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Multi-level Evolutionary Genetic Algorithm for Solving VRPSPD Problem

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Abstract: In the field of industrial production and distribution, in order to meet the production needs of production enterprises, it is necessary to consider the customer's need for simultaneous picking and delivery in the classic vehicle routing optimization problem, which we called VRPSPD(vehicle routing problem with simultaneous pick-up and delivery). In order to minimize the transportation cost and rationally use the distribution vehicle to balance the workload, establishing a VRPSPD target model that considers both the transportation cost and minimizing the maximum transport length difference between distribution lines, and constructing an improved genetic algorithm(GA) based on the characteristics of the model. The algorithm use the RMPCIM insertion method to improve the global search ability and accelerate the iterative process. At the same time, a new multi-level evolution iterative process is adopted in the population iteration to improve the superiority of the algorithm. The accuracy of the algorithm is verified by the simulation of 18 sets of Solomon exextended instances. Compared with different algorithms in the literature,the result shows that the algorithm can weigh the objective function and obtain the optimal objective function.

Key Words: VRP, VRPSPD, Genetic Algorithm, Target Model

1 Introduction

At present, there is a widespread phenomenon of no-load returning vehicles in industrial production and distribution for bulk commodities, which results in waste of transportation resources. In the process of production and distribution, there are customers who exchange goods, return goods, waste materials and the rest of the production materials to be returned to the distribution warehouse. If reverse logistics is integrated into the enterprise's original distribution system, and return vehicles are used to load the goods to be returned, it can not only make full use of transportation resources, but also indirectly increase economic benefits [1]. This vehicle routing problem with simultaneous pick-up and delivery (VRPSPD) was first proposed by Min [2] in 1989, which involves the constraints of vehicle mileage, vehicle capacity and line traffic. Due to the complexity of the problem, VRPSPD is a NP hard problem [1]. In reality, it is difficult to design an effective algorithm to solve large-scale VRPSPD precisely. The main algorithms are heuristic algorithm or sub heuristic algorithm. How to find the optimal solution more quickly and efficiently is a hot topic at present.

In solving VRPSPD problem, different methods are put forward at home and abroad. Emmanuil e. z & Chris t. k put forward the local search heuristic solution [4], which proposed to establish the transportation model in the context of reverse logistics, and added the tabu search method based on the expected standard promise mechanism to coordinate. Tang Montané & Galvão developed a new tabu search algorithm to solve VRPSPD problem [3], which uses three types of movement (relocation, interchange and cross mobile) to form distribution path and strengthen the search ability of the algorithm; Hsiao-fan Wang and Ying-yen Chen [5] proposed a coevolutionary genetic algorithm with minimum cost insertion method for VRPSPD with time window, which accelerated the solution process; Dethloff [6] uses integer programming model and heuristic algorithm to solve the problem, and proposes an insertion rule heuristic algorithm based on vehicle service freedom; Nagy and Salhi S [7] adopt the optimization algorithm based on dynamic programming and branch and bound, and adopt the exchange method of 2-opt and 3-opt to solve VRPSPD problem; Zhang Tao and Zhang Chunmei [8] use the characteristics of heuristic algorithm to construct a hybrid algorithm that combines PSO and SA algorithm. The algorithm designs new coding rules, information exchange strategies and cooling schedule rules in SA algorithm, which improves the algorithm adaptability.

All of the above solutions to VRPSPD are aimed at the minimum number of vehicles or the shortest total driving distance. But there is a contrary utility between the purpose of this paper. In industrial production and distribution, work efficiency should be guaranteed, and the workload of each vehicle should be also balanced. It is not allowed that one vehicle distributes more customers, and the other vehicle distributes less customers, otherwise the workload gap between distribution vehicles will be too large and result low efficiency. Therefore, under the constraints of vehicle capacity and transportation distance, we should not only ensure the minimum transportation cost, but also ensure the workload balance of each vehicle, and also consider environmental factors, customer satisfaction and so on. Chen Xiqiong and Hu Dawei [9] established a VRPSPD dual objective model considering both vehicle capacity and distance constraints, and constructed a multi-objective ant colony algorithm with greedy transfer criteria embedded in the tabu table. However, it can be seen that the established objective model and algorithm are difficult to be compatible, and the two established objective functions are difficult to get the op-

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timal value at the same time. Garcia Najera [10] pointed out the importance of workload in the multi-objective research about the problem of pick-up and delivery.

