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Multi-objective Machine Cell Formation by NSGA-II

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ABSTRACT

Non-dominated Sorting Genetic Algorithm (NSGA)-II is applied for multiple objective machine part cell formation problem. Minimization of cell load variation and minimization of total moves are considered as two conflicting objectives. Pareto optimal solutions are obtained for some test problems. Results are compared with those obtained by other methods. The comparison reveals that Pareto optimal fronts obtained are better than reported and reveal the strength of NSGA-II algorithm suited for integer multiple objective cell formation problems in Cellular Manufacturing Systems.

KEYWORDS

Cellular Manufacturing Systems, Multiple objective problems, NSGA-II, Pareto optimal.

1. INTRODUCTION

In Cellular Manufacturing Systems, part machine cell creation with numerous purposes is a challenging task. Current approaches aim to maximize these challenges with many objectives using various manufacturing operational elements. For integer multiple objective cell creation, multiple objective formulation is employed with NSGA-II. Using the NSGA-II method, Pareto optimum solutions can be obtained. If there isn't another workable way to lower a criterion without also raising at least one other criterion, then a solution to a multi-objective problem is Pareto optimum. Making trade-offs between competing goals is essential [1]. For multiple goal issues that involve several conflicting aims, a variety of heuristic solution approaches have been presented [2]. Work, throughput time, and material handling costs are all impacted by solution quality. Quality of solution affects material handling cost, throughput time, work in process; machine utilization. There is no unique solution to a multiple objectives problem with conflicting objectives. Mostly weighted sum of objectives is used to convert multiple objectives into a single objective [3]. The available multiple objective methods provide a single cell configuration, which might be difficult to implement in reality. These limit the applicability of existing methods. A multiple objective mathematical model is used and a solution methodology based on NSGA-II is applied. NSGA-II algorithm is used in integer domain. Problems are solved which are reported in literature. Results are compared and plotted with those obtained by other methods [7], [16]. Some additional non-dominated values are obtained which provides tradeoff solutions. The cell designer has more information and flexibility while forming cells at the design stage of the machine cell formation. Effectiveness of NSGA-II for getting pareto-optimal solutions in integer domain for multiple objective cell formation problems is demonstrated.

2. LITERATURE REVIEW

This is a brief review of the literature on these topics. The literature on multi-objective techniques for cellular manufacturing systems was examined by Dimopoulos [4]. Using a genetic algorithm, Venugopal and Narendran [5] introduced bi-objective integer programming. While taking into account various cell architectures, Gupta et al. [6], [7] simultaneously minimized the total intracellular and intercellular movements as well as the within-cell load fluctuation. An technique based on Tabu search is also used [8]. Machine workloads and operation sequencing were taken into consideration by Zhao and Wu [9]. Four objectives were included in the multi-objective integer programming model that Solimanpur, Vrat, and Shankar [10] created. A modified Vector Evaluated Genetic Algorithm was used. Yasuda, Hu, and Yin [11] thought of putting genetic algorithms in groups. For the single-objective cell production issues, Dimopoulos [12] presented the single-objective GP-SLCA algorithm, which consists of genetic programming.The previous GP-SLCA method was enhanced by Dimonpoulos [13] for the multi-objective GP_SLCA algorithm and NSGA. Coello Coello [14] provides a review and categorization of various multi-objective genetic algorithms. Their approaches to determining each chromosome's fitness are different. Several multi-objective evolutionary algorithms were categorized by Zitzler, Deb, and Thiele [15]. The use of genetic algorithms is made for solving other problems in cellular manufacturing system [17], [18], [19]. Multi-objective cell formation problems in integer domain are handled by NSGA-II [16].

