Coordinating Asynchronous Agent Activities in a Distributed Scheduling System *

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Abstract

In this paper we investigate issues of agent coordination in a distributed job-shop scheduling system in which agents schedule potentially contentious activities asynchronously in parallel. Agents in such a system will in general have a limited view of the global state of resources and must exchange appropriate state information with other agents in order to schedule effectively. However, even given perfect instantaneous knowledge of other agents' resource requirements, agents may still not be able schedule effectively if they do not also model the possible actions of other agents and the effects of their own actions. We describe two types of agent behaviors, poaching and distraction, arising from the asynchronous nature of distributed systems that decrease scheduling effectiveness and present the results of experiments testing new coordination mechanisms for preventing such behaviors.

1 Introduction

The scheduling of resources and activities is known to be an extremely difficult problem [4, 3, 9, 10]. In a distributed scheduling system, the complexity increases due to the possibility of interactions between scheduling agents such as when agents are allowed to borrow resources from each other to satisfy local goals. Examples of distributed scheduling applications include scheduling of machines in factory floor manufacturing, scheduling of airline ground services in an airport, and scheduling transportation of goods.

In this paper, we explore issues of agent coordination in distributed scheduling. In particular, we study the behavior of agents in an environment in which agents develop schedules simultaneously in batch mode, are cooperative, and agree to share resources.

In previous work, Neiman, *et. al.* [7] have investigated the questions of what types of meta-level information to communicate and how that information is to be used to schedule more effectively. We extend that work by investigating the lack of coordination among agents that can exist even when agents are able to model the global state of resources. We show that when agents are not able to model the state and possible future activities of other agents, they cannot schedule effectively [2]. We investigate two types of behavior resulting from this lack of coordination: *poaching* and *distraction*.

In the following section, we give a brief overview of our experimental sys-

tem, the Distributed Dynamic Scheduling System (Dis-DSS) and our problem domain, airport ground service scheduling. In section 3, we discuss in detail the agent coordination issues and agent behaviors on which we have focused in our most recent experiments with the Dis-DSS. In section 4, we present coordination mechanisms that we have added to our system and the results of experiments indicating that the quality of scheduling can be significantly improved by judicious synchronization of agent activities with no appreciable increase in run time. Finally, in section 5, we conclude and present directions for further study.

2 Experimental System

Our experimental system for investigating resource-constrained scheduling problems is a distributed version of the Dynamic Scheduling System (DSS) [5]. The DSS is a micro-opportunistic scheduler based on a blackboard architecture. A problem instance consists of a set of orders and a set of resources. Each order is represented as a set of tasks and subtasks, and each subtask requiring a resource is assigned a service goal. Service goals are continually re-rated based on the tightness of constraints on the particular task and required resource. The system decides which task to schedule based on a "most-constrained variable" heuristic. At each time step, the system attempts to reserve resources for those goals that are deemed to be most constrained. Service goals are satisfied by attempting three progressively costly methods:

Assignment An assignment simply reserves an available resource to satisfy a service goal.

Preemption A preemption cancels an existing reservation so that the resource can be reserved for a more constrained service goal. It is a limited form of backtracking.

Right-shift A right-shift forcibly relaxes the latest-finish-time constraint in order to satisfy a service goal that would otherwise go unsatisfied. In other words, the time interval of the reservation is shifted later than the service goal's allowable finish time. This almost always causes decreased solution quality in the form of late orders and is a method of last resort.

The Distributed Dynamic Scheduling System (Dis-DSS) [7] extends the DSS by partitioning the order and resource sets and distributing the partitions among several agents. Dis-DSS is a cooperative environment. When unable to satisfy a service goal locally, agents can generate requests in which they ask another agent to satisfy the goal. Agents operate asynchronously, simultaneously developing schedules for their respective order sets.

Each agent is essentially a DSS scheduling agent but uses additional control heuristics to account explicitly for the fact that it is operating in a multi-agent system where other agents are reserving resources at the same time. Heuristics from the single agent DSS system cannot be applied unchanged to a multi-agent system, an observation also made by Decker, *et. al.* in their work on developing control paradigms for a parallel blackboard system [1].

Our test-bed system built on top of Dis-DSS is the Distributed Airport Resource Management (Dis-ARM) system. Dis-ARM solves airport ground service scheduling (AGSS) problems. Each agent is assigned a set of orders, which in the AGSS domain are flights requiring ground service such as loading/unloading baggage, cleaning, refueling, etc. Agents are responsible for scheduling ground service so that its flights are able to meet arrival and departure deadlines.

