Satellite Customer Assignment: A Comparative Study of Genetic Algorithm and Ant Colony Optimization

Sung-Soo Kim, Hyoung Joong Kim and V. Mani

Abstract—The problem of assigning customers to satellite channels is a difficult combinatorial optimization problem and is NP-complete. For this combinatorial optimization problem, standard optimization methods take a large computation time and so genetic algorithms (GA) and ant colony optimization (ACO) can be used to obtain the best and/or optimal assignment of customers to satellite channels. In this paper, we present a comparative study of GA and ACO to this problem. Various issues related to genetic algorithms approach to this problem, such as solution representation, selection methods, genetic operators and repair of invalid solutions are presented. We also discuss an ACO for this problem. In ACO methodology, three strategies, ACO with only ranking, ACO with only max-min ant system (MMAS), and ACO with both ranking and MMAS, are considered. A comparison of these two approaches (i.e., GA and ACO) with the standard optimization method is presented to show the advantages of these approaches in terms of computation time.

Index Terms—satellite customer assignment, genetic algorithm, ant colony optimization, MMAS(Max-Min ant system).

1 Introduction

SATELLITE operation is an expensive business. Success in satellite operation, whether it is commercial or for defence, needs right judgement, analysis, and decision making in various aspects of the system. During the operation of a commercial satellite, one of the problems is assignment of satellite channels to customers. This assignment problem depends on the bandwidth of the channels. An excellent discussion on bandwidth issues related to satellite-based communication is presented in [22]. In this study [22], the problem of satellite customer assignment is considered and an integer programming formulation is presented for the solution to this combinatorial optimization problem. It is also shown in [22] that the optimal assignment of customers to channels has real and observable costs and benefits in terms of both dollars and customer ratings. This is basically an efficient resource utilization problem. In satellite communication, efficient resource utilization is one of the important problems that has received considerable attention [17], [6]. A detailed overview of the scheduling problems that arise in satellite communication is described in [21]. The well-known generalized assignment problem (GAP) is known to be NP-complete combinatorial optimization problem and has received a lot of attention in literature [3], and the satellite customer assignment problem has a lot of similarities with GAP. The GAP involves finding the minimum cost assignment of I jobs to K machines (i.e., agents) such that each job is exactly assigned to only one machine subject to machine's available capacity. Another problem in this context well studied is flow shop scheduling [20]. In this paper, we present a comparative study

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of this satellite customer assignment problem using genetic algorithms or ant colony optimization methodology.

Genetic algorithm (GA) is perhaps the most well-known of all evolution based search technique. GA is a search algorithm based on natural selection that transforms a set of individuals within the population of solutions into a new set for the next generation using genetic operators such as crossover and mutation [12], [11], [5], [19]. A survival of the fittest strategy is adopted to identify the best solutions and subsequently genetic operators are used to create new solutions for the next generation. This process is repeated generation after generation until a satisfactory solution is found.

Genetic algorithm for satellite customer assignment problem works as follows: The search space contains all the search nodes (i.e., all possible assignments of customers to satellite channels) for the given problem. An individual search node is one possible assignment of customers to satellite channels. GA starts with an initial population of search nodes (i.e., assignments) from the search space. Using the objective function, a fitness value is assigned to each of the search nodes. New search nodes are generated for next generation based on the fitness value and applying genetic operators to the current search nodes. These process is repeated for generation after generation until the algorithm converges. The parameters involved in a genetic algorithm are the population size, crossover probability, mutation probability and the number of generations. These parameters determine the performance of the genetic algorithm.

The ant colony optimization (ACO) paradigm has been inspired by the behavior of real ants. In nature the real ants have an ability to find the shortest paths from the nest to food sources. This has inspired the researchers to develop computational algorithms for the solution of optimization problems. In an ant colony, the medium that is used for information communication among individual ants regarding paths is a chemical substance called pheromone. A moving ant deposits a constant amount of pheromone on the ground (i.e., on its path). Another ant, when it encounters a pheromone trail, has to decide whether to follow it or not. If it follows the trail, the ant's own pheromone reinforces the existing trail. The pheromone also evaporates over time.

