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Minimization of Changeover Time in a Brewery Company Using Ant Colony Optimization

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Abstract

This study utilizes Ant Colony Optimization (ACO) approach in solving the asymmetric travelling Salesman problem (aSTP) of a brewery company in Nigeria with a view to minimizing the total Changeover Setup time and obtaining an optimal schedule or schedules.

The acquired secondary data covering the 2013/2014 production year including the peak periods from January to April and August to December was analyzed to determine the expected changeover time. The expected changeover time for the sequence of Stock keeping unit (sku) was then formulated as a Travelling salesman (TSP) matrix, and Branch and bound Method (B&B) of solution was employed to determine a lower bound for the tour, as well as the optimal sequence. Afterward, Ant Colony Optimization (ACO) was applied to obtain possible optimal tours. The Ant algorithm formulated as a program in Matlab 7.5 environment, was used to solve the TSP.

The Ant system algorithm found (after 500 iterations) an optimal route of length 1126.5 Minutes {or 18.78 Hours} in three different parameters settings: parameters α=1, β=3, two alternate optimal sequence ; parameters α=2, β=3, four optimal sequence and parameters α=2, β=4, six optimal sequence returned respectively. The optimal sequence result common to these three parameters setting is : 1-3-8-9-5-2-6-4-7-1 [Grand Beer – Castle Stout – Grand Malt – Beta Malt – Redds Beer – Castle Beer – Trophy Beer – Eagle Beer – Hero Beer –Grand Malt]. The total pairwise distance of the Optimal Sequence of the Branch and Bound method when computed from the formulated Cost matrix of is 1126.75 Minutes and this is also close to the sub-optimal tour Length of the Ant System Algorithm (AS). Finally, the optimal tour length of 1126.5 Minutes generated by the ACO make this model a success.

Keywords: Ant Colony Optimization (ACO), Branch and bound (B&B) Method, Travelling salesman Problem (TSP), Scheduling, Branch and bound, Optimal Tour

Nomenclature

α = Adjustable Parameter describing the weights of the Pheromone	P_{hk} = Penalty of zero cell (h, k)
A = Arc	(h, k) = City located at row h and column k
β = Adjustable Parameter describing the visibility from one city to another	η_{ij} = Visibility of a city j from i
d_{ij} = Distance between city i and j	τ_{ij} = Amount of Pheromones on the edge (i, j)
$f(\pi)$ = Length of Tour	P_{ij}^{k} = Probability that Ant K at city i would move to j
G = Graph	TSP = Travelling Salesman problem
N = Node	aSTP = asymmetric Travelling Salesman problem
m = Number of Ants	ACO = Ant Colony Optimization
n = Number of Cities	AS = Ant System
ρ = Pheromone evaporation rate	SKU = Stocks keeping unit
∞ = Infinity	WSTP = Weighted shortest processing time
K = Ant k	EAS = Elitist Ant System
t_e = Expected changeover time	AS_{Rank} = Rank – Based Ant System
Z = lower bound of the starting cost matrix	MMAS = Max-Min Ant System
Θ = lower bound for partitioning	ACS = Ant Colony System

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1.0 Introduction

Traveling Salesman Problem (TSP) is a typical NP hard problem [1]. Given a number of cities and the distances between them, TSP aims to calculate the shortest tour for the salesman to visit each city exactly once and return to the starting point. Travelling salesman problem (TSP) is one of the well-known and extensively studied problems in discrete or combinational optimization and asks for the shortest round trip of minimal total cost visiting each given city (node) exactly once. Nowadays these traditional methods are not adaptive to real time. So as to make it dynamic, artificial intelligence techniques like Genetic algorithm, Neural Network, Ant Colony Optimization (ACO) and Particle Swarm Intelligence can be used. Ant Colony Optimization (ACO) algorithm [2] is one possible solution for solving TSP problem.

