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A Model for Integration of Process Planning and Scheduling with Outsourcing in Manufacturing Supply Chain†

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생산공급사슬에서의 아웃소싱을 고려한 공정계획 및 일정계획의 통합을 위한 모델

정찬석 · 이영해 · 문치웅

An integrated process planning and scheduling model considering outsourcing in manufacturing supply chain is proposed in this paper. The process planning and scheduling considering outsourcing are actually interrelated and should be solved simultaneously. The proposed model considers the alternative process plans for job types, precedence constraints of job operations, due date of production, transportation time and production information for outsourcing. The integrated states include:(1) Operations sequencing,(2) Machine selection,(3) Scheduling with outsourcing under the due date. To solve the model, a heuristic approach based on genetic algorithm(GA) is developed. The proposed approach minimizes the makespan considering outsourcing and shows the best operation-sequences and schedule of all jobs.

1. Introduction

A supply chain may be defined as an integrated process wherein a number of various business entities(*i.e.*, suppliers, manufacturers, distributors, and retailers) work together in an effort to:(1) acquire raw materials, (2) convert these raw materials into specified final products, and (3) deliver these final products to retailers(Beamon 1998). For years, researchers have mainly investigated the various processes within manufacturing supply chain individually. Recently, however, there has been increasing attention placed on the integrated model of manufacturing supply chain planning. Process planning and scheduling are maybe the most important functions in a manufacturing system. Process planning determines how a job will be manufactured and acts as a bridge between design and manufacturing and scheduling which considers alternative machine is sometimes known as integrated process planning and scheduling(Palmer 1996). Since the alternative machines considering outsourcing are available to process each operation, the scheduling problem becomes more complex.

In practice, any job assigned to a manufacturing system can be scheduled for more than one machine and may have a flexible process sequence. If some jobs have certain operation-sequences, they should be considered for the integrated model with alternative machines. In the traditional approaches, process planning and scheduling are done sequentially, where the process plan is determined before the actual scheduling is performed. Although these methods may be simple, they ignore the relationship between scheduling and process planning. By assuming that scheduling takes over the process plan is determined, the possible choice of the schedule using alternative machines is ignored. Recently, some researches for the integrated process planning and scheduling are presented.

Hankins *et al.*(1984) discussed the advantages of using alternative machine tool routeings to improve

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the productivity of the machine shop. They showed that using alternative machine results in reducing lead-time and in improving overall machine utilization. They stated that with a large number of jobs to schedule, and a large number of alternative machines are available, the use of mathematical programming techniques to balance the workload becomes prohibitive.

Nasr and Elsayed (1990) present two heuristics to determine an efficient schedule for the *n* jobs, *m* machines problem with alternative machine tool routeings allowed for each operation. And the object is to minimize the mean flow time for jobs.

Kusiak and Finke (1987) considered a Flexible Forging Module (FFM) and identified the sequence dependent changeover cost. In order to obtain an optimal schedule, they developed a network model, which easily incorporates both the sequence-dependent changeover costs and the precedence constraints. They employed a branch-and-bound algorithm to solve the model.

Palmer(1996) and Sundaram *et al.*(1988) discussed integrated process planning and scheduling. Palmer used simulated annealing(SA).

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. However, They did not consider the precedence rule for the operation- sequence but only considered the time aspect with non-constraint operational sequence.

The general objective of this research is to develop a model to integrate process planning and scheduling with outsourcing through analysis of the alternative machine selection, the operation-sequencing problem and production capacity under the due date. The integrated states include: (1) Operations sequencing, (2) Machine selection, (3) Scheduling with outsourcing under the due date. To solve the model, a heuristic approach based on genetic algorithm(GA) is developed.

The remainder of the paper is arranged as follows: section 2 described the problem definition and topological sort (TS) is in section 3. An approach model based on GA is presented in section 4. Section 5 describes the experimental results compared with former approach and finally, some discussion and conclusions are given in section 6.

2. Problem definition

A product in the manufacturing system is consists of several components designed by CAD department. For the first step, process planner should recognize the geometrical features of the components and consider the best practices in producing. If each component is required a job, which means a set of machining processes to produce independently, a job may have several operations and each operation needs one machine to complete a job. In this point, the operations of a job may have the precedence constraints. For instance, considering the process of soft-drink products let assume the operations are separated to two processes that one is to fill up the drink and the other is to seal the bottle. Sealing operation is constrained by filling operation.