In order to minimize the total transportation cost and reasonably use the distribution vehicles to balance the workload, a VRPSPD target model is established, which considers the transportation cost and the minimization of the maximum length difference between the distribution lines. According to the characteristics of the model, an improved genetic algorithm is constructed. The algorithm use the RM-PCIM insertion method to improve the global search ability and accelerate the iterative process. At the same time, a new multi-level evolution iterative process is adopted in the population iteration to improve the superiority of the algorithm.

2 Problem Description And Formulation

The VRPSPD studied in this paper can be described as: under the constraint of not exceeding the vehicle capacity and the maximum transportation distance of the vehicle, finding the path of not exceeding m paths to minimize the cost,and maximum balancing of transport length of each delivery path, the definition of the dual-target VRPSPD variables is as follows:

2.1 Problem Description

Define the VRPSPD problem as an undirected connectivity graph $G = (J_0, E)$,where $J_0 = \{j = 0, 1, ..., n\}$ are nodes, E is a collection of edges and $E = \{< i, j > i, j \in J_0, i \neq j\}$. Node 0 represents the distribution warehouse. As a distribution center and collection center,the distribution center has m cars($(V = \{v|v = 1, 2, ..., m\})$),where capacity is $Q_v(v \in V)$.$J = \{1, 2, ..., n\}$ represent customer collection,each customer $j \in J$ has a fixed amount of deliverty D_j and pickup P_j.The VRPSPD studied in this paper can be descried ad: under the constraint of not exceeding the vehicle capacity and the maximum transportation distance of the vehicle,finding the path of not exceeding m paths to minimize the cost,and maximum balancing of transport length of each delivery path,the definition of the target VRPSPD variables is as follows:

J:Customer set,$J = \{i = 1, 2, ..., n\}$.

J_0:Node set (customer collection distribution warehouse),distribution warehouse is represented by the number 0,customer set is represented by number $1, 2, ..., n$,$J_0 = J \cup \{0\}$.

V:Vehicle set,$V = \{v|v = \{1, 2, ..., m\}$.

α::Balance factor,$\alpha \in [0\ \ 1]$.

Q_v:Vehicle v carrying capacity.

c:Driving cost per unit distance.

d_{ij}:Distance between nodes.

W_v: Total length of the path traveled by the vehicle v.

W_{max}&W_{min}:Longest and shortest path length.

D_j:Customer delivery requirements.

P_j: Customer pick-up demand.

M:Arbitraty large positive number, this article sets $1000 < M$

N_{jv}:Access the cumulative distance of customer j to prevent exceeding the maximum distance constraint.

Decision variables:

L_{0v}:Vehicle v load from the distribution center,$v \in V$.

L_j:The remaining load of the vehicle after serving customer j,$j \in J$.

x_{ijv}:Vehicle v driving variable,$x_{ijv} \in \{0, 1\}$.If vehicle v travel from i to j,then $x_{ijv} = 1$,otherwise $x_{ijv} = 0$,where $i, j \in J, v \in V$.

2.2 VRPSPD Target Model

Based on the above questions, the following mathematical model is established:

$$Minimize \quad z = c\,(\alpha f1 + (1-\alpha) f2) \tag{1}$$

$$\begin{cases} Minimize \;\; f_1 = \sum_{i \in J} \sum_{j \in J} \sum_{v \in V} d_{ij} x_{ijv} \\ Minimize \;\; f_2 = W_{max} - W_{min} \end{cases} \tag{2}$$

Restrictions:

$$\sum_{i \in J_0} \sum_{v \in V} x_{ijv} = 1, \; \forall j \in J \tag{3}$$

$$\sum_{i \in J_0} x_{ihv} = \sum_{j \in J_0} x_{hjv} \;\; \forall h \in J, \forall v \in V \tag{4}$$

$$\sum_{j \in J} x_{0jv} = \sum_{i \in J} x_{i0v} \quad \forall v \in V \tag{5}$$