Each agent also owns a set of resources such as gates, baggage trucks, cleaning trucks, fuel trucks, etc. In general, the reservation of a resource for a given task must account for setup and travel times of resources as well as the actual servicing times. These times are dependent upon the type and location of individual resources. Individual resources of the same type are not considered interchangeable. Only the agent owning a particular resource will have exact information regarding the time needed for setup and travel. In addition, because of communication delays, an agent can more readily access it own individual resources than resources owned by another agent.

The search space of alternatives available to the scheduler is quite large due to the number of possible resources, the number of tasks to be scheduled, and the number of constraints between subtasks. Moreover, the search space is dynamic because requests for resources may arrive from other agents at any point during scheduling.

3 Coordination in Distributed Scheduling

In a distributed system, scheduling agents may not have a complete view of global resource availability and demand. To enable more effective scheduling, Dis-DSS agents exchange meta-level control information in the form of texture measures [11], abstract representations of an agent's resource availability, current resource usage, and estimated future demand. By obtaining texture measures from other agents, an agent can build a more global view of the status of resources. Agents use this information to make decisions regarding what service goals to schedule next (based on which are most constrained) and how to satisfy service goals (whether to use a local resource or request a resource from another agent). Agents can also use the information to determine which agents are likely to have a surplus of a given type of resource and thus are good candidates from which to request resources. However, even with complete information about the state of resource availability, agents may not be able to schedule in a globally optimal manner if they do not explicitly account for the possible actions of other agents in the system [2].

In the following sections, we describe two agent behaviors, *poaching* and *distraction*, that may decrease scheduling performance. We use the following notation for describing the conditions under which these behaviors can occur. Let $g^x_{a,i}$ denote service goal i for agent a requiring resource type x, (where a resource type is the set of resources that can satisfy the service goal). Let $R(g^x_{a,i}, t)$ denote the rating at time t of service goal $g^x_{a,i}$ and $E(g^x_{a,i})$ denote its execution time, i.e. the time when agent a attempts to reserve a resource of type x for service goal i.

The best-first heuristic used by each scheduling agent can then be expressed as

$$E(g^x_{a,i}) = t \;\Leftrightarrow\; \forall y \, \forall j \neq i \; R(g^x_{a,i}, t) \geq R(g^y_{a,j}, t) \tag{1}$$

This simply states that agent a will execute service goal i at time t if and only if it is the most highly rated of agent a's goals at time t.

3.1 Poaching

We define a poaching event as one in which an agent reserves a resource, thereby preventing another agent with a more constrained or critical goal from securing that resource. Poaching activity arises due to the fact that

there are multiple agents scheduling asynchronously using a best-first heuristic. An agent may make a locally correct decision by satisfying its most highly rated service goal, but this may not be the appropriate action in a global context – another agent may have a more highly rated goal that overlaps this goal and could be satisfied by the same resource. Poaching activity leads to decreased solution quality when the "poached" goal can no longer be satisfied without expensive constraint relaxation or backtracking activities.

Note that poaching can still be a problem even if two goals requiring the same resource type do not directly overlap temporally. When the resources involved become highly constrained (they are globally scarce or need to be reserved for long periods of time), service goals that normally do not overlap directly will begin to feel the effects of poaching activity due to reduced flexibility in the schedule and the reduced ability of the scheduler to exploit slack in the schedules.

We have defined two general classes of poaching activity.

Type-1 Poaching At time t, agent A and agent B both have as their most highly rated service goals, goals requiring the same resource type X. However, agent B's rating is much lower than agent A's indicating that agent B's goal is less constrained. Because the service goal requiring resource type X is agent B's highest priority, agent B can still reserve the required resource before agent A, despite the lower rating of agent B's service goal. Figure 1(a) shows an example of such a poaching situation.

Formally, we express the situation as

$$\forall x \, \forall k \neq i \; R(g^X_{A,i}, t) \;>\; R(g^x_{A,k}, t) \tag{2}$$

$$\forall x \, \forall l \neq j \; R(g^X_{B,j}, t) \;>\; R(g^x_{B,l}, t) \tag{3}$$

$$R(g^X_{A,i}, t) \;\gg\; R(g^X_{B,j}, t) \tag{4}$$

From equations 1, 2, and 3 we obtain

$$E(g^X_{A,i}) = E(g^X_{B,j}) = t \tag{5}$$

and combining equation 5 with equation 4 we have the following condition:

$$R(g^X_{A,i}, t) \gg R(g^X_{B,j}, t) \;\wedge\; E(g^X_{B,j}) = E(g^X_{A,i}) \tag{6}$$

