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# Evolutionary Algorithm for Process Plan Selection with Multiple Objectives

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**Abstract.** This paper presents a process plan selection model with multiple objectives. The process plans for all parts should be selected under multiple objective environment as follows: (1) minimizing the sum of machine processing and material handling time of all the parts considering realistic shop factors such as production volume, processing time, machine capacity, and capacity of transfer device. (2) balancing the load between machines. A multiple objective mathematical model is proposed and an evolutionary algorithm with the adaptive recombination strategy is developed to solve the model. To illustrate the efficiency of proposed approach, numerical examples are presented. The proposed approach is found to be effective in offering a set of satisfactory Pareto solutions within a satisfactory CPU time in a multiple objective environment,

**Keywords:** Process planning, Process Plan Selection, Multiple Objectives, Genetic Algorithm

## 1. INTRODUCTION

Process planning is an activity for the preparation of a plan that specifies the machines, operations, operation sequence, machining conditions, and tools required to produce that component. Process planning is the critical link between design and manufacturing, both of which need this indispensable interface [5]. Computer-aided process planning (CAPP) is a computerized system for the process planning. During the past two decades, a number of CAPP systems have been developed for the automated planning and improving the efficiency of process planning function. Examples of such systems are TOM [8], TURBO-CAPP [11] and KAPLAN [4].

The implementation of CAPP depends on the development and application of various decision logic, database structure and management, computer programming and intelligent searching methodologies, etc. And, the development of a high-level CAPP system must be based on not only the thorough understanding of process planning principles and methodologies, but also the dynamic information of shop floor and CAD department.

Process plan selection (PPS) is one of the problems linking the process planning with the production planning and control problem are the problem of selecting process plans. Typically, for a part to be manufactured in a modern manufacturing system, multiple process plans are generated [9]. The process planners face the problem of selecting from the set of process plans a subset of process plans with the minimum corresponding costs. For this problem, Kusiak and Finke [7] developed a model for the selection of a set of process plans with the objective of minimizing the manufacturing cost and the number of tools and auxiliary devices used. Heuristic procedures have also been developed to solve the model.

Bhaskaran [2] presented a model for the selection of process plans with the objective of minimizing the total processing time and the total number of processing steps.

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Zhang and Huang [12] provided a fuzzy-based model for the selection of a set of process plans considering the imprecise information of shop floor. Awadh et al. [1] developed a model based on genetic algorithm (GA) for the selection of process plan for a part. More recently, Seo and Egbelu [9] developed a 0-1 integer programming model for the PPS problem based on the product mix and production volume with the objective of the minimizing total material handling and processing time. They solved the problem using tabu search heuristic.

In this paper, a new model is presented for the selection of a set of process plans with multiple objectives of minimizing the total processing and transportation time and balancing the load between machines. The model in this paper differs from those of the above papers as follows: (1) The model considers the operation flexibility. This flexibility is concerned with the possibility of performing an operation on more than one machine, that is, an operation may be performed on alternative machines with the different processing time. (2) The transportation time between machines and the related shop factors are considered. (3) The load balance between machines is considered. To solve the proposed model, an evolutionary algorithm with the adaptive recombination strategy is also developed.

## 2. PROBLEM STATEMENT

Several part types are usually manufactured simultaneously in batches, one process plan for each part needs to be selected with considering shop factors such as production volume, processing time, machine capacity and transportation time. A machine is capable of performing several types of operations, and an operation can be performed on alternative machines. The introduction of flexibility in process planning makes it somewhat easier for machine sequencing to adapt to a changing manufacturing environment. An example of the operation flexibility is shown in Figure 1. In this Figure, the part has 3 alternative process plans for processing of operations. The alternatives are ($M_3$, $M_1$, $M_4$, $M_5$, $M_3$, $M_2$, $M_4$, $M_5$) and ($M_3$, $M_2$, $M_1$, $M_4$.). In these alternatives, only one process plan is selected for the part.

Automated guided vehicles (AGV) system is used for material handling between machines. The AGV has played a significant role in several kinds of modern manufacturing systems by integrating different planning functions as a unified system. In the process plan selection, parts may have a choice between one or more machines at each of their operation stages, and transportation of the parts within the system is handled by an AGV system. The total transportation time is expressed by the sum of the frequency of movements for handling all parts.

The load balance for machines is one of the important issues. The load on each machine is contributed by those operations assigned to it. Therefore, the process plans with unbalanced loads may result in system bottlenecks on the overloaded machine [9].