Where the load constraint:

$$L_{0v} = \sum_{i \in J_0} \sum_{j \in J} d_j x_{ijv} \quad \forall v \in V \tag{6}$$

$$L_j \geq L_{0v} - D_j + P_j - M(1 - x_{0jv}) \quad \forall v \in V \tag{7}$$

$$L_j \geq L_i - D_i + P_j - M(1 - \sum_{v \in V} x_{ijv}) \quad \forall i \in J, \forall j \in J \tag{8}$$

$$L_{0v} \leq Q_v \quad \forall v \in V \tag{9}$$

$$L_j \leq Q_v + M(1 - \sum_{\forall i \in J_0} xijv) \quad \forall j \in J, \forall v \in V \tag{10}$$

Distance constraint:

$$N_{iv} - N_{jv} + (N + d_{ij}) x_{ijv} + (N - d_{ji}) x_{jiv} \leq N \quad \forall i, j \in J, i \neq j, v \in V \tag{11}$$

$$d_{0j} x_{0jv} \leq N_{jv} \leq N + (d_{0j} - N) x_{0jv} \quad \forall j \in J, v \in V \tag{12}$$

$$N_{jv} \leq N \sum_{i \in J} x_{0iv} - d_{j0} x_{j0v} \quad \forall j \in J, v \in V \tag{13}$$

Vehicle travel path length constraints:

$$W_v \geq N_{jv} + d_{j0} x_{j0v} \quad \forall j \in J, v \in V \tag{14}$$

$$W_v \leq N_{jv} + (d_{j0} - N) x_{j0v} + N \sum_{i \in J} x_{0iv} \quad \forall j \in J, v \in V \tag{15}$$

The VRPSPD objective function (1) is to balance the total travel cost of each distribution vehicle, and α is the balance coefficient. The first expression in formula (2) is the total transportation length of distribution vehicles, and the second is the difference between the maximum transportation path and the minimum transportation path of distribution vehicles. The constraints (3) ensures that each customer can only be served by one vehicle. The constraints (4) limits that distribution vehicles must leave after completing distribution for customers to ensure the continuity of the route. The constraints (5) ensures that each vehicle starts from the central warehouse and finally returns to the central warehouse. Constraints (6)- (10) are load constraints of distribution vehicles, which mainly restrict the return load and in transit load of distribution vehicles, as well as the load constraints of distribution vehicles themselves. Constraints (11)- (13) are the constraint on transportation distance, which is less than the specified maximum transportation distance. Constraints (14) and (15) are constraints on the length of travel path about distribution vehicles. Through the establishment of the model, it can solve the problem of the imbalance of vehicle workload in the production and distribution of enterprises, reduce transportation costs and improve economic benefits.

3 Algorithm Design

Genetic algorithm is a classic algorithm. With its own advantages, it is widely used in production and distribution scheduling, data mining, automatic control, image processing, and combination optimization. It relies on each chromosome (individual) in the population for crossover, mutation, and selection operations. And iterating the next generation to get the global best chromosome. Among them, the fitness is evaluated for each chromosome, and a certain number of individuals are selected from the parent as the next-generation population according to the size of the fitness.

Genetic Algorithm (GA) is a global search method that can find good solutions to complex mathematical problems. Therefore, this article considers the use of improved genetic algorithms to solve the VRPSPD problem. The VRPSPD problem, like other NP problems, has more complex problems. Using the genetic algorithm to solve the VRPSPD problem. If the convergence rate is too fast, it will fall into a local optimum. If the convergence rate is too slow, the algorithm's efficiency will be greatly reduced. There is also question. The GA algorithm to obtain the shortest path deliberately will often appears that there is only one customer on a route, which causes a waste of vehicle resources and can't balance transportation resources. This article that uses an improved Multi-level Evolutionary Genetic Algorithm (MEGA) can solve this kind of problem well and this article uses natural number coding, as shown in Figure 1. The MEGA algorithm uses the RMPCIM insertion method to initialize the population first of all. And then the population undergoes a multi-level evolution process to obtain the optimal solution.