3. PROBLEM FORMULATION

The following two minimization but conflicting objectives are considered for the multiple objective cell formulation:

1. Total cell moves
2. Within cell load variation

Minimizing intercellular fluxes is essential to reaping many of the related advantages. In a production setting, this can greatly boost manufacturing productivity. Additionally, intracellular movements need to be taken into account since they contribute to material handling expenses and, in turn, impact industrial productivity. Intercellular and intracellular motions add up to a weighted total of moves. The difference between the machine's workload and the average load on the cell is used to compute cell load variation. This is regarded as the second goal since it facilitates the efficient movement of materials inside each cell, which reduces the amount of labor that needs to be done inside each cell [6], [7]. It is presumed that each machine is assigned to a single cell and that there is no empty cell. The number of cells is specified by the user. Part demand is assumed constant over the given period. A part is assigned to a cell that contributes to the maximum cumulative processing time. The available time on the machine is set to be 8 hours/ day. Extra machines of similar type, required to match the workload, needs to be determined and added to it if workload exceeds its capacity.

The notations used are as per below.

$i = 1, 2\ldots m$ machines

$j = 1, 2\ldots p$ parts

$l = 1, 2\ldots c$ cells

k_j = number of operations scheduled to be performed on part j

t_{ij} = processing time (hours per piece) needed by part j on machine i

T_i = available time on machine i per day

N_j = demand for part j (in a given time period)

W_{ij} = workload of machine i induced by part j

$$= \frac{(t_{ij} \times N_j)}{T_i}$$

θ_1, θ_2 = weights of intercellular moves and intracellular moves are 0.7 and 0.3.

C_{jk} = the cell number in which k^{th} operation on part j is performed

x_{il}, e_{ij}, y_{ik}, and Z_{jkl} are binary variables such that

$$x_{il} = \begin{cases} 1; & \text{if } i^{th} \text{machine is in cell } j \\ 0; & \text{otherwise} \end{cases}$$

$$e_{ij} = \begin{cases} 1; \text{ if } t_{ij} > 0 \\ 0; \text{ otherwise} \end{cases}$$

$$y_{jl} = \begin{cases} 1; \text{ if the part } j \text{ is assigned to cell } l \\ 0; \text{ otherwise} \end{cases}$$

$$Z_{jkl} = \begin{cases} 1; \text{ if the part } j \text{ which has } k^{th} \text{ operation is performed in cell } l \\ 0; \text{ otherwise} \end{cases}$$

Mathematical Formulation

The two objective functions are formulated as follows:

(1) Total Cell Moves: The sequence of operations and the impact of layout of cells are considered while evaluating intercellular and intracellular moves. The linear single row cellular layout and linear double row cellular layout are considered separately. Both layout types are shown in Figure 1. Minimizing the total cellular moves is first objective.

Layout 1 (Single row layout): The total moves is given by

$$\text{Total moves} = \theta_1 \sum_{j=1}^{p} \sum_{k=1}^{k_j-1} \left| C_{jk} - C_{j(k+1)} \right| + \theta_2 \sum_{k=1}^{k_j-1} \sum_{l=1}^{c} Z_{jkl} \times Z_{j(k+1)l} \quad (1)$$

Layout 2 (Double row layout): The total moves is given by

$$\text{Total moves} = \theta_1 \sum_{j=1}^{p} \sum_{k=1}^{kj-1} \left| C_{jk} - C_{j(k+1)} \right| + \theta_2 \sum_{j=1}^{kj-1} \sum_{l=1}^{c} Z_{jkl} \times Z_{j(k+1)l} \quad (2)$$

