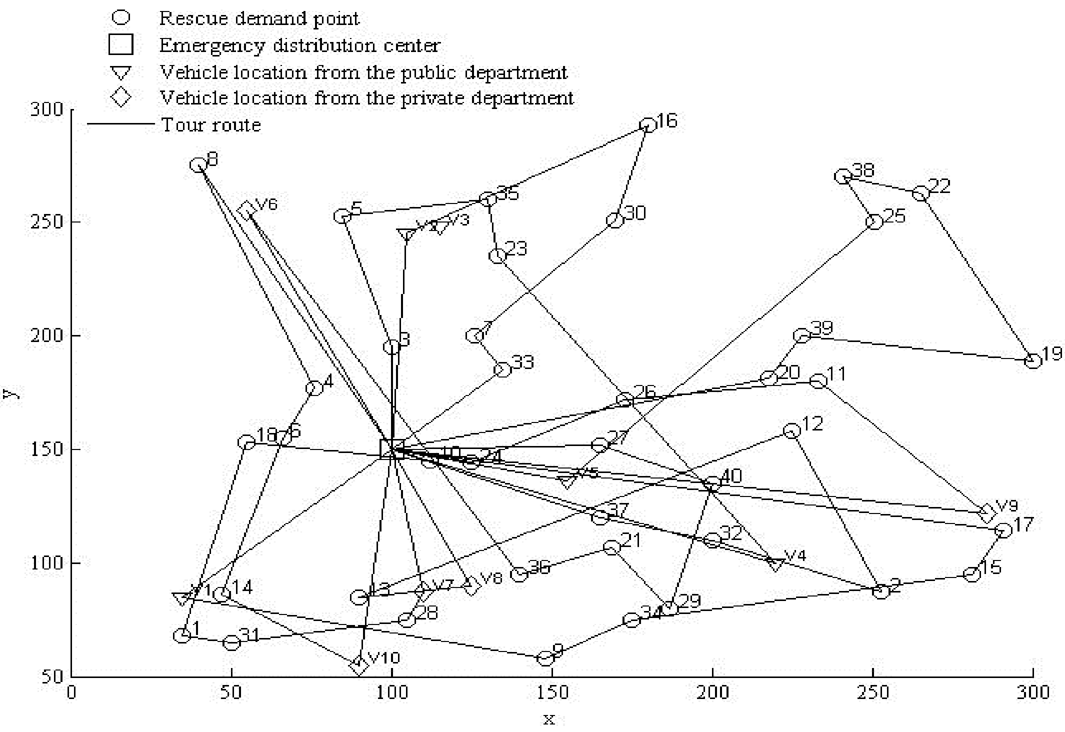

Figure 4: VRPTWE diagram of SGA.

The vehicle routing optimization plan for relief distribution is gained from a hybrid code genetic algorithm (Fig. 5). *Vk* (k = 1, 2, ..., 10) is vehicle number in Fig. 5.

