A Genetic Algorithm (GA) Approach for the Formation of Manufacturing Cells in Group Technology

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Abstract: This paper is about minimizing intercellular movements of parts for the formation of manufacturing cells using GA approach. GA is a search technique based on the process of biological evolution and has been applied as an optimization method for the formation of manufacturing cells. Different GA operators and their importance in the optimization of cellular manufacturing have been discussed. A MAT LAB code has been developed for the calculation of different matrices and fitness values of chromosomes. The initial population of possible solutions (chromosomes) is generated randomly and the fitness value of each chromosome is calculated using code developed for the purpose. The next population is generated by the application of genetic operators process is repeated till stopping criteria is satisfied. Total ten populations are generated by the GA procedure and fitness values of different generations have compared graphically with detailed analysis. It is evident that using GA has minimized the intercellular movements of parts which indirectly improves productivity, profitability and provide competitive edge to the manufacturing enterprise in global environment.

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Key Words: Cellular Manufacturing (CM), Crossover, Group Technology (GT), Genetic Algorithm (GA), Production Flow Analysis (PFA), Mutation

1, Introduction

In Group Technology (GT), the manufacturing system is decomposed into manufacturing cells. Computer integrated manufacturing (CIM), flexible manufacturing systems (FMS) and many other automation programs have close association with GT. Group Technology is not only arrangement of machines into cells, but it also improves productivity of the organization by reducing movement of parts and work in process (WIP) Burbridge, John. L [2]. The reduction in response time to customer orders allows the companies to react quickly to changes in customer requirements and hence maintains a competitive edge in the rapid changes of market demands.

The design of a cellular manufacturing cell is a complex process with issues related to both system structure and operation. The structural issues include the formation of part families and machine groupings, selection of tools and fixtures, selection of material handling equipment and identification of equipment layout. Operational issues include detailed design of product, policies related to maintenance and inspection, procedures for production planning, modification of cost control and reward systems and outline of procedures for interacting with manufacturing system. In this paper, focus is on structural issues, namely the identification of machine groupings and machines layout. Many criteria are used for the formation of manufacturing cells and significant is to minimize the intercellular movement of parts. Important to minimize intercellular movement in cell formation problem involves identification of families of parts and grouping of machines. Some approaches have been developed over the years however due to complex nature of the problem and variety of parameters; it still needs some approaches to find optimal solution. Methods to solve the problem can be classified into two parts, the design oriented approaches based on the design features of the parts and the production oriented approaches based on the routing information of parts. In this paper focus is on production oriented approaches. Some approach are Production Flow Analysis (PFA) Groover, M.P. [3]; Wemmerlov, U., and N.L. Hyer array based clustering Hierarchical clustering [4]; Non-Hierarchical clustering Apple, J.M [5]; Graph theoretic approach, Mathematical programming, Heuristics Offodile et.al [6]; and AI-based approaches Morad, N [7]. AI implementation offers advantages over traditional cell formation methods applied to cellular manufacturing systems. The focus of this paper is to investigate the viability of using genetic based approaches for optimization problems associated with cellular manufacturing systems. One of such problems is formation of manufacturing cells with minimum intercellular movement by using genetic algorithms approach. The motivation to use this technique in manufacturing system is due to the robustness of the algorithms and its ability to find solution even for NP-complete problems which are common in manufacturing systems. GA are different from traditional optimization and search procedures as: they work with a coding of parameter rather than the actual parameter; search from a population of points, not a single point; application of GA operators causes information from the previous generation to be carried over to the next; use probabilistic transition rules, not deterministic rules Goldberg, D.E [1]. Genetic algorithms produce a set of solution and hence are flexible, able to incorporate constraints as well as multi-objective criteria into the algorithm. Although the standard genetic algorithm (SGA) which uses binary representation of chromosomes, most applications based on GA depart from the bit string representation. An attempt was made by some researchers to address the problem Hassan; AMS Zalzala, Norhashima Morad; Y.Yin, K.Yasuda and L. Hu; K.Yasuda, L.Hu and Y.Yin; Y.Yin and K. Yasuda; Albadawi, Z., Bashir, H., Chen, M; Selim, H.M., Askin, R.G., and Vakharia, A.J; Fraser, K., Harris, H., Luong, L [8-15], but focus was on layout design, batch scheduling, material flows, multi objective and development of mathematical models. Some suggested use of AI based tools from human factor perspective, cell penetration problems, industry specific cases and optimization of two stage models Johnson, D.J., Wemmerlov, U; Suresh, G; Chipperfield, A., Fleming, P, Polheim, H., Fonseca, C; Wemmerlov, U. and Johnson, D.J; Y.Yin, C.Xu and L.Hu; Yi Kou, Jianjun Yang [16-21]. The purpose of this work is to minimize the intercellular movement of parts for the formation of manufacturing cells at precise level. An optimized arrangement of machines can be formed to indirectly reduce material handling cost and improve productivity and to investigate the ability of GA in the optimization of cellular manufacturing systems in our environment and the benefits of using GA approach as compared to traditional optimization methods.

