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Cell Formation in a Batch Oriented Production System using a Local Search Heuristic with a Genetic Algorithm: An Application of Cellular Manufacturing System.

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Abstract: - Cellular manufacturing is a production strategy which is capable of solving certain problems in a batch manufacturing system. A batch manufacturing system produces some intermediate varieties of products with intermediate volumes. The volume of any single product may not be sufficient to justify the use of a dedicated set of equipments for its production. Under this condition, a few or several products will have to share the production resources to balance their utilization .Production equipment in batch manufacturing must be capable of performing a variety of tasks. One of the fundamental problems in cellular manufacturing system is the formation of part families and machine cells that is the cell formation. For cell formation the part families are identified that require similar processing on a set of machines. In turn, these machines are grouped into cells. Each cell is capable of satisfying all the requirements of the part family assigned to it. In this paper an approach is used to form the part families and machine cell in a batch oriented production system. This approach combines a local search heuristic with a genetic algorithm. The genetic algorithm is used to generate the sets of machine cells. The evolutionary process, embedded in the genetic algorithm, is responsible for improving the grouping quality of the sets of machine cell generated. When the machine cells are known, it is customary to assign a product to the cell where it visits the maximum number of machines. This is optimal to minimize inter cell movement. However, it does not guarantee good utilization of the machines within a cell. To overcome this problem, a local search heuristic, which takes into consideration both inter -cell movement and machine utilization, is applied. The heuristic consists of an improvement procedure that is repeatedly applied. The objective of the heuristic is to construct a set of machine/part groups and improve it, if possible. The heuristic feeds back to the genetic algorithm the grouping efficacy of the set of machine/part groups it constructs. It is continued until the optimum result is found. After applying this approach, the result with a grouping efficacy is higher than the existing initial machine part matrix. So this approach can useful in cell formation in any batch oriented production system.

Keywords: - *Cellular manufacturing; Local search heuristic; Genetic Algorithm; Grouping Efficacy*

I. INTRODUCTION

Group technology is a manufacturing philosophy in which similar parts are identified and grouped together to take advantages of their similarities in manufacturing and design. Cellular manufacturing is a successful application of group technology (GT) concepts. Burbidge (1979) defined group technology (GT) as an approach to the optimization of work in which the organizational production units are relatively independent groups, each responsible for the production of a given family of products. One of the first problems encountered in implementation of a cellular manufacturing is formation of product families and machine cells. The objective of this product-machine grouping problem is to form perfect groups in which products do not have to move from one cell to the other for processing. When solving this problem previous researchers have concluded that the solution methodologies for the MPCF problem must focus attention on the block-diagonalization of the given machine-part incidence matrix. The best solutions to MPCF problem are those that contain a minimal number of voids(zeros in the diagonal blocks) and a minimal number of exceptions(ones outside of the diagonal blocks).At the conceptual level of cell formation many manufacturing factors are ignored and only the machining operations of the products are considered. This has the advantage that the manufacturing system can be represented by a binary machine-part incidence matrix. In this paper, an attempt has been made to solve the machine and product-grouping problem as a Zero one block diagonalization problem (BDP), to minimize intercellular movement and maximize the utilization of the machines within a cell.

The rest of this paper is organized as follows: Section 2 describes a brief literature review on this topic. Section 3 reviews the problem statement. Methodology and solution procedure are described at section 4. Data collection is presented at section 5 & calculation, result & result analysis are presented at Section 6 & 7 respectively. The rest of the paper is formed of conclusions and references which are regarded in the following sections

1.1 Literature Review

The group technology (GT) concept in manufacturing was first introduced by Flanders in 1925.In 1959, Mitrofonov published a book on scientific principles of GT and Burbidge in 1960 proposed a systematic planning approach for GT called production flow analysis. From then onwards there has been a lot of methods, models and algorithms developed for finding the solution for the primary problem of design of manufacturing cells. In the last three decades of research in cell formation, researchers have mainly used zero-one machine component incidence matrix as the input data for the problem. Graphical method is first approach used by the researcher to solve the cell formation problem in GT. Rajagopalan & Batra(1975) used graph theory to solve the grouping problem. Kumar et al. (1986) solved a graph decomposition problem to determine machine cells and part families for a fixed number of groups and with bounds on cell size. Their algorithm for grouping in flexible manufacturing systems is also applicable in the context of GT. Vannelli and Kumar(1986) developed graph theoretic models to determine machines to be duplicated so that a perfect block diagonal structure can be obtained.Later Kumar and Vannelli(1987) developed a similar procedure for determining parts to be subcontracted in order to obtain a perfect block diagonal structure. Array-based clustering methods perform a series of column and row permutations to form product and machine cells simultaneously. Existing cluster analysis methods are reviewed and a new approach using a rank order clustering algorithm is described which is particularly relevant to the problem of machine-component group formation by King (1980).

A comprehensive comparison of three array-based clustering techniques is given by Chu and Tsai (1990). An efficient nonhierarchical clustering algorithm, based on initial seeds obtained from the assignment method, for finding part-families and machine cells for group technology(GT) is presented by Gupta & Seifoddini(1990) which aim was to minimize the inter-cell movements and blanks(machine idling).Another efficient non-hierarchical clustering algorithm, based on initial seeds obtained from the assignment method, for finding part-families and machine cells for group technology(GT) is presented by Srinivasan & Narendran(1991) which aim is to minimize the exceptional elements(inter cell movements) and blanks(machine idling).Later a clustering approach of the non-hierarchical type was proposed by Nair & Narendran TT(1998) which clusters machines and components on the basis of sequence data. The algorithm gives encouraging results which provide better optimum solution than the previous approaches.

