PSO and ACO Algorithms Applied to Optimizing Location of Controllers in Wireless Networks

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Abstract—The optimal location of controllers in wireless networks is an important problem in the process of designing cellular mobile networks. In this paper, we propose two new algorithms based on Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) for solving it. Our objective functions are determined by the total distance based on finding maximum flow in a transport network using Ford-Fulkerson algorithm and pheromone matrix of ants satisfies capacity constraints to find good approximate solutions. The experimental results show that our proposed algorithms have achieved much better performance than previous heuristic algorithms.

Index Terms—Terminal Assignment (TA), Optimal Location of Controllers Problem (OLCP), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO) and Wireless Networks

I. INTRODUCTION

In the designing of a mobile phone network (cellular network) it is very important to place the basic stations optimally for a cheaper and better customer service. This issue is related to the problems of location of devices (Base station (BTS), Multiplexers, Switches, etc) [1], [2].

The objective of terminal assignment problem (TA) [3] involves with determining minimum cost links to form a network by connecting a given collection of terminals to a given collection of concentrators. The capacity requirement of each terminal is known and may vary from one terminal to another. The capacity of concentrators is known. The cost of the link from each terminal to each concentrator is also known. The problem is now to identify for each terminal the concentrator to which it should be assigned, under two constraints: Each terminal must be connected to one and only one of the concentrators, and the aggregate capacity requirement of the terminals connected to any concentrator must not exceed the capacity of that concentrator.

The assignment of BTSs to switches (controllers) problem introduced in [4]. In which it is considered that both the BTSs and controllers of the network are already positioned, and its objective is to assign each BTSs to a controller, in such a way that a capacity constraint has to be fulfilled. The objective function in this case is then formed by two terms: the sum of the distances from BTSs to the switches must be minimized, and also there is another term related to handovers, between cells assigned to different switches which must be minimized. The optimal location of controller problem (OLCP) [5] is selecting $N$ controllers out of $M$ BTSs, in a way that the objective function given by solving the corresponding TA with $N$ concentrators and $M-N$ terminals is minimal.

Both TA and OLCP are Non-Polynomial (NP)-hard optimization problems so heuristic approach is a good choice. In [1], a simulated annealing (SA) algorithm tackled the assignment of cells to controller problem. The results obtained are compared with a lower bound for the problem, and the authors show that their approach is able to obtain solutions very close to the problem’s lower bound. Authors in [5] have introduced a hybrid heuristic consisting of SA and a Greedy algorithm for solving the OLCP problem. In [6-7], authors proposed a hybrid heuristic based on mixing genetic algorithm (GA), Tabu Search (TS) to solving the BTS-controller assignment problem in such a way that terminal is allocated to the closest concentrator if there is enough capacity to satisfy the requirement of the particular terminal.

In this paper, we propose two new algorithms based on Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) for solving it. Our objective functions are determined by the total distance based on finding maximum flow in a transport network using Ford-Fulkerson algorithm and pheromone matrix of ants satisfies capacity constraints to find good approximate solutions. Numerical results show that our proposed algorithm is much better than previous studies.

The rest of this paper is organized as follows. Section II presents the problem formulation and briefly introduces the main idea of OCLP proposed in [5]. Section III and section IV present our new algorithm for location of controllers in a mobile communication network based on Particle Swarm Optimization and Ant Colony Optimization algorithms. Section V presents our simulation and analysis results, and finally, section VI concludes the paper.

II. PROBLEM FORMULATION

Let us consider a mobile communication network formed by $M$ nodes (BTSs), where a set of $N$ controllers must be positioning in order to manage the network traffic. It is always fulfilled that $N<M$, and in the majority of cases $N \leq M$. We
start from the premise that the existing BTSs infrastructure must be used to locate the switches, since it saves costs. Thus, the OCLP consists of selecting \( N \) nodes out of the \( M \) which form the network, in order to locate in them \( N \) controllers. To define an objective function for the OCLP, we introduce a model for the problem, based on the Terminal Assignment Problem [5].

