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Loading Methodology for a Capacity Constrained Job-Shop

Viraj Tyagi, Ajai Jain, P. K. Jain, Aarushi Jain

***Abstract*—**This paper presents a genetic algorithm based loading methodology for a capacity constrained job-shop with the consideration of alternative process plans for each part to be produced. Performance analysis of the proposed methodology is carried out for two case studies by considering two different manufacturing scenarios. Results obtained indicate that the methodology is quite effective in improving the shop load balance, and hence, it can be included in the frameworks of manufacturing planning systems of job-shop oriented industries.

***Keywords*—**Manufacturing planning, loading, genetic algorithm, Job-Shop.

I. Introduction

IN manufacturing industries, Manufacturing Planning and Control (MPC) systems are used for cost effective management of various activities related to the manufacturing of the products. MPC deals with the complex manufacturing problems such as large product mix and short lead times; moreover, it ensures that acceptable quality products are delivered to the customers by the due dates that are mutually agreed by the customers and the firm. Reference [16] reviewed important MPC approaches and reported that shop loading was not considered adequately by most of the researchers in the past. Further, it was stated that a poorly loaded shop can never yield feasible production schedules. Infeasible production schedule may create serious problems such as longer lead times, less throughput, late deliveries, high work-in-process, longer queues at machines and lower machines utilization at the shop floor [2], [5], [11]. Ultimately, it makes the manufacturing activities inefficient and costly. Thus, shop loading is crucial for efficient working of manufacturing industries. In the present work, shop loading refers to the assignment of various operations of parts under consideration to the available machines of job-shop.

Traditionally, parts that are to be produced are available with Single Process Plan (SPP). A traditional SPP contains only one sequence of operations as well as machines on which these operations are to be performed [6]. Usually, SPPs are not able to cope up with the uncertain conditions such as machine breakdown, non-availability of materials and/or tools that are usually present at the shop floor. The problems associated with SPP can be overcome by ensuring the availability of Multiple Process Plans (MPP) for each part. Moreover, shop loading can be optimized in the presence of MPP. In the present paper, loading problem of a capacity constrained job-shop has been addressed in the presence of MPP for each part to be produced. Job-shop is considered, since a large number of small and medium companies operate, today, in job-shop environment. Job-Shop loading problem is considered to be a "combinatorial optimization" type, and such problems can be effectively addressed by modern heuristic techniques such as Genetic Algorithm (GA), tabu-search and simulated annealing [7]. GA shows better performance in global search and therefore, widely applied to solve the problems related to manufacturing planning [2], [10], [15].

This paper presents a GA based methodology for balancing work load of job shop in which capacity is constrained and alternative process plans (i.e. MPP) for each part type are available.

Viraj Tyagi is with Kurukshetra Institute of Technology & Management, Kurukshetra, India.
Ajai Jain is with National Institute of Technology, Kurukshetra, India (corresponding author, phone: +91-1744233464; fax: +91-1744-238050; e-mail ajaijain12@gmail.com).
P.K. Jain is with Indian Institute of Technology, Roorkee, India.
Aarushi Jain is with Fiserv India Pvt. Ltd, Noida, India.

II. Loading Methodology

Important aspects of the proposed methodology are briefly discussed as follows:

A. Capacity Feasibility of MPS

First of all, the proposed methodology ensures that sufficient capacity of job-shop under consideration is available to produce the parts of given Master Production Schedule (MPS) for a planning horizon of eight weeks. The shop utilization levels, best process plans, and due dates of parts are used to ensure that given MPS is feasible from the capacity consideration of given job-shop. The machines required to process a given part are considered to be available up to Net Available Time (NAT). NAT of a part is computed by multiplying the due date of part under consideration with the shop utilization level. For a part to be feasible from the job-shop capacity view point, load status of any machine as required by the best process plan of part under consideration, should be less than or equal to NAT of the part. If for any part, capacity of any machine is found insufficient, the part is removed from the given MPS. Thus, shop loading is carried out for a capacity feasible MPS. Further, GA is utilized in order to balance the work load of job-shop with the consideration of MPP for each part to be produced.

