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A Novel Model and Algorithm for Solving Dynamic Vehicle Routing Problem on Goods Distribution

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Abstract: For it is very difficult and complex to solve large-scale dynamic vehicle routing problem on distribution goods, propose the multi-objective optimization Dynamic Vehicle Routing Problem with Time Windows (DVRPTW) model for distribution goods, which maximizes the number of customer serviced, minimizes customer waiting time and the total vehicle driving distance and covers dynamic information both random demand and dynamic network. Then a two stage algorithm model based on hill-climbing and genetic hybrid algorithm is designed to solving DVRPTW. At last, we do the simulation experiment with standard test data from Solomon and the result shows that this model and algorithm is quite capable of solving the dynamic vehicle routing problem on distribution goods.

Key words: Distribution goods, dynamic, vehicle routing problem, hill-climbing and genetic hybrid algorithm

INTRODUCTION

With the development of communication and information technology, the research on vehicle routing problem turns static to dynamic problem most (Dynamic VRP, DVRP) [1].

Fleischmann *et al.* (2004) propose the online traffic information DVRP, Branke *et al.* (2005) propose the DVRP waiting strategy, Chen and Xu (2006) propose dynamic column generation method of DVPR with time window, Lu and Tan (2006). propose hybrid Particle Swarm Optimization (PSO) algorithm of random demand VRP, Chen *et al.* (2007). make a study of the random demand VRP and its heuristic algorithms, Liu and Feng (2008). propose the optimization method of dynamic vehicle routing problem. We find that the study of DVRP is focused on the random demand at present.

In this study we take the dynamic vehicle routing problem for distribution goods as research object, describe it as large-scale Vehicle Routing Problem with Time Windows (DTRPTW) and it covers dynamic information both random demand and dynamic network. A two stage algorithm model based on hill-climbing and genetic hybrid algorithm which we design was designed for solving it. In the dynamic solving process, a kind of hill-climbing and genetic hybrid algorithm is used in integrative optimization stage, after an initial solution we do not exchange customers between vehicles but apply the dynamic hill-climbing local search operator to update the service sequence for customers at the point that the vehicle completed a customer service, i.e., to solve a traveling salesman problem (TSP) of traveling routing of each vehicle. At last, we do the simulation experiment with standard test data and the result shows that this model and algorithm is quite capable of solving the dynamic vehicle routing problem.

SOLUTION MODEL OF DVRP FOR DISTRIBUTION GOODS

The practical application background of dynamic vehicle routing problem for distribution goods is: Delivery vehicles in distribution center should finish goods delivery in the customer designated time according to different customer load and the required different goods as far as possible. The dynamic is reflected in these aspects. The traffic fluency in the actual delivery process is uncertain, the delivery time window customer request will change and not all the customers are well known for decision maker before constructing in vehicle route structure. In the actual delivery process, some new customers appear, the delivery vehicles need to arrange delivery according to different requirements of emergency as quickly as possible.

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- In Fig. G = (V, A), V indicates a collection of nodes, Node 0 is the distribution center, the other nodes (Vi) are all points which need to transport goods. The number of customer nodes and some attributes of each customer may change during one plan period(usually a working day), we set the working day time as T
- There are m vehicles with a certain capacity and maximum driving distance, the vehicles can be different types. Set its capacity as Qk and maximum driving distance as Dk
- The attributes of each customer node Vi include: Quantity of demand (qi, Max qi < = Q), the geographical position with usual coordinate (xi, yi), [ai, bi] stands for the time window customer Vi ask for receiving goods
- The time delivery vehicle gets to the next customer = the time delivery vehicle get to the current customer +the time delivery vehicle spends on waiting for discharging in the current customer + the time delivery vehicle spends on discharging in the current customer + the time delivery vehicle spends on the road from the current customer to the next customer. When the vehicle arrives before ai the customer time window began, it has to wait for the customer time window began to discharge, if the vehicle arrives later than or equal to start time of the customer time window, it can discharge without waiting.
- It requests that the vehicle starts from the distribution center, finally back to the station after passing a series of client node and unload the goods. The rule set the task of each client node can only be completed by one vehicle, this vehicle must loading the customer's goods before starting
- Constraint of vehicle loading capacity: the sum of weight of each vehicle can't exceed beyond the vehicle capacity limit
- Constraint of vehicle distance: the drive total distance of each vehicle after serving customers can't exceed the maximum vehicle driving distance when finally return to distribution center. Once the vehicle return to distribution center it has the the maximum vehicle driving distance again
- In the distribution process, the fluent degree of the transportation network will change, the time window customer request delivery is changeable and new customer demand occur random(this study treats customer demand changes as new customer demand default)
- In this study, the system goal is to minimize the total scheme of the vehicle driving distance, minimize the sum of delay time all vehicle distribution out of the customer designated time window