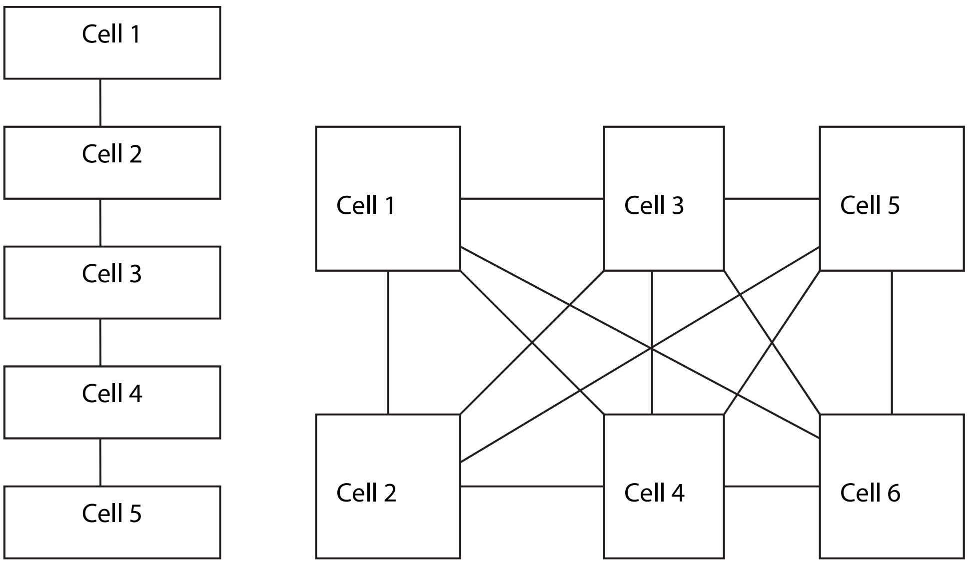

Figure 1: Linear single row cellular layout and double row cellular layout

For calculating intercellular moves, the distance traveled by the part between two cells (for successive operations) depends on the layout of cells. In the present formulation, linear single-row layout with equal distance between the cells is assumed. For double row layout of six cells, Euclidean distances are considered for both layouts as shown in Table 1.

Table 1: Distance matrix for double row layout

Cell	**1**	**2**	**3**	**4**	**5**	**6**
1	0.3	1.0	1.0	1.414	2.0	2.236
2	1.0	0.3	1.414	1.0	2.236	2.0
3	1.0	1.414	0.3	1.0	1.0	1.414
4	1.414	1.0	1.0	0.3	1.414	1.0
5	2.0	2.236	1.0	1.414	0.3	1.0
6	2.236	2.0	1.414	1.0	1.0	0.3

(2) Within Cell Load Variation: The cell load variation is calculated as the difference between the workload on a machine and the average load on the cell to which the machine is assigned. Minimizing this is second objective. The within cell load variation (*CLV*) is expressed as

$$CLV = \sum_{i=1}^{m}\sum_{l=1}^{c} x_{il} \sum_{j=1}^{p} (W_{ij} - m_{lj})^2 \tag{3}$$

Where, m_{lj} = Average cell load on cell l induced by part j

$$= \sum_{l=1}^{m} x_{il} \times w_{ij} / \sum_{l=1}^{m} x_{il} \tag{4}$$

Where, $\sum_{l=1}^{m} x_{il} \times W_{ij}$ represents the totals load on all i (in cell l induced by part j).

Constraints:

(1) A machine is assigned to only one cell

$$\sum_{l=1}^{c} x_{il} = 1, \quad \forall i = 1,2,...,m \tag{5}$$

(2) No cell is empty

$$\sum_{i=1}^{m} x_{ij} \geq 1, \quad \forall l = 1,2,...,c \tag{6}$$

4. DATA USED FOR NSGA-II IMPIMENETAION

The parameters commonly chosen for this problem comprise the NSGA-II algorithm in the suggested strategy. There are 200 chromosomes in this population. Crossover probability of 0.9 and mutation probability of 0.3 were chosen. Seventy generations is enough to use up nearly all of the potential. The information needed is provided, including the number of machines and components needed for the number of cells to be formed, the processing time for each part, the machines that can process it, the order in which it must be processed, and the demand for each part. The type of layout determines the data in the distance matrix. A random population of machine cell chromosomes is generated, with each chromosome fully representing the machines assigned to each cell. Every gene in the chromosome of the machine cell reflects the total assignment of machines to the cells. In the machine cell chromosome, each gene represents the cell to which the machine (in the particular position) is assigned. In the randomly generated population, thus machines are assigned to cells. If any cell is not assigned any machine, then this chromosome is discarded. The population is evaluated on both objectives using equations (1) and (3) for single row layout and equations (2) and (3) for double row layout. The NSGA-II algorithm ranks the chromosomes based on their objective function values and chooses the non-dominated chromosomes for the following generation. Given that parameters affect the quality of the solutions produced by genetic algorithms, the suggested algorithm has been tested with various combinations of these parameters, and the best outcomes are shown. Unlike the current approaches, the proposed algorithm delivers all the non-dominated solutions for varied number of cells between user-specified minimum and maximum number of cells which are taken as 2 and 4 for the first three issues and 4 and 6 for the remaining two problems. The computational results are discussed below. Various experiments are carried out in order to obtain the Pareto optimal solutions, which are described in next section.

