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유전자 알고리즘을 활용한 부품 군의 형성과 수요 변화하의 기계 셀 설계*

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Forming Part Families by Using Genetic Algorithm and Designing Machine Cells under Demand Changes

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본 연구는 기계고장 시 대체경로를 고려한 새로운 유사계수와 주어진 기간 내 수요변화를 고려하여 제조 셀을 구성하는 방법론을 개발하는 것이다. 본 연구의 방법론은 2단계로 나누어진다. 1단계에서는 기계고장 시 이용 가능한 대체경로를 고려하여 새로운 유사계수를 제시하고 유전자 알고리즘을 활용하여 부품 군을 식별하는 것이다. 셀 응용의 성패를 좌우하는 주요한 요소들 중 하나는 수요변화에 대한 유연성으로서 수요변화, 이용 가능한 기계의 능력 및 납기일에 따라 셀을 재구성하기가 쉬운 일은 아닐 것이다. 대부분의 논문에서 제안한 방법들은 단일기간에 대한 고정 수요를 고려하였으나, 수요의 변화로 인하여 셀 설계는 대부분의 연구에서 고려한 단일기간보다는 장기적인 면을 고려해야 할 것이다. 수요가 변화하는 상황에서 운용요소와 일정요소를 고려한 셀 구성에 대한 새로운 방법론을 2단계에 소개한다.

Keywords : roup technology, Cellular manufacturing, Demand changes, Cell design, Genetic algorithm

1. Introduction[4)]

Batch manufacturing is a dominant manufacturing activity in the world, generating much industrial output. The major characteristics of batch manufacturing are high level of product variety and small manufacturing lot sizes. The product variations present design engineers with the problem of a design stage that significantly affects manufacturing cost, quality, and delivery times. The impacts of these product variations in manufacturing are high investment in equipment, high tooling costs, complex scheduling and loading, lengthy setup times and costs, excessive scrap, and high quality control costs. However, to compete in a global market, it is essential to improve the productivity in small batch manufacturing industries. For this purpose, some innovative methods are needed to reduce product cost, reduce lead time, and enhance product quality to help increase market share and profitability. Group technology provides such a link between design and manufacturing. The adoption of group technology concepts, which allow small batch production to gain economic advantages similar to mass production while retaining the flexibility of job shop methods, will help address some of the problems.

The philosophy of group technology(GT) is an important concept in the design of manufacturing cells. Similar parts are arranged into part families. Each family would possess

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similar design and manufacturing characteristics. The processing of each member of a given family would be similar, which results in manufacturing efficiencies.

Cellular manufacturing(CM) is one of the major applications of group technology. The main objective of designing manufacturing cells is to develop a production environment of machining centers, either as a line or in cells, operated manually or automatically for the production of part families that are grouped according to a number of similarities in their design and manufacturing features. This type of manufacturing is known as CM and is used for manufacturing a product in batches. A fundamental issue in CM is the determination of part families and machine cells. This issue is known as the "cell formation"problem. Cell design is normally understood as the problem of identifying a set of part types that are suitable for manufacturing on a group of machines. However, there are many other strategic level issues such as level of machine flexibility, cell layout, type of material handling equipment, and types and number of tools and fixtures that should be considered as part of the cell design problem. Further, any meaningful cell design must be compatible with the tactical and operational goals such as high production rate, low work-in-process(WIP), low queue length at each work station, and high machine utilization. Much research has been reported on various aspects of design, planning, and control of cellular manufacturing systems.