3.1 Initial Population

Many researchers often use the minimum cost insertion method of Clarke and Wright [17] for population initialization. In this method, each customer is individually served by a distribution vehicle, which is the number of vehicles = the number of routes = the number of customers. And then this method attempts to reinstate a single customer. Insert into another distribution route. Later, Osman [13] and Mester [11] made a lot of optimizations. Osman's insertion method uses the cost-saving criterion,$(2c_{ok} + c_{lm}) - (c_{lk} + c_{km})$(slightly modified here, the origin and return of the delivery are the same location in this article), where c_{ij} represents that between two nodes Cost; Mester's insertion method adds a parameter β, using the criterion,$(2c_{ok} + c_{lm}) - \beta(c_{lk} + c_{km})$, where $\beta \in [0.2 \quad 1.4]$ represents a threshold for cost savings. The Mester's insertion method is a multi-parameter insertion method which can obtain high-quality initial solutions and speed up the global search process. This article considers that in addition to finding high-quality initial solutions. The algorithm also needs to be able to provide global search capabilities to avoid falling into a local optimum. Therefore, this article proposes to add a certain randomness to the Mester's insertion method, which is, the RMPCIM insertion method to avoid falling into a local optimum.

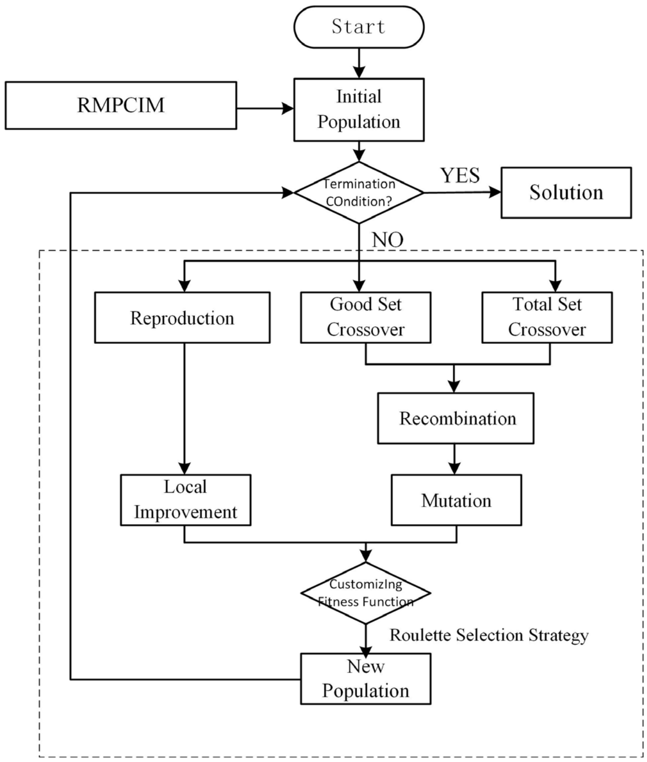

Fig. 1: The Framework of the Algorithm

The Random Multi-parameter Cheapest Insertion Method (RMPCIM) proposed in this paper is based on the Mester [11] insertion method, removing customers on all distribution routes established on the Mester's insertion method, and the remaining customer are rearranged randomly. According to the cost-saving criterion,$(2c_{ok} + c_{lm}) - \beta(c_{lk} + c_{km})$. the random customer sequence is inserted into the generated distribution route in a one-to-one replacement position. Thus the algorithm ensuring the global search ability. When a single customer route is reduced to 0, the insertion stops.

3.2 Multi-level Evolution

The multi-level evolution process iterates the final solution through the operations of Reproduction, Local Improvement, Crossover, Mutation, Recombination, and Selection. As shown in Figure 2, the multi-level evolution process is divided into three parts, namely Evolution I, Evolution II, and Evolution III. Assume that the number of each population is N, and 2N offspring are generated through evolution I; then the 2N offspring compete with each other, and then the excellent next generation is generated through evolution II and evolution III. This iterative process is repeated until the termination condition is met to obtain the optimal solution.

