

Tabu Search for the Flexible-Routing Job Shop Problem

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Abstract

In the classical job shop scheduling problem (JSSP), n jobs are processed to completion on m unrelated machines. Each job requires processing on each machine exactly once. For each job, technology constraints specify a complete, distinct routing which is fixed and known in advance. Processing times are sequence-independent, fixed, and known in advance. Each machine is continuously available from time zero, and operations are processed without preemption. The objective is to minimize the maximum completion time (makespan).

The flexible-routing job shop (FRJS) scheduling problem, or job shop with multi-purpose machines, extends JSSP by assuming that a machine may be capable of performing more than one type of operation. (For a given operation, there must exist at least one machine capable of performing it.) FRJS approximates a flexible manufacturing environment with numerically controlled work centers equipped with interchangeable tool magazines.

This report extends a dynamic, adaptive tabu search (TS) strategy previously described for job shops with single and multiple instances of single-purpose machines, and applies it to FRJS. We present “proof-of-concept” results for three problems constructed from difficult JSSP instances.

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1. Introduction

Tabu search (TS) is a local search metaheuristic which relies on specialized memory structures to avoid entrapment in local minima and achieve an effective balance of intensification and diversification. TS has proved remarkably powerful in finding high-quality solutions to computationally difficult combinatorial optimization problems drawn from a wide variety of applications [Glover and Laguna 1993]. We assume that the reader is familiar with the basic principles of TS [Glover 1989,1990,1994; Glover and Laguna 1993; Glover, Taillard, and deWerra 1993].

TS results in the area of production scheduling have been especially successful [Barnes and Laguna 1991]. In particular, we have previously reported experience with a simple but highly effective TS approach to the classical (JSSP) and flexible (FJS) job shop scheduling problems [Barnes and Chambers 1991a, 1991b, 1992a, 1992b, 1995; Chambers and Barnes 1996a, 1996b].

JSSP approximates a traditional manufacturing process with a permanent, dedicated facility turning out the same product repeatedly and in large volume over an extended period of time. FJS extends the JSSP model to accommodate multiple instances of single-purpose machines. However, much attention has been focused in recent years on flexible manufacturing systems incorporating numerically controlled multi-purpose work centers. Such systems can be easily reconfigured to produce a variety of different items during short, low volume runs.

Clearly, the introduction of flexibility considerations complicates the already difficult classical job shop problem. FMS problems are characteristically NP-hard [Blazewicz *et al.* 1988], and MacCarthy and Liu [1993] have observed that, “Heuristics or AI techniques seem to be unavoidable for FMS scheduling problems.” As with JSSP, only the most trivial cases of flexible scheduling seem amenable to straightforward solution [Brucker and Schlie 1990].

In this report, we extend our successful TS strategy for JSSP/FJS to a flexible scheduling model incorporating multi-purpose machines, that is, machines capable of performing more than one type of operation. We present “proof-of-concept” results for three problems constructed from difficult JSSP instances.

2. Literature

Balas [1970] formulates a framework for consideration of a job shop with identical machine sets similar to an earlier model [Balas 1969] for the classical job shop problem, but reports no computational experience. Brucker and Schlie [1990] consider job shop scheduling with multi-purpose machines, and develop a polynomial graphical algorithm for a 2-job problem after the manner of Akers [1956]. More realistic studies have investigated heuristic procedures, including dispatching [Iwata, Murotsu, and Oba 1980], beam search [Chang, Matsuo, and Sullivan 1989], and a decomposed mixed IP formulation [Nasr and Elsayed 1990].

TS approaches have been described for a job shop with tooling changes, such as might occur in an FMS using finite capacity tool magazines [Widmer 1991], and for a flexible resource flow shop problem [Daniels and Mazzola 1993]. Brandimarte [1993], in particular, studies the feasibility of implementing a TS strategy for the minimum makespan and minimum weighted tardiness flexible problems. A layered memory approach underlies a hierarchical technique which considers sequencing and routing changes in an iterative fashion, and trials of several neighborhood structures using randomly generated problems are discussed.

3. Tabu Search Procedure

Recently [Chambers and Barnes 1996a], we described our experience with an adaptive, dynamic tabu search strategy which demonstrated significantly improved performance for the classical job shop over an earlier study [Barnes and Chambers 1995]. We then extended that strategy to the flexible job shop, and reviewed computational results for sample problems generated from several difficult classical job shop instances [Chambers and Barnes 1996b].

In this report, we extend the classical job shop problem to allow for the possibility that a machine may be capable of performing more than one type of operation. (For a given operation, there must exist at least one machine capable of performing it.) Our approach, employing a concurrent move selection strategy coupled with a dynamic, adaptive tabu search implementation, is identical to that described in [Chambers and Barnes 1996a, 1996b].

