Journal of Al-Nahrain University Vol.14 (1), March, 2011, pp.161-170 Science

A Modified ANT System Optimization Algorithm for the Capacitated Vehicle Routing Problem

Faiz Faiq Showkat
Department of Mathematics and Computer Applications, College of Science,
Al-Nahrain University, Baghdad-Iraq.

Abstract

In this paper we use a modified algorithm of the ant system optimization (ASO) to solve the capacitated vehicle routing problem (CVRP), i.e., finding the (approximate) optimum routes, the main modifications consist of, (1) Adding pheromone to the best three routes found by the ants instead of adding pheromone to the global best route only, (2) Introducing the concept of probability of stagnation which represent the probability of having the previous solution in the next iteration, (3) Adding a local optimizer to improve the global best routes found by artificial ants. We test our modified algorithm on some benchmark problems that have been also tested by other ant colony optimization (ACO) metaheuristics, our results was best in the sense that it is closer to the known optimum routes for these benchmark problems except one problem.

Introduction

Transportation is a major problem domain in logistics and represents a substantial task in the activity of many companies, Toth [1]. An important problem in the field of transportation consist of finding the optimum routes for a fleet of vehicles to serve a set of customers, this problem known as vehicle routing problem (VRP).

Dantizag and Ramser in 1959 proposed the first VRP, Dantizag[2], they introduce the following scenario, consider a depot having a fleet of vehicles with limited capacity and a set of customers each with a certain demand for merchandise or goods to be dispatched, the problem is to determine optimum route for each vehicle to visit every customer exactly once in order to fulfill the demand, the most common goal for optimization is to minimize the overall distance traveled by the vehicles, this problem known as capacitated vehicles routing problem (CVRP), for more information about the (CVRP) and its variant one referred to, Toth[1], Dantizag[2].

Vehicle routing problem:

The VRP can be represented by an undirected graph G = (V,E), Bullnheimer[3], where $V=\{v_0,v_1, v_2 \ldots v_n\}$ is a vertex set and $E=\{(v_i, v_j)|\ v_i, v_j \in V,\ i \neq j\}$ is an edge set, the depot is represented by vertex v_0 and it is from where that (m) identical vehicles of capacity (Q) must serve all the (k) clients (or customers) represented by the set of (n) vertices , for each edge there is a non-negative cost (distance or travel time) represented by a matrix $C=(C_{ij})$ between customers v_i and v_j, each customer v_i has non-negative demand q_i, now if we let $(R_1, R_2, \ldots R_m)$ represent a partition of V representing the routes of the (m) vehicles to serve all customers where $R_i=\{v_0, v_1, v_2, \ldots, v_k, v_{k+1}\}$ with i=1,…,m and $v_0=v_{k+1}$ represent the depot, then the cost for a route is

$$C(R_i) = \sum_{j=0}^{k} C_{j,j+1} \quad \ldots\ldots (1)$$

and the cost of the problem represented by S which we seek to minimize is

$$S = \sum_{i=1}^{m} C(R_i) \quad \ldots\ldots (2)$$

The above representation is of the VRP is general, but when one handles the CVRP the following constraints should be considered:

A. Each customer is visited exactly once by one vehicle

B. The total demand of any route must not exceed the total vehicle capacity (Q), i.e.

$$\sum_{i \in Ri} q_i \leq Q \quad \ldots\ldots (3)$$

C. Some times the route duration or the total distance traveled by each vehicle is also considered as a constraint, in both cases if B is the upper bound then $C(R_i) \leq B$

Although the VRP can be represented by integer mathematical programming and hence the exact optimum routes can be found, Cristofides[4], Fisher[5], but practical application shows that exact optimum routes could not be found when number of customers is greater than (25) in Christofildes branch and bound algorithm, and more than (71)customer for the Fisher k-tree algorithm and no guarantee to find exact optimum routes when the number of customers in less than (71), these limitations raise because the VRP is a combinatorial optimization problem which is NP-hard, Kis[6], Kan[7], this means that we can not find exact optimum solution (i.e., routes) in reasonable time due the huge calculations. This characteristic (NP-hard) encourage researchers to develop new algorithms to find (approximate) optimum routes but in reasonable time, these new algorithms like genetic algorithm, tabu search, neural network and the recent algorithm known as ant colony optimization (AC0) metaheuristics which we will focus on in this paper .