A. The Terminal Assignment Problem

The TA can be defined as follows [3]:

**Problem instance:**
- Terminals: \( l_1, l_2, \ldots, l_{M,N} \)
- Weights: \( w_1, w_2, \ldots, w_{M,N} \)
- Concentrators: \( r_1, r_2, \ldots, r_N \)
- Capacities: \( p_1, p_2, \ldots, p_N \)

where, \( w_i \) is weight, or capacity requirement of terminal \( l_i \). The weights and capacity are positive integers and

\[
\forall i = 1, 2, \ldots, M - N \quad w_i < \min \{ p_1, p_2, \ldots, p_N \} \quad (1)
\]

The terminals and concentrator are placed on the Euclidean grid, i.e., \( l_i \) has coordinates \((l_{i1}, l_{i2})\) and \( r_j \) has located at \((r_{j1}, r_{j2})\).

**Feasible solution:** Assign each terminal to one of concentrator such that no concentrator exceeds its capacity. Let \( \hat{x} = \hat{x}_1, \hat{x}_2, \ldots, \hat{x}_{M,N} \) be a vector such that \( \hat{x}_i = j \) means that terminal \( l_i \) has been assigned to concentrator \( r_j \), with \( \hat{x} \) is an integer such that \( 1 \leq \hat{x} \leq N \)

Capacity of each concentrator must be satisfied:

\[
\sum_{i \in R_j} w_i < p_j, \quad j = 1, \ldots, N \quad (2)
\]

where, \( R_j = \{ i | \hat{x}_i = j \} \), i.e., \( R_j \) represents the terminals that are assigned to concentrator \( r_j \).

**Objective function:** Find \( \hat{x} \) that minimizes:

\[
F(\hat{x}) = \sum_{i=1}^{M-N} \text{cost } t_{ij} \rightarrow \min, \quad j = 1, 2, \ldots, N
\quad (3)
\]

where, \( \text{cost } t_{ij} = (l_{i1} - r_{j1})^2 + (l_{i2} - r_{j2})^2 \), i.e., the result of the distance between terminal \( l_i \) and concentrator \( r_j \). It is important to note that in the standard definition of the TA, there is a major objective (the minimization of the distances between terminals and concentrators), and a major constraint (the capacity constraint of concentrators).

B. The Optimal Controller Location Problem

The complete OCLP has to deal with two issues, first, the selection of the \( N \) controllers in \( M \) nodes, second for each election, an associated TA. This process can be seen in Figure 1.

Authors in [5] used a Greedy algorithm to obtain this objective function that terminals are consequently allocated to the closest concentrator if there is enough capacity to satisfy the requirement of a particular terminal. If the concentrator cannot handle the terminal, the algorithm searches for the next closest concentrator and performed the same evaluation. The terminals are assigned to concentrators following the order in \( \pi l_{M,N} \) - a random permutation of terminals. That algorithm is called by SA-Greedy algorithm.

In [7], the authors considered the following Lower Bound (LB) for the TA, as follows:

\[
LB = \sum_{i=1}^{M-N} \min_{k} d_{ik}
\quad (4)
\]

The Lower Bound comes from the solution obtained by assigning each node \( i \) to the nearest controller \( k \). Hybrid Lower Bound- Greedy algorithm is called by LB-Greedy algorithm.

III. PARTICLE SWARM OPTIMIZATION FOR THE OCLP

A. Particle Swarm Optimization

Particle swarm optimization (PSO) is a stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy [8-9], inspired by social behavior of bird flocking or fish schooling. It shares many similarities with other evolutionary computation techniques such as genetic algorithms (GA). The algorithm is initialized with a population of random solutions and searches for optima by updating generations. However, unlike the GA, the PSO algorithm has no evolution operators such as the crossover and the mutation operator.

In the PSO algorithm, the potential solutions, called particles, fly through the problem space by following the current optimum particle. By observing bird flocking or fish schooling, we found that their searching progress has three important properties. First, each particle tries to move away from its neighbors if they are too close. Second, each particle steers towards the average heading of its neighbors. And the third, each particle tries to go towards the average position of
its neighbors. Kennedy and Eberhart generalized these properties to an optimization technique as below.

