A STUDY FOR MANUFACTURING CELL FORMATION APPROACH CONSIDERING SETUP

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Abstract: This paper proposes a comparison among the exact methods Rank Ordered Cluster, Single Linkage Clustering and the metaheuristics Tabu Search and Genetic Algorithm for Manufacturing Cell Formation Problem. The Manufacturing Cell Formation consists of group machines for processing similar parts or components in order to minimize setup time. Setup time can be defined as the period of downtime between the processing of two consecutive batches. To validate the algorithms results, a metric, group efficacy, is applied to determine the result quality, moreover, the results are compared with examples in the literature.

1 INTRODUCTION

Nowadays, customers increasingly want personalized products, which forces suppliers to produce a wide variety of products in smaller amounts. In this context, the Group Technology (GT) provides an important contribution in managing the conflict between productivity and flexibility in a production line (James et. al., 2007; Papaioannou et al., 2008). The GT is a philosophy of manufacturing in which parts are identified and grouped according to some similarity in design or manufacturing, called Parts Families (PFs) (James et al, 2007).

The Manufacturing Cell Formation Problem (MCFP) consists in determining how the machines should be grouped (James et. al., 2007). The set of parts with similar processing needs to be completely manufactured in the same cell.

This paper approaches the manufacturing cell formation problem using four algorithms: ROC, SLC, the meta-heuristics Genetic Algorithm and Tabu Search. To make the comparison between the quality of the Manufacturing Cells (MC) generated by each algorithm is used the grouping effectiveness metric, proposed by Kumar and Chandrasekharan (1990) and also applied by James et al. (2007).

This paper is divided as follows. Section 2 presents the basic concepts about the manufacturing cells formation problem and the metrics that will be used to evaluate the efficiency of the groups that will be generated. Section 3 presents the techniques that will be used to generate clusters. Section 4 describes the model proposed in this paper. Section 5 presents the results obtained from the experiments and Section 6 presents the conclusions.

2 MANUFACTURING CELL FORMATION PROBLEM

The Manufacturing Cell can be characterized as a grouping of two or more machines which can manufacture a parts family with little or no intercellular movement (James et. al., 2007), providing benefits such as reduced costs with

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movement of materials and setup stops. The MCFP is considered NP - hard (James et al., 2007; Spiliopoulos and Sofianopoulou, 2008).

To solve this problem different methods have been proposed like, exact methods (King, 1980; King and Nakornchai, 1982; Kusiak and Chow, 1987), heuristics (Chan et al., 2002), metaheuristics (Dimopoulos and Mort, 2001; Bajestani et al., 2009), neural networks (Saidi-Mehrabad and Safaei, 2007) and fuzzy theories (Safaei et al., 2008; Papaioannou et al. 2008).

The MCFP can be formulated as a problem of diagonalizing blocks which aims to group the largest number of shares in the same cell, considering the limited size of the magazine, where the matrix A = $[a_{ij}]$ is defined by: a_{ij} = 1 if the j^{th} component visits the i^{th} machine and a_{ij} = 0 otherwise (King, 1980). Figure 1 illustrates an incidence matrix.

PARTES

MÁQUINAS	1	2	3	4	5	6
1			1		1	
2		1	1			
3	1			1	1	
4		1	1		1	
5	1	1		1		1

Figure 1: Incidence Matrix.

Figure 2 shows the result obtained after applying the Cluster Identification Algorithm (Kusiak and Chow, 1987).

PARTES

MÁQUINAS	1	4	6	3	2	5
5	1	1	1		*	
3	1	1				*
4				1	1	1
2				1	1	
1				1		1

Figure 2: Incidence Matrix after processing by CIA.

In Figure 2, we can see that two MC were generated; MC1 with machines 5 and 3 and cell 2 with machines 4, 2 and 1. The asterisk (*) indicates the parts 2 and 5 which need the MC 1 and 2 to be processed. This resource sharing can be interpreted as exceptional elements (King, 1980). In the formulation of Parts Families, the bottlenecks can be represented by machines that are claimed by two or more Parts Families or by parts that must be processed in two or more manufacturing cells.

