Ant Colony Optimization for Dynamical Resource Allocation in a Multizone Temperature Experimentation Platform

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Abstract

In this work, an algorithm based on the Ant System was used for the dynamical resource allocation in a multiple input/output experimentation platform. This platform, which mimics a temperature grid plant, is composed of multiple sensors and actuators organized in zones. The use of ants in this application allows to search the best actuator in each sample time. This allowed us to obtain a uniform temperature over the platform. Good behavior of the implemented algorithm in the experimentation platform was observed.

1 Introduction

Ants are social insects that live in colonies and whose behavior is directed toward the survival of the colony rather than of the individual. These insects have drawn the attention of scientists due to the high structure level that their colonies exhibit when compared to the simplicity of their individuals. A particular ant behavior is its capacity to find the best path between its food source and its origin. In order to achieve this purpose, ants use a form of communication based on chemical agents called pheromones. These substances, deposited by the ant when advances over a path, represent information that is used for the next ants to choose the right path, which is that with more substance concentration. This allows the ants to find the location of the food sources as well as their nest. It has been demonstrated that the pheromone traces allow a slow distributed optimization in which each simple individual gives a little contribution in the search of the best solution. This is an example of a property associated with the colony that is not shown by the individual alone [1].

A model based in how ants behave and the way how they communicate was developed for a multi-agent system applied to discrete combinatorial problems such as the traveling salesman problem (TSP) and the quadratic assignment problem (QAP) [1]. There is currently much ongoing activity in the scientific community to extend and apply ant-based algorithms to different discrete optimization problems. Other applications cover problems such as vehicle routing, sequential ordering, graph coloring, routing in communications networks, and so on [1].

In this paper, an algorithm based on the Ant System is used to dynamically allocate the time of ignition of an actuator in a Multizone Temperature Experimentation Platform (MuTEP) and to achieve a uniform temperature over a particular area. The MuTEP, presented in [2], is a multiple input / output plant that emulates the workings of a system designated to control the temperature over a surface.

The paper is organized as follows. First we show the main concepts of an Ant System. Next we describe the experimentation platform used to proof our algorithm. Later we continue with the explanation of the ant algorithm for dynamical task allocation in the experimentation platform. Finally we show some results when the algorithm was applied to the platform.

2 The Ant System

The Ant System, Developed by Colorni, Dorigo, and Maniezzo [3], was the first of several Ant based algorithms to be developed. This system is the prototype of a number of ant algorithms that collectively implement the Ant Colony Optimization (ACO) paradigm. The Ant System has a set of computational concurrent and asynchronous agents that move through states of the problem and that corresponds to partial solutions of the problem to solve. The agents move by applying a stochastic local decision policy based on two parameters called trails and attractiveness. By moving, each ant incrementally constructs a solution to the problem. When an ant completes a solution, or during the construction phase, it evaluates the solution and modifies the trail value on the components used in its solution.

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This pheromone information will direct the search of the future ants.

In addition, a taboo list is implemented that contains all the moves that are feasible for k ants. On the other hand, the transition probability of a move is calculated by the following equation,

$$\rho_{ij}^{k} = \frac{[\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{k \in allowed_k}[\tau_{ik}]^{\alpha}[\eta_{ik}]^{\beta}} \quad (1)$$

At the end of a search, the pheromone values are actualized by the equations 2 and 3

$$\tau_{ij}(t+n) = \rho\tau_{ij}(t) + \Delta\tau_{ij} \quad (2)$$

$$\Delta\tau_{ij} = \sum_{k=1}^{m}\Delta\tau_{ij}^{k} \quad (3)$$

The Ant System simply iterates a main loop where m ants construct in parallel their solutions, thereafter updating the trail levels. The performance of the algorithm depends in the correct tuning of several parameters (α ,β ,$\tau_{ij}(0)$, m, among others), and the correct selection of a cost function.

3 Experimentation Platform

The Ant algorithm was tested in a Multizone Temperature Experimentation Platform (MuTEP) [2], which was composed of two parts, a process stage, and a data acquisition stage.

The process stage is an emulation of a planar temperature grid. This is a system that exhibits effects that are difficult to model, especially strong interactions between zones. Therefore, it requires the use of particular control strategies. This type of system is mainly used in the semiconductor industry for the elaboration of crystals and the generation of photo resistive layers. This process requires maintaining a constant surface temperature.

