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Application of Max-min Ant System in Modelling the Inspectional Tour of Main Sales Points of Ghacem In Ghana.

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Abstract

Ant colony optimization (ACO) has widely been applied to solve combinatorial optimization problems in recent years. There are few studies, however, on its convergence time, which reflects how many iteration times ACO algorithms spend in converging to the optimal solution. This study aims at using a Max-Min Ant System (MMAS), which belongs to Ants Algorithm to obtain optimal tour of the Travelling Salesman Problem of Ghacem. The study considered a twelve city node graph (major sales point of Ghacem) with the nodes representing the twelve cities, and the edges representing the major roads linking the cities. Secondary data of the inter-city driving distances was obtained from the Ghana Highway Authority. The results showed that the objective of finding the minimum tour from the Symmetric Travelling Salesman Problem (STSP) model by using Max-Min Ants System (MMAS) Algorithm was successfully achieved. The optimal route of total cost distance was found to be 1873Km. Therefore, Ghacem could minimize the cost of transportation as the Directors of Ghacem Ghana go on a tour to check on the sales performance of the twelve key Distributors in the major sales points in Ghana, starting from Tema where the company's Head office is sited. It is very prudent for the company to rely on MMAS model to reduce fuel cost in order to maximize profit. In doing so it go along way to increase the tax revenue of the state.

Keywords: Max-Min Ants System (MMAS), Ant Colony Optimization (ACO), Algorithm, Travelling Salesman (TSP), Ghacem

1. Introduction

Ant colony optimization (ACO) has widely been applied to solve combinatorial optimization problems in recent years. There are few studies, however, on its convergence time, which reflects how many iteration times ACO algorithms spend in converging to the optimal solution. Based on the absorbing Markov chain model, they analyzed the ACO convergence time. Hen Huanq et al. (2008) presented a general result for the estimation of convergence time to reveal the relationship between convergence time and pheromone rate. This general result was then extended to a two-step analysis of the convergence time, which included the following; the iteration time that the pheromone rate spends on reaching the objective value and the convergence time that was calculated with the objective pheromone rate in expectation.

Many strategies for ACO have been studied, but little theoretical work has been done on ACO's parameters α and β, which control the relative weight of pheromone trail and heuristic value. Shengxianq Yang et al. (2011) described the importance and functioning of α and β, and drawn a conclusion that a fixed β may not enable ACO to use both heuristic and pheromone information for solution when α= 1. Abdullah.R.Khader et al. (2008) proposed an ant colony optimization (ACO) algorithm together with traveling salesman problem (TSP) approach to investigate the clustering problem in protein interaction networks (PIN). They named this combination as ACOPIN. Stitizle et al. (1999) gave an overview on the available ACO algorithms for the TSP. they first introduced the TSP.

Shan et al. (2010) addressed an integrated model that schedules multi-item replenishment with uncertain demand to determine delivery routes and truck loads, where the actual replenishment quantity only becomes known upon arrival at a demand location. Yuren et al. (2006) presented the first rigorous analysis of a simple ACO algorithm called (1 + 1) MMAA (Max-Min ant algorithm) on the TSP. Amirahmad et al. (2005) reviewed literature of Ant Colony Optimization for suspended sediment estimation. Yong et al. (2006) presented a paper that proposed an adaptive strategy for the volatility rate of pheromone trail according to the quality of the solutions found by artificial ants. They observed that experimental results of computing traveling salesman problems indicated that the proposed algorithm was more effective than other ant methods.

White et al. (2008) proposed the addition of Genetic Algorithms to Ant Colony System (ACS) applied to improve performance. Two modifications were proposed and tested. They found that the performance of ACS-TSP could be improved by using the suggested values. Eduardo et al. (2009) used a model to solve the municipal waste collection problem by containers was presented, which applies a concept of partial collection sequences that must be joined to minimize the total collection distance. In a case study which chose the well-known travelling salesman problem with time windows, it was clearly demonstrated that Beam-ACO, even when bounding information was replaced by stochastic sampling, may have important advantages over standard ACO algorithms (Lopez et al., 2005).

