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Marc Gravel, Wilson L. Price, Caroline Gagné

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Scheduling continuous casting of aluminum using a multiple-objective ant colony optimization metaheuristic

Marc Gravel [(1)], *Wilson L. Price* [(2)] & *Caroline Gagné* [(2)]

(1) Département d'informatique et mathématique, Université du Québec, Chicoutimi, Québec, G7H 2B1

(2) Faculté des sciences de l'administration, Université Laval, Québec, Québec, G1K 7P4

Abstract

This paper presents an ant colony optimization metaheuristic for the solution of an industrial scheduling problem in an aluminum casting center. We present an efficient representation of a continuous horizontal casting process which takes account of a number of objectives that are important to the scheduler. We have incorporated the methods proposed in software that has been implemented in the plant.

Keywords: scheduling, metaheuristic, ant colony optimization, aluminum, casting, multiple objectives

Résumé

Ce document présente l'utilisation de l'optimisation par colonie de fourmis pour la résolution d'un problème d'ordonnancement industriel dans un centre de coulée d'aluminium. Nous proposons une représentation efficace d'un processus de coulée horizontale tenant compte des objectifs multiples des planificateurs. Ces méthodes sont incorporées dans un logiciel qui est implanté dans l'usine.

Mots-clés: ordonnancement, métaheuristique, optimisation par colonie de fourmis, aluminium, coulée, objectifs multiples

Introduction

In their surveys of the literature, both MacCarthy & Liu [1993] and Bjorndal *et al.* [1995] noted that many published scheduling papers are limited to the treatment of simple, basic problem situations. They feel that this has contributed to creating a gap between theory and industrial practice. This paper addresses this concern and presents results of our industrial scheduling work using metaheuristics. We obtain an efficient representation of a continuous horizontal casting operation using an ant colony optimization metaheuristic and take into account several objectives that are important to the scheduler.

In many industrial situations, exact optimization algorithms require overlong solutions times and cannot produce an acceptable or even feasible solution in the time available. It may also be awkward to represent some of the necessary constraints or objective function characteristics in the algebraic form required by classical optimization methods. It is therefore natural to turn towards the use of metaheuristics which have been shown to offer successful solution strategies for many problems. In their review of solution techniques that have been used for scheduling flexible shops, Blazewicz *et al*. [1996] note that methods such as simulated annealing, tabu search and genetic algorithms are frequently used and have been shown to be powerful techniques for this task. Elsewhere in the scheduling literature, we find the use of neural networks (Huang & Zhang [1994], Sabuncuoglu & Gurgun [1996]) as well as ant colony optimization (Colorni *et al.* [1994], Stützle [1998]).

In their classifications of scheduling problems, Belton & Elder [1996] as well as Nagar *et al.* [1995] point out that reports of research into multiobjective industrial scheduling problems are relatively rare and that this avenue of research is promising. Since that time, a number of studies of multiobjective scheduling have been published. Murata & Ishibuchi [1996], Ishibuchi & Murata [1998], Cavalieri et Gaiardelli [1998], Fanti *et al.* [1998], Brandimarte [1999] et Santos et Dourado [1999] have worked with multiobjective genetic algorithms. Min *et al.* [1998] and

Kim *et al.* [1998] used multiobjective neural networks. Marett & Wright [1996] and Ruiz-Torres et al [1997] proposed the use of simulated annealing in a multiobjective setting. Brandimarte & Calderini [1995] and Marett & Wright [1996] chose multiobjective tabu search methods for the scheduling problems that they treated.

Problem description

This paper treats a scheduling problem encountered in an Alcan aluminium foundry located in the Saguenay region of Québec. In this foundry, two holding furnaces are charged with molten metal from a transfer crucible coming from the refiners as shown in Figure 1. These furnaces continuously feed liquid metal to the horizontal casting rig. A customer's order has specific characteristics, which are the alloy type, the number of pieces to be produced, the dimensions of these pieces and the delivery date. A customer's alloy specification is produced by adding the required ingredients and grain refiners to the molten aluminium in the holding furnaces. These furnaces serve to keep the aluminium in flux while the various ingredients are added. Molten aluminum is poured into channels leading to a basin and a mold having the crossection of the desired ingots. The aluminum flows through the mold taking the proper crossectional shape and, at the same time, fuses. Since the casting is continuous, a large automated circular saw cuts the fused aluminum into the required ingot lengths as it is produced. Changes in the length of ingots produced may be made simply by changing the program of the saw. If the crossection must be changed, then casting must be stopped and the mold changed. A change in the alloy being produced may also require a draining and cleaning to prevent contamination of the alloy to be cast next.

This casting center is amply supplied with pure molten aluminum by several nearby electrolysis plants. However, should the horizontal casting machine lack molten metal for any reason, it will require a costly shut-down and cleaning even if ingots of the same characteristics are to be produced when operations resume. Care must therefore be taken to manage the supply of metal in the two holding furnaces to ensure that the flow of metal to the casting machine is not interrupted. Casting must be restarted with a different mold while the previous one is cleaned. This event will therefore require the rescheduling of all remaining orders including the uncast portion of the stopped order.

The holding furnaces are charged with molten pure metal coming from the refiners as well as with solid metal from various sources. This solid metal, called “remelt”, may be scrap from previous operations or may be purchased from outside suppliers. It can be used to compensate for momentary penuries in metal supply. These occur because the transfer crucible has a capacity of 16MT while each holding furnace can take up to 21MT. If the transfer crucible is itself low in molten metal or empty from previous pours, the furnace will be charged partly or totally with remelt. This will affect the holding furnace preparation time because the solid metal must melt. Stoppages on the casting rig can be avoided if, while one holding furnace supplies metal for the pour, the second is prepared and loaded. The speed of a pour depends on the alloy type and on the number of pieces in the mold. The preparation time of a holding furnace is a function of the quantity of molten metal used, the quantity of solid metal used, and of any draining and cleaning required.