2. Research Methodology

Genetic algorithms are very efficient search algorithms based on the mechanics of natural selection process. They have been used very successfully to solve a wide range of complex optimization problems. As the formation of manufacturing cells in cellular manufacturing is a complex problem GAs are suited to this problem. Genetic algorithms are very effective and flexible optimization tools as they produce optimal or near-optimal solutions not a single solution like traditional optimization methods, hence GAs are flexible in nature. In the formation of manufacturing cells often we need to optimize more than one criterion thus optimization become very difficult and a lot of time would be required to solve problem in such cases. Traditional approaches are normally based on only one criterion to create machine cells and ignore other very important parameters such as processing time of parts and machine capacity. The processing time of parts, machine capacity and the number of parts required which should be known for the formation of manufacturing cells are totally ignored.

In order to overcome the shortcomings of traditional optimization methods and to achieve flexibility when solving complex optimization problems, a GA based fitness function is developed for the formation of manufacturing cells. The objective function used for the formation of manufacturing cells is to minimize the intercellular movement of parts shown in figure 1.

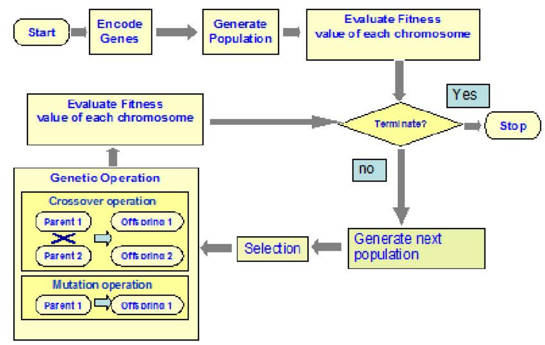

Figure 1 Genetic Operation Process

Table 1 Routing Information of parts

Number of Machines →; Number of Parts ↓

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1			1	1			1							
2			1	1			1							
3		1		1					1	1				
4	1	1											1	
5			1			1	1							
6		1										1		
7		1						1					1	1
8											1	1		
9					1	1			1					1
10							1	1						
11					1								1	
12							1	1						1
13				1						1			1	
14						1	1							
15					1		1		1					1
16						1	1							
17			1	1										
18												1		
19			1											
20			1	1										
21		1									1			
22						1	1							
23			1	1						1				
24										1	1			
25		1			1								1	
26	1			1								1		
27						1	1							
28	1													1
29			1					1	1		1			
30					1					1				1

Different parts of project are being manufactured at shop floor. Manufacturing equipment includes turning machines, milling machines, drilling machines, rolling machine, shearing machine, hydraulic press and surface grinder. The machines are required to be arranged in manufacturing cells in such away that intercellular movement of parts is minimized to a certain level. At present the machines are not arranged in manufacturing cells and different parts are processed on machines according to process plan sheets. As the production requirement of each part increases, there are problems regarding parts movements in machines and material handling. The routing information of each part from process plan sheet of the part is given in table 1.

Since total number of parts = 30; total number of machines = 14; production requirement of each part = 5, this means that total 150 parts have to be manufactured. Based on the routing information of each part a part-machine incidence matrix Eji is written as:

$$Eji = \begin{bmatrix} 0011001000 & 0000 \\ 0011001000 & 0000 \\ 0101000011 & 0000 \\ 1100000000 & 0010 \\ 0010011000 & 0000 \\ 0100000000 & 0100 \\ 0100000100 & 0011 \\ 0000000000 & 1100 \\ 0000110010 & 0001 \\ 0000001100 & 0000 \\ 0000100000 & 0010 \\ 0000001100 & 0001 \\ 0001000001 & 0010 \\ 0000011000 & 0000 \\ 0000101010 & 0001 \\ 0000011000 & 0000 \\ 0011000000 & 0000 \\ 0000000000 & 0100 \\ 0010000000 & 0000 \\ 0011000000 & 0000 \\ 0100000000 & 1000 \\ 0000011000 & 0000 \\ 0011000001 & 0000 \\ 0000000001 & 1000 \\ 0100100000 & 0010 \\ 1001000000 & 0100 \\ 0000011000 & 0000 \\ 1000000000 & 0001 \\ 0010000110 & 1000 \\ 0000100001 & 0001 \end{bmatrix}$$

Where

j = part number; i = machine number

Eji is a 30*14 matrix which shows processing requirement of each part, i = 1; if part is processed on machine and zero otherwise. The objective function is to minimize the intercellular movement of parts. The objective of fitness function is denoted as 'F'.

