A HYBRID ANT COLONY OPTIMIZATION ALGORITHM FOR SOLVING THE TERMINAL ASSIGNMENT PROBLEM

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Abstract: The past two decades have witnessed tremendous research activities in optimization methods for communication networks. One important problem in communication networks is the Terminal Assignment Problem. This problem involves determining minimum cost links to form a network by connecting a collection of terminals to a collection of concentrators. In this paper, we propose a Hybrid Ant Colony Optimization Algorithm to solve the Terminal Assignment Problem. We compare our results with the results obtained by the standard Genetic Algorithm, the Tabu Search Algorithm and the Hybrid Differential Evolution Algorithm, used in literature.

1 INTRODUCTION

In the last decades the literature on telecommunication network problems has grown explosively. This is mainly due to the dramatic growth in the use of the Internet (Salcedo-Sanz and Yao, 2004; Yao et al. 2005). Terminal assignment (TA) is an important issue in telecommunication networks optimization.

The target of the TA problem implies fixing the minimum cost links to form a network between a specified set of terminals and concentrators (Khuri and Chiu, 1997). The objective is to connect terminals to concentrators under three constraints:

1. each terminal is assigned to one (and only one) concentrator;
2. the total number of terminals assigned to any concentrator does not overload that concentrator, i.e. is within the concentrators capacity and,
3. balanced distribution of terminals among concentrators.

Under these constraints, an assignment with the lowest possible cost is sought.

The TA problem is a NP-complete combinatorial optimization problem (Salcedo-Sanz and Yao, 2004). This means that the time required to solve the problem increases very quickly as the size of the problem grows. The intractability of this problem is a motivation for the pursuits of a metaheuristic that produce approximate, rather than exact, solutions. In (Dorigo, 1991; Dorigo et al. 1991; Dorigo et al. 1996) the use of an Ant Colony Optimization algorithm as a new metaheuristic was proposed in order to solve combinatorial optimization problems.

An Ant Colony Optimization algorithm (ACO) is essentially a system based on agents which simulate the natural behavior of ants, including mechanisms of cooperation and adaptation. This new metaheuristic has been shown to be both robust and versatile. The ACO algorithm has been successfully applied to a range of different combinatorial optimization problems (ACO HomePage).

In this paper we present a Hybrid Ant Colony Optimization (HACO) algorithm coupled with a local search, applied to the TA problem. Our algorithm is based on the HACO algorithm proposed by Gambardella et al. (1999) for solving the quadratic assignment problem. The HACO uses pheromone trail information to perform modifications on TA solutions, unlike more traditional ant systems that use pheromone trail

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information to construct complete solutions. The HACO uses also a diversification mechanism that periodically reinitializes all the pheromone trails.

We compare the performance of HACO with three algorithms: Genetic Algorithm (GA), Tabu Search (TS) Algorithm, Hybrid Differential Evolution (HDE) Algorithm, used in literature.

The paper is structured as follows. In Section 2 we describe the TA problem; in Section 3 we describe the implemented HACO algorithm; in Section 4 we present the studied examples; in Section 5 we discuss the computational results obtained and, finally, in Section 6 we report about the conclusions.

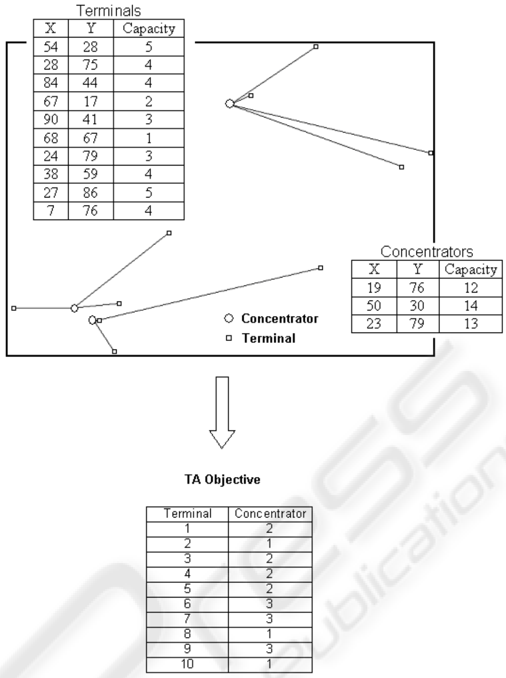
2 TA PROBLEM

The TA Problem can be described as follows:

1. a set N of n distinct terminals;
2. a set M of m distinct concentrators;
3. a vector C, with the capacity required for each concentrator (each concentrator is limited in the amount of traffic that it can accommodate);
4. a vector T, with the capacity required for each terminal (the capacity requirement of each terminal is known and may vary from one terminal to another). The capacities are positive integers and Ti is smaller or equal to min (Ci…Cn);
5. a matrix CP, with the location (x,y) of each concentrator (the concentrators sites have fixed and known locations). The M concentrators are placed on the Euclidean grid.
6. a matrix CT, with the location (x,y) of each terminal (the terminals sites have fixed and known locations). The N terminals are placed on the Euclidean grid.

