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Emplacement Detection Using Ant Colony Optimization

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Abstract: The Ant Colony Optimization (ACO) is a algorithm with metaheuristic and versatile optimization approach based on the behaviour of ants. After a numerous analysis, ACO has been applied to solve different combinatorial problem statements. The ant colony metaheuristic proves itself to be efficient in solving hard problems, often generating the best solution in the shortest amount of time. However, not enough attention has been paid to ACO as a means of solving problems that have optimal solutions which can be found using other methods. The shortest path problem is undoubtedly one of the aspects of great significance to navigation and telecommunications. It is used, amongst others, for determining the shortest route between two geographical locations, for routing in packet networks, and to balance and optimize network utilization. Thus, this article introduces Shortest Path ACO, an Ant Colony Optimization based algorithm designed to find the shortest path in a graph. The algorithm consists of several sub problems that are presented successively. Each subproblem is discussed from many points of view to enable researchers to find the most suitable solutions to the problems they investigate.

I. INTRODUCTION

Over the last 5 - 7 years, with the advent of smart computing devices like tablets, smart-phones, notepads, etc. there has been an explosion in the data consumption. This can be mainly attributed to the ability to use high data-rate services like video streaming, video calls, etc. anywhere, anytime. This has resulted in an exponential growth in the data traffic by the subscribers, leading to network congestion and connection drops.

This broadband data explosion forced the telecom operators to look for alternate resources to decrease the network traffic while providing maximum quality of service (QoS) to the subscribers. In addition to cellular networks, the network operators have been aggressive in deploying different radio access technologies (RATs) which include: Wi-Fi, small cells (micro cells, pico cells, nano cells) etc. in order to share the traffic load across the networks [1]. Over recent times, there has been an exponential growth in the world of Internet of Things (IoT).

The number of sensors deployed to perform sensing, monitoring and actuation tasks has increased tremendously. These IoT-based devices would collect large volumes of data that has to be communicated through the network to some central cloud. However, cellular networks with huge data traffic are already congested and these IoT based traffic would further add to the congestion. Having said that, a significant portion of the data traffic could be offloaded/moved to be communicated through another network [2]. With the number of IoT devices expected to be in billions in the next decade, no single base station (BS) will. be able to manage the computational load for all devices in the network. Also, not all devices in itself can do the resource allocation and network selection by itself [3].

Hence, it is critical that there are new efficient and alternate mechanisms for connectivity and load sharing which takes into account the best practises of both device-centric and network-centric mechanisms. Further, the work in [4], [5] discusses how to combat this problem of data explosion through the coexistence of multiple RATs in overlapping areas; also called as heterogeneous networks. Some of the advantages of such a heterogeneous environment include: reduction in traffic congestion, efficient use of existing infrastructure and seamless mobility. Fig. 1 illustrates a heterogeneous wireless environment where the subscriber is in the range of different RATs covering an area. As can be observed from Fig. 1, there are several radio access networks (RAN), with a subscriber being in range of not only multiple RANs; but also in presence of different other networks like small cells, Wi-Fi, etc. which it would sue to connect to different applications and devices with different operating systems.

II. LITERATURE REVIEW

Cagri G oken [1] analysed the Network Selection Problem for Heterogeneous Environments which tends in wireless networks is that several wireless radio access technologies (RATs) coexist in the same area. forming heterogeneous networks in which the users may connect to any of the available RATs. Victoria Kostina, and François Gagnon [2] created a strategy based on the density of Internet of Things (IoT) devices and k-means algorithm to partition network of edge servers, then an algorithm for IoT devices' computation offloading decisions is proposed, i.e., whether we need to offload IoT devices' workload to edge servers, and which edge server to choose if migration is needed. Sergey Loyka, Victoria Kostina [3] created an optimal RAT selection problem is considered to maximize the total system throughput in an LTE-WiFi system with offload capability. Another formulation is also developed where maximizing the total system throughput is subject to a constraint on the voice user blocking probability. Berkan Dulek[4] proved the convexity properties for the problem of detecting the presence of a signal emitted from a power constrained transmitter in the presence of additive Gaussian noise under the Neyman-Pearson (NP) framework. Ashok Patel and Bart Kosko[5] This paper presents theorems and an algorithm to find optimal or near-optimal "stochastic resonance" (SR) noise benefits for Neyman-Pearson hypothesis testing and for more general inequality-constrained signal detection problems. The optimal SR noise distribution is just the randomization of two noise realizations when the optimal noise exists for a single inequality constraint on the average cost. Berkan Dulek[6] created a Optimal receiver design is studied for a communications system in which both detector randomization and stochastic signaling can be performed. First, it is proven that stochastic signaling without detector randomization cannot achieve a smaller average probability of error than detector randomization with deterministic signaling for the same average power constraint and noise statistics. Hao Chen, Pramod K. Varshney[7] created a theory of the Stochastic Resonance Effect in Signal Detection: Fixed Detectors, which developed the mathematical framework to analyze the stochastic resonance (SR) effect in binary hypothesis testing problems.