Mathematical programming methods treat the clustering problem as a mathematical programming optimization problem. At first Choobineh(1988) used a cluster algorithm to form the part families and an integer programming model was proposed for the cell formation. Then Gunasingh & Lashkari(1989) formulated an integer programming problem to group machines and products for cellular manufacturing systems. A mathematical model and solution procedure for the group technology configuration is proposed by Askin & Chiu(1990) for the grouping of individual machines into cells and the routing of components to machines within cells. A nonlinear mathematical programming model is developed by Adil,Rajamani,& strong(1997) for cell formation that identifies part families and machine groups simultaneously which objective is the minimization of the weighted sum of the voids and the exceptional elements.Later Akturk and Turkcan(2000) proposed an integrated algorithm that solves the machine/product grouping problem by simultaneously considering the within-cell layout problem. Another mathematical programming model for the cell formation problem with multiple identical machines, which minimizes the intercellular flow,is presented by Xambre & Vilarinho(2003).A comprehensive mathematical model for the design of CMS based on tooling requirements of the parts and tooling available on the machines was proposed by Defersha & Chen(2006).Mahdavi et al.(2007) formulated a new mathematical model for cell formation in cellular manufacturing system(CMS) based on cell utilization concept which objective is to minimize the exceptional elements(EE) and number of voids in cells to achieve the higher performance of cell utilization. All the above techniques for cell formation problems are slightly complex and time consumable. None of the approaches presented above guarantees optimal solutions. So that the modern researchers have the tendency to continue their research activities in the field of group technology for machine part cell formation problem by using genetic algorithm. Zulawinski, Punch & Goodman(1995) developed a grouping genetic algorithm for Bin balancing which is better suited for grouping problems than the classical representations and operators usually applied to grouping or reordering problems. After their approach, genetic algorithms become more popular to the researchers for finding the optimum solution for the cell formation problem. Cheng et al.(1998) formulated the cell formation problem as a travelling salesman problem(TSP) and a solution methodology based on genetic algorithms(GAs) is proposed to solve the TSP-cell formation problem. A genetic algorithm (GA) approach to the machine-component grouping problem with multiple objectives: minimizing costs due to inter-cell and intra-cell part movements, minimizing the total within cell load variation and minimizing exceptional elements was given by Zhao and Wu (2000).Dimopoulos and Mort(2001) used a genetic programming for the solution of a simple version of the problem.Onwubolu and Mutingi(2001) developed a genetic algorithm(GA) meta-heuristic based cell formation procedure having the objective function of minimizing the intercellular movement and cell load variation.Zolfagharia and Liang(2003) proposed a new genetic algorithm(GA) for solving a general machine/part grouping(GMPG) problem where processing times, lot sizes and machine capacities are all explicitly considered. An approach has taken by Gonclaves and Resende(2004) for solving the manufacturing cell formation problem in the term of group efficacy where they also used a local search heuristic genetic algorithm. Another genetic algorithm approach was done by Chiang & Lee(2004) for cell formation and inter- cell layout to minimize the actual inter-cell flow cost, instead of the typical measure that optimizes the number of inter-cell movements.Yasuda,Hu and Yin(2005) proposed an efficient method to solve the multi-objective cell formation problem(CFP) partially adopting Falkenauer's grouping genetic algorithm(GGA).The objectives are the minimization of both the cell load variation and intercellular flows considering the machines capacities, part volumes and part processing times on the machines. Brown & Keeling(2007) presented a hybrid grouping genetic algorithm for the cell formation problem that combines a local search with a standard grouping genetic algorithm to form machine-part cells. They used grouping efficacy measurement for computing results for a set of cell formation problem. Pillai et al. (2008) suggested a new approach (robust design) for forming part families and machine cells, which can handle all the change in demands and product mix without any relocation. The method suggests fixed machine cell for the dynamic nature of production environment by considering multi-period forecast of product mix and demand, which is solved by genetic algorithm. Tariq, Hussain and Ghafoor(2009) developed an approach that combines a local search heuristic(LSH) with genetic algorithm(GA).The results show that new approach not only converges to the best solution very quickly but also produces solutions that are as accurate as any results reported so far in literature.

Beside the above approaches, there are some other techniques which were developed by the researchers in different time. Some local heuristic models, non-heuristic network techniques and simulated annealing approaches are formulated to solve the cell formation problem in GT. Waghodekar & Sahu(1984) presented a heuristic approach based on the similarity coefficient of the product type for the problem of machine-component cell formation in group technology.Then Seifoddini & Wolfe(1986) developed a similarity coefficient method(SCM) to form the machine cells in group technology applications which is more flexibility into the machine component grouping process and more easily lends itself to the computer application.Askin & Subramaniam(1987) proposed a heuristic approach to the economic determination of machine groups and their corresponding component families for group technology.The procedure considers costs of work-in-process and cycle inventory,intra-group material handling, set-up, variable processing and fixed machine costs. After that,Srinivasan, Narendran & Mahadevan(1990) presented an assignment model to solve the grouping problem where a similarity coefficient matrix is used as the input to the assignment problem. A non-heuristic network approach is developed by Vohra et al.(1990) to form manufacturing cells with minimum intercellular interactions. At first Kumar & Chandrasekharan(1990) proposed the concept of grouping efficacy which objective is to maximize the grouping efficiency by reducing the number of voids in the cell and inter-cell movements for the cell formation in group technology.Later Boctor(1991) suggested a new linear zero-one formulation to avoid the disadvantages of other alternative formulations to solve the cell formulation problems which having better computational feasibility and efficiency. Finally, a simulated annealing approach is also presented to deal with large-scale problems. . A network flow methodology was developed by Lee & Garcia-Diaz (1993) to measure the functional similarity between machines and then to group the machines into cells in such a way that all the parts in each family can be processed in a machine cell. Heragu & Kakuturi(1997) solved a real-world machine grouping and layout problem in which the objective is not only to identify machine cells and corresponding part families but also to determine a near-optimal layout of machines within each cell and the cells themselves. A cell formation problem is solved by Islam & Sarker(2000) measuring similarity coefficient where a mathematical model is used. They also developed optimum methodology by using a heuristic procedure. Later Adenso-Diaz et al.(2001) proposed a configuration of machine cell to minimize the transportation cost by recommending the alternative path routing for the parts movement. Sarker(2001) presented a critical review of existing grouping measures, introduces a new measure called 'doubly weighted