The first objective is to assign each terminal to one node of the set of concentrators, in such a way that no concentrator oversteps its capacity. The second objective is to minimize the distances between concentrators and terminals assigned to them. Finally, the third objective is to ensure a balanced distribution of terminals among concentrators.

Figure 1 illustrates an assignment to a problem with N = 10 terminal sites and M = 3 concentrator sites. The figure shows the coordinates for the concentrators, terminal sites and also their capacities.



Terminals

X	Y	Capacity
54	28	5
28	75	4
84	44	4
67	17	2
90	41	3
68	67	1
24	79	3
38	59	4
27	86	5
7	76	4

Concentrators

X	Y	Capacity
19	76	12
50	30	14
23	79	13

TA Objective

Terminal	Concentrator
1	2
2	1
3	2
4	2
5	2
6	3
7	3
8	1
9	3
10	1

Figure 1: TA Problem - Example.

3 PROPOSED HACO

ACO is a population-based optimization method for solving hard combinatorial optimization problems. ACO is based on the indirect communication of a colony of simple agents, called (artificial) ants, mediated by (artificial) pheromone trails. In ant colony natural, ants indirectly communicate with each other by depositing pheromone trails on the ground and thereby influencing the decision processes of other ants. This simple form of communication between individual ants gives rise to complex behaviours and capabilities of the colony as a whole.

The first algorithm which can be classified within this framework was presented by Dorigo, Maniezzo and Colorni (1991, 1996), and Dorigo (1991) and, since then, many diverse variants of the basic principle have been reported in the literature.

The real ants behaviour is transposed into an algorithm by making an analogy between:

1. real ants search - set of feasible solutions to the problem;
2. amount of food in a source - fitness function;
3. pheromone trail - adaptive memory.

In ant colony natural, while walking from food sources to the nest or the nest to food sources, each ant deposits a pheromone on the ground. All ants can smell the pheromone while they walks. Therefore, more pheromone on the path will increase the probability of all ants to follow. In short, the best paths will receive a greater deposit of pheromones.

The pheromone trails in ACO serve as a distributed, numerical information which the ants use to probabilistically construct solutions to the problem being solved and which the ants adapt during the algorithm execution to reflect their search experience.

The essential trait of ACO algorithms is the combination of a priori information about the structure of a promising solution with a posterior information about the structure of previously obtained good solutions.

Any high performing metaheuristic algorithm has to achieve an appropriate balance between the exploitation of the search experience gathered so far and the exploration of unvisited or relatively unexplored search space regions. In ACO several ways exist of achieving such a balance, typically through the management of the pheromone trails. In fact, the pheromone trails induce a probability distribution over the search space and determine which parts of the search space are effectively sampled. The management of pheromone trails is the most important component of an ant system. Exploration is a stochastic process in which the choice of the component used to construct a solution to the problem is made in a probabilistic way. Exploitation chooses the component that maximises a blend of pheromone trail values and partial objective function evaluations.

The standard ACO algorithm uses pheromones trail information to construct complete solutions. Gambardella et al. (1999) in their paper present a Hybrid Ant Colony System coupled with a local search (HAS_QAP), applied to the quadratic assignment problem (QAP). HAS-QAP uses pheromone trail information to perform modifications on QAP solutions. Our HACO algorithm uses also pheromone trail information to perform modifications on TA solutions, unlike traditional ant systems that use pheromone trail information to construct complete solutions.

In this paper we will also explore one of the most successful emerging ideas combining local search with a population based search algorithm. HACO uses a modified ACO to explore several regions of the search space and simultaneously incorporates a mechanism (LS algorithm) to intensify the search around some selected regions.