Actually, almost operations of the jobs have the operation-sequences. It means that a certain operation among the operations of a job has a precedence constraint and some operations to complete a job are interrelated each other. Therefore, the operations sequencing problem can be formulated as a well-known Traveling Salesman Problem(TSP) (Dantzig *et al.* 1954, Lawler *et al.* 1985, Malek *et al.* 1989) The manufacturing system under study consists of *m* machines(1, 2, ⋯, *m*) and *n* different jobs(1, 2, ⋯, *n*). All the jobs are loaded and processed continuously as a lot according to a predetermined technological sequence given in the process plan(Nasr *et al.* 1990). Each job, *i*, requires a number of operations. Each of these operations can be performed on a number of alternative, non-identical machines.

The proposed model is developed for the heavy industry such as turbine manufacturing, generator manufacturing and ship engine manufacturing. Some specific characters of the heavy industry are small lot size and long processing time for an operation. Because the heavy industry production is huge size and need long operation time, it is very important to keep the due date of production. At this point we employed the outsourcing factors for the model. If the lot size of production is more than one, operations that are related to a job should search the alternative machines considering outsourcing in each lot number to minimize the makespan of the machine schedule. A machine should be selected among alternate for operation-sequence of each job. For a given production order-job mix and their lot sizes, the alternative machine for operation- sequence should be selected for the maximum efficiency of production of all the jobs.

An integrated model in this paper includes the operations sequencing approach with alternative machines of outsourcing. The process planning and

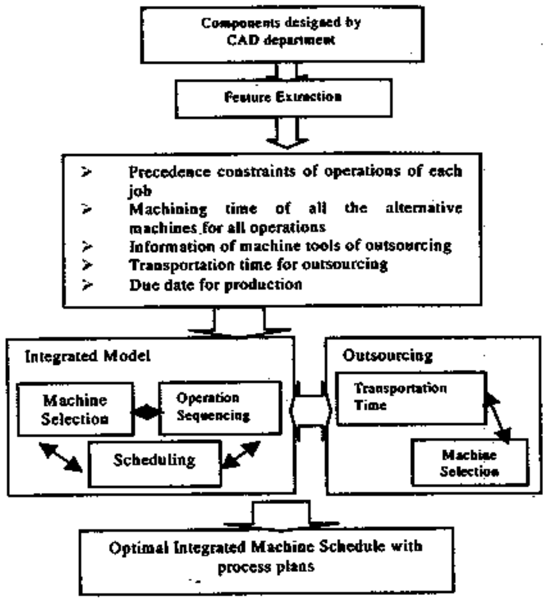


Figure 1. Schematic diagram of integrated model.

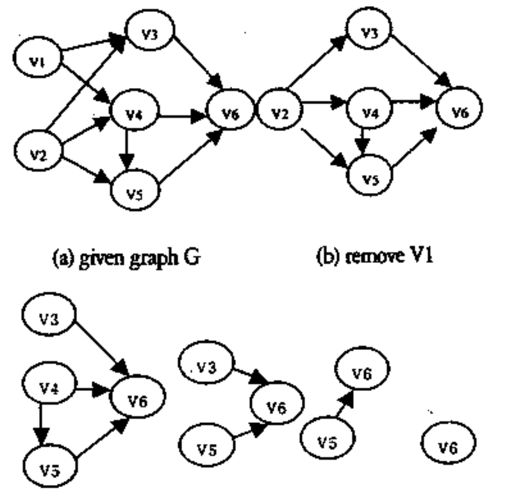
scheduling considering outsourcing as shown in <Figure 1> are actually interrelated and be solved simultaneously under the due date.

3. Topological sort(TS)

TS algorithm(Horowitz *et al.* 1984) is employed to solve the problem that determines the operation-sequence of a job. A directed graph G in which the vertices represent activities and the edges represent precedence relations between activities is an activity on vertex(AOV) network as shown in <Figure 2>. It is clear that a topological order is not possible if the graph has a cycle. A directive graph with no directed cycles is an acyclic graph. TS algorithm to test an AOV network for feasibility will also generate a linear ordering, $v_1, v_2, \cdots, v_n$, of the vertices.

