Insect Societies and Manufacturing

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Abstract

In this paper, we present examples from the literature of successful problem solving systems that have been heavily influenced directly from biological studies of insect societies. Included among these systems are a few of our own. These examples are presented in light of manufacturing applications and only the tip of the iceberg is touched upon. It is our hope that the reader will find a new source of inspiration in problem solving tool design; and realize the potential of coordination mechanisms for multi-agent manufacturing systems inspired by social insects.

1 Introduction

"Could there be an Artificial Ant Colony?" is a question asked by Douglas R. Hofstadter in one chapter of his famous book *Gödel, Escher, Bach: an Eternal Golden Braid* [Hofstadter, 1979]. In that chapter, Hofstadter contemplates on a dialogue in which the character Anteater is telling Achilles about his friend Aunt Hillary. Aunt Hillary is an ant colony seen as a single intelligent entity. The discussion is whether or not collective intelligence can emerge from the interactions of hundreds of simple less-than-intelligent agents and whether or not we can learn anything from studying such natural multi-agent systems at work.

Colonies of social insects have collaboratively solved such problems as resource transportation, routing, task allocation for millenia in efficient manners and there is a great deal that we can learn from them. A little over twenty years have passed since Hofstadter's book was first published and we now have many examples of researchers applying coordination mechanisms based on models of such natural multi-agent systems as ants [Hölldobler and Wilson, 1990], bees [Kirchner and Towne, 1994; von Frisch, 1967], and wasps [Theraulaz *et al.*, 1991] to solve fairly difficult problems.

In this paper, we present examples from the literature of successful problem solving systems that have been heavily influenced directly from biological studies of insect societies. These examples are presented in light of manufacturing applications and only the tip of the iceberg is touched upon. In what follows you will find no equations; those can be found in the cited papers themselves. But rather, it is our hope that you will find a new source of problem solving tools with which to use in tackling your manufacturing problems.

The remainder of this paper is organized as follows. Section 2 presents applications of ant colony coordination including applications to combinatorial optimization problems (Section 2.1) as well as to other more dynamic problems (Section 2.2). In Section 3 we discuss less studied ideas for task allocation (Section 3.1) and task prioritization (Section 3.2) problems based on wasp behavior. And finally, we conclude in Section 4.

2 Coordination in Ant Colonies

An ant colony is an example of a highly distributed natural multi-agent system. It is comprised of hundreds (perhaps thousands) of completely autonomous simple agents (i.e., the ants) and is robust with respect to loss of individual agents and to changes in the environment. The colony continues to function efficiently despite the loss of a few individual ants to predators for example and adapts foraging activity to account for unexpected changes to the local environment. The colony as a whole manages to coordinate its activities – such as foraging, brood care, cemetery formation, etc. – without any direct communication among the individual members. Furthermore, the performance of some of these activities can be seen as highly effective and in some cases optimal or near-optimal. For example, consider the well-known double bridge experiment [Bonabeau *et al.*, 1999]. In this experiment, there are two paths between the nest and a food source. Over time the colony is able to converge upon the use of the shorter of the two paths. The typical biological explanation for this successful outcome is that of pheromone trail laying and following [Hölldobler and Wilson, 1990]. Ants are believed to deposit chemical along the route between the nest and a food source as well as to wander (somewhat at random) in the general direction of heavier concentrations of such pheromone. Shorter paths begin building up concentrations of pheromone at a faster and faster rate as more and more ants begin using the shorter paths; while concentrations on other longer paths decay over time. The explanation is that an ant taking the shorter path both ways will doubly reinforce the path before an ant which took the longer route has a chance to doubly reinforce its path. Thus more ants begin taking this shorter path sooner further reinforcing the short path.

