Ant Colony Optimization with Human-computer Cooperative Strategy for Two-echelon Vehicle Routing Problem

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ABSTRACT

This paper proposed an ant colony optimization with human-computer cooperative strategy for solving the two-echelon vehicle routing problem(2E-VRP). Firstly, we use a computer game to implement the human cognition sampling, which is specially devised for 2E-VRP problem. Secondly, the human satellite-to-customer assignment strategy is applied to analyze the game results for customers' assignment to the satellite. Moreover, a global pheromone updating rule and a solution construction method are exploited to further improve the global search efficiency. The proposed algorithm benefits by giving free rein to enhance the global exploitation ability of ACO by human-computer cooperative strategy. The computational results from public test set indicate the effectiveness and usefulness of our proposed method for the two-echelon vehicle routing problem.

KEYWORDS

human-computer cooperation strategy, ant colony optimization, two-echelon vehicle routing problem

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1 INTRODUCTION

The idea of human-machine cooperation is firstly proposed by Lenat and Feigenbaum [10] in 1991, and the objective of human-computer cooperation is to achieve some mutual advantages when humans and computers cause each other [1]. In fact, the study of human-computer cooperation has become an important research stream, which refers to the study of intelligence between human minds and machines and will be effective by selecting the best approximation strategy in a given situation [11].

The two-echelon vehicle routing problem aims to deliver the freight from the depot to the customers with the capacity constraints via consolidating the freight by the satellites [4]. The customer's assignment to the satellite plays a critical importance while solving 2E-VRP, as presented by the results in [7]. In particular, the customer-to-satellite assignment makes solving the 2E-VRP become more complicated when the possible search spaces become large with the increase in the number of satellites or customers [2]. Ant colony optimization can be used to find approximate solutions to the combinatorial optimization problems [14]. However, ant colony optimization can not make full use of the global information on solving the two-echelon vehicle routing problem (2E-VRP), because the uncertainty of the satellite-to-customer assignment to the 2E-VRP affects the validity of the pheromone sharing of ACO between different satellites. The idea of the human-computer cooperation strategy is utilized to solve searching for the possible global information based on human strategy development capabilities. The game results are analyzed for the satellite-to-customer assignment to 2E-VRP, which can be considered as the global search strategy of different players.

In this paper, we proposed an ant colony optimization with human-computer cooperative strategy(ACO-HCC), which is devised with several attractive features based on the idea of human-computer cooperation for enhancing the optimization performance.

2 ACO WITH HUMAN-COMPUTER COOPERATIVE STRATEGY

In this section, we illustrate the details of the proposed algorithm for the 2E-VRP. First of all, the human satellite-to-customer assignment strategy can deal the game results with decomposed graph G'_{ga} for customers' assignment to satellites. Moreover, to guide the path construction process of each satellite, the pheromone global updating rule of ACO is used to update the pheromone and heuristic information of the artificial ant colony. Finally, the solution reconstruction method is exploited to improve the global search efficiency of the proposed algorithm. In the proposed algorithm, there are d ant groups G_k, $d = 1, 2, ..., s$. each of the ant groups is in charge of finding a feasible solution for the corresponding satellite. The routing problem of each satellite in the second level can be regarded as the vehicle routing problem, which can be solved by [16].

2.1 ACO for 2E-VRP

This section describes the procedure of the ACO for 2E-VRP as an example [13]. The separation strategy (satellite-to-customer assignment) divides the 2E-VRP problem into $s+1$ vehicle routing problems(VRP). Next, the ant colony optimization (ACO)is used to solve the $s+1$ VRP problems. Given the satellite-to-customer assignment to the 2E-VRP, the objective of the ACO is to find a minimal travel distance from each satellites. The ACO mainly consists of the iteration of four steps [6]:

1) Initialization : use the distance-based greedy algorithm to construct a better feasible solution s_0, set the initial pheromone according to Equation (9)

$$\tau_0 = \frac{f(s_0)}{n} \tag{1}$$

where n is number of the customers.

