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Assessing the number of cells for a cell formation problem

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Abstract: Cellular manufacturing design is concerned with the creation and operation of manufacturing cells to take the advantage of flexibility, efficient flow and high production rate. Cell formation problem (CFP) is the assignment of part types and machines to specific cells based on their similarity. Several exact and heuristic methods are provided in literature to solve the problem and test problems in literature are commonly used for comparison. This study presents a Clonal Selection Algorithm (CSA) to solve a classical CFP that outperforms current available heuristics in the literature. The number of cells may be critical in the environments where cell formation costs are high and singletons occur in a design. It is concluded that the CFP results should be assessed not only based on efficacy values but also the number of cells.

Keywords: artificial immune systems, cell formation problem, clonal selection algorithm, group technology.

1. INTRODUCTION

Cellular Manufacturing System (CMS) is the application of Group Technology concept where similar parts are classified into part families and dissimilar machines are assigned into machine cells in order to exploit the cost-effectiveness of mass production and flexibility of job shop together. The design of CMS involves interrelated sub problems, namely machine grouping and part family formation (cell formation), intra-cell layout (machine layout) and inter-cell layout (cell layout) (Arvindh and Irani, 1994). The first and most important research topic in CMS is the process of determining part families and machine groups that is referred to as the CFP. The solution approaches that have been employed for the CFP can be grouped as mathematical programming, heuristics, metaheuristic methodologies, and artificial intelligence strategies (Papaionnaou and Wilson, 2010). Mathematical models developed for CFP are nonlinear or linear integer programming. These formulations have the advantage of being able to incorporate ordered sequences of operations, alternative resource plans, non-constructive part operations on the same machine, setup and processing times, the use of multiple identical machines as well as outsourcing of parts. However, realistically large data sets are computationally intractable. Due to the NP-hard nature of the CFP, heuristic, metaheuristic and hybrid metaheuristic approaches have been successfully proposed to generate acceptable solutions in reasonable time (Boe and Cheng (1991), Brown and Sumichrast (2001), Carrie (1973), Dimopoulos, and Mort (2001), Goncalves and Resende (2004), Islier (2005), Joines et al. (1996), Kumar and Vanelli (1987), Kumar et al. (1986), Moiser and Taube (1985b), Onwubolu and Mutingi (2001), Sarker and Mondal (1999)). Simulated annealing, tabu search, evolutionary algorithm, ant colony optimization, neural networks, and genetic algorithms are the well-known approaches to solve CFP. This study presents a CSA to balance between efficacy value and the number cells in a CFP that is not considered before.

2. CELL FORMATION PROBLEM

The aim in CFP is to group parts and machines so that all parts in a family are processed within a machine group with minimum interaction with other groups. This can be obtained by grouping all "1"s in the diagonal blocks on part-machine incidence matrix. Here, we need some performance measures to compare the algorithms used for CF problem. The performance of a CF algorithm is measured by two main goodness criteria: efficiency and efficacy. One drawback of grouping efficiency is known as the low discriminating capability. When the matrix size increases, the effect of 1's in the off-diagonal blocks become smaller, and in some cases, the effect of inter-cell moves is not reflected in grouping efficiency. Grouping efficacy is not affected by the size of the matrix and is calculated by Equation 2 provided by (Kumar and Chandrasekharan, 1990).

$$\Gamma = \frac{1 - \Psi}{1 + \Phi} \tag{2}$$

where,

$$\Psi = \frac{\#\text{ of exceptiona l elements}}{\text{total \# of operations}}$$

$$\Phi = \frac{\#\text{ of voids in the diagonal blocks}}{\text{total \# of operations}}$$

The grouping efficacy value ranges between 0 and 1. When the value is closer to 1, the grouping is better. In this paper, grouping efficacy is chosen as the measure of performance since several studies in the literature provide efficacy results as a standard measure to report the quality of the grouping.

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3. CLONAL SELECTION ALGORITHM FOR CELL FORMATION PROBLEM

Artificial immune system (AIS) models imitate the mechanisms in the natural immune system. The main characteristics of immune systems such as recognition, robustness, feature extraction, diversity, reinforcement learning, memory, and adaptiveness are imitated in AIS. The main algorithms in AIS are summarized in Figure 1.