2. Approaches to cell formation : An Overview

2.1 Similarity and Dissimilarity Coefficients for Determining Part Families

A number of researchers have used different types of similarity and dissimilarity coefficients for determining part families. McAuley(1972) was the first researcher to apply the Jaccard similarity coefficient to the cell formation problem. Selvam and Balasubramanian (1985) developed a dissimilarity measure based on operation sequences. Dutta et al.(1986) developed a dissimilarity coefficient to cluster parts. Choobineh(1988) proposed a similarity measure which used the manufacturing operations and their sequences in the first stage. Then, the machine cells were formed in the second stage. Gunasingh and Lashkari(1989) suggested a similarity index which expressed the capability between two machines in processing a set of parts that need both machines. The capability of a machine is defined in terms of the tools available to it and tooling requirements of the parts. Tam(1990) also proposed a new similarity coefficient based on the similarity of operation sequences. Gupta and Seifoddini(1990) suggested a new similarity coefficient which was based on the idea that necessary production data should be incorporated in the early stages of the machine- component grouping process. They considered processing requirements of parts, pairwise average production volume, and unit operation time as new production parameters. Vakharia and Wemmerö 1990) proposed a new coefficient for use in the clustering process by considering the within-cell machine sequence and machine loads. In this similarity coefficient, the proportion of machine types required by two parts in the same order is measured. Kusiak and Cho(1992) proposed two new similarity measures in which one was a binary measure that indicated whether one part's process plan is a subset of another part's process plan. The other similarity measure was a modified version of the first which was to be used when the value of the first similarity measure would have been zero. Gupta(1993) suggested a new similarity coefficient which required that alternative routing of parts should be considered while calculating the pairwise similarity coefficient between machines. Kamrani and Parsaei(1993) proposed a weighted dissimilarity coefficient based on a disagreement measure of both design and manufacturing attributes between two parts. Recently, Moussa and Kamel(1996) also proposed a new similarity coefficient which took into consideration the operation sequences and process times during the assignment process.

Most of the suggested approaches in the literature developed new similarity and dissimilarity coefficients, however, these approaches tend to disregard machine failure. The main objective of Phase I is to develop a new similarity coefficient which considers the number of alternative routes available during machine failure(Jeon et al., 1998) and identify part families by using genetic algorithm.

2.2 Mathematical Approaches for Forming Machine Cells

A number of mathematical approaches have been reported for the cell formation problem. Choobineh (1988) proposed a two-stage procedure for the design of a cellular manufacturing system. In the first stage, part families were formed by using the manufacturing operations and operational sequences. The machine cells were formed in the second stage by using an integer programming model. Rajamani et al.(1990) presented the influence of alternative process plans on resource utilization when the part families and machine groups are formed simultaneously. Rajamani et al.(1992a) presented the cell formation for a manufacturing environment in which there are significant sequence-dependent setup times and costs. Rajamani et al.(1992b) also developed a mathematical model which aided in deciding the optimal variety of parts, portion of demand to be produced in cells, machines to select, and plans to produce the parts. Adil et al.(1993) indicated that the current cell design procedures did not consider the operational aspects during cell formation. Therefore, the objective of their study was to consider the investment and operational costs simultaneously during the design of a cellular manufacturing system. Kamrani and Parsaei(1993) proposed a two-phase methodology for identifying part families by using a dissimilarity measure and grouping the manufacturing cells based on relevant operational costs. Kamrani et al.(1995) also developed an optimization model which considered machine cell configuration and operations capacity planning in their third stage. Atmani et al.(1995) introduced a zero one integer programming model for the simultaneous solution of the cell formation and operation problem in cellular manufacturing. The objective of their model was to simultaneously form machine groups and allocate operations of the part types to the regrouped machines in such a way to minimize the total sum of operation, refixturing, and transportation costs. Sankaran(1990) and Shafer and Rogers(1991) also developed goal programming models for cell formation. Won(2000) proposed a two-phase approach to group technology cell formation by using efficient p-median formulation and Won and Lee(2001) introduced group technology cell formation considering operation sequences and production volumes.

Cellular manufacturing is gaining popularity as a way to quickly improve productivity and competitiveness. As a result, much research has been devoted to the development of mathematical models. Unfortunately, only one paper(Adil et al.,1993) has been aimed at cell formation with scheduling aspects which considers sequence-dependent setup time, machine idle time, part WIP inventory, and part early and late finish times. Singh(1993) also indicated in his study that there is a need to develop procedures which integrate scheduling and operational aspects into the cell design process. In addition, one of the major factors contributing to the success of cell implementation is flexibility for demand changes. It is difficult to reorganize the cells according to changes in demand, available machine capacity, and due date. Most of the suggested approaches in the literature tend to use a fixed demand for cellular manufacturing systems. Due to demand changes, cell design should include more than the one period that most researchers consider.