Traveling salesman problem (TSP) is a well-known combinatorial optimization problem in the area of operations research. Because of the complexity, genetic algorithms are developed to obtain the best or optimal solution to this problem. An excellent description of the genetic algorithm methodology to traveling salesman problem is given in [19]. Also in [19] many other combinatorial optimization problems that arise in real world situations are discussed.

This well-known TSP has been the first combinatorial optimization problem considered for solution using ACO [8], and has been published under the name of ant system (AS). In [8], the artificial ants build new solutions stochastically. For building new solutions a combination of heuristic information and an artificial pheromone trails are used by the artificial ants. This pheromone trail is reinforced according to the quality of solutions built by the ants. The AS is able to find optimal solutions for some smaller TSP problems. This study has generated a lot of interest among researchers and this AS has been applied to a variety of combinatorial optimization problems [1], [9]. A detailed description of ant behavior relating to ACO are available in [23], [7].

In this paper, we consider the problem of assigning customers to satellite channels. We can see that the satellite customer assignment problem is a combinatorial optimization problem. Hence, it is advantageous to use genetic algorithms, and/or ant colony optimization to obtain the best or optimal assignment of customers to satellite channels. We present a comparative study of these two methods to this satellite customer assignment problem. The advantage of these methods is that they require only a small amount of computation time compared to the standard optimization methods to obtain the best or optimal assignment.

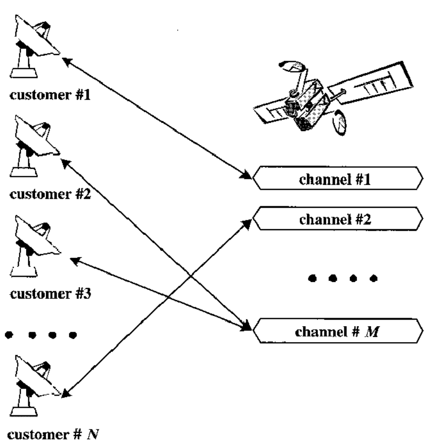

Fig. 1. Concept of customer assignment to satellite channels

2 Satellite Customer Assignment Problem

The concept of customer assignment to satellite channels is shown in Figure 1. For ease of understanding, we follow the same notation used in an earlier study [22] and form the combinatorial optimization problem. Let there be I customers to be assigned to one of the K channels. Each customer i, where $i = 1, 2, ..., I$, has a required bandwidth and required power. Each channel k, where $k = 1, 2, ..., K$, has a maximum available bandwidth and has a maximum available power. We assume, as in [22], the following data is available:

- SBW_k: satellite bandwidth available in channel k
- SP_k: satellite power available in channel k
- CBW_i: bandwidth required by customer i
- CP_i: power required by customer i

The problem here is to assign all the customers ($i = 1, 2, ..., I$) to one of the available channels ($k = 1, 2, ..., K$). The number of possible assignment of customers to satellite channels is K^I. The optimal assignment is the one for which the objective function is a minimum. The objective is to find the assignment for which the total deviation of fraction of bandwidth utilized from fraction of power utilized is a minimum. This is a difficult combinatorial optimization problem. A zero-one non-linear formulation of this problem is given in [22]. In that formulation, the decision variable is x_{ik}. The decision variable $x_{ik} = 1$ if customer i is assigned to channel k, and $x_{ik} = 0$ otherwise. With this, the satellite customer assignment problem is

Minimize

$$\sum_{k=1}^{K} \left| \frac{\sum_{i=1}^{I} CBW_i x_{ik}}{SBW_k} - \frac{\sum_{i=1}^{I} CP_i x_{ik}}{SP_k} \right| . \quad (1)$$