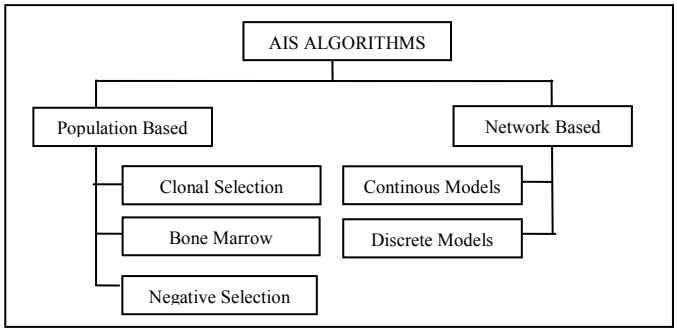

Fig.1. AIS algorithms

The problem types that are mainly studied by means of CSA are grouped in Ulutas and Kulturel (2011) as follows: function optimization (i.e., multi modal optimization and continuous function optimization), pattern recognition (i.e., binary character and face detection), design (i.e., continuous design, electromagnetic design, and hardware/software design), scheduling (i.e., job shop scheduling and project scheduling), industrial engineering (IE) related problems (i.e., facility location, layout, assembly planning, and material handling systems), TSP, and others (i.e., time series prediction, classification, fault diagnosis, machine learning, and virus detection, etc.).

The general steps of CLONALG (CLONal selection ALGorithm) by De Castro and Von Zuben (1999) that was initially proposed to solve pattern recognition problems are defined as follows:

Step 1: Initialization: Randomly initialize a population of individuals (N),

Step 2: Evaluation: Given a set of patterns to be recognized (P), for each pattern, determine its affinity (match) with each element of the population,

Step 3: Selection and cloning: Select a number (n) of the best highest affinity elements of N and generate copies of these individuals proportionally to their affinity with the antigen,

Step 4: Hypermutation: Mutate all the copies with a rate proportional to their affinity with the input pattern,

Step 5: Receptor editing: Add the mutated individuals to the population and reselect a number (d) of the maturated (optimized) individuals as memory,

Step 6: Repeat steps 2–5 until a termination criterion is met.

Mutation operator:

A pairwise interchange mutation is utilized for the CSA to solve CFP. First, two locations on an antibody for machines are selected randomly. Then, the values at these locations are interchanged. For example let the antibody be [1, 2, 1, 3, 1, 3] when i=2 and j=5, the new antibody becomes as [1, **3**, 1, 3, **2**, 3]. The objective function is calculated and based on this, the decision to keep the existing antibody or updating is given. This process is applied p times (where p represents the number of parts). Then, same procedure is also applied for parts section m times (where m represents the number of machines).

Receptor editing operator:

After mutation processes, a percentage of the antibodies (worst $\%B$ of the whole population) in the antibody population are eliminated and randomly created antibodies are replaced with them. This mechanism allows new cell formations and corresponds to new search regions in the total search space. Exploring new search regions may help the algorithm to escape from local optimal.

Termination criterion:

The algorithm terminates when there is no improvement after a certain number of iterations. After preliminary tests, termination criterion is assigned as 250.

4. NUMERICAL EXPERIMENTS

Several test problems are provided in the literature for cell formation problems to assess the performance of algorithms. However, some data are not consistent in a number of test problems. Further, some researchers have not provided the parameters, solution time, and the number of cells. Therefore, 20 well known test problems are considered I this study. Table 1 summarizes the sources of the test problems, number of machines, part, and cells.