4. Computational Experience

Construction of test problems

Previously [Chambers and Barnes 1996b], we constructed “proof-of-concept” flexible job shop problems from three of the more challenging classical job shop problems by replicating machines selected according to two simple criteria. The first criterion we used was the cumulative processing time (CPT) required by a machine. The second criterion was the cardinality of critical operations on a machine, based on our best solution obtained to the classical problem [Chambers and Barnes 1996a].

We follow a similar pattern in this study, constructing FRJS problems from the same classical problems by allowing selected machines to perform more than one type of operation. In the tables which follow, the alternate machine policies are captioned as shown in the chart below. Processing times for operations on alternate machines are assumed to be identical to the original.

p1	operations requiring the machine with the greatest CPT may also be performed on the machine with the smallest CPT
p1,p2	operations requiring the machines with the greatest and second-greatest CPTs may also be performed on the machines with the smallest and second-smallest CPTs, respectively

p1,p2,p3	operations requiring the machines with the greatest, second-greatest, and third-greatest CPTs may also be performed on the machines with the smallest, second-smallest, and third-smallest CPTs, respectively
c1	operations requiring the machine with the greatest number of critical operations may also be performed on the smallest-CPT machine having no critical operations
c1,c2	operations requiring the machines with the greatest and second-greatest number of critical operations may also be performed on the smallest- and second-smallest-CPT machines having no critical operations, respectively

Tabu search results

The method was implemented in C, and run in single user mode on an IBM RS6000 (PowerPC-43) workstation, with a CPU time limit of 1200 seconds and a nonimproving moves limit of 2000 moves (except where noted). For each problem, the short term memory range was taken from the best classical run [Chambers and Barnes 1996a].

Tables 1 - 3 present results for the constructed flexible problems. The first column indicates the alternate machine policy, as described above. The second column gives the best flexible dispatching solution. The third column shows the makespan and time to best achieved by the tabu search. The fourth column gives the frequency with which a move type was selected as best at each iteration.

Table 1 presents results for flexible-routing variations of MT10 [Fisher and Thompson 1963], a 10-job 10-machine problem for which we obtained a classical makespan of 930 (optimal). MT10 has a lower bound dominated by the total processing time required for one job; our best classical solution to MT10 had one critical path, with two machines tied for the maximum number of critical operations. Policies involving one or two alternate machines appear to be dominated by the bounding job and offer only modest improvement. However, tabu search for the variation with three alternate machines succeeds in locating a noticeably improved makespan (887 vs. 930). Some improvement is noted in the *p1p2p3* and *c1* models by setting the limit on nonimproving moves to 5000, although this is at the expense of additional search time. As was the case in our previous FJS study [Chambers and Barnes 1996b], we observe an increasing preference for routing moves associated with increasing flexibility, as expected.

Table 2 presents flexible-routing results for LA24 [Lawrence 1984], a 10-machine 15-job problem for which we obtained a classical makespan of 939. LA24 is machine-time bounded; our best classical solution had one critical path and one machine with a dominant number of critical operations. Tracing suggests that the inferior solutions obtained for policies *p1p2p3* and *c1c2* may be attributable to inappropriate alternate machine selection, leading to contention between operations rerouted to, and critical operations already scheduled on, low-CPT machines. In such a case, tuning of the nonimproving moves limit is of negligible value (model *c1c2*).

Table 3 presents flexible-routing results for LA40 [Lawrence 1984], a 15-machine 15-job problem for which we obtained a classical makespan of 1226. LA40 is machine-time bounded; our best classical solution had one critical path which forks (and later

rejoins itself), and one machine clearly identifiable as having the largest number of critical operations. The tabu search procedure readily takes advantage of increasing flexibility to locate improved solutions. As was the case with MT10, two models, *p1p2p3* and *c1*, realize additional improvement (with a longer time to best) if the limit on nonimproving moves is set to 5000.

Table 4 summarizes the results for MT10, LA24, and LA40. The second column lists the percent improvement over our best classical solution for each alternate machine policy, with the average in italics. Column three gives the percent improvement provided by the tabu search strategy over the initial flexible dispatching solution. This improvement varies from 8.3% to 11.2%, at an overall average of 10.4%. Column four, move type selection frequency, reprises our observation that increasing flexibility is associated with a clear and consistent increase in the frequency with which routing moves are selected by the concurrent neighborhood strategy.

It may be noted from Table 4 that, for each problem, a different alternate machine policy yields a “best” percentage improvement over the classical solution. This is not surprising, given the interaction between the unique constraint structure of each problem and the resource contention created by forcing one or more machines to service multiple operation types. The tests with LA24 using our “proof-of-concept” models suggest that more sophisticated policies for the selection of alternate machines may lead to superior results in realistic problems. In addition, the structure of the original JSSP problem is sufficiently perturbed in FRJS (compared to FJS) that it may be more appropriate to retune the short term memory and maximum nonimproving move count, rather than to rely on the values used for the best classical runs.