The constraints are:

$$\sum_{i=1}^{I} CBW_i * x_{ik} \leq SBW_k, \quad (2)$$

$$\text{for all } k = 1, 2, ..., K,$$

$$\sum_{i=1}^{I} CP_i * x_{ik} \leq SP_k, \quad (3)$$

$$\text{for all } k = 1, 2, ..., K,$$

$$\sum_{k=1}^{K} x_{ik} = 1, \quad (4)$$

$$\text{for all } i = 1, 2, ..., I,$$

$$x_{ik} = 0 \text{ or } 1.$$

This objective function is used in the earlier study [22]. The objective function (1) minimizes the total deviation of fraction of bandwidth utilized from fraction of power utilized. This objective function is based on considerations of battery operations which affect the satellite lifetime [22]. The constraint (2) represents that the capacity restriction of available bandwidth, and the constraint (3) takes into account the capacity restrictions of available power. Constraint (4) ensures that each customer is assigned to only one channel. From the above, we see that, this satellite customer assignment problem is similar to the generalized assignment problem and hence it is NP-complete. Our satellite customer assignment problem is a zero-one non-linear programming problem and can be solved by any standard optimization methods or packages. But, the computation time to obtain the optimal solution is very high. So, we use GA or ACO methods to this problem and obtain the best or optimal assignment. We can also see that the satellite customer assignment problem has a close relationship with bin-packing problem (BPP) which is a generalized assignment problem. BPP has been studied in the framework of ant colony optimization in [18].

3 GA AND ACO TO SATELLITE CUSTOMER ASSIGNMENT PROBLEM

We now briefly describe the methodology of GA and ACO to obtain the best or optimal assignment of customers to satellite channels.

Genetic Algorithm to Satellite Customer Assignment:

In our earlier study [14], we have considered genetic algorithm approach to satellite customer assignment problem. We briefly present the important issues. More details are available in an earlier study [14].

Solution representation is an important issue in genetic algorithms. The solution representation for our problem is an I dimensional vector of integers, where I is the number of customers. The integer values range from 1 to K, the number of channels available. For the case of 5 customers and 3 channels, one possible solution (assignment) in our representation is $\{2 \;\; 3 \;\; 1 \;\; 1 \;\; 2\}$. This means that customers 1 and 5 are assigned to channel 2, customers 3 and 4 are assigned to channel 1, and customer 2 is assigned to channel 3. In this solution representation the constraint (4) is satisfied; i.e., all the customers are assigned to one of the channels. Note that in this representation the constraints (2) and (3) may not be satisfied. Hence, we must keep in mind the constraints (2) and (3) when we generate initial population and design genetic operators. A valid solution in our problem should satisfy both the constraints (2) and (3).

Population Initialization: The first step in genetic algorithms is to create an initial population of solutions to the problem. All the solutions in the initial population should satisfy the constraints (2) and (3). In our study, the initial population is randomly generated. It is possible that some of the solutions in the initial population may not be valid solutions. In other words, some of the solutions may not satisfy the constraints (2) and (3). Hence, we propose a repair algorithm. By using this repair algorithm, we convert any invalid solution in the population to a valid solution. The repair algorithm proposed in our study is given below.

Repair Algorithm: In an invalid solution either constraint (2) or constraint (3) or both are violated. The repair algorithm works as follows: First find the channel number for which the constraints are violated. Then, randomly remove one of the customers assigned to that channel. This removed customer is assigned to another channel. This process is continued till the solution becomes a valid one. We will give a small numerical example to show how the repair algorithm works.

Numerical Example 1: Let the number of customers (I) be 5, and the number of channels (J) be 3. The channels are numbered from 0 to 2. Consider the customers with the following bandwidth requirements: $CBW_1 = 5$, $CBW_2 = 4$, $CBW_3 = 6$, $CBW_4 = 7$, and $CBW_5 = 3$. The satellite bandwidth available in channels are: $SBW_0 = 10$, $SBW_1 = 16$, and $SBW_2 = 14$. Consider the solution $\{2 \;\; 0 \;\; 0 \;\; 2 \;\; 0\}$. In this solution customers 2, 3 and 5 are assigned to channel 0. The available bandwidth of the channel is 10 and the assigned bandwidth is $4 + 6 + 3 = 13$. Hence, this is an invalid solution. We randomly select one of the customers assigned to this channel (say, customer 3) and assign this customer 3 to another randomly selected channel (say, channel 1. Now the solution after this repair algorithm is $\{2 \;\; 0 \;\; 1 \;\; 2 \;\; 0\}$. We can apply this repair algorithm when the constraints (2) or (3) or both are violated. In this manner all the solutions in the initial population are valid solutions.