This linear ordering will have the priority that if v_1 is a predecessor of v_2 in the network then v_1 precedes v_2 in the linear ordering. A linear ordering with this priority is called a topological order(TO). The algorithm to sort the takes into TO is straight-forward and proceeds by listing out a vertex in the network that has no predecessor. Then, this vertex together with all edges leading out from it is deleted from the network.

To find a topological order, the first step is to select any vertex with no incoming edges, and then print this vertex. Next, the printed vertex is removed, along with its edges, from the graph. The



(a) given graph G (b) remove V1

(c) remove V2 (d) remove V4 (e) remove V3 (f) remove V5

Figure 2. The method for selecting topological order.

graph in <Figure 2>, represents the method for selecting TO(Hwang *et al.* 1994).

Six paths can be selected for TOs from <Figure 2>. They are as follows:

1) $v_1 - v_2 - v_3 - v_4 - v_5 - v_6$
2) $v_1 - v_2 - v_4 - v_3 - v_5 - v_6$
3) $v_1 - v_2 - v_4 - v_5 - v_3 - v_6$
4) $v_2 - v_1 - v_3 - v_4 - v_5 - v_6$
5) $v_2 - v_1 - v_4 - v_3 - v_5 - v_6$
6) $v_2 - v_1 - v_4 - v_5 - v_3 - v_6$

Let n be the number of vertices, the TS procedure for TO order can be described as <Figure 3> (Horowitz *et al.* 1984).

From the above TS procedure, we know that a set of tours of AOV can be generated by the TS procedure. Therefore, the goal of AOV is to find a tour, which visits each vertex exactly once and is of shortest path from a set of TOs. By assuming that a directed graph G is a process plan of a job which has six operations with precedence constrains, the shortest path from a set of TOs will be determined operation-sequence of a job.

```
Procedure: Topological sort
  Input: AOV network. Let N be the number of vertices;
  For i = 1 to N do
 Begin
    If every vertex has a predecessor
       Then the network is infeasible stop;
    Else pick a vertex vi which has no predecessors;
       Output vi;
    Delete vi and all edges leading out of vi from the network;
    End;
 End;
```

Figure 3. Procedures of topological sort.

4. GA-based approach for integrated model

GA is one of the evolutionary search methods that can provide optimal or near optimal solutions for the combinatorial optimization problems. It has been applied to a number of fields like engineering, biology, computer science, and social sciences. One of most attractive feature of GA is the flexibility of handling on various kinds of objective functions with fewer requirements on fine mathematical property (Gen *et al.*, 1997).

The main issues in developing a genetic algorithm are chromosome representation, initialization of the population, evaluation measure, crossover, mutation, and selection strategy. Also, the genetic parameters such as population size *pop_size*, number of generation *max_gen*, probability of crossover pc, and probability of mutation *pm*, are determined before execution of GA.

In this section, we propose an efficient GA-based approach, which contains a TS algorithm for solving integrated process planning and scheduling model with precedence constraints.

4.1 Representation and Initialization

In ordering problem using GA, a critical issue is the development of representation scheme to represent a feasible solution. It is very difficult task how to represent a path with precedence constraints in graph. In order to generate a TO, the representation scheme has to capable of generating all possible TOs for a given AOV. Also, any tour of the solution always corresponds to a TO. Suppose there are one job, which is consist of six vertices, named v_1 through v_6. A chromosome structure can be represented as shown in <Figure 4>.

In <Figure 4>, the first row of chromosome means the vertices that matched with randomly selected machine number for each vertex of AOV network. Each vertex randomly selects a machine number within the possible alternative machines. Second row means the priority for candidate selection in case of the vertices with no incoming edges is exist. For example, when v_1 and v_2 have no precedent constrains at the same time as shown in <Figure 4>, v_2 is selected for operation-sequence.

The value of a gene is generated at random within [1, *N*] exclusively, where *N* is the number of vertices. The overall procedure for the feasible solution representation is as shown in <Figure 5>.

