An adaptive hybrid ant colony optimization algorithm for solving Capacitated Vehicle Routing

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Abstract. Ant Colony Algorithm has certain advantages in solving Capacitated Vehicle Routing Problem (CVRP), but there are still easy to fall into local optimum, the search speed etc. To overcome these problems this paper presents an adaptive hybrid Ant colony optimization algorithm for solving Capacitated Vehicle Routing Problem. The adaptive hybrid ant colony optimization algorithm uses genetic algorithms to adjust pheromone matrix algorithm, and designs an adaptive pheromone evaporation rate adjustment strategies, and uses local search strategies to reduce the amount of calculation. Experiment on Some classic problems shows that the presented algorithm for solving the Capacitated Vehicle Routing Problem is effective and has better performance.

Introduction

The Vehicle Routing Problem (VRP) is a complex combinatorial optimization problem, what is a hot interdisciplinary research issue across Operations research, Applied Mathematics, Network Analysis, Graph Theory, Computer Applications, and Transportation in recent decades. It stems from the reality of the road transport sector, and has been widely used in communications, manufacturing, defense and other fields. Capacitated Vehicle Routing Problem (CVRP) refers to the optimization problem that a number of known customers, cargo needs and position coordinates of each customer point are known, and the load capacity of the vehicle is constant, each vehicle starts from the starting point completing a number of delivery tasks and comes back to the starting point [1]. Actually, CVRP can also be generalized to many real life problems that make it attach more great attention from academia and industry. The quality of planning and optimization of CVRP would directly affect the enterprise benefit and the interests of customers [2-3].

Ant Colony Algorithm is a simulated evolutionary algorithm inspired by nature and behavior of the ant colony made. In recent years, many scholars did research in-depth on CVRP using Ant Colony algorithm and presented some classic algorithms, such as Saving Ant Algorithm[4], Sweep based Multiple Ant Colonies Algorithm[5], hybrid meta-heuristics for the vehicle routing problem[6-8]. MAX–MIN Ant System[9]. They are very popular and well done in many applications. Although current Ant Colony Algorithms have certain advantages in solving CVRP, but it is still easy to suffer problems of local optimization and slow search. To overcome these deficiencies, this paper presents an adaptive hybrid ant colony algorithm with high search performance (named as AHASAC) and demonstrates its effectiveness on solving CVRP in compared experiments.

Proposed Methods

2.1 Key improvements of AHASAC

In the proposed AHASAC following tactics are used: firstly, genetic algorithms, for its global convergence, is introduced to adjust the pheromone matrix of Ant colony algorithm in order to escape from local optima while a pheromones adjust strategy is used to prevent the groups lost phenomenon, and improve the result; secondly, a local search strategy is introduced to cut computation, and improve search speed.

2.1.1 Pheromones adjust strategy

2.1.1.1 Methodology of intermingling Ant Algorithm with Genetic Algorithm

Different from the traditional algorithm intermingled Ant Algorithm with Genetic Algorithm what switch each other with a fix iteration number, AHASAC switches Ant Algorithm and Genetic Algorithm while Ant Algorithm evolution stagnation to avoid the algorithm premature convergence and local optimum and cut computation. The main integration procedure is shown below:

Step1: Let Ant Algorithm run certain iteration;

Step2: Judge Ant Algorithm whether reaches the status of evolution stagnation. If it is on the status of evolution stagnation, Genetic Algorithm would be called to optimize the selected ant;

Step3: Update the path selected by the optimized ant into the pheromone table.

2.1.1.2 Improvement based on MMAS

(1) Only the best offspring of each generation or the offspring to build the best optimal path up to now are allowed to release pheromones, in order to accelerate the convergence rate of the algorithm.

Consequently, the modified pheromone trail update rule is given by $\tau_{ij}^{new} = \rho_{ga} \tau_{ij}^{old} + (1 - \rho_{ga}) \Delta \tau_{ij}$.