Selection Function: The selection of a solution from the population of solutions to produce new solutions for next generation plays an important role. Selection methods use survival of the fittest idea. In genetic algorithm literature there are several selection schemes such as roulette wheel selection and its extensions, scaling techniques, tournament, elitist models and ranking methods are presented. In our study, for satellite customer assignment problem, we have used roulette selection method.

Genetic Operators: Genetic operators such as crossover and mutation provide basic search mechanism in genetic algorithms. In our study, we have used uniform crossover method.

Mutation Operator: The mutation operator uses one solution to produce a new solution. Mutation operator is needed to ensure diversity in the population and to avoid premature convergence and local minima problems. We considered two types of mutation, namely, customer mutation and channel mutation. In customer mutation, we randomly select a customer assigned to one channel and assign this customer to another channel. In channel mutation, we randomly select a channel and assign all the customers assigned to this channel to a new channel.

It is possible in the above crossover and mutation methods that some of the new solutions produced may not be a valid solution. In other words, the constraints (2) and/or (3) may not be satisfied. In that situation, we use the repair algorithm and obtain a valid solution.

Fitness Function: In our problem, the objective function minimizes the total deviation of fraction of bandwidth utilized from fraction of power utilized. The calculation of the fitness function is easy. The solution gives the assignment of customers to various channels. In other words, x_{ik}s are given by the solution. We substitute the values of x_{ik} in the objective function and obtain the value. The value represents total deviation of fraction of bandwidth utilized from fraction of power utilized for this solution. Our problem is a minimization problem whereas the genetic algorithms will try to maximize the fitness. Hence, the fitness for our problem is given as follows:

$$F = -\sum_{k=1}^{K}\left|\frac{\sum_{i=1}^{I} CBW_i x_{ij}}{SBW_j} - \frac{\sum_{i=1}^{I} CP_i x_{ij}}{SP_j}\right|. \quad (5)$$

Termination criterion: The most frequently used convergence criterion is the average fitness value from generation to generation. This algorithm stops if these average values are equal. Other convergence criteria are population convergence criterion: the algorithm stops when the solutions in the population are the same in two successive generations. Another criterion used for termination is a specified maximum number of generations. In our studies, we have used average fitness value from generation to generation.

Ant Colony Optimization to Satellite Customer Assignment:

In our earlier study [15], we have considered ant colony optimization methodology to satellite customer assignment problem. We briefly present the important issues. More details are available in an earlier study [15].

Ant systems uses artificial ants to construct a solution from the scratch. A solution is constructed based on a combination of heuristic information and an artificial pheromone trails. At each step an individual ant assigns an unassigned customer i to a channel k with a probability p_{ik}. The probability p_{ik} is given by

$$p_{ik} = \frac{(\tau_{ik})^{\alpha} * (\eta_{ik})^{\beta}}{\sum_{k\in K}\{(\tau_{ik})^{\alpha} * (\eta_{ik})^{\beta}\}}. \quad (6)$$

In Equation 6, K is the set of channel numbers that customer i can be assigned, α is the weighting factor of pheromone, and β is the weighting factor of heuristic information. This heuristic information is also known as "attractiveness" and is used by the ants. The heuristic information η_{ik} is given as

$$\eta_{ik} = \frac{1}{|U - V|}, \quad (7)$$

where

$$U = \frac{SCBW_k + CBW_i}{SBW_k}, \quad (8)$$

$$V = \frac{SCP_k + CP_i}{SP_k}. \quad (9)$$

It is possible that before assigning the customer i to channel k, some other customers are already assigned to the channel k. Hence, $SCBW_k$ is sum of CBW of already assigned customers to channel k. Similarly SCP_k is the sum of CP of already assigned customers to channel k. While obtaining the values of η_{ik}, the constraints (3) and (4) may not be satisfied. In that case the values of the heuristic information are

