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An integrated approach to solving the process plan selection problem in an automated manufacturing system

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Selection of a process plan is a crucial decision making problem encountered in manufacturing systems due to the presence of several alternative process plans arising out of availability of several machines, tools, fixtures etc. capable of performing the same operations of the part. Because of its vital impact on the performance of the manufacturing system, several researchers have addressed the plan selection problem in recent years. Although functional integration plays a significant role in the development of current manufacturing systems, many of the functions in manufacturing systems have been developed without a sense of integration. Therefore, it becomes important to emphasize the integration of functions rather than the individual development of the function itself. This paper attempts to address the plan selection problem taking into account the similarity measures among the process plans of the parts. Four algorithms have been developed to integrate the several segments of the process plan selection problem. Application of these algorithms ensures considerable computational simplicity in yielding the feasible process plans of the parts.

1. Introduction

Process plans are the tools by which most manufacturers ensure consistency and use of good practices in the production of their parts. Process planning consists of several design tasks that must be completed before the actual manufacture of the part type can commence. The process planning function involves several activities such as selection and sequencing of machining operations, selection of machine tools, implementation of operations and setup planning. Process plan selection is a tedious task due to the presence of alternative machines, alternative setups and alternative processes for manufacturing the same part type. The existence of geometrical or tolerance relationships among the several features of the components necessitates the arrangement of different setups for their machining operations. This creates the possibilities of having different processing routes involving several alternative machines, tools, fixtures, etc. for manufacturing the part type. Therefore, process plan selection becomes a crucial exercise in terms of changing shop floor status and its control. Generally, in small batch manufacturing, the shop floor disturbances (like breakdown of machines, non-availability of tools, non-availability of machines due to overloading, etc.) often lead to orders being processed according to a different plan than was originally prepared. Due to such complexities process planning is often carried out without consideration of actual shop floor status and hence results in either abandoning or modifying the plan. The process plans which do not take into account the dynamic and unexpected changes in shop floor status

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are known as linear process plans. Due to the advent of CIM systems for small batch discrete part manufacturing, the need of such process plans as are capable of absorbing shop floor disturbances was felt by the planners. Therefore, the concept of nonlinear process plans has come into existence, which makes all the possible plans for each part before it enters the shop floor. All these possible plans are to be ranked according to process planning criteria stored in the process planning database. Depending on shop floor information, decisions are made regarding the execution of the process plans. Such a nonlinear process plan known as FLEXPLAN has been developed in the University of Hanover, Germany (Tonshoff *et al.* 1989, 1990). Kruth and Detend (1992) have discussed nonlinear process plans not only for the traditional workshop but also for manufacturing cells, under the ESPIRIT project.

Complications in the process plan selection problem arise because of the requirement for several tools and auxiliary devices such as fixtures, grippers and feeders, suggested by different planners. As reported in the literature, the costs associated with the fixtures are high but a limited number of fixtures poses problems with respect to scheduling flexibility. Kusiak and Finke (1988) pointed out that a manufacturing system with a limited number of tool and auxiliary devices is simpler as far as scheduling is concerned, since in such a system, the bottleneck tools and devices can easily be determined and if required the enhancement in scheduling flexibility can be easily insured using multiple tools and auxiliary devices. This choice appears to be less costly than the design and development of special tools and devices. The above-mentioned illustrations have also invited the attention of several researchers towards addressing the issues related to the process plan selection problem.

Process plan selection is an important issue in the nonlinear process planning system too. Kusiak and Finke (1988) have mentioned at least three reasons for solving the process plan selection problem in an automated manufacturing system. These are production cost, tool magazine capacity limitation, and reduction of the number of auxiliary devices. However, Bhaskaran (1990) attempted process plan selection problems by keeping in mind the satisfaction of the following objectives:

(1) Minimization of total time,
(2) Minimization of total number of processing setups,
(3) Minimization of dissimilarity between process plan of the part types.

In this paper, an attempt has been made to solve the process plan selection problem by taking into account the factors such as machine similarity, operation sequence similarity, tool similarity, fixture similarity, etc., among the alternative process plans of the different part types. This approach takes into account the objectives of the process plan selection problem which have been listed so far by the various researchers. The methodology adopted in this research consists of four algorithms to sort out some of the interlinked issues confronting the process plan selection problem. The solution approach suggested in this research also has the adaptability to address plan selection issues in conventional as well as in automated manufacturing systems.

2. Background information on the process plan selection problem

The presence of alternative feasible process plans for a part type and production of several part types in the facilities on the shop floor, where sharing of resources exists, forces the planner to select the best feasible process plan to meet the set of objectives. Kusiak and Finke (1988) have addressed the plan selection problem in automated manufacturing systems by formulating a model with objective of minimizing manufacturing cost and minimizing the usage of number of tools and auxiliary devices. Graph theoretical formulation of the plan selection problem and integer programming formulation for minimizing the total cost by satisfying a set of constraints were considered by the above researchers. However, due to the high computational complexities of integer programming or mixed integer programming models, the practical process plan selection problem is difficult to solve. Therefore, they have addressed the problem by constructing two heuristic algorithms for a quick and efficient solution.

Bhaskaran (1990) addressed the process plan selection problem by formulating an intransigent cost model to encompass the objectives, such as minimization of total time, number of steps and dissimilarity between the process plans. All these objectives have been quantified with a view to minimize the cost associated with the production of the part types. Minimization of dissimilarity between the plans is an indirect approach to minimizing the additional cost associated with several types of machines, tools, fixtures and the part movement. Bhaskaran argued that the objective of minimizing dissimilarity among the process plans cannot be visualized as an optimization problem. He also mentioned that consideration of all the process plans of the part, for all parts types, in minimizing the dissimilarity may possibly lead to the problem being combinatorially explosive. Therefore, it is advisable to adopt a progressive refinement approach to this problem.

The approaches pursued by Kusiak and Finke (1988) and Bhaskaran (1990) are quite promising. They have solved the problems by treating the nature of available information as deterministic.