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Goal Ratings for Agent 2 at Time 51
GOAL-#177 (5024 5051) BAGGAGE-TRUCK  1353 22
GOAL-#213 (5008 5050) BAGGAGE-TRUCK  1180 25
GOAL-#212 (5029 5056) BAGGAGE-TRUCK   666 30
GOAL-#104 (5015 5031) CLEANING-TRUCK  148 43
GOAL-#98  (5014 5032) FUEL-TRUCK      146 45

Goal Ratings for Agent 1 at Time 51
GOAL-#173 (5027 5050) BAGGAGE-TRUCK  3570  5
GOAL-#184 (5024 5050) BAGGAGE-TRUCK  3537  8
GOAL-#191 (5024 5050) BAGGAGE-TRUCK  3537  7
GOAL-#159 (4997 5033) BAGGAGE-TRUCK  3336  9
GOAL-#123 (5019 5046) BAGGAGE-TRUCK  2659 12

Goal Ratings for Agent 0 at Time 51
GOAL-#45  (5009 5035) BAGGAGE-TRUCK  7103  0
GOAL-#38  (5009 5036) BAGGAGE-TRUCK  5283  1
GOAL-#84  (5016 5041) BAGGAGE-TRUCK  3945  2
GOAL-#59  (5009 5036) BAGGAGE-TRUCK  3877  3
GOAL-#73  (5009 5036) BAGGAGE-TRUCK  3877  4
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(a) An example of a type-1 poaching situation. Agent 2 is able to reserve a baggage truck for goal #177 even though is has a much lower rating than agent 0's top-rated goal #45.

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Goal Ratings for Agent 2 at Time 868
GOAL-#157 (4853 4882) CLEANING-TRUCK  5994   0
GOAL-#194 (4863 4887) CLEANING-TRUCK  4716   1
GOAL-#187 (4865 4887) CLEANING-TRUCK  4689   2
GOAL-#188 (4865 4887) FUEL-TRUCK      4231   3
GOAL-#130 (4860 4885) FUEL-TRUCK      3915   5
GOAL-#90  (4857 4880) CLEANING-TRUCK  3907   6

Goal Ratings for Agent 1 at Time 868
GOAL-#6   (4847 4868) CLEANING-TRUCK  3993   4
GOAL-#224 (4865 4892) CLEANING-TRUCK  2537  15
GOAL-#177 (4871 4896) BAGGAGE-TRUCK   1272  41
GOAL-#201 (4852 4890) CLEANING-TRUCK  1272  40
GOAL-#65  (4847 4880) SERVICE-TRUCK   1213  44
GOAL-#51  (4848 4880) SERVICE-TRUCK   1196  48

Goal Ratings for Agent 0 at Time 868
GOAL-#118 (4858 4891) SERVICE-TRUCK    232  99
GOAL-#160 (4823 4891) SERVICE-TRUCK    120 107
GOAL-#36  (4851 4876) CATERING-TRUCK    75 111
GOAL-#59  (4848 4880) CATERING-TRUCK    73 116
GOAL-#179 (4872 4895) CATERING-TRUCK    61 125
GOAL-#140 (4855 4891) CATERING-TRUCK    55 133
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(b) An example of a type-2 poaching situation. Agent 0 is able to reserve a service truck for goal #118 before agent 1 is able to process goal #65 which is much more highly rated.

Figure 1: Trace listings showing the top-rated service goals for each agent in a three-agent system. Each line reporting service goal information contains the goal's number, time interval for which a resource is needed, resource type required, rating, and global ranking. Note that one agent may frequently have the top N-ranked goals.

In this situation, poaching is possible because both agents execute their service goals at the same time step, and therefore it is possible (due to varying response times to remote requests for resources) that agent B can obtain a resource reservation before agent A despite that fact that agent B's service goal has a much lower rating.

Type-2 Poaching At time t, agent A and agent B both have service goals requiring the same resource type X. The ratings for agent A are higher or the same as those for agent B. For agent B, these are its most highly rated service goals. If agent A also has service goals requiring resource type Y, and these are its most highly rated goals (and thus more highly rated than its service goals requiring resource type X), then agent B

can reserve resources of type X while agent A is working on scheduling resources of type Y. Figure 1(b) shows an example of such a situation.