The data acquisition system used was composed of four modules based in a low cost micro controller. Each module controlled a quadrant of the process and enabled communication with a master computer, which contained the management and control algorithm. The basic structure of the system is shown in Fig. 1 and the process stage is shown in Fig 2.

4 Ant Algorithm for Dynamical Task Allocation in MuTEP

We design an algorithm using an ant system based on the strategy shown by Quijano in [4] and [5]. This

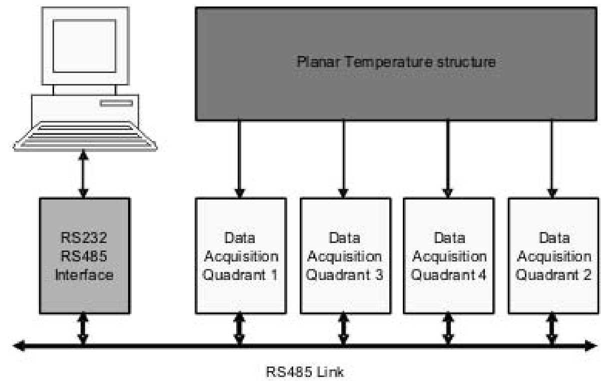

Figure 1. System Architecture of the Multizone Temperature Experimentation Platform (MuTEP) for management from a single Computer

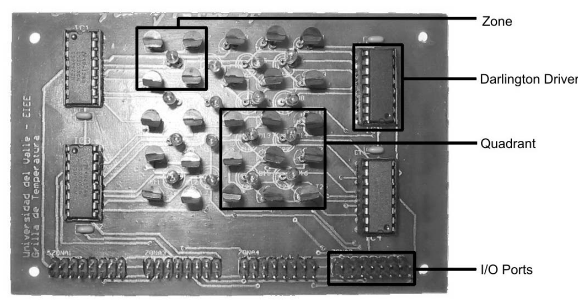

Figure 2. Process stage of the Multizone Temperature Experimentation Platform (MuTEP)

strategy finds the zone with the lowest temperature and assigns the resource to that zone. To assign the resource implies to turn on the bulb of the zone and, as consequence, the temperature of the zone is increased. This is a centralized approach were a single computational agent takes a destination based in global knowledge.

The searches done by the Ant System are usually in discrete spaces. In our application the states (turn on the bulb in a zone) are discrete. This allow to relate the states of the ant system to the zones in the plant.

The objective function used in our proofs was to obtain a maximum uniform temperature over the process surface using a limited amount of actuators over a period of time. The amount of actuators depends of the numbers of ants (agents) used in the algorithm. We done proofs using one, two and four ants. This produce that in each sample time are turn on one, two, or

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four bulbs.

In our algorithm the way as the ant choose the next bulb to turn on is similar to the way as an ant choose the next city to be visited in the implementation of the ACO to solve the TSP (Traveling Salesman Problem). In that implementation, the next city to be visited is chosen finding the nearest city or the city with more amount of pheromone. In our algorithm, the next zone to be visited is chosen finding the zone with more pheromone or the nearest zone. The nearest zone is the zone that has the lowest temperature.

The initial pheromone to all the zones is defined as the average of the zone temperatures. In our case we have sixteen zones and the initial pheromone is calculated using the next equation:

$$\tau_{ij} = \frac{\sum_{i=1}^{16} T_i}{16} \tag{4}$$

The update of pheromone is done using a factor that is inverse proportional to the temperature of the zone. The equations to update pheromone are:

$$\tau_{ij}\left(t+n\right) = \rho\tau_{ij}\left(t\right) + \Delta\tau_{ij} \tag{5}$$

$$\Delta\tau_{ij} = \frac{\tau_{ij}}{T_{ij}^{\beta}} \tag{6}$$

In our implementation $\beta = 2$

Note that in our algorithm only is used a local update of pheromone. A global update of pheromone it not necessary because there is not a tour like TSP problem.

Our algorithm is similar to ACO to solve TSP in the aspect that are used probabilities to explore or exploit the knowledge [6]. An exploitation of the knowledge selects the next state with the highest pheromone value, an exploration of the knowledge uses a lottery based selection where the probability of selection of a state is based in the pheromone.