Intercellular movement of parts = (production requirement of each part) (number of movements of parts to each cell – 1).

Production requirement of each part is represented by a matrix N_j, N_j is a 1*n matrix.

*X_{il} is a machines*cells matrix and*

$$X_{il} = \begin{cases} 1 & \text{if machine i is in cell } l \\ 0 & \text{otherwise} \end{cases}$$

*E_{ji} is an n*m matrix and*

$$E_{ji} = \begin{cases} 1 & \text{if part j is processed on machine i} \\ 0 & \text{otherwise} \end{cases}$$

*Y_{jl} is a parts*cells matrix, and*

$$Y_{jl} = \begin{cases} 1 & if \sum_{i=1}^{m} E_{ji} \text{ x } X_{il} > 0 \; means\ that\ part\ j\ is\ produced\ in\ cell\ l \\ 0 & otherwise \end{cases}$$

In other words matrix Y_{jl} shows cellular movement of parts.

If we represent intercellular movement of parts by F then combining the information given above in mathematical form [22]:

$$F = \sum_{j=1}^{n} N_j \left[\sum_{l=1}^{k} Y_{jl} - 1 \right] \qquad \text{………. 1}$$

Where

j = part number

i = machine number

n = total number of parts

l = cell number

m = total number of machines

k = total number of cells

N_j = production requirement of each part

*Y_{jl} = parts * cell matrix showing information whether the part is in manufacturing cell or not.*

Y_{jl} = 1 if part in cell and zero otherwise.

3. Parameter Settings and Method of Analysis

For using Genetic Algorithm technique for the formation of manufacturing cells the parameters are set as: The initial population (chromosomes) is generated randomly; Integer based chromosome's representation is used which inform length of individual equal to total number of machines; crossover probability = 0.7; mutation probability = 0.07; the initial population size = 10; total no. of generations = 10; twenty percent elitism criteria are used i.e. 02 individuals with the best fitness values are automatically selected for next generation; the position of gene shows machine number and the value of gene shows cell number; for this particular problem let total number of cells equals 3, further gene value varies from one to total number of cells which is three in this problem; generation gap (GGAP) of 0.1 is used for individuals/chromosomes which are the weakest in the process of evolution i.e. only one chromosome is replaced by new one. The above mentioned parameter setting can be illustrated by following chromosome:

[2 1 3 2 3 1 1 2 3 3 1 2 3 2]

There are fourteen digits in the chromosome showing 14 numbers of machines; manufacturing cell 1 (C1) has machines 2, 6, 7 & 11; manufacturing cell 2 (C2) has machines 1, 4,8,12 & 14, and manufacturing cell 3 (C3) has machines 3, 5,9,10 & 13 respectively shown in figure 2.

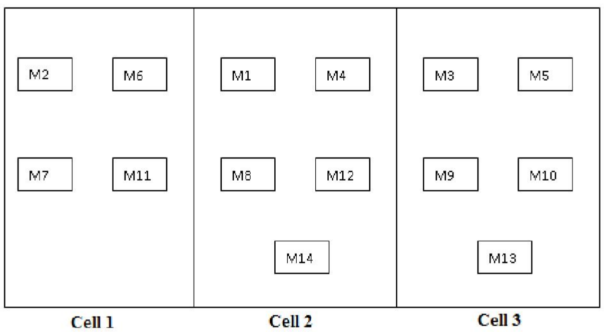

Figure 2 Machines in manufacturing cell

It is shown that part 1 is being processed at machines 3, 4 and 7. Now machine 3 is in cell 3, machine 4 is in cell 2 and machine 7 is in cell 1. So total number of cellular movements for part 1 is 3 and intercellular movements for part 1 are 2 respectively. Similarly intercellular movements for other parts can also be found e.g. Intercellular movements for parts 3, 7, 11, 15, 22, 26, and 30 are 2, 2, 0, 2, 0, 0, and 1 respectively.

