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THE ANALYSIS OF GR202 AND BERLIN 52 DATASETS BY ANT COLONY ALGORITHM

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Abstract - Ant Colony Optimization (ACO) method is inspired by the foraging behaviour of ants to find a good path while searching for food. In ACO method was worked to find in this analysis are the most appropriate parameter values. In Traveling Salesman Problem (TSP) a salesman seeks to find the shortest possible route that visits each city exactly once and returns to the origin city. This study analyses very well-known Berlin 52 and lesser-known Gr202 test problems located in TSPLIB by Ant Colony Optimization.It also aims at finding the proper number of iterations and appropriate parameter values suitable for real world problems. In these test problems with point numbers of 52 and 202, the behaviour of Ant Colony Algorithm was observed. In addition, using these test data, the most appropriate iterations and parameter values were tried to be determined.

Keywords: Graf, Traveling Salesman Problem, Ant Colony Optimization

I. INTRODUCTION

Optimization is the selection of a best element from some set of available alternatives. Aiming at determining the most profitable results by minimum cost finding parameter values affecting the result of a problem with constraints means optimizing the problem. In every real-world problem, it has been the most realistic goal to expect the necessary effort, capital, materials and labor to be at a minimum level while the gain to be at maximum one. In the optimization process, following the identification of the variables that determine the solution of problems, the cost function to be minimized or the profit function to be maximized must be defined in the light of these decision-making parameters(objective function). While defining them, the constraints to the problem regarding the values or the ranges that the decision variables may have must be specified. Some restrictions may be inequations while, some others are equations (constraints).

Within the definition of optimization, there is also the investigation of the precisest and the best results of the problems to be addressed far and wide. Thus, many different naming and classifications of optimization problems are available. Generally, optimization techniques can vary significantly from a problem to another. There is no single approach for solving an optimization problem. Since the complexity of each problem depends significantly on constraints and the objective function, it can show many differences.

Heuristic optimization, optimization techniques are inspired by natural phenomena to reach the optimal result from different solutions for the optimization of any problems. The algorithms used in the solution of heuristic optimization has the property of convergence and can not always guarantee the optimum solution. They can produce results close to optimal ones due to the convergence property. There are now a lot of work in the field of Heuristic Optimization. Some of these[1,2,3].

Metaheuristic algorithms can be defined as more advanced versions of heuristic optimization algorithms. They emerged as a result of using basic heuristic methods together. Considering the expression of 'meta' which means 'high level', these algorithms perform better than simple intuitive algorithms. In addition, all metaheuristic algorithms use randomness and local search alternately. Randomness ensure improvements by global-scale searching for the solutions of optimization algorithms rather than local search[4]. Meta heuristics field of application is very wide[5,6,7].

Swarms are cohabiting animal populations. In other words, they are scattered interactive patterns composed of individuals. Bees, ants, sheep, birds etc. are examples of such swarms. Intelligence, is a general term referring to mental abilities of people such as learning, understanding, abstract thinking, reasoning, planning, problem solving and judging. The swarm intelligence is about inexperienced agents' ,such as ants and other insect colonies, interactive and collective behaviors such as finding fodder, cooperation in transportation, cluster development.

Ants were observed to easily pass over long gaps by using their bodies as bridges within a social structure. Although they show no success individually, as a result of moving in flocks, they can show intelligent behavior. Individuals in the community, benefiting from the behaviors of the best individual or other individuals, can interpret and change their behavior if necessary, continue to interact with other individuals in the nest and take advantage of this experience to solve problems under certain circumstances. Observing the behavior of ant colonies and other insects, nature-inspired metaheuristic optimization algorithms based on swarm intelligence have been developed.

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II. ANT COLONY OPTIMIZATION ALGORITHM(ACO)

ACO is a general purpose heuristic algorithm developed by Dorigo [8] examining the behavior of real ants and it performs the search with a plurality of solutions. It is also a method called the ant system. In recent years, ACO has been successfully applied to a variety of combinatorial optimization problems such as traveling salesman, assembly line balancing, scheduling, vehicle routing, network routing. Problems are solved in different areas today with ACO[9,10,11].