According to Zhang and Huang (1994), shop floor information is normally imprecise. Therefore, a deterministic model for tackling process plan selection issues will not be accurate. Fuzzy logic proves to be a powerful tool for dealing with imprecise information and it has been adopted in this paper to solve the real life process plan selection problem. Each process plan is evaluated by satisfying four objectives: (1) minimizing the number of setups, (2) minimizing the number of processing steps, (3) minimizing the amount of machining time and (4) minimizing dissimiliarity among the process plans selected. The contribution of a process plan to an objective can be defined by a fuzzy membership. Zhang and Huang (1994) first generated alternative optimal process plans for each part type and later consolidated the plans. The objective of the consolidation was to minimize the dissimilarity among the process plans selected.

Another study reported indirectly in the literature for the process plan selection problem is in conjunction with the formation of part families and machine groups in a cellular manufacturing system. Rajamani *et al.* (1990) have addressed the problem of process plan selection using an integer programming model while the broad objective of the research was to model and analyse how the alternative process plans influence resource utilization when the part families and machine groups are formed simultaneously.

Zhang and Mechant (1993) have discussed the integration of process planning and scheduling functions and pointed out the difference between interfacing and integration. In general, interfacing can be achieved at result level while integration is to be addressed at the task level. The integration of the process planning and production scheduling functions has been frequently addressed by many researchers such as Khosnnevis and Chen (1990), Tonshoff *et al.* (1989, 1990), and Zhang and

Mallur (1994). In these works, process plans are generated and based on feedback from the shop floor while they are being executed. In a CIM environment, the integrated process planning approach has been recommended by the aforesaid researchers. However, this paper attempts to tackle the problems of process plan selection in detail assuming that the actual executable process plans are to be decided at the result level.

3. Problem description

The selection of machines, cutting tools, fixtures, setups etc. are the basic elements of the process plan selection problem. Several researchers have dealt with the process plan selection problem with a view to satisfying the objectives of minimizing the machine time, processing, steps and setups etc. As mentioned earlier, the presence of alternative resources is employed to generate several process plans of the part type. But in reality, the shop floor situation may lead to the abandoning of some of the plans due to the unrealistic assumptions of the process planner. Therefore, a good process planning approach is one which compares the resources needed in the plan with those of the other plans of the same part type. Common resources are to be identified and a standard plan of the part is to be generated. The plan selected by such a comparison will take care of the minimization of dissimilarity measures proposed by earlier researchers. Shiko (1992) has suggested a method of process plan family formation by calculating the type coefficient, rank coefficient and similarity of the plan. The objective of his research was approaching and solving the family formation problem in computer aided process planning. Referring to this research work, here an attempt has been made to solve the plan selection problem by comparing machines, tools, operations, and fixtures etc. required for the plans of one component with that of another component. This appears to be an exhaustive exercise of the comparison of resources of plans of several part types but has been simplified by proposing four progressive algorithms. The objectives of these algorithms are to deal with the similarity measures of resources appearing in the different process plans of the part types.

For demonstrating the complexity of problem involved in plan selection in CIM environment, five part types have been taken for analysis. To denote the machines, operations, fixtures, tools etc. required for the plans, a seven digit code has been adopted. For all the five part types, there are altogether 24 process plans. This research aims to select the process plans for each part type by satisfying the objectives such as minimization of machining time, processing time and steps etc.

4. Solution methodology

Four algorithms have been developed to integrate the several segments of the process plan selection problem. The first algorithm deals with part type selection using a fuzzy logic approach. The second enumerates the similarity index among operations of the plans of all part types. The third algorithm is used to calculate the degree of similarity among the process plans of a pair of part types. The pair of part types have been taken from the sequences obtained from algorithm 1. The fourth algorithm calculates the total weightage of every plan and selects the plan having maximum weightage. A problem of five part types with altogether 24 process plans has been formulated in a test model of a computer integrated manufacturing system. The system consists of two processing stations—viz. CNC lathe and milling and a robot for the material handling—linked together and controlled by a computer system. The hierarchical structure of the process plan selection algorithms adopted in this work are mentioned in subsequent sections of the paper.

4.1. *The fuzzy logic based approach to part type selection*

Part type selection in the discrete manufacturing environment plays a significant role in solving loading and scheduling problems. The process plan selection problem cannot be addressed without taking into account the issues involved in the part type selection problem. The decision to have a standard process plan for each part type depends on the manufacturing characteristics and other attributes of the part type to be processed in the system. The due date remaining, batch size of the part and number of features to be machined are some of the attributes which have to be taken care of while addressing the part type selection problem in process planning. In a real manufacturing situation, the information related to the above attributes is imprecise and conflicting in nature. Zhang and Huang (1994) have suggested a fuzzy logic approach to deal with this type of imprecise information. In this work, part type selection has been carried out by satisfying the following objectives:

(1) maximization of batch size;
(2) minimization of time remaining from due dates;
(3) minimization of number of machinable features of the part type.

The individual contribution of a part type to an objective can be defined by a fuzzy membership.

$$\mu_k(x) = \frac{0_{k(\max)} - 0_{k(x)}}{0_{k(\max)} - 0_{k(\min)}}, \tag{1}$$

where

x $1, 2, 3, \ldots, x_{\max}$ part type
k 1, 2, and 3 objectives
$\mu_k(x)$ membership of part type x to objective 0_k
$0_{k(\max)}$ maximum value of the objective 0_k for part type x
$0_{k(\max)}$ minimum value of the objective 0_k for part type x
$0_{k(x)}$ value of the objective 0_k for part type x

If an objective is to be maximized its contribution is given by

$$\mu_{k(x)} = \frac{0_{k(x)} - 0_{k(\min)}}{0_{k(\max)} - 0_{k(\min)}}. \tag{1a}$$

Similarly, a measure of membership for part type x to objective 1, 2, and 3 is defined as

$$\mu_A(x) = \sum_{k=1}^{3} \left(\frac{W_k}{\sum_{k=1}^{3} W_k} \right) \mu_k(x), \tag{2}$$

where

$\mu_{A(x)}$ membership of part type x to the objectives 1, 2, and 3
W_k individual weightage of objective k