5. COMPUTATIONAL RESULTS OF PROBLEM FORMULATION

Four problems from literature are solved. The input values are provided in the Table 2, Table 3, Table 4 and Table 6. Four problems from literature (Gupta et. al, 1996) are solved. These problems have been used extensively by researchers to demonstrate the efficiency of their algorithms and hence the best known results are available for these problems, which can be used as benchmarks in the absence of optimal results. The objective functions are minimizing total moves and minimizing of within cell load variation taking into consideration of single row layout as well as double row layout.

For the problems (Problem 1, 2 and 3) which are of smaller size, therefore, lower values of the parameters are taken. The numbers of cells to be obtained are 2, 3 and 4. The results obtained for single row layout and double row layout are tabulated in Table 5.

The set of Pareto values of both the objective functions obtained are given. These are compared with the values those reported in literature. NSGA-II algorithm has provided better results than those reported. This is clearly identifiable from the Table 5.

Table 2: Workstation – part load matrix for Problem 1

Work stations	Parts						
	1	2	3	4	5	6	7
I		0.5			5.0		1.5
II	2.5	2.0		4.5		1.5	
III		2.5			3.5	0.5	0.5
IV				1.0		0.5	
V	2.5		3.0		1.0		2.0

Table 3: Workstation – part load matrix for Problem 2

Work station	Parts													
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
I		0.69			2.42			2.44	2.48					2.72
II	0.5			0.61	0.90	2.09								
III							1.35			2.5	3.03	0.71	1.61	
IV			3.1						1.03		0.58	0.99		
V		1.22					1.35	4.45						3.84
VI	0.5					4.55		2.26						
VII	0.55			4.74	3.61	1.47			3.87	4.68				

Table 4: Workstation –part load matrix for Problem 3

Work stations	Parts						
	1	2	3	4	5	6	7
I		0.55		4.74	.		1.35
II			1.22		3.61		
III	0.50	1.69		2.42			1.35
IV	0.51		3.10			4.55	
V			0.61	0.90	2.09	1.47	

Table 5: Results for Problems 1, 2 and 3

Problem number	Number of cells	Single Row Layout		Double Row Layout	
		Total moves	Cell load variation	Total moves	Cell load variation
1	2	3.8	0.7197	3.8	0.7197
(5x7)		4.2	0.6865	4.2	0.6865
		4.6	0.4316	4.6	0.4316
	3	5.0	0.4316	5.0	0.4316
		5.4	0.1900	5.4	0.1900
	4	6.9	0.0585	6.49	0.0585
2	2	7.5	1.3710	7.5	1.3710
(7x14)		6.3	1.6123	6.3	1.6123
	3	8.9	1.2042	7.5	1.3240
		9.1	0.8084	8.7	0.8084
	4	9.7	0.9910	9.4	0.73
		12.0	0.6501	10.2	0.4622
		12.7	0.5937	-	-
		11.2	0.4622	-	-
3	2	3.5	0.3890	3.5	0.3890
(5x7)	3	4.3	0.2154	4.3	0.2154
		5.4	0.0923	4.98	0.0923
	4	6.6	0.0441	6.18	0.0441

For Problem 1, for two cells, values obtained are same to that obtained in single objective problem. Since the type of layout does not affect in case of two cells, the values for single row layout as well for double row layout are same. A lowest value for total moves is 3.8 and for cell load variation is 0.4316. Both these extreme values are obtained in the Pareto front. A highest value for total moves is 4.6 and for cell load variation is 0.7197. For three cells, for both the type of layouts, lowest value for total move is 5.0 and for cell load variation is 0.1900. For four cells, for single row layout, for total moves is 6.9 and for cell load variation is 0.0585. For double row layout, for total moves is 6.49 and for cell load variation is 0.0585. These also contain the lowest values obtained by solving the problem with single objective for both the types of layouts as evident from Table 5. Similarly, for problem 2 and prob-lem 3, Pareto optimal values are obtained. The lowest values of the problems for single objective for both the types of layouts can be seen from Table 5.