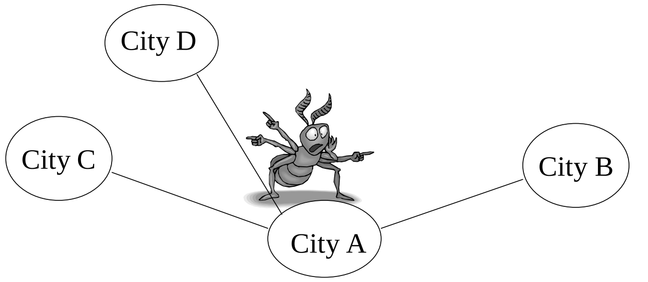

Figure 1: In the Ant Colony System (ACS) of Dorigo et al. as well as in the many other variants of Ant Colony Optimization (ACO) for the Traveling Salesperson Problem (TSP), a population of "ants" stochastically build tours of the cities based on artificial pheromone and heuristic information. The pheromone quantities are updated according to tour quality and the entire process iterated.

2.1 Combinatorial Optimization

Based on this ant foraging analogy, Dorigo et al. have founded a new paradigm of evolutionary computation that has come to be known as Ant Colony Optimization (ACO) [Dorigo and Di Caro, 1999]. ACO is perhaps the most successful application inspired by ants – and perhaps by any insect society. Their initial Ant System (AS) [Colorni *et al.*, 1992b; 1992a; Dorigo *et al.*, 1996] showed promising results with the Traveling Salesperson Problem (TSP). And they later refined their approach in their Ant Colony System (ACS) [Dorigo and Gambardella, 1997a; 1997b] and through the addition of some local search procedures this ACS is competitive with some of the best known heuristics for the TSP. The general idea behind the class of ACO algorithms for the TSP is as follows (also see Figure 1). Begin by laying some initial quantities of artificial pheromone on the edges between the cities in your TSP. Now set loose a population of artificial ants. Each ant builds a tour of the cities by stochastically following the pheromone and heuristic information captured in the city-to-city distances. Next the pheromone levels are updated based on the quality of the tours found by this population. After this pheromone update is performed, the population of ants is set loose again. And this continues until a single path is converged upon or for some large number of iterations.

Since its development, researchers have applied ACO to a number of combinatorial optimization problems. One area particularly important to manufacturing where there has been a lot of work is scheduling. There is at least one ACO-based approach to almost any scheduling problem you can think of. Some of these include: the sequential ordering problem [Gambardella and Dorigo, 1997], job shop scheduling [van der Zwaan and Marques, 1999], flow shop scheduling [Stützle, 1998], vehicle routing [Bullnheimer *et al.*, 1999; Gambardella *et al.*, 1999], bus driver scheduling [Forsyth and Wren, 1997], tardiness scheduling problems [Bauer *et al.*, 1999; den Besten *et al.*, 2000], and resource-constrained project scheduling [Merkle *et al.*, 2000]. In most of these cases, the scheduling problem at hand is reduced to a TSP-like problem in which the problem is to find some optimal path through a graph of some sort.

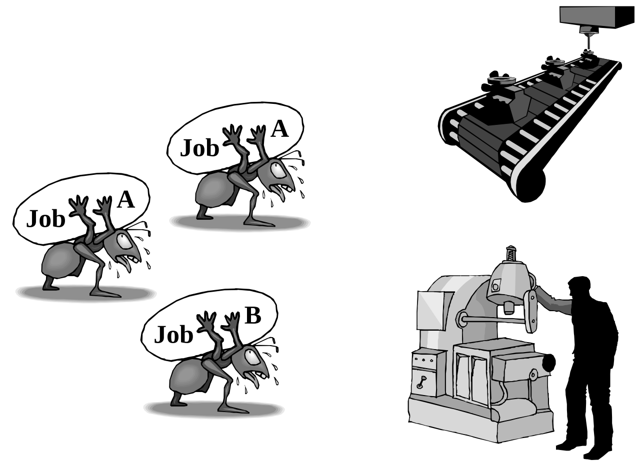

Figure 2: In the Ant Colony Control (AC^2) system of [Cicirello and Smith, 2001a], ant-like agents are assigned to jobs as they arrive at the factory. These "ants" make all routing decisions for their respective jobs stochastically biased according to quantities of artificial pheromone.