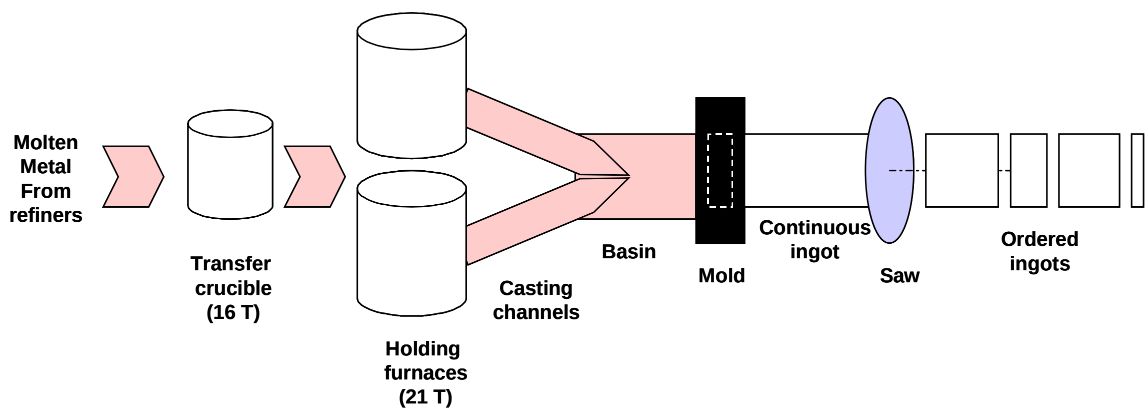
As mentioned above, a change of alloy will also affect the holding furnace preparation time. The metallurgical composition of the new alloy may require that the holding furnace be drained and cleaned before the pour.

The basin (Figure 1) is a holding chamber that retains a small amount of molten metal just before the mold and the availability of basins constitutes a further technological constraint. Molds may be attached only to specific basins and the one required may be undergoing cleaning from a previous usage. For some dimensions, only one example of a basin is available and so some otherwise feasible sequences must be eliminated because successive pours using different molds require the same basin.

A feasible sequence of orders is one that ensures that sufficient pure metal is available for all pours, that basins and molds are available when required for each order and that draining and cleaning of the rig is done when required. A desirable feasible sequence takes into account the objectives of customer service and efficiency. We model the objectives of the scheduler by treating the minimization of unweighted total tardiness for all orders, the minimization of unused production capacity over the planning horizon, the minimization of the total number of drainings for the furnaces and we include a penalty function encouraging efficient transportation of the product. This function favors sequences where orders for the same destination are consecutive and penalizes sequences where this is not the case.

The problem that we describe here is drawn form an actual production setting and has not been simplified to fit a pre-defined theoretical model. In its general form, this problem addresses the scheduling of *n* orders with sequence dependent setup times on one machine while taking into account the technological and logical constraints on equipment and the management of the supply of liquid metal.

Figure 1: *The casting process*



In the literature, we find that this problem has been classed as NP-hard (Conway *et al.* [1967], Lenstra & Rinnooy [1979], Du & Leung [1990]) and is more complex than many described in the survey paper of MacCarthy & Liu [1993].

A number of similar applications drawn from various industrial settings have been reported. França *et al.* [1996] use tabu search to minimize the makespan of a schedule for parallel processors. MacCarthy et Liu [1993] survey a number of scheduling papers that treat industrial cases bearing some similarity to ours. These include a fiberglass factory treated by Leong et Oliff [1990] and a chemical processing installation described by Selen et Heuts [1990]. Lee et Pinedo [1997] seek to minimize the weighted sum of tardiness in a situation comparable to ours using a three-phase heuristic incorporating a simulated annealing algorithm. Rubin et Ragatz [1995] use a genetic algorithm to schedule *n* jobs on one machine so that the sum of weighted tardiness is minimized where setups are sequence dependent. Tabu search has been used by Valls *et al.* [1998] to solve a generalized flexible shop scheduling problem drawn encountered in a Spanish company.

Ant colony optimization

The ant colony optimization metaheuristic (Colorni *et al.* [1991], Dorigo [1992]) was inspired by studies of the behavior of ants (Deneubourg *et al.*, [1983]; Deneubourg & Goss, [1989]; Goss *et al*, [1990]). Ants communicate among themselves through *pheromon*e, a substance they deposit on the ground in variable amounts as they move about. It has been observed that the more ants use a particular path, the more pheromone is deposited on that path and the more it becomes attractive to other ants seeking food. If an obstacle is suddenly placed on an established path leading to a food source, ants will initially go right or left in a seemingly random manner, but those choosing the side that is in fact shorter will reach the food more quickly and will make the return journey more often. The pheromone on the shorter path will therefore be more strongly reinforced and will eventually become the preferred route for the stream of ants.

The works of Colorni, Dorigo & Maniezzo, [1991], Dorigo, Maniezzo & Colorni, [1991], Dorigo, Maniezzo & Colorni, [1996], Dorigo & Gambardella, [1997], Dorigo & Di Caro, [1999] offer detailed information on the workings of the algorithm and the choice of the various parameters.

We use an ant colony optimization metaheuristic to treat the complex problem that we have described, and we will show how the multiple objectives of the scheduler may be simply treated. In the scheduling problem, we must determine the processing sequence for a sequence of orders where set-up times are sequence dependent. Our formulation is based on the well-known traveling salesman problem (TSP). Each order to be processed is represented by a node in a network. If we consider, for the moment, the single-objective case, a matrix D shows the distance between each pair (ij) of nodes where (d_{ij}) represents the setup and processing time required to do job j if it is preceded by job i.