Yunmming et al. (2010) combined with the idea of the Bean Optimization algorithm (BOA), the ant colony optimization (ACO) algorithm was presented to solve the well-known traveling salesman problem (TSP). Recently, researchers have been dealing with the relation of ACO algorithms to the other methods for learning and optimization. An example, Birattari et al. (2002) presented work that relates ACO to the fields of optimal control and reinforcement learning. Meuleau et al. (2002) showed that the pheromone update as outline in the proof-of-concept application to the TSP (Dorigo *et al.* 1991, 1996) is very similar to a stochastic gradient ascent in the space of pheromone values. Blum (2004) proposed the first implementation of SGA-based ACO algorithms where it was shown that SGA-based pheromone updates avoid certain types of search bias. Zlochin et al. (2004) proposed a unifying framework from so-called model-based search (MBS) algorithms. An MBS algorithm is characterized by the use of a (parameterized) probabilistic.

Merkle et al (2002) identified the competition between the ants as the main driving force of the algorithm. Nelson et al. (2009) applied the model to a waste collection sector of the San Pedro de la Paz commune in Chile, obtaining recollection routes with less total distance with respect to the actual route utilized and to the solution obtained by a previously developed approach.

Ghacem company directors are usually tasked in every two months period to embark on tour in order to check the sales of the company's goods. Ghacem has a number of accredited distributor's through-out the country. Their choice of the routes for the visit was done without considering any Mathematical model. This study aims at using a Min-Max Ant System (MMAS), which belongs to Ants Algorithm to obtain optimal tour of the Symmetric Traveling Salesman Problem (STSP).

2. Materials and Methods

2.1 Study Area and Source of Data

Ghacem Ghana is located at both Takoradi and Tema which are coastal cities in the country. The antennary of the inspectoral team of the marketing department of Ghacem Ghana was collected. This antennary shows the tour route of the team whenever they embark the inspectional tour to the key distributors in the various regional

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capitals in the country, Ghana.

