

Comparison of Upgrading Infrastructure Optimal in Next Generation Wireless Network using GA and ACO techniques

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ABSTRACT

A problem of upgrading to the Next Generation Wireless Network (NGWN) is backward compatibility with pre-existing networks. In this paper, we propose new Genetic Algorithm and Ant Colony Optimization Algorithm to optimal of upgrading infrastructure in NGWN. The NGWN topology has two levels in which mobile users are sources and both base stations and base station controllers are concentrators. My objective function is multi-object based on the sources to concentrators connectivity cost as well as the cost of the installation, connection, replacement, and capacity upgrade of infrastructure equipment. I evaluate the performance of my algorithms with data randomly generated. Numerical experiment results show that my algorithms is the best approach to solve this problem.

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1. INTRODUCTION

The Next Generation Wireless Networks (NGWNs) are expected to provide high data rate and optimized quality of service to multimedia and real-time applications over the Internet Protocol networks to anybody, anywhere, and anytime. The wireless network infrastructure consists of equipment required by mobile network operators to enable mobile telephony calls or to connect fix subscribers by radio technology. The interacting layers architecture of next generation wireless network is shown in Fig.1.

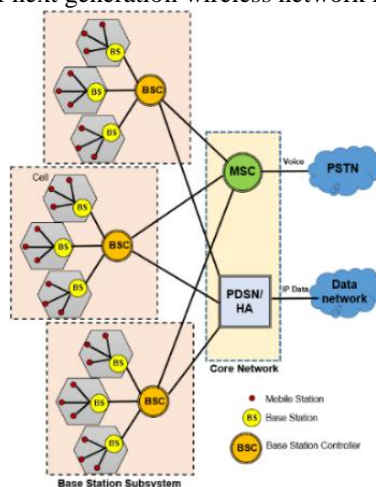


Figure 1. The NGWN infrastructure

The PSTN-cloud covers all network elements to make a standard telephone call, while the data network cloud includes the Internet, Intranets, and other IP based networks [1]. The architectural building blocks enabling mobile telephony are:

- *The core network*: comprised of the mobile switching centers (MSC), the packet data serving nodes (PDSN), and home agents (HA), and
- *The base station subsystem* (BSS) also known as the radio access network, consisting of base station controllers (BSC), base transceiver stations (BS), and mobile stations (MS).

Corresponding to the architectural building blocks of a wireless network, are three types of interconnects [2]. These are (1) mobile device to BS interconnect, which includes both forward and reverse radio links, (2) the BS to BSC interconnect, which is called the backhaul, and (3) BSC to MSC interconnect. The known hierarchical capacitated concentrator location problem, which is an extension of the concentrator location problem to multiple levels and a classical research issue in the telecommunications literature [3-6]. In [7], the authors studied the base station location and service assignment problem in a W-CDMA. A greedy strategy to optimal positioning of BSs for cellular radio networks and capacity planning of UMTS networks studied in [8-9]. A Tabu search and Genetic algorithm approach to cellular capacity expansion to maximizing the coverage area and minimizing the number of transmitters is presented in [10-11]. Yu et al proposed a set covering algorithm for given traffic and finding optimal solution configuration in a CDMA network [12]. An alternate approach to capacity planning and expansion is introduced for 3G network system capacity without an increase in BSs using a cell splitting approach [13].

In this paper, I focus on the multi-objectives optimal of Upgrading Infrastructure in NGWN and propose new GA and ACO algorithms to solve it. The rest of this paper is organized as follows: Section 2 presents the problem formulation. Section 3 presents my new algorithms to solve it based on GA and ACO. Section 4 is my simulation and analysis results, and finally, section 5 concludes the paper.

2. UPGRADING INFRASTRUCTURE OPTIMAL IN NGWN PROBLEM

2.1 Notation definition

In this section, I assume that network topology has m mobile users, n base stations, and p base station controllers. I introduce the following notation in Table 1 below.

Table 1. Notation definition.