Scheduling problems need not be the only manufacturing related problems for which ACO is useful. An ACO-based algorithm can potentially be designed for any combinatorial optimization problem – although easier for some than for others. For instance, ACO seems particularly well suited to problems that require finding some optimal ordering of something. Many combinatorial problems often appear in the domain of manufacturing. For example, the largest common subgraph problem (LCSP) was used by Cicirello and Regli [Cicirello and Regli, 1999; 2001] for retrieving CAD models based on similarity. They used a hill climbing based approach to solve the problem. But perhaps ACO can be of use here (to my best knowledge ACO has not yet been used for the LCSP). If you arbitrarily order the nodes of one graph, the problem reduces to finding an ordering of the nodes of the second graph such that the implied node mapping of the respective orderings defines the largest common subgraph. And thus we have the problem in a form for which some variant of ACO should be well suited.

2.2 Dynamic Problems

The problems discussed so far that can be solved with ant-based algorithms have all been static problems. That is, the problem is defined at the beginning and does not change during problem solving. However, ant-based algorithms are not limited to static problems. For example, based on ACO Schoonderwoerd et al. [Schoonderwoerd *et al.*, 1997a; 1997b] have developed their Ant-Based Control (ABC) system for optimizing the routing tables in circuit-switched networks. And similarly, Di Caro and Dorigo [Di Caro and Dorigo, 1998a; 1998b] incorporate ACO techniques into their AntNet system for the optimization of package-switched network routing tables. These are both systems in which the state of the world is extremely dynamic.

Related to the domain of manufacturing, in [Cicirello and

Smith, 2001a] we presented an ACO-inspired algorithm for shop floor routing in a dynamic factory setting (see Figure 2). As they arrive in the factory, jobs are assigned to ants. These ants are in charge of making all routing decisions for their respective jobs. For single job type factories, our system is able to effectively balance machine load. For multiple job types, multipurpose machines, and sequence-dependent setups, by using multiple ant colonies (one for each job type) the system is able to converge to specialized product lines.

Although not based on ACO, in [Vaughan *et al.*, 2000a; 2000b], Vaughan et al. present a method based on ant trail following behavior and the dance behavior of bees for coordinating resource transportation by a team of robots in uncertain environments. Vaughan et al. list robotic supply columns in FMS as a potential application of their system. In their system, robots begin by searching randomly for the goal location. Upon attaining the goal, they return to the nest with a quantity of resource contained there. As a robot reaches the nest it announces to its teammates the path that it took. This is analogous to the way a foraging bee conveys the location of a food source to the hive upon returning with food through its dance language [Kirchner and Towne, 1994; von Frisch, 1967]. This path information is used by the robots to update a set of what Vaughan et al. call "crumbs". Now when foraging, the robots try to go in the average direction of all nearby "crumbs" in an analogous way to ants following pheromone trails.

Ant trail following behavior is not the only behavior of ants that has served as a useful basis for multi-agent coordination mechanisms. Deneubourg et al. [Deneubourg *et al.*, 1991] used a model of the brood sorting behavior of ants to coordinate a team of robots in the task of sorting different objects by color. Beckers et al. [Beckers *et al.*, 1994] applied a model of ant cemetery formation to coordinate multiple robots in the clustering of objects. Parunak and Brueckner [Parunak and Brueckner, 1999] have used methods based on ant coordination mechanisms for the missionaries and cannibals problem.

3 Coordination in Wasp Colonies

In [Theraulaz *et al.*, 1991], Theraulaz et al. present a model for the self-organization that takes place within a colony of wasps. Interactions between members of the colony and the local environment result in dynamic distribution of tasks such as foraging and brood care. In addition, a hierarchical social order among the wasps of the colony is formed through interactions among individual wasps of the colony. This emergent social order is a succession of wasps from the most dominant to the least dominant. Theraulaz et al. model these two aspects of wasp behavior as distinct behaviors without making any explicit connection between the two. We have used these two independent models of wasp behavior to develop coordination mechanisms for a multi-agent factory control system where each machine is modeled as a wasp nest comprised of wasp-like agents which take part in routing and scheduling activities as seen in Figure 3.

