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Augmentation of Travelling Salesman Problem using Bee Colony Optimization

Anshul Singh, Devesh Narayan

***Abstract*—Animals with social behaviors often uncover optimal solutions to a range of problems when compared to other techniques. This advantage is extensively used nowadays for a variety of applications. The bee colony optimization (BCO) is inspired by bees foraging behavior that includes colonies of artificial bees capable of solving combinatorial optimization problems e.g. Travelling Salesman Problem. K-opt local search for the value of k as 3 repeatedly reconnects random three edges of the graph after disconnecting so as to obtain refined path. In this article BCO and k-opt local search, the two heuristic techniques for optimization, are combined together to acquire sophisticated results. Comparisons of the proposed method with nearest neighborhood approach is performed and shown with presented system proved to be superior to the rest.**

***Index Terms*— Bee Colony optimization, k-opt local search, waggle dance, Travelling Salesman Problem.**

I. INTRODUCTION

Travelling salesman problem (TSP) is about finding the most optimal path in terms of cost or distance while visiting a given set of cities. It is required that each city must be visited only once and the trip should end at the starting city, making the trip round. The aspect of determining a Hamiltonian tour associated with minimum cost makes TSP one of the discrete optimization problems and classified as NP-hard.

TSP could be asymmetric or symmetric.TSP by default is symmetric unless mentioned as ATSP (Asymmetric Travelling Salesman Problem). Symmetric TSP or simply TSP could be shown as:

Let V= $\{v_{1,} ... ,v_n\}$ be a set of cities, A = {(r, s): r,sϵ V} be the edge set, and $d_{rs}= d_{sr}$ be a cost measure associated with edge (r,s) ϵ A. In the case cities v_i ϵ V are given by their coordinates (x_i, y_i) and d_{rs} is the Euclidean distance between r and s then we have an Euclidean TSP.

If $d_{rs} \neq d_{sr}$ for at least one (r, s) then the TSP becomes an ATSP. This paper describes the work in applying the Bee Colony Optimization (BCO) model, which is based on foraging behavior in bee colony, to Traveling Salesman Problem (TSP). This research is inspired by [1], on using a

New honey bee algorithm for dynamic allocation of Internet servers.

In general, these techniques are classified into two broad categories: First are Exact and the other one is Approximation algorithms [2].

Approximation algorithms could be constructive or improvement heuristic. Constructive heuristics includes instances such as, Greedy Heuristics, Nearest Neighborhood, Insertion Heuristics [3], Christofides Heuristics [4] etc.

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Instances in improvement heuristic include k-opt [5], Lin-Kernighan Heuristics [6] [7] [23], Simulated Annealing [8], Tabu Search [9], Evolutionary Algorithms [10] [11] [12], Ant Colony Optimization [13] [14], Bee System [15] etc.

Application of TSP is in areas such as logistics, transportation and semiconductor industries. Collection of parcels and delivery in logistics companies, uncovering an optimized scan chains route in integrated chips testing, are some of the potential applications of TSP. Proficient way out for such areas will guarantee that the tasks are carried out efficiently and thus boost the productivity. As TSP is significant in many industries, it is so far being studied by researchers from various disciplines and it remains as an important test bed for many newly developed algorithms.

Section II discuses the related work, Section III gives an overview of the BCO model, k-opt search is illustrated in section IV, section V presents the proposed approach BCO with 3-opt local search. Section VI demonstrates the results and discussion. The manuscript concludes in Section VII.

II. RELATED WORK

A number of results were developed, by Chandra and Tovey [5] some worst-case and some probabilistic, on the performance of 2- and k-opt local search for the TSP, with respect to both the quality of the solution and the speed with which it is obtained.

An implementation of the Lin-Kernighan heuristic, one of the most effective methods for giving optimal or near optimal solutions for the symmetric TSP is described [7], [13] Computational tests show that the implementation is highly valuable.