Notation	Meaning
M	Index set of Mobile user locations: $M = \{MS_i, \forall i = 1..m\}$
N	Index set of all Base Station (BS): $N = N1 \cup N2 = \{BS_j, \forall j = 1..n\}$ N1: Index set of existing BS; N2: Index set of potential BS
P	Index set of Base Station Controllers (BSC): $P = P1 \cup P2 = \{BSC_k, \forall k = 1..p\}$ P1: Index set of existing BSC; P2: Index set of potential BSC
T_j	Set of types available for $BS_j, \forall j \in N$
S	Set of commodity types: $s = \begin{cases} 1 & \text{if commodity type is voice} \\ 2 & \text{if commodity type is data} \end{cases}$
N_t	Index set of all BS of type t . $N_t = N1_t \cup N2_t$
D_i^s	Demand of commodity type s for mobile user $MS_i, \forall i \in M$
$MaxBS_Cap_i$	Maximum capacity of BS_j of type $t, \forall j \in N_t$.
$MaxBSC_Cap_k$	Maximum capacity of $BSC_k, \forall k \in P$
d_{ij}	Distance of mobile user MS_i from BS_j of type $t \forall i \in M, \forall j \in N_t$
$MaxBS_Cov_j$	Maximum coverage range for BS_j of type t
$cost_connect_{jk}$	Cost of connecting BS_j of type t to BSC_k
$cost_install_k$	Cost of installing $BSC_k, \forall k \in P2$
$cost_upgrade_j$	Per channel cost of upgrading $BS_j, \forall j \in N1$
$cost_setup_j$	Cost of constructing and connecting $BS_j, \forall j \in N2$

2.2 Problem Formulation

The problem in NGWN has two steps the initial assignment of MSs to BS and the connection of BS to BSC and capacity expansion and traffic increase with constraint specifies that:

- Each mobile user MS_i will be assigned to exactly one base station BS_j of type t
- Mobile users are within that base stations' maximum range $MaxBS_Cov$
- At most one base station of type t can exist at location j
- if a base station BS_j is operated, it has to be connected to a BSC_k and the BSC has to be active.

The capacity constraints of the model, in which we argue that BSs must have the necessary capacity to accommodate traffic demand of all demand types s for all MSs assigned to it and the BSC must have the necessary capacity to accommodate all BSs assigned to it.

In the first step, I use the indicator variables are:

$$\alpha_j = \begin{cases} 1 & \text{if } BS_j \text{ of type } t \text{ is operated} \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

$$\beta_{j,k} = \begin{cases} 1 & \text{if } BS_j \text{ of type } t \text{ is connected to } BSC_k \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

$$\delta_k = \begin{cases} 1 & \text{if } BSC_k \text{ is operated in initial assignment} \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

Fig.2 shows an example of an existing initial assignment that each mobile user can be assigned to only one BS, while each BS has to be connected to a single BSC.

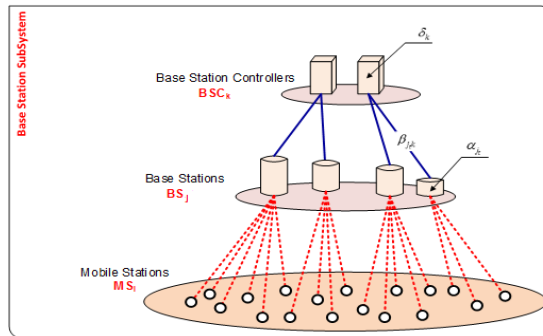


Figure 2. The indicator variables in Initial Assignment step

In the second step, I use the decision variables are:

$$X_{ij} = \begin{cases} 1 & \text{if mobile user } MS_i \text{ is connected to } BS_j \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

$$Y_{j,k} = \begin{cases} 1 & \text{if } BS_j \text{ of type } t \text{ is connected to } BSC_k \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

$$Z_j = \begin{cases} 1 & \text{if } BS_j \text{ of type } t \text{ is operated} \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

$$W_k = \begin{cases} 1 & \text{if } BSC_k \text{ is operated} \\ 0 & \text{otherwise} \end{cases} \quad (7)$$

Fig.3 illustrates an assignment after capacity expansion and traffic increase, and indicates the respective decision variables. New wireless BSS infrastructure equipment with BS and BSC in red shades.