Ant colony optimization metaheuristics

The ant colony algorithms in general are multi agent approach to difficult optimization problems such as traveling salesman problem (TSP), quadratic assignment problem (QAP), vehicle routing problem (VRP) etc. Dorgio[9], the ant algorithms were inspired by the observation of real ant behavior and in particular how it can find the shortest paths between food sources and their nest, it was found that ants while walking from food sources to the nest and vise versa, it deposits on the ground a substance called pheromone, forming in this way a pheromone trail, ant can smell pheromone, and when choosing there way it tend to choose in probability paths marked by strong pheromone concentration, these pheromone trail allows the ants to find their way back to the food source (or to the nest), this pheromone trail can also be used by other ants to find the location of food sources discovered by other ants. It has been shown experimentally, Dorgio[9] that this behaviors of following pheromone trail can give rise once employed by a colony of ants to the emergence of shortest path, this shortest path get another enforcement by noting that the pheromone can evaporate after some time, in this way the less promising paths progressively loss pheromone because less and less ants will use these paths, for more information of real ants behaviors and the experiments done about the ants one referred to Dorgio[11], Doigio[9], Markle[10]

Artificial ants

In the ants colony optimize (ACO) metaheuristics a colony of artificial ants cooperated in order to find good solutions to difficult combinatorial optimization problems, cooperation is a key designed component of ACO algorithms, this cooperation ability resulting from a form of indirect communication known as stigmergy defined as "a method of communication within decentralized system, in which individual parts of the system communicate with one a nether by modifying their local environment", Dorgio[11].

To understand how artificial ants construct (approximate) optimum solution let us consider the minimization problem (S, f, R), where S is the set of solution, f is the objective function which assign to each solution $s \in S$ a cost value $f : s \to R \forall s \in S$ and R is the set of constraints, the goal is to find $s_{opt} \in S$ that is minimum i.e. $f(s_{opt}) \le f(S)$, now keeping in mind that ACO algorithms applicable to combinatorial optimization problems and to those which belong to the group of shortest path, then we have, Markle[10].

A. The solution $s \in S$ can be represented by a finite set of components N= $\{n_1, n_2,...,n_k\}$.

B. The problem presents several states defined upon order component sequence d=<n_1, $n_2 \ldots n_k$> over the element of N .

C. If D is the set of all possible sequences, then $\overline{D}$ is the set of feasible (sub)sequences with respect to the constraints R, and the element in $\overline{D}$ defined the feasible states.

D. There is a neighborhood structure d_2 to d_1 defined as follows:

I. d_2 and $d_1 \in D$.

II. State d_2 can be reached in one logical move from d_1, i.e. if (r) is the last component of the sequence d_1, there must exist a component $k \in N$ such that d_2=<d_1, K>, which means there exist a valid transition between (r) and (k).

III. The feasible neighborhood of d_1 is the set containing all sequences $d_2 \in \overline{D}$ but if $d_2 \notin \overline{D}$ then we say d_2 is in the infeasible neighborhood of d_1.

E. From the above characteristic we can represent the ACO metaheuristics as a graph G = (N, A), where A is the set of edges that connects the set of components N (nodes), this graph usually called the construction graph. We have

I. The set N= $\{n_1, n_2 \dots n_k\}$ is the solution components.

II. The state d (and hence the solution) corresponds to paths in the graph.

III. The edge of the graph a_{rk} is connection or transitions defining the neighborhood structure.

IV. d_2 (=<d_1, k>) is the neighbor of d_1 if node (r) is the last component of d_1 and the edge a_{rk} exist in the path .

F. In general when artificial ants in state d_k =<d_r,k> it can move to any node k of its feasible neighborhood N(r) defined as $N(r)=\{k \mid (a_{rk} \in A)$ and (<d_r,k> $\in \overline{D}$) $\}$.

ANTS transition

We saw before that artificial ants build the solution incrementally using the sequence d_k =<d_r,k>. The calculation of movements of artificial ants through adjacent state of the problem can be represented in form of weighted graph, this movement is made according to the transition rule which is based on local information available at each edge, this local information consist of heuristic and pheromone trail information, and by moving on the construction graph ants incrementally build solution, the general formula of the transition rule is shown bellow, Dorgio[11].

$$P_{rk} = \frac{Ph_{rk}^{a} Y_{rk}^{b}}{\sum_{u \in N(r)} Ph_{ru}^{a} Y_{ru}^{b}} \quad k \in N(r) \quad \text{.........................(4)}$$

Where:

P_{rk} Is the probability that artificial ant at node (r) will move to node (k), i.e. $d_k = \langle d_r, k \rangle$.

