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Multiobjective Hybrid GA for Constraints-based FMS Scheduling in make-to-order Manufacturing

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Abstract - Many manufacturing companies consider the integrated and concurrent scheduling because they need the global optimization technology that could manufacture various products more responsive to customer needs. In this paper, we propose an advanced scheduling model to generate the schedules considering resource constraints and precedence constraints in make-to-order (MTO) manufacturing environments. Precedence of work-in-process (WIP) and resources constraints have recently emerged as one of the main constraints in advanced scheduling problems. The advanced scheduling problems is formulated as a multi-objective mathematical model for generating operation schedules which are obeyed resources constraints, alternative workstations of operations and the precedence constraints of WIP in MTO manufacturing. For effectively solving the advanced scheduling problem, the multi-objective hybrid genetic algorithm (m-hGA) is proposed in this paper. The m-hGA is to minimize the makespan, total flow time of order, and maximum tardiness for each order, simultaneously. The m-hGA approach with local search-based mutation through swap mutation is developed to solve the advanced scheduling problem. Numerical example is tested and presented for advanced scheduling problems with various orders to describe the performance of the proposed m-hGA.

I. INTRODUCTION

Recently, manufacturers with make-to-order (MTO) tend to use a flexible flows strategy, where they manufacture various products in job shop type production and small batch production environment to satisfy various customers' demands. In the theory of MTO scheduling, a set of customer orders is to be processed on a set of facilities in order to satisfy one or more certain performance measures.

Some research works have been published for the advanced scheduling on a MTO environment. Kolish and Hess [1] considered the problem of scheduling multiple, large-scale, MTO assemblies under resource, assembly area, and part availability constraints. They introduced three efficient heuristic methods which were a based random sampling method and TS-based large-step optimization methods. Yang [2] developed a genetic algorithm (GA) based dynamic programming approach for scheduling in flexible manufacturing system environments. They developed a GA-based approach to determine the process plan for a product, schedule for production, and machine for processing of each operation, simultaneously. In a MTO environment, the advanced scheduling has been recommended by the above researches. However, the major weakness of the models introduced so far lies in that they considered the alternative resources for each operation with a fixed sequence when constructing a schedule or the single objective function.

In this paper, we propose a mathematical model for generating operations schedules which are obeyed resources constraints, alternative workstations of operations and the precedence constraints of work in process (WIP) in MTO manufacturing. The objective of the model is to minimize the makespan with total flow time for each order and maximum tardiness for each order. We also develop a multi-objective hybrid genetic algorithm (m-hGA) for minimizing the makespan, total flow time of order and maximum tardiness of order such as advanced scheduling environment. The rest of the paper is organized as follows. In Section II, we describe a hypothetical instance of advanced scheduling problem and mathematical model for the multi-objective advanced scheduling problem is given in Section III. In Section IV, we describe the feature of our method including the chromosome representation, the m-hGA process. In Section V, numerical experiments are presented to demonstrate the efficiency of the proposed method. Finally, some concluding remarks are given in Section VI.

II. ADVANCED SCHEDULING PROBLEM

Advanced scheduling enable companies to reduce their cost of goods sold and increase customer satisfaction by making more of the right products at the right times, using an optimal combination of manufacturing resources. Advanced planning systems utilize complex mathematical algorithms to forecast demand, plan and schedule production within specified constraints, and derive optimal sourcing and product-max solutions. Typical dynamic manufacturing system is composed of multiple workstations, a material handling system, and a loading-unloading station.

Fig. 1 shows basic concept of design of manufacturing systems in advanced scheduling environment. When customers order various products, manufacturing company have to produce customer's products with the limited resources such as manpower, material, and equipment under the appointed date of delivery. So MTO is that the manufacturer does not start to manufacture the product until a customer order is received.

Their objective is to schedule the operations with resources constraints and the WIP precedence constraints about customers various orders in manufacturing company with multiple workstations (or machine centers).