grouping efficiency measure' and evaluates its relative performance with other existing measures. After that,Kim,Baek &Baek(2004) deal with the multi-objective machine cell formation problem to determine the part route families and machine cells such that the total sum of inter-cell part movements and maximum machine workload imbalance are simultaneously minimized. A new Branch-and-Bound(B&B) enhancement is then proposed by Boulif & Atif(2006) to improve the GA's performance which is used to solve the cell formation problem by using the binary coding system that has proved superior to the classic integer coding systems.
Array-based clustering methods perform a series of column and row permutations to form product/part and machine cells simultaneously. The main problem in array- based clustering methods is that the quality of the solution given by these methods depends on the initial configuration of the zero-one matrix. But in case of our approach, the quality of solution does not depend on the initial configuration of the zero-one matrix. Hierarchical methods have the disadvantages of not forming part and machine cells simultaneously. Our approach overcomes these disadvantages. One limitation of graphical method is that the machine cells and part families are not formed simultaneously. These methods are found to depend on the initial pivot element choice. But our method overcomes these limitations. Mathematical programming methods can solve the machine part grouping problem simultaneously by considering the within-cell layout. But this technique is slightly complex & time consuming. Also none of the approaches presented above guarantees optimal solutions. So that the modern researchers have the tendency to continue their research activities in the field of group technology for machine part cell formation problem by using genetic algorithm.Zulawinski, Punch & Goodman (1995) developed a grouping genetic algorithm for Bin balancing which is better suited for grouping problems than the classical representations. After their approach, genetic algorithms become more popular to the researchers for finding the optimum solution for the cell formation problem. The objective of this paper is to present a procedure for obtaining product-machine groupings when the manufacturing system is represented by a binary product-machine incidence matrix.

1.2 Problem Statement

From the study of literature review, a grouping problem is identified. One of the key issues in batch oriented production is determining the best formation of the separate manufacturing cells. This is called the machine –part cell formation (MPCF) problem. This problem includes the identification of parts that have similar processing requirements (a part family) and the identification of the set of machines that can process each family of parts. For cells to operate efficiently, all of the machines within a cell should be fully utilized and the amount of inter cell traffic should be kept to a minimum. In order to determine the utilization of machines and the inter cell flow of parts much research has focused on the machine –part incidence matrix. The proposed approach, in this research, is based on the objective of maximizing the machines utilization within cells and minimization of inter cellular movements in a batch oriented production.

II. METHODLOGY

There are various approaches (discussed in literature review) for solving the problem but none of these approach guarantees the optimal solution. In this paper a genetic algorithm approach is used to create the chromosome. The chromosome contains the information for the machine cell. According to the chromosome the number of machine cell has been selected and the machines have been inserted to the cells. After that the initial machine cell has been formed. The local search heuristic has been applied then to form the part families. Then the machine part matrix has been formed and the corresponding grouping efficacy has been calculated. Then with the help of part families the local search heuristic has been applied again to obtain the new machine cell. Then again the machine part matrix has been formed with the part families and the new machine cell and the corresponding grouping efficacy has been calculated. This process has been continued until the optimum solution has been found. The following figure shows the sequence of steps applied to each chromosome generated by the genetic algorithm. Then the local search heuristic is applied to the sets of machines cells generated by the genetic algorithm. The detail steps of local search heuristic are discussed in the following
section. The local search heuristic is applied to the sets of machine cells generated by the genetic algorithm when the machine cells are known; it is customary to assign a part to the cell where it visits the maximum number of machines. This is optimal to minimize inter-cell movement. However, it does not guarantee good utilization of the machines within a cell. To overcome this problem, a local search heuristic, which takes into consideration both inter cell movement and machine utilization was developed. Srinivasan & Narendran (1991) and Adil,Rajamani & Strong(1997) developed heuristics whose main loop is similar to ours. The main difference between our heuristic and their heuristic is that their heuristic consists in the rule used to assign products/machines to the machine cells/product groups and in the stopping criteria.

