A Comparison of Optimization Techniques for Integrated Manufacturing Planning and Scheduling[1].CSRP 408.

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Abstract. We describe a comparison between Simulated Annealing (SA), Dispatch Rules (DR), and a Coevolutionary Distributed Genetic Algorithm (DGA) solving a random sample of integrated planning and scheduling (IPS) problems. We found that for a wide range of optimization criteria the DGA consistently outperformed SA and DR. The DGA finds 8-9 unique high quality solutions per run, whereas the other techniques find one. On average, each DGA solution is 10-15% better than SA solutions and 30-35% better than DR solutions.

1. Introduction

This paper describes a comparison of SA, DR, and a Coevolutionary DGA applied to a highly generalized class of job-shop scheduling problems. These problems involve the simultaneous optimization of a number of flexible manufacturing plans. The application of Coevolutionary GAs to this class of problems has been inves

Section 2 explains IPS more fully, followed by an overview of each technique used in this study. Problem, cost function and implementation details are then given before the results of the comparison are presented.

2. Integrated Manufacturing Planning and Scheduling

The traditional academic view of job-shop scheduling (JSS) is shown in Figure 1 [French S, 1982; Zweben M and Fox M, 1994]. A number of plans, one for each componen

In order to apply SA to a problem it is necessary to have a solution representation and a set of operators to move from the current solution to ne

Replacement is probabilistic using the inverse scheme to selection. Genetic material remains spatially local and a robust and c

There were 24 available operation methods. The earliest availability date for each machine was randomly generated from an appropriate range. Release and due dates, set-up and machine times, were generated in accordance with lookup tables and random functions [Palmer G, 1994]. Operation times were calculated using the company's estimation program.

4.2 The Cost Function

In addition, machine utilization, U, for each machine can be calculated:

Where is the initial availabe date of machine .

All of Palmer's results reproduced here were found using the compound cost function 'mean flow,

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The provisional status of an operation placement is lost when the time in the event-processing routines reaches the operation completion time. As operations cannot be performed in part, an operation taken off a machine is said to have been waiting all along. No consideration is made for the time an operation has provisionally occupied a machine when conflict arises. The binary table encodes which of the two plans wins machine-use.

6. Results

The results for the SA and dispas

Algorithm	Mean Flow time + Total Tardiness * 2	Mean No. Competing Solutions
GPDGA Cont.	46.54	8.76
GPDGA Grp.	45.56	9.74
SA	53.84	N/A
DR	101.93	N/A

Table 3: MFTT2 Comparison

Further analysis indicated the presence of a few aspects which significantly swung the results for the Total Tardiness criterion. These occur in cases where a problem includes a number of plans generated from the same templates-section. In such cases, the due-dates turn out to be similar for a number of jobs which largely demand the same machines (i.e. the method flexibility required to avoid waiting-times turns out to be particularly limited). Because there are 14 job-types, and 5-10 different jobs per problem, the probability of getting three or more jobs from the same job-type class is ≈0.071 (given 105 jobs, an average of ≈7.5 jobs would be the same as at least two others). This aspect adds to the difficulty of the problem by making the total tardiness hard to minimize. Table 4 shows the results for two identical DGA runs, differing only in the problems used: i.e. two different sets of 100 problems.

Algorithm	Makespan	Proportion Tardy	Total Tardiness	Total time Machining	Machine Utilization	Mean Flowtime
GPDGA 1st	62.75	0.18	16.67	112.86	0.16	23.93
GPDGA 2nd	63.50	0.16	12.89	117.22	0.16	23.99
SA	89.09	0.18	8.87	191.22	0.18	36.10
K&C	95.96	0.31	30.28	218.13	0.19	41.37

Table 4: Comparison of Two sets of 100 Problems (GPDGA Cont. cost function)

The results stay reasonably constant except for tardiness factors. Thus the effect of the MFTT2 in Table 5. This suggests that, although 100 problems would provide statistical significance for most of the optimization criteria, the sample may not be large enough to give a fair comparison of tardiness.

7. Conclusions

We found that for all the optimization criteria described in [Palmer G, 1994] the coevolutionary DGA consistently outperformed the SA algorithm and the DR algorithm. Results suggest that variance in costs due to sample size should be calculated in this sort of comparative study. It is clear that some optimisation criteria are more sensitive to this effect than others. A larger sample than that provided by Palmer would have been desirable. Both DGA cost function configurations investigated improved on the performance of the SA by a factor of over 15%, and on the dispatching rule by more than 35%. The results suggest that a cost function that includes factors that are related to both its individual performance as well as it's group performance will outperform,

Algorithm	MFTT2
GPDGA 1st	57.27
GPDGA 2nd	49.77
SA	53.84
K&C	101.93

Table 5: MFTT2

by about 1%, one which only accounts for the group performance. Unlike the other techniques, the DGA produced a number of unique, high quality solutions, to the problem on each run (typically 8 or 9).

8. References

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