The first step for the HACO implementation involves choosing a representation for the problem. In this work, the solutions are represented using integer vectors. We use the terminal-based representation (Figure 2). Each position in the vector corresponds to a terminal. The value carried by position `i` of the chromosome specifies the concentrator that terminal `i` is to be assigned to.

2	3	1	2	2	2	3	1	3	1

Figure 2: Terminal Based Representation.

For the TA, the set of pheromone trails is maintained in a matrix `T` of size `N*M`, where the entry T_{ij} measures the desirability of assigning terminal i to concentrator j.

The simplest way to exploit the ants search experience is to make the pheromone update a function of the solution quality achieved by each particular ant. In HACO only the best solution found during the search contributes to pheromone trail updating (Gambardella et al. 1999). This makes the search more aggressive and requires less time to reach good solutions. Moreover, this has been strengthened by an intensification mechanism. The intensification mechanics is used to explore neighbourhood more completely.

The algorithm uses also a diversification mechanism after a pre-defined number of `S` iterations without improving the best solution found so far. Gambardella et al. (1999) have shown that pheromone trail reinitialization, when combined with appropriate choices for the pheromone trail update can be very useful to refocus the search on a different search space region and avoid the early convergence of the algorithm.

HACO is based on the schematic algorithm of Figure 3.

The main steps of HACO are the following:

- Initialization of solutions – the initial solutions can be created randomly or in a deterministic form. The deterministic form is based in the Greedy Algorithm proposed by Abuali et al. (1994). This algorithm assigns terminals to the closest feasible concentrator.
- Evaluation of solutions – the fitness function is responsible for performing this evaluation and returning a positive number (fitness value) that reflects how optimal the solution is. The fitness function is based on the fitness function used in (Salcedo-Sanz and Yao, 2004). The fitness function is based on: (1)

the total number of terminals connected to each concentrator (the objective is to guarantee the balanced distribution of terminals among concentrators); (2) the distances between the concentrators and the terminals assigned to them (the objective is to minimize the distances between concentrators and terminals assigned to them); (3) the penalization if a solution is not feasible (the objective is to penalize the solutions when the total capacity of one or more concentrators is overloaded). The objective is to minimize the fitness function.

$$fitness = 0{,}9 * \sum_{c=0}^{M-1} bal_c + \qquad (1)$$

$$0{,}1 * \sum_{t=0}^{N-1} dist_{t,c(t)} + \qquad (2)$$

$$Penalization \qquad (3)$$

$$bal_c = \begin{cases} 10 & if\left(total_c = round\left(\frac{N}{M}\right)+1\right) \\ 20*abs\left(round\left(\frac{N}{M}\right)+1-total_c\right) & \end{cases}$$

$$Penalization = \begin{cases} 0 & if(Feasible) \\ 500 & \end{cases}$$

$$total_c = \sum_{t=0}^{N-1} \begin{cases} 1 & if(c(t)=c) \\ 0 & \end{cases}$$

$$dist_{t,c(t)} = \sqrt{\left(CP[c(t)].x - CT[t].x\right)^2 + \left(CP[c(t)].y - CT[t].y\right)^2}$$

c(t)= concentrator of terminal t
t = terminal c = concentrator
M = number of concentrators N = number of terminals

- Pheromone trail initialization – all pheromone trails T_{ij} are set to the same value
- Modification of solutions – it consists in repeating R modifications. A modification consists on assigning a terminal t to a concentrator c. First a terminal t is randomly chosen (between 1 and N) and after a concentrator c is chosen. A random number x is generated between 0 and 1. If x is smaller than q (parameter), the best concentrator c is chosen in such a way that Ttc is maximum. This policy consists in exploiting the pheromone trail. If x is higher than q the concentrator c is chosen with a probability proportional to the values contained in the pheromone trail. This consists in exploring the solution space.
- Local Search – the LS algorithm consists on applying a partial neighbourhood examination. We generate a neighbour by swapping two terminals between two concentrators C1 and C2 (randomly chosen). If isn't find a better solution then is created another set of neighbours. In this case, one neighbour results of assign one terminal of C1 to C2 or C2 to C1. The neighbourhood size is N(C1)*N(C2) or N(C1)*N(C2) + N(C1)+N(C2). The LS algorithm consists on the following steps:

```
C1 = random (number of concentrators)
C2 = random (number of concentrators)
NN = neighbours of ACTUAL-SOL (one
neighbour results of interchange one
terminal of C1 or C2 with one terminal
of C2 or C1)
SOLUTION = FindBest (NN)
If ACTUAL-SOL is best than SOLUTION
    NN = neighbours of ACTUAL-SOL (one
    neighbour results of assign one
    terminal of C1 to C2 or C2 to C1)
    SOLUTION = FindBest (NN)
    If SOLUTION is best than ACTUAL-SOL
       ACTUAL-SOL = SOLUTION
Else
    ACTUAL-SOL = SOLUTION
```