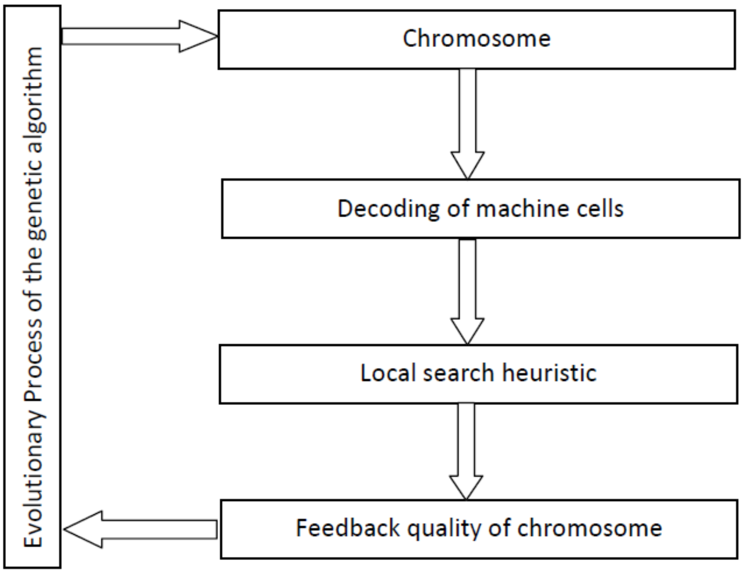

Figure1. Architecture of the research work

The heuristic consists of an improvement procedure that is repeatedly applied. Each iteration $\boldsymbol{K}$ of the procedure starts with a given initial set of machine cells $\mathbf{M}_{K}^{\mathbf{INITIAL}}$ and produces a set of part families $\mathbf{P}_{K}^{FINAL}$ and a set of machine cells $\mathbf{M}_{K}^{FINAL}$. Two block-diagonal matrices can be obtained by combining $\mathbf{M}_{K}^{\mathbf{INITIAL}}$ with $\mathbf{P}_{K}^{FINAL}$ and $\mathbf{M}_{K}^{FINAL}$ with $\mathbf{P}_{K}^{FINAL}$. From these two matrices, the one with the highest grouping efficacy is chosen as the resulting block-diagonal matrix of the iteration $\boldsymbol{K}$. The procedure stops if $\mathbf{M}_{K}^{\mathbf{INITIAL}} = \mathbf{M}_{K}^{FINAL}$ or if the grouping efficacy of the block –diagonal matrix resulting from iteration $\boldsymbol{K}$ is not greater than the grouping efficacy of the block-diagonal matrix resulting from the previous iteration $\boldsymbol{K} - 1$,(for $\boldsymbol{K}>\mathbf{2}$). Otherwise, the procedure sets $\mathbf{M}_{K}^{\mathbf{INITIAL}} = \mathbf{M}_{K}^{FINAL}$ and continues to iteration $\boldsymbol{K}+1$. Each iteration $\boldsymbol{K}$ of the local search heuristic consists of the local search heuristic consists of following two steps:

Step 1: Assignment of parts to the initial set of machine cells $\mathbf{M}_{K}^{\mathbf{INITIAL}}$. (Note that the initial the set of machine cells of iteration 1, $\mathbf{M}_{1}^{\mathbf{INITIAL}}$; is supplied by the genetic algorithm).Parts are assigned to machine cells one at a time (in any order).A part is assigned to the cell that maximizes an approximation of the grouping efficacy, i.e., a part is assigned to the machine cell C^*, given by

$$C^* = \text{argmx} = \frac{N_1 - N_1^{OUT}}{N_1 + N_0^{IN}}$$

Where, argmax argument that maximizes expression,

N_1 = total number of 1's in the matrix;

N_1^{OUT} = total number of 1's outside the diagonal blocks if the part is assigned to cell C;

N_0^{IN} = total number of 0's or blank space inside the diagonal blocks if the part is assigned to cell C.

In this step, the heuristic generates a set of part families $\mathbf{P}_{K}^{FINAL}$.We considered μ_K^1 as the efficacy of the block-diagonal matrix defined by $\mathbf{M}_{K}^{\mathbf{INITIAL}}$ and $\mathbf{P}_{K}^{FINAL}$.

Step2: Assignment of machines to the set of part families $\mathbf{P}_{K}^{FINAL}$ obtained in step(1).Machines are assigned to part families, one at a time(in any order).A machine is assigned to the part family that maximizes an approximation of the grouping efficacy, that is, a machine is assigned to the part family F^*,given by,

$$F^* = \text{argmx} = \frac{N_1 - N_1^{OUT}}{N_1 + N_0^{IN}}$$

Where, argmax argument that maximizes expression,

N_1 = total number of 1's in the matrix;

N_1^{OUT} = total number of 1's outside the diagonal blocks if the part is assigned to cell F;

N_0^{IN} = total number of 0's or blank space inside the diagonal blocks if the part is assigned to cell F.

In this step, the local search heuristic generates a new set of machine cells $\mathbf{M}_K^{\mathbf{INITIAL}}$. We also considered μ_K^2 as the efficacy of the block-diagonal matrix defined by $\mathbf{M}_K^{FINAL}$ and $\mathbf{P}_K^{FINAL}$.The block- diagonal matrix resulting from the iteration has a grouping efficacy given by $\mu_K = \max(\mu_K^1, \mu_K^2)$.If $\mathbf{M}_K^{FINAL} = \mathbf{M}_K^{\mathbf{INITIAL}}$ or $\mu_K \leq \mu_{K-1}(k \geq 2)$; then the iterative process stops and the block-diagonal matrix of iteration k-1 is the result. Otherwise, the procedure sets $\mathbf{M}_{K+1}^{\mathbf{INITIAL}} = \mathbf{M}_K^{\mathbf{INITIAL}}$ and continues to step (1) of iteration k+1.

III. ANALYSIS AND DISCUSSION

3.1 Case study & Data collection

Effective & efficient data collection requires careful planning and judicious use of both the case participant's and the researcher's time (Darke et al.,1998). Data were collected from a leading furniture manufacturing company in Bangladesh. Some data are primary and some are secondary. For collecting data cutting section was selected. This section contains 22 machines and a variety of parts of various models of various products. This is actually a batch manufacturing system. It contains intermediate varieties of products with intermediate volumes. Common two model products were selected for cell formation. Through the two products, the maximum operations of parts are covered. The collected data are listed in table1& 2 respectively.

Table1. Part list

Product Name	Product Model	Part No	Part Name
Common Bed	BDDPO50	1	Head end
		2	Leg end
		3	Side
		4	Side bit
Common Almirah	CBDPO30	5	Side
		6	Door
		7	Bottom front bit
		8	Top
		9	Partition
		10	Bottom
		11	Shelf
		12	Drawer
		13	Back bit
		14	Back ply
		15	Drawer bottom ply

Table 2. Machine list

Machine No.	Machine Name	Machine No.	Machine Name
1	APS_1(Auto Panel Saw)	11	MB_1(Multi Head Boring)
2	APS_2(Auto Panel Saw)	12	MB_2(Multi Head Boring)
3	SS_1(Sliding Saw)	13	NB_1(Normal Boring)
4	SS_2(Sliding Saw)	14	NB_2(Normal Boring)
5	CS_1(Circular Saw)	15	NB_3(Normal Boring)
6	CS_2(Circular Saw)	16	CNC_1(Three spindle CNC Router)
7	DET_1(Double End Tennoner)	17	CNC_2(CNC Router)
8	DET_2(Double End Tennoner)	18	G_1(Grooving)
9	E_1(Edging)	19	HB(Hinged Making Boring)
10	E_2(Edging)		

Processing sequence of various parts is shown in the following figures.

