Solving the Multi-objective Travelling Salesman Problem by an Amalgam of Fruit Fly Optimization and Ant Colony Optimization

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ABSTRACT

In this article, the multi-objective Travelling Salesman Problem (TSP), which includes the optimization of two competing and incompatible goals, is taken into account. There is not a single ideal strategy that enhances all the objective functions at once. Usually, one of the goals is considered a constraint or both goals are combined into one objective function. This work provides an extremely efficient Ant Colony Optimization (ACO)-based multi-objective Fruit Fly Optimization Algorithm (FFOA). Using FFOA, which was normalized and initialized to the pheromone quantity for ACO, the present study first establishes a local solution. To evaluate the optimization results a combined method of FFOA and ACO is carried out.

Keywords-multi-objective travelling salesman problem; fruit fly optimization; ant colony optimization

I. INTRODUCTION

The Travelling Salesman Problem (TSP), an established combinational optimization problem, has numerous applications in a variety of fields. It is an NP-hard problem and extremely challenging to solve. This problem refers to a salesman who wishes to visit n different cities. Assume the salesman is familiar with d_{ij} (i = 1,2….n, j = 1,2….,n), s distances between the points (cities) i and j. The salesman seeks to choose the route that makes a single stop in each city, while requiring the least amount of travel time or cost or distance. The salesperson must return to the place of departure. Nevertheless, the route can start in any location. One might also take into account additional elements like time and cost. Since the majority of real-life issues need the optimization of a number of goals, multi-objective optimization is regarded as a significant research area. Many situations in the actual world have multiple objective issues, yet only one of those issues has a solution. Multi criteria optimization problems, however, identify a number of ideal solutions. The multi criteria optimization [1] is explained as:

$$\min\ Z(x) = \{Z_1(x), Z_2(x), Z_3(x) \ldots\ldots Z_m(x)\} \qquad (1)$$

where $Z_1(x)$,…….., $Z_m(x)$ are the m objective functions, $x = (x_1, x_2, \ldots, x_n)$ represents the parameters of optimization for n destinations, $x \in D$ is an integer permutation from 1 to n that minimizes $Z(x)$, and D is the feasible solution space.

Various exact methods have been deployed. For large size problems, conflicts in problems' objectives make these methods not suitable. To overcome these problems some heuristics and metaheuristic methods have been proposed. These techniques help to discover a satisfying solution when conventional approaches become unfit or fail. Some nature inspired methods, such as Swarm Intelligence [24], Ant Colony Optimization (ACO), Fruit Fly Optimization (FFO), Mayfly Algorithm, Genetic Algorithm (GA) [2,23,25], and Artificial Bee Colony algorithm [3] have been adopted to solve the TSP with multiple variants. Some hybrid approaches, like genetic and simulating annealing algorithms have been also employed [4].

FFOA is a potential meta-heuristic algorithm. This technique is based on the fruit fly's foraging habits (drosophila). The FFOA has two crucial problems, fragrance and vision. Osphresis and vision are the primary characteristics of fruit flies [5, 6, 7]. FFOA is useful to represent various kinds of challenging optimization issues. The Osphresis of the drosophila is so strong that it can detect the source of food from 42 km distance and then fly towards it. Two stages make the FFOA implementation process. The community of flies searches for the position of their meal in the first stage before flying there. The second step starts when the flies reach the food, at which point they use their keen sight to fly to the food direction. Up until the flies reach the food, this procedure is repeated to find the ideal placement [8]. This method's code can be easily understood and constructed, while fast and precise solutions can be found. The FFOA has a small number of adjustment parameters and can find solutions quickly [8-10]. FFOA is more straightforward and effective than other optimization techniques. Authors in [11] developed discrete FFOA and applied it to TSP. They implemented an effective crossover operator to search for neighboring locations of the swarm. They improved the surroundings of the non-optimal food site during testing to increase the DFOA's exploration performance by using an edge intersection removal operator. Authors in [12] enhanced FFOA by suggesting a brand-new visual search technique. They recommended shifting the fruit fly process to prevent the FFOA from settling on local optima. To ameliorate the fruit fly population's positive individuals, an innovative approach was applied.