When an ant moves from node i to node j, it will leave a *trail* analogous to the pheromone on the edge (ij). The trail records information related to the previous use of edge (ij) and the higher this use has been, the greater is the probability of choosing it once again. We will explain later how the trail is initialized and modified.

At time t, the ant chooses the next node using a probabilistic *visibility* rule where η_{ij}, is defined as being $1/d_{ij}$. This is a greedy rule favoring the closer nodes, which is to say, the shorter jobs in terms of both setup and processing. The choice probability is also affected by $\tau_{ij}(t)$, the *trail intensity* on edge *(ij)*. At initialization of the algorithm, the trail on each edge is set to an arbitrary but small positive level, $\tau_{ij}(0)$. Parameters α and β are used to vary the relative importance of the visibility and the trail intensity.

To ensure the production of a feasible tour, nodes that have already been visited on the current tour are excluded from the choice through the use of a tabu list. Each ant k will have its own tabu list $tabu_k$ recording the ordered list of nodes already visited. Note that this concept differs from that used in the usual tabu search methods described, for example, in Glover & Laguna [1993].

Then $p_{ij}^{k}(t)$, the probability of choosing edge (*ij*) is calculated as follows:

$$p_{ij}^{k}(t)=\begin{cases}\dfrac{[\tau_{ij}(t)]^{\alpha}\cdot[\eta_{ij}]^{\beta}}{\sum\limits_{\ell\notin \text{taboo}_k}[\tau_{i\ell}(t)]^{\alpha}\cdot[\eta_{i\ell}]^{\beta}} & \text{if } j\notin \text{taboo}_k\\ 0 & \text{if } j\in \text{taboo}_k\end{cases} \quad \textbf{(1)}$$

At any given time, more than one ant seeks a feasible path. A *cycle* is completed when each of the *m* ants has completed a tour of the *n* nodes. The version of the algorithm proposed in this paper carries out an updating of the trail intensity at the end of each cycle. This allows us to update the trail according to the evaluation of the solutions found in the cycle. Let the length of the tour found by the kth ant be L_k. This tour length will in turn influence $\Delta\tau_{ij}^{k}$, the amount of pheromone that is added to each of the arcs (*ij*) in tour k. This quantity is proportional to the quality of the tour as measured by Q/L_k where Q is a system parameter. The updating of the trail is also influenced by an evaporation factor (1-ρ) that diminishes the trail present during the previous cycle. Figure 2 describes the steps of the ant colony optimization metaheuristic proposed by Colorni et al. [1991].

Figure 2: *Ant colony optimization metaheuristic (Colorni* et al *[1991])*

<u>Step 1:</u> [Initialization]

Set $t := 0$; $NC := 0$; {t is the time counter, NC is the number of algorithm cycles}

For each edge (*i*,*j*), set an initial value $\tau_{ij}(t) := c$ and $\Delta\tau_{ij}^{k} := 0$

{$\tau_{ij}(t)$ is the intensity of trail on edge(i,j) at time t}

{$\Delta\tau_{ij}^{k}$ is the quantity of trail laid on edge(i,j) by the k-th ant}

<u>Step 2:</u> [Starting node]

For each ant *k*:

Place ant *k* on a randomly chosen node and store this information in $tabu_k$

<u>Step 3:</u> [Build a tour for each ant]

For each node *i*:

For each ant *k*:

Choose the node *j* to move to, with the probability $p_{ij}^{k}(t)$ given by the equation (1)

Store this information in $tabu_k$

<u>Step 4:</u> [Update the intensity of trail]

For each ant *k*:

Compute the tour length L_k

Compute the quantities $\Delta\tau_{ij}^{k}$ laid on each edge (*i*,*j*) according to Q/L_k

For each edge (*i*,*j*):

Compute the intensity of trail according to equation $\tau_{ij}(t+1) := \rho\cdot\tau_{ij}(t)+\sum_{k=1}^{m}\Delta\tau_{ij}^{k}$

$t := t + 1$; $NC := NC + 1$; $\Delta\tau_{ij}^{k} = 0$;

<u>Step 5.</u> [Termination conditions]

Memorize the shortest tour found to this point

If ($NC < NC_{MAX}$) and (Not stagnation behavior)

Then Empty all tabu lists and Go to step #2

Else Stop

Solution algorithm

In this section, we describe the adaptations to the ACO metaheuristic that we have devised in order to treat the multi-objective industrial problem that we address in this paper. These adaptations affect, on the one hand, the construction of the distance matrix D, and on the other hand, the rules for updating the pheromone trail at the end of a cycle.

Constructing the D-matrix

For the decisions required at the local level, as an ant is selecting the next node to visit, we construct and use a matrix D that aggregates information on each of the four objectives that we have identified.

The first order in the sequence to be determined is deemed to be the last order in the previous sequence. This allows us to take into account the set-up time required to bridge sequences in successive planning periods. The "distance" matrix is therefore of dimension [$n+1$ x $n+1$] where n is the total of orders in the order book and an additional dimension is added to take into account the last order of the previous sequence.

As previously stated, we have a feasible sequence of orders if sufficient metal is available for all orders, if basins and molds are available when required and if the "drain-and-clean" is done when required. A desirable feasible sequence takes into account the objectives of customer service and efficiency. The coefficients of the matrix represent the various measures or penalties established as a function of each of the objectives. The distance matrix penalizes undesirable and infeasible sequences.