Vanlaarhoven [8] offered a quantitative study of the typical behavior of the simulated annealing algorithm based on a cooling schedule obtainable previously by the authors. The study is based on the analysis of numerical results obtained by systematically applying the algorithm to a 100-city TSP. The prospect and the variance of the cost are analyzed as a function of the control parameter of the cooling schedule

Even though K-OPT are not the fastest TSP solution method, it is widely recognized as a performance benchmark. Tabu search and its application to the symmetric TSP, which is a classic combinatorial optimization problem is shown by Knox [9]The results of Tabu search is compared to the K-OPT procedure using six test problems drawn from the literature

The combination of local search heuristics and genetic algorithm is a capable approach for finding near-optimum solutions to the traveling salesman problem (TSP). An approach is offered in which local search techniques are used to find local optima in a given TSP search space, and genetic algorithms are used to search the space of local optima in order to find the global optimum.

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In this Merz utilized[10] new genetic operators for realizing the proposed approach are described, and the quality and efficiency of the solutions obtained for a set of symmetric and asymmetric TSP instances are discussed.

White and yen give details the development of a Hybrid Evolutionary Algorithm for solving the Traveling Salesman Problem (TSP).[12] The stratagem of the algorithm is to broaden the successful results of a genetic algorithm (GA) using a distance preserving crossover (DPX) by including memory in the form of ant pheromone during the city selection process. The synergistic combination of the DPX-GA with city selection based on probability found out by both distance and previous success adds additional information into the search mechanism. This combination into a Hybrid GA facilitates finding quality solutions for TSP problems with lower computation complexity.

MAX --MIN Ant System, an enhanced version of basic Ant System, and report the results for its application to symmetric and asymmetric instances of Traveling Salesman Problem. Hoos [14] show how MAX --MIN Ant System can be significantly refined extending it with local search heuristics. The results show that MAX --MIN Ant System has the property of effectively guiding the local search heuristics towards promising regions of the search space by generating good initial tours.

Seeley et al. [18] studied the extent to which scout honey bees gain information from waggle dances the whole time their careers as foragers.

Swarm intelligence is a research branch that models the population of interacting agents or swarms that are able to self-organize. An ant colony, a flock of birds or an immune system is a typical example of a swarm system. Bees' swarming around their hive is also an example of swarm intelligence. Artificial Bee Colony (ABC) The approach proposed by Karaboga and Basturk [19] is an optimization algorithm based on the intellectual behavior of honey bee swarm. In this work, ABC algorithm is used for optimizing multivariable functions and the results produced by ABC, Genetic Algorithm (GA), Particle Swarm Algorithm (PSO) and Particle Swarm Inspired Evolutionary Algorithm (PS-EA) have been compared. The results showed that ABC outperforms the other algorithms.

Traditionally, chess has been called the "fruit fly of Artificial Intelligence". In recent years, however, the focus of game playing research has gradually shifted away from chess towards games that offer new challenges highlighted by Rijswijk [20]. These challenges consist of large branching factors and imperfect information. The key ideas about Queen Bee are presented in the approach.

Chong and Gay [21] presented a novel approach that uses the honey bees foraging model to solve the job shop scheduling problem.

Chong and Gay proposed a population-based approach that uses a honey bees foraging model to solve job shop scheduling problems. [22]The algorithm uses an efficient neighborhood structure to search for reasonable solutions and iteratively progress on prior solutions. The primary solutions are generated using a set of priority dispatching rules. Experimental results comparing the proposed honey bee colony approach with existing approaches such as tabu search, ant colony and shifting bottleneck procedure on a set of job shop problems are presented.

III. THE BCO MODEL

Bees, ants, cockroaches, birds, fishes etc are social insects and studying their behavior for finding optimal solutions for various problems comes under swarm intelligence.