ACO is new meta-heuristic algorithm for tackling complex combinatorial optimization problems [13-16]. The properties of actual ant colonies serve as the basis for ACO. Ants frequently move between their nest and the food supply to determine the shortest route for acquiring food. Pheromone trails are the scents that ants leave behind when they go from the colony to the food source. The pheromone trail eventually disappears if no additional pheromone is released. This direct communication style of actual ants is modeled after synthetic ants, which go from one node to another in search of solutions. Additionally, they employ a unique data structure that is kept in memory and utilized as the ants migrate from one node to another. When an ant leaves the first node on its journey, every trail has a constant concentration of pheromone. The ant finishes its journey by pausing at each node, updating the pheromone trail along all pathways. In that way, the pheromone trail of the ant's completed path will be high if it is a good path, and vice versa. Before applying the new pheromone track, pheromone trails in each path are also dissipated. Additionally, the ant takes into account heuristic data that evaluate the fineness of the current challenge while it moves.

II. THE PROPOSED METHOD

In order to solve multi-objective TSP, a hybrid of FFOA and ACO is proposed in this study. In this approach, FFOA is utilized to identify local search, and ACO is used to minimize the entire distance travelled by all salesmen and the longest distance travelled as a multi-objective problem with both equal and unequal conditions. The problem is first solved by treating the distance value as a single objective. The weighted sum approach, which may be expressed as follows [1, 17-19], is used in this instance:

$F=Y1*Z1+Y2*Z2$

where *Z1* denotes the total distance travelled by all salesmen, Z2 denotes the highest distance travelled by a salesman, and *Y1* and *Y2* are weights to balance the total distance travelled and the maximum distance travelled by a salesman where *Y1*+*Y2*=1. ACO determines the global search based on FFOA's findings. ACO starts from a solution obtained by FFOA. By figuring out the ideal combination, in addition to all the factors necessary to excute FFOA and ACO, this work may improve the result and shorten convergence time. The first pheromone track is dispersed evenly for every edge in the ACO approach. However, the initial trail was established in an amalgam FFOA-ACO on the basis of the regional solutions discovered by FOA. The best local options will include adding the pheromones to the edge. This increases the likelihood that ants may visit the edge. The stages involved in the hybrid algorithm are shown in Figure 1.

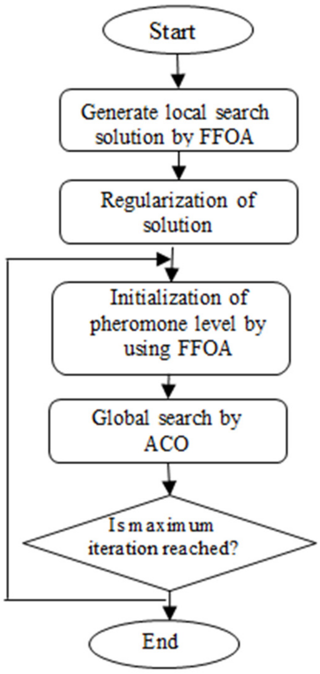


Fig. 1. Flow of the algorithm.

III. LOCAL SEARCH BY FRUIT FLY OPTIMIZATION ALGORITHM

FFOA is suggested for solving single- and multi-objective optimization problems. Fruit flies are better in sensing and perception than other species. Osphresis and vision are the two key components of the drosophila's search mechanism [8, 10]. The following list describes the primary FFOA steps:

Step1: Place randomly the fruit fly swarm throughout the search area.

Step 2: Use osphresis to discover the food by randomly determining the distance and direction for every fruit fly in the search area. The following equation can be used to calculate each fruit fly's random search distance:

$X_i = X + arbitrary\ value$

$Y_i = Y + arbitrary\ value$

were X_i and Y_i are the arbitrary location and length for a single fruit fly's quest for food. The initially coordinates of the fruit fly swarm are X and Y.

Step 3: Assuming that the place of the fruit fly is unknown, determine its distance (*Dist*) from the starting point. The judgement value of the amount of odor (*S*) is then determined:

$Dist = \sqrt{x^2 + y^2}$

$S = \frac{1}{Dist}$

Step 4: Replace the concentration odor value into the concentration judgment function, evaluate the fitness function:

Odor = *Function* (*S*)

where the odor concentration is *Odor* and *Function*(*S*) is the fitness function.

Step 5: Choose the drosophila that produces the highest value of saturation.

[*BOdor BIndex*] = max (*Odor*)

where *BOdor* is the finest saturated value of *Odor* and *BIndex* is the location of the swarm.

Step 6: The crew of fruit flies will make their way in the direction of the food location depending on the strong eyesight after saving the drosophila with the best concentration value of *Odor*.

Odor B =*BOdor*

X = *X* (*BIndex*)

Y= *Y* (*BIndex*)

Step7: Start the next phase of the optimization loop, reprising the execution of steps 2 to 5. Then measure the odor saturation, and compare the current reading to the previous one. If the new best odor is better, carry through step 6, and so on until the food is spotted and the FOA search will be terminated.