Anew methodology for cell formation, which considers the scheduling and operational aspects in cell design under demand changes, is introduced in Phase II. Machines are assigned to part families by using an optimization technique. This optimization technique employs sequential and simultaneous mixed-integer programming models for a given period to minimize the total costs which are related to the scheduling and operational aspects.

3. A two-phase procedure

3.1 Similarity Coefficient for Part Families for Phase I

A similarity coefficient is a calculated value that presents the relationship between two parts. Most research in this area uses similarity coefficients that range from zero to one. The larger the value of the similarity coefficient, the more similar the two parts/machines and the smaller the value of the dissimilarity coefficient, the more similar the parts/machines. This condition implies that the dissimilarity coefficient = 1- similarity coefficient which means the coefficients are symmetric and nonnegative.

Assumptions for the new similarity coefficient are as follows : ıch operation can be performed on more than one machine, independent machine failure exists for each machine, and two alternative routes which have different machine sequences for two parts on the same machines are considered to be the same. The mathematical expression for the similarity coefficient will be given in Eq.(1).

3.1.1 Nomenclature

S_{ij} : milarity coefficient between part types i and j

r_{ik} : k^{th} alternative route for part type i

t_{ijp} : p^{th} alternative route of new arrangement between part types i and j

$$r_{ik}^{(m)} = \begin{cases} 1, & \text{if the } k^{th} \text{ alternative route for part type } i \text{ still exists when machine type } m \text{ fails} \\ 0, & \text{otherwise} \end{cases}$$

$$t_{ijp}^{(m)} = \begin{cases} 1, & \text{if the } p^{th} \text{ alternative route of a} \neq w \text{ arrangement for part types } i \text{ and } j \text{ still } \exists \text{ when machine type } m \text{ fails} \\ 0, & \text{otherwise} \end{cases}$$

3.1.2 Proposed Steps for Determining the New Similarity Coefficient

The proposed steps for determining the new similarity coefficient between parts i and j are as follows :

Step 1 : rrange all alternative routes for each part.

Step 2 : leasure $r_{ik}^{(m)}$ for part i and $r_{jl}^{(m)}$ for part j.

Step 3 : alculate $\sum_{mk} r_{ik}^{(m)}$ for part i and $\sum_{ml} r_{jl}^{(m)}$ for part j.

Step 4 : rrange the new alternative routes(t_{ijp}) for parts i and j.

Substep 4.1 : ind two common alternative routes for parts i and j. These two common alternative routes will be selected as two new elements of the new alternative route set.

Substep 4.2 : ind two alternative routes which have different machine sequences with the same machine types for parts i and j. These alternative routes will also be selected as two new elements of the new alternative route set.

Substep 4.3 : ind two alternative routes which have different machine sequences with the same machine types for each part i and j. Either one (an alternative route which does not appear in a new alternative route set, i.e., does not duplicate the same routes) of these two routes will be selected as a candidate to be an element of the new alternative route set, if either one of these two alternative routes has already been selected in Substep 4.1 or Substep 4.2.

Substep 4.4 : ind the remaining alternative routes which were not found in Substep 4.1, 4.2, or 4.3. These routes will be disregarded in the new alternative route set.

Step 5 : leasure $t_{ijp}^{(m)}$ and calculate $\sum_{mp} t_{ijp}^{(m)}$ for parts i and j during machine failure.

Step 6 : alculate the new similarity coefficient by using Eq.(1) below.

$$S_{ij} = \frac{\frac{\sum_{mp} t_{ijp}^{(m)}}{2}}{\sum_m \left(\sum_k r_{ik}^{(m)} + \sum_l r_{jl}^{(m)} \right) - \frac{\sum_{mp} t_{ijp}^{(m)}}{2}} \quad \cdots\cdots (1)$$

where,

$$0 \le \sum_{mp} t_{ijp}^{(m)} \le \sum_m \left(\sum_k r_{ik}^{(m)} + \sum_l r_{jl}^{(m)} \right)$$

If $\sum_{mp} t_{ijp}^{(m)} = 0$, then $S_{ij} = 0$.