$$\eta_{ik} = 0 \text{ if } U > 1 \text{ or } V > 1.$$

At the end of the run, the ants update the pheromone information τ_{ik} as

$$\tau_{ik}(t+1) = (1-\rho) * \tau_{ik}(t). \quad (10)$$

In this update procedure, ρ is the evaporation rate between times t and $(t+1)$ and $0 < \rho < 1$. The evaporation rate ρ is used in order to reduce the effect of past experience and to explore new and alternate solutions. The local pheromone update is given by

$$\tau_{ik}(t+1) = \tau_{ik}(t) + \Delta\tau_{ik}^{j}, \quad (11)$$

where

$$\Delta\tau_{ik}^{j} = \begin{cases} \frac{Q}{L_j} & \text{if } M(i,k) \in S_j \\ 0 & \text{otherwise.} \end{cases}$$

In the above local pheromone update, S_j is the set of ant movements for the j-th ant, L_j is the evaluation value of the j-th ant, and Q is the pheromone update constant. $M(i,k)$ is the movement of an ant for assigning customer i to the channel k. In other words, $\Delta\tau_{ik}^{j}$ is the amount of pheromone deposit by the ant j for assigning customer i to the channel k.

Ranking strategy: In order to enhance the performance of ant system, a ranking pheromone update strategy is presented in [2]. In this strategy, the pheromone update is done as

$$\tau_{ik}(t+1) = \tau_{ik}(t) + \frac{(w+1-r)}{2}\Delta\tau_{ik}^{r}, \quad (12)$$

where

$$\Delta\tau_{ik}^{r} = \begin{cases} \frac{Q}{L_r} & \text{if } M(i,k) \in S_r \\ 0 & \text{otherwise.} \end{cases}$$

In this strategy, r is the r-th best ant, S_r is the set of ant movements for the r-th ant, L_r is the evaluation value of the r-th ant, and w is the w-th best ants for ranking strategy. The global pheromone update is done as

$$\tau_{ik}(t+1) = \tau_{ik}(t) + \sigma \times \Delta\tau_{ik}^{*}, \quad (13)$$

where

$$\Delta\tau_{ik}^{*} \begin{cases} \frac{Q}{L_{go}} & \text{if } M(i,k) \in S_{go} \\ 0 & \text{otherwise,} \end{cases}$$

where S_{go} is the set of ant movements for the global optimal ant, L_{go} is the evaluation value of the global optimal ant, and σ is a positive constant for weighting factor of the elitist one.

Max-Min Strategy: Another strategy known as max-min strategy is proposed in [24] to improve the performance of original ant system.

TABLE 1
Satellite Bandwidth (SBW_k), and Power (SP_k) for the channels:

Problem	SBW_1	SBW_2	SBW_3	SP_1	SP_2	SP_3
1.1	30	35	40	40	45	50
1.2	9	11	9	21	17	11
1.3	18	11	19	21	21	21

This MMAS strategy introduces upper and lower bounds to the values of the pheromone trails. The allowed range of the pheromone trail strength is limited in the following interval:

$$\tau_{min} \leq \tau_{ij} \leq \tau_{max} \text{ for all } \tau_{ij} \quad (14)$$

A flowchart for ant colony optimization is given in Figure 2. In the next section, we present a comparative study of the performance of genetic algorithm and ant colony optimization methods to our satellite customer assignment problem.

4 Comparative Study: Simulation Results

Our interest is to compare the performance of genetic algorithm and ant colony optimization methods to our satellite customer assignment problems. For this purpose, two sets of test problems are generated. The first set of problem is generated with 5 customers and 3 channels. This set of test problem is simple. The number of possible solutions is 3^5 and considered as small problem. For this first set of problem (with I=5 and K=3), the customer bandwidth requirements and power requirements are kept as: $CBW_1 = 5$, $CBW_2 = 4$, $CBW_3 = 6$, $CBW_4 = 7$, and $CBW_5 = 3$. The customer power requirements are: $CP_1 = 7$, $CP_2 = 9$, $CP_3 = 8$, $CP_4 = 6$, and $CP_5 = 5$. The values of satellite bandwidth available in channels (SBW) and the satellite power available (SP), used in our study are given in Table 1.