We must also take into account several objectives that are important to the scheduler:

- The first objective function refers to the minimization of unused capacity due to setup times, drainings and time lost owing to technological constraints such as a lack of molten metal. We can compute this as the clock time from the start of operations to the termination of the final order, less actual casting time.
- The second objective function refers to the total tardiness of the set of orders. The tardiness of a job is the amount by which its completion time exceeds its due date. (Baker [1974]).
- The third objective function refers to the minimization of the total number of drainings required when changing alloys.
- The fourth objective function is a transportation penalty function that computes the total unused vehicle capacity. Metal is loaded and removed as it is ready because there is no storage available. Because vehicles can serve only one destination on a given trip, this function will be minimized if we tend to consecutively sequence orders having the same destination while taking into account vehicle capacity.

Note that the first three of these objectives are somewhat related. Other things being equal, tardiness is likely to be reduced if capacity utilization is high and if the number of drainings is low. Unused capacity includes drainings, as well as mold changes, so that these functions will tend to move in the same direction. The transport planning function, however, is quite unrelated to the first three objectives.

The coefficients of the matrix of d_{ij} are determined as shown in Table 1. Of course, the various constants used above can be changed if required. We have found the values shown to be useful in finding operational solutions.

Table 1 : *Rule-based procedure for constructing the D-matrix*

(1) The matrix is initialized to $d_{ij} = 1$ for all ij.

(2) To encourage respect of the due-dates of the orders and to minimize the unweighted total tardiness, a penalty corresponding to twice the ratio of the [max(0,order slack)/maximum slack for all orders] is calculated and added, where:
order slack = (order due-date) - (production start date) - (order processing time).

(3) Where successive orders have different alloys such that a drain-and-clean would be required between orders, a penalty of +2 is added to d_{ij}.

(4) Where a mold change is required between successive orders, a further penalty of +2 is added to d_{ij}.

(5) If the destinations differ for two successive orders, again a penalty of +2 is added to d_{ij}.

(6) A penalty of +500 is added to a matrix element where the sequence (*ij*) violates one of the technological constraints, for example that concerning the availability of basins.

Updating the trail intensity

During the schedule construction, the ants are guided by the D-matrix. However, once a cycle is completed, the schedule found by the k^{th} ant is then directly evaluated for each objective h (h = 1,2,3,4). Let these evaluations be called L_k^h.

The four objectives are ranked in order of importance by the company planner. Let the most important objective be h = *h'* and the evaluation of the schedule for ant k according to this function be $L_k^{h'}$. The contribution to the update of the trail for ant *k* is then calculated as follows:

$$\Delta\tau_{ij}^{k} = Q/ L_k^{h'}.$$

Because of the nature of the procedure, at the end of a cycle we may have found more than one schedule with the same value of the primary objective function. If such is the case, we choose the schedule to retain by a lexicographic sort on the values of the remaining objectives.

In summary, the D-matrix is used in the local computations during a cycle, where ants choose the next order to process. At the end of a cycle, one of the four individual objectives is used in the global trail-updating .

Numerical example and results

Let us consider the order book presented in Table 2. Note that the order designates as order 0 is deemed to be the last order produced during the previous planning period.

Table 2: *Sample data from the order book*

Order	Alloy type	Dimension	Basin	Duration (hours)	Destination	Metric Tons	Due date
0	Alloy 1	Mold 8	1	-			-
1	Alloy 1	Mold 1	2	21.26	1	33.869	3
2	Alloy 1	Mold 2	2	52.29	3	112.763	2
3	Alloy 1	Mold 3	1	29.8	3	44.323	7
4	Alloy 1	Mold 4	1	7.61	1	25.548	5
5	Alloy 1	Mold 4	1	10.33	2	34.676	5
6	Alloy 2	Mold 5	2	10.17	4	34.155	2
7	Alloy 3	Mold 6	1	7.95	2	21.978	5
8	Alloy 3	Mold 6	1	10.09	4	17.312	8
9	Alloy 2	Mold 5	2	5.98	2	20.079	8
10	Alloy 2	Mold 5	2	8.24	3	27.670	3

The results of the construction of matrix of d_{ij} are presented in Table 3 .

Table 3: *Matrix of d_{ij} for the sample order book data*

To / From	0	1	2	3	4	5	6	7	8	9	10
0	0	3.55	3	500	500	500	3.41	500	500	5	3.69
1	0	0	500	6.49	4.21	6.18	500	6.20	6.96	500	500
2	0	500	0	4.49	6.21	6.18	500	6.20	6.96	500	500
3	0	5.55	5	0	500	500	5.41	500	500	5	5.69
4	0	3.55	5	500	0	4.18	5.41	500	500	7	5.69
5	0	5.55	5	500	4.21	0	5.41	500	500	5	5.69
6	0	500	500	8.49	8.21	8.18	0	8.20	6.96	5	3.69
7	0	5.55	5	500	500	500	5.41	0	4.96	5	5.69
8	0	5.55	5	500	500	500	3.41	4.20	0	7	5.69
9	0	500	500	8.49	8.21	6.18	3.41	6.20	8.96	0	3.69
10	0	500	500	6.49	8.21	8.18	3.41	8.20	8.96	5	0

For the data of Tables 2 and 3, and using the capacity function as the primary objective for updating the trail, the best solution that we find has an unused capacity (L^1) of 1.64 days, 6.97 days of total tardiness (L^2), requires 2 drainings (L^3) and an unused transport capacity (L^4) of 12.71 metric tons. The value that is calculated for L^1 corresponds to six mold changes of a duration of 6 hours each and six mandatory preheating periods of 20 minutes each as well as two drainings of 36 minutes each following an alloy change. The value that is calculated for L^2 corresponds to a delay of 0.515 days for order 1, of 4.973 days for order 2 and of 1.478 days for order 3. These delays are shown as cross-hatched areas for the orders in question in Figure 3. The value that is calculated for L^3 corresponds to the two drainings necessary between alloys 2 and 1 on both furnaces. A truckload between 26 and 36 metric tons bears no penalty. Taking this into account, the value that is calculated for L^4 corresponds to changes in destination between orders 7 and 8 causing a penalty of 4.02 metric tons and a second change between orders 8 and 2, causing a penalty of 8.69 metric tons.

