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INTEGRATED PRODUCTION PLANNING AND SCHEDULING IN CELLULAR MANUFACTURING USING GENETIC ALGORITHMS

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Abstract

This paper describes the integration of production planning and scheduling in order to find better schedules. The conventional method which seeks the planning of production before going in scheduling could cause some schedules to be less optimal. In cellular manufacturing, most processes can be done on more than one machines which have different processing capabilities and processing times. In the proposed method based on genetic algorithms, the processing capabilities of the machines which includes the processing cost as well as number of rejects produced in alternative machines are considered simultaneously with the scheduling of the jobs. The formulation is based on weighted-sums multi-objective which are to minimize makespan, to minimize total rejects produced and to minimize the total cost of production.

Keywords: multi-objective genetic algorithms, process planning and scheduling

1. Introduction

Manufacturing systems involves a lot of problems that are actually integrated and should be solved concurrently. The traditional method of engineering design is done sequentially or serially and known as sequential or serial engineering. Traditionally, the machine to process a certain operation is chosen based on the unit cost of operation. While this method could be easier to schedule, it could cause some machines to be overloaded and could create bottlenecks. Consequently, more jobs can become tardy. This approach unnecessarily restricts the capability of the manufacturing cells, where most operations can be processed in more than one machines in the cell.

In practice, scheduling and planning problems rarely involve only a single consideration as manifested in classic combinatorial problems (Zentner et. al (1994)). These problems involve multiple objectives which need to be addressed simultaneously. Hence, the actual optimization problem is to determine the process plan and schedule concurrently. Due to the alternative machines available, the scheduling problem becomes more complicated since the search space is increased.

In the proposed method, the optimization is done concurrently using multi-objective GAs based on weighted-sums approach. Due consideration is given to the capabilities of the alternative machines available. The machines have different tolerance limits as well as different costs to operate. This consideration is shown in the form of minimizing number of rejects and minimizing total production cost objectives. The objective associated with scheduling, which is minimizing makespan is also included in the evaluation. These objectives are optimized simultaneously and results are compared with the conventional method of choosing the machine based on unit cost of processing followed by scheduling based on dispatching rule of shortest processing time (SPT).

The rest of the paper is arranged as follows: Section 2 describes previous work on production planning and scheduling. Section 3 gives a description on the interaction between design and manufacturing followed by the proposed method based on evolutionary algorithms in Section 4. Simulation results and a comparison with the conventional method are given in Section 5 followed by discussions in Section 6. Finally, Section 7 gives some conclusions of the paper.

2. Integrated Process Planning and Scheduling

Process planning or production planning is concerned with the selection of machines to convert a design specification into a product. In other words, process planning acts as a bridge between design and manufacturing by translating the design specifications into manufacturing process details. In process planning, the machines in which the operations are to be performed as well as the machining parameters to be used along with any alternative machines to perform the same operation are specified. Scheduling, on the other hand, is concerned with finding the best sequence of operations along with the associated machines to satisfy certain criterion/criteria.

In the traditional method, the process planning and scheduling are done sequentially, where the process plan is determined before the actual scheduling is performed. In processing the parts, there may be several ways to produce a given design, with alternative machines for each operations. The basic criteria for evaluating the suitability of a machine to process an operation are normally based on the machine that could produce a unit of product with the least amount of cost, or normally known as unit cost of production, manufacturing lead time and quality (Singh (1996)). Although, this method may be simple, it ignores the inherent relationship between scheduling and process planning. By assuming that once the process plan is determined, scheduling takes over, the possible choices of the schedule using alternative machines are ignored. This criterion restricts the schedule to only one machine per operation and could lead to certain machines being under-utilized or over-utilized. As a result, the completion times of products could be lengthened unnecessarily.

The idea of the integrated process planning and scheduling approach is relatively new and is considered necessary with the advance of technology where most operations can be processed in more than one machine. This concept is in line with the concept of Concurrent Engineering (CE). Concurrent Engineering is a management and engineering philosophy for improving quality and reducing costs and lead time from product conception to product development for new products and product modifications. It is defined as a systematic approach to the integrated, concurrent design of products and their related processes, including manufacture and support. This approach is intended to cause the developers, from the outset, to consider all elements of the product life cycle from conception to disposal, including quality, cost, schedule and user requirements (Pennell and Winner, 1989).