3.1 Calculation Methodology and Chromosome Representation

$$X_{il} = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

For the chromosome [2 1 3 2 3 1 1 2 3 3 1 2 3 2], matrix X which shows information of different machines into manufacturing cells is written as:

X_{il} is a machines* cells matrix

E_{ji} is a parts*machines matrix; and $A=E_{ji}*X_{il}$ (parts*machine matrix)*(machine*cell matrix)

Matrix A is a parts*cells matrix showing number of parts movements to each manufacturing cell.

Y_{jl} is 1 if part visits manufacturing cell and zero otherwise;

B = Y_{jl}'; matrix B is transpose of Y_{jl} matrix to calculate no. of cellular movements of each part

Columns 1 through 13

```
[1  1  1  1  1  1  1  1  1  1  0  1  0
 1  1  1  1  0  1  1  1  1  1  0  1  1
 1  1  1  1  1  0  1  0  1  0  1  0  1
```

Columns 14 through 26

```
 1  1  1  0  0  0  0  1  1  0  1  1  0
 0  1  0  1  1  0  1  0  0  1  0  0  1
 0  1  0  1  0  1  1  0  0  1  1  1  0
```

Columns 27 through 30

```
 1  0  1  0
 0  1  1  1
 0  0  1  1]
```

C = sum (B)

Matrix C shows number of cellular movements of each part.

Columns 1 through 13
[3 3 3 3 2 2 3 2 3 2 1 2 2
Columns 14 through 26
1 3 1 2 1 1 2 1 1 2 2 2 1
Columns 27 through 30
1 1 3 2]

D = C-1; matrix D shows number of inter cellular movements of each part

Columns 1 through 13
[2 2 2 2 1 1 2 1 2 1 0 1 1
Columns 14 through 26
0 2 0 1 0 0 1 0 0 1 1 1 0
Columns 27 through 30
0 0 2 1]

E = D'; E is transpose of matrix D, transpose is taken so that it can be multiplied with matrix N

N = matrix N shows part demand for each part

Columns 1 through 13
N=[5 5 5 5 5 5 5 5 5 5 5 5 5
Columns 14 through 26

5 5 5 5 5 5 5 5 5 5 5 5 5
Columns 27 through 30
5 5 5 5]

F=N*E =140

For the chromosome mentioned above the total number of intercellular movements are 140 to manufacture thirty different parts of quantity five each. For easing the above mentioned calculation MAT LAB code has been developed and implemented.

Each population consists of ten chromosomes/individuals. Integer based chromosomes representation is used. Length of individual (LIND) = total number of machines:

[2 1 3 2 3 1 1 2 3 3 1 2 3 2]

The chromosome shows that there are total 14 machines, and integers 1, 2, and 3 show numbers of manufacturing cells. Gene value varies from one to total number of manufacturing cells which is 3 in this case shows cell number. Further gene position shows the machine number and chromosome machines 2, 6, 7, and 11 are in cell 1, machines 1, 4, 8, 12, and 14 are in cell 2, and machines 3, 5, 9, 10, and 13 are in cell 3. The initial population is generated randomly. Initial population is denoted by P (0) and consists of 10 chromosomes.

$$P(0)=\begin{bmatrix} 23213123122313 \\ 13221321113223 \\ 11221332233133 \\ 23221132331132 \\ 13221321231133 \\ 11231233221312 \\ 13123112231233 \\ 13221321231331 \\ 32321311313122 \\ 23123212113221 \end{bmatrix}$$

3.2 Evaluation and Generation

Evaluation of Generation 1

Objective function values for the initial population (10 randomly generated chromosomes) are calculated by using code The values are:

[155, 150, 120, 145, 130, 140, 120, 120, 170, 150]

Average value of fitness function = 140

The individuals in the current generation are used to create children that make up the next generation. Individuals in the current generation with the best fitness values are called elite children. Beside elite children genetic algorithm creates crossover children by selecting genes from a pair of individuals in the current generation and combines them to form children. the before and after crossovers are given below:

Parent 1 1 1 2 3 1 2 3 3 2 | 2 1 3 1 2
Parent 2 2 3 1 2 3 2 1 2 1 | 1 3 2 2 1
Crossover point

After crossover

Child 1 1 1 2 3 1 2 3 3 2 1 3 2 2 1
Child 2 2 3 1 2 3 2 1 2 1 2 1 3 1 2

Crossover enables the algorithm to extract the best genes from different individuals and recombine them into superior children. Another important genetic algorithm operator is mutation. In mutation random changes are applied to a single individual in the current generation to create a child. For example

Child 1 1 1 2 3 1 2 3 3 2 1 3 2 2 1 before mutation
1 1 2 3 2 2 3 3 2 1 3 2 2 1 after mutation
(Muted child)

Mutation increases the likelihood that algorithm will generate individuals with better fitness values otherwise algorithm could produce individuals whose genes were a subset of the combined genes in the initial population.