2) Path Construction: Ant k (k = 1,2,...,l) in customer i decides to visit the next customer j (customer i and customer j are served by the same satellite k), according to the transition probability given in

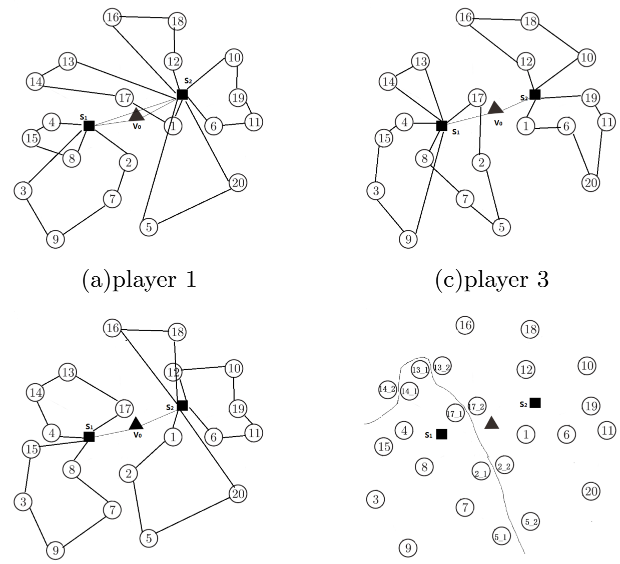
$$p_k(i,j) == \begin{cases} \frac{[\tau(i,j)]^\alpha[\eta(i,j)]^\beta}{\sum_{u\in\psi_l}[\tau(i,j)]^\alpha[\eta(i,j)]^\beta} & j \in \psi_l \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

where $\tau(i,j)$ denotes the pheromone on edge(i,j), $\eta(i,j) = \frac{1}{d_{ij}}$ represents the heuristic information, where d_{ij} is the distance from customer i to customer j. Let ψ_l denote an edge set which records all edges an ant have visited. Let α and β represent the weight factors that measure the corresponding importance between the pheromone and the heuristic information.

3) Implement local search to the ant's solution [5].

4) Update the pheromone pheromone information by using Equation (11)

$$\tau_k(i,j) = (1-\rho)\tau_k(i,j) + \rho\triangle\tau_k(i,j) \tag{3}$$



(a)player 1 (c)player 3

(b)player 2 (d)decomposition result

Figure 1: An illustrative example of the human satellite-to-customer assignment method(there are three players' feasible solutions in (a), (b) and (c), and decomposition of the game result with added auxiliary customers for satellite-to-customer assignment in (d)).

where the parameter $\rho \in (0,1)$ denotes the evaporation coefficient. The term is represented as $\triangle\tau_k(i,j) = \frac{1}{f(Solution_{gb})}$, which is associated with the best solution.

2.2 Human Satellite-to-Customer Assignment Strategy

The human satellite-to-customer assignment strategy attributed the customer to different satellites based on the personal preferences of different players. Game playing, which is specially devised according to the instances of the 2E-VRP problem, can be regarded as human cognition sampling. The game result can be simply seen as player's global searching process of routing related problem, and each players' game result is recognized as a feasible solution.

Fig.1 illustrates an example of the human satellite-to-customer assignment strategy. Fig.1(a), Fig.1(b) and Fig.1(c) show the feasible solutions which is generated by game playing. The details of satellite-to-customer assignment to three players' game results are illustrated with Table 1. As we can be seen from Table 1, six customers (v_3, v_4, v_7, v_8, v_9 and v_{15}) are only assigned to the satellite S_1, nine customers (v_1, v_6, v_{10}, v_{11}, v_{12} , v_{16}, v_{18}, v_{19} and v_{20}) are only assigned to the satellite S_2, but five customers (v_2, v_5, v_{13}, v_{14} and v_{17}) are assigned to the satellites S_1 and S_2. The decomposition