Where, ρ_{ga} is the residual parameters of genetic algorithm for the pheromone update, and

 $\Delta \tau_{ij} = \begin{cases} \frac{1}{d_{ij}^{3}}, & \text{If } d_{ij} \text{ is the best in current generation} \end{cases}$

(2) The pheromone update method is based on the maximum and minimum pheromone method, whose concentration range of pheromone on the path is limited. For any τ_{ij} , it holds $\lim_{t\to\infty} \tau_{ij}(t) = \tau_{ij} \leq \frac{1}{1-\rho} \frac{1}{f(s^{\text{opt}})}$ there are explicit limits τ_{\min} and τ_{\max} on the minimum and maximum pheromone trails such that for all pheromone trails $\tau_{ij(t)}$, $\tau\min \leq \tau_{ij(t)} \leq \tau_{\max}$.

$$\tau_{\max} = \frac{1}{(1-\rho)L_{global}}, \qquad \tau_{\min} = \frac{\tau_{\max}}{5}$$

After iteration, one has to ensure that the pheromone trail respects the limits. If we have $\tau_{ij(t)} > \tau_{max}$, we set $\tau_{ij(t)} = \tau_{max}$; analogously, $if\tau_{ij(t)} < \tau_{min}$, we set $\tau_{ij} = (\tau_{min} + \tau_{max})/2$.

(3) The pheromone initial value is set as the reciprocal of the distance between two cities, to make the algorithm faster convergence in the initial stage.

3.1.2 Adaptive pheromone evaporation rate

Generally, Genetic Algorithm updates the pheromone can help Ant Colony Algorithm escape from local optima, but would result in the Ant Colony Algorithm losing its outstanding factor and damage the original pheromone table created by the Ant colony algorithm. Therefore, we present a new adaptive evaporation rate to update the pheromone. In this method, the amount of pheromone updated by calling Genetic Algorithm at the early stage is less, then increase the pheromone evaporation rate of pheromone in Genetic Algorithm gradually in pheromone update process. The

pheromone evaporation rate ρ_{ga} formula $\rho_{ga}^{new} = \rho_{ga}^{ole} + \Delta t$. Where, ρ_{ga}^{new} is the new pheromone evaporation rate, and Δt is the increment pheromone evaporation rate.

2.2 Genetic algorithm design

2.2.1 Chromosome encoding

In the proposed AHASAC, the natural numbers encoding way is used for the chromosome encoding of genetic algorithm. For example, the chromosome "0123045060" represents the arranged path of transport tasks of three cars six customers, these three paths are as following:

Path 1: Warehouse -> Customer 1 -> Customer 2 -> Client 3 -> Warehouse

Path 2: Warehouse -> Client 4 -> Client 5 -> Warehouse

Path 3: Warehouse -> customer 6 -> Warehouse

As above example shown, "0" is warehouses. There are four "0" what divide the chromosome into three sections representing the three paths.

2.2.2 Cross operation

Using ordinary cross operation will have great probability to produce a lot of offspring did not

comply with constraints, or to cause loss of good genes, because of CVRP constraint conditions. It can result in the algorithm search results deteriorated. To overcome this drawback, SHASA use an improved maximum retention cross scheme to ensure increase the probability for good gene segments, as described in the following procedure:

(1) Select two adjacent zero crossover position randomly;

(2) Put the segment between two "0" into the header of the new offspring, then, compare the two selected cross- segments, and add the unrepeated elements to the end of the new offspring;

(3) Swap the position of the unselected parts of the two cross-genes and add the elements not "0" to the end of the new offspring arranged according to the original order;

(4) Do the insertion zero operation for two new offspring after step (3). Zero is inserted into the end of each chromosome to ensure zero is the end element of chromosomes.