Consider the optimization problem \( P \). First, we randomly initiate a set of feasible solutions; each of single solution is a “bird” in search space and called “particle”. All of particles have fitness values which are evaluated by the fitness function to be optimized, and have velocities which direct the flying of the particles. The particles fly through the problem space by following the current optimum particles. The better solutions are found by updating particle’s position. In iterations, each particle is updated by following two "best" values. The first one is the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called \( pBest \). Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and called \( gBest \). When a particle takes part of the population as its topological neighbors, the best value is a local best and is called \( lBest \).

After finding the two best values, the particle updates its velocity and positions with following equation (5) (which use global best \( gBest \)) or (6) (which use local best \( lBest \)) and (7).

\[
v_l = v_l + c_1 \cdot \text{rand}() \cdot (pBest_l - \text{present}_l) + c_2 \cdot \text{rand}() \cdot (lBest_l - \text{present}_l)
\]

(5)

\[
v_l = v_l + c_1 \cdot \text{rand}() \cdot (pBest_l - \text{present}_l) + c_2 \cdot \text{rand}() \cdot (lBest_l - \text{present}_l)
\]

(6)

\[
\text{present}_l = \text{present}_l + v_l
\]

(7)

In those above equation, \( \text{rand}() \) is a random number between 0 and 1; \( c_1 \) and \( c_2 \) are cognitive parameter and social parameter respectively.

The stop condition mentioned in the above algorithm can be the maximum number of interaction is not reached or the minimum error criteria are not attained.

B. Solving the OCLP based on PSO

In this section, we present application of PSO technique for the OCLP problem. Our novel algorithm is described as follows.

We consider that configurations in the evolution algorithm are sets of \( N \) nodes which will be evaluated as controllers for the network.

1) Represent and decode a particle: The encoding of the configuration is by means of binary string of length \( M \), say \( x = x_1,x_2,...,x_M \) where \( x_i = 1 \) in the binary string means that the corresponding node has been selected to be a controller, whereas a 0 in the binary string means that the corresponding node is not a controller, but serves as BTS. We must select \( N \) nodes to be the controllers of the network.

2) Initiate population: We use fully random initialization in order to initialize the population. After that, the particle \( x \) will have \( p \) 1s.

We present Particle Repair function to ensure that all binary strings in the particles have exactly \( N \) 1s representing \( N \) controllers.

3) Fitness function: Each particle \( x \) has exactly \( N \) 1s representing \( N \) controllers. We construct a transport network \( G = (I,J,E) \) corresponding particle \( x \), where \( I = 1,2,..,N \) is the set of controllers, \( J = 1,2,..,M-N \) is the set of BTSs and \( E \) is the set of edge connections between controller \( r_i \) and the BTS \( I_j \).

We find the maximum flow (max-flow) of the transport network \( G \) by adding two vertices \( S \) (Source) and \( D \) (Destination) is shown in Figure 2.

The weight of the edges on the graph is defined as follows:
• The edges from vertex $S$ to the controllers $r_i$ is capacity of $r_i$, denoted as $c(S,r_i)=p_i$, $(i=1..N)$.
• The edges from BTS $l_j$ to vertex $D$ is weight of $l_j$, denoted as $c(l_j,D)=w_j$, $(j=1..M-N)$.
• The edges from the controllers $r_i$ to the BTSs $l_j$ is denoted as $c(r_i,l_j)=w_i$, $(i, j \in E)$.

From the transport network $G$, we find the max-flow satisfies capacity constraints given by the formula (4) based on Ford-Fulkerson algorithm [10].

The fitness value of this particle is computed with the max-flow based on the total distance is given by:

$$F(x) = \sum_{i=1}^{N} \sum_{j=1}^{M-N} \sqrt{(r_i - l_j)^2 + (r_{i-1} - l_{j-1})^2}$$

(8)

4) Stop condition: The stop condition used in this paper is defined as the maximum number of interaction $N_{gen}$ ($N_{gen}$ is also a designated parameter).