Formally, we express the situation as

$$\forall x \, \forall k \neq i \; R(g^Y_{A,i}, t) > R(g^x_{A,k}, t) \quad (7)$$

$$\forall x \, \forall l \neq j \; R(g^X_{B,j}, t) > R(g^x_{B,l}, t) \quad (8)$$

$$R(g^X_{A,m}, t) \geq R(g^X_{B,j}, t) \quad (9)$$

From equations 1, 7, and 8 we obtain

$$E(g^X_{B,j}) = E(g^Y_{A,i}) = t \quad (10)$$

From equation 7, we know that

$$R(g^Y_{A,i}, t) > R(g^X_{A,m}, t) \quad (11)$$

and thus

$$E(g^Y_{A,i}) < E(g^X_{A,m}) \quad (12)$$

Finally, combining equations 9, 10, and 12 we have the following condition

$$R(g^X_{A,m}, t) \geq R(g^X_{B,j}, t) \; \wedge \; E(g^X_{B,j}) < E(g^X_{A,m}) \quad (13)$$

In this situation, poaching is quite likely because agent B executes its service goal earlier than agent A.

If the poaching activity continues and resource type X becomes constrained, then eventually agent A's ratings for service goals requiring resource type X will rise to be the most highly rated, and agent A will begin competing with agent B for the same resources. Depending on the global resource availability of that resource type and on the communication delay for exchanging texture measures, the damage can be done before agent A is able to respond. In fact, in some situations we do not want agent A to respond at all because shifting agent A's attention away from resource type Y to compete for resources of type X can have a detrimental effect on overall scheduling performance as we will see in the next section.

Finally, an interesting phenomenon in a distributed system is that an agent can actually "poach" on its own goals (that is, satisfy goals out of

order) due to the communication delays in dealing with remote requests. An agent may execute service goals in order with respect to their ratings, but the times at which the resources are actually reserved (which depend on the actions of other agents) may not be in order.

3.2 Distraction

One effect of the use of texture measures combined with a most-constrained-variable heuristic in a micro-opportunistic system is that agents tend to synchronize their scheduling activities. As agents begin to reserve resources, a particular type of resource becomes constrained and service goals requiring that resource type become more highly rated causing agents to increasingly focus on scheduling those service goals. This causes more reservations of the given resource type causing the resource to become even more constrained. This feedback process continues until eventually, all agents are focused on scheduling the same type of resource, the globally most constrained type.

Synchronization can be an undesirable feature in some situations. Not only does it promote poaching, the exchange of texture measures, by providing agents with a global view, allow agents to be distracted by the scheduling activities of other agents. *Distraction* [6] occurs whenever an agent receives information from another agent and based on this information pursues an undesirable course of action. In our system, we have encountered an analog to distraction in which an agent is prevented from executing important precursor activities by the increasing pressure of external events. Note that in [6], distracting information had the connotation of being noisy or misleading and the receiving agent had the responsibility of interpreting it as such and pursuing more critical computations. Here, we present a situation in which the communicated information is good, and the receiving agent is placed on the horns of a dilemma; either it reacts to the incoming information, leaving time critical processing unperformed, or it ignores the new information, thereby failing to compete for critical resources. Unlike the original distraction scenario encountered in HEARSAY, it is the *distracting* agent that should act responsibly, either by working in a less globally sensitive area or by simply idling until other agents are capable of synchronizing planning activities. Such behavior is only possible if the distracting agent has enough information to gauge the effects of its actions.

Distraction is particularly evident in our system in cases where agents possess dramatically different loads. An agent who has very few orders to

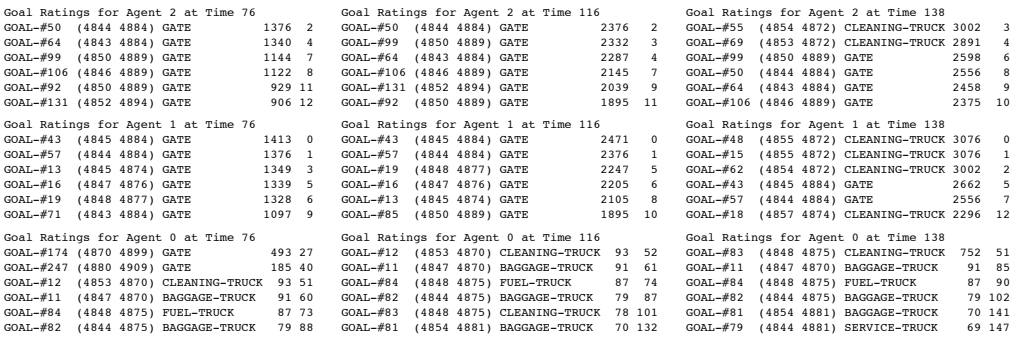


Figure 2: An example of distraction. Agent 0 has finished assigning gates before the other two agents and has begun to assign cleaning trucks. This forces agents 1 and 2 to begin competing for cleaning trucks instead of finishing their gate assignments.