2.2 Connectivity matrix for the twelve major sales points cities of Ghacem in Kilometers (Km)

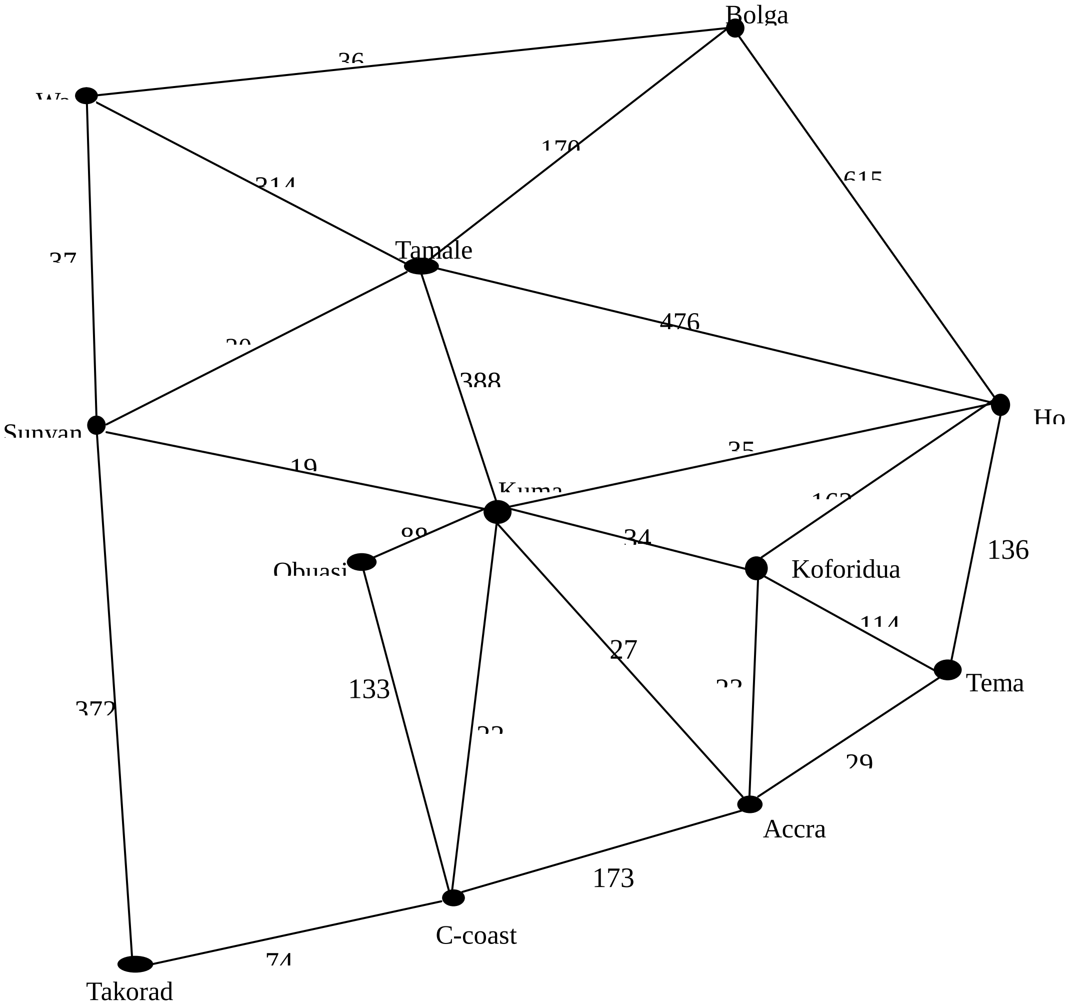

Figure 1. The road network of the twelve (12) major sales points of Ghacem and their geographical locations on the map of Ghana**.**

2.3 The distance matrix was formulated from the connectivity graph of figure 1 .Where the cities have no direct link ,the minimum distance along the edges are considered .The cells indicated inf shows that there is no direct distance , thus $c_{ij} = c_{ji} = 0$ from equation (1) below.

Table 1: Ghana Highways Authority data indicating the matrix for the weighted graph of the major roads linking twelve major Sales of points of Ghacem in Ghana in Kilometers

City/cityj	Tema	Accra	C-coast	Takoradi	Obuasi	Kumasi	Koforidua	Sunyani	Wa	Bolga	Tamale	Ho
Tema	0	29	inf	Inf	Inf	Inf	Inf	Inf	inf	Inf	inf	136
Accra	29	0	144	Inf	Inf	270	85	Inf	inf	Inf	inf	165
C-coast	inf	144	0	74	133	221	Inf	Inf	inf	Inf	inf	inf
Takoradi	inf	Inf	74	0	Inf	242	Inf	Inf	inf	Inf	inf	inf
Obuasi	inf	Inf	133	Inf	0	88	Inf	Inf	inf	Inf	inf	inf
Kumasi	inf	270	221	242	88	0	194	130	inf	Inf	388	inf
Koforidua	inf	85	inf	Inf	Inf	194	0	Inf	inf	Inf	inf	inf
Sunyani	inf	Inf	inf	Inf	Inf	130	Inf	0	378	Inf	388	inf
Wa	inf	Inf	inf	Inf	Inf	Inf	Inf	378	0	368	314	inf
Bolga	inf	Inf	inf	Inf	Inf	Inf	Inf	Inf	368	0	170	614
Tamale	inf	Inf	inf	Inf	Inf	388	Inf	300	314	170	0	476
Ho	136	165	Inf	Inf	Inf	Inf	163	Inf	inf	614	476	0

Table 2: Twelve major sales points of Ghacem in Ghana and their numerical representation

City	Allocated number
Tema	1
Accra	2
Cape Coast	3
Takoradi	4
Obuasi	5
Kumasi	6
Koforidua	7
Sunyani	8
Wa	9
Bolgatanga	10
Tamale	11
Ho	12

2.3 Mathematical Formulation of TSP Model

The problem can be defined as follows: Let $G = (V,E)$ be a complete undirected graph with vertices V, $|V|=n$, where n is the number of cities, and edges E with edge length *dij* for *(i,j)*. We focus on the symmetric TSP case in which $C_{ij} = C_{ji}$, for all *(i,j)*. Where C_{ij} = The cost matrix representing the distance from city i to city j.