IV. ANT COLONY OPTIMIZATION FOR THE OCLP

A. Ant Colony Optimization

The ACO algorithm is originated from ant behavior in the food searching. When an ant travels through paths, from nest food location, it drops pheromone. According to the pheromone concentration the other ants choose appropriate path. The paths with the greatest pheromone concentration are the shortest ways to the food. The optimization algorithm can be developed from such ant behavior.

The first ACO algorithm was the Ant System [11], and after then, other implementations of the algorithm have been developed [12-13].

B. Solving the OCLP based on ACO

In this section, we present application of ACO technique for the OCLP problem. Our new algorithm is described as follows.

We consider that configurations in the evolution algorithm are sets of $N$ nodes which will be evaluated as controller for the network. The encoding of the ant $k$ configuration is by means of binary string of length $M$, say $k = x_1, x_2, ..., x_M$

where $x_i=1$ in the binary string means that the corresponding node has been selected to be a controller, whereas a 0 in the binary string means that the corresponding node is not a controller, but serve as BTS. We must select $N$ nodes to be the controllers of the network.

We use fully random initialization in order to initialize the ant population. After that, the ant $k$ will have $p$ 1s. We present Ant_Repair function to ensure that all binary strings in ants have exactly $N$ 1s representing $N$ controllers.

In this case the pheromone matrix is generated with matrix elements that represent a location for ant movement, and in the same time it is possible receiver location. Each ant $k$ has exactly $N$ 1s representing $N$ controllers is associated to one matrix.

We use real encoding to express an element of matrix $A_{m \times n}$ (where $n$ is the number of controllers, $m$ is number of BTSs).

Each ant can move to any location according to the transition probability defined by:

$$P_{ij}^k = \frac{[\tau_{ij}^k]^{[\eta_{ij}]}^{[\beta]}}{\sum_{l \in \mathcal{N}_k} [\tau_{ij}^k]^{[\eta_{ij}]}^{[\beta]}}$$

where, $\tau_{ij}^k$ is the pheromone content of the path from controller $i$ to BTS $j$. $N_i^k$ is the neighborhood includes only locations that have not been visited by ant $k$ when it is at controller $i$, $\eta_{ij}$ is the desirability of BTS $j$, and it depends of optimization goal so it can be our cost function.

The influence of the pheromone concentration to the probability value is presented by the constant $\alpha$, while constant $\beta$ do the same for the desirability. These constants are determined empirically and our values are $\alpha=1$, $\beta=10$.

The ants deposit pheromone on the locations they visited according to the relation.

$$\tau_{ij}^{new} = \tau_{ij}^{current} + \Delta \tau_{ij}^k$$

(10)

where $\Delta \tau_{ij}^k$ is the amount of pheromone that ant $k$ exudes to the BTS $j$ when it is going from controller $i$ to BTS $j$.

This additional amount of pheromone is defined by:

$$\Delta \tau_{ij}^k = \frac{1}{d_{ij}}$$

(11)

In which, $d_{ij}$ is the distance between controller $i$ to BTS $j$ is given by $d_{ij} = \sqrt{(r_i - l_j)^2 + (r_{i-1} - l_{j-1})^2}$

The cost function for the ant $k$ is the total distance between controllers to BTSs is given by:

$$f_k = \sum_{i=1}^{N} \sum_{j=1}^{M-N} \sqrt{(r_i - l_j)^2 + (r_{i-1} - l_{j-1})^2}$$

(12)

The stop condition we used in this paper is defined as the maximum number of interaction $N_{max}$ ($N_{max}$ is also a designed parameter).