If $\sum_{mp} t_{ijp}^{(m)} = \sum_m \left(\sum_k r_{ik}^{(m)} + \sum_l r_{jl}^{(m)} \right)$, then $S_{ij} = 1$.

3.2 Genetic Algorithm

A gene stands for a family number. An integer string of family numbers constitutes a chromosome. The chromosome has one gene for each part. Thus, the length of the part family chromosome is equal to the number of parts. Two genetic operators, i.e., the single-point crossover operator and mutation operator were used in this algorithm. The fitness function is to maximize total sum of similarity coefficients for two parts.

3.3 Mixed-Integer Programming Models to Form Machine Cells for Phase II

3.3.1 Nomenclature

λ_i : rival time for part i

ν_i : ɜmand for part i

c_m : vestment cost for machine type m

t_m : ׳ailable time for machine type m

t_{moi} : ɔerating time for machine type m to perform operation o for part i

c_{moi} : ɔerating cost for machine type m to perform operation o for part i

h_{io} : ventory holding cost for part i per unit time of operation o

ϖ_m : /erage waiting time due to machine type m failure

α_i : ırly finish penalty cost per unit time for part i

β_i : te finish penalty cost per unit time for part i

d_i : ıe date for part i

n : inimum number of machine failures

$\max_c$: aximum allowable number of machines in cell c

BM : ıdget available to purchase machines of all types

BO : ıdget available for operation of all parts

W_{io} : aiting time for part i due to a machine failure for operation o

E_i : ne by which part i is early compared to its due date

L_i : ne by which part i is late compared to its due date

T_{io} : ɔmpletion time for part i and operation o

N_{mc} : ımber of machine types m for the first period in cell c

NP_{mc} : ldditional number of machine types m for the next period in cell c

γ_{mc} = 1, if machine type m is assigned to cell c
= 0, otherwise

$X_{(mo)}ic$ = 1, if machine type m, which performed operation o for part i, belongs to cell c
= 0, otherwise

Y_{moi} = 1, if machine type m fails while performing operation o for part i
= 0, otherwise

Z : tal cost

3.3.2 Sequential and Simultaneous MIP Models

The overall sequential and simultaneous mixed- integer programming Models I, II, and III for the first period and next periods are as follows :

Sequential MIP Model I

Minimize

$$Z=\sum_{io} v_i * h_{io} * W_{io} + \sum_i v_i * E_i * \alpha_i + \sum_i v_i * L_i * \beta_i + \sum_{moic} v_i * c_{moi} * X_{(mo)}ic + \sum_{mc} c_m * N_{mc} \quad \cdots\cdots (2)$$

subject to

$$T_{io} \geq \lambda_i + v_i * \left[\sum_{mo}(t_{moi} * X_{(mo)}ic + W_{io})\right] all\ i \text{ and } o = 1 \cdots\cdots (3)$$

$$T_{io} = v_i \left[\sum_{mo}(t_{moi} * X_{(mo)}ic + W_{io})\right],\ all\ i \text{ and } o = 2, .., O \cdots\cdots (4)$$

$$W_{io} = \sum_m \varpi_m * Y_{moi},\ all\ i, o \cdots\cdots (5)$$

$$\sum_{moi} Y_{moi} = n \cdots\cdots (6)$$

$$\sum_m X_{(mo)}ic = 1,\ all\ i, c, o \cdots\cdots (7)$$

$$\sum_{io} v_i * t_{moi} * X_{(mo)}ic \leq t_m * N_{mc},\ all\ m, c \cdots\cdots (8)$$

$$\sum_m N_{mc} \leq \max_c,\ all\ c \cdots\cdots (9)$$

$$E_i - L_i = d_i - T_{io},\ all\ i \text{ and } o = O \cdots\cdots (10)$$

$$\sum_{mc} c_m * N_{mc} \leq BM \cdots\cdots (11)$$

$$\sum_{moic} v_i * c_{moi} * X_{(mo)}ic \leq BO \cdots\cdots (12)$$

$$X_{(mo)}ic \geq Y_{qoi},\ all\ m, o, i, c \text{ and } q = A - m \cdots\cdots (13)$$