Ph_{rk} Is the net pheromone trail value along the path (**rk**) i.e. edge a_{rk} .

Y_{rk} The heuristic value (also called desirability) of the path (**rk**) and depend on the nature of the problem being solve, for example in TSP and VRP problems it is equal to $\left(\frac{1}{L_k}\right)$ where L_k is the distance between nodes (**r**) and (**k**).

a, b are control variables (see equation 4 above) which determine the relative influence of pheromone trail () $\mathbf{ph_{rk}}$ and heuristic $\mathbf{Y_{rk}}$, so when **a**=0 we depend only on heuristic value in calculating transition rule, but when **b**=0 we depend only on pheromone trails.

Pheromone update

When the solution construction ends i.e. after each ant has completed a tour, the pheromone trails are update, in this way the next generation of ants make use of result found by the current generation of ant (stigmergy concept), in general this pheromone update is carried out in three steps, Markle[10],they are:

A Lowering the pheromone trail by a constant factor know as evaporation rate (r), where 0< r <1, this will avoid unlimited accumulation of the pheromone trails and enable the algorithm to forget previous bad decision, this is done to every edge of the construction graph and hence the new pheromone trails are

$\mathbf{Ph_{rk}} \neg \mathbf{Ph_{rk}} (\mathbf{1} - r)$ For each edge of the construction graph ....(5)

B. Allowing each ant to trace back the edges it follow to construct the solution (i.e. current iteration route) and strength the pheromone associate with it by an amount T, i.e.

$\mathbf{Ph_{rk}} \neg \mathbf{Ph_{rk}} + \mathbf{T}$ ....(6)

Where

$$\mathbf{T} = \begin{cases} Q/L_k & \text{if edge } (\mathbf{rk}) \text{ part of the current iteration solution (i.e. route)} \\ 0 & \text{elsewhere} \end{cases} \quad \text{.............................(7)}$$

Where

Q Is a constant

$\mathbf{L_k}$ Is the iteration route length

C. An important improvement called the elitist strategy was introduced, Dorgio[11], it consists of giving the best tour (i.e. solution found) since the start of the algorithm called $\mathbf{T^{gb}}$ (**gb** stands for global best) a strong additional weight, in practice each time the pheromone trails are update, those belonging to the edges of the global best solution get an additional amount of pheromone, i.e

$$\mathbf{Ph_{rk}} \;\neg\; \mathbf{Ph_{rk}} + s\ \mathbf{T^{gb}} \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots (8)$$

Where

s Is the number of elitist ants, usually taken (20 -50) ants.

$$\mathbf{T^{gb}} = \begin{cases} \mathbf{1/L_{gb}} & \text{if edge } (\mathbf{rk}) \text{ part of the global best solution(i.e. route)} \\ \mathbf{0} & \text{elsewhere} \end{cases} \qquad (9)$$

where

$\mathbf{L_{gb}}$ is the global best solution found from the start of the algorithm

Another important factor about the pheromone update is when to update, Markle[10],in general there are two methods:

A. During the construction procedure, so when an ant move from one node to another in the construction graph it update the pheromone trail of the edge immediately, this method of update known as online step-by-step pheromone trail update.

B. The other method allow the ants to update the pheromone trail only after it finish the construction, so after an ant build a path (solution) it trace back the traveled paths and update the edges it passes through, this method known as online delayed pheromone trail update.

The modified ASO algorithm

There are mainly (5) algorithms for the ACO metaheuristics, Ant System Optimization (ASO) with its variant, Ant Colony System ACS, Min.Max Ant System (MMAS), Rank-Based Ant System (As_{rank}) and Best-Worst Ant System. The ASO is the oldest one introduced by Dorigo in the 90's, Dorgio[11], all other algorithms are modified or extension of the ASO, the main differences between these algorithms is the calculation method of transition rule (also known as probability distribution of transition) and/or pheromone update method, for more information one referred to Dorgio[9], Dorgio[11]. In this paper we will use the ASO (the As-cycle variant) where equation (4) will be used to find the probability distribution of transition, and equation (5-8) for pheromone update method, also the following modifications will be applied.