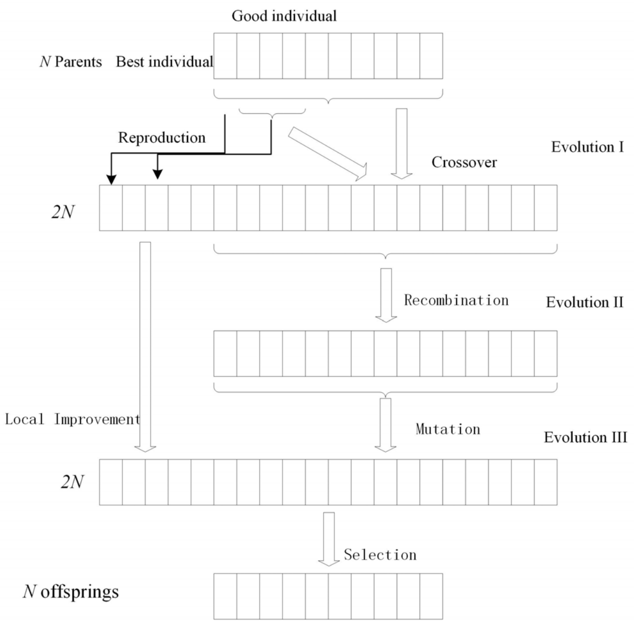

Fig. 2: Evolution Flow chart

Among them, the parents and offspring of Evolution I are further divided into high-class parents and high-class offspring, and massive parents and massive offspring. High-class parents evolve to generate high-class offspring, and massive parents evolve to generate massive offspring. The 2N children in Evolution I are generated by high-class offspring and massive offspring according to a certain ratio. In order to generate the high-class offspring in Evolution I, the $1+\sqrt{N}$ high-class parents in Evolution I are needed. 1 represents the optimal parent individual in Evolution I. $\sqrt{N}$ is the high-class parents individual in Evolution I, and the massive offspring in Evolution I is obtained by mixing the high-class parents and massive offspring in Evolution I. The specific evolution process is described below.

3.2.1 Reproduction

As shown in Figure 2, it can be seen from the evolution process that Reproduction in the Evolution I is to copy the best individuals in each group to the offspring. The best individual is the individual with the lowest target value. The minimum target value can be the minimum transport vehicle or the shortest transport path. This article is a dual target value, depending on the parameters. The replication of the best individual is also known as the elite strategy, which guarantees GA's high quality solution. In Evolution I, $\sqrt{N}$ good individuals is also copied into the offspring(total $1 + \sqrt{N}$), and the evaluation of the good individual is evaluated according to the fitness function.

3.2.2 Crossover

The massive offspring in Evolution I are generated by the intersection of some high-class parents and massive parents. The modified crossover algorithm is as show in Table 1. The algorithm does not produce deviations in any particular direction, and it allows the offsprings to inherit good features from the parents, inherit as many routes as possible. Once the route is selected, the route is considered a seed route. Inserting the remaining customers into the seed route or other individual customer routes. The criterion of the insertion using the RMPCIM insertion method mentioned in the previous section.

Table 1: Crossover Algorithm

Begin
Repeat
Copy as many routes as possible from parents;
Until:no more inherited routes are feasible;
All un-routed customers form single customer routes;
Reduce all single customer routes by RMPCIM;
End

3.2.3 Recombination

The recombination operator is a remove-insert mechanism which preserves the wide searching ability. In the first step, the algorithm randomly removes many customers from their routes, generally taking $1/5$ customers. Then, the reinsertion of isolated customers is done by RMPCIM, where the existing routes are regarded as seed routes.

3.2.4 Local Improvement

Two types of Local Improvement are used in this work: Reinsertion Improvement and Swap Improvement.

Reinsertion Improvement: This operator reinserts one single customer into alternative positions in the solution vector by Osman[13] cost savings criterion. For a customer k currently serviced between customers i and j, reinserting into another distribution route,which is considering the position between the adjacent customers l and m, the cost savings is evaluated as:

$$(c_{ik} + c_{kj} + c_{lm}) - (c_{lk} + c_{km} + c_{ij}) \quad (16)$$

Swap Improvement: This operator swaps the position of two customers simultaneously in the solution vector by Osman [13] cost savings criterion. For customers k and h currently serviced between customers i and j, and l and m, respectively, the swap possibility is evaluated on cost savings as:

$$(c_{ik} + c_{kj} + c_{lh} + c_{hm}) - (c_l k + c_{km} + c_{ih} + c_{hj}) \quad (17)$$

3.2.5 Mutation

The Mutation operator of the algorithm refers to the Mutation process in Hsiao-Fan Wang[5]. These Mutation operators are necessary conditions for algorithm iteration. It inputs new features to the current population, and the Mutation operator expands the search space to accelerate the evolution of genes. As shown in Figure 3, randomly select a customer and try to migrate the customer to another vehicle.