Real ants are capable of docking with finding the shortest path between their nest and the place where they find food. While doing so, they do not use their eyesight. In addition, when an obstacle is placed on their path or when there is a change in the path due to the geographical events, they adapt themselves to this new situation by finding the shortest path. [12]

Thanks to the pheromones they leave on the route, ants can create a certain path and follow it each time. Ants ,with undeveloped eyesight, tend to follow pheromone scent to find their way. That is to say, they prefer the route with more amount of pheromone to that with the less, which gives us tips on how they find the shortest path. When an obstacle which they cannot pass over is placed in their way, they come up with two alternative ways .

When they encounter obstacles placed on their path, because there is no pheromone to follow, they will equally likely to go to the right or the left. Therefore, approximately half of ants go to the right, while others go to the opposite side .

Ants following the shorter side of the obstacle will leave more amount of pheromone in a unit of time. Thus, it will increase the number of ants that prefer the shortest path over time. With this positive feedback process, all ants after a certain time, will use the short side of the barrier.

It is possible to explain how more amount of pheromone is accumulated on the short route although the amount of pheromone is approximately the same as their road speed. It takes longer to use the long path. Given that there is a return on both sides, in a certain period of time, the number of the ants crossing the short track will be more thereby leading to more amount of pheromone left.

In the KS algorithm proposed by Dorigo [12] for solving the traveling salesman problem, artificial ants use probabilistic transition rule to move from one node to another on the network structure of the traveling salesman problem. During the initial phase, each ant is placed on a random node on the network . Then, each ant builds a solution comprising all the nodes by moving to the nodes they have not visited before.

For Ant K, transition probabilities $\left(P_{ij}^{k}(t)\right)$ to node j from node i, are calculated using the equation below. (1.1) [12].

$$P_{ij}^{k}(t)=\frac{\left[\tau_{ij}t\right]^{\alpha}\left[\eta_{ij}\right]^{\beta}}{\sum_{u\in J_i^k}\left[\tau_{iu}t\right]^{\alpha}\left[\eta_{iu}\right]^{\beta}} \tag{1.1}$$

t is the cycle index value (discrete-time variable). τ_{ij} t, t cycle is the amount of pheromone trail on (i,j) bond. η_{ij} is intuitive information on the (i,j) bond, which is a measure for artificial ant's vision from node i to node j. Generally in the traveling salesman problems (i, j) path is calculated as the inverse of its length. This information can be changed according to specific criteria designated for a certain problem. J_i^k stands for the set of nodes Ant K on the node i have not visited before. α and β are the parameters which determine the effects of the amount of the pheromone trail and intuitive knowledge on the specification of the probability value. The transition rule provides the next node selection according to the the probability calculated by the equation (1.1) [12]. The amount of pheromone traces on the path are updated by the equation (1.2) when all the solutions are made by the ants. In the first part of this equation, task-position pheromone amounts are evaporated depending on the specified ρ value. In the second part of the equation, the amount of pheromone is increased. The solutions with bad results as a result of pheromone update hardly or do not increase the pheromone amount while the solutions with good results further increases the amount of pheromone [12].

$$\tau_{ij}t+1=1-p\,\tau_{ij}t+\Delta\tau_{ij}t \tag{1.2}$$

ρ parameter is the evaporation rate which can take values in (0,1) range. $\Delta\tau_{ij}t$ is the sum trace amount value which will be add to (i,j) path at the end of cycle t.The sum of trace amounts all ants using (i,j) path is calculated using equation (1.3) [12].

$$\Delta\tau_{ij}t=\sum_{k=1}^{m}\Delta\tau_{ij}^{k}(t) \tag{1.3}$$

$\Delta\tau_{ij}^{k}(t)$ is the amount of trace will be left on (i,j) path by Ant k at the end of the cycle t and it is calculated by eaution (1.4) [12].

$$\Delta\tau_{ij}^{k}(t) = \begin{cases} \dfrac{Q}{L_K}, if \mid i,j \in \psi_k, \\ \\ \text{If not } 0. \end{cases} \quad (1.4)$$

Q is a constant value. L_K is the tour length generated by ant *k.* Updating the pheromone traces at the end of each circle by (1.2) equation, increases the amount of traces on good routes while it decreases the amount on low-quality routes. In this case, increasing the number of cycles with equation 1.1 created with transition probabilities, the path to the solution of good quality will increase the probability of selection [12].