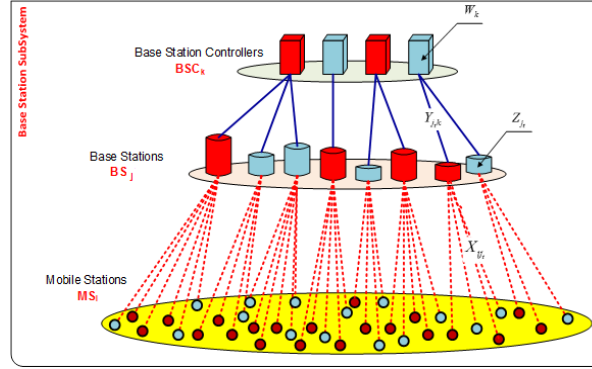


Figure 3. The assignment after capacity expansion and traffic increase with decision variables

The objective of problem is to minimize the total cost of expanding an initial wireless BSS to accommodate increased traffic demand. Finally, the problem can be defined as follows:

$$\begin{aligned} \text{Min} & \left(\sum_{j=1}^n \sum_{k=1}^p \sum_{t \in T_j} \text{cost_connect}_{j,k} (Y_{j,k} - \beta_{j,k}) + \sum_{k \in P_2} \text{cost_install}_k (W_k - \delta_k) \right) \\ & + \sum_{j \in N_1} \text{cost_upgrade}_j \left(\sum_{t \in T_j} \text{MaxBS_cap}_{j_i} (Z_{j_i} - \alpha_{j_t}) \right) + \sum_{j \in N_2} \sum_{t \in T_j} \text{cost_setup}_{j_i} (Z_{j_i}) \end{aligned} \quad (8)$$

Subject to:

$$\sum_{j=1}^n \sum_{t \in T_j} X_{ij} = 1, \quad \forall i = \overline{1..m} \quad (9)$$

$$d_{ij} X_{ij} \leq \text{MaxCov}_{j_i} Z_{j_i}, \quad \forall i = \overline{1..m}, j = \overline{1..n}, t \in T_j \quad (10)$$

$$\sum_{t \in T_j} Z_{j_i} \leq 1, \quad \forall j = \overline{1..n} \quad (11)$$

$$Z_{j_i} \leq \sum_{k=1}^p Y_{j,k}, \quad \forall j = \overline{1..n}, t \in T_j \quad (12)$$

$$Y_{j,k} \leq W_k, \quad \forall k = \overline{1..p}, j = \overline{1..n}, t \in T_j \quad (13)$$

$$\sum_{i=1}^m \sum_{s=1}^2 D_i^s X_{ij} \leq \text{MaxBS_Cap}_{j_i} \times Z_{j_i}, \quad \forall j = \overline{1..n}, t \in T_j \quad (14)$$

$$\sum_{j=1}^n \sum_{t \in T_j} Y_{j,k} \leq \text{MaxBSC_Cap}_k \times W_k, \quad \forall k = \overline{1..p} \quad (15)$$

$$\begin{aligned} X_{ij} & \in \{0,1\}, Y_{j,k} \in \{0,1\}, Z_{j_i} \in \{0,1\}, W_k \in \{0,1\} \\ & \forall i = \overline{1..m}, j = \overline{1..n}, k = \overline{1..p}, t \in T_j \end{aligned} \quad (16)$$

3. UPGRADING INFRASTRUCTURE OPTIMAL USING GA AND ACO

3.1 Upgrading Infrastructure Optimal in NGWN using GA

In this section, I present a new GA for this problem with two populations POP_X and POP_Y . The encoding of the POP_X configuration is by means of matrix $X = (x_{ij})_{n \times m}$, ($i = \overline{1..n}, j = \overline{1..m}$) where $x_{ij}=1$ means that mobile user MS_i has been connected to base station BS_j , and otherwise, $x_{ij}=0$. The encoding of the POP_Y

configuration is by means of matrix $Y = (y_{jk})_{mp}$, ($j = 1..m, k = 1..p$), where $y_{jk}=1$ means that base station BS_j has been connected to base station controller BSC_k , and otherwise, $y_{jk}=0$. I use fully random initialization in order to initialize the individuals POP_x ensure that the individual x satisfies constraints in (9)(10)(14) and (16). Each individual x , I fully random initialization in order to initialize the individuals POP_y ensure that the individual y satisfies constraints in (12)(13)(15) and (16).