The problem PI is;

$$\text{Minimize } Z = \sum_{i \in v} \sum_{j \in v} c_{ij} x_{ij} \qquad (1)$$

Subject to

$$\sum_{\substack{j \in v \\ j \neq i}} x_{ij} = 1 \qquad i \in v \qquad (2)$$

$$\sum_{\substack{i \in v \\ i \neq j}} x_{ij} = 1 \qquad j \in v \qquad (3)$$

$$\sum_{i \in s} \sum_{j \in s} x_{ij} \leq |s| - 1 \qquad \forall s \subset v, s \neq \emptyset \qquad (4)$$

$$x_{ij} \leq 0 \, or \, 1 \qquad i, j \in v \qquad (5)$$

The problem is an assignment problem with additional restrictions that guarantee the exclusion of subtours in the optimal solution. Recall that a subtour in *V* is a cycle that does not include all vertices (or cities). Equation (1) is the objective function, which minimizes the total distance to be traveled.

Constraints (2) and (3) define a regular assignment problem, where (2) ensures that each city is entered from only one other city, while (2) ensures that each city is only departed to on other city. Constraint (4) eliminates subtours. Constraint (5) is a binary constraint, where x_{ij} = 1 if edge *(i,j)* in the solution and x_{ij} = 0, otherwise.

2.3.1 Algorithm

The Pseudo-code of the algorithm applied to solve the MMAS is shown below.

Procedure of MMAS

Step 1

The Directors Inspectional Tour (DIT), whose serve as Artificial Ants in this study, graph was transformed into a TSP graph

Step2

The initial pheromone matrix was computed in Table 5.

Set $L_g best = \infty$,iterate=TRUE, i=0

While iterate = TRUE

Set i=i+1

For h =1 to m

Set tabu _h= $\emptyset$

Step 3

A city , C_{ij} was randomly selected by ant k as the starting point of the path

C_{ij} was added to tabu_h

For j=I to n-1

Step 4

The next city ,C, was selected according to probability decision rule in (2.2)

City C was added to tabu_h

End-for

Step 5

Compute the length of the path L(h)

If L_g _best >Lb

Set L_g _best >Lb=Lb

If L_g _best has not been improved during the last 15 iterations

Set iterate = FALSE
end -if

If $Lx = Ly, \ {}^{y}\!/\!_{x} \neq y, 1 \leq x, y \leq m$

Step 6

Reset the pheromone matrix trails to the value τ_{Max}

else
update the pheromone matrix according to the expression in (4.5)
end-if
end while
Step 7
The TSP solution was then transformed into DIT solution.

2.4 Computational Method

The MMAS proposed by Stuuzle and Hoos, (2000) was coded in Matlab language. The tests were performed on a personal computer, Dell core 5 Dual processor, 3.0GHZ with RAM 2G memory and working on Window 7 operating system.

3. Analysis and Results

Table 3: Connectivity matrix for the twelve major sales points cities of Ghacem in Kilometers (Km) (All pair shortest path from Table 2 by Floyd Warshall's Algorithm)

City/cityj	1	2	3	4	5	6	7	8	9	10	11	12
1	0	29	173	247	352	299	114	429	816	750	612	136
2	29	0	144	218	358	270	85	400	778	770	641	165
3	173	144	0	74	133	221	229	351	729	779	609	309
4	247	218	74	0	213	242	303	372	750	800	630	383
5	352	358	133	213	0	88	282	218	596	646	476	445
6	299	270	221	242	88	0	194	130	508	558	388	357
7	114	85	229	303	282	194	0	324	702	752	582	163
8	429	400	351	372	218	130	324	0	378	470	300	487
9	816	778	729	750	596	508	702	378	0	368	314	790
10	750	770	779	800	646	558	752	470	368	0	170	615
11	612	641	609	630	476	388	582	300	314	170	0	476
12	136	165	309	383	445	357	163	487	790	615	476	0

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In this study each edge in the graph is given an initial pheromone value
$\tau_0 = \frac{1}{n} = \frac{1}{12} = 0.0833$, where $n = 12$.