Many efforts have been made to solve the problems of traditional ACO algorithm. For example, Dorigo et al [2] proposed an Ant system with positive feedback, distributed computation, and a constructive greedy heuristic. Gajpal et al [3] applied ACO to the route selection of tucks, and the search all the customers during the routing path using a multi-route search principle. Amiolemhen and Haruna [4] applied ACO to six-cities travel salesman problem

Chan and Swarnkar [5] stated that the Ant Colony System (ACS) parameters *should* be chosen carefully, as they might lead to poor performance of the algorithm, and they investigated the parameter behaviors graphically in their study. Simon et al65] indicated that it is only through the appropriate selection of parameters that it will be possible for the ACS to show a high level of convergent behavior.

A branch and bound based algorithm for the asymmetric TSP is proposed in [7] . The algorithm uses a Lagrangean relaxation of the degree constraints and sub-gradient algorithm to solve the Lagrangean dual. A review of algorithms and complexity for various scheduling problems that involves batching is given in [8].

2.0 The Ant Colony Optimization Methodology

In AS, m (artificial) ants concurrently build a tour of the TSP. Initially, ants are put on randomly chosen cities. At each construction step, ant k applies a probabilistic action choice rule, called random proportional rule, to decide which city to visit next. In particular, the probability with which ant k, currently at city i, chooses to go to city j is

$$P_{ij}^{k} = \frac{[\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{l\in N_i^k}[\tau_{il}]^{\alpha}[\eta_{il}]^{\beta}}, \quad \text{if } j\in N_i^k \qquad (1)$$

where $\eta_{ij} = 1/d_{ij}$ is a heuristic value that is available a priori, α and β are two parameters which determine the relative influence of the pheromone trail and the heuristic information, and N_i^k is the feasible neighborhood of ant k when being at city i, that is, the set of cities that ant k has not visited yet (the probability of choosing a city outside N_i^k is 0). By this probabilistic rule, the probability of choosing a particular arc (i, j) increases with the value of the associated pheromone trail τ_{ij} and of the heuristic information value η_{ij}. The role of the parameters α and β is the following. If α = 0, the closest cities are more likely to be selected: this corresponds to a classic stochastic greedy algorithm (with multiple starting points since ants are initially randomly distributed over the cities). If β = 0, only pheromone amplification is at work, that is, only pheromone is used, without any heuristic bias. This generally leads to rather poor results and, in particular, for values of α > 1 it leads to the rapid emergence of a stagnation situation, that is, a situation in which all the ants follow the same path and construct the same tour, which, in general, is strongly suboptimal [2].

Each ant k maintains a memory M^k which contains the cities already visited, in the order they were visited. This memory is used to define the feasible neighborhood N_i^k in the construction rule given by equation (1.0). In addition, the memory M^k allows ant k both to compute the length of the tour T^k it generated and to retrace the path to deposit pheromone.

Concerning solution construction, there are two different ways of implementing it: parallel and sequential solution construction. In the parallel implementation, at each construction step all the ants move from their current city to the next one, while in the sequential implementation an ant builds a complete tour before the next one starts to build another one. In the AS case, both choices for the implementation of the tour construction are equivalent in the sense that they do not significantly influence the algorithm's behavior.

Update of Pheromones Trails: After all the ants have constructed their tours, the pheromone trails are updated. This is done by first lowering the pheromone value on all arcs by a constant factor, and then adding pheromone on the arcs the ants have crossed in their tours. Pheromone evaporation is implemented by

$$\tau_{ij} \leftarrow (1-\rho)\tau_{ij}, \quad \forall (i,j)\in L \qquad (2)$$

Where 0<ρ<1 is the pheromone evaporation rate. The parameterρ is used to avoid unlimited accumulation of the pheromone trails and it enables the algorithm to "forget" bad decisions previously taken. In fact, if an arc is not chosen by the ants, its associated pheromone value decreases exponentially in the number of iterations. After evaporation, all ants deposit pheromone on the arcs they have crossed in their tour:

$$\tau_{ij} \leftarrow \tau_{ij} + \sum_{k=1}^{m} \Delta\tau_{ij}^{k}, \qquad \forall (i,j) \in L \tag{3}$$