The pseudo-code of my algorithm as follows:

BEGIN

INITIALISE population POP_x with random candidate solutions;

REPEAT

1. SELECT parents in POP_x ;

2. RECOMBINE pairs of parents in POP_x ;

3. CROSSOVER the resulting offspring in POP_x ;

4. MUTATION the resulting offspring in POP_x ;

5. FOR each candidate $x \in POP_x$ DO

5.1 INITIALISE population POP_y with random candidate solutions $y \in POP_y$ follows candidate $x \in POP_x$;

5.2. SELECT parents in POP_y ;

5.3. RECOMBINE pairs of parents in POP_y ;

5.4. CROSSOVER the resulting offspring in POP_y ;

5.5. MUTATION the resulting offspring in POP_y ;

5.6. COMBINE Solution $s = \{(x, y) | x \in POP_x, y \in POP_y\}$

6. EVALUATE FUNCTION new solutions s by formula (8);

7. SELECT individuals x for the next generation;

UNTIL (TERMINATION CONDICTION is satisfied)

END

This operator mimics the mating process in the nature. To do crossover in POP_x , two individuals are picked first and two integer numbers (i, j)(crossover point is x_{ij}) are generated randomly between $[1, n]$ and $[1, m]$ (where n is number of MSs and m is number of BSs). Then the offspring is generated by interchanging the second halves of its parent. In the crossover stage, the algorithm examines all pairs of individuals. It begins with the pairs that include the individual with a higher fitness value until the population size becomes twice of the original size. Similar, we apply crossover operator to POP_y . The mutation operation is one kind of random change in the individual of POP_x . In our algorithm, pointwise mutation is adopted, in which one gene in the individual is changed with a certain probability, referred to as the mutation probability. This operator allows the algorithm to search for new and more feasible individuals in new corners of the solution spaces. To do mutation, an individual is randomly selected from the BS and the selected BS is called the mutation point. The mutation stage is implemented until either population size becomes twice of the original size or all individuals in the current generation are examined.

Similar, I apply mutation operator to POP_y . After the mutation, each solution

$$s = \{(x, y) | x \in POP_x, y \in POP_y\} \quad (17)$$

is satisfies constraints in (9)-(16). The cost function of solution s computed by (8).

3.2 Upgrading Infrastructure Optimal in NGWN using ACO

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 [14], and after then, other implementations of the algorithm have been developed [15].

In the first step of my algorithm, I construct a transport network $G1=(V1,E1)$, where $V1=M \cup N1 \cup P1$ in which $M = \{1,2,\dots,m\}$ is the set of MSs, $N1 = \{1,2,\dots,n1\}$ is the set of existing BSs, $P1 = \{1,2,\dots,p1\}$ is the set of existing BSCs and $E1$ is the set of edge connections between MS_i to existing BS_j and existing BS_j to existing BSC_k satisfy constraints. I find the maximum flow of the transport network $G1$ by adding two vertices S (*Source*) and D (*Destination*) is shown in Fig.4 to define indicator variables.