A. Our base algorithm is the As-cycle variant of the ASO, this variant in general update the pheromone of the edge of the constructed route by adding an amount equal to ($\mathbf{1/L_k}$) where ($\mathbf{L_k}$) is the route length, we change this method and add a predetermined fixed quantity of pheromone (**Z**) instead of ($\mathbf{1/L_k}$), it worth to note here that other variants of ASC (i.e. As-density and As-quantity) use this method of adding a fixed amount of pheromone to the constructed route, Markle[10], but they use online step–by-step pheromone update method not like As-cycle which use the online delayed pheromone update method, this means equation (6) become

$$\mathbf{Ph_{rk}} \;\neg\; \mathbf{Ph_{rk}} + \mathbf{Z} \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (10)$$

B. Stagnation represent a situation where all ants follow the same path and construct the same solution of the previous iteration, which in general are strongly suboptimal, in our algorithm we calculate the probability of such a situation, we call it probability of stagnation, now if we let the best global route represented by

$\mathbf{R^{gb}} = \{\mathbf{v_0}, \mathbf{v_1}, \mathbf{v_2}, \ldots, \mathbf{v_{k+1}}\}$ with $\mathbf{v_0} = \mathbf{v_{k+1}} =$ the depot, then with help of equation (4) we can find that

$$\mathbf{P_{sg}} = \overset{\mathbf{k}}{\underset{\mathbf{i=0}}{Õ}} \mathbf{P_{i,i+1}} \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (11)$$

Where

$\mathbf{P_{sg}}$ Is the stagnation probability

$\mathbf{P_{i,i+1}}$ Is the transition probability from state (**i**) to state (**i+1**) ,see equation (4).The main advantage of introducing the probability of stagnation is to detect if the ants fall in local optima and if it does we stop the calculation and consider the best global route as the approximate optimum solution

C. In our modified algorithm we put constraint only on the minimum value the pheromone, this is inspired from the MMAS model, we adopt this method because we want to give chance even if it is very small (but not zero) for each edge to be part of the constructed route, the maximum value constraint was neglected because its bad effect on the calculation of the probability of stagnation

D. In the original algorithm elite strategy added pheromone to the edge of the global best solution only, in our algorithm we update the edges of the best three solutions (instead of global best only) found by the ants, if we represent these three best solutions by $\mathbf{T_1^b, T_2^b}$, and $\mathbf{T_3^b}$ respectively then we have $\mathbf{T_1^b}$ £ $\mathbf{T_2^b}$ £ $\mathbf{T_3^b}$ and $\mathbf{T^{gb}} = \mathbf{T_1^b}$. After each iteration we check if $T \leq T_3^b$ when it is true this means that we get a (new) better solution so we sort in decreasing order T, T_1^b, T_2^b and T_3^b, and neglect the last one which is the worst solution (i.e. route), but if $\mathbf{T} > \mathbf{T_3^b}$ we continue with our previous three best solutions found so far without change, Although we force elite ants to deposit a fixed quaintly of pheromone (**Z**) to the edges of $\mathbf{T_1^b, T_2^b}$, and $\mathbf{T_3^b}$ but the number of elite ants is different for each solution, now if we let s represent the number elite ants adding pheromone to the edges of solution $\mathbf{T_1^b}$, then s /2 and s /3 elites ants will add pheromone to $\mathbf{T_2^b}$, and $\mathbf{T_3^b}$ respectively, this means equation (8) become:

$$ph_{rk}^{i} \leftarrow ph_{rk}^{i} + \frac{\sigma}{i} z \quad \mathbf{i=1,2,3} \ \ldots\ldots\ldots\ldots\ldots (12)$$

E. At last we add a local optimizer that use neighborhood search method, Duncan [12], to improve the ants global best route, $\mathbf{R^{gb} = \{v_0, v_1, v_2 \ldots . v_{K+1}\}}$ with v0=v_{K+1}=the depth. this local optimizer consist of three operators, they are

I. **Swapping operator**, in this operator two customers v_i for i=1, 2…..k-1 and v_j for j=i+1…k are swap their position and the new rout is divided into sub routes according to capacity constraint, then the total cost is calculated, if it happen to be less than ants global best route cost, then we simply neglect the ants global best route and replace it with this new (global best) route, if not we re-swap the customers and keep the ants global best route as the optimum route found so far.

II. **Reinsert operator**, in this operator a customer v_i for i=1, 2……..k is removed from its position and reinserted in new position between two new customers (v_j,v_{j+1}) for j=0…..k with i≠j, after finding the sub routes and total cost as in swapping operator we check if this new position lead to a better (i.e. minimum) cost then it will be considered as the new global best route otherwise we back the customer v_i to its previous position.