IV. SOLUTION REGULARIZATION AND INITIALIZATION

The ACO pheromones are initialized after FFOA regularized the solution by assuming there are q solutions as routes. The pheromones on the edges present in the route obtained from FFOA are combined. The parameters for introducing pheromones are based on the following equation of the improved solutions:

$$\Delta t_{(i,j)} = \frac{(1+q-k)}{q} \tag{2}$$

From the existing q solutions the edge between i, j represents the k^{th} best solution. This will result in the first-best solution's edge receiving more pheromones than the second-best solution's edge. Therefore the q candidate most passed edges will receive the greatest pheromone addition. In order to perform the ACO with the fewest agents and iterations, the initial pheromones are established with varying quantities depending on the local FFOA solutions.

V. GLOBAL SEARCH BY ACO

The Multi-Colony Ant Algorithm (MCAA) [20, 21], considers to optimize time, cost, quality, and quantity. An equal number of colonies and objectives is set. Each colony makes use of a particular pheromone structure and heuristic data. The following is an expression for the state vector strategy for shifting an ant from node i to node j at time t:

$$j = \begin{cases} \arg_{j\in allowed} \max[\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta} \\ J \text{ otherwise} \end{cases} \tag{3}$$

where τ is the amount of pheromone on edge i, j, η is a heuristic function which assigns some value to the edges.

The symbol τ_{ij} represents the overall sum of pheromone track discharges on the path from i to j at time t. Using input from the goal functions, η represents the heuristic value of the path between i and j, where j is a node. In (3), the parameters denote the relevance of the pheromone track and the heuristic facts, respectively. Equation (4) is utilized to determine the probability distribution of nodes:

$$P_{ij} = \begin{cases} \frac{[\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}}{\sum[\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}}, j \in \text{allowed} \\ 0 \text{ otherwise} \end{cases} \tag{4}$$

For non-dominated solutions, the global update is carried out as follows once every ant in a colony has finished its tour:

$$\tau_{ij}(t+1) = \rho\tau_{ij}(t) + \Delta\tau_{ij}, \tag{5}$$

where ρ is the evaporation rate.

$$\Delta\tau_{ij} = \begin{cases} \frac{Q}{nP(k)}, \text{if the kth ant traverses edge}(i.j) \\ 0, \quad \text{otherwise} \end{cases} \tag{6}$$

The evaporation parameter in basic ACO has a constant value, which lowers the pheromone quality in every edge to a particular point. The changed formula in (7) in this study changes the constant coefficient to a variable coefficient. Consequently, this coefficient modifies and increases the algorithm's efficiency by altering the algorithm's state. To get a better solution, here the evaporation rate is modified, motivated from [15, 16], where the algorithm loop repetitions are represented by n, i represents iterations from 1 to maximum, ρ is the new rate of evaporation which increases with time. ρ_{l+1} is defined as:

$$\rho_{l+1} = \alpha\rho_l + \beta\left(1 - \cos\frac{\pi l}{2n}\right) \tag{7}$$

where $0 \le \rho_{l+1} \le 1$, for $0 \le \rho_l \le 1$, $0 \le \alpha \le 1$, and $0 \le \beta \le 1$, whereas l changes from 1 to n iterations.

Proof:

$$\rho_{l+1} = \beta\rho_l + \alpha\left(1 - \rho_l\cos\frac{\pi l}{2n}\right) \le 0.1 + 1(1-0) = 1$$

and:

$$\rho_{l+1} = \beta\rho_l + \alpha\left(1 - \rho_l\cos\frac{\pi l}{2n}\right) \ge 1.0 + 0(1-1) = 0$$

Thus, (7) is true.

VI. MATHEMATICAL MODELING

In a traditional TSP, there is a collection of nodes 1, ….., n denoted by N, and a distance $n \times n$ matrix (d_{ij}), wherein each node corresponds to a city and d_{ij} indicates the distance from city i to city j. With the exception of the initial city, the goal of the task is to find an optimal route while visiting every city precisely once. Multiple objectives are to be minimized in a scenario involving multi-objective optimization [22], which can be expressed as: m objective functions of the form $Z(k)$ =($Z_1(x)$, $Z_2(x)$,……, $Z_m(x)$), k = 1, 2, ..., m must be minimized:

$$Z_1(x) = Y_1 * TD^1 + Y_2 * MD^1$$

$$Z_2(x) = Y_1 * TD^2 + Y_2 * MD^2$$

…

$$Z_m(x) = Y_1 * TD^m + Y_2 * MD^m$$

where $TD^k = \sum_{j=1}^{l} ID_j^k$ and $MD^k = max_{i \le j \le l} ID_j^k$.