In each sample time the ants choose the next zone to be visited. When an ant visit a zone it turns on the bulb in that zone to increase the temperature on it. An ant finish its circuit when it has visited the six zones. To avoid the repetition of states in a circuit, and to restrict the collisions between agents, we use a taboo lists. The taboo list is filled with the zones that an ant has visited.

With these considerations, the developed algorithm can be presented as follows [7]:

1. The initial pheromone is evaluated as the average of the initial temperatures. Equation 4.
2. In the beginning of a circuit the taboo lists are initialized in zeros. Each ant is randomly located in a zone. The number of ants per zone is restricting to one.
3. For each zone the temperature vector obtained is stored with the value of the current zone as zero.
4. The transition probability is calculated using the equation 1.
5. A selection between the exploitation and exploration is made. This determinates the next move of the ant.
6. If the exploitation is selected the state with the maximum pheromone and no used by other ant is selected. Otherwise the lottery selection is performed.
7. The taboo list is actualized to avoid repetition of states.
8. The update of pheromone is realized using equations (5,6). In our implementation $\rho = 0.8$.
9. Each ant repeated steps 3 to 8 until its circuit is finished.
10. Repeat all the process from step 2.

5 Results

For the execution of our algorithm different sizes of the population were used. First, taking in account that each ant used turns on an actuator, the maximum size of the population is four ants. The experiments carried on used populations of one, two and four ants. The results for one ant are shown in 3, for two ants in Fig. 4, and for four ants in Fig. 5.

This method uses more the actuators in the corners of the surfaces. This situation is similar to the described in [5]. Besides, the temperature increment is related to the amount of used agents. It can be seen in Figures 3a, 4a and 5a that there is a tendency to choose more actuators from the first column. Although the central actuators are used, all of them are used in the same proportion, that can be related to the random component of the algorithm. The figures 3b, 4b and 5b show that there is a lower temperature increment over the edges of the surface, and a fast stabilization of the temperature obtained. For the multiagent populations, the temperature shows a mayor spreading.

For the results evaluation, a series of parameters where used to check if the obtained temperature surface gets the control goal. These are:

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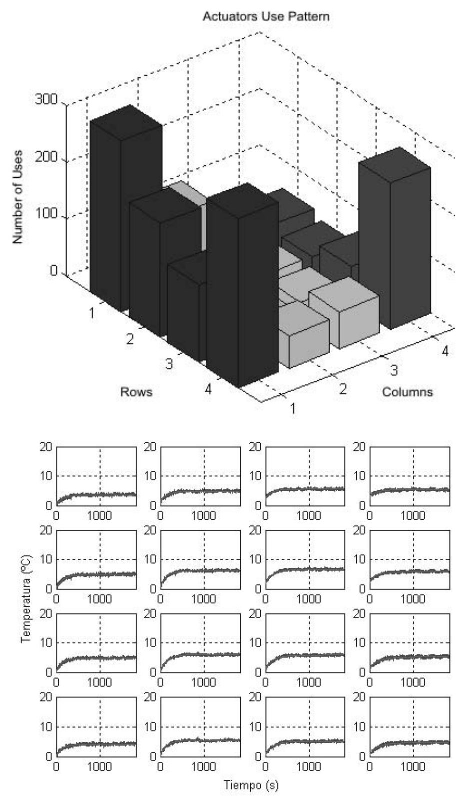

Figure 3. Results of the experiment obtained with a single ant: (a-top) shows the number of times an actuator is used in the experiment, (b-bottom) shows the zones' temperatures over the experiment