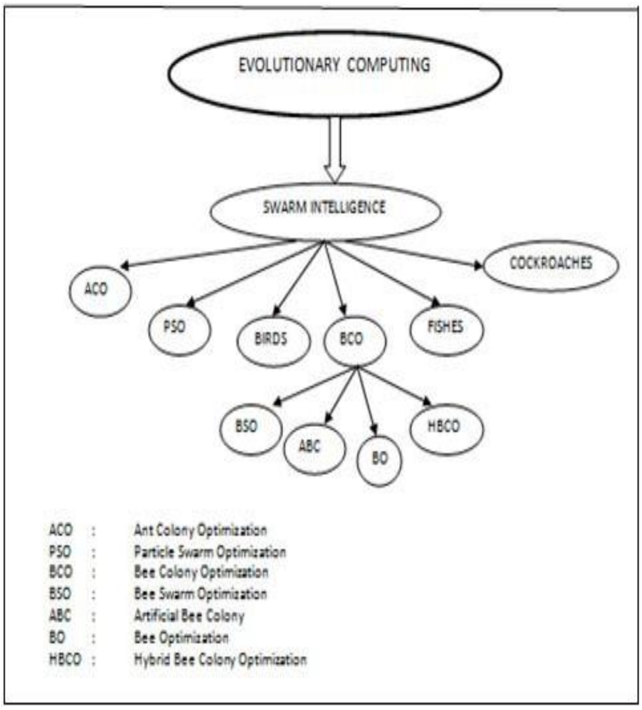

Fig.1 BCO as a classification of swarm intelligence

The Bee Colony Optimization or BCO is based on bees foraging behavior, in which bees while searching for food, finds the most favorable path for nectar. The search process is shown in the Fig.2.

This biologically motivate approach is currently being employed to solve continuous optimization problems, to optimize locations of traffic sensors on highways, in finding routing protocol in MANET, training neural networks, for solving multi-dimensional knapsack problem, in mechanical and electronic components design optimization, combinatorial optimization problems such as job shop scheduling, the internet server optimization problem, the travelling salesman problem, etc.

There are three stages in Bees foraging process:

1. The Employed Bee stage
2. The Onlooker Bee stage
3. The Scout Bee stage

The Employed Bee Stage: In this stage the bees stay on a food source and provide the neighborhood of the source in its memory.

The Onlooker Bee Stage: Bees get the information of food sources from the employed bees in the hive and select one of the food sources to gather the nectar.

The Scout Bee Stage: It is responsible for finding new food, the new nectar, sources.

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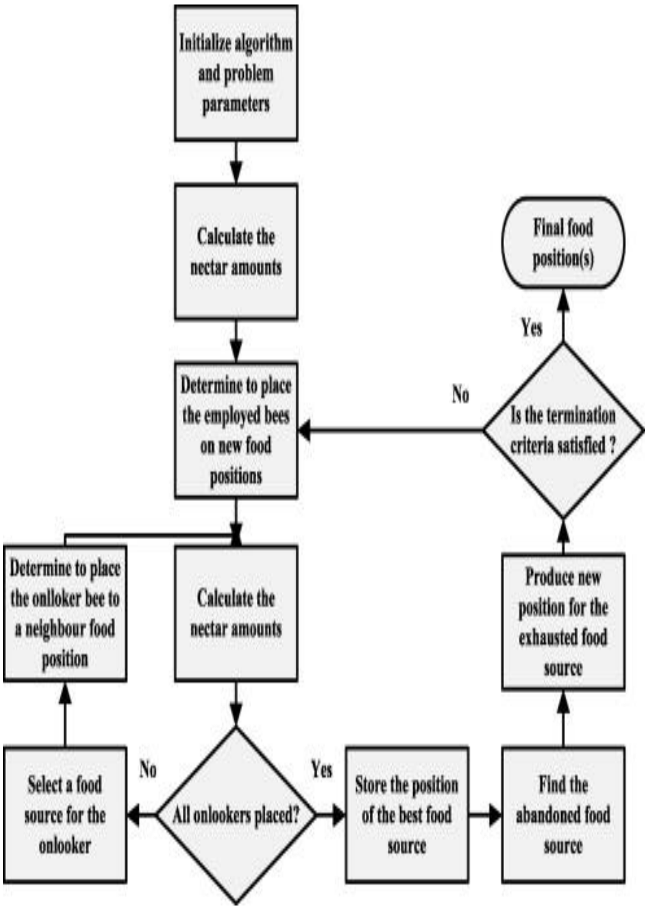