Where $\Delta\tau^{k}_{ij}$ is the amount of pheromone ant k deposits on the arcs it has visited. It is defined as follows:

$$\Delta\tau_{ij}^{k} = \begin{cases} 1/C^{k}, \text{ if arc } (i,j) \text{ belongs to } T^{k}; \\ 0, \qquad \text{Otherwise;} \end{cases} \tag{4}$$

Where c^k, the length of the tour T^k built by the k-th ant, is computed as the sum ofthe lengths of the arcs belonging to T^k. By means of equationEq. 4, the better an ant's tour is, the more pheromone the arcs belonging to this tour receive. In general, arcs that are used by many ants and which are part of short tours, receive more pheromone and are therefore more likely to be chosen by ants in future iterations of the algorithm.

3.0 Numerical Experiment

The brewery company under study produces drinks of different kinds and packaging. The company operates a plant from where it supplies several depots located in different cities. The products are produced in standard batches of Stock keeping Unit (sku).

Demand is highest in the peak period which begins from August in a preceding year to April in any current year. The acquired secondary data covers the 2013/2014 production year including the peak periods from January to April and August to December and it will be analyzed with a view to determining the expected changeover time. The brewery company being studied has three lines. The focus is on one, the Glass line (G-Line). The G-line produces nine (9) different products in sku's. The nine (9) sku's of the company includes: Gb01 (Ground Beer); Cb02 (Castle Beer); Cs03 (Castle Stout); Eb04 (Eagle Beer); Rd05 (Redds Beer); Tb06 (Trophy Beer); Hb07 (Hero Beer); Gm08 (Grand Malt) and Bm09 (Beta Malt).

4.0 Results and Discussion

4.1 Results

4.1.1 The Branch and Bound Results

Table 1: Complete Tour

	1	2	3	4	5	6	7	8	9
1			■						
2							■		
3								■	
4	■								
5		■							
6				■					
7						■			
8									■
9					■				

Result summary:

1-3 - Sub tour
2-7 - Sub tour
3-8 - Sub tour
4-1 - Sub tour
5-2 - Sub tour
6-4 - Sub tour
7-6 - Sub tour
8-9 - Sub tour
9-5 - Sub tour

The complete tour is: 1-3-8-9-5-2-7-6-4-1 (Gbo1-Cs03-Gm08-Bm09-Rd05-Cbo2-Hb07-Tb06-Eb04-Gb01)
The best sequence that minimizes the total downtime in a cycle is:
Grand Beer-Castle Stout-Grant Malt-Beta Malt-Redds-Castle Beer-Hero Beer-Trophy Beer-Eagle Beer-Grand Beer.
Total downtime = 117+121+122+125+159+121+120+120+122 = 1127 Minutes(18.78 hrs)

4.1.2 The Ant System Results

The formulated aTSP matrixwas run on a Matlab 7.5 software program of an Ant System (AS) Algorithm. The Ant System parameter β was varied in accordance with stated Standard in the literature. Different iteration was also run, ranging from 50 to 500 iterations and the results are recorded. The result obtained is shown below:

Table 2: Alternate Optimal Sequence (Parameters α=1,β=3)

ALTERNATE OPTIMAL TOUR AND TOUR LENGTH ; Parameters α=1,β=3

1	3	8	9	5	2	6	4	7	1	**1126.50**
1	3	8	9	5	2	6	4	7	1	**1126.50**
6	4	7	1	3	8	9	5	2	6	**1126.50**

Table 3: Alternate Optimal Sequence (Parameters α=2,β=3)