The integrated approach has been proposed by several researchers. Sundaram and Fu (1988) developed a heuristic to solve the problem. Proth (1994) developed a Petri-net for planning and scheduling an on-line manufacturing system. Brandimarte and Calderini (1995) developed a two phase hierarchical tabu search for efficient planning and scheduling. Palmer (1996) developed a method based on simulated annealing, and Khoshnevis and Chen (1990) used the dispatching rule approach. Even though the dispatching rule approach is simple and easy to implement, the shortcoming of this approach is that decisions are based with no forward planning and could lead to poor scheduling decisions. Husbands et. al. (1991) developed an eco-system model using genetic algorithms for integrated process planning based on the features to be processed.

3. Interactions Between Design and Manufacturing

The analysis of the interaction between design and manufacturing process is given as follows (Singh (1996)):

Suppose that all parts that do not meet the manufacturing tolerances will be rejected. This means that the parts below and above the tolerance limits will be scrapped. The fraction of scrap (*SC*) is calculated as follows:

$$SC_j = \frac{Y_j^s}{Y_j^i} \tag{1}$$

where:
SC=fraction of scrap
Y^S=scrap units
Y^i=input units
j=operation

The mass balance equation at the transformation stage is given as:

$$Y_j^i = Y_j^o + Y_j^s \tag{2}$$

where Y^O is the output unit.

The technological coefficients per unit output to represent the input requirement and scrap generated are given as:

$$k_j^i = \frac{Y_j^i}{Y_j^o} \tag{3}$$

$$k_j^s = \frac{Y_j^s}{Y_j^o} \tag{4}$$

At the transformation process, the dollar inflow rate equals the dollar outflow rate. The cost flow rate can be calculated as:

$$X_j^i Y_j^i + Y_j^i f(Y_j^i) = X_j^o Y_j^o + X_j^s Y_j^s \tag{5}$$

where X_j^i, X_j^o and X_j^s are the unit average cost of input, output and scrap respectively and $f(Y_j^i)$ is the processing cost per unit. By dividing Eqn (5) with Y_j^o, and simplifying, the unit cost of output, X_j^o, or sometimes known as the unit cost of production for operation j is given as:

$$X_j^o = k_j^i X_j^i - k_j^s X_j^s + k_j^i f(Y_j^i) \tag{6}$$

Since all machines have different tolerance limits, the number of scrap units produced will be varied from one machine to another. Hence the total production cost is dependent on the unit cost of production as well as the number of input units required which differ from one machine to another due to tolerance constraint. The number of scrap produced is an indicative of the quality level of each machine.

The time required to process a certain units of output is given as:

$$T_j = S_j + t_j k_j^i Y_j^o \tag{7}$$

where:
T_j = processing time for jth operation
S_j = setup time
t_j = unit processing time

4. A Genetic-Based Method

The proposed method uses the concept based on genetic algorithms, founded upon the principle of evolution (Goldberg (1989), Michalewiczs (1994)). In line with the concept of CE, the proposed algorithm optimizes the process plan along with the schedule simultaneously. This algorithm is formulated as a multi-objective GAs with several objective functions: minimize the number of rejects produced (based on machine capability), minimize total processing cost and minimize makespan.

4.1 Problem Description

The problem is based on a situation in a flexible manufacturing cell. Not unlike the FMS, the cells may consist of CNC machines that are able to do different operations by just changing the tools or setup. This type of Flexible Manufacturing Cell (FMC) is also known as interchangeable FMC where it is composed of a replicated multi-functional machine such as machining centre. Any part family operation assigned to this cell can be scheduled to more than one machines

Consider a cell that has m number of machines to process n number of parts. These parts have different operations, *op*, and each operation can be processed on more than one machines. However, the machine capability, processing times, and also processing cost differs from one machine to another.