The part type having the highest membership to the objectives maximizes the function

$$\sum_{x=1}^{x_{\max}} \mu_{A(x)} \cdot a_x$$

where

$$a_x = \begin{cases} 1 & \text{if the part type is selected} \\ 0 & \text{otherwise.} \end{cases}$$

4.2. *Algorithm 1—Algorithm for part type selection*

Step 0. Input the number of part types x, where $x = 1, 2, 3, \ldots, x_{\max}$.
Step 1. For every x, input the value of objective 0_k where $k = 1, 2$, and 3.
Step 2. Find out the maximum and the minimum values of objectives $0_1, 0_2$, and 0_3.
Step 3. Compute $\mu_{k(x)}$ using equation (1). If objective k is to be minimized, then replace $\mu_{k(x)}$ by $(1 - \mu_{k(x)})$ otherwise go to next step.
Step 4. Input the value of W_k for $k = 1, 2$, and 3.
Step 5. Find the total membership $\mu_{A(x)}$ using equation (2).
Step 6. Arrange the part types in the decreasing order of membership and then form a set of part types $\{C\}$.

4.3. *Algorithm 2—Algorithm for evaluating the* similarity index *of process plans*

Step 0. Input the number of part types x where $x = 1, 2, 3, \ldots, x_{\max}$.
Step 1. For $x = 1$ to $x_{\max}$, input the number of process plans y where $y = 1, 2, 3, \ldots, y_{\max}$.
Step 2. For every x, for every y, input the process plans in the form of operation codes.
Step 3. If PP_{xy} denotes the yth process plan of xth part type, then for every PP_{xy}, count the number of operations j where $j = 1, 2, 3, \ldots, j_{\max}$.
Step 4. For every PP_{xy},
(a) Evaluate $\Delta(0_j, 0_{j+1})$, where

$$\Delta(0_j, 0_{j+1}) = \frac{\text{Cardinality of } \{0_j \cap 0_{j+1}\}}{\text{Cardinality of } \{0_j \cup 0_{j+1}\}},$$

where
0_j denotes the jth operation of a plan
$\{0_j \cap 0_{j+1}\}$ is a set of operation parameters codes that are common to both operation 0_j and 0_{j+1} of a plan
$\{0_j \cup 0_{j+1}\}$ is a set of union of operation parameters of 0_j and 0_{j+1} of a plan.
Cardinality of a set is defined as the number of elements of the set.
(b) Increment j by 1.
(c) If $j < j_{\max}$, got to step 4 (a) else go to next step.
(d) Compute *similarity index* of the plan PP_{xy} using

$$PP_{xy}(\text{S.I.}) = \frac{\sum_{j=1}^{j_{\max}-1} \Delta(0_j, 0_{j+1})}{j_{\max} - 1} \tag{3}$$

Step 5. Arrange $PP_{xy}s$ in the decreasing order of similarity index and store them in the set $\{PP_x(SI)\}$. This set contains the process plans of the xth part type arranged in the decreasing order of their similarity index, as its element.

4.4. *Degree of similarity calculation*

The degree of similarity is defined for process plans PP_{xy} and $PP_{x'y'}$, for x is not equal to y. It is a measure of accounting for the similarity among the several process plans of the different part types. It results from the comparison of their constituent elements, namely the operation codes. It is obtained by combining four components which quantify four main operation features of the coding adopted in this paper. The operation code used in this paper refers to the following features:

(1) machine tool used (first digit of the code);
(2) operation that is to be performed (second and third digits);
(3) tool used for the operation (fourth and fifth digits);
(4) fixtures required (sixth and seventh digits).

The calculation of the degrees of similarity of two process plans takes the following similarity indices for accounting the above mentioned features:

(1) machine similarity index;
(2) operation sequence similarity index;
(3) tool similarity index;
(4) fixture similarity index.

The process plan for a part type consists of different operations, and operation parameters arranged in sequence which are directly connected with the main geometrical form of the part and hence they determine the subsequent way of manufacturing. The feature similarity index is an index to determine the similarity among the features of the part type. This index is inherent in all the above four indices. Proper weightages are assigned to all these indices while calculating the *total weightages* of the plans so as to take care of real shop floor status and the dynamically changing information of manufacturing environment.

Before presenting the degree of similarity calculation for the two process plans PP_{xy} and $PP_{x'y'}$, from the sets $\{PP_{xy}(SI)\}$ and $\{PP_{x'y'}(S.I.)\}$ respectively, it is essential to describe the following definitions and notation.

- An operation j is common for both the process plans PP_{xy} and $PP_{x'y'}$ if $PPOC(y, j) \neq 0$ and $PPOC(y', j) \neq 0$.
- An operation j is identical for both process plans if $PPOC(y, j) = PPOC(y', j) \neq 0$.
- CARDINALTY $\{A\}$ is the number of elements of set $\{A\}$.
- $N_{PP_{xy}}$ = CARDINALITY $\{PPOC(y, j);\ j = 1 \text{ to } j_{max}\}$, i.e. it is the number of operations in the process plans y of part type x.
- $Nm_{PP_{xy} \cap PP_{x'y'}}$ = CARDINALITY $\{PPMC(y, j) \cap PPMC(y', j);\ j = 1 \text{ to } j_{max}\}$, i.e. it is the number of common machines resulting from the union of process plans PP_{xy} and $PP_{x'y'}$.
- $N_{max}(PP_{xy}, PP_{x'y'})$ = maximum of CARDINALITY $\{PPOC(y, j);\ j = 1 \text{ to } j_{max}\}$ and CARDINALITY $\{PPOC(y', j),\ j = 1 \text{ to } j_{max}\}$ i.e. the maximum number of operations between the process plans PP_{xy} and $PP_{x'y'}$.
- $PPOC(y, j)$ is the jth operation of the yth process plan.