This problem is presented as the first problem of size 10 in Table 4. The order sequence obtained is (6-10-9-5-4-1-7-8-2-3). The computation time was 2.5 seconds using Pentium III computer having a clock speed of 600Mhz and 258MB of RAM. The computer implementation was done in C in the Windows 98 environment.

Figure 3 shows how this solution is presented to the scheduler in our software implementation. The remaining seven problems have between twenty and eighty orders and cover the range of problem sizes that we meet in practice.

We have carried out a number of numerical experiments to illustrate the effectiveness of the multiobjective procedure that we propose. We compare the results found using our metaheuristic to the results obtained using the same metaheuristic with a single objective. Each result shown in Table 4 is derived from ten trials of the metaheuristic for the particular problem instance. We show the mean and the standard deviation for each of the four objectives.

The left half of Table 4 (a, b, c, d) presents the results obtained by the ant colony optimization metaheuristic for eight problems where each of the four objective functions is designated in turn as the primary objective. In Table 4a, the unused capacity is the primary objective, in Table 4b total tardiness is primary, in Table 4c the number of drainings is primary and in Table 4d the unused transportation capacity is primary.

The right half of each part of Table 4 shows the results of a single objective optimization on each of the functions in turn. In these computations, the values of the d_{ij} include penalties pertaining only to the primary objective. For example, in the case where the primary function is L^1, only steps 1, 3, 4 and 6 are used to create the D-matrix. For L^2, steps 1, 2, 3, 4 and 6 are used, but the penalty applied in steps 3 and 4 is of value 1 rather than 2. The change in these penalties was made to give more relative weight to the due-dates without eliminating the impact of draining and mold changes. For L^3 steps 1, 3 and 6 pertain, and finally for L^4 steps 1, 5 and 6 apply. For the solutions found, the values of the remaining three functions have been calculated at termination, but they play no part in the computation itself. Again, ten trials were made for each problem and the mean and standard deviation of the results are shown.

The results of the ant colony optimization metaheuristic presented in Table 4 were obtained using parameter choices based both on results presented in the literature and on our own series of numerical experiments. For each of the problems in Table 4, the values of the other parameters $\{\alpha, \beta, \rho, Q,\}$ are $\{1, 5, 0.5, 100\}$. The intensity of the initial trail ($\tau_{ij}(0)$) on each of the arcs (*ij*) was fixed at 0.05, the number of ants (m) was set to 40 and the maximum number of cycles (NC_{MAX}) was set to 20. Note that each problem was restarted 10 times.

The results of Table 4 show that when the D-matrix is constructed using all four of the objectives, the results for the objective designated as primary (noted in Table 4 in bold type) are somewhat worse than those obtained when the primary objective is used alone in building the D-matrix. Overall, however, the results are better for the other objectives and in some cases markedly so.

In the industrial application, the multi-objective approach is therefore more likely to yield attractive solutions than is the single objective approach. For example, in Table 4(a), for problems ranging from 40 to 80 orders, the value found for unused capacity is slightly above what was found by single objective optimization, but there is a major improvement in the transport function. Tardiness is also often improved. More drainings, however, occur with the multiple objective procedure. For Table 4(b), similar remarks may be made but we point out that the results for the 20 order problem may be somewhat surprising. The mean result produced by the multi-objective procedure is slightly better for the primary function. This may be considered to be an artifact that will inevitably occur for some examples. In Tables 4 (c) and (d), the multiobjective procedure has produced better or equal results on all objective functions for all problems save the 10 order problem of Table 4 (d), where the tardiness is less in the single objective case.

Table 4 (a): *Results obtained when "unused capacity" is the primary objective. The first result is the mean of ten trials and the second is the standard deviation.*

Problem size	Multiple objective ACO				Single objective ACO			
	Capacity	Tardiness	Draining	Transport	**Capacity**	Tardiness	Draining	Transport
10	**1.64** **0.00**	6.97 0.00	2 0.00	12.71 0.00	**1.64** **0.00**	6.97 0.00	2 0.00	12.71 0.00
20	**3.69** **0.00**	53.49 5.30	0 0.00	0 0.00	**3.69** **0.00**	68.50 4.53	0 0.00	5.18 4.46
30	**3.69** **0.00**	97.26 11.11	0 0.00	0.43 0.00	**3.69** **0.00**	111.33 8.26	0 0.00	2.08 2.95
40	**3.80** **0.00**	100.52 11.99	2 0.00	14.83 7.64	**3.69** **0.00**	170.24 11.51	0 0.00	21.2 4.69
50	**4.85** **0.00**	183.12 12.07	2 0.00	7.31 8.80	**4.75** **0.00**	243.76 15.94	0 0.00	69.38 10.78
60	**4.90** **0.08**	279.52 53.20	2.00 0.00	12.53 6.67	**4.75** **0.00**	337.31 24.99	0 0.00	72.17 18.72
70	**4.93** **0.08**	441.76 42.29	2.00 0.00	13.64 13.01	**4.75** **0.00**	496.59 22.40	0 0.00	107.73 25.62
80	**4.88** **0.06**	674.37 131.13	1.60 0.80	5.34 8.72	**4.75** **0.00**	713.49 52.47	0 0.00	84.49 26.25

Table 4 (b): *Results obtained when "total tardiness" is the primary objective. The first result is the mean of ten trials and the second is the standard deviation.*