Fig.2: flowchart of foraging process

Bees complete one cycle when they have explored all the food sources. The bee which finds considerable amount of nectar is allowed to perform waggle dance on the vertical comb after reaching the hive. The dance will be round if the food source is nearby, while it will be waggle for a distant food source conveying information about distance and direction of rich nectar source. The way bees move is shown in the Fig.3 when performing waggle dance, the long run indicates the distance and rounds taken gives idea about direction of source with respect to sun. The profitability of a bee is compared with average profitability of the colony, if it is more than the bee is allowed to dance for more duration. The dance duration D_i of bee i, is determined by the following formula:

$D_i = K. (Pf_i / Pf_{colony})$

$Pf_i = (1/ L_i)$, L_i = tour length

$$Pf_{colony} = (1/n) \sum_{i=1}^{n} Pf_i = (1/n) \sum_{i=1}^{n} (1/L_i)$$

K denotes the waggle dance scaling factor
Pf_i denotes the probability score of bee i
Pf_{colony} denotes the bee colony's average probability
n denotes number of bees performing waggle dance

IV. 3-OPT LOCAL SEARCH

The critical idea of 3-opt heuristic is to eliminate three arcs in R in order to obtain three different paths. These three paths are then reconnected in the other possible way.

Steps followed in 3-opt local search is as follows:

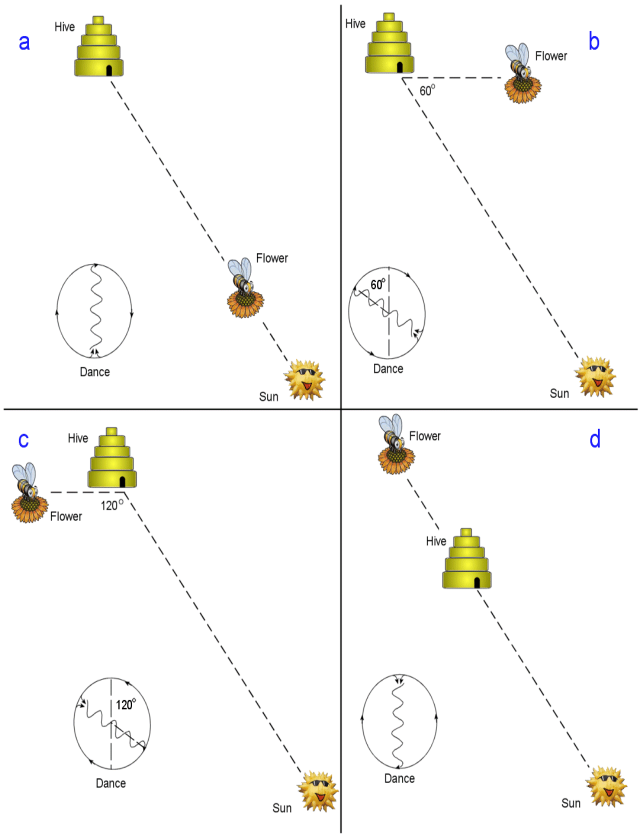

Fig.3: Information conveyed by honey bees through waggle dance

1. Produce a pseudorandom feasible solution, R.
2. Perform a transformation on R to produce R'.
3. Replace R with R' if R' is found to be better than R. Repeat step 2 until no improvement is observed. At this stage, R is said to be locally optimal.
4. Repeat step 1 to step 3 until a pre-defined computation time is exceeded or when a satisfactory result is gained.