Let heuristic value (η) be equal to the reciprocal of the distance, ie . $\eta_{ij} = \frac{1}{d_{ij}}$. where d_{ij} is the distance between city(i) to city(j). The probability of selecting an edge is given by

$$p_{ij}^{k} = \frac{[\tau_{ij}]^{\alpha} * [\eta_{ij}]^{\beta}}{\sum_{l \in N} [\tau_{il}]^{\alpha} * [\eta_{il}]^{\beta}}, \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (6)$$

where N = 12 (the set of neighboring Cities (nodes) to be visited by the artificial Ants (The inspectional Team of Ghacem, Ghana) α and β are parameters that control the relative weight of pheromone trial and heuristic value. In this study, the values of α and β are set be 1. Again τ_{Max} and τ_{Min} are set to be 1.0 and 0.01 respectively. In this work, we considered several values for the evaporation rate such as 0.1, 0.02, 0.1,0.2, and so on.

The Table 4 below shows the Heuristic value ((η) between nodes of the twelve major sale points of Ghacem in Ghana. These values were obtained through the use of the model $\eta_{ij} = \frac{1}{d_{ij}}$.

Table 4: The heuristic value (η) for each edge (major roads) of Ghacem in Ghana

City/cityj	1	2	3	4	5	6	7	8	9	10	11	12
1	0.000	.0.034	0.006	0.004	0.003	0.004	0.009	0.002	0.001	0.001	0.002	0.007
2	0.034	0.000	0.007	0.005	0-003	0.004	0.012	0.003	0.001	0.001	0.002	0.006
3	0.006	0.007	0.000	0.014	0.008	0.005	0.004	0.003	0.001	0.001	0.002	0.003
4	0.004	0.005	0.014	0.000	0.005	0.004	0.003	0.003	0.001	0.001	0.002	0.003
5	0.003	0.003	0.008	0.005	0.000	0.011	0.004	0.005	0.002	0.002	0.002	0.002
6	0.004	0.004	0.005	0.004	0.011	0.000	0.005	0.008	0.002	0.002	0.003	0.003
7	0.009	0.012	0.004	0.003	0.004	0.005	0.000	0.003	0.001	0.001	0.002	0.006
8	0.002	0.003	0.003	0.003	0.005	0.008	0.003	0.000	0.003	0.002	0.003	0.002
9	0.001	0.001	0.001	0.001	0.002	0.002	0.001	0.003	0.000	0.003	0.003	0.001
10	0.001	0.001	0.001	0.001	0.002	0.002	0.001	0.002	0.003	0.000	0.006	0.002
11	0.002	0.002	0.002	0.002	0.002	0.003	0.002	0.003	0.003	0.006	0.000	0.002
12	0.007	0.006	0.003	0.003	0.002	0.003	0.006	0.002	0.001	0.002	0.002	0.000

Mathematical Theory and Modeling
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Vol.4, No.9, 2014

Table 5: Initial pheromone value (τ_0) for each edge (major roads**)**

City/cityj	1	2	3	4	5	6	7	8	9	10	11	12
1	0	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083
2	0.083	0	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083
3	0.083	0.083	0	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083
4	0.083	0.083	0.083	0	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083
5	0.083	0.083	0.083	0.083	0	0.083	0.083	0.083	0.083	0.083	0.083	0.083
6	0.083	0.083	0.083	0.083	0.083	0	0.083	0.083	0.083	0.083	0.083	0.083
7	0.083	0.083	0.083	0.083	0.083	0.083	0	0.083	0.083	0.083	0.083	0.083
8	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0	0.083	0.083	0.083	0.083
9	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0	0.083	0.083	0.083
10	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0	0.083	0.083
11	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0	0.083
12	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0

The Table 5 shows the initial pheromone value (τ_0) for each edge. In this study each edge in the graph is given an initial pheromone value $\tau_0 = \frac{1}{n} = \frac{1}{12} = 0.0833$ .where n is the number of cities to be visited by the Ant. The MMAS algorithm was coded used to find the minimum tour of each ant and then selected the best ant tour. After performing 6652800 iterations the result for the tour of each ant is shown in Table 6 below.