- Intensification – the intensification mechanism permits to explore the neighbourhood more completely and permits to return to previous best solutions. If the intensification is active and the solution X in the beginning of the iteration is better, the ant comes back to the initial solution X. The intensification is activated when the best solution found so far has been improved and remains active while at least one ant succeeds on improving its solution during the iteration.
- Pheromone trail update – to speed-up the convergence the pheromone trails are updated by taking into account only the best solution found so far (Gambardella et al. 1999). The pheromone trails are updating by setting: $T_{ij}=(1-x1)*T_{ij}$, where $0<x1<1$ is a parameter that controls the evaporation of the pheromone trail $T_{iXi}*=T_{iXi}*+x2/f*(X*)$, where $0<x2<1$ is a parameter that controls the influence of the best solution X* in the pheromone trail.
- Diversification – this mechanism restarts the pheromone trails and creates new solutions for each ant. We kept for the following iteration the best solution found so far.

More information about ACO can be found in (ACO HomePage).

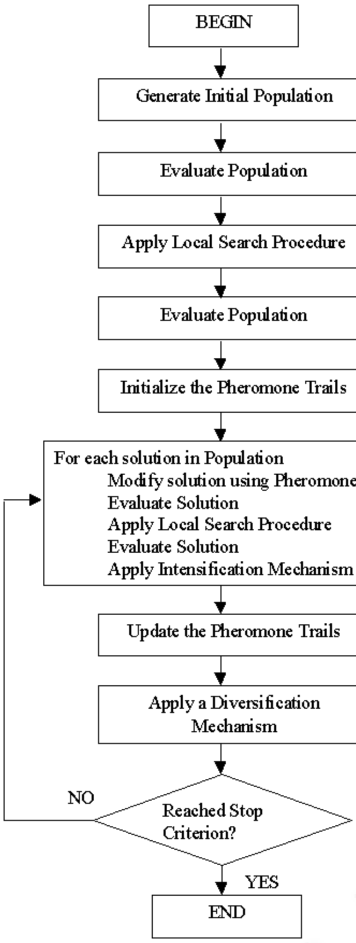


Figure 3: HACO Algorithm.

4 EXAMPLES

In order to test the performance of our approach, we use a collection of TA instances of different sizes. We take 9 problems from literature (Bernardino et al. 2008).

Table 1 presents the 9 problems that were used to test our algorithm.

Table 1: TA Instances.

Problem	N	M	Total T	Total C
1	10	3	35	39
2	20	6	55	81
3	30	10	89	124
4	40	13	147	169
5	50	16	161	207
6	50	16	173	208
7	70	21	220	271
8	100	30	329	517
9	100	30	362	518

5 RESULTS

To compare our results we consider the results produced with the classical Genetic Algorithm, the Tabu Search Algorithm and the Hybrid Differential Evolution Algorithm. The GA was first applied to TA by Abuali et al. (1994). The GA is widely used in literature to make comparisons with other algorithms. The GA adopted uses "one-point" method for recombination, "change order" method for mutation and tournament method for selection. In "change order", two genes are randomly selected and exchanged. TS was applied to this problem by Xu et al. (2004) and Bernardino et al. (2008). We compare our algorithm with the TS algorithm proposed by Bernardino et al. (2008). HDE was applied to this problem by Bernardino et al. (2009).

Table 2 presents the best-obtained results with HACO, GA, TS and HDE. The first column represents the problem number (Prob) and the remaining columns show the results obtained (Fitness, Time – Run Times) by the four algorithms.

The algorithms have been executed using a processor Intel Core Duo T2300.

The HDE and GA were applied to populations of 200 individuals. The initial solutions were created using the Greedy Algorithm.

The run time corresponds to the average time that the algorithms need to obtain the best feasible solution.

The values presented have been computed based on 100 different executions for each test instance.

The four algorithms reach feasible solutions for all test instances. In comparison, the HACO obtains better solutions for larger instances. The TS is the faster algorithm because can find good solutions in a better running time. In HDE the crossover probability is applied to each gene, generating several perturbations by generation, for which the algorithm slows down. Besides, in HDE is necessary to carry out a concentrator conversion so that the concentrator obtained stays always inside of the defined range.

