A Genetic Algorithm Based Approach to Solve Process Plan Selection Problems

M.K.Tiwari*, S.K.Tiwari*, D. Roy*, N.K.Vidyarthi and S.Kameshwaran*****

* Department of Manufacturing Engineering,
National Institute of Foundry and Forge Technology,
Hatia, Ranchi-834 003,India.
** Department of Mechanical Engineering
NERIST, Nirjuli, Itanagar-791 109,India.
***SriVenkateshNagar, Chennai-600092, India.

ABSTRACT

Selection of a process plan is a crucial decision making problem in manufacturing systems due to the presence of alternative plans arising from the availability of several machines, tools, fixtures etc. Because of its impact on the performance of a manufacturing system, several researchers have addressed the plan selection problem in recent years. Selecting an optimal set of plans for a given set of parts becomes a NP complete problem under multiobjective and fairly restrictive conditions. In this paper, a Genetic Algorithm (GA) is used to obtain a set of feasible plans, for given part types and production volume, to minimize the processing time, setup time and materials-handling time constrained by not overloading the machines. Obtaining near optimal solutions by using different weights for different objectives in GA, is also studied.

INTRODUCTION

Process planning is the systematic organization of detailed methods by which parts are manufactured from raw material to finished product. With the possibility of alternate machines, setups, and processes to manufacture a particular part, plan selection in a manufacturing environment has become a crucial problem. Moreover, modern manufacturing systems may require a part to be produced simultaneously with any combination of part types and volume, and to be re-routed adaptively to alternative machines in case of breakdown or overloading of the pre-assigned machine. Because of it has a vital impact on manufacturing system performance, several researchers have examined the plan selection problem in recent years. Kusiak and Finke [1] developed a model to select a set of process plans with minimum cost of removing material and minimum number of machine tools and other devices. Bhaskaran [2] provided a model to account for factors such as, flow rate, processing time and processing steps. Zhang and Huang [3] extended the Bhaskaran [2] model using a fuzzy approach due to imprecise, conflicting objectives in plan selection. Seo and Egbelu [4] used Tabu search to select a plan based on product mix and production volume. Tiwari and Vidyarthi [5] addressed plan selection by accounting for similarity measures among the plans of the parts.

In this paper, we use Genetic Algorithm (GA) to obtain a set of process plans for a given set of parts and production volume. GAs are search and optimization algorithms based on the mechanics of natural genetics and natural selection. It has been recognised as a powerful method to obtain near optimal solutions for combinatorial optimization problem. (Davis [6], Goldberg [7], Deb [8]). We have used GA to obtain a set of process plans for a given variety of parts and production volume with the objective of minimizing the total processing time, setup time and material handling time constrained by not overloading the machines.

PROBLEM DESCRIPTION

The analytical model for the process plan selection in our approach, consider the following parameters – processing time, setup time and material handling time. The objective is to minimize the above parameters. But these objectives may overload a few workstations shared by most process plan and cause a system bottleneck. Hence a constraint function which caters the needs of not overloading any workstations is used to obtain a practically feasible optimal solution. The notations used in this problem are:

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a	1, 2, ... N parts
b_a	batch size of part a
P_{aj}	set of process plans for part type a, $P = \{P_{a1}, P_{a2}, .. P_{an}\}$ where P_{aj} is the jth process plan for part a, $n = \mid P_a \mid$
K	1, 2,.. K work stations
t_{ajk}	processing time on work station k for the process plan P_{aj}
mt_{aj}	material handling time for part a associated with process plan jth process plan of part a
s_{aj}	total setup time for P_{aj} for a batch size of b_a
ws_k	maximum allowable time on workstation k
o	objectives of minimizing processing time (1), setup time (2) and material handling time (3).
w_o	Weight of objective o. $\Sigma\, w_o = 1$
x_{ai}	1-if P_{aj} is selected for part a, 0-otherwise

The weighted cost of a process plan for P_{aj} is defined as

$$T_{aj} = w_1 \Sigma_k t_{ajk} b_a + w_2 s_{aj} + w_3 mt_{aj} b_a$$

The objective is to minimize the total weighted process plan cost (T) for a set of process plans, given by,

$$T = \Sigma_a T_{aj}\, x_{aj} \qquad 1.$$

subject to the constraints

$$[\, \Sigma_a t_{ajk} b_a x_{aj} \,] <= ws_k, \ \forall\, k = 1, 2, .. K \qquad 2.$$

and

$$\Sigma_j x_{aj} = 1 \ \forall\, a = 1, 2,.. N \qquad 3.$$

Constraint (2) prevents the occurrence of an overloaded machines and constraint (3) ensures that only one process plan per part is selected.

GA BASED SOLUTION METHODOLOGY

For a given set of N parts with na process plans for part a, the number of feasible solutions is given by Π^Nna. Thus for 6 parts with 5 process plans each, 15625 solutions need to be exhaustively searched to find the optimal solution and the search space increases combinatorially for further increase in the number of parts. Genetic algorithms are found to be potential search and optimization algorithms (Deb, [8]) for complex engineering optimization problems. They mimic the principles of natural selection (reproduction) and natural genetics (crossover and mutation) to constitute search and optimization procedures. Sets of initial feasible solutions are selected randomly and fitness values proportionate to their objective function are evaluated. The solutions with higher fitness values are selected with higher probability for next generation to perform crossover and mutation, thus conserving the Darwin's theory of fittest of survival. Since, GAs start with a set of initial points in the search space, the near optimal solutions are obtained in the increasing generations. The objective function to be minimized in our algorithm is:

$$OB = \Sigma_i T_{aj}\, x_{aj} + (mc * M)$$

where mc = number of workstations that are overloaded and M is a high scalar value that penalizes the OB by increasing it to higher values.