Time-driven with batching is widely used in existing VRP handling strategies. It can surely allot vehicles for clients, but is too difficult to set the time slice rationally. Global optimization can't provide high performance, even may allot one client different vehicles, but actually the goods could only stay on one vehicle. We use the Strategy of integrative optimization before split optimization and local optimization based on the time point that the vehicle completed a customer service. It avoids allotting one client different vehicles and at the sometime it demotes the problem to Single Vehicle Routing Problem vehicle, leaving out vehicle positioning and route search. The traffic monitoring module needs just monitoring routes between each customer point.

THE SYSTEM MODEL AND ALGORITHM STRUCTURE OF DVRP FOR DISTRIBUTION GOOD

In Fig. 1, the system model of dynamic vehicle routing problem for distribution goods consists of dynamic event processing module, system module, single vehicle module, system database module. The dynamic event processing module is mainly used for processing dynamic flow of information that the system received. At the start the system module is used for optimizing the overall distribution scheme, then splitting the overall schemes into several single vehicle schemes. Late the system module is used for monitoring the real-time information of vehicles, inserting new clients to single vehicle schemes. And the single vehicle module is used for optimizing and executing the single vehicle schemes, communicating with system module while inserting the new customer.

The general thought: First the system gives an optimal driving scheme as far as possible according to current information of the system, customer demand, road condition and vehicles. Then demote the scheme to several sub-schemes, each vehicle follows one sub-scheme. During the transportation, the vehicle updates its information immediately arriving every customer which consists of the information of road condition and customer time window within the scope of services. And then recalculate the route optimization, transport as the new driving directions, it will not return to the yard until all the goods are distributed up.

At the overall optimization stage, it is impossible to use precise algorithm for generally around one hundred customers' large-scale vehicle routing problem and the efficiency of common algorithm can't be guaranteed. In order to get a global path as optimal as possible, this study designs a mixed algorithm the Generic Algorithm

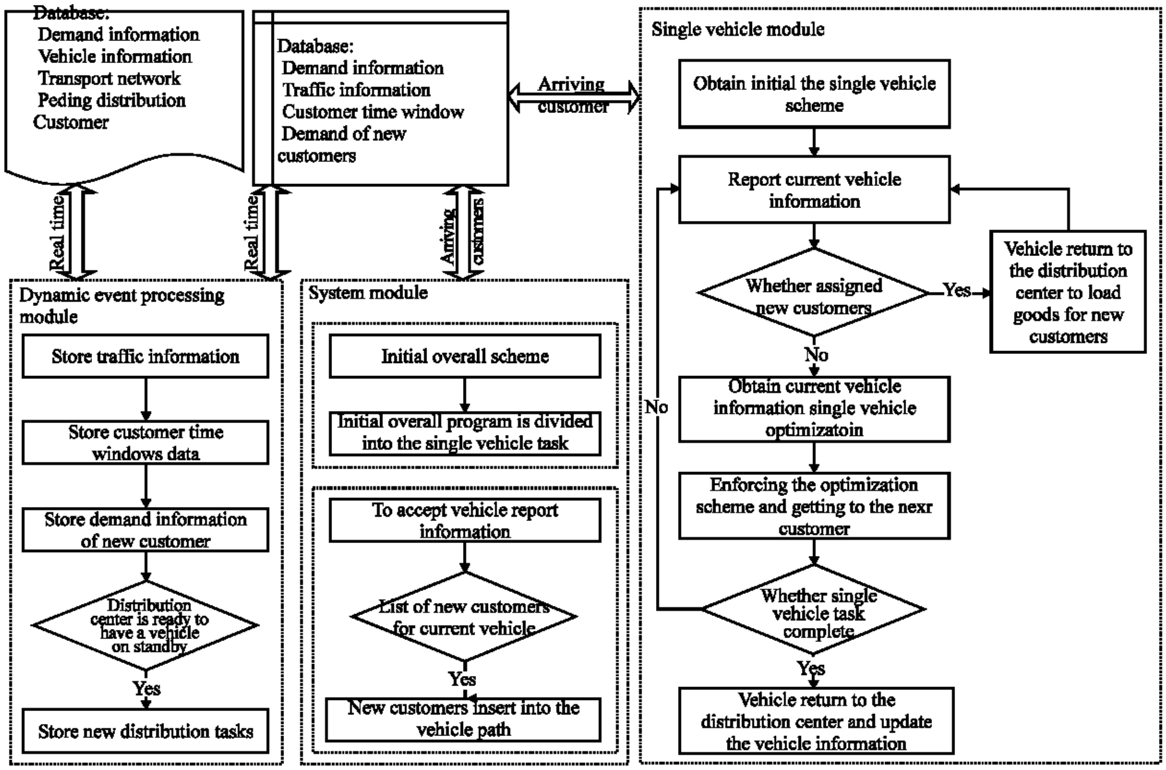

Fig. 1: The system model

and Hill-Climbing Algorithm and it proves that this algorithm can deal with constraints well and jump out of local optimum, giving an approximate global optimal solution.