$X_{(mo)}ic$ and Y_{moi} are (0/1) variables,

$N_{mc} \geq 0$ and is a set of integer variables,

$$W_{io},\ E_i,\ L_i,\ T_{io} \geq 0 \cdots\cdots (14)$$

The objective function, Eq. (2), will minimize the total sum of inventory holding cost based on the waiting time due to a machine failure, early/late finish penalty cost due to the deviation between completion time and due date, operating cost, and machine investment cost. Eq. (3) and Eq. (4) represent completion times for the first operation and the remaining operations, respectively. Eq. (5) represents waiting time due to machine failure. Eq. (6) shows the minimum number of machine failures as a constraint. Eq. (7) shows selection of a machine among the available machines. Eq. (8) shows that the capacity of each machine type for the first period in each cell is not violated. Eq. (9) restricts the maximum number of machines allowed in each cell. Eq. (10) shows the early/late completion times of a part compared to its due date. Eq. (11) restricts the amount of capital expenditure for a machine. Eq. (12) restricts the budget for a given period of operation. Eq. (13) represents selection of an alternative machine due to a machine failure. The constraints in Eq. (14) ensure that $X_{(mo)}ic$ and Y_{moi} are set of integer variables and that N_{mc} is a set of integer variables greater than or equal to zero. Also, waiting time, early/late finish times, and completion time are greater than or equal to zero.

Sequential MIP Model II

The sequential Model II is same as Model I except objective function (2), Eqs. (8), (9), (11), (14) are replaced by Eqs. (15), (16), (17), (18), and (19), respectively. The notation NP_{mc} replaces N_{mc} in Eqs. (15), (17), and (18). $X_{(mo)}ic$ and N_{mc} are also no longer variables in Eqs. (16) and (19). Eq. (16) allows for additional machine types in the same cells(γ_{mc} is no longer variable because machine cells are already formed) for the next period.

Minimize

$$Z = \sum_{io} v_i * h_{io} * W_{io} + \sum_i v_i * E_i * \alpha_i + \sum_i v_i * L_i * \beta_i + \sum_{moic} v_i * c_{moi} * X_{(mo)}ic + \sum_{mc} c_m * NP_{mc} \quad \cdots\cdots (15)$$

subject to

$$\sum_{io} v_i * t_{moi} * X_{(mo)}ic \le t_m * (NP_{mc} + N_{mc}) * \gamma_{mc}, all\ m, c \cdots\cdots (16)$$

$$\sum_m NP_{mc} \ge \max_c,\ all\ c \cdots\cdots (17)$$

$$\sum_{mc} c_m * NP_{mc} \le BM \cdots\cdots (18)$$

Y_{moi} *are sets of integer variables,,*
$NP_{mc} \ge 0$ and *is a set of integer variables,*
W_{io}, E_i , L_i and T_{io} ≥ 0 ·········· (19)

Simultaneous MIP Model III

For a simultaneous mixed-integer program for a given period, additional index p is considered in Model III. $X_{(mo)}ipc$, N_{mc}, and NP_{mc} are variables that determine the selection of machines, number of machines, and additional number of machines for a given period, respectively.