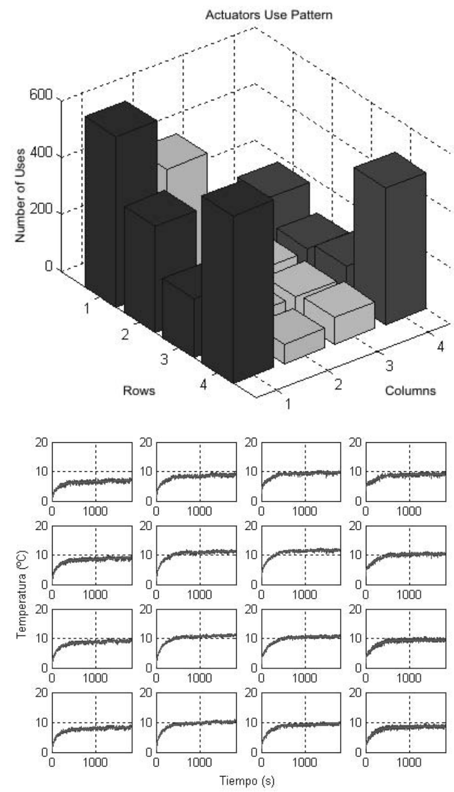

Figure 4. Results of the experiment obtained with two ants: (a-top) shows the number of times an actuator is used in the experiment, (b-bottom) shows the zones' temperatures over the experiment

- Maximum average temperature ΔT: Corresponds to the maximum variation of the average surface temperature. With $t_p\,(t)$ the average temperature at 0 and $t_p\,(t_{fin})$ the average temperature at the end of the experiment ΔT is defined by the equation 7. The results are shown in Fig. 6.

$$\Delta T = t_p\,(t_{fin}) - t_p\,(t) \tag{7}$$

- Settling time t_{est}: Corresponds to the settling time taken to achieve the maximum average temperature. The results are shown in Fig. 6.

- Settling temperature spreading σ: Correspond to the error of the surface to the average temperature. The results are shown in Fig. 7.

- Spreading percentage $\%\sigma$: The comparision of the sperading and the achived average tempeature is allowed. The results are shown in Fig. 7.

- Control action average CA: Corresponds to the average number of actuators used in a sample. The identification of the control effort used to raise the temperature is allowed and calculated by the equation 8. The results are shown in Fig. 8.

$$CA = \frac{1}{t_{fin}} \sum_{i=0}^{t_{fin}} \sum_{j=1}^{L} u_j\,(i) \tag{8}$$

6 Conclusions

In this paper, the implementation and proof of ant algorithms for dynamical resource allocation in the MuTEP platform was presented. This work represents the first study of these techniques at the Universidad del Valle and represents the first step toward the implementation of a complex intelligent controller. The

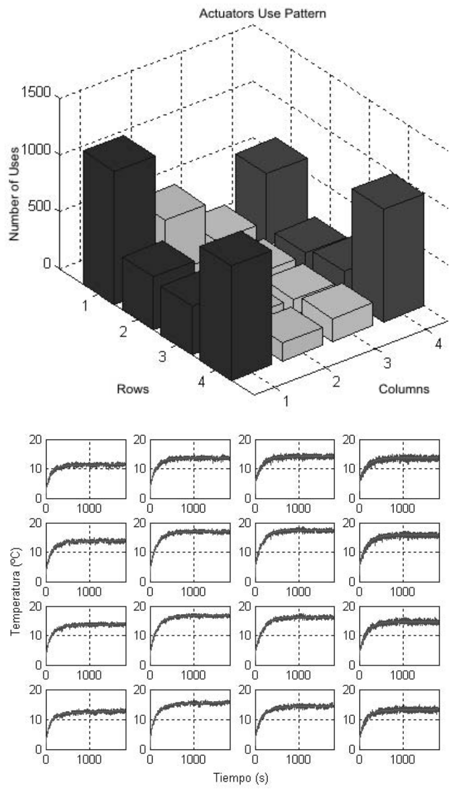

Figure 5. Results of the experiment obtained with four ants: (a-top) shows the number of times an actuator is used in the experiment, (b-bottom) shows the zones temperatures over the experiment

Ants presented an intelligent behavior that allowed the achievement of good results, although they are not optimal, they use the most adecuated actuators.

The experiment showed that at a large population the temperature variation is increased. The analysis of the results showed that the ant algorithm allowed a shorter establishing time than the algorithms showed in [2].

Further work will include the construction of a model based controller for each zone or for the whole system, using an ant algorithm for continuous-space optimization. The development of this controller will include restrictions in the number of actuators used, magnitude of the control action, and continuous operation different from the on-off approximation used in this experiment.