At the single vehicle optimization stage, there are generally a dozen customers. As the system is a multi-threaded parallel execution at this moment, it requires high execution efficiency. So the Hill-Climbing Algorithm with simple structure and high efficiency is used in this study.

Example analysis

Example 1: It is to verify the feasibility of the overall optimization. This study designs Hill-climbing algorithm, tabu search algorithm, simulated annealing algorithm, Genetic algorithms and Hill-climbing and genetic hybrid algorithm. R103 data that comes from famous Solomon testing data is used for testing algorithm. Various algorithm parameters are set as follows:

- Data model: r103.dat; optimal mileage value: 1292.8
- HCA: the number of executions: 10000;
- TSA: Iterative steps: 4000, the number of neighbors: 200, tabu length: 20
- SAA: Initial temperature: 250, cooling times: 4000, cooling coefficient: 0.98, the number of iterations: 40;

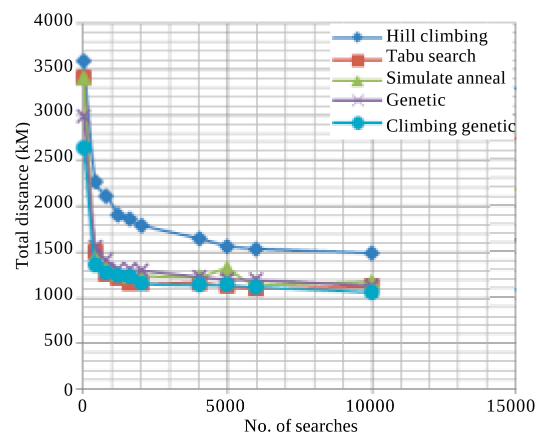

Fig. 2: Solving curve

- GA: Population scale: 50, crossover rate: 0.9, mutation rate: 0.09, evolution algebra: 4000;
- HCGA: population size: 50, crossover rate: 0.9, mutation rate: 0.09, climbing evolution algebra: 4000;
- Weight setting 1,0,0 (that is only consider the shortest distance), the number of searches and the corresponding solution results are shown in Fig. 2. Solving Curve

In Fig. 2 Solving Curve we can see the result of Hill-climbing algorithm performs worst in four algorithms as its simple structure, that means Hill-climbing algorithm could not dealing with problems with multiple constraint on a large scale very well. Tabu search algorithm performs very well at the beginning of the search, but the speed of increasing is slowing down. Simulated annealing algorithm performs the worst at the beginning and improves slowly, but by late of iteration its quality improves obviously even it is the only to keep the solution improving rapidly. Genetic algorithm also perform outstanding, it keeps good quality of the solution all the time. As Genetic algorithm has the nature of randomness, it is mainly the result of chromosome mutation. Obviously Hill-climbing and Genetic Hybrid Algorithm performs the best, it combines the advantages of Hill-climbing and Genetic algorithm giving the best solution, it is right to choose Hill-climbing and Genetic Hybrid Algorithm at the global optimization phase.

Example 2: It is to verify algorithm feasible at single optimization stage. This study has designed a set of test data: distribution center has five vehicles and each vehicle load 8 tons, the maximum travel distance of 50 km, they can service 20 customers. Customer demand, customer coordinates and service time windows are randomly generated. Various algorithm parameters are set as follows:

- Customer number: 20; The number of vehicles: 5
- HCA: the number of executions: 2000
- TSA: iterative steps: 400, the number of neighbors: 40, tabu length: 10
- SAA: Initial temperature:100, cooling times:50, cooling coefficient: 0.9, the number of iterations: 20;
- GA: population scale: 40, crossover rate: 0.9, mutation rate: 0.09, evolution algebra: 400
- HCGA: population size: 40, crossover rate: 0.9, mutation rate: 0.09, climbing evolution algebra:400
- Weight setting 1,0,0 (that is only consider the shortest distance), each algorithm runs 10 times, the results shown in Fig. 3 error curve