Table 1. Sources for the test problems

Prob. No	Source	No of machines	No of parts
1	King and Nakornchai (1982)	5	7
2	Woghodekar and Sahu (1984)	5	7
3	Seiffodini (1989)	5	18
4	Kusiak and Cho (1992)	6	8
5	Askin and Standrige (1993)	6	8
6	Zolfaghari and Liang (2002)	7	8
7	Kusiak and Chow (1987)	7	11
8	Boctor (1991)	7	11
9	Seiffodini and Wolfe (1986)	8	12
10	Chandrasekharan and Rajagopalan (1989)	8	20
11	Chandrasekharan and Rajagopalan (1989)	8	20
12	Moiser and Taube (1985a)	10	10
13	Chan and Milner (1982)	10	15
14	deWitte (1980)	12	19
15	Askin and Subramanian (1987)	14	24
16	Stanfel (1985)	14	24
17	McCormic et al. (1972)	16	24
18	Srinivasan et al. (1990)	16	30
19	King (1980)	16	43
20	Burbidge (1979)	16	43

Based on the author's previous studies; the population size is assigned as 100 and receptor editing parameter is assigned as 10%. The algorithm terminates when there is no improvement after 250 iterations. Table 2 provides the worst, average, and best results generated by CSA also number of

cells obtained by the best solution that are the average of 30 replications.

Table 2. Results generated by CSA

Prob No	Best		Average		Worst	
	Solution	CPU time	Solution	CPU time	Solution	CPU time
1	0.8235	0	0.8235	0	0.8235	0
2	0.6957	0	0.6957	0	0.6957	0
3	0.7959	0	0.7959	0	0.7959	0
4	0.7692	0	0.7692	0	0.7692	0
5	0.8889	0	0.8889	0	0.8889	0
6	0.7391	0	0.7391	0	0.7391	0
7	0.6087	0	0.6087	0	0.6087	0
8	0.7083	0	0.7083	0	0.7083	0
9	0.6944	0	0.6936	1	0.6829	2
10	0.8525	1	0.8525	1	0.8525	1
11	0.5872	0	0.5872	3	0.5872	7
12	0.7500	0	0.7500	1	0.7500	1
13	0.9200	1	0.9200	1	0.9200	1
14	0.5699	2	0.5696	10	0.5670	19
15	0.7206	8	0.7206	12	0.7206	17
16	0.7183	6	0.7182	13	0.7162	26
17	0.5474	24	0.5445	43	0.5376	75
18	0.6899	8	0.6899	26	0.6899	47
19	0.5724	32	0.5696	82	0.5617	165
20	0.5517	29	0.5485	66	0.5436	119

Based on the results, it can be stated that CSA results are robust. For the 16 of 20 test problems, CSA was able to obtain the best result in short CPU times. Further, in 8 test problems the results, best results were generated in less than 1 CPU time.

The solution result at each iteration is recorded. Figure 2 illustrates the results for problem 15. An efficacy value can range between 0 and 1. Best efficacy value (=0.721) is reached at the 222th iteration. CSA for CFP is terminated if there is no improvement after 250 iterations. Therefore, the algorithm is terminated at the 473th iteration.

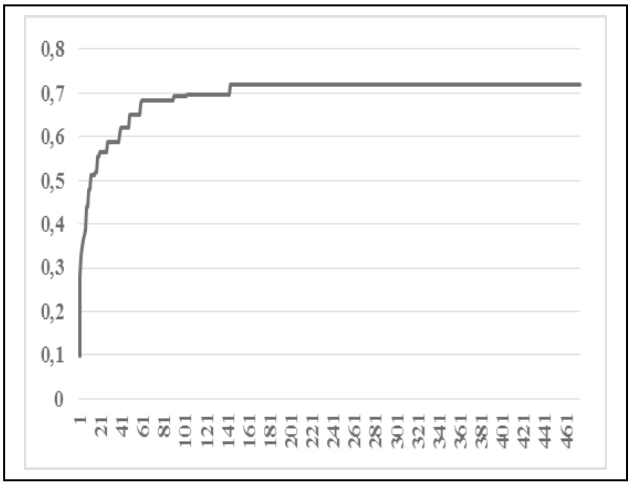

Fig.2. Convergence graph for problem 15

The best results by CSA are compared with the best known solutions so far. Number of cells generated are also stated for the best known solutions and CSA. The algorithm provided the best results for 16 of the 20 test problems. There were 0.562% improvement on the average for the solution quality. Since the test problems were not solved in the same platforms, and many of the sources have not provided the solution times, it was not possible to make a comparison for solution times.