To verify the assignment of customers to satellite channels (obtained using genetic algorithms and ant colony optimization) we

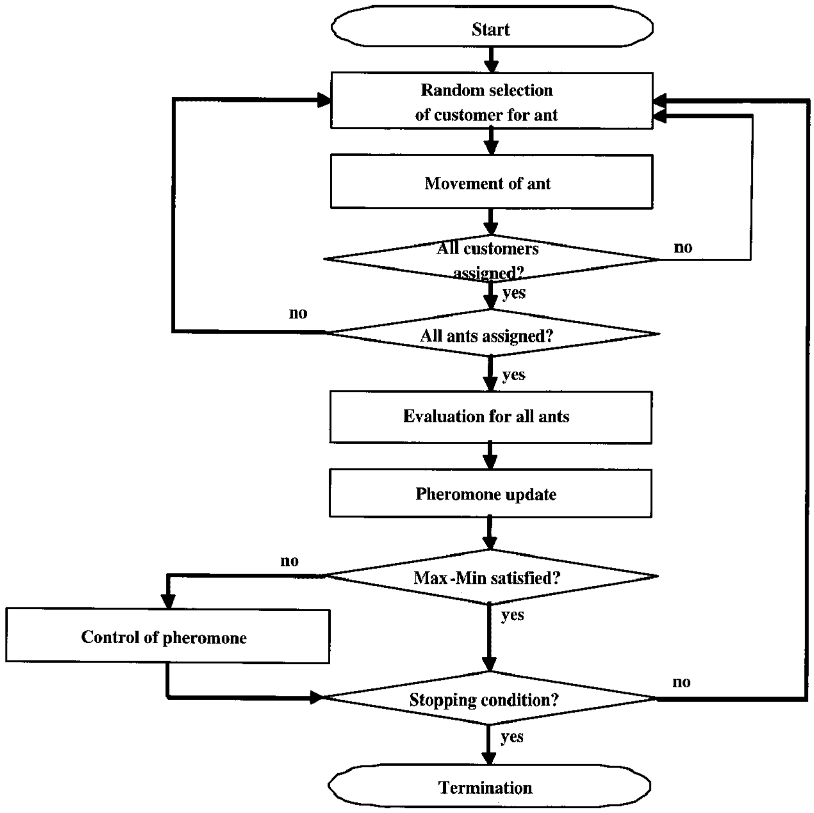

Fig. 2. Flowchart of the algorithm

have solved the same problems (1.1-1.3) using the zero-one linear programming formulation given in [22]. The objective function in our problem is non-linear and hence the following approach is used in [22].

It is shown in [22] that the number of possible solutions to this problem is J^I. For our problem with 5 customers (i.e., I=5) and 3 channels (i.e., J=3), the number of possible solutions is 243. Note that all the 243 solutions may not be feasible. We have solved the problems (1.1-1.3) formulated as zero-one linear programming using CPLEX solver. The best assignment obtained from genetic algorithm approach and ant colony optimization methods are the same as the optimal assignment obtained from CPLEX solver for all the problems. The computation time is almost same for the genetic algorithm approach, ant colony methods and the CPLEX solution. There is not much change in the computation time among these methods because this is a small problem.

Next, we consider a 20 customer (i.e., I=20) and 10 channel (i.e., K=10) problem. This is really a tough problem because the number of possible solutions are 10^{20}. Hence, the genetic algorithm and ant colony optimization approach will be very much useful here. The numerical values of satellite bandwidth available in channels (SBW) and the satellite power available (SP) used in our study are given in Table 2.

For the problem 2.1, the values of CBW_i for the customers from 1 to 20 are 5, 5, 5, 5, 4, 4, 3, 7, 6, 5, 6, 3, 6, 7, 4, 3, 6, 6, 4, and 4, respectively. The values of SP_i for customers from 1 to 20 are 5, 8, 9, 5, 7, 6, 8, 6, 7, 8, 6, 7, 9, 9, 7, 7, 5, 7, 5, and 9, respectively.