The Figure 3 presents process of our algorithm to solving OCLP based on ACO.
V. EXPERIMENTS AND RESULTS

A. The problems tackled

For the experiments, we have tackled several OCLP instances of different difficulty levels. There are 10 OCLP instances with different values for $N$ and $M$, and size networks shown in Table I.

| Problem # | Nodes (M) | Controllers (N) | Grid size |
|-----------|-----------|-----------------|-----------|
| 1         | 10        | 2               | 100x100   |
| 2         | 15        | 3               | 100x100   |
| 3         | 20        | 4               | 100x100   |
| 4         | 40        | 6               | 200x200   |
| 5         | 60        | 8               | 200x200   |
| 6         | 80        | 10              | 400x400   |
| 7         | 100       | 15              | 600x600   |
| 8         | 120       | 20              | 800x800   |
| 9         | 150       | 25              | 1000x1000 |
| 10        | 200       | 50              | 1500x1500 |

B. PSO algorithm specifications

In our experiments, we have already defined parameters for the PSO algorithm shown in Table II.

| TABLE II. THE PSO ALGORITHM SPECIFICATIONS |
|--------------------------------------------|
| Population size | $P = 1000$ |
| Maximum number of interaction | $N_{max} = 500$ |
| Cognitive parameter | $c_1 = 1$ |
| Social parameter | $c_2 = 1$ |
| Update population according to | Formula (6) and (7) |
| Number of neighbor | $K = 3$ |

C. ACO algorithm specifications

In our experiments, we have already defined parameters for the ACO algorithm shown in Table III:

| TABLE III. THE ACO ALGORITHM SPECIFICATIONS |
|---------------------------------------------|
| Ant Population size | $K = 100$ |
| Maximum number of interaction | $N_{max} = 500$ |
| Parameter | $\alpha=1, \beta=10$ |

D. Numerical Results

Our proposed algorithms (PSO, ACO) are used to optimize location of controllers in wireless networks, and the results are compared with results obtained by SA, SA-Greedy, LB-Greedy.

The experimental results show in Figure 4 (Red color is the best solutions). The objective function of our algorithms has achieved a much better performance than other algorithms. The results show that problems with the small grid size and small number of nodes such as problem #1, #2 and #3, all algorithms has approximate results. However, when the problem size is large, the experimental results are considerable different such as problem #6, #7, #8, #9 and #10.

In some cases, LB-Greedy, SA-Greedy, ACO and PSO algorithms choose the same set of nodes to be controllers, but the objective function results of PSO or ACO are much better. The results show that PSO has better properties compared to ACO algorithm. Figure 5 shows the results of the simulator of solutions for the problem #4 given by SA, SA-Greedy, LB-Greedy, ACO and PSO algorithms.

VI. CONCLUSION AND FUTURE WORK

In this paper, we have proposed two new algorithms based on Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) for the optimal location of controllers in wireless networks, which is an important problem in the process of designing cellular mobile networks. Our objective functions are determined by the total distance based on finding maximum flow in a transport network using Ford-Fulkerson algorithm and pheromone matrix of ants satisfies capacity constraints to find good approximate solutions. Numerical results show that our proposed algorithm is much better than previous studies.

The experimental results show that our proposed algorithm has achieved a much better performance than other heuristic algorithms. It is also proved to be a cost-effective solution. Optimizing location of controllers in wireless networks with profit, coverage area and throughput maximization is our next
research goal.

Figure 4. The results obtained in the OCLP instances tackle

| Problem # | 1    | 2    | 3    | 4    | 5    | 6    | 7    | 8    | 9    | 10   |
|-----------|------|------|------|------|------|------|------|------|------|------|
| SA        | 187.4| 315  | 428.3| 1784.7| 2135.9| 4863.2| 7955.6| 12683.7| 23686.6| 157894.2|
| SA-Greedy | 187.4| 315  | 427.2| 1798.5| 2215.1| 4863.2| 8027.2| 13753.8| 26624.3| 168253.7|
| LB-Greedy | 187.4| 315  | 419.6| 1658.2| 1976.3| 4627.5| 7371.9| 10663.7| 19569.2| 143665.4|
| PSO       | 187.4| 315  | 412.7| 1615.3| 1911.9| 4503.4| 7137.1| 9563.6| 18661.3| 141235.8|
| ACO       | 187.4| 315  | 418.7| 1615.3| 1916.6| 4518.1| 7136.5| 9578.4| 16874.7| 141257.2|

Figure 5. Solutions for the problem #4 given by SA, SA-Greedy, LB-Greedy ACO and PSO algorithms
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