B. Shop Loading Methodology

GA is basically a computerized search algorithm that is inspired by the Darwin's theory of survival of the fittest. The present work uses permutation type of encoding. In this scheme of representation, part is combined together with its

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process plan to form a bit (gene) of a chromosome. The scheme of encoding used in the present work is explained with the help of an example. For case study 1, part types 3, 5, and 10 are to be produced during week 1, and each part type can be processed by any one of its available multiple process plans. This information can be suitably represented as: {(3 3), (5 4), (10 1)} as shown in Fig. 1. Thus, in the proposed encoding scheme, length of the chromosome is controlled by the number of parts to be produced in a week.

In the present work, population of GA is initialized randomly as suggested in the literature of GA [1], [3]. The population size that remains fixed during different iterations of GA is kept ten. In GA, fitness function is derived from the objective of the problem. Thus, pre-selected fitness function is used in successive iterations for evaluating the individuals that represent the expected solutions of the problem under consideration.

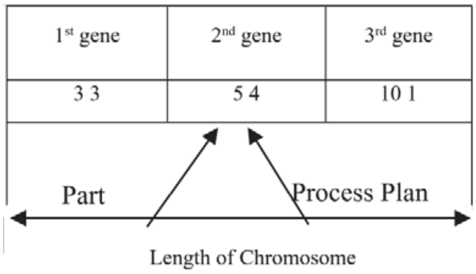

Fig. 1 Chromosome Structure for Week 1 of Case Study 1

In the present work, the objective is to minimize the system unbalance for each week of planning horizon under consideration. In GA, reproduction is considered as the backbone of GA [9]. If satisfactory solution is not found during initial iteration(s), reproduction is desired to create new population that is to be used during next iteration. Selection Operator is applied with the aim to select fitter individuals of current population for the given objective. The selected individuals form the mating pool. Number of individuals to be selected for mating pool depends upon the generation gap (G_GAP). In the present work, G_GAP is taken as 0.70. In the present study, Linear Ranking selection method with Stochastic Universal Sampling (SUS) is applied to select the individual for mating pool. Maximum value of individual for rank selection is taken as 1.5. Further, a simple Two-point Crossover with the crossover probability (p_c = 0.80) is applied on the individuals of mating pool [12]. Then, Point Mutation with mutation probability (p_m = 0.40) is applied on the individuals of mating pool including offsprings produced after crossover operation [12]. In order to ensure the transfer of few good individuals from the previous population to the population of next generation, elitism strategy is applied [4]. In elitism, the individuals of mating pool including offsprings produced after crossover and mutation along with the individuals of parent population form the extended population. From this extended population, population for next generation is formed by taking all individuals of mating pool including offsprings and the remaining individuals are taken from the parent population in the order of their fitness values. The results obtained during GA iterations, indicate that fitness value of best individual in all scenarios stabilizes well before 800 numbers of generations. The individual that yields best fitness value of the fitness function among three simulation runs is selected for each week. Then, the selected individual provides process plans that are to be followed during the processing of parts of that week.

III. Result and Discussion

In the present study, six non-identical machines are considered to be available in the job-shop under consideration. This job-shop operates in shifts; only one shift a day and each shift is of eight-hour duration. Further, planning horizon is of eight weeks with the consideration of five days per week. Thus, each machine of job-shop is available for 2400 minutes. In order to carry out performance analysis of the proposed methodology, two case studies are taken into consideration. Table I summarizes various parameters of the case studies. In the present work, production orders of parts are assumed to be available at the start of each week and due dates are assigned by following Total WorK Content (TWK) method [8], [14]. The total processing time of a part as desired by TWK method for assigning its due date is taken from the process plan that takes the maximum time to produce it. The proposed methodology optimizes job-shop load by applying GA with the objective of minimization of system unbalance.