schedule relative to other agents can begin scheduling certain resources well before other agents. This may cause a resource to become constrained, which in turn causes other agents to begin scheduling that resource instead of what they were scheduling. This is a problem when the order in which resources are scheduled is important. For example, in the AGSS domain, scheduling a gate location for a flight allows the scheduler to better estimate travel times for other resources such as baggage trucks and fuel trucks needed to service that flight. Without a fixed gate assignment, the scheduler must assume the maximum travel time when scheduling these other resources; this can cause a task to appear more constrained than it really is. It is clearly beneficial for agents to schedule gates early on in a scheduling episode. In the situation with an unbalanced load among agents, one agent can distract other agents from scheduling gates early. Figure 2 shows an example trace of such a situation.

For the Dis-ARM system, we would like for the following to be true

$$\forall a, i, j \, \forall y \neq G \;\; E(g^y_{a,i}) > E(g^G_{a,j}) \tag{14}$$

where G represents the gate resource type. That is, we would like each agent to finish executing their service goals requiring gates before starting to execute other service goals.

If the order distribution is not balanced evenly among agents we have the possibility that an agent (say B) may begin to schedule at time t_1 a non-

gate resource type $Y \neq G$ before another agent A has finished all of its gate assignments:

$$E(g^Y_{B,i}) = E(g^G_{A,j}) = t_1 \tag{15}$$

This creates a possible increase in agent A's rating of goals requiring resource type Y, and at some time $t_2 > t_1$ we may have

$$R(g^Y_{A,k}, t_2) > R(g^G_{A,l}, t_2) \tag{16}$$

and thus

$$E(g^Y_{A,k}) < E(g^G_{A,l}) \tag{17}$$

which violates our desired condition that all agents schedule gates before any other resource type.

In the next section we present coordination mechanisms for addressing the problems of poaching and distraction and the results of experiments for testing their effectiveness.

4 Discussion of Experimental Results

In the following sections, we present coordination mechanisms for addressing the problems of poaching and distraction, and we present the results of experiments for testing their effectiveness. We show the effect of adding these mechanisms to two reference systems: (1) a system in which agents only have a local view of resource availability and demand (which we refer to as the "local-view heuristic") and (2) a system in which agents exchange texture measures for building a global view of resources (which we refer to as the "texture-based heuristic").

Because of the complexity of interactions among scheduling agents, the addition of our new coordination mechanisms does not guarantee an increase in scheduling performance in all cases. For some individual runs, we observe a decrease in performance, but on average, the system performance increased significantly. Performance is measured in terms of the total tardiness in the schedules of all agents (and thus, smaller numbers are better with zero tardiness being the best). For each performance comparison we present the results for each individual run as well as the average difference in performance. We also present significance values (p-values) for the matched pair t-test.

Each set of experiments consists of 21 runs, grouped into five different load distribution conditions (see table 1(a)). Each run within a condition

Run #	Number of orders: Agent 0	Agent 1	Agent 2
1-5	16	16	17
6-10	10	16	23
11-15	10	10	23
16-20	5	22	22
21	0	0	49

(a) Order distribution for each set of experiments.

Resource type	Number of resources: Agent 0	Agent 1	Agent 2
Gates	17	16	16
Fuel trucks	6	6	6
Catering trucks	4	4	4
Service trucks	1	2	2
Baggage trucks	11	11	11
Cleaning trucks	3	3	2

(b) Resource distribution for all experiments.

Table 1: Order and resource distributions among agents.

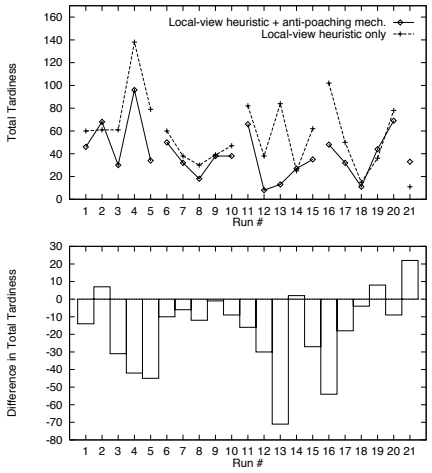
has a different order distribution among three agents (orders were assigned randomly). Orders are taken from a set of 49 actual Northwest Airlines flights requiring service at Detroit International Airport during a one hour period.

Resources are distributed more or less evenly among the agents for all runs. The total number of resources is set to be minimally sufficient for satisfying the requirements of the 49 orders. Table 1(b) gives the exact resource distribution among the three agents.