V. N. Hari, G. V. Anand, A. B. Premkumar, and A. S. Madhukumar[8] created a Design and Performance Analysis of a Signal Detector Based on Suprathreshold Stochastic Resonance. Ahmet Dundar Sezer ∗, Sinan Gezici ∗, and Hazer Inaltekin[9] Optimal channel switching is proposed for average capacity maximization in the presence of average and peak power constraints. A necessary and sufficient condition is derived in order to determine when the proposed optimal channel switching approach can or cannot outperform the optimal single channel approach, which performs no channel switching.

III. METHODOLOGY

The Ant Colony Optimization has mainly two methodologies in algorithm. They are: 1) Edge selection 2) Phermone Update

Edge Selection: To select the next edge in its tour, an ant will consider the length of each edge available from its current position, as well as the corresponding pheromone level. At each step of the algorithm, each ant moves from a state ***x*** to state ***y*** corresponding to a more complete intermediate solution. Thus, each ant k computes a set $A_k(x)$ of feasible expansions to its current state in each iteration, and moves to one of these in probability.

$$p_{xy}^k = \frac{(\tau_{xy}^{\alpha})(\eta_{xy}^{\beta})}{\sum_{z\in \mathrm{allowed}_x}(\tau_{xz}^{\alpha})(\eta_{xz}^{\beta})}$$

Where p_{xy}^k is the probability of ant ***k*** moving from state ***x*** to state ***y*** depends on

the combination of two values, η_{xy} is the attractiveness of the move, τ_{xy} is the trail level represents a posteriori indication of the desirability of that move.

Pheromone update: Trails are usually updated when all ants have completed their solution, increasing or decreasing the level of trails corresponding to moves that were part of "good" or "bad" solutions, respectively. An example of a global pheromone updating rule is

$$\tau_{xy} \leftarrow (1-\rho)\tau_{xy} + \sum_{k}^{m} \Delta\tau_{xy}^k$$

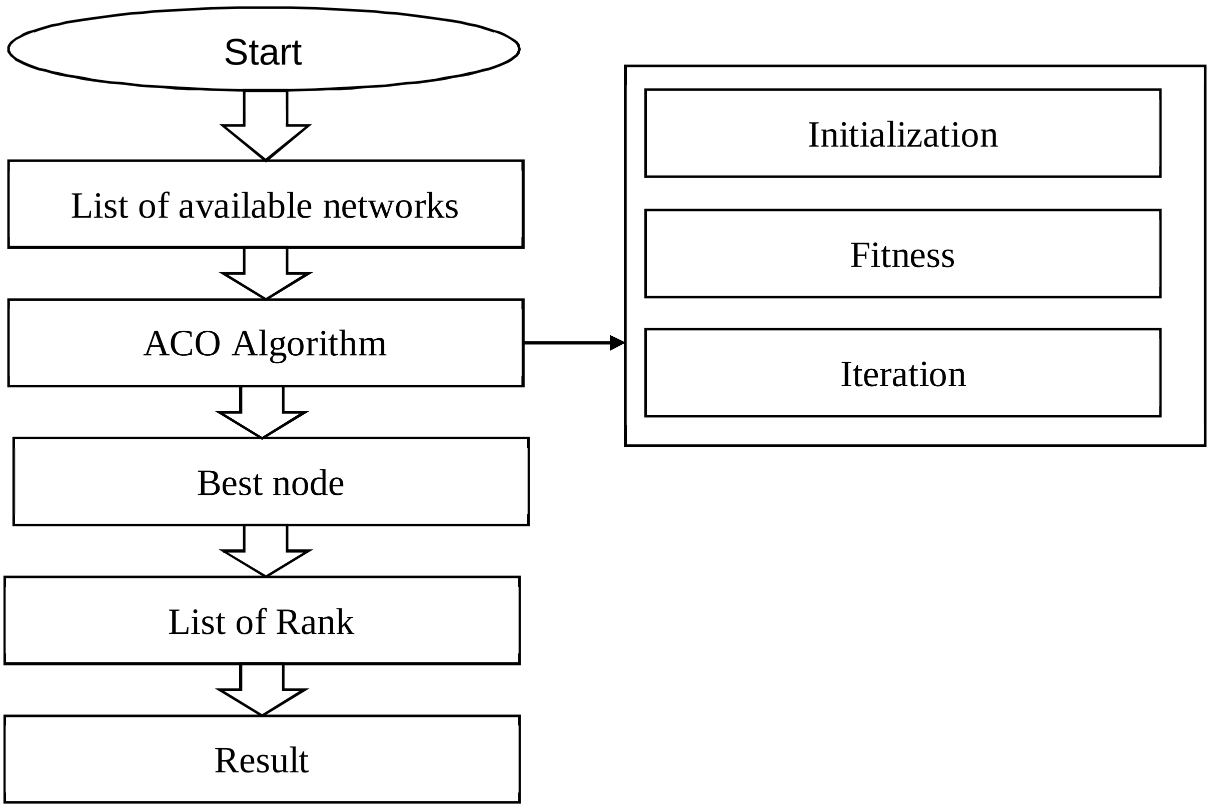
τ_{xy} is the amount of pheromone deposited for a state transition ***xy***, ρ is the pheromone evaporation coefficient, ***m*** is the number of ants