Minimize

$$Z = \sum_{iop} v_{ip} * h_{iop} * W_{iop} + \sum_{ip} v_{ip} * E_{ip} * \alpha_{ip} + \sum_{ip} v_{ip} * L_{ip} * \beta_{ip} + \sum_{moipc} v_{ip} * c_{moi} * X_{(mo)}ipc + \sum_{mc} c_m * (N_{mc} + NP_{mc}) \quad (20)$$

subject to

$$T_{iop} \ge \lambda_{ip} + v_{ip}\left[\sum_{mo}(t_{moi} * X_{(mo)}ipc + W_{iop}\right], all\ i, p \text{ and } o = 1 \cdots (21)$$

$$T_{iop} = v_{ip}\left[\sum_{mo}(t_{moi} * X_{(mo)}ipc + W_{iop})\right], all\ i \text{ and } o = 2, \ldots, O \cdots (22)$$

$$W_{iop} = \sum_m \varpi_m * Y_{moip},\ all\ i, o, p \cdots\cdots (23)$$

$$\sum_{moi} Y_{moip} = n_p,\ all\ p \cdots\cdots (24)$$

$$\sum_m X_{(mo)}ipc = 1,\ all\ i, p, c, o \cdots\cdots (25)$$

$$\sum_{io} v_{ip} * t_{moi} * X_{(mo)}ipc \le t_m * (N_{mc} + NP_{mc}),\ all\ m, p, c \cdots (26)$$

$$N_{mc} \ge NP_{mc},\ all\ m, c \cdots\cdots (27)$$

$$\sum_m N_{mc} \le \max_{pc},\ all\ c \text{ and } p = first\ period \cdots\cdots (28)$$

$$\sum_m NP_{mc} \le \max_{pc},\ all\ c \text{ and } p = additional\ period \cdots\cdots (29)$$

$$E_{ip} - L_{ip} = d_{ip} - T_{iop},\ all\ i, p \text{ and } o = O(last\ operation) \cdots (30)$$

$$\sum_{mc} c_m * (N_{mc} + NP_{mc}) \le BM \cdots\cdots (31)$$

$$\sum_{moicp} v_{ip} * c_{moi} * X_{(mo)}ipc \le BO \cdots\cdots (32)$$

$X_{(mo)}ipc \ge Y_{qoip}$, *all* m, o, i, c and $q = A - m$ ···· (33)
$X_{(mo)}ipc$ and Y_{moip} *are* (0/1) *variables,*
$N_{mc} \ge 0$ and *is a set of integer variables,*
$NP_{mc} \ge 0$ and *is a set of integer variables,*
W_{io} , E_{ip} , L_{ip} , T_{iop} ≥ 0 ·········· (34)

Maximum Level of Demand Model IV

The output of Model II is optimal, that is, it is a machine cell that does not require additional machines. The mathematical program for Model IV gives important information about the maximum demand level that a previous machine cell can produce. For example, if the part demand for the next period is greater than the maximum level of demand that is identified from Model IV, a previous machine cell will not be optimal and must be changed. The maximum level of part demand, output from Model IV will be used as future management strategy.

Minimize

$$Z' = \sum_i v_i \cdots\cdots (35)$$

subject to

$$\sum_{io} v_i * t_{moi} \le t_m * N_{mc} * \gamma_{mc},\ all\ m, c \cdots\cdots (36)$$

$$v_i \ge \delta_i,\ all\ i \cdots\cdots (37)$$

$$v_i \ge 0 \text{ and } is\ an\ integer\ variable \cdots\cdots (38)$$

The objective function is to maximize the total demand level(v_i). The first constraint ensures that the capacity of each machine type in each cell is not violated(γ_{mc} is no longer variable because machine cells are already formed). The second constraint ensures that the maximum level of demand is greater than or equal to the minimum level of demand (δ_i, assumed to be given). The third constraint ensures that the maximum level of demand for each part is nonnegative.

4. Illustrative example

4.1 Phase I

An example that illustrates the application of the new similarity coefficient is shown below. It is composed of 10 types of parts and seven types of machines. <Table 1> presents the operation sequences with some operations that can be performed on more than one machine.