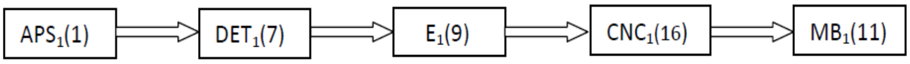

Figure 2. Processing sequence for Head end (Part1) and Leg end (Part2)

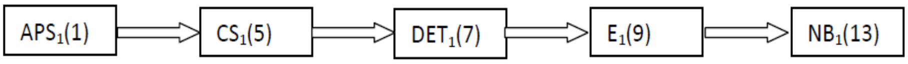

Figure 3. Processing sequence for Side (Part3) and Side bit (Part4)

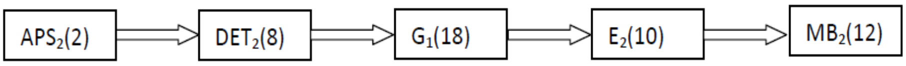

Figure 4. Processing sequence for Side (Part5)

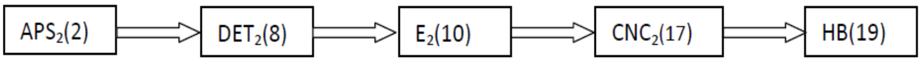

Figure 5. Processing sequence for Door (Part6)

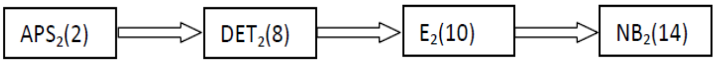

Figure 6. Processing sequence for Bottom front bit (Part7)

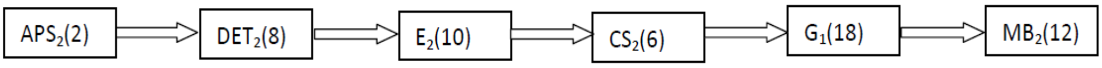

Figure 7. Processing sequence for Top (Part8)

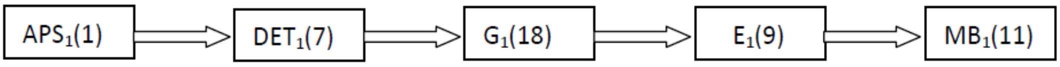

Figure 8. Processing sequence for Partition (Part9) and Bottom (Part10)

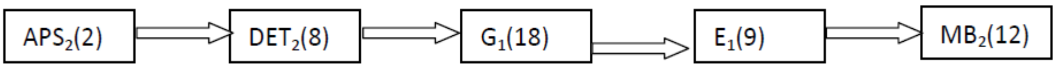

Figure 9. Processing sequence for Shelf (Part11)

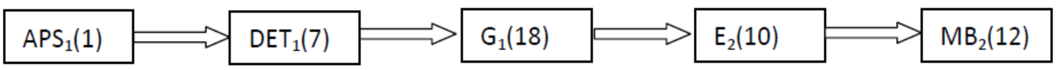

Figure 10. Processing sequence for Drawer (Part12)

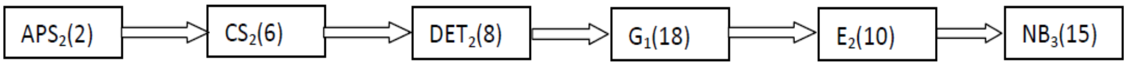

Figure 11. Processing sequence for Back bit (Part13)

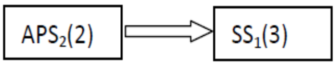

Figure 12. Processing sequence for Back ply (Part14)

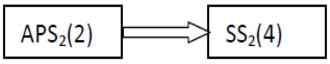

Figure 13. Processing sequence for Drawer bottom ply (Part15)

From the processing sequence of the parts of the machines, the machine part incident matrix obtained is shown in the table below.

Table 3.Initial machine part incident matrix

Part	Machine																	
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	1						1		1		1					1			
2	1						1		1		1					1			
3	1				1		1		1				1						
4	1				1		1		1				1						
5		1						1		1		1						1	
6		1						1		1							1		1
7		1						1		1				1					
8		1				1		1		1		1						1	
9	1						1		1		1							1	
10	1						1		1		1							1	
11		1						1	1			1						1	
12	1						1			1		1						1	
13		1				1		1		1					1			1	
14		1	1																
15		1		1															

3.2 Calculations & Result

The grouping efficacy for the exiting initial machine part matrix as shown in table 3 is given by

$$\mu_{initial} = \frac{70-0}{70+215} = 24.56\%$$

Now for our proposed approach suppose we start with the initial set of chromosome given by the genetic algorithm created randomly which is shown below.

Chromosome =1421123324221142545 |12345

For the left string, digit length indicates total machine number, eight digit position indicates the corresponding machine number and each digit represents the machine cell it goes. For the right string, digit length indicates total number of machine cell and each digit represents the corresponding machine cell.

Here number of cells =5

Machine cell 1= {1, 4, 5, 13, 14}

Machine cell 2= {3, 6, 9, 11, 12, 16}

Machine cell 3= {7, 8}

Machine cell 4= {2, 10, 15, 18}

Machine cell 5= {17, 19}

The initial machine cell obtained, $\mathbf{M_1^{INITIAL}}$= {(1, 4, 5, 13, 14), (3, 6, 9, 11, 12, 16), (7, 8), (2, 10, 15, 18), (17, 19)}.Now the corresponding grouping efficacy has been calculated using local search heuristic which is shown below.