For developing a model, we consider a multiple objective environment. Though there are several important objectives associated with the process plan selection, explicit consideration of too many objectives is difficult. Hence, we limit our scope to two objectives as follows:

(1) Minimize the total processing and transportation time for producing the part mix
(2) Minimize the load variation between machines

The problem involves the selection of individual process plan for each part from their competing process plans and the decision of available machine for operations. The total time is affected by the combination of process plan selected for producing the parts. Therefore, the process plan selection in this paper is to find optimum selection of process plans for all the parts and to minimize the load variation for the smooth flow of materials within a manufacturing system.

## 3. MODEL DEVELOPMENT

In order to formulate a PPS model, the following notations are introduced:

- $i$ part ($i$ = 1, 2, 3, …, $np$)
- $j$ operation ($j$ = 1, 2, 3, …, $no_i$)
- $k$, $l$ machine ($k$, $l$ = 1, 2, 3, …, $nt$)
- $pt_{ijk}$ unit processing time to perform operation $j$ of part type $i$ using machine

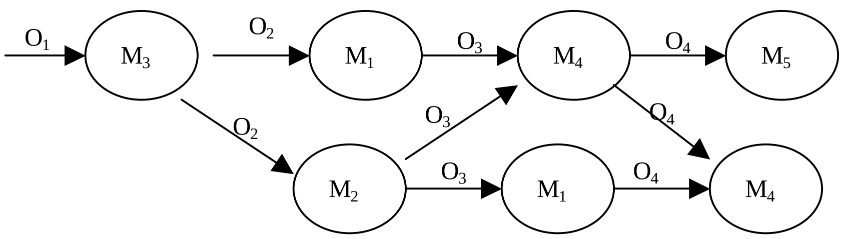


**Figure 1.** An example of operation flexibility

$kpv_i$ production volume for part type $i$
$cm_k$ maximum available time of machine $k$
$tm_{kl}$ transportation time from machine $k$ to $l$
$abl$ available capacity of AGV per trip
$tw_k$ load in machine $k$

$$tw_k = \frac{pt_{ijk} \times pv_i}{cm_k}$$

$ew$ average load of machines

$$x_{ijk} = \begin{cases} 1 & \text{if machine } k \text{ selected to perform operation } j \text{ of part } i \\ 0 & \text{otherwise} \end{cases}$$

$$s_{ikl} = \begin{cases} 1 & \text{if two machines } k,\ l \text{ for part type } i \text{ are used successively} \\ 0 & \text{otherwiae} \end{cases}$$

### 3.1 Objective Functions

The problem is concerned with the selection of individual process plans for all parts while minimizing the total processing and transportation time. The sum of processing time ($f_1$) for all part is determined by the production volume of the parts to be processed and the processing time associated with operations. The total time is defined as follows:

$$f_1 = \sum_{i=1}^{np} \sum_{j=1}^{no_i} \sum_{k=1}^{nt} pv_i \cdot pt_{ijk} \cdot x_{ijk} \qquad (1)$$

For the definition of transportation time, $n_{ikl}$, the number of trips between machines $k$ and $l$ for part type $i$, can be calculated as follows:

$$n_{ikl} = s_{ikl} \times \left\lceil \frac{pv_i}{abl} \right\rceil \qquad (2)$$

where the $\lceil w \rceil$ means the minimum integer value more than or equal to $w$. $t_{ikl}$, transportation time between machines $k$ and $l$ for part type $i$, can be calculated as follows:

$$t_{ikl} = n_{ikl} \times tm_{kl} \qquad (3)$$

Therefore, the total transportation time associated with process plans for all parts is defined as follows:

$$f_2 = \sum_{i=1}^{np} \sum_{j=1}^{no_i - 1} \sum_{k=1}^{nt} \sum_{l=1}^{nt} t_{ikl} \cdot x_{ijk} \cdot x_{i(j+1)l} \qquad (4)$$

Consequently, the objective function to minimize the total processing and transportation time can be formulated as follows:

$$F_1 = f_1 + f_2 \qquad (5)$$

The second objective function ($F_2$) for balancing the load between machines can be formulated as follows:

$$F_2 = \sum_{k=1}^{nt} \frac{(tw_k - ew)^2}{nt} \qquad (6)$$

### 3.2 Bicriteria Mathematical Model

The overall mathematical model can be formulated as follows:

Min $F_1$
Min $F_2$

$$\text{s. t} \sum_{k=1}^{nt} x_{ijk} = 1, \ \forall (i, j) \qquad (7)$$

$$\sum_{i=1}^{np} \sum_{j=1}^{no_i} pv_i \cdot pt_{ijk} \cdot x_{ijk} \le cm_k, \ \forall k \qquad (8)$$

$$\sum_{i=1}^{np} \sum_{j=1}^{no_i} x_{ijk} \ge 1, \quad \forall k \qquad (9)$$

$$x_{ijk} = \{0, 1\}, \ \forall (i, j, k) \qquad (10)$$

The operation flexibility means that an operation can be performed on alternative machines with different processing time. The first constraint ensures that only one machine is selected for each operation of a part type. For the machining of part types, several machines are used. The total processing time within a machine is less than or equal to one's available time. This constraint can be expressed as Equation (8). Sometimes, several operations can be concentrated on a special machine. This is a cause of overload at any machine. Thus, we can include a constraint to prevent the overload at each machine and for the load balancing of all machines. The constraint is given as Equation (9).

There is no unique optimal for the above mathematical model with conflicting objectives. Instead, a set of best or satisfactory solutions will have been found in the two-dimensional feasible area. To solve this problem efficiently, a GA based approach is developed in the next section.

## 4. GENETIC ALGORITHM APPROACH

GA is an evolutionary search algorithms based on the principles of natural genetics and genetic selection. It is one of the suitable methodologies to solve the large scale and complex engineering design problems [3]. So, the GA that has been used to solve many NP-complete problems, can also be applied to the process sequencing problem. GA starts with a set of initial solutions called population, and the individual of population is called chromosome. The chromosome is evaluated by some fitness measures through successive iterations. The key operators of GA are crossover, mutation, and selection operator. These operators for generating new chromosomes play an important role in GA.

### 4.1 Representation and Initialization

In the PPS, each part type has a set of operations and a machine can be selected for an operation. Therefore, a gene of chromosome should contain the information of selected machine standing for each operation. A chromosome representation defined as a set of operations for all the parts is shown as follows:

Part 1 Part 2 Part 3…Part *np*

$$[\ \boxed{4231}\ \boxed{34nt231}\ \boxed{342nt1}\ldots\boxed{4561}\ ]$$

In this chromosome, the number of elements for each part means the number of operations and the assigned values to the elements mean machine number for the machining of operations. For example, for a PPS problem with three parts, five machines and the number of operations for the parts are five constantly, a chromosome can be represented as follows:

$$[\ \boxed{45132}\ \boxed{53245}\ \boxed{52431}]$$

where [4 5 1 3 2] stands for the process plan of part 1, [5 3 2 4 5] stands for part 2, and [5 2 4 3 1] stands for part 3. The initial population of chromosomes is generated randomly within the range [1, *nt*].

### 4.2 Pareto Solution

As the evaluation function for survival, the weighted sums method is used to construct the fitness function which multiple objective functions $F_1(C_k)$ and $F_2(C_k)$ are combined into one overall objective function at hand. The fitness function is handled in the following way.

(1) At generation *t*, choose the solution points which contain the minimum $F_1^{\min}$ (or $F_1^{\max}$) and $F_2^{\max}$ (or $F_2^{\min}$) corresponding to each objective function, then compare with the stored solution points at the previous generation and select the best points to store again.

$$F_q^{\min(t)} = \min_k\{F_q^{\min(t-1)}, F_q(C_k) | k = 1,2, \ldots, i\_size\},\ q = 1,2$$

$$F_q^{\max(t)} = \max_k\{F_q^{\max(t-1)}, F_q(C_k) | k = 1,2, \ldots, i\_size\},\ q = 1,2$$

where $F_q^{\max(t)}(F_q^{\min(t)})$ is the maximum (minimum) value of objective function *q* at generation *t*. And *i_size* is the number of individuals on current generation, i.e. the sum of population and generated offspring.

(2) Solve the following equations to get weights for evaluation function:

$$\delta_1 = F_1^{\max(t)} - F_1^{\min(t)},\ \delta_2 = F_2^{\max(t)} - F_2^{\min(t)}$$

$$w_1 = \frac{\delta_1}{\delta_1 + \delta_2}, \qquad w_2 = \frac{\delta_2}{\delta_1 + \delta_2}$$

(3) Calculate the fitness value for each chromosome($C_k$) as follows:

$$eval(C_k) = w_1 F_1(C_k) + w_2 F_2(C_k) \qquad (11)$$

In multiple objective optimization context, usually the Pareto optimal solutions are characterized as the solutions of the multiple objective decision making problem. In this stage, the module for Pareto optimal solutions consists of two steps:
(1) evaluate chromosomes by the objective function, and
(2) select Pareto solutions based on evaluation values.