<Table 1> Operation sequences/Available machine types

	Part 1	Part 2	Part 3	Part 4	Part 5	Part 6	Part 7	Part 8	Part 9	Part 10
Operation 1		m=2 m=5			m=2 m=5		m=2 m=5	m=2 m=5		m=2 m=5
Operation 2		m=3 m=7	m=3 m=7			m=3 m=7			m=3 m=7	
Operation 3	m=1 m=4			m=1 m=4			m=1 m=4		m=1 m=4	
Operation 4			m=3 m=6	m=3 m=6					m=3 m=6	m=3 m=6
Operation 5	m=1 m=5				m=1 m=5	m=1 m=5	m=1 m=5			m=1 m=5
Operation 6		m=2 m=7		m=2 m=7		m=2 m=7		m=2 m=7		
Operation 7	m=4 m=6		m=4 m=6		m=4 m=6			m=4 m=6		

Based on Table 1, Eq.(1) gives the values of the new similarity coefficient for parts i and j based on the number of alternative routes during machine failure. <Table 2> presents the values of the similarity coefficient for two part

Based on the values of the new similarity coefficient, the next step is to identify the part families by using genetic algorithm. The problem was solved with the following parametric values : opulation size 20, chromosome length 10, crossover probability 0.80, mutation probability 0.01, and maximum number of generations 500. Genetic algorithm gives three part families : Part Family 1 {3,4,9}, Part Family 2 {1,5,7,8,10}, and Part Family 3 {2,6} with a fitness value of 1.97.

<Table 2> Similarity coefficient for two parts

S_{ij}	j=1	j=2	j=3	j=4	j=5	j=6	j=7	j=8	j=9	j=10
i = 1	-	0	0	0	0.23	0	0.14	0	0	0.06
i = 2	0	-	0	0	0	0.32	0	0	0	0.06
i = 3	0	0	-	0.13	0	0	0	0	0.32	0
i = 4	0	0	0.13	-	0.06	0.14	0	0	0.32	0.14
i = 5	0.23	0	0	0.06	-	0	0.32	0.13	0	0.33
i = 6	0	0.32	0	0.14	0	-	0	0	0.06	0.13
i = 7	0.14	0	0	0	0.32	0	-	0.06	0	0
i = 8	0	0	0	0	0.13	0	0.06	-	0	0.06
i = 9	0	0	0.32	0.32	0	0.06	0	0	-	0
i =10	0.06	0.06	0	0.14	0.33	0.13	0	0.06	0	-

4.2 Phase II

Input data are arrival time for each part, operating time and cost, part demand in a given period, part due date, early and late finish penalty cost per hour, inventory holding cost per hour, average waiting time due to machine failure, machine available time in a given period, maximum allowable number of machines for each cell during a given period, minimum number of machine failure in a given period, investment cost for each machine, and the budget available for all operations and machines. The number of periods was assumed to be two. Operation sequences and operating time and cost of each part were assumed to be the same for these two periods. Part arrival time was assumed to be zero for all part types, inventory holding cost per hour was assumed to be $0.4 for all parts.

The proposed mixed-integer programming Models I, II, and III for the first and second periods were solved by using ILOG/CPLEX (V7.5, ILOG). <Table 3> lists the selection of machines to perform the operations on each part (sequential). <Table 4> and <Table 5> list the selection of machines to perform operations on each part (simultaneous).

<Table 3> Selection of machines (Periods 1 and 2)

	Part 1	Part 2	Part 3	Part 4	Part 5	Part 6	Part 7	Part 8	Part 9	Part 10
Operation 1		m=5			m=2		m=2	m=2		m=2
Operation 2		m=3	m=7			m=3			m=7	
Operation 3	m=4			m=4			m=4		m=4	
Operation 4			m=3	m=3					m=3	m=6
Operation 5	m=1				m=1	m=5	m=1			m=1
Operation 6		m=2		m=7		m=2		m=2		
Operation 7	m=6		m=4		m=6			m=4		

<Table 4> Selection of machines (Period 1)

	Part 1	Part 2	Part 3	Part 4	Part 5	Part 6	Part 7	Part 8	Part 9	Part 10
Operation 1		m=5			m=2		m=5	m=2		m=2
Operation 2		m=3	m=3			m=7			m=3	
Operation 3	m=1			m=4			m=4		m=4	
Operation 4			m=3	m=6					m=3	m=6
Operation 5	m=5				m=1	m=5	m=5			m=1
Operation 6		m=7		m=2		m=2		m=2		
Operation 7	m=6		m=6		m=4			m=4		