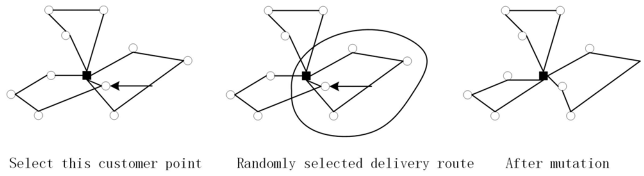

Fig. 3: Mutation:Random Customer Reinsertion

3.2.6 Selection

Selecting N good children from $2N$ parents is an important key to adopting the appropriate fitness function as the condition for selecting the next generation. According to the objective function model established in the previous section, in order to balance the workload of the vehicle, we choose to modify the objective function as the fitness, and add parameter α. The fitness is defined as follows:

$$fitness(u) = \alpha TD + (1-\alpha)(W_{max} - W_{min}) \quad u \in U \tag{18}$$

Refer to the target model established in Section 2.1, where TD is the total distance traveled by all distribution routes in the solution.$W_{max}\&W_{min}$ is the longest and shortest path length in the solution's distribution routes.$U = \{u = 1, 2, ..., m\}$ represents the set of individuals in the population.

In all the literature selection strategies, the roulette wheel selection strategy is the best one. According to the roulette wheel selection strategy, the cumulative probability is defined as:

$$pr(u) = \frac{fitness(u)}{\sum_{u=1}^{m} fitness(u)} \quad u \in U \tag{19}$$

In this way, according to the above strategy, select excellent offsprings and enter the iterative loop.

4 Numerical Experiments And Results Analysis

4.1 Parameter Setting And Simulation

In order to evaluate the performance of the proposed algorithm, 18 large VRPSPD instances in Montanè and Galvão [3] were introduced. These examples contain 100 to 400 clients. These examples were first developed by Solomon [1] to solve the VRP problem with time windows. The distance between customers is the Euclidean distance between customer coordinate points.Table 2 lists the basic characteristics of the example, where,n: number of customer nodes, Q: vehicle capacity, D: total delivery demand,P:total pickup demand.

The algorithm simulation experiment was carried out on the above example. As shown in Figure 4, the total 100 customer in the rc101 instance start simulation experiment. The crossover rate, the mutation rate and the recombination rate in the reorganization operator were 0.9, 0.09 and 0.1 respectively. The value of the RMPCIM insertion method parameter β is 0.2. It can be seen from the figure that for the rc101 example, 9 transportation vehicles are required, corresponding to all the simulation data in Table 3. Compared with other algorithms, it not only balances the workload of the distribution vehicles, but also ensures the superiority of the algorithm.

Table 2: Solomon Extended Instances Characteristics

Instances	n	Q	D	P
r101	100	200	1458	2339
r201	100	1000	1458	2262
c101	100	200	1810	300
c201	100	700	1810	2910
rc101	100	200	1724	1912
rc201	100	1000	1724	2076
r1_2_1	200	200	3513	4406
r2_2_1	200	1000	3513	4358
c1_2_1	200	200	3530	5370
c2_2_1	200	700	3770	6010
rc1_2_1	200	200	3558	4473
rc2_2_1	200	1000	3558	4299
r1_4_1	400	200	7109	10433
r2_4_1	400	1000	7109	9571
c1_4_1	400	200	7190	12470
c2_4_1	400	700	7560	10050
rc1_4_1	400	200	7127	10065
rc2_4_1	400	1000	7127	10100