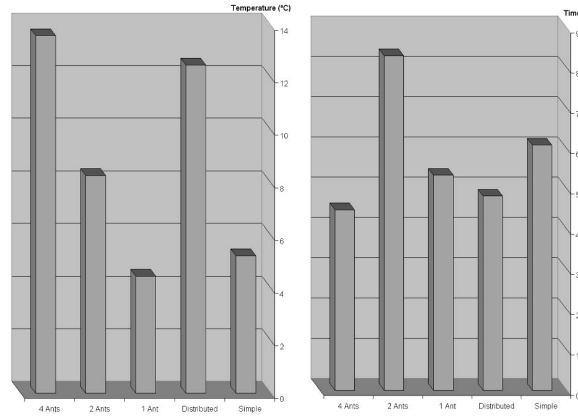

Figure 6. Maximum average temperature ΔT (left) and Settling time t_{est} (right) with the ant algorithm and the algorithms described in [2]. The graphics shows that an increase of the population achieves a higher temperature, while the settling time stays around a determinated range.

7 Acknowledgments

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References

[1] M. Dorigo, G. Di Caro, and L. M. Gambardella. Ant algorithms for discrete optimization. *Artificial Life*, 5(3):137172, 1999.

[2] M. A. Mu noz, J. A. López, and E. F. Caicedo. Implementation of a distributed control experimenta-

Method	ΔT	t_{est}	σ	$\%\sigma$	CA
Simple	5,2275	609	0,3568	6,83	1,0000
Distributed	12,4800	482	0,5748	4,61	3,1189
1 Ant	4,4483	534	0.7532	16.93	1,0000
2 Ants	8,2744	831	1,2089	14,61	1,9872
4 Ants	13,5954	448	1,6402	12,06	3,7740

Table 1. Evaluation Parameters Values of the experiment

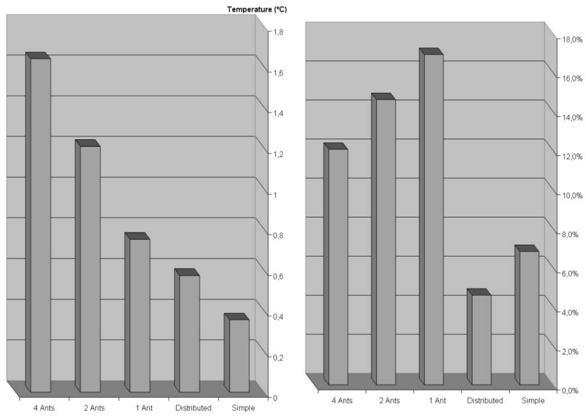

Figure 7. Settling temperature spreading σ (left) and Spreading percentage $\%\sigma$ (right) with the ant algorithm and the algorithms described in [2]. The graphic shows that an increase of the ant population increases the temperature spreading.

tion platform. In *IEEE 2005 Conference on Industrial Electronics and Control Applications*, 2005.

[3] V. Maniezzo, L. M. Gambardella, and F. de Luigi. *Ant Colony Optimization*, chapter 1, pages 101–117. Springer-Verlag Berlin Heidelberg, 2004.

[4] N. Quijano. Experiments and technologies for decentralized temperature control. Master's thesis, The Ohio State University, 2002.

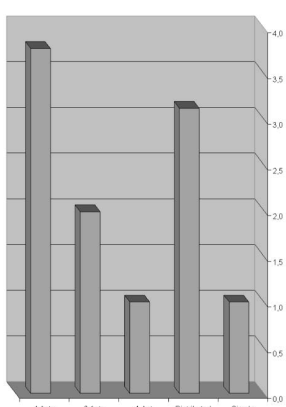

Figure 8. Control action average CA with the ant algorithm and the algorithms described in [2].

[5] N. Quijano, A. E. Gil, and K. Passino. Experiments for dynamic resource allocation, scheduling and control. *IEEE Control Systems magazine*, pages 63–79, 2005.

[6] M. Dorigo and L. M. Gambardella. Ant colony system: A cooperative learning approach to the traveling salesman problem. *IEEE Transactions on Evolutionary Computation*, 1(1):53–66, 1997.

[7] M. A. Mu noz. Asignación dinámica de recursos con técnicas bio inspiradas para un sistema de control de temperatura mimo, 2005.