The fitness function evaluated for a solution in GA is given by:

$$F = S/(1+OB)$$

where S is a suitable scalar such that $0<F\leq 100$.

EXPERIMENT AND RESULTS

For solving the process plan selection problem by our proposed GA approach, we considered the problem given in Table 1. A part mix of 8 different parts was considered each with different batch sizes and a set of process plans. The shop floor has 4 workstations and each was allowed a maximum machining time of 1000 units. The objective is to select an optimal set of process plans with the minimum objective function OB, from the solution space of 139,968,000. Weights, w_o ={0.6,0.2,0.2}, were used for the objectives. GA was then applied to the problem with a population size of 10 for 30 generations. Single point crossover was used and mutation was performed over each crossovered string with the given mutation probability. The convergence of the GA to the optimum solution for different sets of GA operators is shown in Figure 1. GA1 with crossover (0.6) and mutation probability (0.1) converges faster to the optimal than GA2 with crossover (0.1) and mutation probability (0.8). The set of process plans selected by GA1 and GA2 are {3,3,2,4,2,3,2,3} and {2,3,2,4,2,2,4,3} respectively. The convergence of GA1 to the optimal is due to the fact that higher crossover rates result in better solutions. When all objectives were given equal weights, w_k={0.33,0.33,0.33}, the optimal set of process plans selected was {2,3,2,4,2,3,4,3}.

Table 1. Data for the process plan selection problem.

Part No	Batch Size	Process Plan	WS1	WS2	WS3	WS4	Setup Time	Material Handling Time
1	15	1	0	24	18	0	60	5
		2	10	10	8	9	90	15
		3	15	0	10	14	75	9
2	12	1	8	10	9	10	100	16
		2	0	12	10	17	70	12
		3	15	0	5	10	80	10
3	18	1	13	16	0	16	85	18
		2	0	15	11	12	65	14
4	8	1	10	10	10	10	100	16
		2	12	12	10	0	88	10
		3	0	12	12	10	75	12
		4	12	0	8	10	65	14
5	15	1	14	12	8	0	89	15
		2	15	0	16	0	80	10
		3	13	0	9	10	90	11
6	6	1	7	0	3	13	75	11
		2	9	5	0	7	70	13
		3	0	8	4	4	65	12
7	12	1	3	8	12	0	55	12
		2	4	6	0	7	64	14
		3	8	11	0	0	50	12
		4	0	4	7	6	55	11
8	5	1	0	4	8	12	65	11
		2	0	9	11	0	60	9
		3	6	4	3	0	68	13

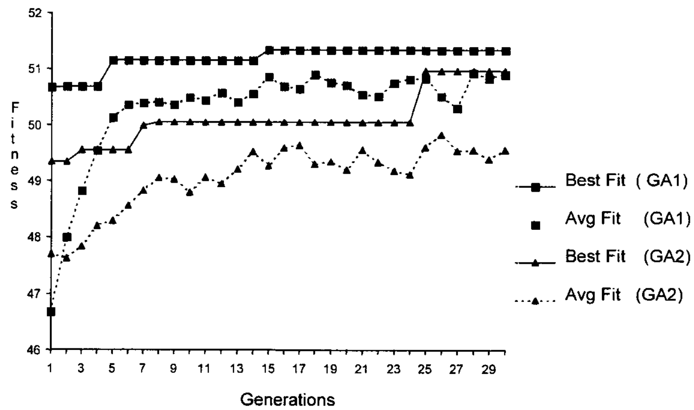

Fig. 1. Performance of the proposed GA Algorithm.
(GA1 - *Cr. Prob = 0.6, Mutt. Prob = 0.1* , GA2 - *Cr.Prob = 0.1, Mut. Prob = 0.8*)

CONCLUSION

Process Plan selection is a crucial problem in an automated manufacturing environment. Further, selecting a set of optimal process plans for a variety of parts with different production volume is a combinatorial optimization problem, which makes the exhaustive search technique a practically infeasible solution. Various researchers have attempted the problem using heuristics and other optimization techniques like Tabu Search and Simulated Annealing. In our approach, we used GA to find a optimal set of process plans that minimizes the total processing time, setup time and material handling time, meanwhile avoiding system bottleneck by not overloading the workstations .GA, which starts with different initial points in the search space, ultimately finds a near optimal solution for the complex combinatorial problem of process plan selection .By varying the weights of the different objective function, different set of optimal solutions were obtained which eases the post design issues following process plan selection in the automated manufacturing systems.

REFERENCES

1. A. Kusiak, G.Finke, 1998. Selection of Process Plans in Automated Manufacturing Systems, IEEE J. of Robotics and Automation. 4 (4), 397-402.
2. K. Bhaskaran, 1990. Process Plan Selection. Inter. J. of Production Research. 28 (8), 1527-1547.
3. H.C. Zhang, S.H. Huang, 1994. A Fuzzy Approach to Process Plan Selection. Inter. J. of Production Research. 32 (6), 1265-1279.
4. Y. Seo, P.J. Egbelu, 1996. Process Plan Selection Based on Product mix and Production Volume. Inter. J. of Production Research. 34 (9), 2369-2655.
5. M. K. Tiwari, and N. K. Vidyarthi, 1998. An Integrated Approach to Solving the Process Plan Selection problem in an Automated Manufacturing System. Inter. J. of Production Research. 36 (8), 2167-2184.
6. L. Davis, 1991. Handbook of Genetic Algorithm, Van Nostrand, Reinhold.
7. D. E. Goldberg, 1989. Genetic Algorithm in Search. Optimization and Machine Learning, Addision Welsey, Reading, MA.
8. K. Dev, 1996. Optimization for Engineering Design. Algorithms and Examples, Prentice Hall, New Delhi, India.