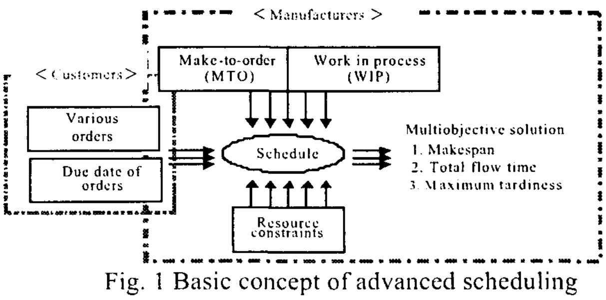

Fig. 1 Basic concept of advanced scheduling

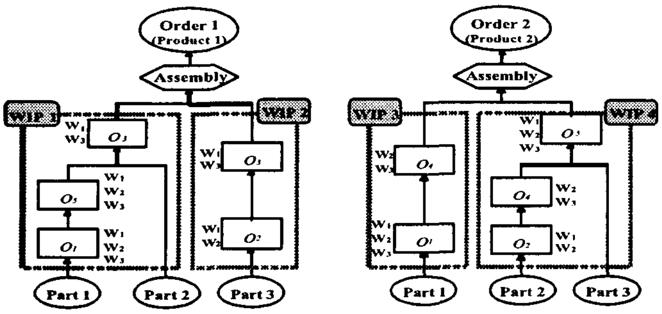

Fig. 2 Example of flexible WIP process as MTO

Fig. 2 shows flexible WIP process of the operations as MT O to make two products. Then the following MTO process is legal:

(Order1) = WIP1($o_1 \rightarrow o_5 \rightarrow o_3$) ⊕ WIP2($o_2 \rightarrow o_3$),
(Order2) = WIP3($o_1 \rightarrow o_4$)⊕ WIP4($o_2 \rightarrow o_4 \rightarrow o_5$).

where WIP means the progress of work for constraining operations precedence, and ⊕ means the WIP processes which have to assemble together when get the some orders. In order to minimize WIP, a precedence feasible schedule is constructed in which the operations a re scheduled at processing time and constrained resource.

III. MATHMETICAL MODEL

In order to formulate an integrated model, the following Indices, variable and parameters are introduced:

indices

- i : operation index, $i = 1,2,\cdots,I$.
- j : workstation index, $j = 1,2,\cdots,J$ (or $W_j, j = 1,2,\cdots,J$).
- k : order index, $k = 1,2,\cdots,K$ (or $E_k, k = 1,2,\cdots,K$).

variable

- t_{ijk}^F : (the integer valued) finish processing time of operation o_i on selected workstation W_j for each order E_k.

parameters

- t_k^D : due date of the each order E_k (the promised completion time of each order).
- p_{ijk} : processing time of operation o_i on workstation W_j for each order E_k.
- r_{ijk} : amount of resource required by operation o_i on workstation W_j for each order E_k.
- R_j :maximum-limited resource required on workstation W_j.
- wip_l: precedence of operation in WIPs.

In advanced scheduling problem, the objectives of the model are to minimize the makespan t_M, total flow time of order t_F and maximum tardiness $T_{\max}$. The problem can be formulated as follows:

$$\min\ t_M = \max_{i,j,k}\{t_{ijk}^F\} \tag{1}$$

$$\min\ t_F = \sum_{k=1}^{K} \max_{i,j}\{t_{ijk}^F\} \tag{2}$$

$$\min T_{\max} = \sum_{k=1}^{K} T_k \tag{3}$$

$$T_k = \max\{\max_{i,j}\{t_{ijk}^F\} - t_k^D, 0\},\ \forall k \tag{4}$$

s. t.

$$t_{ijk}^F - t_{(i-1)jk}^F \geq p_{(i-1)jk},\ i \in wip_l, \forall l, j \tag{5}$$

$$\sum_i \sum_k r_{ijk} \leq R_j,\ \forall j \tag{6}$$

$$t_{ijk}^F \geq 0, i \in wip_l, \forall l, j, k$$

In equation (1), we define makespan t_M that is the lastly finished processing time of operation o_i on workstation W_j for each order E_k. t_M is the actual time required to complete all orders. So this first objective minimizes total project processing time. Equation (2) defines total flow time that is the finish processing time of last operation o_i on workstation W_j for each order E_k. Equation (3) defines to minimize the tardiness with the maximum tardiness $T_{\max}$ out of tardiness of each order E_k defines in Equation (4). Tardiness of each order E_k defines the absolute difference between its completion time and its processing time, given that the former is larger than the latter in Equation (4). Constraint (5) ensures that none of the precedence constraints are violated. Constraint (6) ensures that the amount of resource used by all activities does not exceed its limited quantity in any period.

