Integrated Process Planning with Scheduling System in Cellular Manufacturing

Leem, Choon-Woo*
임 춘 우
Kim, Young-Il*
김 영 일
Kim, Wong-Joong**
김 원 중

ABSTRACT

The objective of this paper is to outline an integrated cellular manufacturing system (ICMS) which integrates process planning and scheduling in the cellular manufacturing environment. It combines design systems with manufacturing systems in batch production. Furthermore, it is developed to overcome the difficulties that exist in the current manufacturing practices.

1. Introduction

Cellular manufacturing (CM) is perceived as a philosophy and an innovation used to increase production efficiency by identifying and exploiting the similarity of parts and operation processes in manufacturing. The major feature of CM is to decompose the overall complexity of manufacturing systems into smaller units of manufacturing cells which are less difficult to handle in terms of planning and scheduling. The success of a total system utilizing CM is to integrate overall functions into an operable manufacturing system. In production planning and control, there are three major functions which are related "how" and "how much." The functions are process planning, manufacturing cell formation and cell scheduling.

Process planning is the first step in production planning. It involves the "how" aspect of manufacturing. It links the gap between Computer-Aided Design (CAD) and Computer-Aided Manufacturing (CAM). The main objective of process planning is to generate technological plans which optimize all elements and variables in a given manufacturing environment. The process planning activity has no time element associated with it. That is, process planning explains what will happen at the schedule time zero and how it will happen (Afzulpurkar et al., 1992; Rembold *et al.*, 1993).

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* LG생산기술원 시스템기술Group
** 아주대학교 산업공학과

Manufacturing cell formation is an intermediate stage between process planning and cell scheduling for organizing the production system. It is defined as a function to form manufacturing cells based on similarities where part families machine cells are included. A part family is a list of parts which are similar because they can be processed on the same group of machines. A machine cell is a list of machines that will complete the processing of a given family of parts (Burbidge, 1975). The recognition of similarities is essential for classification of part families and machine cells based on their criteria. One common basis for similarity is the characteristics of the parts which can be shape, size or material. Another common basis for similarity is the characteristics of manufacturing processes for the parts, such as process sequences or routings and types of machines to be used.

Cell scheduling addresses with the "when and how much" aspects. It schedules parts in a cell and between cells through manufacturing equipment to optimize given performance criteria. Scheduling is time driven while process planning explains what will happen with the scheduled time zones and how it will happen (Rembold et al., 1993). It is well known that scheduling is one of the most difficult manufacturing functions because it involves the time ordered arrangement of parts to be processed on machines while optimizing the given criteria.

Some relationships can be found among these functions. The main relationship is that the quality of schedules in manufacturing cells is dependent not only on how a part family and a machine cell are grouped into manufacturing cells but also on how the process planning is accomplished. Accordingly, it is necessary to integrate these three functions in a real time basis. However, it is frequently reported that the process plan is routinely modified because of the scheduling conflicts on the shop floor. That is, process planning is considered an independent feature that is unrelated to and unaffected by other manufacturing functions (Khoshnevis and Chen, 1989; Srihari and Greene, 1988). There can be found many unrealistic assumptions which are used in manufacturing such as:

1) Only one machine is processed for a particular shape of a part,
2) Most of the manufacturing cell formation algorithms utilize fixed routings for parts,
3) Process plans assume unlimited resources at the shop,
4) Process plans assume a 100% idle factory,
5) The desirable machines are repeatedly selected by various process planners,
6) Only one process plan for a given part is generated, and
7) Scheduling follows the process planning stages.

2. Integration of Process Planning/Scheduling in Cellular Manufacturing

A primary objective of most process planning systems aims at generating an optimal process plan for a given part in manufacturing environment. The current process planning systems usually select and recommend a preferred manufacturing process based on technological and economic considerations. As a result, one sequence and one set of machines for each part are selected. Some machine can be overloaded, while others are under utilized. The overloaded machines can easily become a bottleneck (Hou and Wang, 1991). The dynamic process planning approach is presented by Srihari and Greene (1988) to avoid the conflict between process planning and scheduling. It has the ability to generate alternative process plans considering current facility status.