In Fig. 3 Error Curve we can see that Hill-climbing algorithm is not the worst any more in small-scale VRP. It may get better solution in smaller vehicle routing problems. Tabu search algorithm still performs well with minimum variance and good stability. In the experiment Simulated annealing algorithm does the worst in five algorithms, because the iterative steps are limited in small-scale VRP, it improves slowly and it is consistent with Example 1. In the experimental process, Genetic

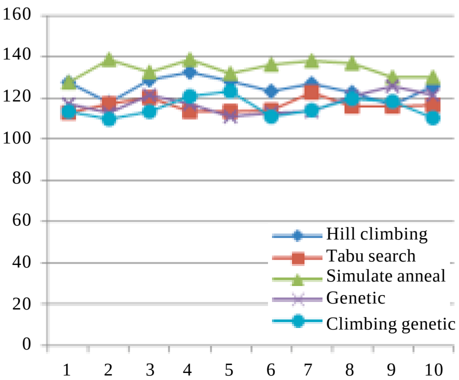

Fig. 3: Error curve

Table 1: The vehicle running track of the overall optimization stage

Vehicle No.	The vehicle running track
Vehicle No. 0:	0-46-8-45-84-5-61-97-75-56-39-4-21-26-0
Vehicle No. 1:	0-10-62-11-90-63-64-49-36-47-19-48-7-88-0
Vehicle No. 2:	0-28-53-58-96-59-93-85-38-14-92-0
Vehicle No. 3:	0-13-87-42-43-15-41-22-23-67-98-99-60-82-18-0
Vehicle No. 4:	0-89-83-17-86-16-44-91-37-100-57-2-74-72-73-40-0
Vehicle No. 5:	0-94-95-6-52-69-1-20-66-65-71-35-9-50-0
Vehicle No. 6:	0-31-70-32-30-51-81-33-34-78-79-3-77-0
Vehicle No. 7:	0-12-54-55-25-24-29-80-68-76-27-0
Total distance:	1085.39399882101

algorithm still performs well, as its nature of heredity it gives bad result and largest variance. Hill-climbing and Genetic Hybrid Algorithm keeps the best performance; it gives the optimal solution but big variance and it is possible for us to pay attention on running efficiency and the variance, so we choose the Hill-climbing algorithm to get high efficiency during local optimization.

Example 3: It is to verify the feasibility of the system model. This study adopts R103 data that is from the Solomon test data to simulation experiments; operating parameters: the number of customers: 100, the number of vehicles: 15, weight setting: 1,0,0, genetic algorithm parameters: population scale: 50, crossover rate: 0.9, mutation rate: 0.09 evolution algebra: 4000. The climbing algorithm parameters: climbing number of times: 200 times. The results of the simulation run are showed in Fig. 4, Fig. 5, the operational data, such as Table 1, Table 2.

Comparing the routings of planning stage and actual running stage, we find that most of the actual routings are not consistent with the planning cases. What caused it is the changing information during actual running such as the traffic congestion, the customers' time window change, new customers appear etc. It embodies the definition of VRP, routings change while information changes. To be sure, in some cases the actual operation results are better than planned; part of the reason is that