In the proposed method, we plan to integrate the process planning and the scheduling of the parts as well. The parts to be processed has alternative process plans, meaning it can be processed using different machines. However, operating parameters of the machines are not the same. The machines have different operating costs, different processing times and different tolerance limits, producing different percentage of rejects. Assuming that all rejected parts will be scrapped, different machines will require different quantities of input units to produce a certain output units due to different processing capabilities. This will consequently affect the total processing times.

4.2 Chromosome Representation

Grefenstette (1987) has indicated that the chromosome should represent the system to be optimized as much as possible in order for the GA to be effective. Bagchi et. al. (1991) has identified that the chromosome that comprises of the entire search space could produce better results compared to chromosomes that only partially encompass the search space, for example chromosomes which only based on the permutation of job orders.

As suggested by Bagchi, a problem-specific chromosome representation is used. The chromosome consists of the job order as well as the operations and machines to perform the operation. The GA will find the order of jobs, the operations to perform and the machines to do the processing. A schedule builder is required to determine the actual schedule by ensuring that the schedule proposed is legal. For example, the same machines cannot do two operations at the same time. It is only from the actual schedule that the fitness of the schedule can be evaluated.

4.3 Genetic Operators

The genetic operators used are the position based operators, the order-based operators (Syswerda (1991)) and the plan/resource operators (Bagchi (1993)).

1. Order based operators

In the order-based crossover, the order of tasks in the selected position in one parent is imposed on the corresponding tasks in the other parent. The order-based mutation interchanges the positions of the jobs at random.

2. Position-based Operators

In the position-based crossover, the position of tasks in the selected position in one parent is imposed on the corresponding tasks in the other parent. The position-based mutation places the second task selected before the selected first task.

3. Plan-Resource Operators

While the order-based and position based operators changes the sequence of the parts to be processed, the plan resource operators changes the process plan as well as the machines to perform the operation. The sequence of the parts to be processed remains the same. An example of the plan-resource crossover is shown in Figure 1. In the plan-resource mutation, the process plans as well as the machines are re-chosen at random.

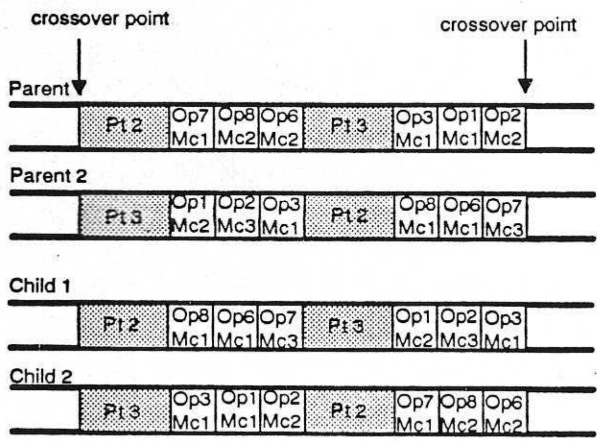

Figure 1: Plan/resource crossover

4.4 Fitness Evaluation

The inclusion of process plan in the problem requires optimization criterion/criteria which are different from the criteria associated with scheduling only. While the scheduling criterion is more towards optimizing the time in processing the jobs, process planning is involved with optimizing the resources and processing costs as well as the processing times. The objective functions used associated with the process planning is to minimize the number of rejects produced and the total processing cost. The third objective function used is to minimize the makespan.

a)minimizing total number of rejects

The total number of rejects can be calculated by adding all the number of scraps produced.

$$F1 = \sum_{l=1}^{n} Y_l^s$$

$$= \sum_{l=1}^{n} Y_l^o \left[\sum_{j=1}^{op} k_j^s \right] \tag{8}$$

b)minimizing total processing cost

The total processing cost can be calculated by summing all the processing cost for all the operations.

$$F2 = \sum_{l=1}^{n} N_l^i \sum_{j=1}^{op} (k_{lj}^i X_{lj}^i - k_{lj}^s X_{lj}^s + k_{lj}^i f(Y_{lj}^i)) \tag{9}$$

where
N^i = number of input units
n = total number of parts
op=total operations per part

c)minimizing makespan

Makespan (M) is described as the time required to complete all n jobs. The value of the completion time (Cj) for the last job is the makespan in this problem. The value of the makespan is found by decoding the chromosomes using a schedule builder which ensures that the schedules proposed are legal.