It is illustrated as follows:

**Module for Pareto optimal solutions:**
**begin**
**for** generation index $t = 0$ **to** *max_gen*;
count the number of chromosomes from generated offspring *off_size*:
*chr_size* *pop_size* + *off_size*;
**for** $k = 1$ **to** *chr_size*;
evaluate a chromosome $C_k$;
obtain the solution vector $\mathrm{F}_k = [F_1(C_k), F_2(C_k)]$;
register Pareto optimal solutions and delete non-Pareto solutions;
**endfor**
**endfor**
**end**

### 4.3 Recombination Strategy

For the recombination, we revised the adaptive scheme drawn from the study of Srinivas and Patnaik [10]. This scheme considers both the exploitation and exploration properties in the convergence process of GA; the capacity to converge at an optimum after locating the region containing the optimum, and the capacity to explore new regions of the solution space in the search of the global optimum. The balance between these characteristics of the GA is adaptively regulated by the values of crossover rate ( $p_C$ ) and mutation rate ( $p_m$ ) at each generation: increasing the values of $p_C$ and $p_m$ promotes exploration at the expense of exploitation. By this basic scheme, $p_C$ and $p_m$ are increased when the population tends to get stuck at a local optimum and are decreased when the population is scattered in the search space of the GA. The detailed scheme for a minimization problem is as follows:

$$p_C = \begin{cases} \alpha_1 (f_{\max} - f_{cro}) / (f_{\max} - f_{avg}), & f_{cro} > f_{avg} \\ \alpha_3, & f_{cro} \le f_{avg} \end{cases} \tag{12}$$

$$p_m = \begin{cases} \alpha_2 (f_{\max} - f_{mut}) / (f_{\max} - f_{avg}), & f_{mut} > f_{avg} \\ \alpha_4, & f_{mut} \le f_{avg} \end{cases} \tag{13}$$

where $f_{\max}$ and $f_{avg}$ are the maximum fitness and average fitness values at each generation, respectively, $f_{cro}$ is the larger of the fitness values of the individuals to be crossed, and $f_{mut}$ is the fitness value of the *i*th individual to which the mutation with a rate $p_m$ is applied. The values of $\alpha_1, \alpha_2, \alpha_3$, and $\alpha_4$ are 1, 0.5, 1, and 0.5, respectively.

The adjusted rates should not exceed the range from 0.5 to 1.0 for the $p_C$ and the range from 0.00 to 0.05 for the $p_m$.

## 5. NUMERICAL EXAMPLES

We now demonstrate the proposed approach for solving the process plan selection with two examples. First, a system with 4 machines and 4 part types is considered. The part types 1, 2, 3 and 4 have 6, 4, 5 and 4 operations respectively. The machining data is given in Table 1.

In Table 2, the transportation time between machines by AGV is given.

The GA is implemented on IBM/PC compatible with Pentium 133. The GA is applied with the parameters as follows: *max_gen*=1000 and *pop_size*=100. In this parameters setting, 7 Pareto solutions are always obtained and their corresponding best chromosomes as shown in Figure 2.

These Pareto solutions are found after running average 21 generations with population size 100. This means that only 2100 calls (generation times by best solution × population size) of the fitness function are required to find the whole set of Pareto solutions. The average CPU time taken to solve the first example is 13 seconds. These indicate the remarkable effectiveness of the proposed approach. The Pareto frontier is illustrated in Figure 3.