Table 3 provides the best known efficacy values in the literature and corresponding number of cells for the best solution. CSA has formed exactly the same number of cells for 8 problems among 20 test problems. If the number of cells for the best known solutions are not presented they are represented as n/a in the table.

Table 3. Comparison of CSA results with the literature

Prob. No	Source	Best known		CSA		Imp. %
		Solution	No of cells	Solution	No of cells	
1	James et al. (2007)	0,8235	2	0,8235	2	0
2	Tunnikij and Hicks (2008)	0,6957	2	0,6957	2	0
3	Tunnikij and Hicks (2008)	0,7959	3	0,7959	2	0
4	Tunnikij and Hicks (2008)	0,7692	2	0,7692	2	0
5	Islier (2001)	0,8889	n/a	0,8889	3	0
6	Islier (2001)	0,7391	n/a	0,7391	3	0
7	Tunnikij and Hicks (2008)	0,6087	5	0,6087	3	0
8	Tunnikij and Hicks (2008)	0,7083	4	0,7083	3	0
9	Tunnikij and Hicks (2008)	0,6944	4	0,6944	3	0
10	Tunnikij and Hicks (2008)	0,8525	3	0,8525	3	0
11	Tunnikij and Hicks (2008)	0,5872	2	0,5872	2	0
12	Tunnikij and Hicks (2008)	0,7500	5	0,7500	3	0
13	Tunnikij and Hicks (2008)	0,9200	3	0,9200	3	0
14	Ozturk et al. (2006)	0,5699	n/a	0,5699	3	0
15	James et al. (2007)	0,7206	7	0,7206	5	0
16	James et al. (2007)	0,7183	7	0,7183	5	0
17	Tunnikij and Hicks (2008)	0,5275	8	0,5474	6	3,7725
18	Tunnikij and Hicks (2008)	0,6889	6	0,6890	4	0,0145
19	Tunnikij and Hicks (2008)	0,5753	8	0,5724	5	-0,5041
20	Ozturk et al. (2006)	0,5110	n/a	0,5517	8	7,9648

Figure 3 illustrates a solution for test problem 12 where singletons occur. The best known result in the literature was also reported to have singletons. Although grouping efficacy value is high, the singleton cells where one machine is assigned to a cell, can cause problem for real life applications and can be misleading.

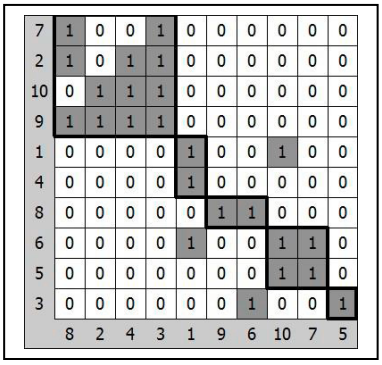

Fig.3. Best grouping for test problem no 12

In this study, CSA is revised to optimize both the efficacy value and the number of cells. Test problem no 20 is selected to assess how the number of the cells may effect efficacy value because best improvement is obtained in this test problem among the others. CSA is run with the population size as 250 and receptor editing parameter is as 10%. The algorithm was terminated when there is no improvement after 250 iterations. 10 replications were made for each test after assigning the max cell number for the solution. A solution with one cell means that all the machines are grouped together. Table 4 illustrates the best, average, and worst results with the related CPU time.

Table 4. CSA results for problem no 20

No of max cells	Best		Average		Worst	
	Solution	CPU time	Solution	CPU time	Solution	CPU time
1	0.1788	0	0.1788	0	0.1788	0
2	0.3017	4	0.3017	6	0.3017	9
3	0.3904	12	0.3880	23	0.3810	44
4	0.4650	33	0.4637	78	0.4519	112
5	0.5115	78	0.5112	104	0.5086	124
6	0.5380	31	0.5380	56	0.5380	74
7	0.5503	107	0.5481	170	0.5455	229
8	0.5517	47	0.5493	96	0.5484	160
9	0.5517	42	0.5489	85	0.5430	153
10	0.5517	82	0.5505	116	0.5490	160
11	0.5517	69	0.5503	113	0.5467	172
12	0.5517	145	0.5503	285	0.5484	456
13	0.5517	62	0.5503	132	0.5484	189
14	0.5524	72	0.5497	156	0.5461	248
15	0.5517	67	0.5498	129	0.5473	225
16	0.5524	140	0.5506	237	0.5467	450