III. **Re-link operator**, in this operator the ant global best route is broken in two positions (edges) like (i, i+1) for i=1, 2…k-2 and (j, j+1) for j=i+2…k and re-linked as shown in Fig.(1) bellow.

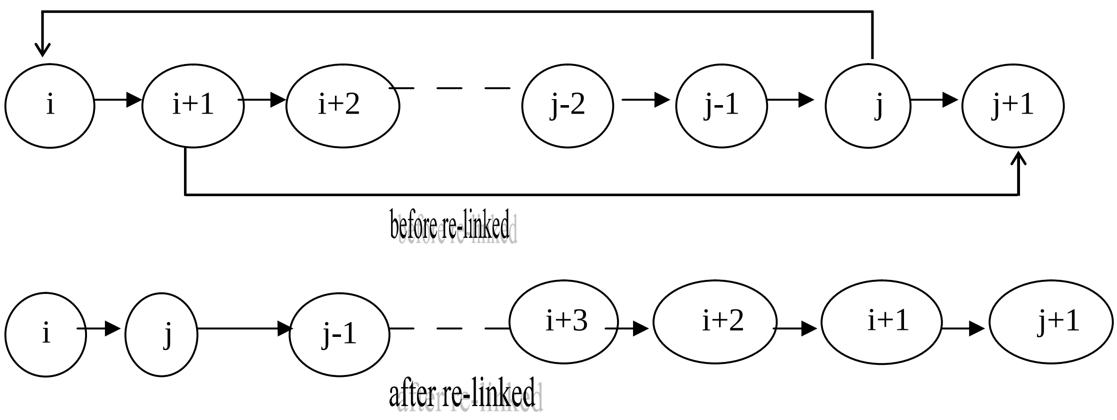

Fig. (1) Global best route before and after re –linked between (i,i+1) and (j,j+1).

And as usual the sub routes found and if the cost is minimized we neglect the current global best route and take the new re-linked route as the global best route

The three operators work sequentially beginning with swapping operator and ending with re-linked operator, at any time a new global best route emerge the local optimizer is reset and a new sequence of (swap, reinsert and re-linked) operators is started

Experiments and Results

We test our modified ASO algorithm on some benchmark problems which have known and published optimum solution (i.e. routes), we take the total distance traveled as an objective function which we seek to minimize, these benchmark problems also have an approximate optimum solution found by applying hybrid ant colony optimization metaheuristics which use some CVRP special specifications to improve the usual ant solution, this means that these hybrid ant system can only be used for the CVRP, now although we didn't use any special specification of the CVRP our approximate solution was better and closer to the known optimum solution of these benchmark problems.

Flow chart of our modified ASO algorithm is shown in Fig.(2) and Fg. (3), the first one represent the ant search part, while the second represent the local search optimization calculations. We apply with the following initial values to all the benchmark problems used in our test, the initial values are a=1, b=5, ρ=0.85, initial pheromone value=100, minimum pheromone value=10, and Z =10, the local optimizer begin when the probability of stagnation > 0.95 or maximum number of iterations (in our algorithm=500) is reached