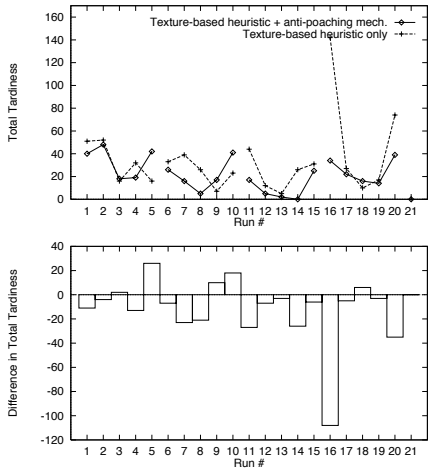
We include one order distribution that assigns all 49 orders to a single agent in order to approximate a centralized scheduler. It is an approximation in that one agent must schedule all of the orders but it does not own all the resources and will need to request resources from other agents. Because the other agents do not have any orders of their own to schedule, these requests will be handled promptly. This "centralized" scenario produced very good results indicating that the tardiness we encounter during scheduling is, in fact, an artifact of the asynchronous and distributed nature of the system.

4.1 Anti-poaching Mechanism

We hypothesize that in order to prevent poaching, agents need to communicate goal ratings for their top n service goals in addition to information about resource supply and usage in the texture measures. By exchanging this information agents can determine whether their top priority scheduling



(a) Local-view heuristic. Average change in total tardiness is -17.1 (standard error = 4.9, p-value = 0.0011).



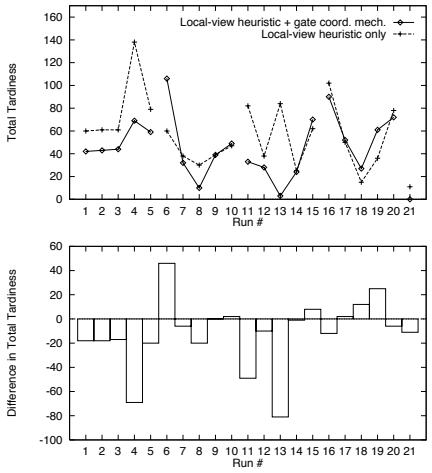
(b) Texture-based heuristic. Average change in total tardiness is -11.3 (standard error = 5.8, p-value = 0.033).

Figure 3: Change in performance due to the anti-poaching mechanism.

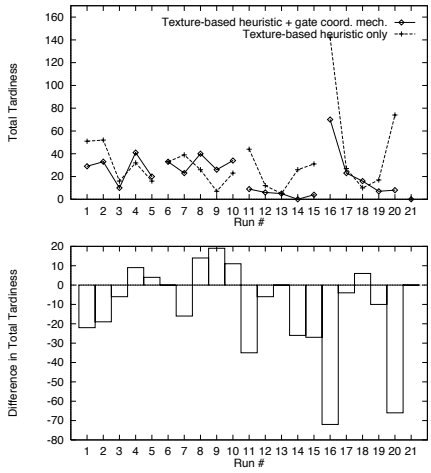
activities would poach on another agent's activities. Our anti-poaching mechanism works as follows: Before scheduling a service goal, each agent checks whether the goal is rated above a given threshold and therefore accessing a highly contested resource. It then checks whether any other agent has a service goal that is rated much more highly (where "much" is a parameterized value) than its own, and if so the agent will not schedule its service goal but instead idle to avoid a possible poaching activity.

Both heuristics show a significant performance increase with the addition of the anti-poaching coordination mechanism. Figures 3(a) and 3(b) show the change in total tardiness observed in our experiments.

It is interesting to note that the anti-poaching mechanism improves performance for the local heuristic as well as the texture heuristic. Our mechanism is based on exchanging information about agents' goal ratings and assumes that these goal ratings are comparable so that the decision about which agent has the more constrained goal is correct. With the texture-based heuristic, agents are able to build a view of global resource constraints and thus ratings are comparable. With the local-view heuristic, it is not immedi-



(a) Local-view heuristic. Average change in total tardiness is -11.6 (standard error = 6.2, p-value = 0.038).



(b) Texture-based heuristic. Average change in total tardiness is -11.7 (standard error = 5.2, p-value = 0.033).

Figure 4: Change in performance due to the gate coordination mechanism.

ately obvious that ratings are comparable. However, an agent with a locally highly constrained resource (and corresponding highly rated goal) will benefit from the opportunity to rapidly transmit requests regarding that resource to other agents.