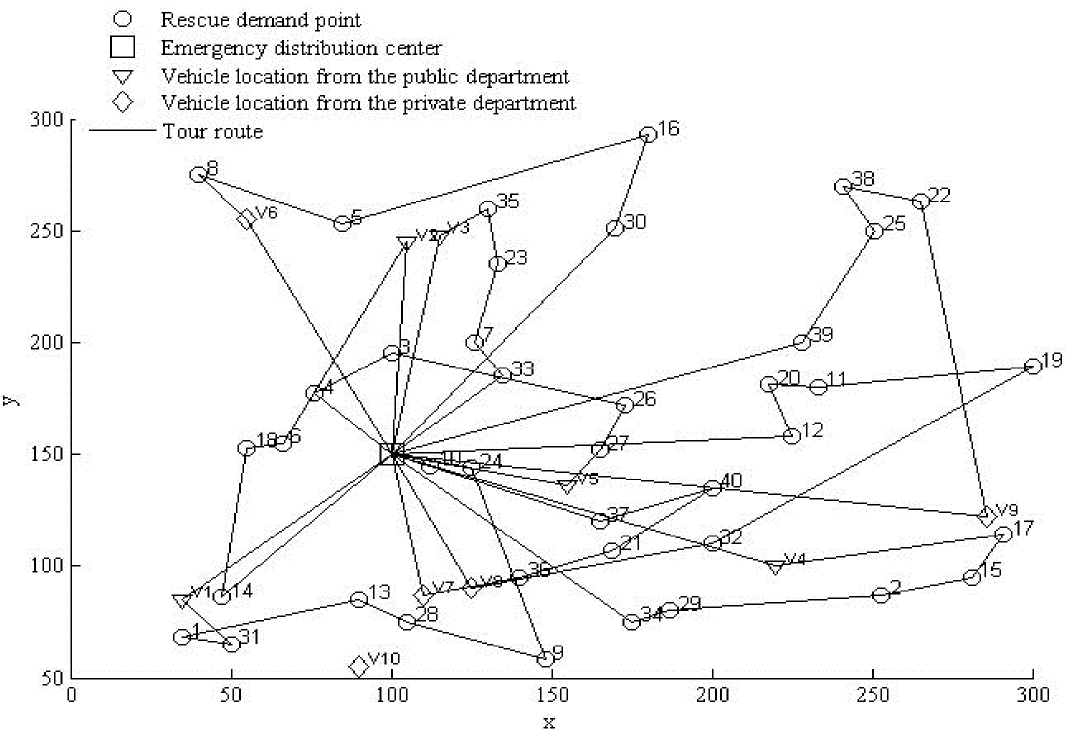

Figure 5: VRPTWE diagram of HCGA.

The stability of the designed hybrid code genetic algorithm was tested. The optimal values of 10 operations are 72.08, 71.75, 71.83, 70.95, 65.11, 67.94, 68.81, 65.81, 70.73, and 72.02, with a mean of 69.70. The absolute values of the differences between every optimal solution and the mean are 2.13, 2.05, 2.38, 1.25, 4.59, 1.76, 0.89, 3.89, 1.03, and 2.32, respectively.

These absolute values are very close, thus which indicates that the designed hybrid code genetic algorithm has very strong stability, and it is appropriate to be used in problem solving.

4.3 Comparison and analysis of calculation results

In order to test the performance of the hybrid code genetic algorithm, it is compared with the traditional classical SGA. Given the same parameters of algorithms, the calculation scheme results are listed in Table III.

Table III: Results of two algorithms.

Schemes	**SGA**	**HCGA**	**Percentage differences**
Routes	Vehicle 1: 17-15-34-9	Vehicle 1: 24-9-28-13-1-31	
	Vehicle 2: 33-7-30-16	Vehicle 2: 14-18-6	
	Vehicle 3:	Vehicle 3: 33-7-23-35	
	Vehicle 4: 3-5-35-23	Vehicle 4: 34-29-2-15-17	
	Vehicle 5: 20-39-19-22-38-25	Vehicle 5: 4-3-26-27	
	Vehicle 6: 27-40-29-21-36	Vehicle 6: 30-16-5-8	
	Vehicle 7: 10-18-1-31-28	Vehicle 7: 10-37-40-21-36	
	Vehicle 8: 37-32-2-12-13	Vehicle 8: 12-20-11-19-32	
	Vehicle 9: 24-26-11	Vehicle 9: 39-25-38-22	
	Vehicle 10: 8-4-6-14	Vehicle 10:	
Computation time	863.72 s	740.70 s	14.24 %
Total time	73.67 h	65.11 h	11.62 %

According to the results of the algorithms, given the same parameters, the computation time of the proposed hybrid code genetic algorithm is 14.24 % lower, and the total relief distribution time is 11.62 % lower compared with those of the traditional classical SGA. Hence, the solution quality of HCGA is significantly better than SGA. Since the hybrid coding scheme is convenient for genetic operations, a dynamic mutation is more suitable to use in the solving process. The mutation rate is relatively high at the early stage, and the searching solution space is expanded to assure great differences between the individual optimal value of every generation and the mean of the generation. In contrast, the mutation rate is relatively low at the late stage, which makes the differences between the individual optimal value of each generation and the mean of the generation decrease gradually. The rate of convergence increases accordingly, thus enabling the prevention of the early-maturing problem of the algorithm.