Nonetheless, it is interesting to observe that the results for the machine policies using one or two alternate machines (especially based on cumulative processing time) are reasonably competitive with the results obtained for the corresponding replication policies studied in [Chambers and Barnes 1996b]. In such cases, the tradeoff between replication of a single purpose machine and the use of a multipurpose machine may be of interest to the facility manager. The power of tabu search to rapidly evaluate a variety of flexibility strategies is significant in this regard.

5. Future Directions

Recent investigations [Battiti and Tecchiolli 1994; Battiti 1995; Barnes and Carlton 1995; Carlton 1995] suggest that it may be possible to construct a dynamic TS approach which is fully adaptive to changing search conditions without the need for extensive parameterization or tuning. An implementation for generalized flexible scheduling problems is under investigation.

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Table 1
Flexible tabu search results using MT10
(nonflexible makespan = 930)

Alternate machine policy	Dispatching	Tabu Search (1200s)^a	Move type % routing/sequencing
p1	1023	925 33.59	16.6 / 83.4
p1,p2	1000	912 121.78	36.1 / 63.9
p1,p2,p3	1008	887 ^b 556.41	43.8 / 56.2
c1	1007	928 ^c 0.27	20.5 / 79.5
c1,c2	980	926 117.19	34.4 / 65.6

a) nonimproving moves set to 2000

b) achieved 878 in 974.87s using max nonimproving moves of 5000

c) achieved 918 in 50.95s using max nonimproving moves of 5000

Table 2
Flexible tabu search results using LA24
(nonflexible makespan = 939)

Alternate machine policy	Dispatching	Tabu Search (1200s)^a	Move type % routing/sequencing
p1	1055	929 <i>107.04</i>	13.2 / 86.8
p1,p2	1072	925 <i>126.81</i>	29.7 / 70.3
p1,p2,p3	1058	941 <i>470.29</i>	35.7 / 64.3
c1	1077	919 <i>321.18</i>	21.6 / 78.4
c1,c2	1077	943 ^b <i>329.28</i>	34.0 / 66.0

a) nonimproving moves set to 2000

b) 941 achieved in 93.74s using max nonimproving moves of 5000

Table 3
Flexible tabu search results using LA40
(nonflexible makespan = 1226)

Alternate machine policy	Dispatching	Tabu Search (1200s) ^a	Move type % routing/sequencing
p1	1366	1219 <i>828.05</i>	17.6 / 82.4
p1,p2	1296	1156 <i>714.81</i>	28.3 / 71.7
p1,p2,p3	1303	1167 ^b <i>408.64</i>	35.1 / 64.9
c1	1332	1207 ^c <i>99.19</i>	13.2 / 86.8
c1,c2	1296	1206 <i>165.34</i>	23.6 / 76.4

a) nonimproving moves set to 2000

b) 1163 achieved in 944.04s using max nonimproving moves of 5000

c) 1203 achieved in 1107.6s using max nonimproving moves of 5000

Table 4
Flexible tabu search summary results for Tables 1 - 3

Alternate machine policy	% Improvement (flexibility)		% Improvement (tabu search)^a		Move type % routing/sequencing	
p1	0.5		9.6		16.6 / 83.4	
	1.1	<i>0.7</i>	11.9	<i>10.8</i>	13.2 / 86.8	<i>15.8 / 84.2</i>
	0.6		10.8		17.6 / 82.4	
p1,p2	1.9		8.8		36.1 / 63.9	
	1.5	<i>3.0</i>	13.7	<i>11.1</i>	29.7 / 70.3	<i>31.4 / 68.6</i>
	5.7		10.8		28.3 / 71.7	
p1,p2,p3	4.6		12.0		43.8 / 56.2	
	-0.2	<i>3.1</i>	11.1	<i>11.2</i>	35.7 / 64.3	<i>38.2 / 61.8</i>
	4.8		10.4		35.1 / 64.9	
c1	0.2		7.8		20.5 / 79.5	
	2.1	<i>1.3</i>	14.7	<i>10.6</i>	21.6 / 78.4	<i>18.4 / 81.6</i>
	1.5		9.4		13.2 / 86.8	
c1,c2	0.4		5.5		34.4 / 65.6	
	-0.4	<i>0.5</i>	12.4	<i>8.3</i>	34.0 / 66.0	<i>30.7 / 69.3</i>
	1.6		6.9		23.6 / 76.4	

10.4

a) nonimproving moves set to 2000