4.2 Gate Coordination Mechanism

In our AGSS domain, distraction is primarily a problem when agents are distracted from scheduling gates early on in a scheduling episode. To prevent this distraction effect, we have added a gate coordination mechanism to DisARM which simply disallows scheduling of resources other than gates until all agents have finished their gate assignments. Obviously, a similar heuristic can be developed for any sufficiently critical prerequisite operation in a scheduling or planning environment.

Both local and texture-based heuristics show a significant performance increase with the addition of the gate coordination mechanism. Figures 4(a) and 4(b) show the change in total tardiness observed in our experiments.

Coordination mechanism	Avg. diff. in tardiness	p-value
none	-24.4	6.8
Anti-poaching	-24.6	5.4
Gate	-18.6	4.2

Table 2: Average difference in performance between the local heuristic and the texture heuristic.

Heur/Mech	Total KS	p-value	Preempt KS	p-value
Local/Gate	-77.5	0.002	-5.1	0.038
Local/Anti-poach	41.4	0.6	2.2	0.672
Texture/Gate	-112.1	0.003	-7.8	0.004
Texture/Anti-poach	-99.5	0.04	-9.9	0.017

Table 3: Average change in total number of KS executions and the average change in number of KS executions that are preemptions.

4.3 Effectiveness of Texture Measures

In previous work, Neiman *et. al.* have shown the effectiveness of using the information contained in the communicated texture measures for scheduling [7, 8]. Here, we present a similar comparison of scheduling performance with and without the use of texture measures. The following data are the same as those presented in the previous two sections, but are displayed so that the texture-based heuristic and local heuristic are directly compared.

Figures 5, 6(a), and 6(b) show the difference in performance between the local-view heuristic and the texture-based heuristic with and without the additional coordination mechanisms. Even though the local heuristic does gain by using the additional mechanisms, the texture-based heuristic still performs significantly better when using the same coordination mechanisms. Table 2 gives the average decrease in total tardiness and significance values for the three cases.

4.4 Effect of Coordination Mechanisms on Parallelism

While our coordination mechanisms decrease total tardiness in flight schedules, they also decrease parallelism which in turn may lead to increased run times. We have found that on average, run times in fact do not increase and in some cases even decrease. This is due to fewer backtracking episodes;

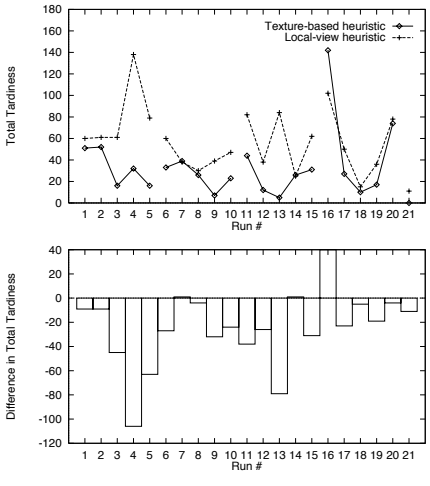
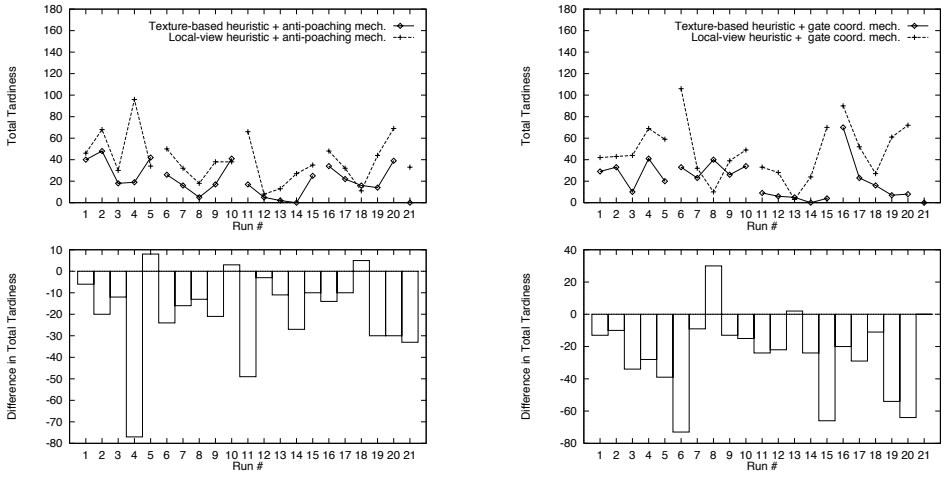


Figure 5: Difference in performance between texture-based heuristic and local-view heuristic with no additional coordination mechanisms.



(a) Anti-poaching mechanism.