5. CONCLUSION

To minimize the total time of relief commodities distribution, the VRP for relief distribution under the public-private collaborations was examined in the study. A comparative analysis of relief distribution schemes, which were calculated by the traditional classical SGA and the hybrid code genetic algorithm, was carried out. Some conclusions could be drawn:

(1) SGA uses binary codes to make every chromosome string longer than that of the hybrid code genetic algorithm, and it requires more memory spaces. The computation time of SGA is longer than that of the hybrid code genetic algorithm. This result is mainly because SGA using binary codes needs to be decoded, which reduces the computational efficiency.

(2) The hybrid code genetic algorithm is superior to SGA in terms of dynamic mutation effect, which agrees with the negative correlation between the convergence rate and the mutation rate. The mixed coding scheme used in the hybrid code genetic algorithm is convenient for genetic operation, and dynamic mutation is more appropriate to use in the solving process. The hybrid code genetic algorithm not only increases solution space searching capability, but it may also not cause adverse impacts on convergence characteristics and may

have strong stability. In addition, it can solve the early-maturing problem of the traditional classical SGA effectively.

(3) The vehicle routing scheme for relief distribution in the hybrid code genetic algorithm is generally better than that in SGA. The hybrid code genetic algorithm takes advantages of characteristics of mixed coding rules. This benefit not only allows a coding string set to obtain a natural description of problems easily, but it is also convenient in processing the complicated decision variable constraints. As a result, the calculation of the fitness function is further simplified. According to comparison, the hybrid code genetic algorithm can optimize the relief distribution scheme better and achieve the minimum total time of relief distribution by attracting private and public resources. Hence, introducing a high-efficiency, economic, and feasible heuristic algorithm is an essential selection to optimize VRP in the emergency.

The emergency logistics network is dynamic. Therefore, further studies on multi-stages and multi-types of VRP in emergencies are needed. Moreover, the influences of road blocking, traffic jams, and uncertainty caused by severe emergencies on VRP are among the important research directions in the future.

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REFERENCES

[1] Yao, X.; Huang, R.; Song, M.; Mishra, N. (2018). Pre-positioning inventory and service outsourcing of relief material supply chain, *International Journal of Production Research*, Vol. 56, No. 21, 6859-6871, doi:10.1080/00207543.2018.1495853

[2] Dantzig, G. B.; Ramser, J. H. (1959). The truck dispatching problem, *Management Science*, Vol. 6, No. 1, 80-91, doi:10.1287/mnsc.6.1.80

[3] Diehlmann, F.; Luttenberg, M.; Verdonck, L.; Wiens, M.; Zienau, A.; Schultmann, F. (2021). Public-private collaborations in emergency logistics: A framework based on logistical and game-theoretical concepts, *Safety Science*, Vol. 141, Paper 105301, 16 pages, doi:10.1016/j.ssci.2021.105301

[4] Solomon, M. M.; Desrosiers, J. (1988). Survey paper-time window constrained routing and scheduling problems, *Transportation Science*, Vol. 22, No. 1, 1-13, doi:10.1287/trsc.22.1.1

[5] Montero, A.; Miranda-Bront, J. J.; Méndez-Díaz, I. (2017). An ILP-based local search procedure for the VRP with pickups and deliveries, *Annals of Operations Research*, Vol. 259, No. 1, 327-350, doi:10.1007/s10479-017-2520-5

[6] Leggieri, V.; Haouari, M. (2018). A matheuristic for the asymmetric capacitated vehicle routing problem, *Discrete Applied Mathematics*, Vol. 234, 139-150, doi:10.1016/j.dam.2016.03.019

[7] Eshragh, A.; Esmaeilbeigi, R.; Middleton, R. (2020). An analytical bound on the fleet size in vehicle routing problems: A dynamic programming approach, *Operations Research Letters*, Vol. 48, No. 3, 350-355, doi:10.1016/j.orl.2020.04.007

[8] Bianchessi, N.; Irnich, S. (2019). Branch-and-cut for the split delivery vehicle routing problem with time windows, *Transportation Science*, Vol. 53, No. 2, 442-462, doi:10.1287/trsc.2018.0825

[9] Brandão, J. (2020). A memory-based iterated local search algorithm for the multi-depot open vehicle routing problem, *European Journal of Operational Research*, Vol. 284, No. 2, 559-571, doi:10.1016/j.ejor.2020.01.008