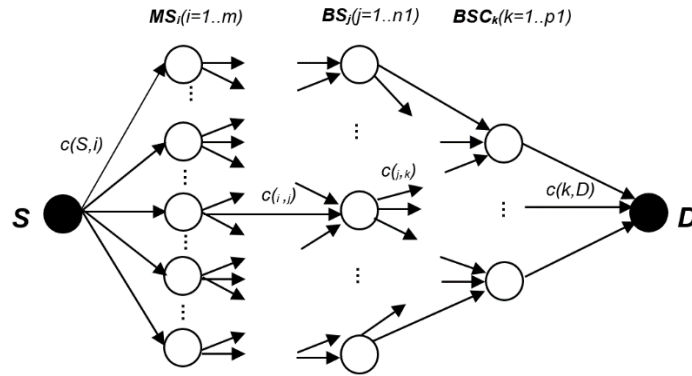


Figure. 4. The Initial Graph G1

In Fig.4, nodes has white color is set of existing MS, BS, BSC. The weight of the edges on the graph $G1$ is defined as follows:

- The edges from vertex S to MS_i is demand of commodity type s for mobile user, denoted as $c(S,MS_i)=D_i^s$, ($i=1..m$).
- The edges from MS_i to BS_j is capacity of MS_i if MS_i is connected to BS_j , denoted as $c(i,j)=D_i^s$, ($i=1..m, j=1..n1$).
- The edges from BS_j to BSC_k is total capacity of MS_i is connected to BS_j , denoted as

$$c(j,k) = \sum_{MS_i \text{ connected } BS_j} D_i^s, (j=1..n1, k=1..p1) \quad (18)$$

- The edges from BSC_k to vertex D is total capacity of BS_j connected to BSC_k , denoted as

$$c(k,D) = \sum_{BS_j \text{ connected } BSC_k} c(i,j), (j=1..n1, k=1..p1). \quad (19)$$

In the second step, I construct a transport network $G2=(V2,E2)$, where $V2=M \cup N \cup P$ in which $M = \{1,2,\dots,m\}$ is the set of MSs, $N = \{1,2,\dots,n\}$ is the set of BSs, $P = \{1,2,\dots,p\}$ is the set of BSCs and $E2$ is the set of all edge connections between MS_i to BS_j and BS_j to BSC_k .

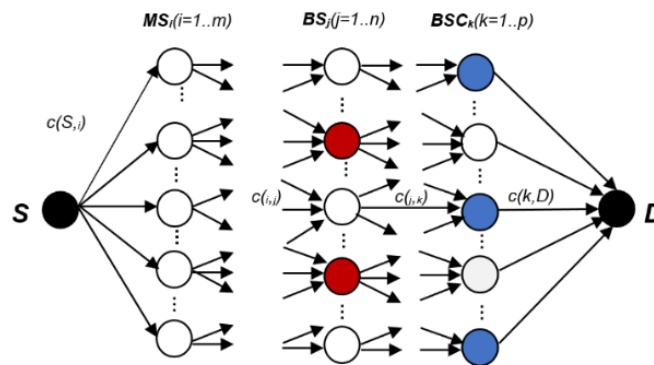


Figure 5. The Full Graph G2

Fig.5 shows all edge connections possible satisfy the constraints (9)-(16). In which, red nodes are set of potential BSs, and blue nodes are set of potential BSCs. A colony of artificial ants is created to find solutions. Optimization problems solutions can be expressed in terms of feasible paths on the graph $G2$. The encoding of the ant Ant_k configuration is by means of binary string $Ant_k = \{x_1, x_2, \dots, x_{m+n+p}\}$, where

$$x_i = \begin{cases} 1 & \text{if } i \in [1..m] \text{ then } MS_i \text{ is operated} \\ 1 & \text{if } i \in [m+1..m+n] \text{ then } BS_j \text{ is operated } (j = i - m) \\ 1 & \text{if } i \in [m+n+1..m+n+p] \text{ then } BSC_k \text{ is operated } (k = i - m - n) \\ 0 & \text{otherwise} \end{cases} \quad (20)$$