ALTERNATE OPTIMAL TOUR AND TOUR LENGTH ; Parameters α=2,β=3

2	6	4	7	1	3	8	9	5	2	1126.50
1	3	8	9	5	2	6	4	7	1	1126.50
1	3	8	9	5	2	6	4	7	1	1126.50
1	3	8	9	5	2	6	4	7	1	1126.50
6	4	7	1	3	8	9	5	2	6	1126.50
2	6	4	7	1	3	8	9	5	2	1126.50
4	7	1	3	8	9	5	2	6	4	1126.50

Table 4: Alternate Optimal Sequence (Parameters α=2,β=4)

ALTERNATE OPTIMAL TOUR AND TOUR LENGTH ; Parameters α=2,β=4

2	6	4	7	1	3	8	9	5	2	**1126.50**
1	3	8	9	5	2	6	4	7	1	**1126.50**
6	4	7	1	3	8	9	5	2	6	**1126.50**
2	6	4	7	1	3	8	9	5	2	**1126.50**
4	7	1	3	8	9	5	2	6	4	**1126.50**
5	2	6	4	7	1	3	8	9	5	**1126.50**
8	9	5	2	6	4	7	1	3	8	**1126.50**

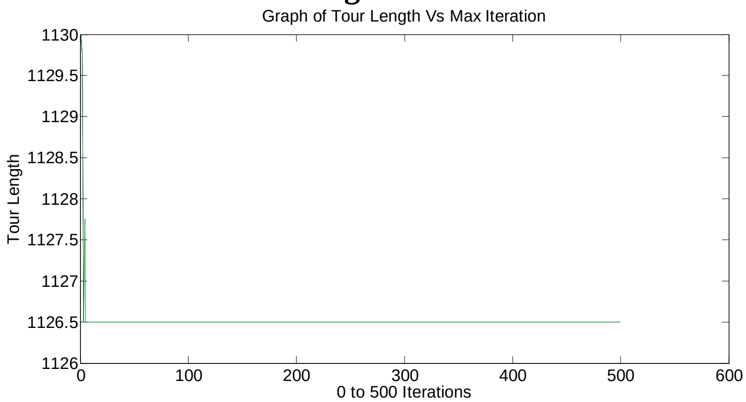

Fig. 1: Parameters α=2, β=6; Best tour Length=1127; Worst Tour Length=1129.3