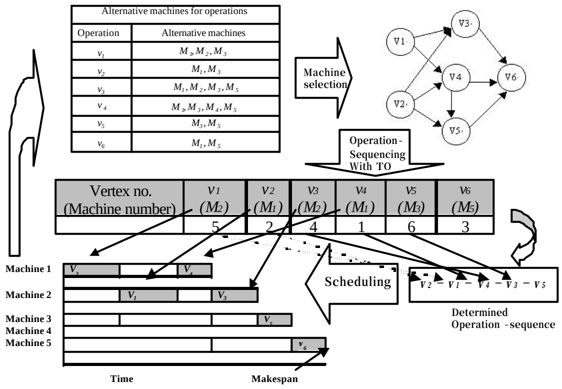


Figure 4. Chromosome representation.

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Procedure: Feasible solution representation
  Input data:
     Number of jobs and machines and number of operations for each job ;
        Let the  (i=1,…, N) be the N operations for n jobs in
          the orderly manner;
       Precedence sequence of each operation;
     Alternative machine and time for each operation including outsourcing;
       Transportation time for outsourcing
  Begin:
    Generate Chromosome with Machine selection:
       Allocate a randomly selected machine to each operation;
       Generate random priority number (1 to N) for each operation;

    Generate operations sequencing:
      Determine the operation-sequence of each job with the generated
          random priority number and TO;

    Determine the makespan time for each machine to complete all job:
        For i=1 to k ( i is machine number)
             M_i = 0;
          For j = 1 to m do (j is j_th operation of each job)