TABLE I
Details of Parameters of Case Studies

S. No.	Parameter	Value/ Type
1	Number of parts to be produced per week	3-5
2	Batch size per part per week	20-50 Pieces
4	Planning horizon	8 Weeks
5	Number of operations per part	3-5
6	Number of machines on which an operation can be performed	3
7	Types of parts	10
8	Processing times of different operations of parts	10-45 Minutes
9	Number of alternative process plans available (i.e. MPP)	4

In GA, generally a fitness function is derived from the objective of the problem. In the present work, individuals of population during different iterations of GA are evaluated by using following fitness function [12]:

Maximize ‘f’ = (SUmax - SUind) / (SUmax - SUmin)

Here, *SUmax* is taken as 14400 min. [number of machines available in job-shop (6) x time available on each machine (2400 min.)] and *SUmin* as 0 min. *SUind* is the system unbalance corresponding to an individual of GA population under consideration. In order to assess the performance of proposed loading methodology, SPP and MPP environments are considered for manufacturing the parts of given MPS. In SPP environment, parts are assumed to be processed following their best process plans, and alternative process plans are usually not available, whereas in MPP environment, alternative process plans for each part are available. Thus, before scheduling the parts on machines, shop loading can be optimized for the given objective. In the present work, four MPPs are considered and these are ranked on the basis of the minimum total production time criterion; thus, process plan that takes minimum time to produce a part is ranked as best process plan.

Table II presents the fitness values of system balance for all eight weeks of the planning horizon under SPP as well as MPP environment for the considered case studies. It reveals that higher system balance is obtained in MPP environment as compared to SPP environment. For example, for case study 1 and at 70% shop utilization level, average fitness value of system balance is 0.6744 in MPP environment which is much higher than 0.2937 of SPP environment. Similarly, for case study 2 and at 90% shop utilization level, system balance is 0.6651 in MPP environment as compared to 0.2283 of SPP environment. The proposed methodology attempts to improve the load balance among the machines of job-shop, and thus, higher average fitness values are obtained for MPP environment. This is true for all other scenarios as well, as indicated by Table II. Further, in some scenarios of SPP environment, very poor system balance is found as indicated by negative system balance. For example, for week 5 of case study 1, values of system balance are -0.0326, -0.0515, and -0.0515 at 70%, 80%, and 90% shop utilization levels, respectively. It happens in such a situation when *SUind*>*SUmax*, indicating that the load among the machines is highly unbalanced.

TABLE II
SYSTEM BALANCE IN SPP AND MPP ENVIRONMENTS

Case Study	Week	System Balance (Fitness Values)					
		SPP Environment			MPP Environment		
		Shop Utilization Level (%)					
		70	**80**	**90**	**70**	**80**	**90**
1	1	0.3759	0.3759	0.3759	0.6478	0.6478	0.6478
	2	0.4321	0.4321	0.4321	0.6460	0.6460	0.6460
	3	0.4064	0.4064	0.4064	0.6645	0.6645	0.6645
	4	0.1816	0.1816	0.1816	0.7265	0.7265	0.7265
	5	-0.0326	-0.0515	-0.0515	0.8064	0.7331	0.7331
	6	0.0656	-0.0944	-0.0944	0.6494	0.4759	0.4759
	7	0.3879	0.2572	0.0593	0.5258	0.8401	0.8824
	8	0.5330	0.3408	0.0261	0.7289	0.7507	0.8862
	Average Fitness Value	**0.2937**	**0.2310**	**0.1669**	**0.6744**	**0.6852**	**0.7078**
2	1	0.6749	0.6749	0.6749	0.8283	0.8283	0.8283
	2	0.3316	0.3316	0.3316	0.5578	0.5578	0.5578
	3	0.4692	0.4692	0.4692	0.6103	0.6103	0.6103
	4	0.2380	0.2380	0.2380	0.6011	0.6011	0.6011
	5	0.1030	0.1101	0.1101	0.4837	0.6572	0.6572
	6	0.1776	-0.0677	-0.0677	0.7545	0.6151	0.6151
	7	0.3437	0.0555	-0.0494	0.6337	0.6812	0.6599
	8	0.5674	0.2792	0.1201	0.8546	0.8332	0.7910
	Average Fitness Value	**0.3632**	**0.2613**	**0.2283**	**0.6655**	**0.6730**	**0.6651**

In MPP environment, higher system balance is obtained due to the fact that alternative machines are available during shop loading. Ultimately, higher system balance yields feasible and efficient production schedules for the shop floor implementation [13]. Further, it is important to mention that in order to achieve higher system balance, process plan selected for a part may be different from one week to another.

Thus, it can be concluded that the proposed methodology is quite effective for balancing the job-shop load. Moreover, it can be included in the frameworks of manufacturing planning systems with the aim to manage operational problems of job-shop oriented industries, especially when alternative process plans are available for parts to be produced.

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