4.4.1. *Machine similarity index*

In order to quantify the factor 'machine tool' used, a term $\alpha_{PP_{xy},PP_{x'y'}}$ has been defined for x not equal to x' as the ratio of number of common machines required for the execution of the plan PP_{xy} and $PP_{x'y'}$, to the number of all types of machines used in the union of both the plans.

$$\alpha_{PP_{xy},PP_{x'y'}} = \frac{Nm_{PP_{xy}\cap PP_{x'y'}}}{Nm_{PP_{xy}\cup PP_{x'y'}}}, \tag{4}$$

where

$$0 \le \alpha_{PP_{xy},PP_{x'y'}} \le 1.$$

$\alpha_{PP_{xy},PP_{x'y'}} = 0$ when CARDINALITY $\{PPMC(y,j) \cap PPMC(y',j);\ j = 1 \text{ to } j_{max}\} = 0$. i.e. when there is no common machine for performing the operations of the plan PP_{xy} and $PP_{x'y'}$.

$\alpha_{PP_{xy},PP_{x'y'}} = 1$ when CARDINALITY $\{PPMC(y,j) \cap PPMC(y',j);\ j = 1 \text{ to } j_{max}\} =$ CARDINALITY $\{PPMC(y,j) \cup PPMC(y',j);\ j = 1 \text{ to } j_{max}\}$ i.e. when all the machines required for performing the operations of the plan PP_{xy} and $PP_{x'y'}$ are the same.

4.4.2. *Operation sequence similarity index*

The term $\beta_{PP_{xy},PP_{x'y'}}$, estimates the similarity of operation sequences of the plan PP_{xy} and $PP_{x'y'}$ (for $x \ne x'$). Sequences are compared only for operations of same type, i.e. common operations, because the comparison between two operations with a different type of machining carried out by different machine tools does not have any practical significance.

$$\beta_{PP_{xy},PP_{x'y'}} = \frac{\sum OPSESI_{PP_{xy},PP_{x'y'}} \text{ for } j \in \{OP_{PP_{xy}\cap PP_{x'y'}}\}}{N_{PP_{xy}\cap PP_{x'y'}}} \tag{5}$$

where $OPSESI_{PP_{xy},PP_{x'y'}}$ is the operation sequence similarity index defined for process plans PP_{xy} and $PP_{x'y'}$ and only for that operation in which $PPOC(y,j) \ne 0$ and $PPOC(y',j) \ne 0$.

$$\begin{aligned} OPSESI_{PP_{xy},PP_{x'y'}} &= 1 - OPSEDI_{PP_{xy},PP_{x'y'}} \\ &= 1 - \frac{\text{Absolute difference between two common operations of } PP_{xy} \text{ and } PP_{x'y'}}{\text{Maximum difference}} \\ &= 1 - \frac{\text{Abs}[PPOC(y,j) - PPOC(y',j)]}{N_{max}(PP_{xy}, PP_{x'y'}) - 1} \end{aligned}$$

$$0 \le OPSESI_{PP_{xy}.PP_{x'y'}} \le 1 \text{ and}$$

$$0 \le \beta_{PP_{xy},PP_{x'y'}} \le 1.$$

The maximum difference in the operation sequence similarity occurs when an operation is last in the longest plan and first in the shortest plan.

$OPSESI_{PP_{xy},PP_{x'y'}} = 1$ when both the plans possess the same operation which is being executed in the same sequence.

$\text{OPSESI}_{\text{PP}_{xy},\text{PP}_{x'y'}} = 0$ when there is one common operation pair.
$\text{OPSESI}_{\text{PP}_{xy},\text{PP}_{x'y'}} = 1$ when there is no common operation pair.

4.4.3. *Tool similarity index*

The term $\tau_{\text{PP}_{xy},\text{PP}_{x'y'}}$ estimates the similarity of tools required for the execution of plan PP_{xy} and $\text{PP}_{x'y'}$. The higher the tool similarity index, the lesser is the number of types of tool to be loaded on the tool magazine for the processing of the part types of the batch.

$$\tau_{\text{PP}_{xy},\text{PP}_{x'y'}} = \frac{\text{CARDINALITY OF}\left\{\left\{\tau_{\text{PP}_{xy}}\right\} \cap \left\{\tau_{\text{PP}_{x'y'}}\right\}\right\} \text{ where } x \neq x'}{\text{CARDINALITY OF}\left\{\left\{\tau_{\text{PP}_{xy}}\right\} \cup \left\{\tau_{\text{PP}_{x'y'}}\right\}\right\} \text{ where } x \neq x'} \tag{6}$$

and

$$0 \leq \tau_{\text{PP}_{xy},\text{PP}_{x'y'}} \leq 1.$$

- $\left\{\tau_{\text{PP}_{xy}}\right\}$ is the set of tools required for the operations of the yth process plan of the xth part type.
- $\left\{\tau_{\text{PP}_{x'y'}}\right\}$ is the set of tools required for the operation of the y'th process plan of the x'th part type.

4.4.4. *Fixture similarity index*

The term $\lambda_{\text{PP}_{xy},\text{PP}_{x'y'}}$ is used to quantify the similarity of fixtures between the process plans PP_{xy} and $\text{PP}_{x'y'}$ for $x \neq x'$.

$$\lambda_{\text{PP}_{xy},\text{PP}_{x'y'}} = \frac{\text{CARDINALITY OF}\left\{\left\{\lambda_{\text{PP}_{xy}}\right\} \cap \left\{\lambda_{\text{PP}_{x'y'}}\right\}\right\} \text{ where } x \neq x'}{\text{CARDINALITY OF}\left\{\left\{\lambda_{\text{PP}_{xy}}\right\} \cup \left\{\lambda_{\text{PP}_{x'y'}}\right\}\right\} \text{ where } x \neq x'} \tag{7}$$

and

$$0 \leq \lambda_{\text{PP}_{xy},\text{PP}_{x'y'}} \leq 1$$

- $\left\{\lambda_{\text{PP}_{xy}}\right\}$ is the set of fixtures required for the operations of the yth process plan of the xth component.
- $\left\{\lambda_{\text{PP}_{x'y'}}\right\}$ is the set of fixtures required for the operations of the y'th process plan of the x'th component.