             If the j_th operation has no idle time according
                   to the determined operation-sequences
              Then M_i = M_i + machining time of j_th operation;
             Else compute the idle time according
                   to the determined operation-sequences
              Then M_i = M_i + idle_time + machining time of j_th operation;
          End;
   End;
```

Figure 5. Feasible solution representation.

The first step in genetic algorithm is to initialize the population of chromosomes. The initialization process is executed with a randomly generated population.

4.2 Selection and Fitness evaluation

In this paper the formulation considers only one objective function, for the integration of process planning and scheduling. The objective is to minimize makespan, which describes, as the time required completing all *n* jobs, thus the completion time of the last job will be the makespan time under the limited production time according to the due date. For the best makespan time, we need a procedure to determine the allocation of operations to each

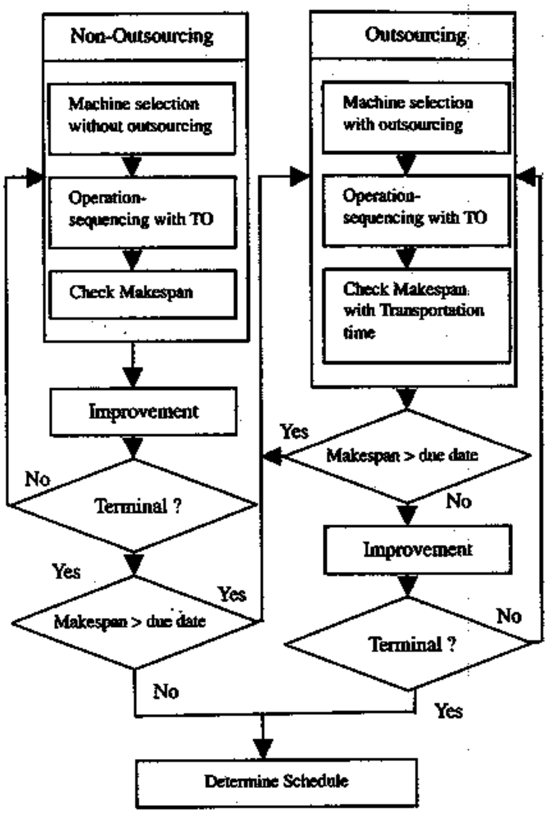


Figure 6. Flow chart for fitness evaluation.

machine constrained by determined operation sequences considering outsourcing.

Fitness evaluation has some specific constrained factors: (1) the makespan should be less than the limited production time (due date), (2) when a certain operation of a job need outsourcing, it is necessary to consider the transportation time for outsourcing as shown in <Figure 6>.

4.3 Crossover and mutation

To create the next generation, new set of chromosomes called offspring is formed by the execution of genetic operators such as selection, crossover and mutation. In particular, the crossover operator acts as the main operator and exercises a great influence on performance of the GA approach. While the mutation operator acts a background operator. In this paper, the order-based crossover is employed. 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 rankings at random.

An example of the order-based crossover is illustrated in <Figure 7>. Suppose that two chromosomes are parent 1 = [5 1 2 4 6 3] and parent 2 = [2 6 1 4 3 5], assuming each 2 columns from the left are job1, job2 and job3 respectively.

With the same procedure, we can produce a modified parent 1 as [6 1 2 4 3 5]. The swap mutation operator is introduced here. The swap scheme is select two genes within a chromosome at random and then swap these contents.

(1) Select the sub-string from parent 1 at random

job1 selected sub-string (job2) job3

	v_1	v_2	v_3	v_4	v_5	v_6
Parent 1	5	1	2	4	6	3

	v_1	v_2	v_3	v_4	v_5	v_6
Parent 2	2	6	1	4	3	5

(2) Produce a modified parent 1

	v_1	v_2	v_3	v_4	v_5	v_6
Parent 1	5	1	2	4	6	3

	v_1	v_2	v_3	v_4	v_5	v_6
Offspring	6	1	2	4	3	5

	v_1	v_2	v_3	v_4	v_5	v_6
Parent 2	2	6	1	4	3	5

Figure 7. Illustration of the order-based crossover.

4.4 GA-based approach test with TO

Numerical test have been provided in order to demonstrate the effectiveness and efficiency of the proposed GA approach on AOV. A number of problems of varying sizes were solved using GA with varying genetic parameter values. The test considered 6 vertices and 9 precedence constraints as shown in <Figure 2>. We impose the distances between the vertices v_i and v_j as shown in <Table 1>.

Table 1. TSP data

v_i \ v_j	v_1	v_2	v_3	v_4	v_5	v_6
v_1	∞	7	3	12	5	8
v_2	4	∞	2	10	9	3