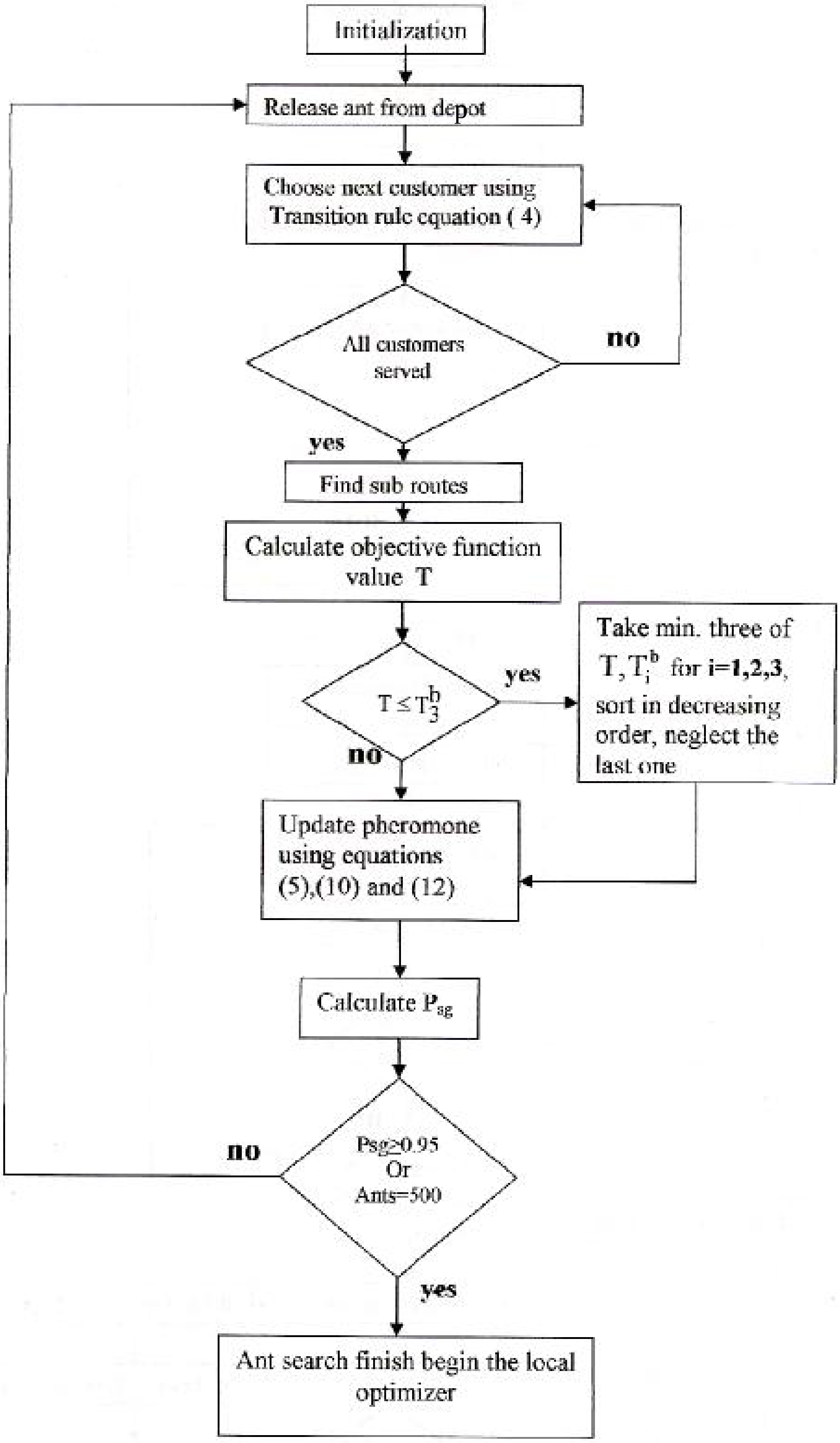

Fig.(2) The flow chart of the ant-cycle calculations.