Iteration 1:

Step1: Determining the set of part families

Table 4. Computations for step1 of the local search heuristic

Parts	Parts Machines	Machine Cells				
		(1, 4, 5, 13, 14)	(3, 6, 9, 11, 12, 16)	(7, 8)	(2, 10, 15, 18)	(17, 19)
		μ_c	μ_c	μ_c	μ_c	μ_c
1	1,7,9,11,16	(70-4)/(70+4) =89.19%	**(70-2)/(70+3) =93.15%**	(70-4)/(70+1) =92.96%	(70-5)/(70+4) =87.84%	(70-5)/(70+2) =90.28%
2	1,7,9,11,16	(70-4)/(70+4) =89.19%	**(70-2)/(70+3) =93.15%**	(70-4)/(70+1) =92.96%	(70-5)/(70+4) =87.84%	(70-5)/(70+2) =90.28%
3	1,5,7,9,13	**(70-2)/(70+2) =94.44%**	(70-4)/(70+5) =88%	(70-4)/(70+1) =92.96%	(70-5)/(70+4) =87.84%	(70-5)/(70+2) =90.28%
4	1,5,7,9,13	**(70-2)/(70+2) =94.44%**	(70-4)/(70+5) =88%	(70-4)/(70+1) =92.96%	(70-5)/(70+4) =87.84%	(70-5)/(70+2) =90.28%
5	2,8,10,12,18	(70-5)/(70+5) =86.67%	(70-4)/(70+5) =88%	(70-4)/(70+1) =92.96%	**(70-2)/(70+1) =95.77%**	(70-5)/(70+2) =90.28%
6	2,8,10,17,19	(70-5)/(70+5) =86.67%	(70-6)/(70+5) =85.33%	(70-4)/(70+1) =92.96%	(70-3)/(70+2) =93.05%	**(70-3)/(70+0) =95.71%**
7	2,8,10,14	(70-3)/(70+4) =90.54%	(70-4)/(70+6) =84.21%	(70-3)/(70+1) =94.37%	**(70-2)/(70+2) =94.44%**	(70-4)/(70+2) =91.67%
8	2,6,8,10,12,18	(70-6)/(70+5) =85.33%	(70-4)/(70+4) =89.19%	(70-5)/(70+1) =91.55%	**(70-3)/(70+1) =94.37%**	(70-6)/(70+2) =88.89%
9	1,7,9,11,18	(70-4)/(70+4) =89.19%	(70-3)/(70+4) =90.54%	**(70-4)/(70+1) =92.96%**	(70-4)/(70+3) =90.41%	(70-5)/(70+2) =90.28%
10	1,7,9,11,18	(70-4)/(70+4) =89.19%	(70-3)/(70+4) =90.54%	**(70-4)/(70+1) =92.96%**	(70-4)/(70+3) =90.41%	(70-5)/(70+2) =90.28%
11	2,8,9,12,18	(70-5)/(70+5) =86.67%	(70-3)/(70+4) =90.54%	(70-4)/(70+1) =92.96%	**(70-3)/(70+2) =93.05%**	(70-5)/(70+2) =90.28%
12	1,7,10,12,18	(70-4)/(70+4) =89.19%	(70-4)/(70+5) =88%	(70-4)/(70+1) =92.96%	**(70-3)/(70+2) =93.05%**	(70-5)/(70+2) =90.28%
13	2,6,8,10,15,18	(70-6)/(70+5) =85.33%	(70-5)/(70+5) =86.67%	(70-5)/(70+1) =91.55%	**(70-2)/(70+0) =97.14%**	(70-6)/(70+2) =88.89%
14	2,3	(70-2)/(70+5) =90.67%	(70-1)/(70+5) =92%	(70-2)/(70+2) =94.44%	**(70-1)/(70+3) =94.52%**	(70-2)/(70+2) =94.44%
15	2,4	(70-1)/(70+5) =92%	(70-2)/(70+6) =89.47%	(70-2)/(70+2) =94.44%	**(70-1)/(70+3) =94.52%**	((70-2)/(70+2) =94.44%

Table 4 presents the value of μ_c for each part and each machine cell. A part is assigned to the cell with the highest value of μ_c(the cells bold in table 4).From table 4 the set of part families obtained is given by $\mathbf{P_1}^{FINAL}$ = {(3,4),(1,2),(9,10),(5,7,8,11,12,13,14,15),(6)}.

The resulting machine part matrix after step1 is given in table 5.

Table 5 . Machine part matrix after step1

Part	Machine																	
	1	4	5	13	14	3	6	9	11	12	16	7	8	2	10	15	18	17	19
3	**1**		**1**	**1**				1				1							
4	**1**		**1**	**1**				1				1							
1	1							**1**	**1**		**1**	1							
2	1							**1**	**1**		**1**	1							
9	1							1	1			**1**					1		
10	1							1	1			**1**					1		
5										1			1	**1**	**1**		**1**		
7					1								1	**1**	**1**				
8							1			1			1	**1**	**1**		**1**		
11								1		1			1	**1**			**1**		
12	1									1		1			**1**		**1**		
13							1						1	**1**	**1**	**1**	**1**		
14						1								**1**					
15		1												**1**					
6													1	1	1			**1**	**1**

The grouping efficacy after step 1 is $\mu_1^{1} = \frac{70-36}{70+26} = 35.42\%$