The algorithm in which ants update the amount of trace to be left according to equation 1.4 and traces are updated by 1.2 equation is called ant-cycle[12].

A. Determination of Parameters

In the first step ACO algorithms, parameters are determined as in other optimization problems. Determining parameters which will give suitable results for the problem directly affects the quality of the produced results. Some important parameters used in ACO algorithms are as follows:

α (alpha): It is used when choosing the solution components in solution creation process. It determines how much to consider the amount of the pheromone trace in the selection process.

β (beta): It is used when choosing the solution components in solution creation process. It determines how much to consider intuitive knowledge in the selection process.

ρ (rho): It is used in the process of updating the pheromone trails. It determines the pheromone evaporation rate.

m: It determines the number of artificial ants to be used in the algorithm.

End condition: It determines how much the algorithm will work. This condition can be a specific time, a certain iteration number or a solution quality desired to be reached.

B. Initialization of the pheromone traces

Pheromone traces are generally determined as a value close to zero to be equal for all solutions. As the algorithm continues, these values will be updated by the ants and differ and the solutions on the good solutions will be intensify.

C. Forming Solutions

A certain number of artificial ants generate their own solutions in the search space. By getting around each solution component in the combinatorial optimization problems worked on in particular order, the solution is completed. While ants are creating their own solution, they choose solution component through a probabilistic calculation. The amount of pheromone trace and intuitive knowledge on the path going to the solution component are included in this probability calculus. Among the alternative solution components, those with high amount of pheromone trace and intuition will more probably to be selected compared to others.

D. Local Search

It is applied after the solution creation process and before pheromone update process. The qualities of the produced solutions are aimed to be improved. Some of the widely used local search algorithms are 2-opt methods. As local search is dependent on problem structure, this stage is determined optionally.

E. Pheromone trace update

After the creation of the solution by each ant, the pheromone traces among the solution components are updated. This updating process consists of two stages. At the first stage, the existing pheromone values are evaporated at the rate of a particular factor. After evaporation, reduction occurs in the pheromone values. At the second stage, pheromone values are increased according to solution qualities found. The pheromone values of good solution components increase more compared to the others.

III. TRAVELING SALESMAN PROBLEM

In this section, general information is given about the traveling salesman problem (TSP).TSP is one of the most studied optimization problems. TSP is used widely mainly because it has a difficult solution, it can be applied to many areas and its formulation is easy. In the literature, there are many kinds of traveling salesman problems and generalizations [13].TSP is one of the NP-hard problems. Although many final solution algorithms are proposed for the TSP, the best method has been branch and bound method so far [14].

TSP is one of the most well-known relational optimization problems. In Traveling Salesman Problem (TSP) a salesman seeks to find the shortest possible route that visits each city exactly once and returns to the origin city. The total route length will vary depending on the city to be visited. So, traveling salesman problem is a problem to find the best city rank in terms of the route length.

IV. TEST RESULTS

A. GR202 Dataset

In this section GR202,one of TSPLIB [15] data sets, was used. This is because it has more nodes. Data set; the optimum path length for 202 cities in Europe is estimated to be 40160 km.

Table 1. GR202 Data Set information

Data Set Name	GR202
Data Set Type	TSP
Size	202
Optimal Results	40160

First, the data set was obtained and was formed into the 202x202 distance matrix. Then, the optimal path was aimed to be rapidly converged using Ant Colony Optimization program.