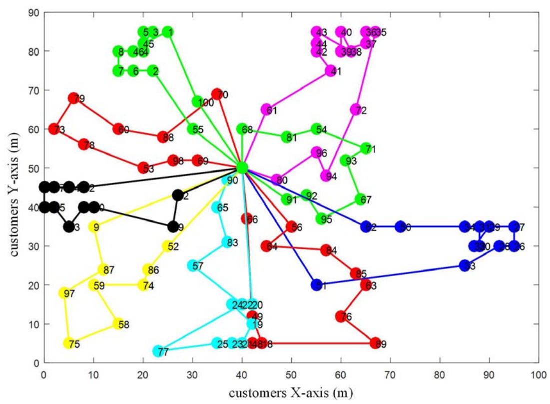

Fig. 4: 100 Customers Delivery Paths in the rc101 Instances

4.2 Simulation Effect And Comparison

Applied in the above 18 VRPSPD instances, the simulation test results of the improved multi-level evolutionary genetic algorithm (MEGA) proposed in this article are shown in Table 3, Where, AVG represents the average value of each parameter in the solution, $BEST$ represents the optimal value of each parameter in the solution, Z represents the total distribution distance (m), k represents the distribution vehicle (vehicle), and t represents the algorithm running time (S), $\%gap$ represents the percentage of the difference between the average distribution distance and the optimal distribution distance. Tested 10 times for each instance, it can be seen that the MEGA algorithm shows quite stable characteristics. The error between the optimal total transport distance and the average total transport distance of 10 runs ranges from 0.0% to 1.34%. The error is 0.55%. Especially for the 100 customer instances, it can be seen that the 10 operations basically obtain almost the same result, and the front and back errors do not exceed 1.5, which shows the stability of the algorithm.There is also a low level of solution time

Table 3: Summary of MEGA Results on the Solomon Extended Instances

Instances	AVG			$BEST$			$\%gap$
	Z	k	t	Z	k	t	
r101	1056.5	11.5	14.35	1055.1	11	14.2	0.13
r201	675.25	3	12.4	675.01	3	12.4	0.035
c101	1255.51	15.1	13.85	1249.6	15	13.45	0.47
c201	667.3	5	12.3	665.12	5	12.10	0.32
rc101	1090.46	9.5	12.6	1085.41	9	12.03	0.46
rc201	674.2	3	12.1	674	3	12.1	0.02
r1_2_1	3401.8	22	57.86	3399.6	22	57.45	0.06
r2_2_1	1710.65	5	55.5	1708.11	5	55.12	0.14
c1_2_1	3703.84	26.4	55.4	3680.85	26	55.1	0.6
c2_2_1	1770.5	8.5	66.45	1765.4	8	65.94	0.28
rc1_2_1	3390.96	20.5	60.47	3380.65	20	59.12	0.30
rc2_2_1	1633.4	5	55.13	1625.50	5	55.1	0.48
r1_4_1	9980.31	51.7	280.31	9900.56	51	275.12	0.79
r2_4_1	3650.64	9.2	291.49	3610.91	9	289.44	1.08
c1_4_1	11504.16	60.8	250.46	11380.85	59	250.40	1.07
c2_4_1	3801.4	13.5	190.28	3750.3	13	188.16	1.34
rc1_4_1	9760.7	48	260.41	9653.13	47	260.00	1.10
rc2_4_1	3751.1	10	299.14	3704.7	10	295.5	1.23
AVG							0.55

Table 4: Summary of MEGA Results on the Solomon Extended Instances

Instances	TS			APA			PGA			$gap(k)$
	Z	k	t	Z	k	t	Z	k	t	
r101	1042.62	12	13.20	1009.95	12	24.6	1055.1	11	14.2	1
r201	671.03	3	12.02	666.20	3	22.9	675.01	3	12.4	0
c101	1259.79	17	12.07	1220.99	16	19.2	1249.6	15	13.45	2
c201	666.01	5	12.40	662.07	5	18.7	665.12	5	12.10	0
rc101	1094.15	11	12.30	1059.32	10	25.2	1085.41	9	12.03	2
rc201	674.46	3	12.07	672.92	3	19.0	674	3	12.1	0
r1_2_1	3447.20	23	55.56	3375.19	23	73.5	3399.6	22	57.45	1
r2_2_1	1690.67	5	50.95	1665.58	5	67.4	1708.11	5	55.12	0
c1_2_1	3792.62	29	52.21	3641.89	28	79.0	3680.85	26	55.10	3
c2_2_1	1767.58	9	65.79	1726.73	9	74.8	1765.4	8	65.94	1
rc1_2_1	3427.19	24	58.39	3316.94	23	75.7	3380.65	20	59.12	4
rc2_2_1	1645.94	5	52.93	1560.00	5	66.9	1625.50	5	55.1	0
r1_4_1	10027.81	54	330.42	9668.18	53	395.6	9900.56	51	275.12	3
r2_4_1	3695.26	10	324.44	3560.73	10	306.0	3610.91	9	289.44	1
c1_4_1	11676.27	65	287.12	11125.14	63	408.5	11380.85	59	250.4	4
c2_4_1	3723.00	15	330.20	3549.20	15	367.7	3750.3	13	188.16	2
rc1_4_1	9883.31	52	286.66	9520.06	51	377.0	9653.13	47	260	5
rc2_4_1	3603.53	11	328.16	3414.90	11	289.5	3704.7	10	295.5	1
AVG										0.55