$\Delta\tau_{xy}^{k}$ is the amount of pheromone deposited by ***k***th ant

$$\Delta\tau_{xy}^{k} = \begin{cases} Q/L_k & \text{if ant } k \text{ uses curve } xy \text{ in its tour} \\ 0 & \text{otherwise} \end{cases}$$

where L_k is the cost of the ***k***th ant's tour

IV. FLOW DIAGRAM



V. ALGORITHM

1) *Step-1:* Begin
2) *Step-2:* Initialize pheromone and other parameters
3) *Step-3:* Generate a population of n ants
4) *Step-4:* for each ant k Calculate fitness value
5) *Step-5:* Determine best position
6) *Step-6:* Determine best global ant (solution)
7) *Step-7:* Update pheromone trail
8) *Step-8:* Check stopping criteria, if criteria is found goto step-3
9) *Step-9:* End

VI. CONCLUSION

After a thorough examination of the results, it is observed that the algorithms based on the metaheuristic of ant colonies do not guarantee finding an optimal solution in all possible cases. An evaluation of the duration time and the quality of returned solutions will provide information for making a decision on the implementation of a given scheme as being of optimum quality or an alternative to more time-consuming procedures or procedures with higher computational cost.

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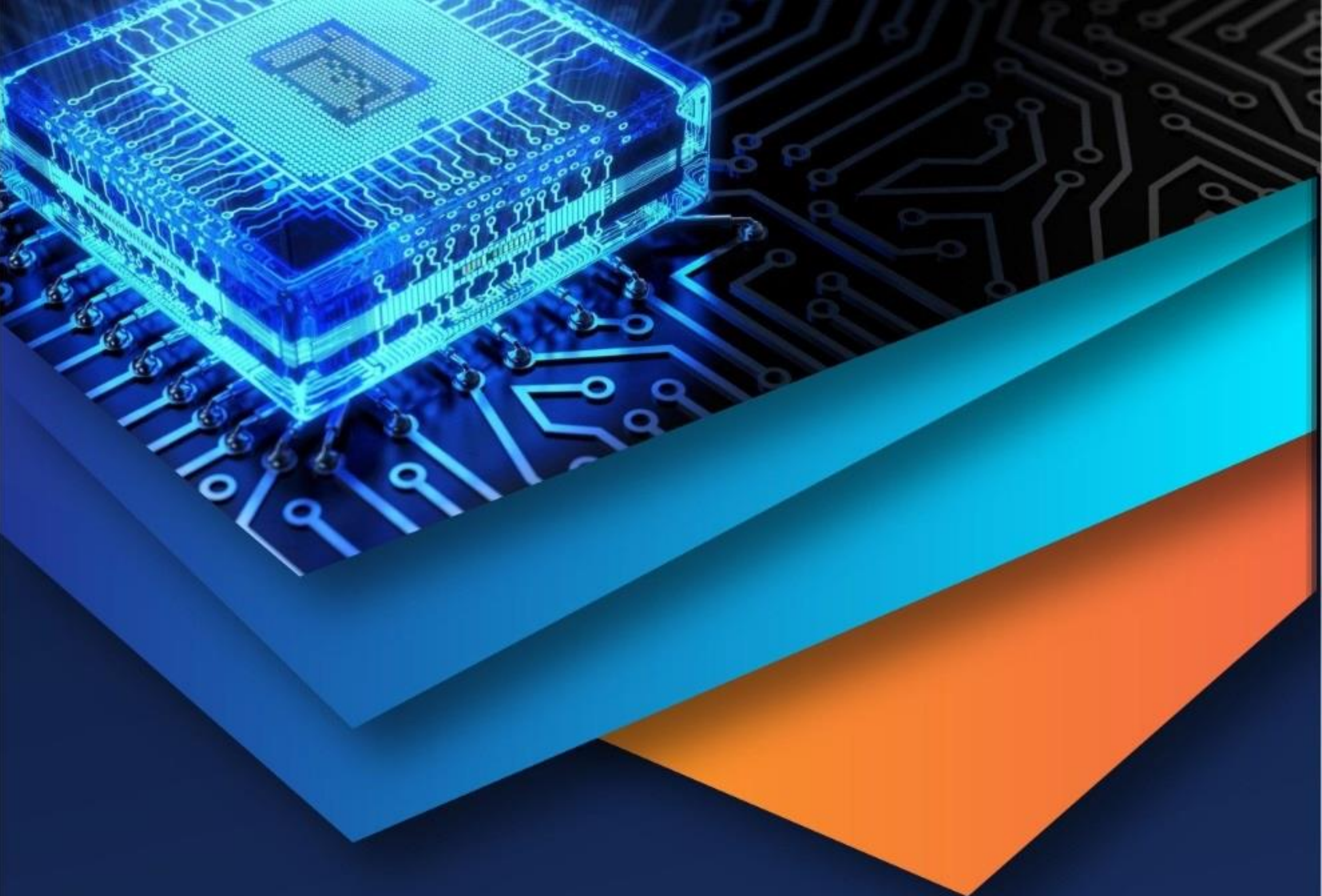

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