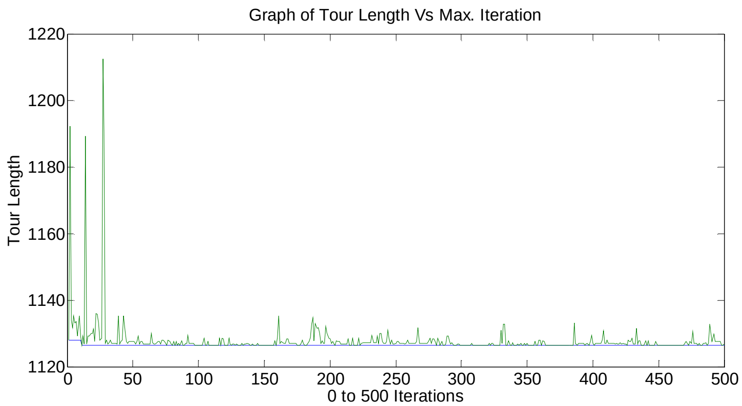

Fig. 2: Parameters α=1, β=2; Best tour Length=1126.7; Worst Tour Length=1273

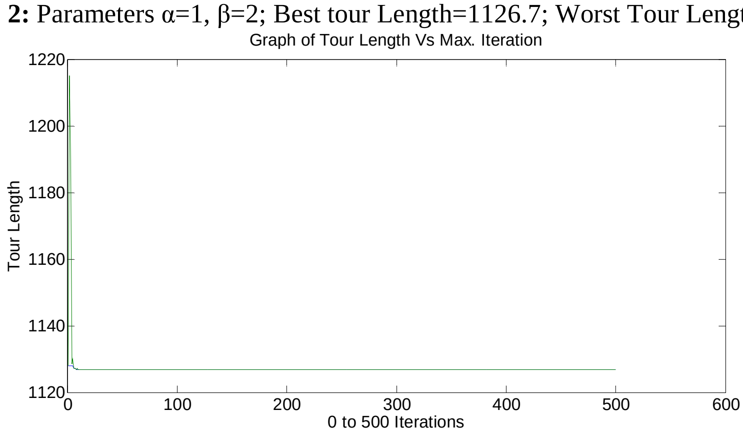

Fig. 3: Parameters α=2, β=2; Best tour Length=1126.7; Worst Tour Length=1217

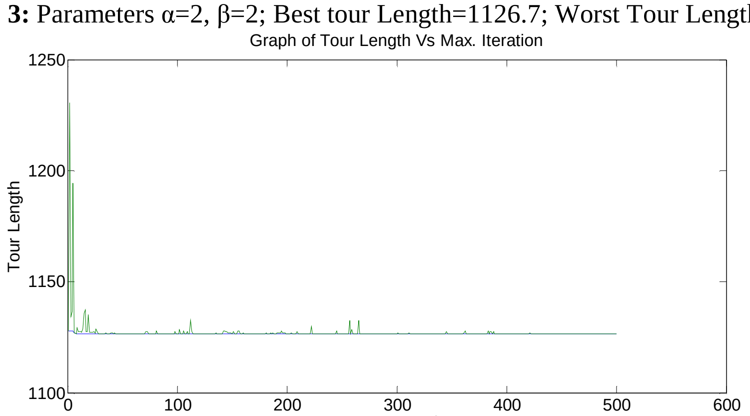

Fig. 4: Parameters α=1, β=3; Best tour Length=1126.5; Worst Tour Length=1264.8

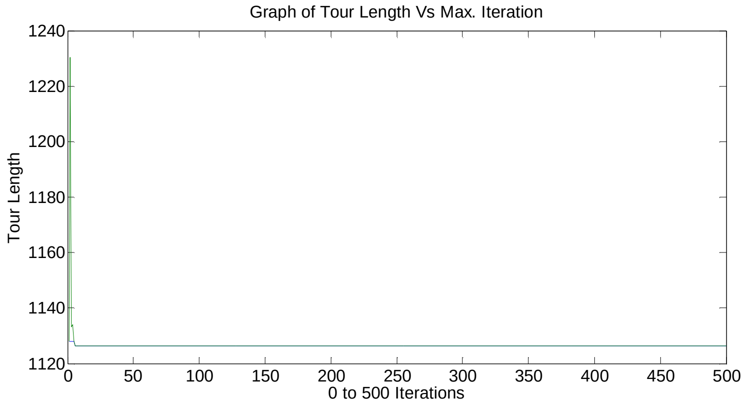

Fig. 5: Parameters α=2, β=3; Best tour Length=1126.5; Worst Tour Length=1231

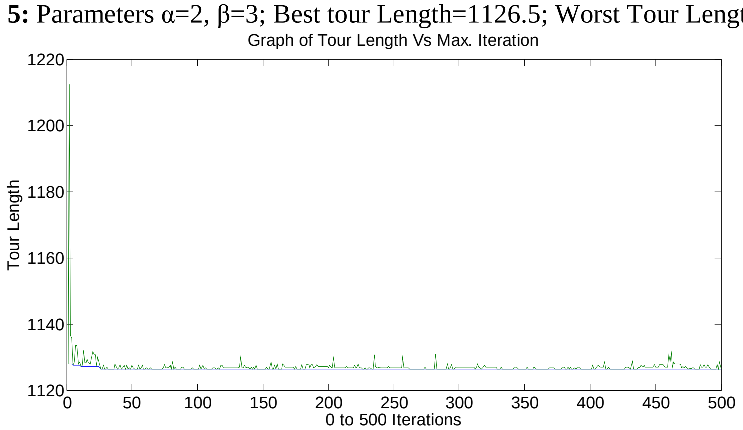

Fig. 6: Parameters α=1, β=4; Best tour Length=1127; Worst Tour Length=1227.5

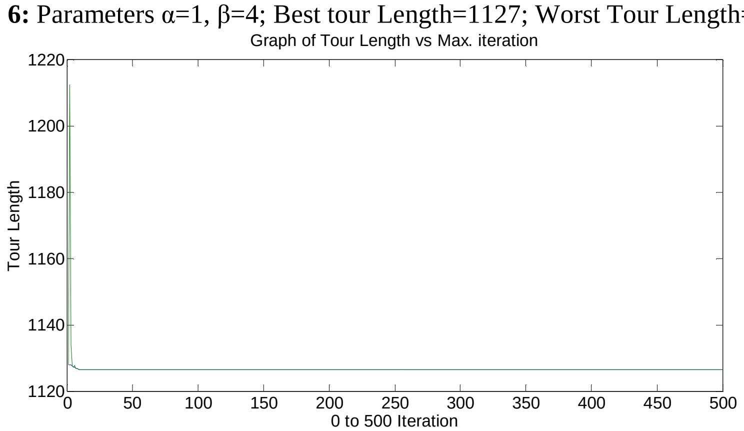

Fig. 7: Parameters α=2, β=4; Best tour Length=1126.5; Worst Tour Length=1212