For the problem 2.2, the values of CBW_i for each customer are: 6, 7, 7, 7, 4, 7, 4, 6, 6, 4, 3, 3, 6, 3, 6, 6, 4, 3, 7, and 6, respectively. The values of SP_i are 8, 6, 9, 8, 6, 7, 6, 9, 8, 9, 9, 9, 8, 7, 5, 8, 6, 7, 7, and 7, respectively. We will use problems 2.1 and 2.2 to study the performance comparison of genetic algorithm, ant colony optimization, and CPLEX methods.

TABLE 2
Satellite Bandwidth (SBW_k), and Power (SP_k) for the channels:

Problem	SBW_1	SBW_2	SBW_3	SBW_4	SBW_5	SBW_6	SBW_7	SBW_8	SBW_9	SBW_{10}
2.1	22	13	15	20	15	15	15	22	19	13
2.2	20	22	16	17	23	14	14	15	21	14
Problem	SP_1	SP_2	SP_3	SP_4	SP_5	SP_6	SP_7	SP_8	SP_9	SP_{10}
2.1	31	19	24	26	25	24	18	28	23	29
2.2	33	18	30	26	28	31	28	19	33	18

Parameter Determination for GA: It is known that the performance of genetic algorithm depends on the parameters used. The parameters are the values of crossover probability and mutation probability used for the solution of problems 2.1 and 2.2. We have conducted a study to obtain the optimal values of these probabilities. The optimal value of crossover probability obtained is 0.9 and the optimal value of mutation probability obtained is 0.1.

Parameter Determination for ACO: Some definitions used in our study are given below. One-ant cycle is the cycle for evaluation and pheromone update for each ant in the colony. Generation is a period for the evaluations and pheromone updates for an ant colony of one generation. The following values are used in our simulations: Evaporation rate is 0.5, initial pheromone is 0.01, Q is 0.005, max and min values are 0.01 and 1.0, respectively, w is 10, and σ is 7. We have conducted a study to obtain the optimal values of the weighting factors α and β. The optimal value of α obtained is 1 and the optimal value of β obtained is 0.8.

In our simulations a total number of 40,000 cycles based on number of ants and generations are considered. The results are given in Table 3. In this Table 3, the second column corresponds to 20 ants and the generations are 2,000 and hence a total of 40,000 cycles are considered. In the same manner we consider the number of ants 40, 100, 160 and 200 with corresponding generations so that the total number cycles is 40,000. The objective function value for these cycles is given in this Table 3 for the test problems.

We have used three strategies in ant colony optimization methodology. The three strategies are ACO+rank (ACO with only ranking), ACO+MMAS (ACO with only MMAS), and ACO+rank+MMAS (ACO with both ranking and MMAS). We have considered only problems 2.1 and 2.2 because they are hard problems. We can see from Tables 4 and 5 that the minimum value of the objective function obtained in ACO+MMAS and ACO+rank+MMAS are zero which is the optimal value for problem 2.1. But the computation time increases when these strategies are included.

We now compare the computation time of the following three methods: GA, ACO+rank+MMAS, and CPLEX optimization. Here, the stopping criterion used for ACO+rank+MMAS is as follows: The objective function value is zero or without improvement during 1,000 cycles. We can see from Tables 6 and 7 that the computation time required in our approach is very much smaller in comparison with CPLEX.

From these results, we observe that GA is faster than the ACO with rank and MMAS. But the quality of solution found using ACO+rank+MMAS is better than GA. As expected the CPLEX takes a long time to obtain the solution.

We have also observed that the test problem 2.1 does not have a unique optimal schedule. The schedule we obtain for problem 2.1 using CPLEX is S_1, using ACO+rank+MMAS is S_2, and using GA is S_3. The schedules are given below:

TABLE 3
ACO Results for Test Problems

Problems	20 × 2000	40 × 1000	100 × 400	160 × 250	200 × 200
2.1	0.013274	0.013284	0.013717	0.013350	0.015171
2.2	0.051543	0.048220	0.052316	0.060514	0.059127

TABLE 4
ACO Performance Comparisons of the three strategies: Problem 2.1

Algorithm	Average	Minimum	Maximum	Deviation	Comp. time (sec)
ACO+rank	0.035884	0.007229	0.159086	0.016547	2.88
ACO+MMAS	0.008309	0.00	0.024526	0.004735	26.44
ACO+rank+MMAS	0.007139	0.00	0.022416	0.004005	29.41