**Table 1.** Machining data for the first example

| | $P_1$ | | | | | | $P_2$ | | | | $P_3$ | | | | | $P_4$ | | | | $MAT_k$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $M_k$ \ $O_j$ | 1 | 2 | 3 | 4 | 5 | 6 | 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 | 5 | 1 | 2 | 3 | 4 | |
| 1 | 7 | -- | 3 | -- | 8 | 5 | 4 | 7 | 6 | 5 | -- | 5 | 2 | 7 | 8 | 7 | -- | 7 | 3 | 1500 |
| 2 | 8 | 3 | -- | 6 | 2 | 8 | 7 | 5 | -- | 4 | 4 | 7 | 2 | -- | 3 | 3 | 7 | 4 | -- | 1700 |
| 3 | -- | -- | 5 | 5 | 6 | 4 | 6 | 4 | 7 | 7 | 7 | 4 | 5 | 3 | 2 | 4 | 3 | 5 | 8 | 1800 |
| 4 | 5 | 2 | 7 | 9 | 5 | 3 | 3 | 8 | 6 | 8 | 4 | 5 | 3 | 7 | 3 | 7 | -- | 7 | 3 | 1400 |
| $PV_i$ | 50 | | | | | | 52 | | | | 48 | | | | | 55 | | | | |

$O_j$: operations for each part  $M_k$ : machines  $PV_i$ : production volume  $MAT_k$ : machine capacity

**Table 2**. Transportation time between machines by AGV

| From \ To | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| 1 | 12 | 9 | 7 | 12 |
| 2 | 4 | 6 | 8 | - |
| 3 | - | 12 | 8 | 12 |
| 4 | 8 | 7 | 12 | 7 |

1. $F_1$=4075, $F_2$=0.020855 : 4 4 1 3 2 3 4 2 1 2 2 3 2 3 3 2 3 2 1
2. $F_1$=4088, $F_2$=0.018399 : 4 4 1 3 2 3 4 2 1 2 2 1 2 3 3 2 3 2 1
3. $F_1$=4093, $F_2$=0.006181 : 4 4 1 3 2 3 4 2 1 2 4 4 1 3 3 2 3 2 1
4. $F_1$=4095, $F_2$=0.005944 : 4 4 1 3 2 3 4 2 1 2 4 3 2 3 3 2 3 2 1
5. $F_1$=4108, $F_2$=0.003326 : 4 4 1 3 2 3 4 2 1 2 4 1 2 3 3 2 3 2 1
6. $F_1$=4124, $F_2$=0.002347 : 4 4 1 3 2 3 1 3 4 2 2 1 2 3 3 2 3 2 1
7. $F_1$=4132, $F_2$=0.001734 : 4 4 1 3 2 1 4 3 4 2 2 1 2 3 3 2 3 2 1

**Figure 2.** Result of the first example

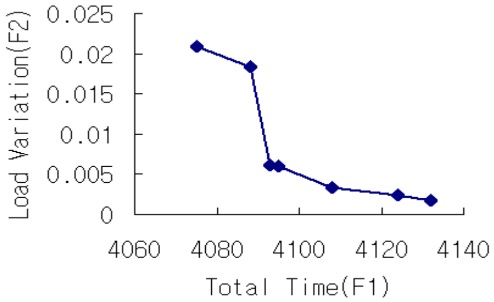


**Figure 3.** Pareto frontier

In this result, a solution of the corresponding process plans for all parts when the case of $F_1$=4075 and $F_2$=0.020855 is as follows:

Part 1 : $4 \rightarrow 4 \rightarrow 1 \rightarrow 3 \rightarrow 2 \rightarrow 3$
Part 2 : $4 \rightarrow 2 \rightarrow 1 \rightarrow 2$
Part 3 : $2 \rightarrow 3 \rightarrow 2 \rightarrow 3 \rightarrow 3$
Part 4 : $2 \rightarrow 3 \rightarrow 2 \rightarrow 1$

The second example involves 8 parts, 6 machines and 36 operations. Table 3 and 4 show the processing and transportation time for the second example. The available processing times for each machine during planning period are as follows:

$$\begin{bmatrix} Machine & : & 1 & 2 & 3 & 4 & 5 & 6 \\ Available time & : & 6000 & 6200 & 6500 & 6200 & 6600 & 5400 \end{bmatrix}$$

The GA is applied with the parameters as follows:

$max\_gen$ = 1000 and $pop\_size$ = 300 .