We use parameter values in the program as : Number of ants; 200 Number of cities; 202, Alpha: 1, Beta: 4, Pheromone evaporation: 0.2 respectively. The number of iterations was run as 100 for 20 times. Results are shown in the following table.

Table 2. ACO parameter values

The algorithm used	Ant System Algorithm
Number of Ants	202
Number of city	202
Alpha	1
Beta	4
Pheromone evaporation:	0.2
Iteration	100 and 1000

The parameter values were based on previous studies and various experiments. After many tests, as when the alpha value is low, pheromone value is less considered, it was observed that by working as a greedy algorithm, the algorithm gave worse results.

Table 3. Data of GR202, 20 Times Study Results Analysis

Number of iterations	100	1000
Number of elements of the array	20	20
Mod (peak values)	45987 46325	44658
Mode frequency (number of repetitions of the peak value)	2	2
Median	45987	44917.5
Arithmetic mean	45921.1	44974.2
Standard deviation	457.5	506.09
Standard deviation variance	209306.5	256127.5
Standard error	102.3	113.1
Range	1486	1764
The smallest number in the series	45137	44201
The largest number in the series	46623	45965
The total of the numbers in series	918423	899484

From this problem, it can be clearly seen that 1000 iterations give better results than 100 iterations.

B. Berlin 52 Dataset

In this section, as in the previous section, Berlin 52,one of the TSPLIB [17] Datasets, was used for the optimal path length

Table 4. GR202 Dataset information

Data Set Name	Berlin 52
Data Set Type	TSP
Size	52
Optimal Results	7542

Table 5. ACO parameter values for Berlin 52

The algorithm used	Ant System Algorithm
Number of Ants	52
Number of cities	52
Alpha	0.7
Beta	4
Pheromone evaporation	0.5
Iteration	100 and 1000

When the pheromone evaporation was set as 0.5 for Berlin 52, it was found to be very good results. In addition, when the alpha value is 0.7, the results are more rapidly optimized.

Table 6. Berlin 52 data 20 Times Study Results Analysis

Number of iterations	100	1000
Number of elements of the array	20	20
Mod (peak values)	7679	7669
Mode frequency (number of repetitions of the peak value)	5	5
Median	7682	7665.5
Arithmetic mean	7702.8	7666.3
Standard deviation	52.45	14.5
Standard deviation variance	2751.32	212.05
Standard error	11.72	4.39
Range	192	50
The smallest number in series	7662	7645
The largest number in series	7854	7695
The total of numbers in series	154056	153322

As can be seen in Table 6 , for Berlin 52 data, there is no noticeable difference between 100 and 1000 iterations. The reason for this is that it already finds the best result in 100 iterations. This was not the case in GR202. Even in 700 or 800 iterations, there could be better results.

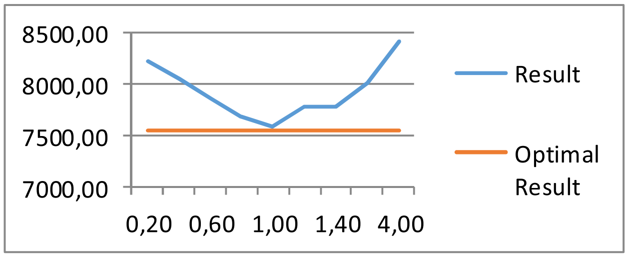
C. Selection of the optimum parameters

When calculating the optimal parameters alpha and beta Berlin 52 database was used.

1) The Best Alpha Value

The most appropriate alpha values were found in a series of test results. Beta value was chosen 4. Alpha values were given between 0.2 and 4. The best result is the value 1 as shown for alpha.