Problem size	**Multiple objective ACO**				**Single objective ACO**			
	Capacity	**Tardiness**	Draining	Transport	Capacity	**Tardiness**	Draining	Transport
10	1.93 0.36	**6.88** **0.11**	2.80 0.98	11.55 1.78	2.30 0.22	**6.72** **0.12**	3.80 0.60	10.48 1.93
20	3.77 0.00	**17.86** **0.64**	2 0.00	0.00 0.00	3.87 0.13	**17.93** **0.50**	2 0.00	0.00 0.00
30	4.40 0.27	**38.62** **2.95**	2 0.00	7.84 7.58	4.43 0.27	**36.01** **0.92**	2 0.00	6.01 6.66
40	4.48 0.45	**75.15** **4.93**	2 0.00	33.65 7.47	5.32 0.34	**66.36** **2.78**	2.20 0.60	22.80 10.74
50	7.13 0.43	**88.68** **8.96**	3.40 0.92	11.28 15.15	6.97 0.68	**66.39** **5.71**	3.00 1.00	58.92 15.27
60	8.54 0.65	**142.86** **7.68**	4.20 1.08	17.91 12.99	8.19 0.97	**111.37** **5.43**	3.60 1.20	68.94 15.26
70	8.37 0.89	**277.29** **17.35**	4.20 0.60	11.99 13.78	9.21 1.23	**237.90** **10.08**	5.40 1.28	79.30 33.51
80	8.81 0.50	**384.39** **17.63**	4.20 0.60	8.41 8.75	8.76 1.17	**338.59** **15.64**	3.80 0.60	63.08 15.49

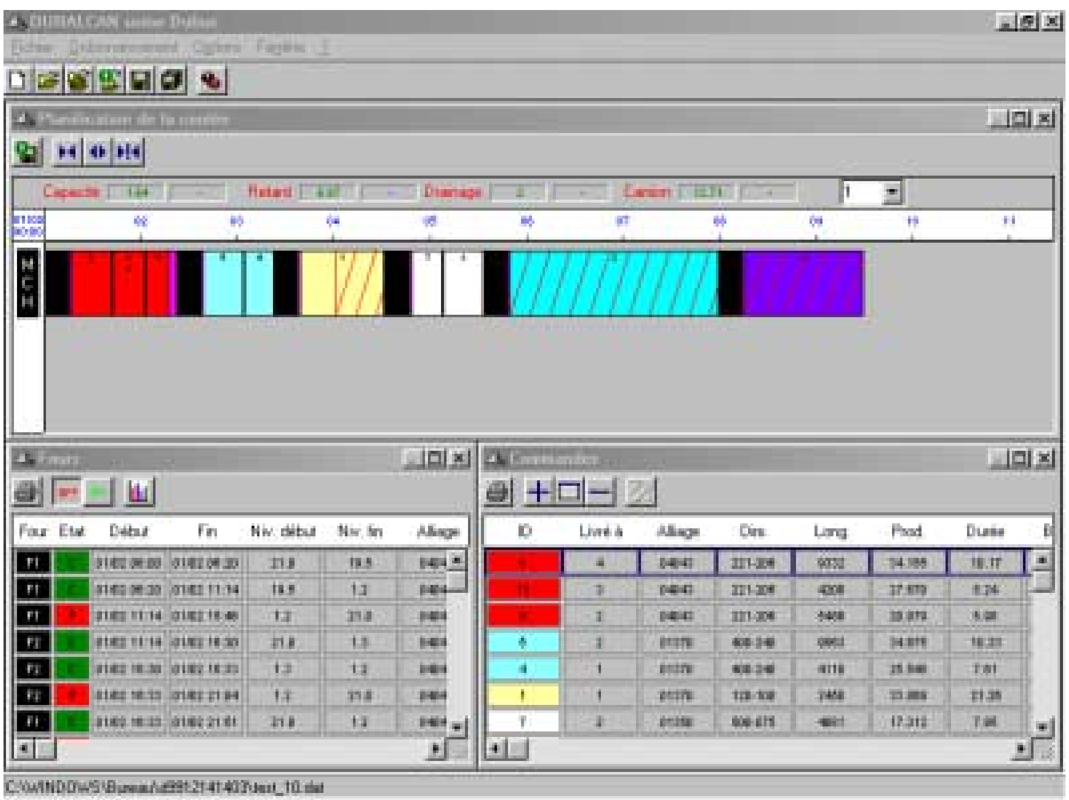
Table 4 (c): *Results obtained when "drainings" is the primary objective. The first result is the mean of ten trials and the second is the standard deviation.*

Problem size	**Multiple objective ACO**				**Single objective ACO**			
	Capacity	Tardiness	**Draining**	Transport	Capacity	Tardiness	**Draining**	Transport
10	1.64 0.00	6.97 0.00	**2** **0.00**	12.71 0.00	1.64 0.00	6.97 0.00	**2** **0.00**	13.30 1.87
20	3.69 0.00	53.27 4.71	**0** **0.00**	0 0.00	3.84 0.13	81.68 13.62	**0** **0.00**	2.59 4.17
30	3.69 0.00	98.62 13.08	**0** **0.00**	0.43 0.00	4.45 0.19	130.86 18.86	**0** **0.00**	2.66 4.98
40	3.88 0.12	157.42 17.71	**0** **0.00**	17.91 0.47	7.16 0.34	247.74 22.57	**0** **0.00**	26.62 11.30
50	5.12 0.13	222.67 33.14	**0** **0.00**	3.69 7.69	9.36 0.34	366.70 56.27	**0** **0.00**	68.60 19.98
60	5.23 0.16	370.32 26.99	**0** **0.00**	2.70 5.41	10.99 0.46	526.90 66.74	**0** **0.00**	71.76 11.60
70	5.20 0.21	532.67 63.65	**0** **0.00**	7.18 7.28	13.21 0.42	808.70 73.83	**0** **0.00**	94.20 14.97
80	5.01 0.21	817.63 74.26	**0** **0.00**	0.00 0.00	14.48 0.49	1241.42 112.20	**0** **0.00**	60.21 17.35