Figure 4 illustrates the best solution when maximum number of cells are denoted. It is clear that increasing the number of cells improves the efficacy value then stays steady. The worst efficacy value was generated for one cell design. When maximum cell number is assigned 8 or more, the solutions generated best results with either 8 or 9 cells. The extreme case where each machine is assigned to a cell (number of cells=16) was not available for this test problem.

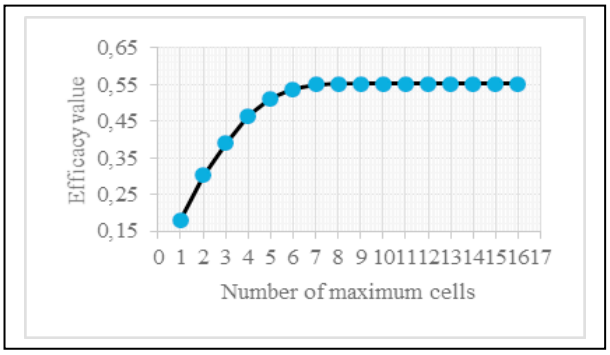

Fig.4. Effect of denoting maximum number of cells to the efficacy value

The solutions for test problem no 20 with various cell numbers ranging from 1 to 9 are represented in the Appendix. Note that the solutions with 7, 8, and 9 cells include singletons. Further, the solution with 9 cells in fact represents a solution with 8 cells. Because no machine is assigned to one of the cells (cell2). The results imply that, cell formation problem requires assessing efficacy value along with the number of cells in the best solution.

5. CONCLUSIONS

A CSA is introduced to generate optimal cell assignment based on machine/part matrix. The performance of the algorithm is tested among other nature based heuristics by using 20 test problems from the literature. Computational results illustrate that the proposed approach does not require long computing times and generates the best known solutions provided in the recent literature. The study also considers a balance between the efficacy value and the number of cells. In a real life problem, in order to reduce the inter-cell moves, it is required to keep the number of cells within a limit. Although efficacy value is high, the number of cells may be high, further the solution may include singletons. To attract attention to the problem, this study analysis the results obtained by CSA for a test problem. It was observed the goodness of the results should be evaluated not only by considering the efficacy values but also the number of cells. Considering the number of cells may be critical in environments where cell opening costs are high.

This study only considers the best efficacy values in the literature. Following studies can consider other related test problems to assess the performance of CSA. Also, the algorithm can be revised to solve CM problems such as alternative routes of parts, duplicate machines, and machine utilizations in cells.

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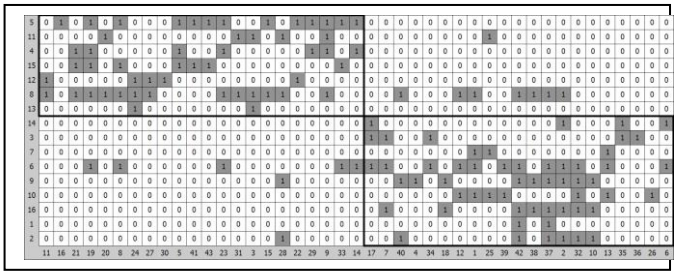
APPENDIX.