Step2: Determining the set of machine cell

Table6 . Computations for step2 of the local search heuristic

Machines	Machines Parts	Part Families				
		(3,4)	(1,2)	(9,10)	(5,7,8,11,12,13,14,15)	(6)
		μ_c	μ_c	μ_c	μ_c	μ_c
1	1,2,3,4,9,10,12	**(70-5)/(70+0) =92.86%**	**(70-5)/(70+0) =92.86%**	**(70-5)/(70+0) =92.86%**	(70-6)/(70+7) =83.12%	(70-7)/(70+1) =88.73%
2	5,6,7,8,11,13,14,15	(70-8)/(70+2) =86.11%	**(70-8)/(70+2) =86.11%**	(70-8)/(70+2) =86.11%	**(70-1)/(70+1) =97.18%**	(70-7)/(70+0) =90.00%
3	14	(70-1)/(70+2) =95.83%	(70-1)/(70+2) =95.83%	(70-1)/(70+2) =95.83%	(70-0)/(70+7) =90.90%	**(70-1)/(70+1) =97.18%**
4	15	(70-1)/(70+2) =95.83%	(70-1)/(70+2) =95.83%	(70-1)/(70+2) =95.83%	(70-0)/(70+7) =90.90%	**(70-1)/(70+1) =97.18%**
5	3,4	**(70-0)/(70+0) =100%**	(70-2)/(70+2) =94.44%	(70-2)/(70+2) =94.44%	(70-2)/(70+8) =87.18%	(70-2)/(70+1) =95.77%
6	8,13	(70-2)/(70+2) =94.44%	(70-2)/(70+2) =94.44%	(70-2)/(70+2) =94.44%	(70-0)/(70+6) =92.10%	**(70-2)/(70+1) =95.77%**
7	1,2,3,4,9,10,12	**(70-5)/(70+0) =92.86%**	**(70-5)/(70+0) =92.86%**	**(70-5)/(70+0) =92.86%**	(70-6)/(70+7) =83.12%	(70-7)/(70+1) =88.73%
8	5,6,7,8,11,13	(70-6)/(70+2) =90.28%	(70-6)/(70+2) =90.28%	(70-6)/(70+2) =90.28%	**(70-1)/(70+3) =94.52%**	(70-5)/(70+0) =92.86%
9	1,2,3,4,9,10,11	**(70-5)/(70+0) =92.86%**	**(70-5)/(70+0) =92.86%**	**(70-5)/(70+0) =92.86%**	(70-6)/(70+7) =83.12%	(70-7)/(70+1) =88.73%
10	5,6,7,8,12,13	(70-6)/(70+2) =90.28%	(70-6)/(70+2) =90.28%	(70-6)/(70+2) =90.28%	**(70-1)/(70+3) =94.52%**	(70-5)/(70+0) =92.86%
11	1,2,9,10	(70-4)/(70+2) =91.67%	**(70-2)/(70+0) =97.14%**	**(70-2)/(70+0) =97.14%**	(70-4)/(70+8) =84.62%	(70-4)/(70+1) =92.96%
12	5,8,11,12	(70-4)/(70+2) =91.67%	(70-4)/(70+2) =91.67%	(70-4)/(70+2) =91.67%	**(70-0)/(70+4) =94.59%**	(70-4)/(70+1) =92.96%
13	3,4	**(70-0)/(70+0) =100%**	(70-2)/(70+2) =94.44%	(70-2)/(70+2) =94.44%	(70-2)/(70+8) =87.18%	(70-2)/(70+1) =95.77%
14	7	(70-1)/(70+2) =95.83%	(70-1)/(70+2) =95.83%	(70-1)/(70+2) =95.83%	(70-0)/(70+7) =90.90%	**(70-1)/(70+1) =97.18%**
15	13	(70-1)/(70+2) =95.83%	(70-1)/(70+2) =95.83%	(70-1)/(70+2) =95.83%	**(70-0)/(70+7) =90.90%**	**(70-1)/(70+1) =97.18%**
16	1,2	(70-2)/(70+2) =94.44%	**(70-0)/(70+0) =100%**	(70-2)/(70+2) =94.44%	(70-2)/(70+8) =87.18%	(70-2)/(70+1) =95.77%
17	6	(70-1)/(70+2) =95.83%	(70-1)/(70+2) =95.83%	(70-1)/(70+2) =95.83%	(70-1)/(70+8) =88.46%	**(70-0)/(70+0) =100%**
18	5,8,9,10,11,12,13	(70-7)/(70+2) =87.50%	(70-7)/(70+2) =87.50%	(70-5)/(70+0) =92.86%	**(70-2)/(70+3) =93.15%**	(70-7)/(70+1) =88.73%
19	6	(70-1)/(70+2) =95.83%	(70-1)/(70+2) =95.83%	(70-1)/(70+2) =95.83%	(70-1)/(70+8) =88.46%	**(70-0)/(70+0) =100%**

Table 6 presents the value of μ_k for each part and each machine cell. From table 6 the set of machine families obtained is given by $\mathbf{M}_2^{FINAL}$={(1,5,13),(7,16),(9,11),(2,8,10,12,18),(3,4,6,14,15,17,19)}.The resulting machine part matrix after step 2 is given in table 7.

Table7. Machine part matrix after step2

Part	Machine																		
	1	5	13	7	16	9	11	2	8	10	12	18	3	4	6	14	15	17	19
3	1	1	1	1		1													
4	1	1	1	1		1													
1	1			1	1	1	1												
2	1			1	1	1	1												
9	1			1		1	1					1							
10	1			1		1	1					1							
5								1	1	1	1	1							
7								1	1	1						1			
8								1	1	1	1	1			1				
11						1		1	1		1	1							
12	1			1						1	1	1							
13								1	1	1		1			1		1		
14								1					1						
15								1						1					
6								1	1	1								1	1

The grouping efficacy after step 2 is $\mu_1^{2}=\frac{70-28}{70+19}$ = 47.19%. Similarly at iteration 2, the set of part families obtained is P_2^{FINAL}={(3,4),(1,2,9,10),(14,15),(5,6,7,8,11,12,13)}& the grouping efficacy after step 1 is $\mu_2^{\,1}$= 50%. The set of machine families obtained after step 2 is $\mathbf{M}_3^{FINAL}$=