Table 6: The tour of an individual Ant and their various distance covered

Ant tour		Dist. Cov. By ant
Ant 1	9 12 2 1 7 4 3 5 6 8 11 10	1874
Ant 2	9 10 11 8 6 5 3 4 7 2 1 12	2238
Ant 3	10 5 6 8 4 3 1 2 7 12 11 9	2272
Ant 4	10 8 6 5 7 2 1 12 3 4 11 9	2445
Ant 5	12 3 4 6 5 11 10 8 9 7 1 2	2908
Ant 6	5 9 10 11 6 4 3 1 2 7 12 8	2397
Ant 7	9 7 2 1 12 11 10 8 6 5 3 4	2541
Ant 8	12 1 2 7 6 5 3 4 10 11 8 9	3041
Ant 9	9 6 5 4 3 1 2 7 12 11 10 8	2319
Ant10	8 4 3 5 6 1 2 7 12 10 11 9	2348
Ant11	9 11 10 8 6 4 3 5 7 2 1 12	2541
Ant12	12 2 1 7 3 4 5 6 8 11 10 9	2505

Considering the total distances covered by the individual Ants, the optimal tour came out to be

$$1-7-4-3-5-6-8-11-10-9-12-2-1$$

This was obtained by Ant 1.Thus the total tour distance came out to be optimal solution, which has a total distance of 1874km, representing the tour Tema → Koforidua → Takoradi→ Cape coast → Obuasi → Kumasi → Sunyani → Tamale → Bolgatanga → Wa → Ho → Accra → Tema would be preferred to the usual route which is represented as Tema → Accra → Cape coast → Takoradi → Obuasi → Kumasi → Koforidua → Sunyani → Wa → Bolgatanga → Tamale → Ho → Tema. The total cost distance of their usual tour is 2319Km.

4. Conclusion

The objective of finding the minimum tour from the symmetric TSP model by using Max-Min Ants System (MMAS) Algorithm was successfully achieved. The optimal route is represented as

Tema → Koforidua → Takoradi→ Cape coast → Obuasi → Kumasi → Sunyani → Tamale → Bolgatanga → Wa → Ho → Accra → Tema

The total cost distance of the optimal route is $1874km$ which is far better than their usual tour distance of $2319km$. The Ghacem company is therefore advise to make use the of programme to obtain the optimal tour in the event of cities to be visited being perturbed. We therefore suggested that plying the routes that came out of the MMAS model would be of help to minimize their cost since the route gave the optimal cost of 1874Km. We once again recommend further research into this study by researchers.