4.5. *Degree of similarity*

If w_1, w_2, w_3, and w_4 are the weightages assigned to the machine similarity index, operation sequence similarity index, tool similarity index and fixtures similarity index then the *degree of similarity index* $\text{DS}_{\text{PP}_{xy},\text{PP}_{x'y'}}$ is given by:

$$\frac{w_1 \times \alpha_{\text{PP}_{xy},\text{PP}_{xy'}} + w_2 \times \beta_{\text{PP}_{xy},\text{PP}_{x'y'}} + w_3 \times \rho_{\text{PP}_{xy},\text{PP}_{x'y'}} + w_4 \times \lambda_{\text{PP}_{xy},\text{PP}_{x'y'}}}{w_1 + w_2 + w_3 + w_4}, \tag{8}$$

where

$$0 \leq \text{DS}_{\text{PP}_{xy},\text{PP}_{x'y'}} \leq 1.$$

4.5.1. *Algorithm 3—Algorithm for enumerating the degree of similarity of process plans of different part type*

Step 0. Input the set $\{PP_x(SI)\}$ of the process plans of part type x. The part type x is the first element of set $\{C\}$. Input the set $\{PP_{x'}\}$ of the process plans of the part type x', where x' is the second element of the set $\{C\}$.

Step 1. Generate a matrix $DS^{x,x'}_{y_{max}\times y'_{max}}$ called the degree of similarity matrix, the element of which is the degree of similarity of pair combinations of the process plans of part types x and x'. If y_{max} be the cardinality of the set $\{PP_x\}$ and y'_{max} be the cardinality of the set $\{PP_{x'}\}$, then order of the matrix is $y_{max} \times y'_{max}$. The elements of the matrix are obtained by equation (8).

Step 2. (a) Increase x and x' by 1 i.e. $\{PP_{x+1}(S.I.)\}$ and $\{PP_{x'+1}(SI)\}$ are the sets of process plans of the part types $x+1$ and $x'+1$ respectively. (These part types are the second and third elements of the set $\{C\}$.)
(b) Go to step 0 if $x' \leq x_{max}$.

Step 3. Store the matrix $DS^{x,x'}_{y_{max}\times y'_{max}}$ for all $x = 1, 2, \ldots, x_{max}$.

4.6. *Algorithm 3—Algorithm for the selection of the process plan of the part type*

Step 0. For $x = 1$ and $x' = x + 1$, input the matrix $DS^{x,x'}_{y_{max}\times y'_{max}}$.

Step 1. Find the total weightages of a process plan PP_{xy}. Total weightage of PP_{xy} is obtained by

$$TW[PP_{xy}] = \sum_{y'=1}^{y'_{max}} [(SI \text{ of } PP_{xy}) \times (DS_{y\times y'})] \tag{9}$$

This equation explains the total weightage of a plan as the sum of product of the similarity index of the plan and the degree of similarity of plan pairs formed by combination of plans of the part types under consideration.

Step 2. Increase y by 1 and go to step 1 if $y \leq y_{max}$.

Step 3. Select the process plan with maximum $TW[PP_{xy}]$

Step 4. Find the total weightages of a process plan $PP_{x'y'}$. Total weightage of $PP_{x'y'}$ is obtained by

$$TW[PP_{x'y'}] = \sum_{y=1}^{y_{max}} [(SI \text{ of } PP_{x'y'}) \times (DS_{y\times y'})] \tag{10}$$

Step 5. Increase y' by 1 and go to step 4 if $y' \leq y'_{max}$.

Step 6. Select the process plan with maximum $TW[PP_{x'y'}]$ These are the selected process plans for the components x and x'.

Step 7. Increase x by 1 and go to step 0 if $x \leq x_{max}$.

Step 8. For $x = 1$ to x_{max}, output the process plans selected and their individual similarity indices. This is stored as the elements of set {§} which is a set of selected process plans with maximum possible similarity taking into account the real shop floor status and information.

5. An illustrative example

In this section, the application of proposed algorithms has been illustrated for a problem described in the previous section. The coding of the operations along with the tools and fixtures required are listed in table 1. The part types under consideration are shown in figure 1. The alternative process plans of each part type in the form of operation code are listed in table 2. For part selection, the related data of the part types are given in table 3. Application of algorithm 1 yields the individual and total contribution of the part type to the objectives which are listed in table 4.

By arranging the part type in the decreasing order of the total contribution, the following sequence has been obtained:

Part type numbers: 4, 1, 5, 2 and 3.
Therefore, $\{C\} = \{4, 1, 5, 2, 3\}$.

The next step is the calculation of the similarity index of the process plans of the part types using algorithm 2. For example, the similarity index (SI) of process plan PP_{11} i.e. L010101, L020201, L030201 and L100701 is explained as follows:

Equation 3 of algorithm 2 gives:

$$PP_{xy}(SI) = \frac{\sum_{j=1}^{j_{max}-1} \Delta(0_j,\ 0_{j+1})}{j_{max}-1},$$

$$PP_{11}(SI) = \frac{\sum_{j=1}^{3} \Delta(0_j, 0_{j+1})}{3},$$

$$\text{and } \Delta(0_1, 0_2) = \frac{\text{CARDINALITY } \{L, 01\}}{\text{CARDINALITY } \{L, 01, 02, 01, 02, 01\}} = \frac{2}{6} = 0.33.$$

$$\Delta(0_2, 0_3) = \frac{3}{5} = 0.60,$$

$$\Delta(0_3, 0_4) = \frac{2}{6} = 0.33.$$

Substituting these values in the above equation:

$$PP_{11}(SI) = \frac{0.33 + 0.60 + 0.33}{3} = 0.422.$$

Table 5 shows the similarity indices of the process plans of the part types. Degree of similarity calculation:

$$\text{For part type 4, } PP_4(SI) = \{PP_{41}(0.25),\ PP_{42}(0.17)\}$$

$$\text{For part type 1, } PP_1(SI) = \{PP_{13}(0.93),\ PP_{11}(0.42),\ PP_{12}(0.40),\ PP_{15}(0.32),\ PP_{14}(0.31),\ PP_{16}(0.20)\}.$$