3.1 Applications of Task Allocation Behavior

The model of [Theraulaz *et al.*, 1991] describes the nature of interactions between an individual wasp and its local environment with respect to task allocation. They model the colony's self-organized allocation of tasks using what they refer to as response thresholds. An individual wasp has a response threshold for each zone of the nest. Based on a wasp's threshold for a given zone and the amount of stimulus from brood located in that zone, a wasp may or may not become engaged in the task of foraging for that zone. A lower threshold for a given zone amounts to a higher likelihood of engaging in activity given a stimulus. Bonabeau, Theraulaz, and Deneubourg discuss in [Bonabeau *et al.*, 1998] a model in which these thresholds remain fixed over time. But in [Theraulaz *et al.*, 1998], a threshold for a given task decreases during time periods when that task is performed and increases otherwise. Bonabeau et al. [Bonabeau *et al.*, 1997] demonstrate how this model leads to a distributed system for allocating mail retrieval tasks to a group of mail carriers.

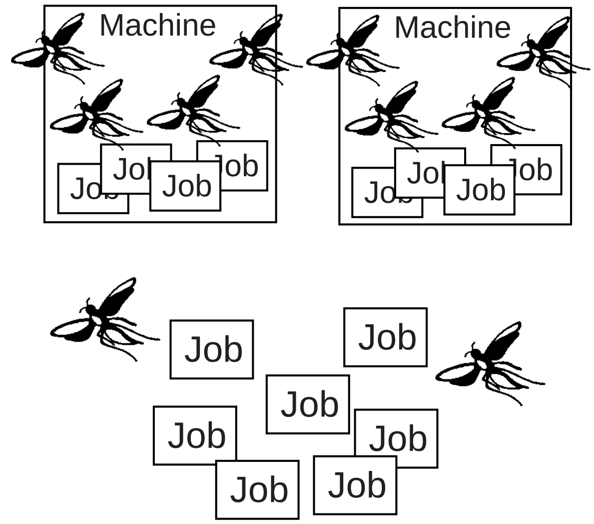

Figure 3: Machines in the factory are modeled as wasp nests comprised of colonies of wasp-like agents in charge of scheduling and routing activities. (Figure originally appeared in [Cicirello and Smith, 2001d].)

In [Cicirello and Smith, 2001d; 2001b], we present an approach to dynamic shop floor routing based on this computational model of wasp task allocation (see Figure 4 for an illustration of the approach). In factory environments comprised of multipurpose machines and sequence-dependent setups, our system successfully allocates jobs to the various machines, constrained by the job mix, so as to limit the amount of required setup time accrued by the system and thus optimize system throughput performance based on current product demands.

But this is not the only potential use for this wasp model of task allocation. One of the goals of Theraulaz et al. when they originally presented this model in [Theraulaz *et al.*, 1991] was to point out its potential use in coordinating teams of robots. Given a group of agents, whether they be hardware or software agents, with similar or overlapping capabilities, this model can be of great use in the self-coordination of task assignment amongst the agents. Manufacturing systems based

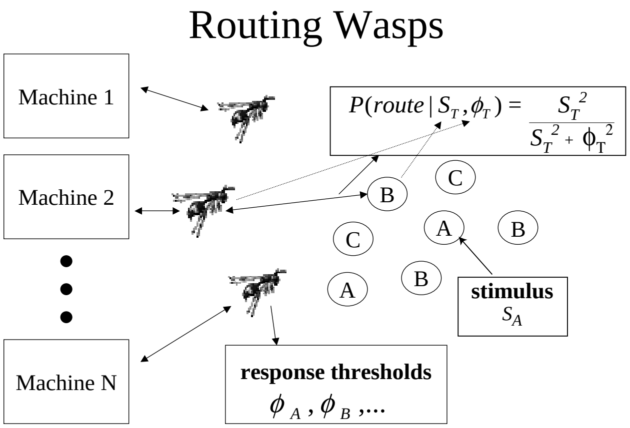

Figure 4: Routing wasps are wasp-like agents used for distributed assignment of jobs to machines based on the self-allocation of tasks among real wasps. Each wasp-like agent is in charge of routing jobs to its respective machine and maintains response thresholds for the different types of jobs its machine can process. (Figure originally appeared in [Cicirello and Smith, 2001b].)