[10] Martins, L. D. C.; Bayliss, C.; Juan, A. A.; Panadero, J.; Marmol, M. (2020). A savings-based heuristic for solving the vehicle routing problem with pick-up and delivery, *Transportation Research Procedia*, Vol. 47, 83-90, doi:10.1016/j.trpro.2020.03.082

[11] Pankratz, G. (2005). A grouping genetic algorithm for the pickup and delivery problem with time windows, *OR Spectrum*, Vol. 27, No. 1, 21-41, doi:10.1007/s00291-004-0173-7

[12] Liu, M. L.; Zhang, C.; Wu, Q. L.; Meng, B. R. (2021). Vehicle routing problems with soft time windows of cargo transport O2O platforms, *International Journal of Simulation Modelling*, Vol. 20, No. 2, 351-362, doi:10.2507/IJSIMM20-2-564

[13] Nazif, H.; Lee, L. S. (2012). Optimised crossover genetic algorithm for capacitated vehicle routing problem, *Applied Mathematical Modelling*, Vol. 36, No. 5, 2110-2117, doi:10.1016/j.apm.2011.08.010
[14] Sabar, N. R.; Bhaskar, A.; Chung, E.; Turky, A.; Song, A. (2019). A self-adaptive evolutionary algorithm for dynamic vehicle routing problems with traffic congestion, *Swarm and Evolutionary Computation*, Vol. 44, 1018-1027, doi:10.1016/j.swevo.2018.10.015
[15] Klodawski, M.; Jacyna, M.; Vasek, R.; Klimek, P.; Jachimowski, R.; Szczepanski, E.; Lewczuk, K. (2020). Route planning with dynamic information from the EPLOS system, *Technical Journal*, Vol. 14, No. 3, 332-337, doi:10.31803/tg-20200710130158
[16] Yahyaoui, H.; Kaabachi, I.; Krichen, S.; Dekdouk, A. (2020). Two metaheuristic approaches for solving the multi-compartment vehicle routing problem, *Operational Research*, Vol. 20, No. 4, 2085-2108, doi:10.1007/s12351-018-0403-4
[17] Jayanthi, N.; Balasubramanian, K. (2021). Modelling of lossless and contactless power transformer using improved particle swarm optimization algorithm, *Dyna*, Vol. 96, No. 6, 666-672, doi:10.6036/10093
[18] Hong, J.-D.; Jeong, K.-Y. (2020). Cross-evaluation based super efficiency DEA approach to designing disaster recovery center location-allocation-routing network schemes, *Journal of Humanitarian Logistics and Supply Chain Management*, Vol. 10, No. 4, 485-508, doi:10.1108/JHLSCM-03-2020-0019
[19] Jia, H.; Ordóñez, F.; Dessouky, M. M. (2007). Solution approaches for facility location of medical supplies for large-scale emergencies, *Computers & Industrial Engineering*, Vol. 52, No. 2, 257-276, doi:10.1016/j.cie.2006.12.007
[20] Abounacer, R.; Rekik, M.; Renaud, J. (2014). An exact solution approach for multi-objective location-transportation problem for disaster response, *Computers & Operations Research*, Vol. 41, 83-93, doi:10.1016/j.cor.2013.08.001
[21] Sheu, J.-B. (2010). Dynamic relief-demand management for emergency logistics operations under large-scale disasters, *Transportation Research Part E: Logistics and Transportation Review*, Vol. 46, No. 1, 1-17, doi:10.1016/j.tre.2009.07.005
[22] Sakiani, R.; Seifi, A.; Khorshiddost, R. R. (2021). A novel structure to model the distribution of relief items in a post-disaster situation, *Journal of Modelling in Management*, Vol. 16, No. 2, 441-463, doi:10.1108/JM2-11-2019-0257
[23] Akbari, V.; Salman, F. S. (2017). Multi-vehicle synchronized are routing problem to restore post-disaster network connectivity, *European Journal of Operational Research*, Vol. 257, No. 2, 625-640, doi:10.1016/j.ejor.2016.07.043
[24] Oruc, B. E.; Kara, B. Y. (2018). Post-disaster assessment routing problem, *Transportation Research Part B: Methodological*, Vol. 116, 76-102, doi:10.1016/j.trb.2018.08.002