For the Problem 4, of size 15 machines and 30 parts, as given in Table 6 and Table 6A, which is comparatively larger in size. The numbers of cells to be obtained are 4, 5 and 6. The results for single row layout as well as double row layout are tabulated in Table 7. The results are compared with those results reported. The reported results provided are of the common strings (strings with the same cellular arrangement) from both the populations which had given satisfactory solutions to both the objective functions. For comparison purpose, the results of obtained for both the objectives as well as the values reported are provided in the Table 7.

Table 6: Work station – part load matrix for Problem 4

Work station	Parts														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
I		0.8			1.2		0.5			1.8		2.0			
II	0.1							1.7	1.7	1.3				1.7	
III	0.9				1.8	0.7					0.5				
IV			0.4					0.6			0.8				
V				0.9			1.5	0.9	0.1					0.6	1.9
VI	1.2	1.1					1.0						0.6		
VII	0.1			1.3		0.2									
VIII	0.6	1.2	1.7				1.4				2.0				
IX							0.4		1.3			0.8	1.2		
X							1.5		1.4				1.8		
XI	0.3	0.4													
XII								0.1	1.5			1.5	0.2		
XIII				1.4			0.3				1.7	1.6	1.5		
XIV		1.6							1.3						1.0
XV						0.3			0.4		1.3			0.5	

Table 6A: Work station – part load matrix for Problem 4

Work station	Parts														
	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
I							0.5								
II				0.8						1.1		1.9			
III	0.2			1.4	0.3	0.3								1.7	
IV		0.5			1.1	1.7	1.4	1.9				0.3			
V	0.4				0.6			1.2					0.7		
VI	1.9				2.0										1.3
VII													1.8		
VIII				1.8		1.0									
IX											0.9		1.4		1.9
X			0.7		0.2		1.7		1.3		1.5				0.7
XI								1.7		1.8		1.5	1.3		
XII						1.1			1.4						1.8
XIII	1.3	1.2	0.4	0.4		0.7	0.1								
XIV												0.3			1.6
XV		0.5					1.9		1.5		0.2	0.3			

For total moves, for number of cells 4, 5 and 6, difference of 13.3, 23.9 and 45.6 are obtained while for cell load variation, difference of 0.02, 0.038 and -0.002 are obtained respectively, in case of single row layout. Similarly, in case of double row layout, for number of cells 4, 5 and 6, for total moves, difference of 3.92, 9.89 and 6.86 are obtained and for cell load variation, a difference of 0.004, -0.033 and 0.013 are obtained as evident from the Table 7.

Table 7: Results obtained and reported by Gupta for Problem 4 (Source: Gupta et al.1996)