The better results obtained with HACO use R between N/20 and N/3, x1>0.4 and x2>0.4 (Figure 4), Q=100, S between N*2 and N*4, q>0.4 (Figure 4) and Number of ants ={30,40}. These parameters were experimentally found to be good and robust for the problems tested.

In our experiments we use a growing number of ants. The number of ants was set to {10, 20, 30, 40, 50, 60, 70, 80, 90, 100}. We studied the impact on the execution time, the average fitness and the number of best solutions

Table 2: TA Instances.

Prob	GA		Tabu Search		HDE		HACO	
	Fitness	Time	Fitness	Time	Fitness	Time	Fitness	Time
1	65,63	<1s	65,63	<1s	65,63	<1s	65,63	<1s
2	134,65	<1s	134,65	<1s	134.65	<1s	134.65	<1s
3	284,07	<1s	270,26	<1s	270,26	<5s	270,26	<1s
4	286,89	<1s	286,89	<1s	286,89	<5s	286,89	<1s
5	335,09	<1s	335,09	<1s	335.09	<5s	335.09	2s
6	371,48	1s	371,12	<1s	371,12	58s	371,12	3s
7	401,45	2s	401,49	1s	401,21	118s	401,21	4s
8	563,75	4s	563,34	1s	563,19	274s	563,19	14s
9	703,78	5s	642,86	2s	642,83	456s	642,83	25s

found. A higher number of ants significantly increase algorithm execution time (Figure 5).

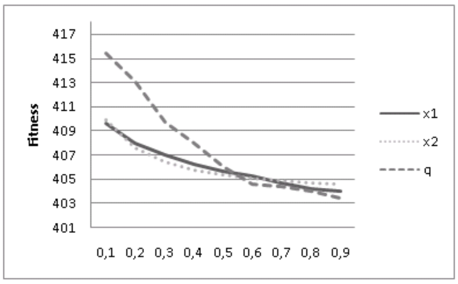


Figure 4: Influence of parameters – Problem 7.

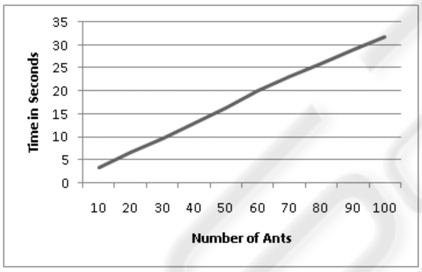


Figure 5: Number of Ants – Execution Time – Problem 7.

The results show that the best values are `30` and `40`. With these values the algorithm can reach in a reasonable amount of time a higher number of best solutions (Figure 7). With a higher number of ants the algorithm can reach a better average fitness (Figure 6) but it needs much more time.

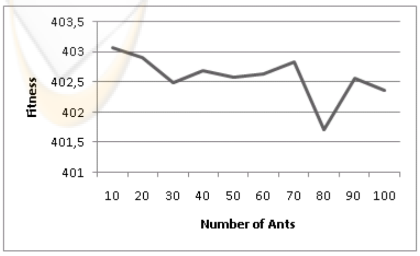


Figure 6: Number of Ants – Average Fitness – Problem 7.

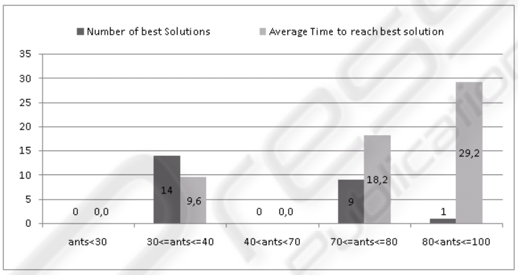


Figure 7: Number of Ants – Number of Best Solutions – Problem 7.

We also observe that a small number of ants allows an initial faster convergence, but a worse final result, following to an increased amount of suboptima values (Figure 8). This can be explained because the quality of the initial best-located solution previous to the first restart, depends highly on the population size: they need more population diversity – it depends on the population size – to avoid premature stagnation.

For parameter `R`, the number of swaps executed using pheromone trail information, `R` between `[N/20...N/3]` has been shown experimentally to be more efficient (Figure 9). In our experiments `R` was set to `{0, 1, 2, …, N}`.