In my case, I use real encoding to express an element of the pheromone matrix is generated by graph $G2$ that represent a location for ant movement, and in the same time it is possible receiver location. A path by each Ant_k , pheromone intensities on links are evaporated with a pheromone update rule. Each edge (i, j) of the graph $G2$ is associated a total pheromone concentration τ_{ij} . At each node, each Ant_k executes a decision policy to determine the next node of the path. If Ant_k is currently located at node i and it selects the next node $j \in N_i^k$ according to the transition probability defined by:

$$P_{ij}^k = \frac{[\tau_{ij}]^\alpha [\eta_{ij}]^\beta}{\sum_{l \in N_i^k} [\tau_{ij}]^\alpha [\eta_{ij}]^\beta} \quad (21)$$

where, τ_{ij} is the pheromone content of the path from node i to node j , N_i^k is the neighborhood includes only locations that have not been visited by ant k when it is at node i , η_{ij} is the desirability of node j , and it is a problem-dependent function to be minimized given by:

$$\eta_{ij} = \frac{1}{d_{ij}} \quad (22)$$

where d_{ij} is the cost of connect from MS_i to BS_j or BS_i to BSC_j . The influence of the pheromone concentration to the probability value is presented by the constant α , while constant β do the same for the desirability. The ants deposit pheromone on the locations they visited according to the relation.

$$\tau_j^{new} = \tau_j^{current} + \Delta\tau_j^k \quad (23)$$

where $\Delta\tau_j^k$ is the amount of pheromone that Ant_k exudes to the node j when it is going from node i to node j . This additional amount of pheromone is defined by:

$$\Delta\tau_j^k = \frac{1}{(\text{cost_connect}_{ij} + \text{cost_intall}_j + \text{cost_upgrade}_j + \text{cost_setup}_j)} \quad (24)$$

The cost function for the Ant_k by (1). This algorithm will terminate either when the maximum number of iterations is reached or an acceptable solution is found.

The pseudo-code of ACO algorithm as follows:

INITIALIZATION:

Algorithm parameters: α, β Ant population size: K .Maximum number of iteration: N_{Max} .

GENERATION:

Generating the pheromone matrix for the Ant_{*k*}.Update the pheromone values and set $x^*=k$; $i=1$.

REPEAT

FOR $k = 1$ TO K DOComputing the cost function for the ant k by the formula (8)

Computing probability move of ant individual by the formula (21)

IF $f(k) < f(x^*)$ THEN

Update the pheromone values by the formula (23)

Set $x^*=k$.

ENDIF

ENDFOR

UNTIL $i > N_{Max}$

4. EXPERIMENTS AND RESULTS

4.1 Experiment Scenarios

In my experiments, I have tackled several instances of different difficulty levels. There are 10 instances with values for M , N and P is shown in Table 2.

Table 2. Main characteristic of the problems tackled.

Problem #	Mobile Users (M)	Base Stations			Base Stations Controllers				
		N	N1	N2	Types	P	P1	P2	Types
1.	10	4	3	1	1	3	2	1	1
2.	30	6	3	3	3	4	2	2	3
3.	100	10	6	4	4	5	2	3	3
4.	250	25	15	10	5	15	10	5	5
5.	500	50	30	20	8	20	10	10	6
6.	1000	150	90	60	10	50	30	20	8
7.	2500	350	200	150	20	100	40	60	10
8.	5000	550	350	200	30	150	100	50	15
9.	7500	750	450	300	40	200	150	50	20
10.	10000	950	650	300	50	300	200	100	30

4.2 Parameters of GA and ACO algorithms

I have already defined parameters for the GA and ACO algorithms shown in Table 3 and Table 4.

Table 3. The GA Algorithm Specifications

Representation	Matrix $X = (x_{ij})_{n \times m}$, $Y = (y_{jk})_{m \times p}$
Recombination	One point crossover
Recombination probability	70%
Mutation	Each value inverted with independent probability p_m per position
Mutation probability	$p_m = 1/m$
Parent selection	Best out of random two
Survival selection	Generational
Population size	$POP_x = POP_y = 500$
Number of offspring	500
Initialization	Random
Termination condition	No improvement in last 100 generations

Table 4. The ACO Algorithm Specifications

Ant Population size	$K = 100$
Maximum number of interaction	$N_{Max} = 500$
Parameter	$\alpha=1, \beta=10$

4.3 Numerical Analysis

I evaluate the performance of our algorithms to optimize of capacity expansion with multi-objectives. The experiment was conducted on Genuine Intel® CPU Duo Core 3.0 GHz, 2 GB of RAM machine. I ran experiment GA algorithm implemented using C language. Comparing values of objective function between initial solution and optimal solution of GA and ACO algorithm shown in Fig.6 and Fig.7 shown the time processing of GA and ACO algorithm.