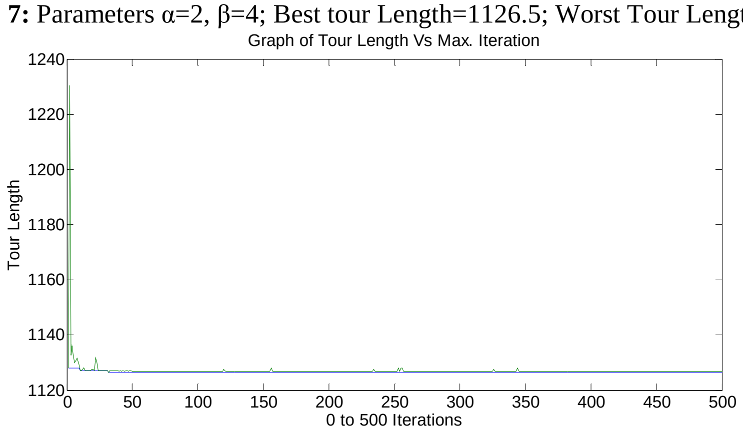

Fig. 8: Parameters α=1, β=5; Best tour Length=1126.7; Worst Tour Length=1205.5

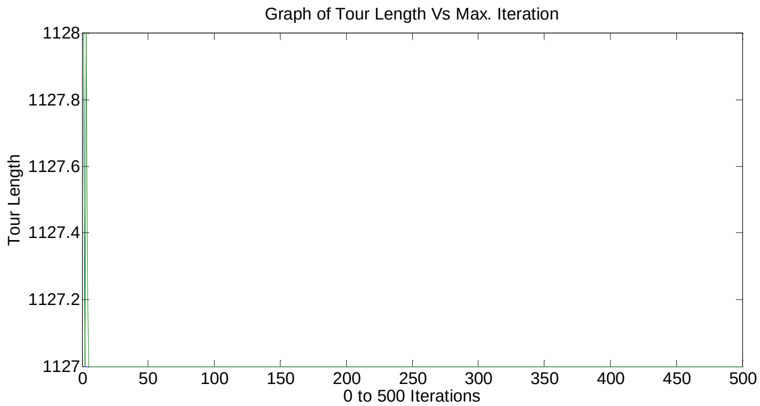

Fig. 9: Parameters α=2, β=5; Best tour Length=1127; Worst Tour Length=1128

4.2 Discussion

The Ant System algorithms represent a new promising approach to solving optimization problems that is based on the simulation of the behavior of ant colonies. An ant colony can be regarded as a multi-agent system where each agent (ant) is functioning independently by very simple rules. The behavior of ants in transporting food, overcoming obstacles, building anthills, and other operations is almost optimal.