Table 1: The details of satellite-to-customer assignment to three players' game results

	v_1	v_2	v_3	v_4	v_5	v_6	v_7	v_8	v_9	v_{10}	v_{11}	v_{12}	v_{13}	v_{14}	v_{15}	v_{16}	v_{17}	v_{18}	v_{19}	v_{20}
player 1	S_2	S_1	S_1	S_1	S_2	S_2	S_1	S_1	S_1	S_2	S_2	S_2	S_2	S_2	S_1	S_2	S_2	S_2	S_2	S_2
player 2	S_2	S_2	S_1	S_1	S_2	S_2	S_1	S_1	S_1	S_2	S_2	S_2	S_1	S_1	S_1	S_2	S_1	S_2	S_2	S_2
player 3	S_2	S_1	S_1	S_1	S_1	S_2	S_1	S_1	S_1	S_2	S_2	S_2	S_1	S_1	S_1	S_2	S_1	S_2	S_2	S_2

of the game result with added auxiliary customers is shown in Fig.1(d), where the five customers (v_2, v_5, v_{13}, v_{14} and v_{17}) are repeatable assigned to the corresponding satellites based on the game results statistics of the satellite-to-customer assignment.

2.3 Pheromone Global Updating Rules

In this paper, pheromone is applied to provide essential guidance of the artificial ant colony to gradually search for the optimal solution to the vehicle routing problem of each satellite in 2E-VRP problem. In order to guide the search effectively, ACO-HCC employs a new pheromone updating mechanism using multiple pheromone tables. We associate each artificial ant colony with a pheromone table. Each table record the pheromone of the artificial ants over the routes of the satellite independently for each generation.

Let τ_0 be initial pheromone, and τ_0 is set to the value $\frac{f(Solution_{gb}(G_{ga}))}{n}$ for all pheromone tables. At different generations, the ants are in charge of finding the optimal routes for the satellites, and the auxiliary customers are responsible for sharing the pheromone in different tables. The pheromone is designed to be associated with the total cost of the current best solution and the cost of respective satellites. Moreover, $\triangle\tau_k(i,j)$ for the satellite S_k is calculated by the expression $\triangle\tau_k(i,j) = \frac{n}{f(Solution_{gb}(G_{ga}))} + \frac{n_k}{f(Solution(G_z^k))}$, where G_z^k is the route cost of the satellites S_k and n_k is the number of the customers served by the satellite S_k. The pheromone values are gradually updated in pheromone tables as the procedure of the ant colony searching.

In summary, the pheromone global updating rules mainly relied on the rewarding schemes for each satellite to guide the construction of feasible solution.

2.4 Solution Reconstruction Method

It is well known that the prematurity often occurs to A-CO and may result in reducing global search capability [12]. Hence, we develop the solution reconstruction method to further to enhance the global exploitation ability for the 2E-VRP problem. The solution reconstruction method consists of two parts. Firstly, we integrate with the solutions $Solution(G_z^k), k = 1, 2, ..., s$, for the satellites in the first level, generate the routes on the first level by the savings algorithm [3] and obtain a complete solution $Solution(G_z)$. Besides, we select the auxiliary customers, and employ roulette wheel method to delete repeatable customer which ensures that each customer is only served once. The roulette wheel method is based on the distance between the customer and the corresponding satellite. The auxiliary customers do well to share the local search information on different satellites, which can also improve the global exploitation ability based on human satellite-to-customer assignment strategy.

3 COMPUTATIONAL RESULTS

3.1 Instances and Parameter Description

To evaluate the performance of our algorithm, we have considered the instance Set S from the literature [8]. Set S contain small instances with up to 50 customers and include two or three satellites. To ensure the fairness of the comparison, all solution procedures were implemented in the same language (Matlab) and computer system (Xeon E5620 2.40Ghz). All the experiments were carried out for 30 independent executions, the number of the initial game solutions is 100 , and the number of ants for each satellite is 6. Other parameters are set as follows: $\rho = 0.2$, $\alpha = 1$ and $\beta = 2$ [16].

3.2 Performance Evaluation

This section will present the experiments and results. We compare our algorithm with an adaptive large neighborhood search heuristic (ALNS) algorithm [9] and human-computer cooperative brain storm optimization(HCC-BSO) algorithm [15] to show the effectiveness of the proposed algorithm. The game results for HCC-BSO algorithm and the proposed algorithm is the same, and the experiments are summarized in Table 2. Columns 2-5 present the results from ACO-HCC algorithm including the best solution, the average solution, the average evaluation times and average running time (second). The numbers in bold are the results as the best-known solutions among three algorithms. Columns 6-9 show the results from HCC-BSO algorithm, and Columns 10-13 present the results from ALNS algorithm. The evaluation times in ACO-HCC and HCC-BSO are one thousand times, and the evaluation times in ALNS is five thousand times.