In case of a high `R` the resulting permutation tends to be too close to the best solution used to perform global pheromone trail updating, which makes it more difficult to generate new improving solutions. A high `R` has also a significant impact on the execution time (Figure 10). On the contrary, a small `R` did not allow the system to escape from local minima because after the local search, the resulting solution was in most cases the same as the starting permutation.

For `S<N*2` and `S>N*4` phenomena of stagnation and insufficient intensification have been observed (Figure 11).

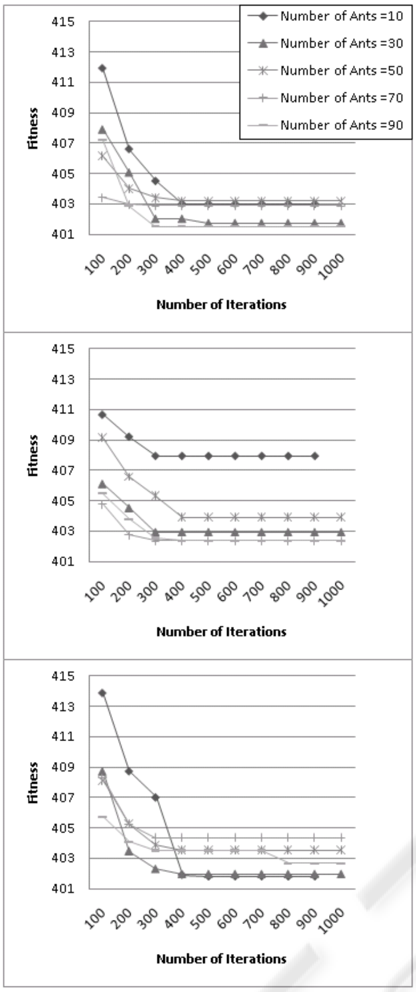


Figure 8: Number of Ants – Convergence – Three different initial populations – Problem 7.

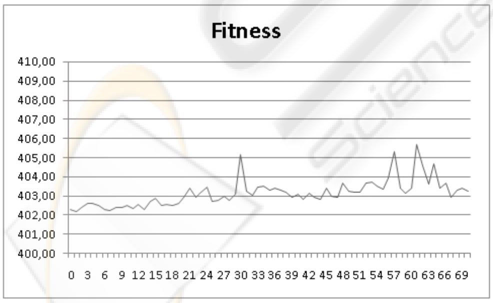


Figure 9: Number of modifications – Average Fitness – Problem 7.

Large types of experiments and considerations have been made to define other parameters.

In general, experiments have shown that the proposed parameter setting is very robust to small modifications.

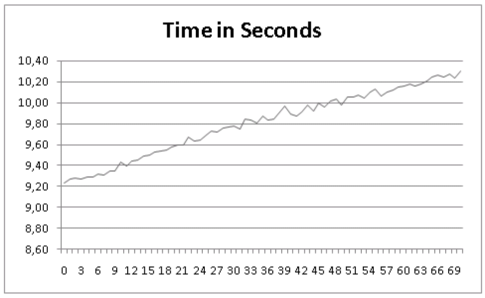


Figure 10: Number of modifications – Execution Time – Problem 7.

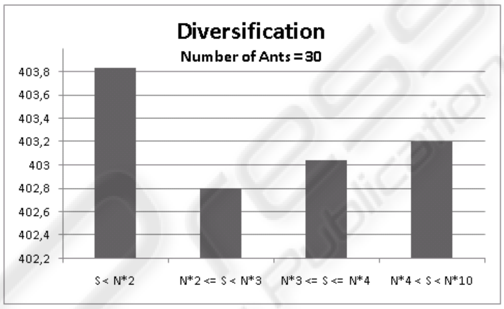


Figure 11: Diversification – Average Fitness – Problem 7.

6 CONCLUSIONS

In this paper we present a new Hybrid Ant Colony Optimization Algorithm to solve the Terminal Assignment Problem. The performance of' our algorithm is compared with three algorithms: a classical GA, a TS algorithm and a HDE algorithm.

Experimental results demonstrate that the proposed HACO algorithm is an effective and competitive approach in composing fairly satisfactory results with respect to solution quality and execution time for the Terminal Assignment Problem.

The HACO presents better results for larger problems. Our algorithm provides better solutions with smaller fitness values for larger problems. The TS is the faster algorithm.

In literature the application of HACO for this problem is nonexistent, for that reason this article shows its enforceability in the resolution of this problem.

The implementation of parallel algorithms will speed up the optimization process.

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