for MEGA algorithms, which is much lower than other algorithms. The running time of 100 cases is controlled within 14.5 seconds, and the running time of 200 cases is controlled within 65 seconds. The running time of 400 examples is controlled within 300 seconds.

Since the target model established in this article is to pursue the workload balance of the vehicle, the algorithm of this paper will compare the usage of the vehicle and the algorithm running time in the literature. As shown in Table 4,including the tabu search algorithm (TS) of Tang Montanè and Galvão [3], the local search heuristic algorithm (APA) of Emmanouil E. Zachariadis and Chris T. Kiranoudis [4] and the MEGA algorithm of this paper, Where k is the distribution vehicle (vehicle), t is the algorithm running time (s), and gap (k) is the minimum difference (vehicle) of the MEGA algorithm compared with other algorithms.

It can be seen that the efforts made in this article to balance the workload of each distribution route have reduced the use of the vehicle. The unreasonable delivery of the original route is greatly reduced. For example, in the c101 instances, the usage of the vehicle distributed by the algorithm is reduced by 2, and in the c1_2_1 instances, the number of distribution vehicles is reduced by 3. In addition, As shown in Figure 5, due to the advantages of adopting a multi-level genetic evolution method, the average running time of the algorithm is less than that of TS and APA algorithms.

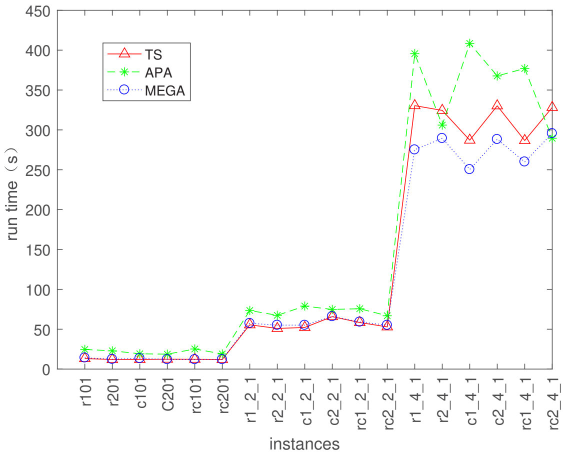

Fig. 5: Running Time of Different Algorithms

5 Conclusions

In this paper, a new VRPSPD model is proposed. Under the premise of considering vehicle capacity and the limitation of the maximum driving distance, the target model of minimizing the maximum length difference between each distribution route is constructed to balance the workload of each vehicle. A multi-level evolutionary genetic algorithm (MEGA) is proposed to solve the target model problem, and the RMPCIM insertion method is introduced to improve the global search ability and accelerate the iterative speed. Through the simulation and comparison of 18 Solomon extended instances in the literature, it shows that the algorithm can use vehicles in a better distribution distance and a reasonable time, which greatly improves the distribution efficiency of enterprises.

The multi-objective improved genetic algorithm (MEGA) proposed in this paper has room for improvement in initializing the population and evolution part. The improved algorithm in this paper is more about balancing the workload of the distribution vehicle than too much other objective factors. The multi-objective VRPSPD model proposed in this paper can also be applied to VRPSPDTW model with time window, or other combinatorial optimization problems, which will be very worthy of study.

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