v_3	6	7	∞	11	1	7
v_4	7	3	1	∞	8	3
v_5	2	10	2	7	∞	3
v_6	4	11	7	6	3	∞

By the method in <Figure 5>, we could determine the possible TO pass and the values as follows:

$v_1 - v_2 - v_3 - v_4 - v_5 - v_6$: value 32
$v_1 - v_2 - v_4 - v_3 - v_5 - v_6$: value 22
$v_1 - v_2 - v_4 - v_5 - v_3 - v_6$: value 34
$v_2 - v_1 - v_3 - v_4 - v_5 - v_6$: value 29
$v_2 - v_1 - v_4 - v_4 - v_5 - v_6$: value 21
$v_2 - v_1 - v_4 - v_5 - v_3 - v_6$: value 33

To solve the problem using the proposed genetic algorithm, the genetic parameters are set as maximum generation, $max\_gen = 30$; population size, $pop\_size = 20$; crossover probability, $pc = 0.5$; mutation probability, $pm = 0.2$. From this experiment, the proposed GA approach can be reached at the optimal solution at most times. The optimal value is 21 and the optimal tour $x_{21} = 1$, $x_{14} = 1$, $x_{43} = 1$, $x_{35} = 1$, and $x_{56} = 1$ are generated. Then, the optimal sequence is $v_2 - v_1 - v_4 - v_3 - v_5 - v_6$ with the corresponding value 21.

5. Experiments

5.1 Experiment for integrated model with GA-based approach

The data that consists of five jobs and five machines (including one outsourcing machine) is used here to test the proposed model as shown in <Table 2>. The proposed model is developed for the heavy industry. Some specific characters of the heavy industry are small lot size and long time for an operation. In experimental data, the number 5 machine belongs to outsourcing and the transportation time (one way) is 10 per one lot size.

Each job conducts 4 different operations in a specified order. Let the $v_i (i = 1, \cdots, 20)$ be the operations for five jobs in the orderly manner. The lot size is two and the due date is 70. The genetic parameters for integrated model are as follows:

- Population size :100,
- Number of generation : 1000
- Probability of crossover : 0.4
- Probability of mutation : 0.1
- Lot size : 2
- Due date :70

This experiment considers precedence operation constraints. The precedence constraints are as shown in <Figure 8>.

As a result of the best chromosome and the machines for all n jobs are as shown in <Table 3>.

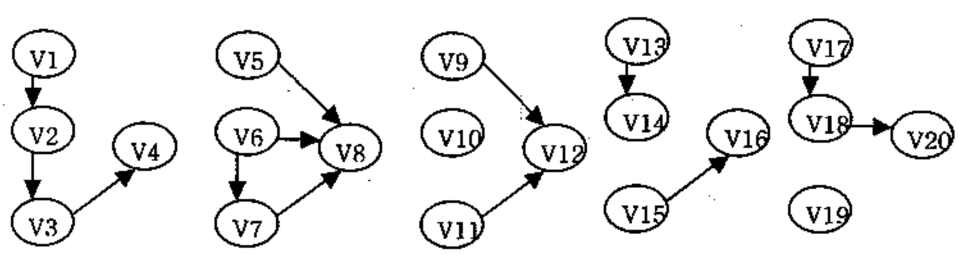
By the above chromosome, the best operation sequences for all n jobs are determined. When the operations sequencing is considered, the minimized makespan is 66 as shown in <Table 4> and <Figure 9>.

5.2 Comparing with former researches

The data provided in Sundaram and Fu(1988),

Table 2. Machining time for operations

Operation / Machine NO.	v_1	v_2	v_3	v_4	v_5	v_6	v_7	v_8	v_9	v_{10}	v_{51}	v_{12}	v_{13}	v_{14}	v_{15}	v_{16}	v_{17}	v_{18}	v_{19}	v_{20}
	Job1				Job2				Job3				Job4				Job5			
1	5	∞	∞	∞	7	∞	∞	∞	4	∞	∞	4	∞	∞	∞	∞	3	∞	∞	5
2	3	7	∞	3	∞	4	∞	5	5	∞	∞	∞	2	∞	∞	6	∞	∞	∞	∞
3	∞	∞	6	∞	∞	6	7	∞	8	∞	∞	∞	6	8	3	∞	5	7	∞	∞
4	∞	∞	∞	3	∞	∞	7	∞	∞	5	6	∞	∞	∞	8	7	∞	∞	9	∞
5(outsourcing)	∞	∞	∞	4	∞	∞	∞	10	∞	∞	5	4	∞	∞	∞	4	∞	∞	6	3



(a) Job 1 (b) Job 2 (c) Job 3 (d) Job 4 (e) Job 5

Figure 8. Precedence constraints for each job.

Table 3. The best chromosome with machines and operation-sequences for all *n* jobs

v_1 (*M2*)	v_2 (*M2*)	v_3 (*M3*)	v_4 (*M2*)	v_5 (*M1*)	v_6 (*M2*)	v_7 (*M4*)	v_8 (*M2*)	v_9 (*M1*)	v_{10} (*M4*)	v_{11} (*M4*)	v_{12} (*M5*)	Etc.
19	5	6	17	2	1	13	14	7	12	11	20	

	Determined operation-sequences			
	1	2	3	4
Job 1	1	2	3	4
Job 2	6	5	7	8
Job 3	9	11	10	12
Job 4	13	15	14	16
Job 5	19	17	18	20