Referring to the routes of the plan mentioned in table 2,

$$PP_{41}(0.25)\left[\text{L010101, L020201, L060401, L120101, M171504}\right]$$

$$PP_{13}(0.93)\left[\text{L010101, L020201, L030301, M100704}\right]$$

The machine similarity index for process plans PP_{41} and PP_{13} is

Machine	Operation number	Operation	Tools required	Fixtures required	Code
Lathe	1	Facing	01	01	L010101
	2	Turning	02	01	L020201
	3	Step turning	02	01	L030201
	4	Taper turning	02	02	L040202
	5	Internal threading	03	01	L050301
	6	External threading	04	01	L060401
	7	Knurling	05	01	L070501
	8	Grooving	06	01	L080601
	9	Predrilling	07	01	L090701
	10	Drilling	08	01	L100801
	11	Boring	09	01	L110901
	12	Chamfering	01	01	L120101
	13	Parting	10	01	L131001
Milling	1	Slab milling	11	03	M011103
	2	Side milling	12	03	M141203
	3	Slot milling	13	04	M151304
	4	Form milling	14	04	M161404
	5	T-slot milling	15	04	M171504
	6	Drilling	08	04	M100804
	7	Gear cutting	16	05	M181605

Table 1. Operations and their codes.

Part number	Plan number	Process plan
1	1	L010101, L020201, L030201, L100701
	2	L010101, L020201, L030201, L090701, L110901
	3	L010101, L020201, L030201, M100704
	4	M011103, L020201, L030201, L100701
	5	M011103, L020201, L030201, L090701, L110901
	6	M011103, L020201, L030201, M100704
2	1	L010101, L020201, L030201, M151304, L080601
	2	L010101, L020201, L030201, M151304, L120801
	3	M011103, L020201, L030201, M151304, L080601
	4	M011103, L020201, L030201, M151304, L120801
3	1	L010101, L020201, L070501, L080601, L120101, L100801, L050301
	2	L010101, L020201, L070501, L080601, L120101, M100704, L050301
	3	L010101, L020201, L070501, L131001, L120101, L100801, L050301
	4	L010101, L020201, L070501, L131001, L120101, M100704, L050301
	5	M011103, L020201, L070501, L080601, L120101, L100801, L050301
	6	M011103, L020201, L070501, L080601, L120101, M100704, L050301
	7	M011103, L020201, L070501, L131001, L120101, L100801, L050301
	8	M011103, L020201, L070501, L131007, L120101, M100704, L050307
4	1	L010101, L020201, L060401, L120101, M171504
	2	M011103, L020201, L060401, L120101, M171504
5	1	L010101, L020201, L030201, L040202, M151304, L100807
	2	L010101, L020201, L030201, L040202, M151304, M100804
	3	M011103, L020201, L030201, L040202, M151304, L100801
	4	M011103, L020201, L030201, L040202, M151304, M100804

Table 2. Alternative process plans of the part types.

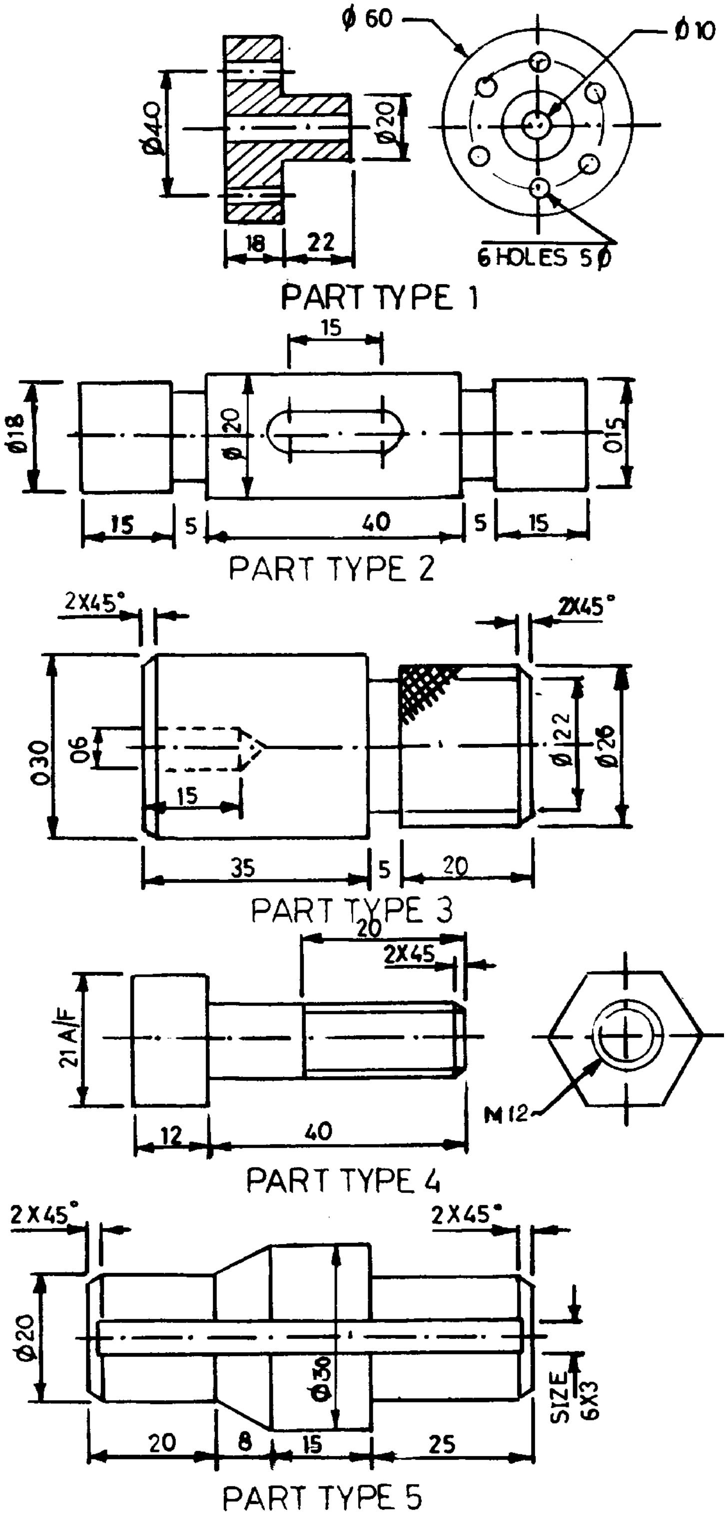

Figure 1. Different part types.