**Table 3.** Processing time for the second example

| $P_i$ | $O_j$ \ $M_k$ | 1 | 2 | 3 | 4 | 5 | 6 | $PV_i$ | $P_i$ | $O_j$ \ $M_k$ | 1 | 2 | 3 | 4 | 5 | 6 | $PV_i$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| P1 | 1 | 9 | 8 | - | 4 | 5 | 2 | 32 | P5 | 1 | 8 | 8 | 9 | 3 | 7 | 4 | 20 |
| | 2 | 11 | 3 | - | 2 | 4 | 5 | | | 2 | 4 | 5 | 8 | 5 | 4 | 6 | |
| | 3 | 3 | - | 5 | 7 | 3 | 9 | | | 3 | 3 | 4 | 5 | - | 5 | 3 | |
| | 4 | 9 | 6 | 5 | 9 | - | - | | | 4 | 5 | 6 | 4 | 3 | 4 | - | |
| P2 | 1 | 4 | 7 | 6 | 3 | 8 | - | 40 | P6 | 1 | 9 | 6 | 9 | 2 | 8 | 3 | 48 |
| | 2 | 7 | 5 | 4 | 8 | 6 | 6 | | | 2 | 8 | 7 | 6 | - | 2 | - | |
| | 3 | 6 | - | 7 | 6 | 2 | 3 | | | 3 | 9 | 12 | 8 | 5 | 4 | 9 | |
| | 4 | 5 | 4 | 7 | 8 | 6 | 9 | | | 4 | - | 9 | 8 | 7 | 6 | 7 | |
| | 5 | - | 6 | 7 | 2 | 5 | 2 | | P7 | 1 | 2 | - | 4 | 3 | - | 7 | 35 |
| | 6 | 2 | - | 3 | 9 | 3 | 6 | | | 2 | 2 | - | - | 8 | 4 | 5 | |
| P3 | 1 | - | 4 | 7 | 4 | 8 | 8 | 25 | | 3 | - | 3 | 5 | 3 | 3 | 2 | |
| | 2 | 5 | 7 | 4 | 5 | 9 | 5 | | | 4 | 4 | 6 | 5 | 9 | 6 | - | |
| | 3 | 2 | 2 | 5 | 3 | 9 | 2 | | | 5 | 8 | 2 | 6 | 5 | 3 | 2 | |
| | 4 | 7 | - | 3 | 7 | 6 | 7 | | P8 | 1 | 5 | - | 4 | 7 | 3 | 7 | 25 |
| P4 | 1 | 7 | 3 | 4 | 7 | 3 | 3 | 34 | | 2 | - | 7 | - | - | 8 | - | |
| | 2 | - | 7 | 3 | - | 2 | - | | | 3 | 7 | 4 | 5 | 7 | 6 | 3 | |
| | 3 | 7 | 4 | 5 | 7 | 6 | 2 | | | 4 | - | 4 | 8 | 3 | - | 2 | |
| | 4 | 3 | - | 8 | 3 | 4 | 6 | | | | | | | | | | |
| | 5 | 4 | 7 | 9 | 5 | 7 | 5 | | | | | | | | | | |

**Table 4.** Transportation time between machines for the econd example

| From \ To | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| 1 | 15 | 9 | 7 | 12 | - | 8 |
| 2 | 4 | 8 | 8 | - | 12 | 7 |
| 3 | - | 12 | 8 | 12 | - | 8 |
| 4 | 18 | 13 | 12 | 17 | 18 | 9 |
| 5 | 9 | 10 | 7 | 12 | 20 | 17 |
| 6 | 19 | 20 | 7 | 12 | 20 | - |

For the example, 3 Pareto solutions were obtained which are shown in Figure 4. The same results are generated for each parameter settings. After running 63 generations, these solutions were obtained. The average CPU time taken to solve the example is 1.23 minutes.

| | |
|---|---|
| $F_1 = 4940$ | $F_2 = 0.000415$ |
| $F_1 = 4942$ | $F_2 = 0.000349$ |
| $F_1 = 4944$ | $F_2 = 0.000320$ |

**Figure 4.** Pareto solutions for the second example

The above results show that the proposed approach can be applied to process sequencing problem with multiple objectives. This gives the process planner the flexibility to select alternative solutions according to the shop requirements. It is clear that the GA approach generates much better solutions and the same Pareto solutions were obtained for all situations. Furthermore, it can be effectively used to solve the complex and large size process plan selection.

## 6. CONCLUSION

A PPS model for the process planning system is studied by considering the operation flexibility, realistic shop factors and transportation time of AGV system simultaneously. This problem is formulated as a multiple objective mathematical model and a GA with the adaptive recombination strategy is developed to solve the model. The approach provides the process planner with alternative process plans for manufacturing.

The proposed approach is found to be effective in offering a set of satisfactory Pareto solutions within a satisfactory CPU time, which is essential in a multiple objective environment, to enable to decision maker to determine the best solution. This approach can be effectively used to solve the complex and large size PPS problem in process planning.

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