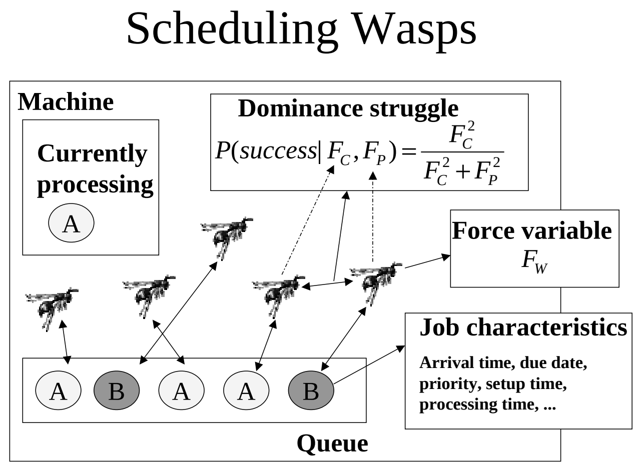

Figure 5: Scheduling wasps are wasp-like agents that use a model of the self-organized social hierarchies of real wasps to prioritize jobs in a machine's queue. Each wasp-like agent is in charge of a job in the queue and takes part in dominance contests with other scheduling wasps. The outcome of these contests determines the priorities of the respective jobs. (Figure originally appeared in [Cicirello and Smith, 2001c].)

on a multi-agent design paradigm can greatly benefit from such a model in distributing tasks among its various component agents.

3.2 Applications of Dominance Hierarchies

The model of [Theraulaz *et al.*, 1991] also describes the nature of wasp-to-wasp interactions that take place within the nest. When two individuals of the colony encounter each other, they may with some probability interact with each other. If this interaction takes place, then the wasp with the higher social rank will have a higher probability of dominating in the interaction. Social rank is modeled by what they call the individual's force variable F. And the successful wasp is chosen stochastically based on the force variables of the two wasps. The value of F is increased for the successful wasp and decreased for the unsuccessful. Through such interactions as these, wasps within the colony self-organize themselves into a dominance hierarchy. In [Theraulaz *et al.*, 1995], Theraulaz, Bonabeau, and Deneubourg discuss in greater detail the self-organization of dominance hierarchies among wasps. For example, they discuss a number of ways of modeling the probability of interaction during an encounter which range from always interacting to interacting based upon certain tendencies of the individuals.

To my knowledge, there are currently only two applications of this part of Theraulaz et al.'s model. The first we present in [Cicirello and Smith, 2001d; 2001c] where we use the concept of force to model job priority in a dynamic factory scheduling environment, and exploit this wasp-to-wasp interaction model to prioritize jobs in a given queue (see Figure 5 for illustration). High priority jobs correspond to high ranking wasps in the social hierarchy of the nest. In [Cicirello and Smith, 2001d] we were trying to optimize system throughput under the constraint of sequence-dependent setups. Currently, we are extending this model to the weighted tardiness objective [Cicirello and Smith, 2001c].

The second application we present in [Cicirello and Smith, 2001b] as a refinement to our shop floor routing approach. If two or more machines want the same job, they take part in a tournament of dominance contests to decide the winner. So in a sense, despite no connection between the two biological models of wasp behavior for task allocation and social hierarchy formation, we have combined aspects of both into an effective system for task assignment in a factory environment.

4 Conclusion

In this paper we presented a brief overview of example systems that have at their foundation the coordination mechanisms of insect societies. Some of these systems deal simply with statically defined manufacturing related problems; but others take a more active decision-making role in dynamic factory environments. From these examples, it is clear that computational models of complex biological systems offer promise as a means of designing and coordinating manufacturing processes. This makes sense since manufacturing systems and processes inherently require effective interaction among multiple agents in dynamic environments and the mechanisms employed by insect societies have survived the evolutionary cycle of survival of the fittest for millenia. We hope that you are now convinced that social insect coordination models deserve a place in the toolbox of the AI researcher working in the domain of manufacturing; or at the very least, we hope that you believe the answer to Hofstadter's question which began this paper is "Yes."

Acknowledgments

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