Part number	Batch size	Due dates remaining	Features
1	10	25	4
2	08	20	6
3	04	30	5
4	12	18	5
5	08	14	5

Table 3. Data related to the part types.

Part number	$\mu_{1(x)}$	$\mu_{2(x)}$	$\mu_{3(x)}$	μ_A
1	0.75	0.31	1.00	0.68
2	0.50	0.62	0.00	0.38
3	0.00	0.00	0.50	0.17
4	1.00	0.75	0.50	0.75
5	0.50	1.00	0.50	0.67

Table 4. Contribution of the part types to the objective functions.

Part type number	Process plan number	Similarity index
1	1	0.42
	2	0.40
	3	0.93
	4	0.31
	5	0.32
	6	0.20
2	1	0.23
	2	0.23
	3	0.15
	4	0.15
3	1	0.33
	2	0.22
	3	0.33
	4	0.22
	5	0.27
	6	0.17
	7	0.27
	8	0.17
4	1	0.25
	2	0.17
5	1	0.20
	2	0.27
	3	0.13
	4	0.20

Table 5. Similarity index of process plans.

$$\alpha_{PP_{41},PP_{13}} = \frac{Nm_{PP_{41}\cap PP_{13}}}{Nm_{PP_{41}\cup PP_{13}}} = \frac{2}{2} = 1.$$

The operation sequence similarity for the process plans PP_{41} and PP_{13} is

$$\beta_{PP_{41},PP_{13}} = \frac{\sum OPSESI_{PP_{41},PP_{13}\ \text{for}\ j\in\{OP_{PP_{41}\cap PP_{13}}\}}}{N_{PP_{41}\cap PP_{13}}}.$$

Operations	01	02	03	04	05	06	07	08	09	10	11	12	13	01	14	15	16	17	10	18
Plan PP_{41}	1	2				3						4						5		
Plan PP_{13}	1	2	3							4										

$$\beta_{PP_{41},PP_{13}} = \frac{\left(1-\left(\frac{abs(1-1)}{4}\right)\right)+\left(1-\left(\frac{abs(2-2)}{4}\right)\right)}{2},$$

$$\beta_{PP_{41},PP_{13}} = 1.$$

The tool similarity index for process plans PP_{41} and PP_{13} is

$$\tau_{PP_{41},PP_{13}} = \frac{\text{CARDINALITY OF}\{\{\tau_{PP_{41}}\}\cap\{\tau_{PP_{13}}\}\}}{\text{CARDINALITY OF}\{\{\tau_{PP_{41}}\}\cup\{\tau_{PP_{13}}\}\}}.$$

Since

$$\{\tau_{PP_{41}}\} = \{01, 02, 04, 15\}\ \text{and}\ \{\tau_{PP_{13}}\} = \{01, 02, 03, 07\},$$

therefore,

$$\tau_{PP_{41},PP_{13}} = \frac{2}{6} = 0.33.$$

The fixture similarity index of plane PP_{41} and PP_{13} is given by:

$$\lambda_{PP_{41},PP_{13}} = \frac{\text{CARDINALITY of}\ \{\{\lambda_{PP_{41}}\}\cap\{\lambda_{PP_{13}}\}\}}{\text{CARDINALITY of}\ \{\{\lambda_{PP_{41}}\}\cup\{\lambda_{PP_{13}}\}\}}.$$

As

$$\{\lambda_{PP_{41}}\} = \{01, 04\}\ \text{and}\ \{\lambda_{PP_{13}}\} = \{01, 04\}$$

and

$$\lambda_{PP_{41},PP_{13}} = 1.$$

If $w_1 = w_2 = w_3 = w_4 = 1$, then

$$DS_{PP_{41},PP_{13}} = \frac{1 + 1 + 0.33 + 1}{4} = 0.84.$$

Similarly, the degree of similarity matrix is constructed for all the process plans of part types 4 and 1 and is given in table 6.

Selection of process plans: The selection procedure of the process plans of part types 1 and 4 is shown as follows.

Part type 1 →		PP_{13}	PP_{11}	PP_{12}	PP_{15}	PP_{14}	PP_{16}
Part type 4	PP_{41}	0.66	0.41	0.32	0.43	0.44	0.52
↓	PP_{42}	0.56	0.35	0.34	0.55	0.56	0.65

Table 6. The elements of degree of similarity matrix $DS^{4,1}_{2\times 6}$.