The importance of the integration of these two functions is that the planned

schedule will not follow on the shop floor if process planning and scheduling are separated. It results in production scheduling lacking flexibility and adaptability (Dong et al., 1992). The integration of these two functions should be considered carefully because process planning and scheduling have conflicting objectives; the process planning emphasizes the technological aspect of a job, whereas the scheduling function emphasizes the resource allocation aspect of it (Khoshnevis and Chen, 1989). The benefits of integration are that it can:

1) reduce scheduling conflicts,
2) reduce human intervention,
3) reduce production cycle,
4) increase resource utilization,
5) provide the uniform flow of jobs on shop floor, and
6) balance machines and machine tool load.

Limited research has been done, since integrated approaches to process planning and scheduling have been studied. Hankins et al. (1984) used Computer-Aided Time Standards (CATS) for alternative machine tools, for process planning, where the importance of alternative machine tools was stressed. Khoshnevis and Chen (1989) developed a heuristic approach to show the potential impact of the integrated system of planning and scheduling. Zhao and Kops (1987) developed an integrated CAPP/Scheduling system, where an automatic CAPP system was based on the Group Technology (GT) concept. Hou and Wang (1991) investigated the integration a CAPP system and FMS, the resulting integration called ALT-CAPP, which is a variant CAPP system based on KK-3 GT codes to form part families.

3. Proposed Approach

This paper outlines an integrated Cellular Manufacturing System (ICMS). The objective of ICMS is to maximize the system performance by integrating three major functions: process planning, manufacturing cell formation and cell scheduling. In implementing ICMS, a number of decisions need to be made due to the interaction of these functions. The system architecture of ICMS is shown in Fig. 1.

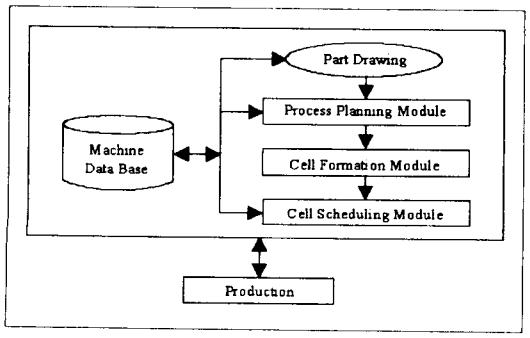

Fig. 1 Architecture of ICMS

3.1 Process Planning Module

When the design of parts or product is completed, process planning can be started. The results of the design are manufacturing data including the drawing and the bill of materials. Process planning is a link between design (the definition of the parts) and the manufacturing of process planning should be a series of steps such as interpretation of the design data, machine tool selection, operation sequence selection and economic justification.

For justifying the selected process plans, ICMS utilizes a new process plan selection algorithm (Leem et al., 1995). Assume that process planner ω, ω=1, ⋯, n, selects one of M different process plans, $B_1, \cdots, B_M$. Each process plan is characterized by the multiple attributes. The attribute A_i is classified into K categories using linguistic variables, $C_1, \cdots, C_K$. The data for the modified process plan selection algorithm is given in Table 3.1.

Table 3.1 Data for the Modified Process Plan Selection Algorithm

Process Planner	Alternatives $B_1, \cdots, B_M$	Attribute A_i $C_1, \cdots, C_K$
1	$\mu_{B_1}(1), \cdots, \mu_{B_M}(1)$	$\mu_1(1), \cdots, \mu_K(1)$
⋯	⋯	⋯
ω	$\mu_{B_1}(\omega), \cdots, \mu_{B_M}(\omega)$	$\mu_1(\omega), \cdots, \mu_K(\omega)$
⋯	⋯	⋯
n	$\mu_{B_1}(n), \cdots, \mu_{B_M}(n)$	$\mu_1(n), \cdots, \mu_K(n)$

Table 3.1 has two different fuzzy sets, the fuzzy alternative set and the fuzzy attribute set. The fuzzy alternative set is a matrix for the preferences of process plans where $\mu_{B_i}(\omega)$ expresses the degree of preference for *ith* process plan. The constraints on the fuzzy alternative set are represented as follows:

a) $0 \le \mu_{B_j}(\omega) \le 1$ for $j = 1, \cdots, M$, (3.1)

b) $\sum_{j=1}^{M} \mu_{B_j}(\omega) = 1$ for $\omega = 1, \cdots, n$, and (3.2)

c) $\sum_{\omega=1}^{n} \mu_{B_j}(\omega) > 0$ for $j = 1, \cdots, M$. (3.3)

Constraint (3.1) ensures that membership value $\mu_{B_i}(\omega)$ is restricted not to a binary value [0, 1] but to a value {0, 1}. It means that a process planner can select more than one feasible process plan at the same time with different degrees of preference. Constraint (3.2) ensures that only one process plan is selected among alternative feasible process plans. Constraint (3.3) indicates that each process plan is selected from at least one process planner.