No. of cells	Single row layout				Double row layout			
	Total Moves		Cell load Variation		Total moves		Cell load variation	
	Proposed	Gupta	Proposed	Gupta	Proposed	Gupta	Proposed	Gupta
4	46.7	44.3	1.400	1.54	42.0	42.64	1.423	1.60
	47.6	47.3	1.373	1.48	42.7	43.76	1.400	1.48
	51.3	50.5	1.369	1.43	42.9	46.47	1.373	1.41
	52.9	56.3	1.344	1.38	48.0	47.03	1.334	1.39
	56.4	61.7	1.333	1.36	48.3	50.49	1.317	1.34
	56.8	64.7	1.330	1.34	48.9	53.30	1.312	1.31
	58.2	68.9	1.298	1.33	51.0	56.57	1.270	1.29
	63.5	76.8	1.270	1.29	53.1	57.02	1.266	1.27
	-	79.4	-	1.28	-	-	-	-
5	52.2	58.1	1.290	1.44	44.5	46.72	1.260	1.27
	53.1	58.5	1.260	1.30	47.0	47.70	1.231	1.25
	54.8	60.6	1.251	1.26	47.1	50.80	1.222	1.22
	55.6	65.7	1.219	1.24	48.6	51.70	1.195	1.18
	56.2	69.0	1.212	1.23	51.8	61.69	1.173	1.14
	58.7	71.9	1.195	1.20	52.7	-	1.165	-
	61.2	73.4	1.144	1.19	54.6	-	1.156	-
	65.4	74.7	1.124	1.17	56.9	-	1.113	-
	66.2	89.8	1.126	1.14	63.5	-	1.101	-
	71.0	94.9	1.092	1.13	-	-	-	-
6	57.5	68.9	1.151	1.21	48.3	48.24	1.087	1.26
	60.0	74.2	1.132	1.13	50.7	50.30	1.054	1.20
	60.9	77.1	1.087	1.12	54.9	50.30	1.044	1.20
	67.2	79.7	1.054	1.10	55.9	53.12	1.043	1.02
	67.8	80.6	1.023	1.07	56.5	56.01	1.032	1.01
	70.9	86.8	1.012	1.04	57.4	56.47	0.996	1.00
	75.1	97.0	0.996	1.00	57.9	59.63	0.989	0.98
	78.2	102.2	0.992	0.98	58.9	65.76	0.983	0.97
	82.8	120.2	0.971	0.97	63.3	-	0.0977	-
	84.3	129.9	0.952	0.95	66.2	-	0.962	-

Both the values are plotted and the graphs are shown in Figure 2 for single row layout and Figure 3 for double row lay-out for four cells formed. Figure 4 and Figure 5 shows the graphs obtained for five cells considering single row layout and double row layout respectively. While for six cells formation for single row layout is shown in Figure 6 and double row layout is shown in Figure 7. It is evident that the performance of NSGA-II is better in the cases considered.