Calculation for Second Generation

Fitness function values from generation 1

[155, 150, 120, 145, 130, 140, 120, 170, 120, 150]

Average fitness function value = sum of the individual values/number of individual= 140

The steps to select individuals for 2nd generation in which 20% elitism criterion is used i.e. from 10 individuals in the generation 02 individuals with best fitness value will selected in 2nd generation. These are called elite children. The remaining 08 individuals are obtained by universal stochastic sampling and then new children for 2nd generation are created by crossover and mutation operations and shown in figure 2. Crossover probability of 0.7 is used which means that the number of crossover children will be 0.7*8=5.6 rounded off to 06, and the remaining 02 children will be muted children.

Table 2 Fitness values and selection probability of chromosomes of initial population.

Number of individuals	**Fitness value**	**Selection probability = individual fitness value/ sum of individual values**
1	155	0.110
2	150	0.107
3	120	0.085
4	145	0.103
5	130	0.092
6	140	0.100
7	120	0.085
8	170	0.121
9	120	0.085
10	150	0.107

In stochastic sampling selection probability of each individual is calculated and represented on scale. To select 08 individuals so 08 pointers will be drawn according to the method: Say 1st pointer position is 0.1 as it should be in the range of [0, 1/8=0.125], Interval between pointers=total probability-position of 1st pointer/no. of pointers

=1.0-0.1/8

= 0.9/8=0.1125

So, 1st pointer is at 0.1, 2nd at 0.225 and so on.

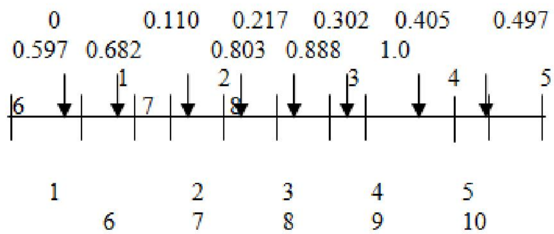

Figure 3 Stochastic Universal Sampling

By universal stochastic sampling individuals shown in figure 3, 10 are not selected and individuals 1, 2, 4, 5, 6, 7, 8, and 9 are selected to perform genetic operators (crossover and mutation) to generate next population (generation).

After crossover of chromosomes 3 & 4, 5 & 6, 7 & 8, and 9 & 10; and mutation of 5 & 6

Evaluation of Generation 2

Fitness function value of each chromosome in generation 2 is calculated by using MAT LAB and method given above. The fitness values are: [120, 120, 145, 125, 140, 140, 155, 140, 140, 155].

Average value of fitness function for generation 2 = 138 and comparison of generation 1 and 2 is shown in figure 4.

Generation 1	Fitness function Values		After universal stochastic sampling
2 3 2 1 3 1 2 3 1 2 2 3 1 3	155		2 3 2 1 3 1 2 3 1 2 2 3 1 3
1 3 2 2 1 3 2 1 1 1 3 2 2 3	150		1 3 2 2 1 3 2 1 1 1 3 2 2 3
1 1 2 2 1 3 3 2 2 3 3 1 3 3	120	Elite 1	not selected during sampling
2 3 2 2 1 1 3 2 3 3 1 1 3 2	145		2 3 2 2 1 1 3 2 3 3 1 1 3 2
1 3 2 2 1 3 2 1 2 3 1 1 3 3	130		1 3 2 2 1 3 2 1 2 3 1 1 3 3
1 1 2 3 1 2 3 3 2 2 1 3 1 2	140		1 1 2 3 1 2 3 3 2 2 1 3 1 2
1 3 1 2 3 1 1 2 2 3 1 2 3 3	120	Elite 2	1 3 1 2 3 1 1 2 2 3 1 2 3 3
1 3 2 2 1 3 2 1 2 3 1 3 3 1	170		1 3 2 2 1 3 2 1 2 3 1 3 3 1
3 2 3 2 1 3 1 1 3 1 3 1 2 2	120		3 2 3 2 1 3 1 1 3 1 3 1 2 2
2 3 1 2 3 2 1 2 1 1 3 2 2 1	150		not selected during sampling