Matrix $DS^{4,1}_{2\times 6}$ is given as:

$$DS^{4,1}_{2\times 6} = \begin{array}{c} \\ \\ PP_{41} \\ (0.25) \\ PP_{42} \\ (0.17) \end{array} \begin{array}{c} \begin{array}{cccccc} PP_{13} & PP_{11} & PP_{12} & PP_{15} & PP_{14} & PP_{16} \\ (0.93) & (0.42) & (0.40) & (0.32) & (0.31) & (0.20) \end{array} \\ \begin{bmatrix} 0.66 & 0.41 & 0.32 & 0.43 & 0.44 & 0.52 \\ \\ 0.56 & 0.35 & 0.34 & 0.55 & 0.56 & 0.65 \\ \end{bmatrix} \end{array}.$$

The total weightages of the process plans are:

$$TW\left[PP_{x'y'}\right] = \sum_{y=1}^{y_{max}} \left[\left(\text{SI of } PP_{x'y'}\right) \times \left(DS_{y\times y'}\right)\right]$$

$$TW\left[PP_{41}\right] = \sum_{y=1}^{6} \left[\left(\text{SI of } PP_{41}\right) \times \left(DS_{1\times y}\right)\right]$$

$$= 0.25 \times \left[0.66 + 0.41 + 0.32 + 0.43 + 0.44 + 0.52\right] = 0.69.$$

Similarly,

$$TW\left[PP_{42}\right] = 0.50,\ TW\left[PP_{13}\right] = 1.14,\ TW\left[PP_{11}\right] = 0.32$$
$$TW\left[PP_{12}\right] = 0.26,\ TW\left[PP_{15}\right] = 0.31,\ TW\left[PP_{14}\right] = 0.13$$
$$\text{and } TW\left[PP_{16}\right] = 0.23.$$

For part type 4, the highest weighted plan is PP_{41} and for part type 1, the highest weighted plan is PP_{13}.

If the shop floor status allows execution of plans PP_{41} and PP_{13}, then they are selected. Otherwise go for the next highest weighted plans of the part types.

Table 7 lists the process plans selected for the respective part types.

Part type number	Process plan selected	Route of the plan
1	3	L010101, L020201, L030201, M100704
2	2	L010101, L020201, L030201, M151304, L120801
3	5	M011103, L020201, L070501, L080601, L120101, L100801,L050301
4	1	L010101, L020201, L060401, L120101, M171504
5	2	L010101, L020201, L030201, L040202, M151304, M100804

Table 7. Process plans selected for the part types.

6. Summary and conclusion

Conventional and automated manufacturing systems are facing the problems of plan selection due to unpredictable disruption observed in the shop floor. Process plans are a benchmark for developing the schedule, tooling list, and routeing for manufacturing the part type. Therefore, the selection of feasible process plans among the other competing plans will have a vital impact on the performance of the manufacturing system. The application of the process plan selection model can be incorporated in two phases of manufacturing viz. design and planning. In most manufacturing systems, process plans are designed by different process planners.

The integrated approach of part type and process plans selection adopted in this work covers in depth most of the parameters that have some influence on the plan selection process. The concept of dissimilarity measures proposed by several researchers in the form of plan consolidation is an inherent characteristic of the algorithm proposed in this work. The similarity measures proposed stem from their application to group technology. So far as computational simplicity is concerned, the hierarchical algorithms proposed stand better over other methods of dealing with the plan selection problem. This approach not only suggests the standard process plan for each component but also provides the next alternative plans to be pursued in case of disruptions on the shop floor due to the weightages of the plans. This aspect of the approach enables it to fall into the category of nonlinear process plan which was recommended by earlier researchers for CIM systems.

The selected process plans for the manufacturing of the part types under consideration, as mentioned in table 2, show a high degree of resemblance (highest possible degree of similarity) among the several operations and sequences, machines, tools and fixtures of the plans of the part types. In subsequent feasible plans of the part type the degree of resemblance goes down, therefore the resources needed to manufacture the parts increase.

As mentioned by Bhaskaran (1990), the reduction in dissimilarity among the process plans simplifies the scheduling process and minimizes manufacturing cost. A balance is to be maintained between the saving in cost as a result of minimizing the dissimilarity and an additional cost, accrued as a result of shifting from minimizing the processing cost of the plan, which is unknown because of the problems in quantifying the intangible variables such as simplification of the scheduling process. Therefore, he argued that minimization of dissimilarity among the process plans cannot be viewed as an optimization problem. Such a step does not feature in the proposed method because of the presence of dissimilarity measures right from the beginning of the plan selection exercise. The concept of the fuzzy approach, known for dealing with the imprecise and conflicting nature of information, has been adopted to solve the part selection problem before the plan selection exercise begins.

Hopefully, the ideas presented in this research will be able to solve the several kinds of process planning problem frequency encountered in industry.

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References

Bhaskaran, K., 1990, Process plan selection. *International Journal of Production Research*, **28** (8), 1527–1539.

Khoshnevis, B., and Chen, Q., 1990, Integration of process planning and scheduling functions. *Journal of Intelligent Manufacturing*, **1**, 165–176.

Kruth, J. P., and Detand, J., 1992, A CAPP System for nonlinear process plans. *Annals of the CIRP*, **41** (1), 489–492.

Kusiak, A., and Finke, G., 1988, Selection of process plans in automated manufacturing systems. *IEEE Journal of Robotics and Automation*, **4** (4), 397–402.

Rajamani, D., Singh, N., and Aneja, Y. P., 1990, Integrated design of cellular manufacturing systems in the presence of alternative process plans. *International Journal of Production Research*, **28** (8), 1541–1554.

Shiko, B., 1992, A process planning oriented approach to the part family formation problem in group technology applications. *International Journal of Production Research*, **30** (8), 1730–1752.

Tonshoff, H. K., Beckendorff, U., and Andres, N., 1989, Flexplan – a concept for intelligent process planning and scheduling. *Proceedings of the CIRP International Workshop on Computer Aided Process Planning*, Hanover University, Germany.

Tonshoff, H. K., Beckendorff, U., Andres, N., and Detend, T., 1990, A process description concept for process planning, scheduling a job shop control. *Proceedings of the 22nd CIRP International Seminar on Manufacturing Systems*, University of Twente Enschede, The Netherlands.

Zhang, H. C., and Huang, S. H., 1994, A fuzzy approach to process plan selection. *International Journal of Production Research*, **32** (6), 1265–1279.

Zhang, H. C., and Mallur, S., 1994, An integrated model of process planning and production scheduling. *International Journal of Computer Integrated Manufacturing*, **7** (6), 356–364.

Zhang, H. C., and Mechant, M. E., 1993, IPPM – A prototype to integrate process planning and job shop scheduling functions. *Annals of the CIRP*, **42** (1), 513–518.