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Appendix A

Appendix B

Matlab Programme

```
function ACOtest(inputMatrix)
clc
%% START declare of own Variable for testing
global ASAdded
[row,col] = size(inputMatrix);
if row > col || col > row
end

ASAdded.inputMatrix = inputMatrix;
ASAdded.row = row;
ASAdded.col = col - 1;
ASAdded.MaxDist = max(max(inputMatrix)) * ASAdded.col;
Dimension = ASAdded.row;

NodeWeight = [];

disp(['AS start at ',datestr(now)]);
%%%%%%%%%%%%% the key parameters of Ant System %%%%%%%%%
data_input = ASAdded.inputMatrix
MaxITime=1e3;
AntNum=Dimension; %depends on # of nodes
alpha=1;
```

```
beta=5;
rho=0.65;
%%%%%%%%%%%%% the key parameters of Ant System %%%%%%%%%
fprintf('Showing Iterative Best Solution:\n');

finalOutput = ...
AS(NodeWeight,AntNum,MaxITime,alpha,beta,rho);

disp(['AS stop at ',datestr(now)]);
function [GBTour,GBLength,Option,IBRecord]=AS(WeightMatrix,AntNum,MaxITime,alpha,beta,rho)
%% (Ant System) date:070427
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%
% Reference ï¿½ ï¿½
% Dorigo M, Maniezzo Vittorio, Colorni Alberto.
% The Ant System: Optimization by a colony of cooperating agents [J].
% IEEE Transactions on Systems, Man, and Cybernetics--Part B,1996, 26(1)
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%
global ASOption Problem AntSystem ASAdded
ASOption = InitParameter(AntNum,alpha,beta,rho,MaxITime);
Problem = InitProblem(WeightMatrix);
AntSystem = InitAntSystem();

ITime = 0;
ASAdded.ITime = ITime;
IBRecord = [];

while 1
 InitStartPoint();
 for step = 2:ASOption.n
 for ant = 1:ASOption.m
  P = CaculateShiftProb(step,ant);
  nextnode = Roulette(P,1);
  RefreshTabu(step,ant,nextnode);
 end
 end

 ITime = ITime + 1;
 CaculateToursLength();

 GlobleRefreshPheromone();
 ANB = CaculateANB();
 [GBTour,GBLength,IBRecord(:,ITime)] = GetResults(ITime,ANB);
```

```
  %==================================================
 deltaTau = (ASAdded.MaxDist)./(AntSystem.lengths);
 [deltaMax_val,deltaMax_indx] = max(deltaTau);
 ASAdded.deltaMax_tour = AntSystem.tours(deltaMax_indx,:); %update InitStartPoint
 %==================================================
  if Terminate(ITime,ANB)
 Ant_Tour = AntSystem.tours
 format bank
 Ant_Tour_Delta = [AntSystem.tours, deltaTau]
 format short
 Distance_Covered_By_Ant = AntSystem.lengths
 [BestVal,BestIdx] = max(Ant_Tour_Delta(:,end));
 BestTour = AntSystem.tours(BestIdx,:)
 break;
 end

end
Option = ASOption;
%% ---------------------------------------------------------------
function ASOption = InitParameter(AntNum,alpha,beta,rho,MaxITime)
global ASAdded
ASOption.n = ASAdded.row;
ASOption.m = AntNum;
ASOption.alpha = alpha;
ASOption.beta = beta;
ASOption.rho = rho;
ASOption.MaxITime = MaxITime;
ASOption.OptITime = 1;
ASOption.Q = 10;
ASOption.C = 100;
ASOption.lambda = 0.15;
ASOption.ANBmin = 2;
ASOption.GBLength = inf;
ASOption.GBTour = zeros(ASAdded.row,1);
ASOption.DispInterval = 10;
rand('state',sum(100*clock));
%% ---------------------------------------------------------------
function Problem = InitProblem(WeightMatrix)
global ASOption
n = ASOption.n;
MatrixTau = (ones(n,n)-eye(n,n))*ASOption.C;
Distances = WeightMatrix;
SymmetryFlag = false;
if isempty(WeightMatrix)
```

```
  Distances = CalculateDistance;
  SymmetryFlag = true;
end
Problem = struct('dis',Distances,'tau',MatrixTau,'symmetry',SymmetryFlag);
%% --------------------------------------------------------------
function AntSystem = InitAntSystem()
global ASOption
AntTours = zeros(ASOption.m,ASOption.n);
ToursLength = zeros(ASOption.m,1);
AntSystem = struct('tours',AntTours,'lengths',ToursLength);