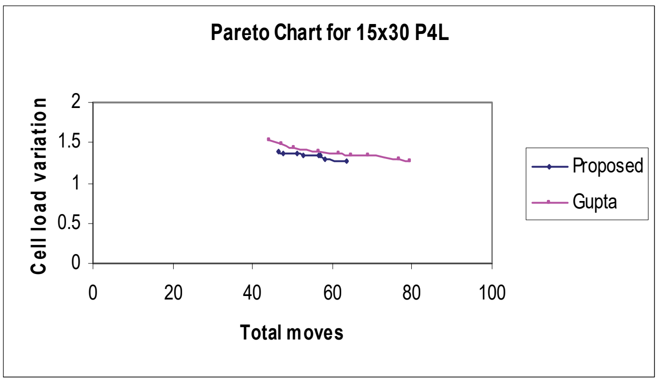

Figure 2: Pareto Chart for 4 cells single row layout

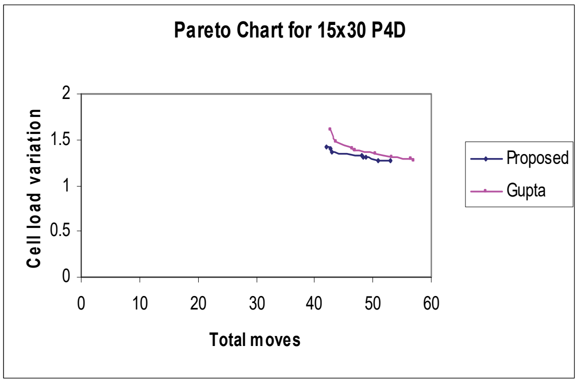

Figure 3: Pareto Chart for 4 cells double row layout

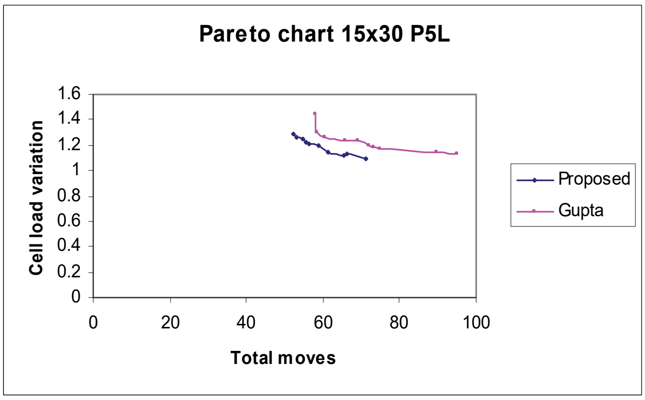

Figure 4: Pareto Chart for 5 cells single row layout

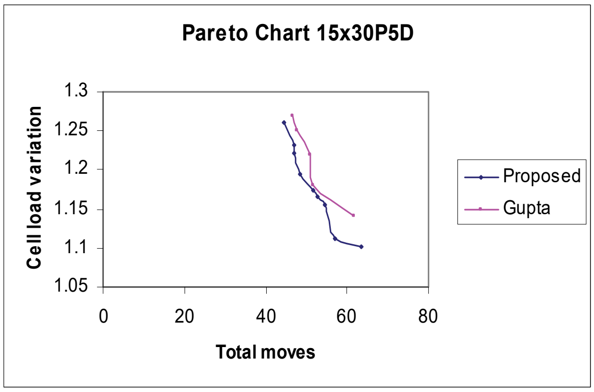

Figure 5: Pareto Chart for 5 cells double row layout

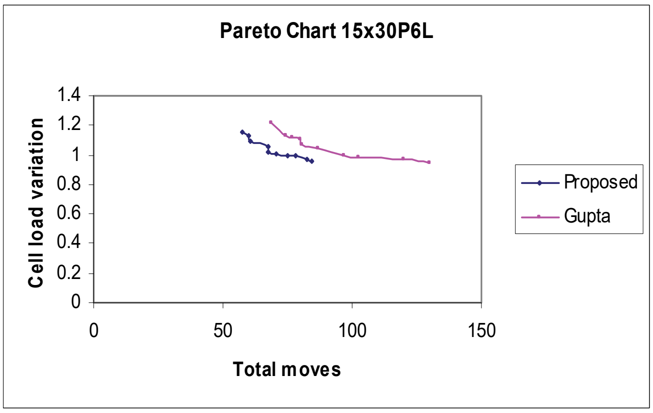

Figure 6: Pareto Chart for 6 cells single row layout

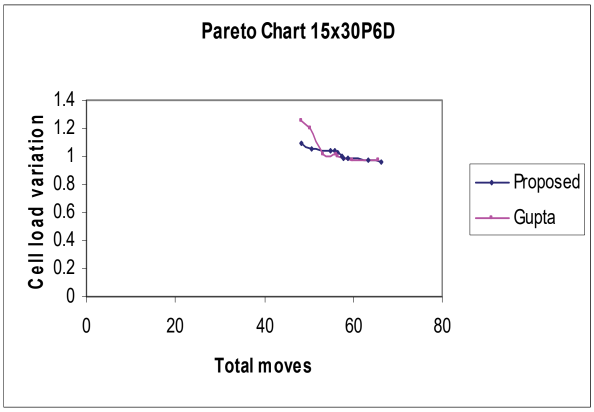

Figure 7: Pareto Chart for 6 cells double row layout

6. CONCLUSIONS

A significant problem in cellular manufacturing systems is multi-objective cell creation. There is a set of Pareto optimal solutions for multi-objective problems. A collection of non-dominated integer domain solutions with Pareto optimum fronts is offered by NSGA-II. An evolutionary approach based on Pareto optimality is introduced to reduce both the variance in cell load and the total number of moves at the same time. Consideration is given to the production factors including operation times and sequencing. The outcomes of Gupta et al. (1996), who did not employ the concept of Pareto optimality, are contrasted with those of the suggested method, which is based on Pareto optimality. The comparison demonstrates that, for a single objective problem, the Pareto set always contains one of the best solutions, and the value of its matching value is also found. Some additional non-dominated values are obtained which provides tradeoff solutions. Thus the cell designer has more information and flexibility while forming cells at the design stage of the cell formation. Effectiveness of NSGA-II for getting pareto-optimal solutions for multi-objective cell formation problem is demonstrated. Better Pareto fronts are obtained.

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