IV. MUlTI-OBJECTIVE HYBRID GA

In a multi-objective optimization problem, multiple objective functions need to be optimized simultaneously. In this case of multiple objectives, there does not necessarily exit a solution that is best with respect to all objectives because of incommensurability and confliction among objectives. A solution may be best in one objective but worst in another. Therefore, there usually exist a set of solutions for the multi-objective case which cannot simply be compared with each other. For such solutions, called Pareto optimal solution, no improvement is possible in any objective function without sacrificing at least one of the other object functions [4]. We propose a random-weight approach to obtaining a variable search direction toward the Pareto solution as shown in Fig. 3.

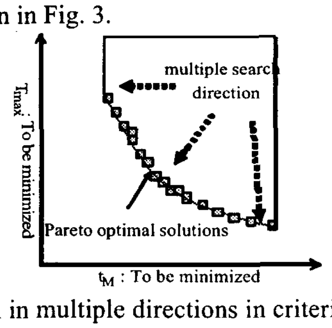

Fig. 3 Search in multiple directions in criterion space.

A. Initialization

This operation permutation encoding is one-to-one mapping for advanced scheduling problem as shown in Fig. 5, so it is easy to decoding and evaluate. This method randomly generates an initial population containing individuals. We randomly generate an initial population of the population size

pop_size solutions. Fig. 4 shows one operation permutation which randomly generated for example of the advanced scheduling problem.

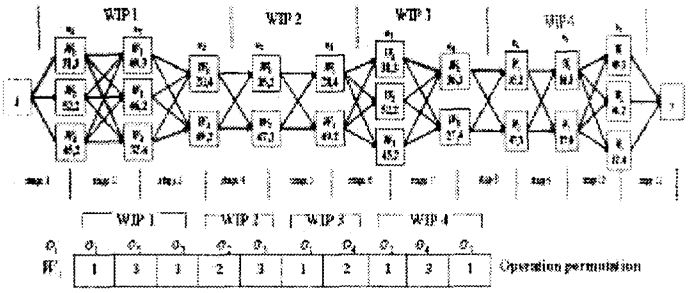

Fig. 4 Operation permutation for the example of advanced scheduling problem

B Evaluation

We calculate the values of q objective functions for each individual, and update a tentative set of Pareto solutions. A tentative set of Pareto solutions is stored and updated at each generation. For a problem with q objectives, there are N extreme points in the Pareto solutions, each of which minimizes one objective. An elite preserving strategy is suggested for putting the N extreme points plus some randomly selected Pareto solutions into the next population.

C. Selection

We use the adaptive weight approach which utilizes some useful information from the current population to readjust weight to obtain a search pressure toward a positive idea point. The adaptive weight w_i is calculated by the equation.

$$w_i = \frac{1}{z_i^{\min} - z_i^{\max}}, \quad i = 1,2,\cdots,q \tag{7}$$

This is probably the some adaptive method of all classical multi-objective methods. It is multiple objectives such as makespan t_M minimization, total flow time t_F minimization and maximum tardiness $t_{\max}$ minimization are combined with the help of subjectively adaptive weight factors into a weighted-sum objective function, as follows:

$$Z = \sum_{i=1}^{q} w_i (z_i^{\min} - z_i) = \sum_{i=1}^{q} \frac{z_i^{\min} - z_i}{z_i^{\min} - z_i^{\max}}$$
$$= \frac{z_i^{\min} - t_M}{z_i^{\min} - z_i^{\max}} + \frac{z_i^{\min} - t_{\max}}{z_i^{\min} - z_i^{\max}} + \frac{z_i^{\min} - t_F}{z_i^{\min} - z_i^{\max}} \tag{8}$$

Before selecting a pair of parents for crossover operation, a new set of adaptive weights is specified by equation (7), and fitness values for each individual are calculated by equation (8). The selection probability p_i for individual i is then defined by the following linear scaling function:

$$p_i = \frac{Z_i - Z_{\max}}{\sum_{m=1}^{pop\_size} (Z_m - Z_{\max})} \tag{9}$$

where $Z_{\max}$ is the worst fitness value in current population.