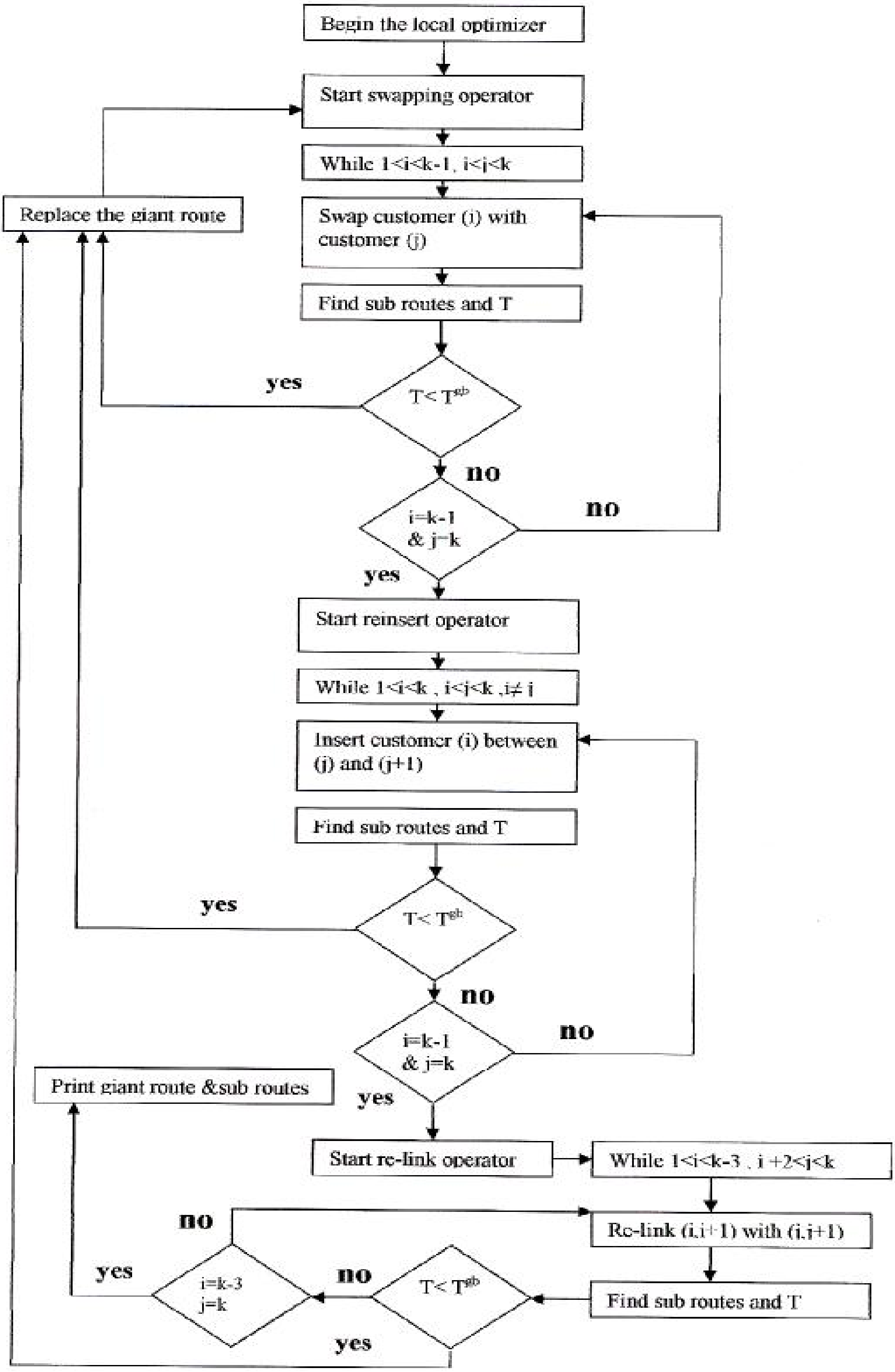

Fig.(3) The local optimizer calculations.

The first set of benchmark problems we tested known as (Augerat et al., 1988), Lopez[8], detailed information available at (http://neo.lcc.uma.es/radi-aeb/WebVRP) we take (6) instances which are also solved by Lopes[8], in which he used a modified method that calculate the pheromone added to each edge as a function of the percentage of the demand served by each tour (i.e., vehicle). Table (1) bellow shows the optimum (minimum) total traveled distance, Lopez total traveled distance, and our modified ASO algorithm total traveled distance , it is clear that the routes found by our modified algorithm are better and more closer to the optimum cost.

We test our modified ASO algorithm also on (3) instances from a second set of benchmark problems, this set solved by Cristofied[4] and his results considered as the (best) optimum solution (i.e. routes) found (yet) , Ballnhemer[3], also solved this set of benchmark problems using a hybrid ant system (HAS) that modified the transition rule by introducing the saving measure method, the capacity utilization method, and also a local optimizer known as 2-opt (very much like re-linked operator in our local optimizer). Our result as compared to Ballnhemer result was best in instance (c2 and c3), as shown in Table (2) bellow, but not in case of instance (c1) where he succeed in finding the optimum route introduced by Cristofied, the difference between our result and Ballnhemer was less than 0.24%.

Table (1)
Optimum cost, Lopez cost, and our modified ASO algorithm cost.

instance	*Number of customers*	*Max. Vehicle capacity*	*Maximum number of vehicles*	*Optimum cost*	*Lopes cost*	*Our cost*
A.n32.k5	32	100	5	784	798.29	79704
A.n.37.k6	37	100	6	949	984.24	958.67
A.n53.k7	53	100	7	1010	1043.13	1028.242
A.n60.k9	60	100	9	1358	1420.43	1361
A.n80.k10	80	100	10	1763	1886.13	1804.331

Table (2)
Optimum cost, Ballnhemer cost, and our modified ASO algorithm cost.