TABLE 5
ACO Performance Comparisons of the three strategies: Problem 2.2

Algorithm	Average	Minimum	Maximum	Deviation	Comp. time (sec)
ACO+rank	0.078833	0.046062	0.103765	0.012594	7.58
ACO+MMAS	0.046936	0.028040	0.070021	0.008930	26.39
ACO+rank+MMAS	0.040877	0.025973	0.068094	0.007430	27.32

TABLE 6
Performance Comparisons of GA and ACO methods with CPLEX: Problem 2.1

Algorithm	Average	Minimum	Maximum	Deviation	Comp. time (sec)
ACO+rank+MMAS	0.007139	0.00	0.022416	0.004005	29.41
GA	0.020331	0.00	0.424020	0.008375	0.72
CPLEX	-	0.00	-	-	298.56

TABLE 7
Performance Comparisons of GA and ACO methods with CPLEX: Problem 2.2

Algorithm	Average	Minimum	Maximum	Deviation	Comp. time (sec)
ACO+rank+MMAS	0.040877	0.025973	0.068094	0.007430	27.31
GA	0.045029	0.023186	0.073005	0.010526	0.95
CPLEX	-	0.0129	-	-	887.78

$S_1 = \{8\ 2\ 0\ 3\ 0\ 8\ 3\ 0\ 3\ 4\ 3\ 5\ 0\ 5\ 8\ 4\ 8\ 2\ 4\ 2\}$
$S_2 = \{0\ 2\ 7\ 0\ 5\ 6\ 3\ 3\ 3\ 2\ 6\ 0\ 5\ 4\ 4\ 0\ 7\ 0\ 3\ 4\}$
$S_3 = \{3\ 7\ 4\ 3\ 6\ 4\ 5\ 6\ 5\ 2\ 7\ 1\ 5\ 3\ 1\ 3\ 1\ 2\ 6\ 2\}$

The objective function value is zero for all the schedules S_1, S_2, and S_3. We see that channels 1, 8, and 9 are not used in the assignments (S_1) and (S_2). Channels 0, 8, and 9 are not used in the assignment (S_3).

The schedule we obtain for problem 2.2 using CPLEX is S_4, using ACO with rank and MMAS is S_5, and using GA is S_6. The schedules are given below:

$S_4 = \{6\ 4\ 3\ 9\ 7\ 4\ 7\ 8\ 8\ 3\ 8\ 6\ 3\ 4\ 1\ 4\ 9\ 6\ 7\ 8\}$
$S_5 = \{4\ 1\ 0\ 7\ 8\ 4\ 4\ 6\ 0\ 0\ 6\ 8\ 3\ 0\ 1\ 3\ 7\ 3\ 8\ 4\}$
$S_6 = \{4\ 4\ 9\ 8\ 7\ 7\ 2\ 3\ 0\ 2\ 0\ 8\ 0\ 4\ 1\ 8\ 7\ 3\ 4\ 3\}$

The objective function values for these schedules S_4, S_5 and S_6 are 0.012987, 0.025973 and 0.023186, respectively.

5 Discussions and Conclusions

A comparative study of GA and ACO is presented for the problem of assigning customers to satellite channels which is a difficult combinatorial optimization problem. In ACO methodology, three strategies, ACO with only ranking, ACO with only max-min ant system (MMAS), and ACO with both ranking and MMAS, are used to obtain the assignment. In the experiments the ACO+rank+MMAS is relatively more accurate and less faster among ACO strategies. Both GA and ACO methods are able to obtain the best or optimal solution with less computational effort than CPLEX, optimal solver. In the experiments, we observe that GA is faster than the ACO with rank and MMAS. But the quality of solution found using ACO+rank+MMAS is better than GA.

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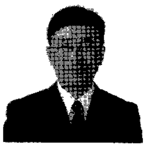

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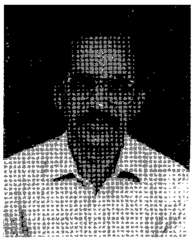

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