TD is the total traveling distance of all salesmen, *MD* is the maximum traveling distance of a single salesman, *ID* is the individual traveling distance, and l is the number of salesmen.

VII. EXPERIMENTAL RESULTS

The experiment was carried out in MATLAB-R2015a on an individual laptop with an Intel(R) Core(TM) i5 8250U 1.80 GHz processor and 4.00 GB of RAM. The current study ran an algorithm to determine the best optimal solution for the FFOA to use when conducting a local search. A total of 100 iterations of a local search using FFOA are conducted. The improved optimal solution for two objective functions by FFOA is illustrated in Figure 2. Ten multi-objective TSP cases in the sizes of 100, 150, and 200 were examined. For the sake of simplicity, bi-objective TSP problems were taken into consideration: KROAB100, KROAC100, KroAD100, KROAE100, KROBC100, KROAB150, KROAB200 and EucliAC100, Euclid AD100, Euclid AE100. To find a comprehensive search FFOA and ACO were combined and tested over several common problem instances, some of them with optimal solutions, as evidenced in Figure 3. In this case, run time was not considered for comparison as different computers were used. The algorithm was performed for 50 ants, 100 cities and 100 iterations with α = 0.5 and β = 0.5. Given that each iteration of these metaheuristic algorithms weaves in a new answer, they were run multiple times for every instance. Table I presents the optimal solutions that were obtained.

TABLE I. OPTIMAL SOLUTIONS

Instances	No of Ants	Iterations	Cities	Best solution
KROAB100	50	100	100	2978
KROAC100	50	100	100	3133
KROAD100	50	100	100	2786
KROAE100	50	100	100	3018
KROBC100	50	100	100	3199
EUCLIDAC100	50	100	100	3037
EUCLIDAE100	50	100	100	2947
EUCLIDAD100	50	100	100	2947
KROAB150	50	100	100	3245
KROAB200	50	100	100	3201

(a)

(b)

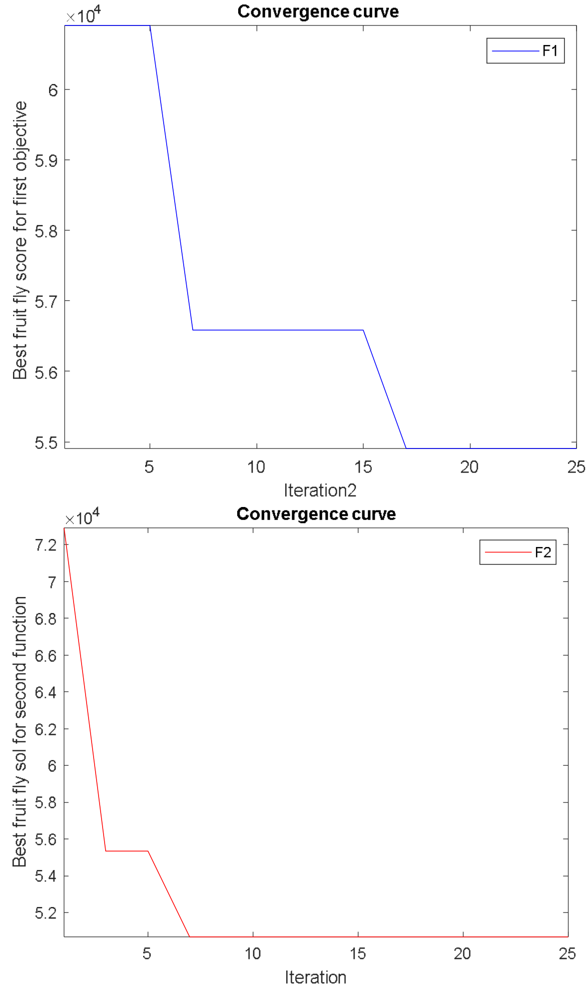
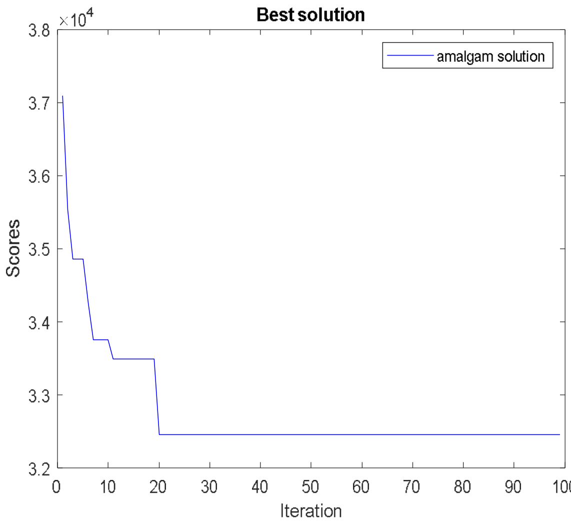