Considering the results from Table 2, we can observe that ALNS is not good as the performance of ACO-HCC in most instances even with much evaluation times as well as the HCC-BSO algorithms. The human global searching ability does favor to enhance the performance of our proposed algorithm with less evaluation times. Besides, ACO-HCC can get the best solution in 14 instances, but HCC-BSO and ALNS can obtain best solution in 8 instances and 7 instances respectively. This may be attributing to that the proposed algorithm integrated the the human-computer cooperative strategy into ACO algorithm for making good use of global information of

Table 2: Results on the set S in term of the solution costs

Instances	ACO-HCC				HCC-BSO				ALNS			
	best	ave.cost	times	t(s)	best	ave.cost	times	t(s)	best	ave.cost	times	t(s)
E-n22-k4-s13-14	**526.15**	526.15	1000	12	**526.15**	526.15	1000	30	**526.15**	526.15	5000	43
E-n22-k4-s13-16	**521.09**	521.09	1000	12	**521.09**	521.09	1000	22	**521.09**	521.09	5000	44
E-n22-k4-s13-17	**496.38**	496.38	1000	8	496.39	496.39	1000	24	**496.38**	496.38	5000	49
E-n22-k4-s14-19	**499.1**	499.1	1000	15	500.12	500.28	1000	23	499.81	499.81	5000	43
E-n22-k4-s17-19	**512.8**	512.8	1000	5	**512.8**	512.8	1000	20	512.81	512.81	5000	26
E-n22-k4-s19-21	**520.42**	520.42	1000	11	520.5	520.50	1000	11	**520.42**	520.42	5000	34
E-n33-k4-s16-22	672.93	672.94	1000	14	672.19	672.2	1000	25	**672.17**	672.17	5000	76
E-n33-k4-s16-24	**666.02**	666.04	1000	24	666.09	666.91	1000	34	669.12	669.12	5000	77
E-n33-k4-s19-26	**680.37**	680.37	1000	17	**680.37**	680.37	1000	46	**680.37**	680.37	5000	84
E-n33-k4-s22-26	**680.24**	680.24	1000	26	**680.24**	680.24	1000	38	680.37	680.37	5000	77
E-n33-k4-s24-28	**670.43**	670.43	1000	21	670.5	670.5	1000	48	672.45	670.49	5000	88
E-n33-k4-s25-28	**650.32**	650.32	1000	22	650.58	650.58	1000	35	650.58	650.58	5000	63
E-n51-k5-s12-18	**692.37**	692.37	1000	13	693.59	694.32	1000	38	692.59	692.59	5000	147
E-n51-k5-s12-41	683.05	683.14	1000	21	**682.03**	682.04	1000	28	684.05	684.65	5000	133
E-n51-k5-s12-43	710.42	710.42	1000	19	**710.41**	710.41	1000	39	**710.41**	710.41	5000	217
E-n51-k5-s39-41	728.54	728.54	1000	18	**728.52**	728.52	1000	69	728.54	728.54	5000	155
E-n51-k5-s40-41	**722.25**	722.25	1000	38	723.75	723.75	1000	38	726.15	726.15	5000	154
E-n51-k5-s40-43	**751.32**	751.32	1000	44	752.15	752.15	1000	79	752.15	752.17	5000	158

the best solution(best), the average solution(ave.cost), the average evaluation times(times) and average running time (t(s))

the 2E-VRP problem. In fact, the uncertainty of the satellite-to-customer assignment to the 2E-VRP makes the global information on routing related problem more importantly.

With the use of human-computer cooperative strategy to improve the global exploitation ability of our algorithm, thereby improving the efficiency of problem-solving. Regarding the computation efficiency, we find that ACO-HCC can find better solutions in an acceptable time for 2E-VRP.

4 CONCLUSIONS

This paper proposed an ACO-HCC algorithm based on human-computer cooperative strategy to tackle the 2E-VRP problem. ACO-HCC constructs feasible solutions with the help of human-computer cooperation strategy, which benefits by giving free rein to the mutual advantages of the human and the computer.

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