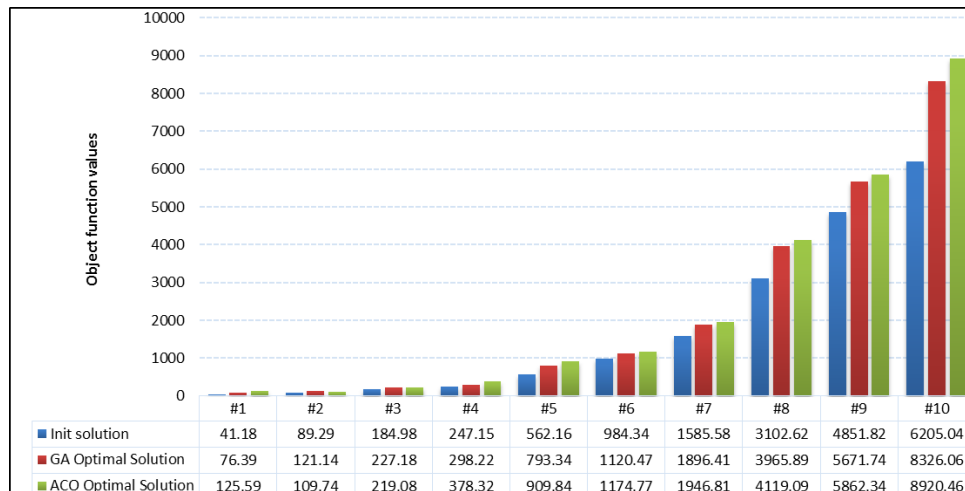


Figure 6. Comparing value of capacity expansion of instances tackle between GA and ACO.

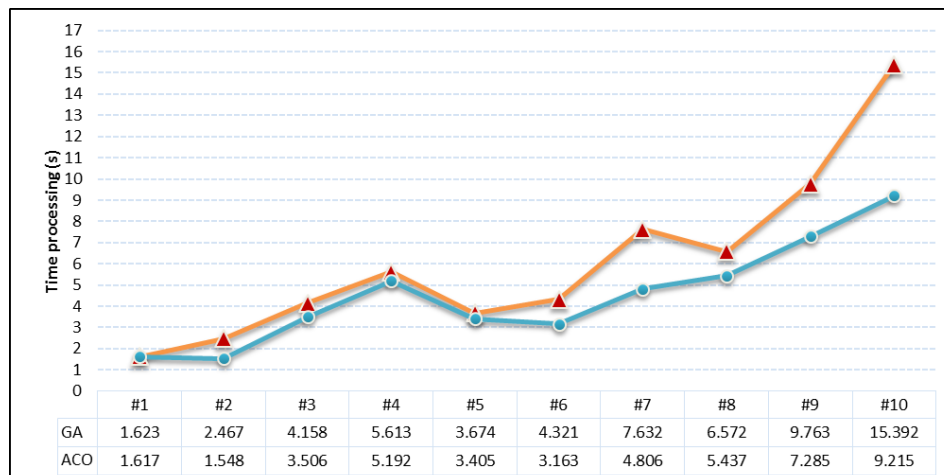


Figure 7. Comparing time processing of instances tackle between GA and ACO

The results show that problems with the small number of M , N , P such as problem #1, #2, #3, #4 and #5, both GA and ACO algorithm has approximate optimal results fast with small interactions. However, when the problem size is large, the optimal results may be slower such as problem #6, #7, #8, #9 and #10. Convergence speed is not the same and depend on the distribution of parameters data.

Fig.8 show an existing initial assignment of problem #2. In which, three types of base station are (BS1, BS6), (BS2, BS3), (BS4, BS5); BS2, BS3 BSC2, BSC4 are existing BSCs; BSC1, BSC3 are potential BSCs; BS3, BS4, BS6 are existing BSs; BS1, BS2, BS5 are potential BSs. MS6, MS16, MS22, MS29 are not connected.