Table 4. Schedule output with operations sequencing

Machine #1

Lot#	Op#	Start	End
1	9	0	4
1	9	6	13
1	17	16	19
1	20	29	34
2	1	34	39
2	17	39	42
2	5	42	49
2	20	49	54
2	12	54	58

Run=43 End=58 idle=15
Util=0.741379

Machine #2

Lot#	Op#	Start	End
1	13	0	2
1	6	2	6
1	1	6	9
1	2	9	16
1	8	22	26
1	4	26	29
1	16	29	34
2	9	34	39
2	2	39	46
2	16	57	62
2	8	62	66

Run=49 End=66 idle=17
Util=0.742424

Machine #3

Lot#	Op#	Start	End
1	15	2	5
1	14	5	13
1	3	16	22
1	18	22	29
2	13	29	35
2	6	35	41
2	18	42	49
2	14	49	57
2	3	57	63

Run=57 End=63 idle=6
Util=0.904762

Machine #4

Lot#	Op#	Start	End
1	11	4	10
1	10	10	15
1	7	15	22
2	19	22	31
2	15	35	43
2	11	43	49
2	10	49	54
2	7	54	61
2	4	63	66

Run=56 End=66 idle=10
Util=0.848485

Machine #5 (Outsoucing)

Lot#	Op#	Start	End	Transportation (In/Out)
1	19	0	16	0 / 10
1	12	16	30	10 / 0

The Best Makespan = 66

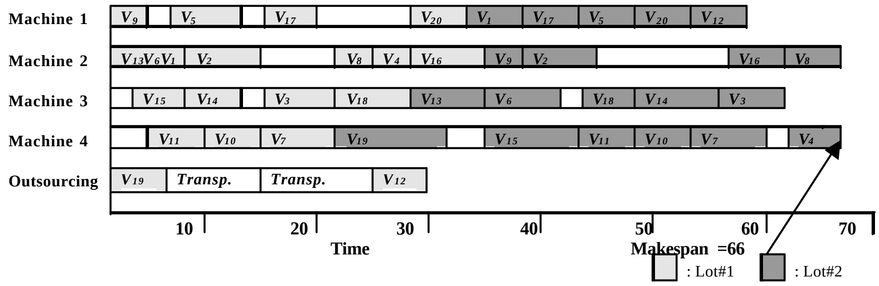


Figure 9. Schedule output in the form of a Gantt chart.

Table 5. Machining time for operations(Sundaram and Fu)

Operation / Machine NO.	v_1	v_2	v_3	v_4	v_5	v_6	v_7	v_8	v_9	v_{10}	v_{11}	v_{12}	v_{13}	v_{14}	v_{15}	v_{16}	v_{17}	v_{18}	v_{19}	v_{20}
	Job1				Job2				Job3				Job4				Job5			
1	5	∞	∞	∞	7	∞	∞	∞	4	∞	∞	∞	∞	∞	∞	∞	3	∞	∞	∞
2	3	7	∞	3	∞	4	∞	∞	5	∞	∞	∞	2	∞	∞	6	∞	∞	∞	∞
3	∞	∞	6	∞	∞	6	7	∞	8	∞	∞	∞	6	8	3	∞	5	7	∞	∞
4	∞	∞	∞	3	∞	∞	7	∞	∞	5	6	∞	∞	∞	8	7	∞	∞	9	∞
5	∞	∞	∞	4	∞	∞	∞	10	∞	∞	5	4	∞	∞	∞	4	∞	∞	6	3

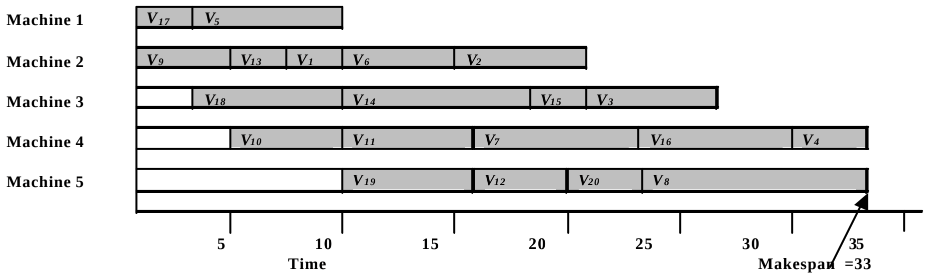


Figure 10. Schedule output in the form of a Gantt chart.

consisting of 5 jobs and 5 machines is used here to test the developed GA-based approach. Let the v_i (i=1, ⋯, 20) be the operations for 5 jobs in the orderly manner. Alternative machines of processing the parts are given in <Table 5>. Sundaram and Fu (1988) did not consider the operation sequencing and each job conducts 4 different operations in a sequential order. So the operations of v_1, v_5, v_9, v_{13}, v_{17} have no precedence constraints and the other operation v_i is a predecessor of v_{i+1} in the network.

Using the GA-based approach, the best makespan value obtained is 33 as shown in <Figure 10> compared to the value of 38 obtained using the heuristic reported by Sundaram and Fu (1988). Palmer (1996) used simulated annealing for this problem and obtained the same result of 33 as shown in <Table 6>. These results mean that the GA-based approach is better than the former researches.

Table 6. The compared result with former researched methods

	Sundaram and Fu	Palmer	Proposed Method
Makespan	38	33	33

6. Conclusions

Even though there has been a lot of studies on scheduling, it still remains one of the concerning issues among researchers in manufacturing optimization. The traditional method, which is limited to having non-sequential operations, does not address the availability of these alternative machines and operations with precedence constraints. The Integrated model presented in this paper determines the best schedules with operation-sequences and alternative machines considering outsourcing. This is rarely studied so far and there is no similar paper, which considered the precedence constraints of operations. From the experimental results, we know that the proposed approach is suitable the integrated process planning and scheduling problems. For the future study, our model will be extended to integrate the order units in make-to-order manufacturing supply chain.

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