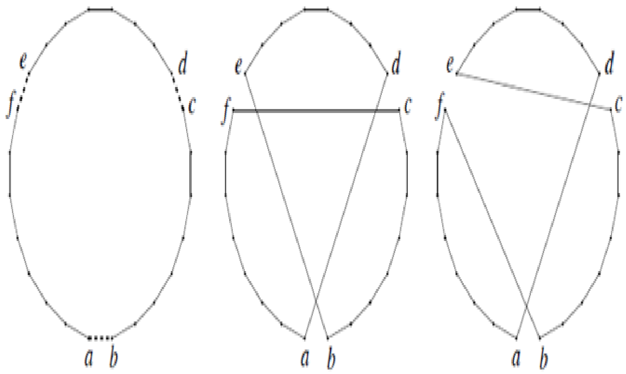

Fig.4: two possible moves of 3-opt local search

V. BCO WITH 3-OPT LOCAL SEARCH

Before leaving the hive, the bee will randomly observe dances performed by other bees. The bee is then equipped with a set of moves which are observed from the dance. This set of moves, named as "preferred path" and denoted as θ, will then serve as guidance in its foraging process. θ basically contains a complete tour that had been explored previously by its mate and it will direct the bee towards the destination.

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There are two set of cities that are maintained one is set of allowed next cities $A_i(t)$, and preferred next cities $F_i(t)$, that helps in the path construction process. $A_i(t)$ contains all the feasible next cities that can be reached from city i. $F_i(t)$ contains a single city which is favored to reach from city i as recommended by θ.

The selection of next city depends on state transition probability. Probability is decided by arc fitness and heuristic distance. State Transition Probability is given by the formula:

$$P_{ij}(t)= \frac{[\rho_{ij}(t)^{\alpha} \,.\, [1/d_{ij}]^{\beta}}{\sum_{j\epsilon Ai(t)} [\rho_{ij}(t)]^{\alpha}.[1/d_{ij}]^{\beta}}$$

Where $\rho_{ij}(t)$ is the arc fitness given by

$$\rho_{ij}(t) = \begin{cases} \lambda & , j\epsilon F_i(t) \\ \dfrac{1-\lambda \,|\, A_i(t) \cap F_i(t)|}{|A_i(t)|-|A_i(t) \cap F_i(t)|} & , j\epsilon F_i(t) \\ 1 & , |A_{i,n}|=1 \end{cases}$$

The BCO model with 3-opt local search is given by:

```
Procedure BCO
 Initialize_Population()
   While stop criteria are not fulfilled do
     while all bees have not built a complete path do
       observe_Dance()
       Forage_ByTransRule()
       Perform_3-Opt()
       Perform_Waggle_Dance()
    end while
  end while
End procedure BCO
```

Fig.5: BCO model with 3-opt local search for TSP

VI. RESULTS AND DISCUSSION

Table1. Comparison of nearest neighbor and bco with 3-opt local search

NO OF CITIES	COST_BY_NEAREST_NEIGHBOR	COST_BY_BCO_WITH_3-OPT_LOCAL_SEARCH	% DIFFERENCE
20	31544.16	29019.27	8.004305 % Better
22	46188.7	38368.34	16.93132 % Better
24	42590.27	37286.85	12.45219 % Better
26	42969.93	36442.28	15.19121 % Better
28	59607.39	44943.18	24.60134 % Better
30	54715.59	45544.46	16.76146 % Better
32	44653.06	38475.06	13.83557 % Better
34	48653.89	37755.53	22.39977 % Better
36	54489.42	43406.28	20.33998 % Better
38	65829.2	45448.18	30.96046 % Better
40	63922.63	52810.14	17.38428 % Better
42	69692.84	54885.7	21.24629 % Better
44	63413.89	46289.96	27.00344 % Better
46	62844.67	52979.96	15.69697 % Better
48	65159.74	54582.51	16.23277 % Better
50	64556.1	55765.64	13.61678 % Better
SUM	880831.48	714003.3	18.939852 % Better

VII. CONCLUSION

The article presents BCO with 3-opt local search which outperforms other existing techniques for solving TSP like nearest neighbor and bee colony optimization. The table shows the comparative result of nearest neighborhood method and bco with 3-opt local search. We hope to use other features of bees like its smelling power etc for further enhancing the performance. Constructive heuristics can also be included for refining the results.

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