Fig. 2. (a) Kroa150, (b) Kroa150.

(a)



(b)

(c)

(d)

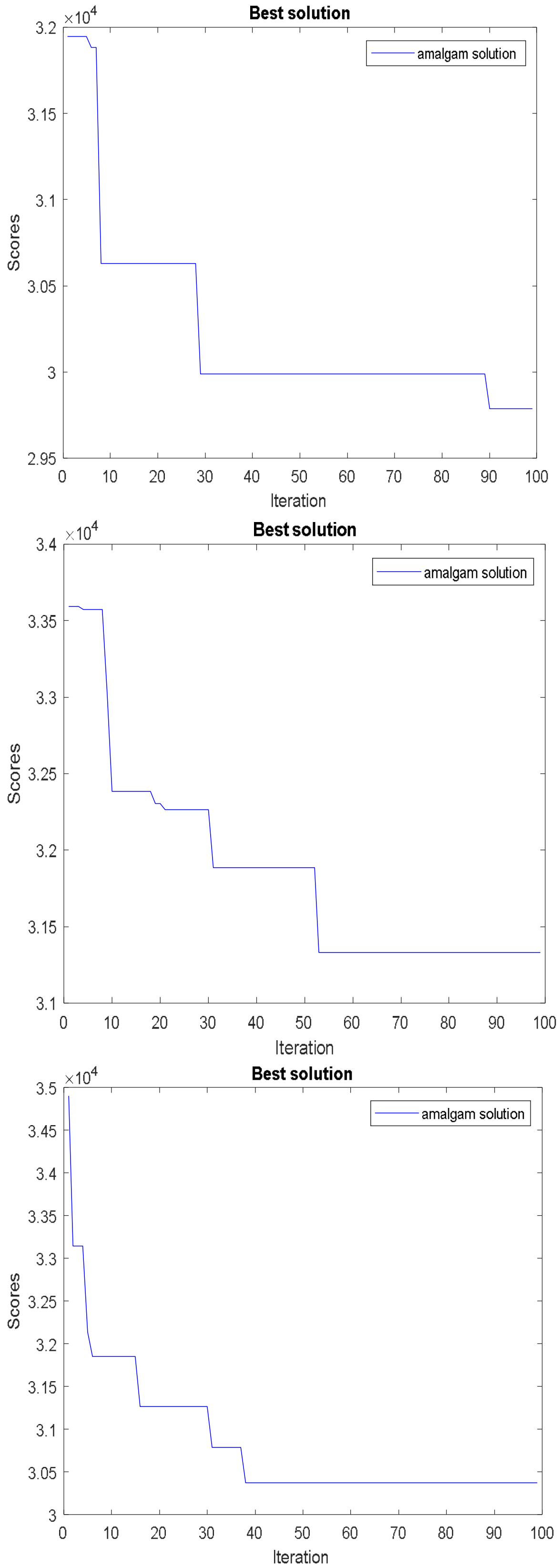


Fig. 3. Best solutions: (a) Kroab150, (b) Kroab100, (c) Kroac 100, (d) Euclidac 100.

VIII. CONCLUSIONS AND FUTURE WORK

In this study, an amalgam process based on FFOA and ACO for solving multi-objective travelling salesman problems was presented. In this proposed method, FFOA was initially utilized for the local search of two objective functions with weighted sum, while ACO was employed for global search after modification of evaporated rate. Parameter setting is crucial for meta-heuristic algorithms because it drives the algorithm to reach values for its parameters, increasing the likelihood that it will find its optimal values for the test cases. The ideal parameters to implement an amalgam FFOA-ACO to solve objective travelling salesman problem is 50 ants, 100 cities alpha=0.5, beta=0.5. The experiment results exhibit that the amalgam FFOA-ACO provides improved efficiency. Compared to ACO, this technique produced the enhanced result. In the future an attempt will be made to use the proposed method for real life problems.

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