5. Simulation Results

The integrated approach based on genetic algorithm is compared with the traditional method which sequentially chooses the process plan and then find the schedule. Results obtained using an example given in the appendix is described here.

5.1 Results using genetic approach

The values of the parameters used in the algorithm is given in Table 1. The order-based and position-based operators are given an equal chance to perform.

To prevent premature convergence, ranking is applied with a selective pressure of 2.0 (Baker (1985)). To enable the GA to converge faster, an elitist strategy is applied with generation gap (GGAP) of 0.9 which means 10% of the best population is generated into the next generation.

Parameter	Description	Value
NIND	Number of Individuals	30
GGAP	Generation Gap	0.9
PXovr	Position-based Xovr	0.7
PMut	Position-based Mutation	0.3
OXovr	Order-based Xovr	0.7
OMut	Order-Based Mutation	0.3
PRXovr	Plan-Resource Xovr	0.5
PRMut	Plan-Resource Mutation	0.3

Table 1: Values of the parameters used

5.2 Comparison with the traditional method

Results using the genetic based approach is compared with the results obtained using sequential method. In the process planning part, the best machine to perform the operations are chosen based on the machine which has the least processing cost.

Based on the machines chosen, a schedule is constructed using the dispatching rule of the shortest processing time (SPT) where the sequence of the operations follows the ascending processing times. A Gantt chart is used to calculate the makespan of the problem. Figure 2 shows a makespan obtained using the traditional method. In this problem, given in the Appendix, the operations can be done in any sequence. Figure 3 shows the schedule obtained, in the form of Gantt chart, using the integrated approach but using only one objective function (minimizing makespan). The schedule obtained using all three objectives is given in Figure 4.

Table 2 shows the results obtained using the integrated approach with only makespan as the objective function and with the combined objectives, compared to the traditional approach. Since the integrated approach with only minimizing makespan as the objective produces more than one solution, the average values are calculated and given here.

	Traditional Method	Makespan only	All Obj.
Makespan	2030	1265	1265
No. of rejects	18	16	17
Total Processing Cost	759	1268	759

Table 2: Results obtained

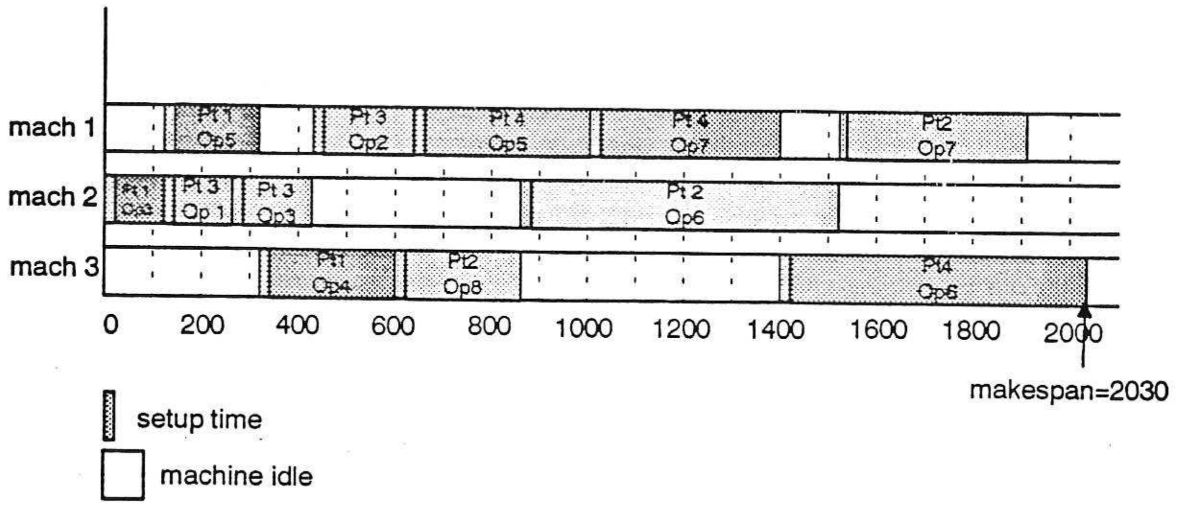

Figure 2: Makespan found using the traditional method with shortest processing time dispatching rule.