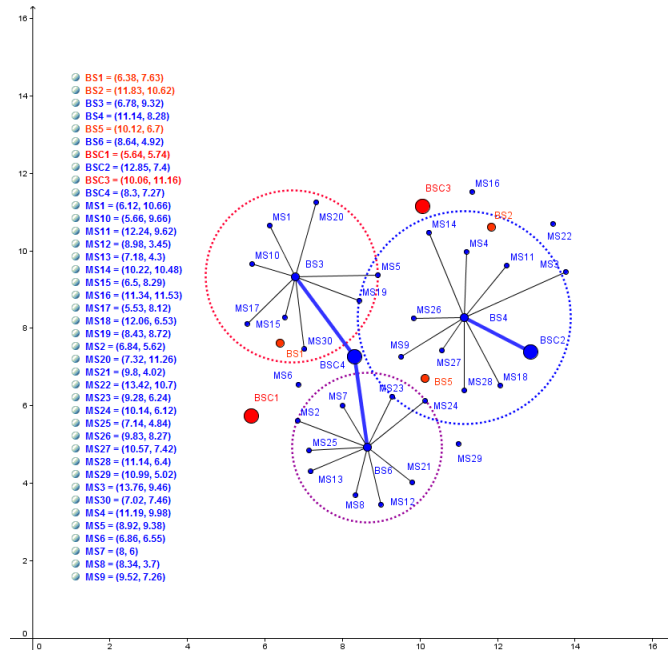


Figure 8. An existing initial assignment of problem #2

Fig.9 and Fig.10 show an optimal solution of GA and ACO with BSC2 is replaced by BSC3, BS4 is replaced by BS2 and BS5. BS1 is added and connect to BSC4. However, there are some different between GA and ACO optimal solutions. We can see and compare the red edges are replace connections and black edges are existing connections in two optimal solutions.

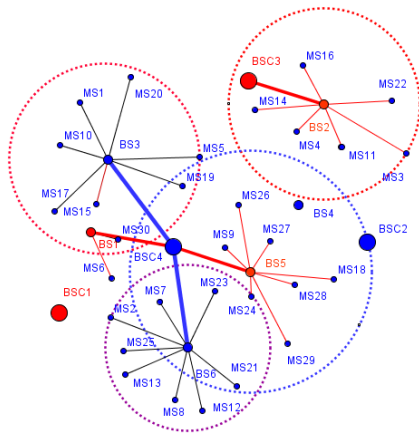


Figure 9. The optimal solution for problem #2 of GA

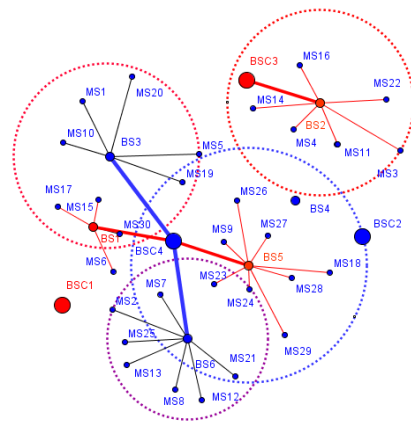


Figure 10. The optimal solution for problem #2 of ACO

Comparing Advantages and Disadvantages between GA and ACO to upgrading Infrastructure Optimal in NGWN:

- GA is more reduce the time of coding than ACO
- ACO is more reduce the executive time than GA
- ACO is used to get the optimal solution while GA is used to achieve near optimal solution.

5. CONCLUSIONS

In this paper, I propose new Genetic Algorithm and Ant Colony Optimization Algorithm to optimal of upgrading infrastructure in NGWN. The NGWN topology has two levels in which mobile users are sources and both base stations and base station controllers are concentrators. My objective function is multi-object based on the sources to concentrators connectivity cost as well as the cost of the installation, connection, replacement, and capacity upgrade of infrastructure equipment. I evaluate the performance of my algorithms with data randomly generated. Numerical experiment results show that our algorithms is the best approach to solve this problem.

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