2.3 Algorithm framework of AHASAC

(1) Initialize parameters. Set iterations Nc = 0, and set value for the maximum number of iterations Nmax and the genetic algorithm iterations Nga; Place *m* Ants on the *n* cities, and set

 $\tau_{ij}^{\text{begin}} = 1/d_{ij}$ and the initial $\Delta \tau_{ij} = 0$ and Ants taboo table index number k = 1.

(2) Nc = Nc +1, k = k + 1.

(3) The ant selects the city j using roulette with the transition probability and estimates it whether meet the load constraints. If it met then run the city j, or else it returns the warehouse.

(4) The ant moves to the selected city which is added into the taboo table of this ant after.

(5) Traverse all the cities orderly.

(6) Update the pheromone according to the maximum and minimum pheromone strategy.

(7) Judge Ant Algorithm whether reaches the status of evolution stagnation. If it is on the status of evolution stagnation goes to step (8), or else goes to step (12).

(8)Select a certain ant population using roulette.

(9) Genetic Algorithm runs to optimize the ant path. If the offspring is better than the parents after genetic operation, then replace the parents.

(10) If it meets the end conditions of Genetic Algorithm, stop Genetic Algorithm.

(11) Update the path selected by the optimized ant into the pheromone table.

(12) if $N_c \ge N_{max}$, then the algorithm end and output the result, or else clear the taboo table and reset k = 1, and then jumps to step(2).

Test results

In this section, some experiments using AHASAC for selected CVRP problems are designed to justify the effectiveness of AHASAC. The main parameters in our experiment are set as following: the number of ant as 34,the pheromone as 3, τ max as 4,the iteration times as 1000, the population of Genetic algorithm as 40, the iteration times of Genetic algorithm as 50,the number of nearly city as 25,the ant stagnation times as 50.

3.1 Test for CVRP problem presented in cited literature

The Table 1 shows the result of the proposed algorithm averaged 10 times running and others for solving the Capacitated Vehicle Routing Problem cited from the literature 5 and literature 7.

Problem	Gaskell's	Sweep	Location	Set	Direct	Genetic	MAX-MIN	The
scale	saving	algorithm	Based	Partitioning	tree-search	Algorithm	Ant System	proposed
	approach		algorithm	algorithm	approach			AHASAC
50	585	532	524.9	524	534	521	533.6	533
100	886	851	832.9	833	832.9	840.5	827.7	826.9

Table 1 comparing to different algorithms

As shown in Table 1, the proposed algorithm performs better than five of seven algorithms mentioned in literature 5 and literature 7, except for Set Partitioning algorithm and Genetic Algorithm and Sweep algorithm, on the problem scale as 50, while it performs better than all other seven algorithms on the problem scale as 100. It reveals that the bigger scale of problem the more superior is the proposed algorithm shown. So, it performs better in the more complex problem.

3.2 Test for international benchmark

In this section, the proposed AHASAC method is compared with the classic ant colony algorithm experiment on the VRP benchmarks solomon100 problem solving to show its superiority. The paper selects five test cases randomly from the solomon100. They are r101, rc101, c101 and c201. And the results are shown in Table 2.

test cases	classic Ant Colony Algorithm	the proposed AHASAC		
R101	885.118	880.247		
rc101	1026.498	1024.363		
c101	827.946	827.787		
c201	587.857	586.631		

Table 2 Results of AHASAC on solving VRP benchmarks

As showed in Table 2, the proposed algorithm performs better than classic Ant Colony Algorithm on all five random test cases from the solomon100. It reveals that the proposed algorithm solving benchmarks is effective.

Conclusion

A novel adaptive ant colony algorithm mainly mix some pheromones adjust strategy and Genetic Algorithms and selection strategy based near the node and MMAS is proposed. Compared experiment results demonstrate it has better convergence and better optimal solution. However, this method still has the disadvantages due to the lack of rigorous mathematical proof, and therefore some parameters are determined empirically. However, this method will have the most potential future on solving VRPTW, TSP and other NP-hard problem.

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