(b) Gate coordination mechanism.

Figure 6: Difference in performance between the texture-based heuristic and local-view heuristic with coordination mechanisms in place.

by enforcing idleness in agents that may be about to poach or distract, the mechanisms reduce the number of mistakes that must be undone later. The amount of time spent idle is compensated by avoiding costly chains of backtracking.

Table 3 shows the average change (along with the p-value significance for the paired t-test) in the number of knowledge source (KS) executions due to the addition of our mechanisms. The table shows the average change in the total number of KS executions (a measure of system run time) and the average change in number of KS executions that are preemptions (a measure of backtracking) for each mechanism and heuristic tested.

We see that in most cases, there is a decrease in system run time and in the amount of backtracking performed. One exception was that the addition of the anti-poaching mechanism to the local heuristic did not significantly change the run time or amount of backtracking performed. This is not unexpected because the anti-poaching mechanism is only truly effective if the underlying system makes use of non-local information about goal ratings.

5 Conclusions and Future Work

In an attempt to understand better the issues involved in distributed scheduling we have investigated in detail the dynamic behavior of the Dis-DSS scheduler. In doing so, we have observed poaching and distraction events affecting the performance of the distributed scheduling system and have developed simple mechanisms to reduce or eliminate such events. Our mechanisms suggest that in addition to state information about resource availability, agents need to model the likely future actions of other agents.

While our mechanisms have been shown to increase schedule quality, they are also highly serializing. By enforcing idle time for agents that are about to poach or distract, the mechanisms we have described reduce the parallelism that is the *raison d'être* for distributed systems. Although we have also shown that this reduction in parallelism does not increase the system run time, we hope to develop more sophisticated mechanisms that prevent agents from poaching or distracting while allowing them to pursue other scheduling activities that will not negatively affect other agents. One possible way to do this is to consider higher level classes of activities rather than individual service goals.

Finally, the complexity of a real-world domain such as the AGSS has lim-

ited us to studying relatively small problem instances. A better understanding of distributed systems may be gained by looking at problem instances with many more orders and scheduling agents. In the near term, we plan to continue testing our system on additional sets of orders to give us a better understanding of the issues in distributed scheduling.

References

[1] Keith S. Decker, Alan J. Garvey, Marty A. Humphrey, and Victor R. Lesser. Control heuristics for scheduling in a parallel blackboard system. *International Journal of Pattern Recognition and Artificial Intelligence*, 7(2), 1993.

[2] Edmund H. Durfee, Victor R. Lesser, and Daniel D. Corkill. Coherent cooperation among communicating problem solvers. *IEEE Transactions on Computers*, 36(11), 1987.

[3] Mark S. Fox. *Constraint-Directed Search: A Case Study of Job-Shop Scheduling*. PhD thesis, Carnegie Mellon University, Pittsburgh, PA, December 1983.

[4] Michael R. Garey and David S. Johnson. *Computers and Intractability: A Guide to the Theory of NP-Completeness*. W.H. Freeman, New York, 1979.

[5] David W. Hildum. *Flexibility in a Knowledge-Based System for Solving Dynamic Resource-Constrained Scheduling Problems*. PhD thesis, Computer Science Department, University of Massachusetts, Amherst, MA, May 1994.

[6] Victor R. Lesser and L. D. Erman. Distributed interpretation: A model and an experiment. *IEEE Transactions on Computers – Special Issue on Distributed Processing*, C-29(12):1144–1163, December 1980.

[7] Daniel E. Neiman, David W. Hildum, Victor R. Lesser, and Tuomas W. Sandholm. Exploiting meta-level information in a distributed scheduling system. In *Proceedings of the Twelfth National Conference on Artificial Intelligence*, Seattle, WA, July 1994.

[8] Daniel E. Neiman and Victor R. Lesser. A cooperative repair method for a distributed scheduling system. In *Proceedings of the Third International Conference on Artificial Intelligence Planning Systems*, Edinburgh, Scotland, May 1996.

[9] Norman Sadeh. *Look-Ahead Techniques for Micro-Opportunistic Job Shop Scheduling*. PhD thesis, Carnegie Mellon University, Pittsburgh, PA, March 1991.

[10] Stephen F. Smith, Mark S. Fox, and Peng Si Ow. Constructing and maintaining detailed production plans: Investigations into the development of knowledge-based factory scheduling systems. *AI Magazine*, 7(4):45–61, Fall 1986.

[11] K. Sycara, S. Roth, N. Sadeh, and M. Fox. Distributed constrained heuristic search. *IEEE Transactions on System, Man and Cybernetics*, 21(6), December 1991.