Let E_size denotes of elite size to preserve. We repeat the following steps to select E_size pairs of parents: Specify adaptive weights by equation (7), calculate fitness value by equation (8), calculate selection probability by equation (9), and select a pair of parent solutions from the current population.

D. Swap mutation

We apply a mutation operator to each of the selected E_size pairs of parent. The swap mutation was used with one operator out of selected E_size, which simply selects two orders at random and swaps their contents.

E. Local search-based mutation

Local search methods seek improved solutions to a problem by searching in the neighborhood of an incumbent solution. The implementation of local search requires an initial incumbent solution, the definition of a neighborhood for an incumbent solution, and a method for choosing the next incumbent solution. The idea that locates an improved solution by making a small change can be used in mutation operator.

F. Elitist strategy

In multi-objective optimization problems, a solution with the best value of each objective can be regarded as an elite individual. Therefore we have q elite individuals for an q-objective problem. It is natural to think that such solutions are to be preserved to the next generation in GAs. This elite preserve strategy has an effect on keeping the variety in each population in our m-hGA.

We randomly select E_size individuals from the tentative set of Pareto solutions, and add the selected solutions E_size individuals generated in the foregoing steps to construct the pop_size population of individuals.

G Termination condition

If a prespecified stopping condition is satisfied, stop the run; otherwise, return to evaluation.

V. NUMERICAL EXPERIMENT

For the numerical experiment, we consider the manufacturing system problem that finds the optimal solution with ten operations on five workstations as three orders from customers. The proposed algorithms are implemented in JAVA language on IBM-PC with Pentium 1.4GHz speed and 256MB RAM. Fig. 5 shows flexible WIP process of the operations as MTO to make five products. Table 1 shows the processing time and resource of each operation on workstations as MTO of an advanced scheduling problem.

In Table 2 depicts relevant data pertaining to five orders labeled WIP 1, WIP 2,..., WIP 10 that must be scheduled in this system. The evolutionary environment for this experiment was set as follows: population size was 1000, swap mutation and local search-based mutation were 0.3, respectively, and maximum generation was 500. In the exam ple of advanced scheduling problem, limited resource which the amount of resource used by all activities does not exceed its limited quantity is 10.

In this Section, we demonstrate the effectiveness of our m-hGA by computer simulations on a multi- objective advanced scheduling problem with bi-objectives: to minimize the makespan and the maximum tardiness.