{(5,6,13,14,15),(1,7,9,11,16),(3,4,17,19),(2,8,10,12,18)} & the grouping efficacy after step 2 is $\mu_2^{\,2}$ =55.43%.
Again at iteration 3, the set of part families obtained after step 1 is P_3^{FINAL} ={(1,2,3,4,9,10),(14,15),(5,6,7,8,11,12,13)}& the grouping efficacy after step 1 is $\mu_3^{\,1}$= 58.88%.
The set of machine families obtained after step 2 is$\boldsymbol{M_4^{FINAL}}$={(1,5,7,9,11,16),(3,4,6,14,15,17,19),(2,8,10,12,18)} & the grouping efficacy after step 2 is $\mu_3^{\,2}$= 54.80%. At each iteration step 1 & step 2 are repeated until the final machine cell is obtained. The iteration will be stopped when the machine cell after iteration will equal to its any previous machine cell or the grouping efficacy will not increase for any further iteration. In step 1 at iteration 3, the grouping efficacy is 58.88% which seems to be maximum, but the following machines (5,6,13,14,15) are not assigned to any cell. So this machine part matrix is not selected. Similarly in step 2 at iteration 3, the grouping efficacy is 54.80% which is smaller than the value obtained at iteration 2(55.43%).So the iteration is stopped and we got the maximum efficacy at iteration 2 is 55.43%.So the final machine cell is obtained at iteration 2.From the calculations the final machine cell and the corresponding part families are $\boldsymbol{M_3^{FINAL}}$={(5,6,13,14,15),(1,7,9,11,16),(3,4,17,19),(2,8,10,12,18)}
P_2^{FINAL}={(3,4),(1,2,9,10),(14,15),(5,6,7,8,11,12,13)} & the grouping efficacy is $\mu_2^{\,2} = \mu_{Final}$=55.43%.

3.1 Result analysis

To demonstrate the performance of the method, the grouping efficacy of the existing initial machine part matrix and the grouping efficacy of the final machine part matrix obtained through calculations are shown below. The grouping efficacy of the existing initial machine part matrix is 24.56% & the grouping efficacy of the final machine part matrix is 55.43%. So it is clear that using our method the grouping efficacy has improved by 30.87%. The grouping efficacy obtained at different iterations is shown in figure below. Figure 14 shows that the maximum grouping efficacy is obtained at iteration 2.2. A comparison between the grouping efficacy of the initial machine part matrix and the final machine part matrix is given in figure below.From figure 15 we can see that the grouping efficacy of the final machine part matrix is higher than the grouping efficacy of the initial machine part matrix.

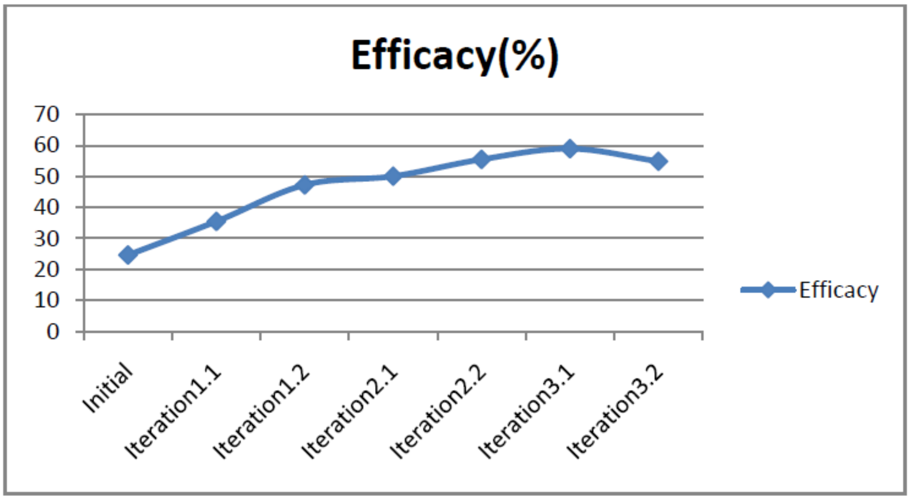

Figure14. Grouping efficacy at different iterations

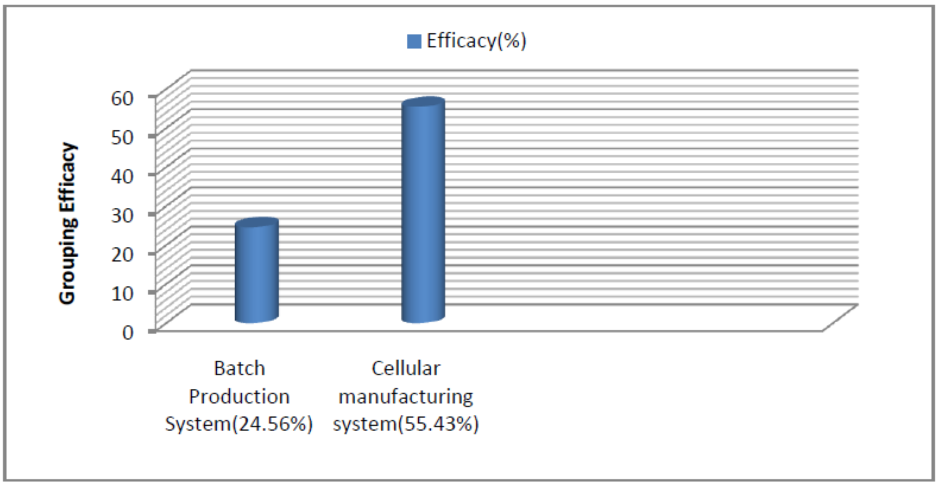

Figure15. Grouping efficacy comparison

IV. CONCLUSION

The aim of this research was machine part cell formation in a batch oriented production system.The cell formation has been done for an existing problem.For this cell formation,an approach is used which is a combination of a genetic algorithm and a local search heuristic.In order to evaluate the performance of machine part cell,the grouping efficacy has been chosen. Cellular manufacturing system has greater flexibility because it uses the benefits of job shop layout,flow shop layout & batch manufacturing.If a new product enters the system, the cellular manufacturing system will easily satisfy all the requirements for processing this.That means the cellular manufacturing system has quick response to the change in product.So a change in product model or part variety the system has quick adaption. As cellular manufacturing system removes unwanted movements of parts as well as waiting time,the productivity increases.The precedence relationship of various parts has been used to form the initial machine part matrix. Using this initial machine part matrix the final machine part matrix has been achieved.So the precedence relationship has been embedded in the final matrix.As a result the final matrix follows the precedence relationship.

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