Table 4 (d): *Results obtained when "transport penalty function" is the primary objective. The first result is the mean of ten trials and the second is the standard deviation.*

Problem size	Multiple objective ACO				Single objective ACO			
	Capacity	Tardiness	Draining	**Transport**	Capacity	Tardiness	Draining	**Transport**
10	1.64	15.03	2	**0.00**	2.10	12.95	3.80	**0.00**
	0.00	0.00	0.00	**0.00**	0.03	1.99	0.63	**0.00**
20	3.69	54.79	0	**0.00**	4.10	70.01	2.40	**0.00**
	0.00	9.70	0.00	**0.00**	0.12	15.24	0.84	**0.00**
30	3.77	67.23	2	**0.00**	4.97	103.60	2.80	**0.00**
	0.00	9.00	0.00	**0.00**	0.12	24.24	1.40	**0.00**
40	3.88	113.71	2	**0.00**	7.69	237.04	5.40	**0.00**
	0.12	23.71	0.00	**0.00**	0.24	37.96	1.26	**0.00**
50	4.94	203.23	1.60	**0.00**	9.92	306.91	5.50	**0.00**
	0.11	42.19	0.80	**0.00**	0.19	33.29	2.37	**0.00**
60	4.97	306.26	1.80	**0.00**	12.22	535.99	9.20	**0.00**
	0.12	39.58	0.60	**0.00**	0.45	87.75	0.63	**0.00**
70	4.98	529.69	1.60	**0.00**	14.23	792.97	10.50	**0.00**
	0.11	82.17	0.80	**0.00**	0.25	68.07	1.84	**0.00**
80	4.89	759.12	1.40	**0.00**	15.81	1185.29	10.40	**0.00**
	0.08	111.21	0.92	**0.00**	0.27	71.97	2.27	**0.00**

Figure 3: *Screen image from the software implementation*



Conclusions

We have described a successful adaptation of the ant colony optimization metaheuristic for a computerized scheduling application in an Alcan Inc production facility. Our implementation allows us to take into account a number of objectives that are important to the scheduler while preserving the characteristics of the original procedure. It has succeeded in giving robust solutions in short computing times. A typical order book contains about 60 orders and may be solved in approximately 40 seconds. Schedulers we have encountered in this project use the results produced by the metaheuristic and feel that it well represents the constraints and objectives with which they are faced.

In previous implementations (Gravel *et al.* [2000]), we used a genetic algorithm to solve similar problems with good results. In comparison testing of the single objective models, we found the results of the ant colony optimization metaheuristic to give much better quality results in much shorter computing times. We would agree that further tuning of the genetic algorithm could speed up its convergence and improve solution quality. We cite this comparison merely as evidence that the ant colony optimization metaheuristic is quite competitive with other metaheuristics.

We consider that the multiobjective procedure presented here is simple and robust and that it offers good quality solutions in short computation times. We have, as one might expect, produced solutions of a better overall quality than those found by single objective optimization. We have not, however, attempted to ensure that the solutions suggested are Pareto-efficient in order to reduce computing effort.

This method may be enriched somewhat without difficulty. For example, the preferences of the scheduler might be better represented by a form of weighted aggregation of the L_k^h or by changing the components in the calculation of the $p_{ij}^k(t)$. Tuning of the elements of the D-matrix are likely to be required to adapt the procedure to different industrial environments. In the longer term, we seek to investigate the usefulness of other, more comprehensive, multiobjective methods.

References

Baker Kenneth R. [1974], *Introduction to sequencing and scheduling*, John Wiley & Sons, New York.

Belton V., Elder M.D. [1996], *Exploring a multicriteria approach to production scheduling,* The Journal of the Operational Research Society, 47, 1, 162-175.

Bjorndal M.H., Capara A., Cowling P.I., Della Croce F., Lourenço H.R., Malucelli F., Orman A.J., Pisinger D., Rego C., Salazar J.J [1995], *Some thoughts on combinatorial optimization*, European Journal of Operational Research, 83, 253-270.

Blazewicz J., Wolfgang D., Pesch, E. [1996], *The job shop scheduling problem: conventional and new solution techniques*, European Journal of Operational Research, 93, 1-33.

Brandimarte P., [1999], *Exploiting process plan flexibility in production scheduling: A multi-objective approach*, European Journal of Operational Research, 114, 1, 59-71.

Brandimarte P., Calderini M. [1995], *A hierarchical bicriterion approach to integrated process plan selection and job-shop scheduling*, International Journal of Production Research, 33, 161-181.

Cavalieri S., Gaiardelli P. [1998], *Hybrid genetic algorithms for multiple-objective scheduling problem*, Journal of Intelligent Manufacturing, 9, 4, 361-367.

Colorni A., Dorigo M., Maniezzo V. [1991], *Distributed optimization by ant-colonies*, in Proceedings of the European Conference on Artificial Life (ECAL'91), edited by F. Varela and P. Bourgine, 134-142, Cambridge, Mass, USA, MIT Press

Colorni A., Dorigo M., Maniezzo V., Trubian M. [1994], *Ant system for job-shop scheduling*, Belgian Journal of Operations Research (JORBEL), Statistics and Computer Science, 34, 1, 39-53.

Conway R.W., Maxwell W.L., Miller L.W. [1967], Theory of scheduling, Addison-Wesley, 294 pages.

Davis L. [1985], *Applying adaptive algorithms to epistactic domains*, in proceedings of the International Joint Conference on Artificial Intelligence, Los Angeles, 162-164.