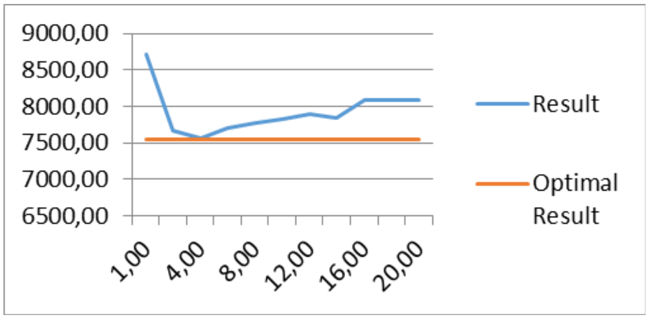
Table 7. best alpha value table



2) The Best Beta Value

After finding the best alpha value using the value found the best beta value. Alpha value was choosen 1. And beta values were given between 1 and 20. The best result is between 2 and 6.

Table 8. best beta value table for



V. Conclusion and Future Work

In this study ACO was analyzed under various conditions. This analysis also found by testing the optimal parameter values for the algorithm. Two dataset were used in this study.

As a result, thanks to ant colony optimization, the solution was seen to be rapidly converged. The parameter values were based on previous studies and various experiments. After many tests, as when the alpha value is low, pheromone value is less considered, it was observed that by working as a greedy algorithm, the algorithm gave worse results. It was also observed that when the Beta value was low, intuition disappeared and there became poor results. The total number of studies were specified as 20 with 100 and 1000 iterations. In the table below, the average, standard deviation, median and mode etc. values related to the results of 20 studies are given. Figure 1 and Figure 2 are shown the best results. The most appropriate alpha values between 0.7-1.5 and the beta value was found to be the most suitable 3-7 for Berlin 52.

Different optimization algorithm can be used in future studies to find the optimal parameters. Thus, the algorithm is made more efficient and convenient.

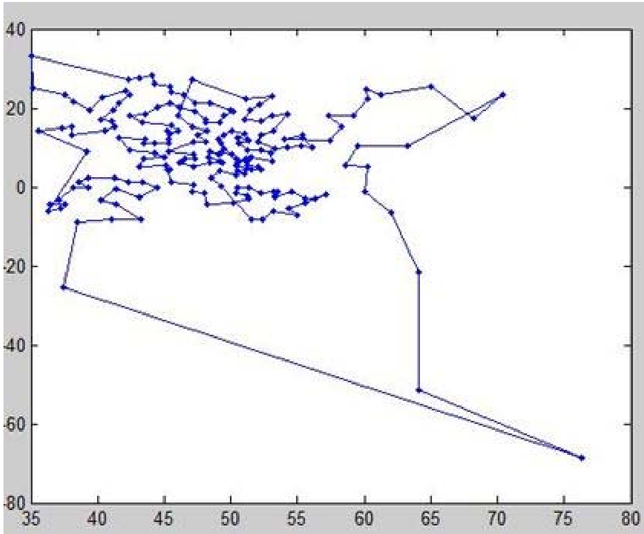


Figure 1: Best solution (44393) for GR202

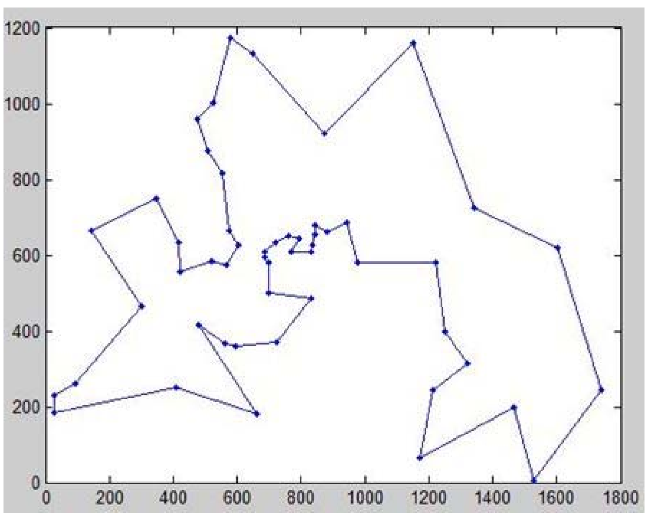


Figure 2: Best solution (7662) for Berlin 52

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