The fuzzy attribute set is a matrix for the values of attributes where $\mu_i(\omega)$ is the degree of response to category C_i for the most preferred process plan of ωth process planner. The constraints for fuzzy attribute matrix C are as follows:

a) $0 \le \mu_i(\omega) \le 1$ for $i = 1, \cdots, K$ and (3.4)

b) $\sum_{\omega=1}^{n} \mu_i(\omega) > 0$ for $i = 1, \cdots, K$. (3.5)

Constraint (3.4) requires membership value to take a value {0, 1}. That is, each attribute is

classified into K number of categories. Constraint (3.5) ensures each category to be chosen from at least one process planner to represent the characteristics of the attribute. For example, a process planner evaluates three different process plans. The preferences of three process plans are given by $(\mu_{B_1}(1), \mu_{B_2}(1), \mu_{B_3}(1)) = (0.7, 0.3, 0.0)$. The cost attribute can be classified into three categories, *"expensive," "average,"* and "cheap." Then, the membership values, $\mu_1(1), \mu_1(2)$, and $\mu_3(1)$,, for cost category are expressed by $(\mu_1(1), \mu_2(1), \mu_3(1)) = (0.1, 0.2, 0.8)$.

The main goal of the algorithm is to express the structure of the fuzzy alternative set on the real number axis using the linear equation of category vector $\boldsymbol{C}$ for the attribute A_i. However, in the algorithm, the solution requires information about the relative importance of each category for the given attributes. It should be given by a set of weights normalized to sum to 1. Let $y(\omega)$ be the objective function of the ωth process planner and w be the relative weight vector for attributes. Then, the linear equation can be expressed by

$$y(\omega) = \sum_{i=1}^{K} w_i \mu_i(\omega) \quad \text{for } \omega = 1, \cdots, n. \tag{3.6}$$

In other words, the algorithm determines the relative weight vector w which gives the best separation of the fuzzy alternative set on the real number axis. The degree of separation of the fuzzy sets is defined as a fuzzy variance ratio η^2. That is, we have

$$\eta 2 = \frac{SS_B}{SS_T}, \tag{3.7}$$

where η^2 : the degree of separation of the fuzzy sets,
SS_B : variation between fuzzy alternative set,
SS_C : variation between fuzzy attribute set, and
$SS_T = SS_B + SS_C$

The terms SS_T and SS_B are expressed in quadratic forms using a weight vector $\boldsymbol{C}$ such that $SS_T = C^t TC$ and $SS_B = C^t BC$, where C^t is the transpose of $\boldsymbol{C}$. Let the matrices T and B be the matrices P and Q, respectively. Then, the solution for the algorithm is derived by

$$\begin{aligned} &Max.\ \eta^2, \\ &\quad subject\ to \\ &(B - \eta^2 T)C = 0. \end{aligned} \tag{3.8}$$

From the category vector $\boldsymbol{C}$, the components of the relative weight vector w can be obtained from

$$w_1 = \frac{c_i}{\sum_{i=1}^{K}} \quad \text{for } i = 1, \cdots, K. \tag{3.9}$$

From the relative weight vector w, the objective values for participating process planners are derived using equation (3.6).

The proposed algorithm can be used to select a process plan among a number of process plans by comparing multiple attributes. There are a number of plans for a given

part. These process plans can be characterized by their relative cost and suitability for a given manufacturing environment (Sanii and Davis, 1990). The best process plan is the one that minimizes manufacturing cost and processing time and maximizes quality.