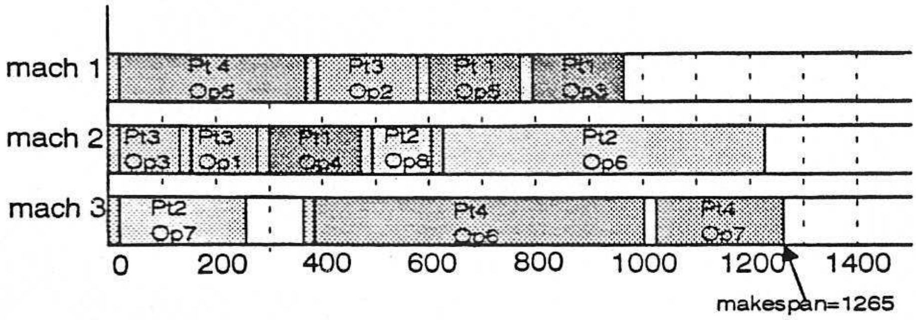

Figure 3: Gantt chart showing the makespan found using minimizing makespan as the objective function

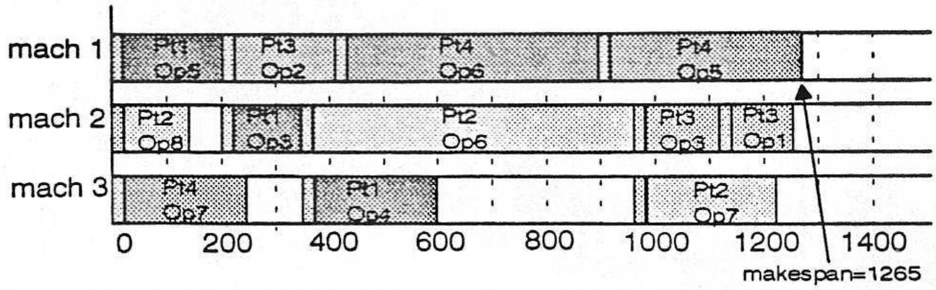

Figure 4: Makespan found using minimizing makespan, minimizing rejects and minimizing total production cost as total objective

6. Discussions

Results showed that the integrated approach using genetic algorithms outperformed the traditional sequential method. Even though results for the makespan produced using only minimizing makespan as the objective and the aggregation of all objectives, are the same, the total processing cost has been greatly decreased. The simultaneous optimization of process plan and scheduling allows a more distributed loading of the machines and at the same time reduce the total processing cost.

7. Conclusions

Most problems in manufacturing systems are inter-related and should be solved simultaneously. This paper describes a genetic-based method which integrates the production planning and scheduling using weighted-sums multi-objective approach. Results showed that the proposed method can produce better results compared with the conventional method which determines the process planning before scheduling.

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Appendix : Sample Problem

Setup time: 5 units of time for each operation

Part	Operation	Machine	Processing time	Processing Cost	% Scrap
1	3	M1,M2,M3	15,10,20	20,15,10	5,10, 15
	4	M2,M3	15,20	50,15	5,10
	5	M1,M3	15,20	20,25	5,10
2	6	M1,M2,M3	20,25,25	50,15,15	5,10,10
	7	M1,M3	15,10	15,50	5,5
	8	M2, M3	5,10	90,5	5,10
3	1	M1,M2	15,10	60,15	15,10
	2	M1,M2,M3	15,20,15	15,15,50	10,10,5
	3	M1,M2,M3	15,10,20	50,15,20	5,10,15
4	5	M1,M3	15,20	20,25	5,10
	6	M1,M2,M3	20,25,25	50,15,15	5,10,10
	7	M1,M3	5,10	15,50	5,5

	Part 1	Part 2	Part 3	Part 4
Output units required (No)	10	20	10	20
Raw cost ($/unit)	10	20	30	40
Scrap cost ($/unit)	2	3	4	5