Deneubourg J.L., Pasteels J.M., Verhaeghe J.C. [1983], *Probabilistic behaviour in ants: A strategy of errors?*, Journal of Therical Biology, 105, 259-271.

Deneubourg J.L., Goss S. [1989], *Collective patterns and decision-making*, Ethology & Evolution, 1, 295-311.

Dorigo M. [1992], Optimization, learning and natural algorithms, Ph.D. Thesis, Politecnico di Milano, Italy.

Dorigo M., Di Caro G., [1999], *The Ant Colony Optimization Meta-Heuristic*', In: D. Corne, M. Dorigo and F. Glover Editors, New Ideas in Optimization, McGraw-Hill.

Dorigo M., Gambardella L.M. [1997], *Ant colonies for the traveling salesman problem*, BioSystems, 43, 73-81.

Dorigo M., Maniezzo V., Colorni A. [1991], Positive feedback as a search strategy, Technical Report No 91-016, Politecnico di Milano, Italy, 20 pages.

Du J., Leung J.Y. [1990], *Minimizing total tardiness on one machine is NP-hard*, Mathematics of operations research, 15, 483-494.

Fanti M.P., Maione B., Naso D., Turchiano B. [1998], *Genetic multi-criteria approach to flexible line scheduling*, International Journal of Approximate Reasoning, 19,1-2, 5-21.

Glover F., Laguna M. [1993], *Tabu search*, In: Modern Heuristic Techniques for Combinatorial Problems, Wiley & Sons, New York, 70-150.

Goss S., Beckers R., Deneubourg J.L., Aron S., Pasteels J.M. [1990], *How trail laying and trail following can solve foraging problems for ant colonies*, In: Behavioural Mechanisms of Food Selection, R.N. Hughes ed., NATO-ASI Series, vol. G20, Berlin: Springler-Verlag.

Gravel M., Price W., Gagné C. [2000], *Scheduling jobs in a Alcan aluminium factory using a genetic algorithm*, International Journal of Production Research, 38 (13), p. 3031-3041.

Grefensette J.J. [1985], *Genetic algorithms for the traveling salesman problem*, In proceedings of the First Int. Conf. on Genetic Algorithms (ICGA '85], 160-168.

Grefensette J.J. [1987], Incorporating problem specific knowledge into genetic algorithms. In *Genetic algorithms and Simulated Annealing*, Pitman Press, New York, 49-67.

Holland J.H. [1975], Adaptation in natural and artificial systems, The University of Michigan Press, Ann Arbor, Michigan

Huang S.H., Zhang H.-C. [1994], *Artificial neural network in manufacturing: Concepts, applications and perspectives*, IEEE Transactions on Components, Packaging and Manufacturing Technology - Part A., 17, 2, 212-228.

Ishibuchi H., Murata T. [1998], *A multi-objective genetic local search algorithm and its application to flowshop scheduling*, IEEE Transactions on Systems, Man and Cybernetics-Part C: Applications and reviews, 28, 3, 392-403.

Kim C.-O., Min H.-S., Yih Y. [1998], *Integration of inductive learning and neural networks for multi-objective FMS scheduling*, International Journal of Production Research, 36, 9, 2497-2509.

Lee H.L., Pinedo M. [1997], *Scheduling jobs on parallel machines with sequence-dependent setup times*, European Journal of Operational Research, 100, 3, 464-474.

Lenstra J.K., Rinnooy Kan A.H.G. [1979], *Computational complexity of discrete optimization problems*, Annals of Discrete Mathematics, 4, 121-140.

Leong G.K., Oliff M.D. [1990], *A sequencing heuristic for dependent setups in a batch process industry*, Omega, 18, 283-297.

Maccarthy B.L., Liu J. [1993], *Addressing the gap in scheduling research: a review of optimization and heuristic methods in production scheduling*', International Journal of Production Research, 31, 1, 59-79.

Marett R., Wright M. [1996], *A comparison of neighborhood search techniques for multi-objective combinatorial problems*, Computers & Operations Research, 23, 5, 465-483.

Min H.-S., Yih Y., Kim C.-O. [1998], *A competitive neural network approach to multi-objective scheduling*, International Journal of Production Research, 36, 7, 1749-1765.

Murata T., Ishibuchi H., Tanaka H. [1996], *Multi-objective genetic algorithm and its applications to flowshop scheduling*, Computers & Industrial Engineering, 30, 4, 957-968.

Nagar A., Haddock J, Heragu S. [1995], *Multiple and bicriteria scheduling: A literature survey*, European Journal of Operational Research, 81, 88-104.

Rubin P.A., Ragatz G.L.[1995], *Scheduling in a sequence dependent setup environment with genetic search*, Computers and Operations Research, 22,2, 85-99.

Ruiz-Torres A.J., Enscore E.E., Barton R.R. [1997], *Simulated annealing heuristics for the average flow-time and the number of tardy jobs bi-criteria identical parallel machine problem*, Computers & Industrial Engineering, 33, 1-2, 257-260.

Sabuncuoglu I., Gurgun B. [1996], *A neural network model for scheduling problems*, European Journal of Operational Research, 93, 2, 288-299.

Santos A., Dourado A. [1999], *Global optimization of energy and production in process industries : A genetic algorithm application*, Control Engineering Practice, 7, 549-554.

Selen W.J., Heuts R.M.J. [1990], *Operational production planning in a chemical manufacturing environment*, European Journal of Operational Research, 45, 38-46.

Stützle T., [1998], *An ant approach to the flow shop problem*, Proceedings of EUFIT '98, 1560-1564.

Valls V., Perez M.A., Quintanilla M.S., [1998], *A tabu search approach to machine scheduling*, European Journal of Operational Research, 106, 277-300.