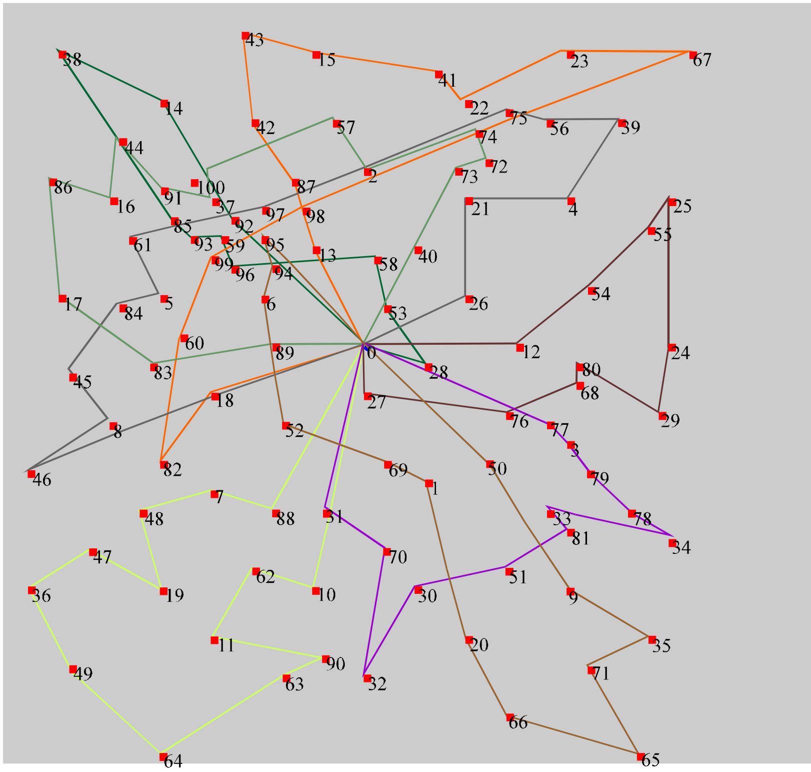

Fig. 4: The plan driving route

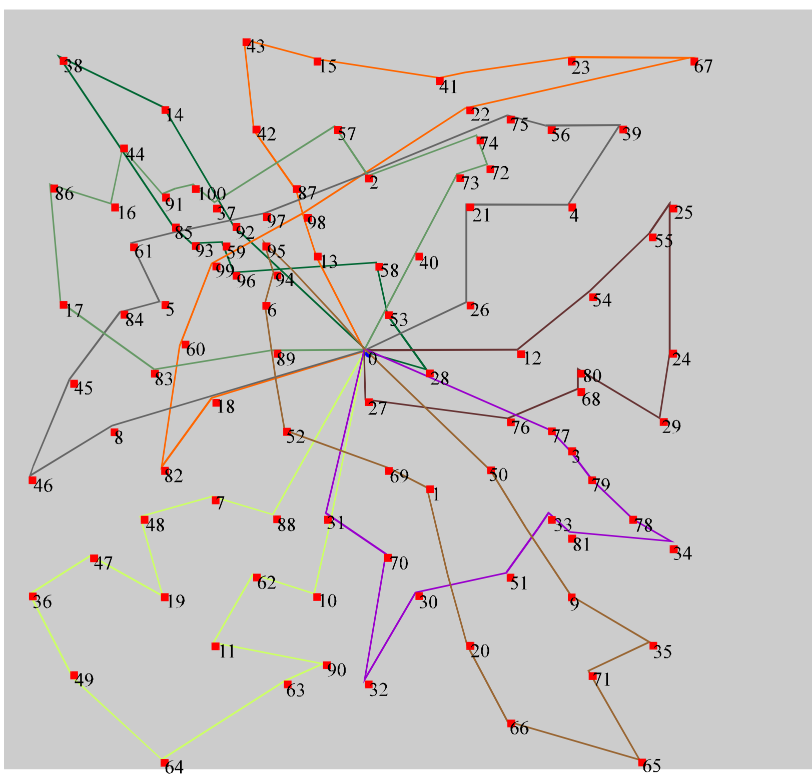

Fig. 5: The actual driving route

Table 2: The actual driving track after the single vehicle optimization

Vehicle No.	The vehicle running track
Vehicle No. 0:	0-8-46-45-84-5-61-97-75-56-39-4-21-26-0
Vehicle No. 1:	0-10-62-11-90-63-64-49-36-47-19-48-7-88-0
Vehicle No. 2:	0-28-53-58-96-59-93-85-38-14-92-0
Vehicle No. 3:	0-13-87-42-43-15-41-23-67-22-98-99-60-82-18-0
Vehicle No. 4:	0-89-83-17-86-16-44-91-100-37-57-2-74-72-73-40-0
Vehicle No. 5:	0-95-94-6-52-69-1-20-66-65-71-35-9-50-0
Vehicle No. 6:	0-31-70-32-30-51-33-81-34-78-79-3-77-0
Vehicle No. 7:	0-12-54-55-25-24-29-80-68-76-27-0
Total distance:	1073.93937139387

Hill-climbing algorithm does not search out the optimal solution in overall optimization phase especially dealing with large-scale VRP, a chromosome maybe superior overall, but some gene segments are not optimal, big chromosome is divided into small short sub- chromosome while running, the short sub-chromosome is local optimized with Hill-climbing algorithm, the results are always better than the right sub-chromosome which make the last global assessment improving a lot.

CONCLUSIONS

This study takes the Dynamic Vehicle Routing Problem for Goods distribution as the research object, embodies the realistic distribution that the goods owned to one customer could not be distributed on different vehicles. We use for reference of problem reduction approach based on two aspects dynamic information of random demand and dynamic network, we choose the strategy of integrative optimization first and split optimization as vehicle second and the split optimization start at point that the vehicle completed a customer service. In actual processing of VRP problem, both making full use of real-time information and balancing the long-term statistical rule of traffic are important, few of traditional single algorithms can balance the two aspects. But in this study, the algorithm models we propose take the two aspects into account perfectly and the analysis of example shows that it is effective and feasible.

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