1	1 1 2 2 1 3 3 2 2 3 3	1 3 3	Elite 1
2	1 3 1 2 3 1 1 2 2 3 1	2 3 3	Elite 2
3	2 3 2 1 3 1 2 3 1 2 2	3 1 3	
4	1 3 2 2 1 3 2 1 1 1 3	2 2 3	
5	2 3 2 2 1 1 3 2 3 3 1	1 3 2	
6	1 3 2 2 1 3 2 1 2 3 1	1 3 3	
7	1 1 2 3 1 2 3 3 2 2 1	3 1 2	
8	1 3 1 2 3 1 1 2 2 3 1	2 3 3	
9	1 3 2 2 1 3 2 1 2 3 1	3 3 1	
10	3 2 3 2 1 3 1 1 3 1 3	1 2 2	
		Crossover point	

Crossover	Mutation	Generation 2
1 1 2 2 1 3 3 2 2 3 3 1 3 3	1 1 2 2 1 3 3 2 2 3 3 1 3 3	1 1 2 2 1 3 3 2 2 3 3 1 3 3
1 3 1 2 3 1 1 2 2 3 1 2 3 3	1 3 1 2 3 1 1 2 2 3 1 2 3 3	1 3 1 2 3 1 1 2 2 3 1 2 3 3
2 3 2 1 3 1 2 3 1 2 2 2 2 3	2 3 2 1 3 1 2 3 1 2 2 2 2 3	2 3 2 1 3 1 2 3 1 2 2 2 2 3
1 3 2 2 1 3 2 1 1 1 3 3 1 3	1 3 2 2 1 3 2 1 1 1 3 3 1 3	1 3 2 2 1 3 2 1 1 1 3 3 1 3
2 3 2 2 1 1 3 2 3 3 1 1 3 3	2 3 2 2 2 1 3 2 3 3 1 1 3 3	2 3 2 2 2 1 3 2 3 3 1 1 3 3
1 3 2 2 1 3 2 1 2 3 1 1 3 2	1 3 2 2 1 3 1 1 2 3 1 1 3 2	1 3 2 2 1 3 1 1 2 3 1 1 3 2
1 1 2 3 1 2 3 3 2 2 1 2 3 3	1 1 2 3 1 2 3 3 2 2 1 2 3 3	1 1 2 3 1 2 3 3 2 2 1 2 3 3
1 3 1 2 3 1 1 2 2 3 1 3 1 2	1 3 1 2 3 1 1 2 2 3 1 3 1 2	1 3 1 2 3 1 1 2 2 3 1 3 1 2
1 3 2 2 1 3 2 1 2 3 1 1 2 2	1 3 2 2 1 3 2 1 2 3 1 1 2 2	1 3 2 2 1 3 2 1 2 3 1 1 2 2
3 2 3 2 1 3 1 1 3 1 3 3 3 1	3 2 3 2 1 3 1 1 3 1 3 3 3 1	3 2 3 2 1 3 1 1 3 1 3 3 3 1

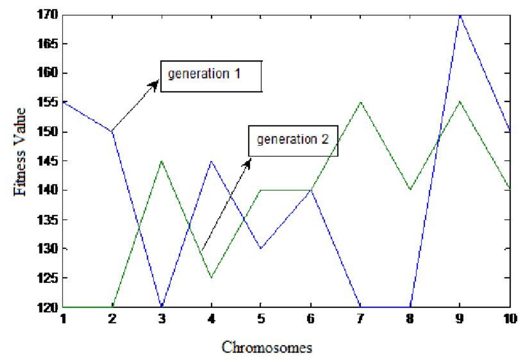

Figure 4 Comparison of fitness values of generation 1 and 2.

In the same way total 10 generations/populations are created by GA procedure and the fitness values are calculated for each chromosome in the generations. A generation gap (GGAP) of 0.1 is used for generation number 6, 7, 9, and 10. This means that only 1 Chromosome is replaced by new chromosome in the selected individuals of generations 5, 6, 8, and 9 used to create generations 6, 7, 9, and 10. The particular chromosome that is being replaced having largest fitness value and objective is to minimize the intercellular movements of parts so chromosome with largest fitness value is replaced by new one.