instance	*Number of customers*	*Max. Vehicle capacity*	*Maximum number of vehicles*	*Optimum cost*	*Ballnhemer cost*	*Our cost*
C1	50	160	5	524.61	524.61	525.91
C2	75	140	10	835.26	870.58	868.10
C3	100	200	8	826.14	879.43	864.330

Conclusion and further work

We present in this paper a modified Ant System Optimization algorithm based on the ant-cycle which is a variant of the Ant System Optimization metaheuristics, the main modifications consist of (1) introducing the probability of stagnation which used to detect if the ants stack in local (or global) optimum, (2) instead of updating the global best solution by the elite ant we update the best three solution found by the ant system (3) we add local optimizer to the algorithm of the ant system in order to improve the global best solution found by the ants, this local optimizer consist of three operators (swapping, re insertion and re line)

The modified model was tested on some benchmark problems which have known optimum solution and also approximate optimum solution found by hybrid ant system, our result was best because they are closer to the known optimum solution

For further work , we think it is a good idea to improve the local optimizer by using the tabu search specially when there are huge number of customers, also our modified algorithm was tested only on two dimensional problems a further test is required on problems of three dimensions.

References

[1]. Toth P., and Vigo D., "The Vehicle Routing Problem", Monographs on Discrete Mathematics and Applications, SIAM, Philadelphia, 2001

[2]. Dantizag G. B., and Ramser J. H., "The Truck Dispatching Problem", Management science, vol. 16, 1959

[3]. Ballnhemer B., HAR R.F., and Strauss C., "Applying The Ant System To The Vehicle Routing Problem", 2nd International conference on metaheuristics, France, 1997.

[4]. Cristofied D., Mingozzi A., and Toth P., "Exact Algorithm For The Vehicle Routing Problem Based On Spanning Tree And Shortest Path Relaxation", Mathematical Programming 20, PP 253-282, 1981.

[5]. Fisher M.L., "Optimal Solution For Vehicle Routing Problems Using K-tree", Operation research, vol.42, PP 626-642, 1994.

[6]. Kis T, "On The Complexity of The Sequencing Problem", Operation research letter, 32, PP 331-335, 2004.

[7]. Kan L.J., "Complexity of Vehicle Routing Problem and Scheduling Problem", Networks, vol.11, PP 221-227, 1981.

[8]. Lopes H.S., Dalle Molle V.L., and Eriglima C.R., "An Ant Colony Optimization System For The Capacitated Vehicle Routing Problem", proceeding of the XXVI Iberian Latin-American congress on computational Methods, Engineering CIL AMCE 2005, Brazil.

[9]. Dorgio M., Dicaro G., and Gamberdella L.M., "Ant Algorithms For Discrete Optimization" Artificial life, Vol. 5, No.2, PP 137-172, 1999.

[10]. Markle D., and Middendorf M., "Ant Colony Optimization With Relative Pheromone Evaluation Method", proc. 3rd European workshop on scheduling and time tabling, Kin sate-Ireland, LNCS 2279, PP 325-333, 2000.

[11]. Dorgio M., and Stuzle T., "Ant Colony Optimization", A bradferd book, MCT press, England, 2004.

[12]. Duncan T., "Experiments In The Use Of Neighborhood Search Techniques For Vehicle Routing" AIAI-TR-176, 1995.

[13]. Stuzle T. and Hoos H., "Improvement On The Ant System: Introducing The Max-Min Ant System", 3rd International conference on artificial Neural Network Genetic Algorithm, 1997.

الخلاصة

نقدم في هذا البحث خوارزمية معدلة لحسابات نظام النمل للامثلية يمكن الاستفادة منها لايجاد افضل المسارات (بشكل تقريبي) للعجلات المحددة الحمولة، يشمل التعديل (1) اضافه احتماليه الركود والغرض منها ايقاف الحسابات بشكل مبكر عند ظهور حاله تكرار الحل او المسار، (2) قمنا باضافه قيم الفيرمونت لافضل ثلاثه حلول بدلا من اضافتها الى افضل حل فقط كما هو متعارف عليه، (3) تحسين الحل المقدم من قبل سريه النمل باضافه محسن محلي. تم اختبار الخوارزميه المعدلة على مجموعة من المسائل القياسية وحصلنا على حلول افضل من الحلول المنشورة باستخدام الخوارزميات العادية لنظام النمل للامثلية فقد كانت حلولنا اقرب الى الحلول المثلى باستثناء مسألة واحدة.