The solutions for test problem no 20 with various cell numbers



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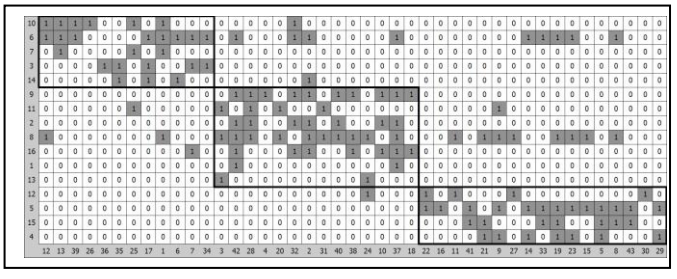

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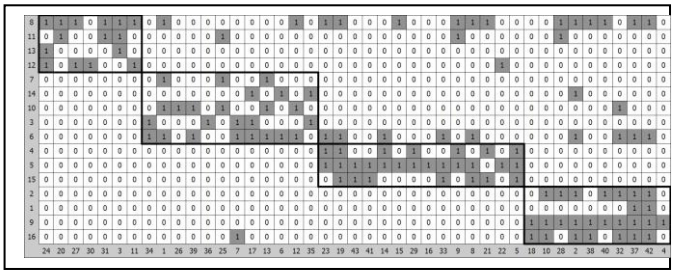

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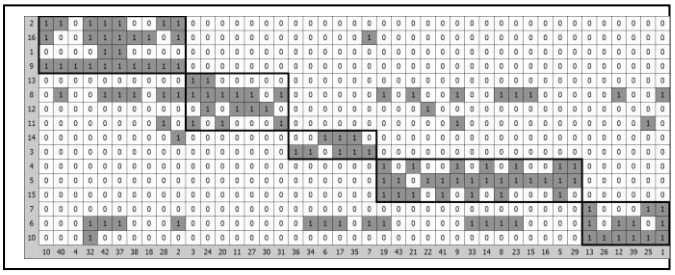

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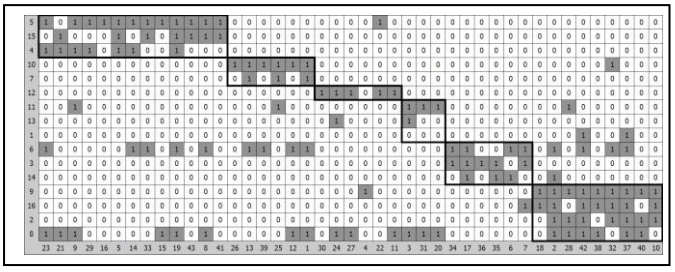

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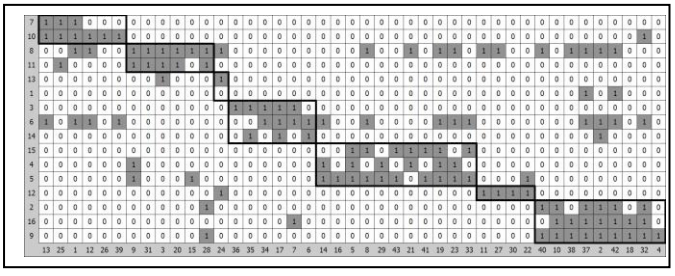

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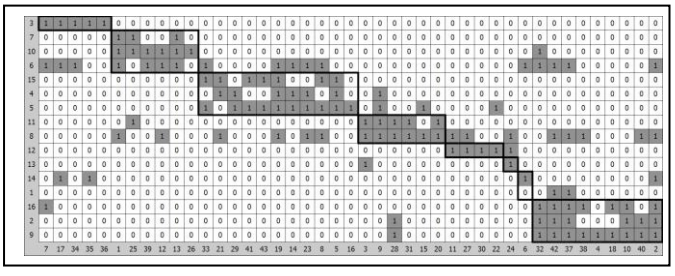

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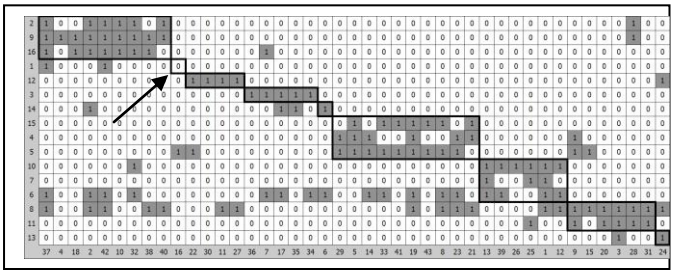

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