4. Analysis and Discussion

Generation 1		*Generation 10*	
2 3 2 1 3 1 2 3 1 2 2 3 1 3	155	1 3 3 3 2 1 1 1 2 3 3 3 3 1	75
1 3 2 2 1 3 2 1 1 1 3 2 2 3	150	3 3 2 2 2 1 1 1 2 2 3 3 2 1	80
1 1 2 2 1 3 3 2 2 3 3 1 3 3	120	2 3 2 2 2 1 1 2 2 3 1 1 3 1	115
2 3 2 2 1 1 3 2 3 3 1 1 3 2	145	2 3 2 2 2 1 1 1 1 2 3 3 2 1	85
1 3 2 2 1 3 2 1 2 3 1 1 3 3	130	1 3 2 1 3 1 1 1 2 3 3 3 3 1	100
1 1 2 3 1 2 3 3 2 2 1 3 1 2	140	3 3 2 2 2 1 1 1 2 2 3 3 3 1	80
1 3 1 2 3 1 1 2 2 3 1 2 3 3	120	1 3 1 2 2 1 1 1 2 2 3 3 2 1	95
1 3 2 2 1 3 2 1 2 3 1 3 3 1	170	1 3 2 2 3 1 1 1 2 2 3 3 2 1	105
3 2 3 2 1 3 1 1 3 1 3 1 2 2	120	2 3 3 3 1 1 1 1 2 3 3 3 3 1	75
2 3 1 2 3 2 1 2 1 1 3 2 2 1	150	1 3 2 2 2 1 1 2 2 3 1 1 3 1	110

In the process of evolution from generation 1 to 10 by using genetic operators and code, there is a random variation in the values of fitness function of chromosomes. During this process the weakest individuals tend to die over the period of time i.e. in the next generations.

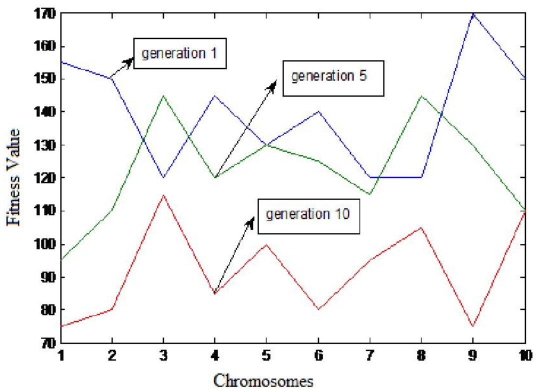

Figure 4 Comparison of fitness values of generations 1, 5 & 10.

Figure 4 compares the fitness values of chromosomes of generations 1, 5 and 10. It is clear that in the process of evolution by using GA the fitness value i.e. the intercellular movement of parts is decreasing. The process of evolution from generation 1 to generation 10 the chromosomes with the best fitness values tend to survive and the chromosomes with which least fit are replaced by new chromosomes by using different genetic operators. The use of different genetic operators enables the population size (number of chromosomes) to remain constant from generation 1 to generation 10 and fitness values of different chromosomes can be compared as shown in figure 4. The areas of search space with better fitness values are identified. Generation 10 has chromosomes 1, 9 with fitness value 75, chromosomes 2, 6 have fitness value 80 and the chromosome 7 has fitness value 85. These close fitness values (minimum number of intercellular movements) are very encouraging in making decisions where the best solution cannot be implemented due to economic constraints. The figure 5 shows the effectiveness of GA in the formation of manufacturing cells.

Figure 5 shows the values of chromosome in each generation. It is evident from figure 5 that fitness values change randomly in the process of evolution. The figure 6 shows fitness values of elite chromosomes at each generation. As total number of generations are 10 and 20% elitism criteria has been used so figure 6 shows the fitness values of 20 elite chromosomes. For first two generations the fitness value of elite chromosomes is constant. Proceeding towards next generations in the evolutionary process there are random changes in the fitness values of chromosomes for generations 4, 5, and 6. For generations 7, 8, and 9 there are slight changes in fitness values of chromosomes with the fitness value decreasing all the time. Last generations 02 chromosomes with minimum fitness value is obtained.

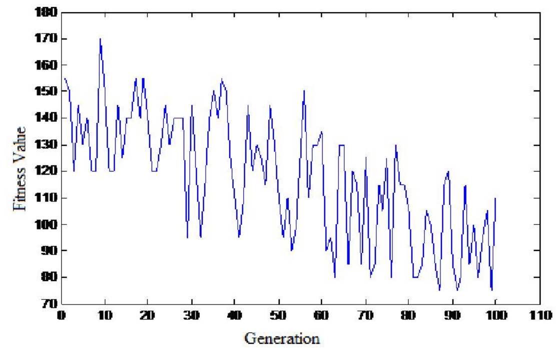

Figure 5 Fitness value of each chromosome in all generations.