%% --------------------------------------------------------------
function InitStartPoint()
global AntSystem ASOption ASAdded
AntSystem.tours = zeros(ASOption.m,ASOption.n);
rand('state',sum(100*clock));
if ASAdded.ITime == 0
  AntSystem.tours(:,1) = randperm(ASAdded.row)';
else
  AntSystem.tours(:,1) = ASAdded.deltaMax_tour';
end
AntSystem.lengths = zeros(ASOption.m,1);
%% --------------------------------------------------------------
function Probs = CaculateShiftProb(step_i, ant_k)
global AntSystem ASOption Problem
CurrentNode = AntSystem.tours(ant_k, step_i-1);
VisitedNodes = AntSystem.tours(ant_k, 1:step_i-1);
tau_i = Problem.tau(CurrentNode,:);
tau_i(1,VisitedNodes) = 0;
dis_i = Problem.dis(CurrentNode,:);
dis_i(1,CurrentNode) = 1;
Probs = (tau_i.^ASOption.alpha).*((1./dis_i).^ASOption.beta);
if sum(Probs) ~= 0
  Probs = Probs/sum(Probs);
else
  NoVisitedNodes = setdiff(1:ASOption.n,VisitedNodes);
  Probs(1,NoVisitedNodes) = 1/length(NoVisitedNodes);
end
%% --------------------------------------------------------------
function Select = Roulette(P,num)
m = length(P);
flag = (1-sum(P)<=1e-5);
Select = zeros(1,num);
rand('state',sum(100*clock));
r = rand(1,num);
```

```
for i=1:num
  sumP = 0;
  j = ceil(m*rand);
  while (sumP<r(i)) && flag
  sumP = sumP + P(mod(j-1,m)+1);
  j = j+1;
  end
  Select(i) = mod(j-2,m)+1;
end
%% ---------------------------------------------------------------
function RefreshTabu(step_i,ant_k,nextnode)
global AntSystem
AntSystem.tours(ant_k,step_i) = nextnode;
%% ---------------------------------------------------------------
function CaculateToursLength()
global ASOption AntSystem
x = CalculateDistance;
p = AntSystem.tours;

Lengths = zeros(ASOption.m,1);

for j=1:ASOption.n
  pRow = p(j,:);
  sumRow = 0;
  for i=1:ASOption.n-1
  sumRow = sumRow + x(pRow(i),pRow(i+1));
  end
  Lengths(j) = sumRow;
end
AntSystem.lengths = Lengths;
%% ---------------------------------------------------------------
function [GBTour,GBLength,Record] = GetResults(ITime,ANB)
global AntSystem ASOption
[IBLength,AntIndex] = min(AntSystem.lengths);
IBTour = AntSystem.tours(AntIndex,:);
if IBLength<=ASOption.GBLength
      ASOption.GBLength = IBLength;
      ASOption.GBTour = IBTour;
      ASOption.OptITime = ITime;
end
GBTour = ASOption.GBTour';
GBLength = ASOption.GBLength;
Record = [IBLength,ANB,IBTour]';
%% ---------------------------------------------------------------
```

```
function GlobleRefreshPheromone()
global AntSystem ASOption Problem
AT = AntSystem.tours;
TL = AntSystem.lengths;
sumdtau=zeros(ASOption.n,ASOption.n);
for k=1:ASOption.m
  for i=1:ASOption.n
  sumdtau(AT(k,i),AT(k,i))=sumdtau(AT(k,i),AT(k,i))+ASOption.Q/TL(k);
  if Problem.symmetry
    sumdtau(AT(k,i),AT(k,i))=sumdtau(AT(k,i),AT(k,i));
  end
  end
end
Problem.tau=Problem.tau*(1-ASOption.rho)+sumdtau;
%% ------------------------------------------------------------
function flag = Terminate(ITime,ANB)
global ASOption
flag = false;
if ANB<=ASOption.ANBmin || ITime>=ASOption.MaxITime
  flag = true;
end
%% ------------------------------------------------------------
function ANB = CaculateANB()
global ASOption Problem
mintau = min(Problem.tau+ASOption.C*eye(ASOption.n,ASOption.n));
sigma = max(Problem.tau) - mintau;
dis = Problem.tau - repmat(sigma*ASOption.lambda+mintau,ASOption.n,1);
NB = sum(dis>=0,1);
ANB = sum(NB)/ASOption.n;
%% ------------------------------------------------------------
function Distances = CalculateDistance
global ASAdded
Distances = ASAdded.inputMatrix;
%% ------------------------------------------------------------
```

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