In this study of asymmetric travelling salesman (aSTP) of nine cities, the ant system found (after 500 iterations) an optimal route of length 1126.5 Minutes {or 18.78 Hours} in three different parameters adjustment, i.e. in Fig.4.0 (parameters α=1,β=3); Fig.5.0 (parameters α=2,β=3) and Fig.7.0 (parameters α=2,β=4) . For the parameters: α=1, β=3 there is two alternate optimal sequence; α=2, β=3 four alternate optimal tour and α=2, β=4 six alternate optimal tour returned by the Algorithm respectively. One of the optimal sequence result common to these three parameters setting is : 1-3-8-9-5-2-6-4-7-1 [Grand Beer – Castle Stout – Grand Malt – Beta Malt – Redds Beer – Castle Beer – Trophy Beer – Eagle Beer – Hero Beer –Grand Beer].The other alternate Optimal tour is shown in: Table 2.0; Table 3.0 and Table 4.0 respectively.

The Optimal tour length of 1126.5 Minutes generated by the ACO fall within the lower bound of the cost matrix formulated, when it was solved using the exact method (B&B) , where the lower bound was Z=1126 Minutes. Also, the total pairwise distance of the Optimal Sequence of the Branch and Bound method (exact Method) when computed from the Cost matrix is 1126.75 Minutes and this is close to the sub-optimal tour Length of the Ant System Algorithm (AS) in Parameters settings of Fig.2.0 and Fig.3.0 (Best Tour length is 1126.7 Minutes: see details in the figures above).

To guarantee that the optimum tour is found, the number of iterations in the algorithm should be increased up to five hundred and even above. In fact the more the number of city, the higher the number of iterations. If higher numbers of iterations is applied, the algorithm prevents the set of solutions from being degenerated to a single route selected by all Ants and would always generates new solutions at each iteration.

When ACO is Compared to the exact methods (i.e. the method of B&B), the Ant algorithm is faster in finding suboptimal solutions even for problems of low dimensions.

5.0 Conclusion

In general TSP is a very difficult computational problem and finding exact best solution often requires many years of CPU time. For this reason people has developed different heuristic approaches for this problem - heuristic means that the algorithm usually finds a very good solution, but not necessarily the optimal one. ACO is exactly one of such heuristic approaches.

In recent years, there has been a significant impact of biosciences on mathematics and computer technologies, leading to the genesis of a new science, technobiology, which uses biological principles to improve technology and information processes [8]. The ant algorithms can be attributed to technobiology, since they are based on the self-organization mechanisms of social insects. Proposed in the early 1990s, the ant algorithms, for ten years, have turned from "toy" demonstrations to an important field of theory of optimization.

The ant algorithms can be applied to optimization problems that are reduced to searching for the shortest path on a graph with certain constraints. The virtual ants select routes on the graph by a probability rule, based on the pheromone value and heuristic methods for solving specific problems. Computer experiments have attested that the ant algorithms ensure a good balance between the solution accuracy and the optimization time.

This Project is success to solve the Travelling Salesman Problem by ACO under the MATLAB environment. The results show the good optimization capability of ACO. The Performance of ACO for the TSP has been analyzed under various parameters which shows that most optimal paths are obtained when the number of ants is equal to the number of cities as well as the value of α should be close to 1 and $3 \le \beta < 6$. In addition, we also find that the ACO has a problem of stagnation, how to combat this problem is worthy tobe studied. In this study, the information gathered from the company revealed that the company does not base its policy on any model but on the rule-of-thumb and based on the above mentioned results, the current policy needs revision. Any of the alternate optimal sequence generated by the Ant System Algorithm can be followed by the company in their production cycle in other to avoid exceeding the minimum total downtime of 1126.5 minutes (18.78 hours) required in the system. It is recommended that for all industries that runs on multi-pack production line, which base their policy on the rule of thumb, there is need for a change of policy.

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