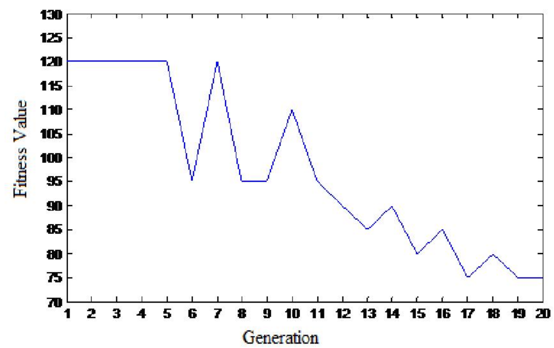

Figure 6 Fitness values of elite chromosomes at each generation.

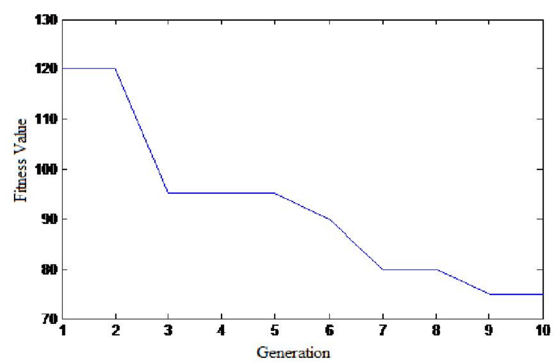

Figure 7 Lowest fitness values at each generation.

The figure 7 shows the lowest fitness value at each generation. For generation 1 the lowest value of fitness function is 120 and for last generation the lowest value is 75. Hence the value of fitness function i.e. the intercellular movement of parts is considerably reduced from generation 1 to 10.

The figure 8 shows the average fitness function value at each generation. The average value of fitness function for generation 1 is 140 and in the process of evolution it has minimized to 92 for generation 10. Hence it is found that intercellular movements of parts are minimized by genetic algorithm approach. The plotted results show slow move towards the optimized value (minimum value of intercellular movement of parts). Although the process towards optimization is slow but it is encouraging that GA can produce optimized results for complex problems faced in modern manufacturing systems.

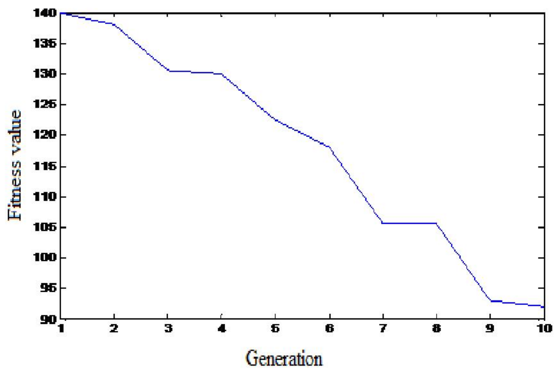

Figure 8 Average fitness values at each generation.

5. Conclusion

It is evident that genetic approach has minimized intercellular movements of parts i.e. for generation 1, the minimum value of intercellular movements is 120 and in the process of evolution in the next generations the value of intercellular has minimized continuously reaching the minimum value of 75 for generation 10. Minimization of the intercellular movements will result in material handling cost reduction which indirectly improve productivity, profitability and give competitive edge to the manufacturing enterprise. The set of solutions gives the flexibility required in manufacturing systems where certain things may happen which will not allow the best solution to be implemented due economic constraints and decision maker can choose other solutions which are not the best but good without having to run the program again. A small change in the value and position of gene in a chromosome causes significant reduction in intercellular movements of parts thus enabling us to make flexible decisions. Hence it is concluded that even changing the position of one machine in a cellular manufacturing system results in significant optimization results. The fitness value of elite chromosomes at first 02 generations is constant. In the evolutionary process for generations 3, 4, 5 and 6 there are random changes in the fitness values of elite chromosomes. There are slight changes in the fitness values of elite chromosomes for generations 7, 8, and 9. This shows that the implementation of GA procedure in the formation of manufacturing cells gradually improves the search space until a minimum fitness value is achieved for last generation. The last generation has 02 elite chromosomes with the same fitness value. In this paper genetic algorithm approach has been used to minimize the intercellular movements of parts for the formation of manufacturing cells and the algorithm developed is for parts which are being processed on different machines. Development and modification of the algorithm to include alternative machines is a subject of further research. In this work fitness function is for one objective i.e. to minimize the intercellular movement of parts; a multi-objective genetic algorithm fitness function can be generated. By applying different genetic operators (different types of crossover, mutation, and reinsertion) and parameter settings in the evolutionary process, comparative effectiveness of the GA operators and algorithm can be checked and used for fine-tuning of solutions obtained from evolutionary process. Further research work is to minimize the backtracking movements of parts for the formation of manufacturing cells in cellular manufacturing systems.

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