3.2 Manufacturing Cell Formation Module

The functions of cell formation are to specify the machines in the manufacturing cell and allocate parts to the machines. It is a very critical step in designing and manufacturing, since the cell layout is determined by the result of cell formation. The location and layout will influence intercell move times and bottlenecks (Afzulpurkar et al., 1993).

The inputs of this module are selected process plans for given parts from the process planning module. The relationship between parts and machines to be used in the process plan can be expressed by a machine-part incidence matrix. From this information, ICMS determines manufacturing cells using the proposed clustering algorithm (Leem and Chen, 1994). Suppose that there are m machines and p parts to be grouped into c cells. The binary machine-part incidence matrix is shown below:

Table 3.2 Binary Machine-Part Incidence Matrix

Machine	Part				
	P1	*P2*	*P3*	···	*Pp*
M1	μ_{11}	μ_{12}	μ_{13}	···	μ_{1p}
M2	$^{*}\mu_{21}$	μ_{22}	μ_{23}	···	μ_{2p}
M3	μ_{31}	μ_{32}	μ_{33}	···	μ_{3p}
.	.	.	.	···	.
.	.	.	.	···	.
.	.	.	.	···	.
Mm	μ_{m1}	μ_{m2}	μ_{m3}	···	μ_{mp}

$$* \mu_{ij} = \begin{cases} 1 & \textit{if part } j \textit{ is processed by machine } i, \\ 0 & \textit{otherwise.} \end{cases}$$

The notation μ_{ij} denotes the relationship between machine i and part j. Because of the limitations of the binary matrix approach explained in the previous section, the nonbinary matrix approach is presented. The nonbinary matrix scheme offers a unique approach to the cell formation problem since it has more flexibility in grouping and clustering than the binary logic approach (Li, et al., 1988). The nonbinary machine-part incidence matrix is shown in Table 3.2.

Table 3.3 Nonbinary Machine-part Incidence Matrix

Machine	Part				
	P1	*P2*	*P3*	···	*Pp*
M1	μ_{11}	μ_{12}	μ_{13}	···	μ_{1p}
M2	μ_{21}	μ_{22}	μ_{23}	···	μ_{2p}
M3	μ_{31}	μ_{32}	μ_{33}	···	μ_{3p}
.	.	.	.	···	.
.	.	.	.	···	.
.	.	.	.	···	.
Mm	μ_{m1}	μ_{m2}	μ_{m3}	···	μ_{mp}

The constraints are such that

a) $0 < \mu_{ik} < 1$ for $i=1,\cdots,m$ and $k=1,\cdots,p$ and (3.10)

b) $\sum_{k=1}^{p} \mu_{ik} > 0$ for $i=1,\cdots,m$. (3.11)

The constraint (3.10) ensures that the membership value μ_{ik} is restricted not to a binary value [0, 1] but to a value {0, 1}. The constraint (3.11) requires that a part shape be processed by more than one machine.

Similarity Coefficient

The similarity coefficient approach is a well-known methodology in cellular manufacturing because it is the most efficient in forming machine cells (Seifoddini and Wolfe, 1986). In the case of binary machine-part incidence matrix, the similarity coefficients defined in SLCA (McAuley, 1972) and ALCA (Seifoddini and Wolfe, 1986) are commonly used.

In the nonbinary machine-part incidence matrix, Li et al. (1988) proposed different types of the similarity coefficient. In this research, a similarity coefficient (S_{ij}) for machines i and j is defined as

$$S_{ij} = \frac{\sum_{k=1}^{p}(\mu_{ik} \wedge \mu_{jk})}{\sum_{k=1}^{p}(\mu_{ik} \vee \mu_{jk})} \quad \text{for } i=1,\ldots,m,\ j=1,\ldots,m, \text{ and } i \neq j \qquad (3.12)$$

The similarity coefficient in equation (3.12) reflects the proportion of degree for parts visiting M_i and M_j. The values of the similarity are standardized such that the value near one is more desirable to form M_i and M_j into the same cell. If all the elements μ_{ij} are identical, the similarity coefficient indicates one. Also, if all the elements are inverse, the similarity coefficient is zero. The value near zero means comparatively unimportant. The values of S_{ij} have the following properties:

a) $0 \leq S_{ij} \leq 1$ *for* $i \neq j$, (3.13)

b) $S_{ij} = S_{ji}$, *and* (3.14)

c) $S_{ii} = 1$. (3.15)