<Table 5> Selection of machines (Period 2)

	Part 1	Part 2	Part 3	Part 4	Part 5	Part 6	Part 7	Part 8	Part 9	Part 10
Operation 1		m=5			m=2		m=2	m=2		m=5
Operation 2		m=3	m=3			m=7			m=3	
Operation 3	m=4			m=4			m=4		m=4	
Operation 4			m=3	m=6					m=3	m=6
Operation 5	m=5				m=1	m=5	m=1			m=5
Operation 6		m=7		m=2		m=2		m=2		
Operation 7	m=6		m=6		m=6			m=4		

<Table 6> lists the part families and corresponding machine cells from the results of Phases I and II. <Table 7> lists sum of the total cost for a given period.

<Table 6> Part families and corresponding machine cells

Cell	Part Type	Machine Type (number allocated)			
		Sequential MIP		Simultaneous MIP	
		Period 1	Period 2	Period 1	Period 2
1	3, 4, 9	m3 (1) m4 (1) m7 (1)	m3 (1) m4 (1) m7 (1)	m2 (1) m3 (2) m4 (1) m6 (1)	No additional machines
2	1, 5, 7, 8, 10	m1 (1) m2 (3) m4 (1) m6 (2)	m1 (1)	m1 (1) m2 (2) m4 (1) m5 (1) m6 (1)	
3	2, 6	m2 (1) m3 (1) m5 (1)	m3 (1)	m2 (1) m3 (1) m5 (1) m7 (1)	

<Table 7> Total cost

	Sequential MIP		Simultaneous MIP
	Period 1	Period 2	Period 1and 2
Inventory holding cost Early/late penalty costs Operating cost	\$ 41,796	\$ 81,710	\$ 88,581
Machine investment cost	\$ 454,000 (initial)	\$ 205,000 (additional)	\$ 533,000
Sum	\$ 495,796	\$ 286,710	\$ 621,581
Total Cost	Period 1+ Period 2 \$ 782,506		\$ 621,581

As a result of these two mixed-integer programs, the machine investment costs for the first and second periods were \$454,000(1^{st} period, sequential), \$205,000(2^{nd} period, sequential), \$533,000(1^{st} period, simultaneous), and zero (2^{nd} period, simultaneous). The total costs for these two models for a given period were \$782,506 (sequential) and \$621,581 (simultaneous). These results show that the sequential model gives a lower initial machine investment cost than simultaneous model. However, the total cost for the cells in the sequential model for a given period was higher than the total cost for the cells in the simultaneous model because of the selection of machines(Tables 3, 4, and 5). The selection of machines is fixed for the first period of the sequential model. For the second period, this selection of machines will not change(Table 3). On the other hand, the selection of machines for the first and second periods by using the simultaneous model is flexible(Tables 4 and 5). This flexibility causes a difference in the total costs for the sequential and simultaneous models.

5. Conclusions

A two phase procedure was developed for configuring a cellular manufacturing system in this study. In the first phase, a new similarity coefficient for two parts which considers the number of alternative routes during machine failure, was presented. Based on the proposed similarity coefficient, the part families were identified by using genetic algorithm. As a result of Phase I, part families based on the number of alternative routes during machine failure will provide more attractive data for the next phase. In the second phase, sequential and simultaneous mixed-integer programming models, which considered the scheduling and operational aspects under demand changes for a given period, were developed. These models determined the completion time, early and late finish times, selection of machine types, number of machines, additional number of machines, and maximum levels of demand for future management strategy.

The proposed similarity coefficient for Phase I was implemented by using a computer program written in the C++ language. This program facilitates the process of the development of the proposed similarity coefficient. Borland C++(Ver. 4.0) was used to identify part families by using genetic algorithm and a linear programming package, ILOG/CPLEX (Ver. 7.50, ILOG), was used to solve the mixed-integer programming models developed to group machines into part families in Phase II.

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