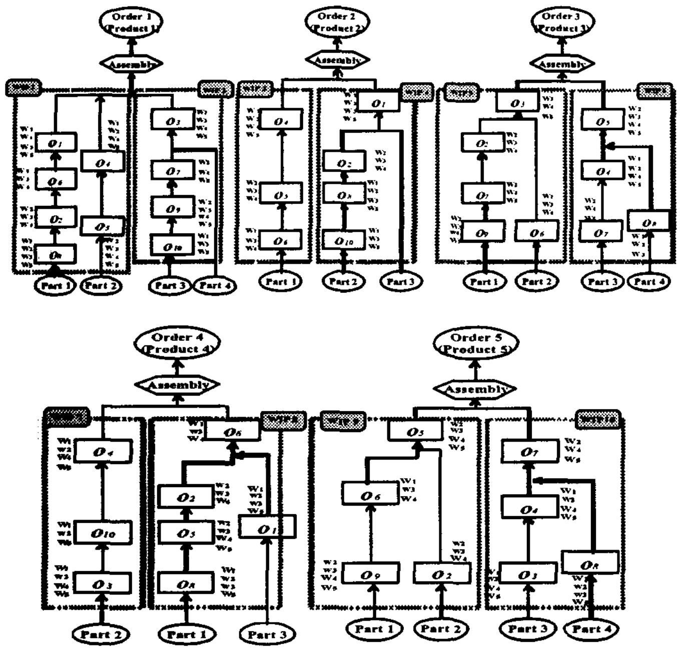

Fig. 5 Example of flexible MTO process

Table 1 Processing times and resources

	Required processing times and resources									
	W_1		W_2		W_3		W_4		W_5	
o_1	47	5	36	6	26	7	∞	∞	65	3
o_2	∞	∞	64	3	54	4	46	5	∞	∞
o_3	63	2	∞	∞	82	1	79	2	27	7
o_4	55	4	43	5	∞	∞	87	1	36	6
o_5	∞	∞	62	3	29	7	53	4	84	1
o_6	48	5	∞	∞	74	2	29	7	∞	∞
o_7	∞	∞	29	6	∞	∞	48	5	63	3
o_8	82	1	17	8	65	3	∞	∞	42	5
o_9	∞	∞	46	5	48	4	27	6	38	6
o_{10}	48	5	∞	∞	28	6	∞	∞	64	3

Table 2 Order-related operation of the advanced scheduling problem

E_k	WIP No.	Required operations	t_k^D
1	WIP1 ⊕ WIP 2	$\{o_8, o_2, o_6, o_1, o_5, o_4\}$ ⊕ $\{o_{10}, o_9, o_7, o_3\}$	300
2	WIP 3 ⊕ WIP 4	$\{o_6, o_5, o_4\}$ ⊕ $\{o_{10}, o_8, o_2, o_1\}$	300
3	WIP 5 ⊕ WIP 6	$\{o_9, o_7, o_2, o_6, o_3\}$ ⊕ $\{o_7, o_4, o_8, o_5\}$	250
4	WIP 7 ⊕ WIP 8	$\{o_3, o_{10}, o_4\}$ ⊕ $\{o_8, o_5, o_2, o_1, o_6\}$	280
5	WIP 9 ⊕ WIP 10	$\{o_9, o_6, o_2, o_5\}$ ⊕ $\{o_3, o_4, o_8, o_7\}$	270

We also apply our algorithm to the multi-objective advanced scheduling problem with the tri-objectives: to minimize the makespan, the maximum tardiness, and the total flow time. In Fig. 6 shows the tentative set of Pareto optimal solutions obtained by the proposed m-hGA with the bi-objective problem.

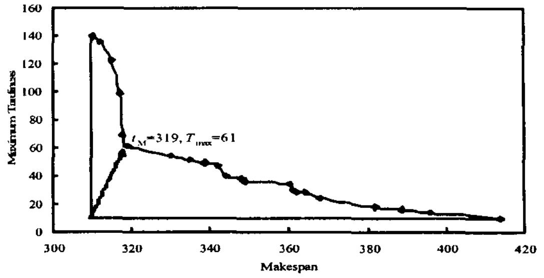

Fig. 6 Pareto solution using our m-hGA with bi-objective problem

About tri-objective problem, the criterions proposed by Lo and Chang [3] are introduced to evaluate the performances. The major points to be compared are listed as follows: (1) the numbers of Pareto randomly generate solutions (S_P) of each approach after the approaches are compared with each other. (2) the numbers of obtained solution (S_o) searched by each approach (except of Pareto optimal solutions). (3) percentage of Pareto optimal solutions (S_p / S_o). The average performance of bi-objective and tri-objective problem over the 20 trials using m-hGA is shown in Table 1.

Table 3 The performance result of bi-objective and problem using m-hGA

	S_P	S_o	Ration: S_P / S_o	CPU time (sec)
t_M, T_{max}	16.25	19.28	84.28%	11.52
t_M, t_F, p_T	85.65	98.37	87.07%	13.72

VI. CONCLUSION

In this paper, we have formulated a multi-objective mathematical model for the advanced scheduling problem and proposed a multi-objective hybrid genetic algorithm (m-hGA) approach with local search-based mutation through swap mutation in a flexible process environment characterized by precedence and resource constraints for make-to-order (MTO) and alternative workstations with different processing times. The quality results from the evolutionary generation of order and work-in-process (WIP) sequences through the swap mutation and local optimization of partial schedules in the local search-based mutation. In computational experiment, it is found that the proposed m-hGA approach could produce best results in terms of the makespan, total flow time and maximum tardiness of order.

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