Pairwise similarity can be arranged in a matrix form as follows:

$$S = \begin{vmatrix} 1 & S_{12} & \cdots & S_{1p} \\ S_{21} & 1 & \cdots & S_{2p} \\ \vdots & \vdots & \vdots & \vdots \\ S_{m1} & S_{m2} & \cdots & 1 \end{vmatrix}. \qquad (3.16)$$

Machine-chaining Problem

The machine-chaining problem can arise when the machines are assigned in cells improperly. Seifoddini and Wolfe (1986) and Chow and Hawaleshka (1992) have introduced efficient algorithms to overcome such a problem. The key for the machine-chaining problem is to regard all steps of the procedure as continuous ones. If the machines M_i and M_j have maximal similarity value, then M_i and M_j are formed into the same cell and elements in M_i and M_j are transformed into a single unit. The transformation of elements in M_i and M_j into a new machine unit, $M_{(i,j)}$, is as follows:

$$M_{(i,j)} = (\mu_{ik} \vee \mu_{jk}) \quad \text{for } k=1,\cdots,p. \tag{3.17}$$

Since the output of the previous step is the input to the next step, such a continuous re-evaluation is repeated until the desired number of cells are clustered. For instance, there are five parts and the membership values for M_i and M_j are shown in equations (3.18) and (3.19). Then the new elements for $M_{(i,j)}$ in equation (3.20) are transformed as follows:

$$M_i = (0.1,\ 0.3,\ 0.0,\ 0.0,\ 0.7), \tag{3.18}$$

$$M_j = (0.3,\ 0.1,\ 0.1,\ 0.0,\ 0.0), \text{ and} \tag{3.19}$$

$$M_{(i,j)} = (0.3,\ 0.3.\ 0.1,\ 0.0,\ 0.7). \tag{3.20}$$

The machine-chaining problem should be considered in the manufacturing-cell design stage. When similar machines are formed in a cell, the density of a cell can be increased while those of other cells can be decreased. It may result in decreasing overall machine utilization in machine cell. However, the cost of intercellular and intracellular movements can be reduced when this problem is considered. Therefore, before a manufacturing cell is designed, the objective of the system should be identified.

Machine-cell Formation Procedure

The proposed procedure consists of three basic rules. The first rule is to calculate the similarity values among the machines using equation (3.12) and to construct a similarity matrix. The second rule is to form the cell including the machines having maximal similarity values. The final rule is to transform the elements of selected M_i and M_j into the new machine unit using equation (3.17). The combination of these three rules provides the machine cells and part families. The procedure is described as follows:

Step 0) Initialization

Set the Current Number of Cells (CNC) to be m and the desired numbers of cells to be c. Compute the similarity values of the given machine-part incidence matrix.

Step 1) Cell Formation

Find the machines M_i^* and M_j^* that have the maximal similarity coefficient, and include these two machines into the same cell $M_{(i^*,j^*)}$.

Step 2) Transformation

Transform the elements of the machines M_i^* and M_j^*, and rearrange the machine-part incidence matrix.

Step 3) Similarity Values Calculation

Update the similarity values from the rearranged machine-part incidence matrix and reduce the CNC to one unit.

Step 4) Evaluation

Check the CNC. If the CNC > c, go to Step 1, otherwise repeat it until the CNC = c.

3.3 Cell Scheduling Module

Cell scheduling is the final step in ICMS. On the basis of the results of the process planning and manufacturing cell formation modules, the cell operation is determined. The inputs of this module are the information in each manufacturing cell such as part list, machine list, processing time, operation sequence and production quantity. In

ICMS, the exchange heuristic algorithm (Yang et al., 1989) is used since the problem is classified Job Shop type manufacturing strategy. It is an efficient algorithm, which is able to provide a good schedule in a short period of time for generalized job shop scheduling problems.

4. Conclusion

In this paper, ICMS assumed to be a system in which a product design is taken as the input. This input is processed resulting in a process plan that includes a manufacturing schedule utilizing a cellular manufacturing. The integration of the process planning and scheduling functions seeks to resolve traditional problems of conflicts between two functions. Many such problems arise from the basic nature of the two functions.

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