To quantify the efficiency of the generated clusters, several metrics have been proposed (Sarker, 2001). In the literature, there are two measures frequently used to evaluate the quality of solutions. The first one is called grouping efficiency that was proposed by Chandrasekharan and Rajagopolan (1989) and given by equation (1).

$$n = q n_1 + (1 - q)\, n_2 \tag{1}$$

As such, q is the weighting factor, n_1 is the relationship between the number of 1s in the diagonal blocks and the total number of 0s and 1s on the diagonal blocks, n_2 is the ratio between the number of 0s outside the diagonal blocks and the total number of 0s and 1s outside the diagonal blocks (Chandrasekharan and Rajagopolan, 1989). Grouping efficiency ranges from 0 to 1 and the higher it is, the better the solution. As the q factor is increased, an important relationship between the use of machines and intercellular movement can be obtained, but this metric has a low discriminatory power as the array size increases (Sarker, 2001; James et. al., 2007).

Kumar and Chandrasekharan (1990) proposed a metric called effective clustering that overcomes the matrix size problem (Sarker, 2001). This metric is given by the equation (2).

$$\tau = \frac{e - e_0}{e + e_v} \tag{2}$$

In this equation, e is the total number of 1s in the incidence matrix, e_v is the number of 0s in the blocks diagonal and e_0 is the number of exceptional items.

3 METHODS TO SOLVE THE MANUFACTURING CELL FORMATION PROBLEM

Below it is presented the methods that will be implemented to generate the Parts Families.

3.1 Rank Order Clustering

The Rank Order Clustering (ROC) was proposed by King (King, 1980), this algorithm aims to calculate the weight of each row and each column in the incidence matrix and to reorder the incidence matrix as these values.

Considering n = number of parts, m = number of machines and a variable k, the weights for each row i and column j are calculated by the equations 3 and 4 respectively.

$$\text{Row i} = \sum_{K=1}^{n} a_{ik} . 2^{n-k} \tag{3}$$

$$\text{Column j} = \sum_{k=1}^{m} a_{jk} . 2^{m-k} \tag{4}$$

The equation (3) defines the calculation used to find the total weight of each line. The equation (4) means calculation used to find the total weight of each column. After applying ROC to the incidence matrices, the Cluster Identification Algorithm (Kusiak and Chow, 1987) was applied in order to identify the clusters so that the metrics calculation could be possible.

3.2 Single Linkage Clustering

The Single Linkage Clustering (SLC) is a hierarchical method for the formation of MC. The similarity coefficient between the parts is calculated using the Jaccard Similarity Coefficient (JSC) giving by

$$JSC_{jk} = \frac{Njk}{Njj + Nkk - Njk} \quad (5)$$

Where JSC_{jk} is the Jaccard Similarity Coefficient between *j* and *k*. N_{jk} is the number of machines that the component *j and k* have in common in their manufacturing and N_{jj} is the number of machines that the component *j* must be manufactured. In this case, the number of Parts Families is directly linked to the similarity coefficient, limiting the space search process.

3.3 Genetic Algorithm

The expression Genetic Algorithm (GA) was presented by Holland (1975) and consists of a heuristic method that simulates the evolutionary process of natural selection and survival of the fittest (James et al., 2007). Genetic algorithm has been applied in a number of fields; e.g.: mathematics, engineering, biology, and social science (Reeves, 2003).

The majority of the studies applying GA to the MCFP use an integer code to represent solutions. The objective function (OF), also known as evaluation function or fitness, has the goal of evaluating the actual solution quality. In the GA case, each chromosome or individual represents a solution, therefore, the OF calculation is done for each chromosome. The objective function used in this paper consists of the evaluation of the clustering efficiency given by the equation below.

$$\text{Minimize } Z = \sum_{j=1}^{n} P_j + K \quad (6)$$

Where:

P_j = sum of the number of exceptional parts;

K= number of individual's cells and it is defined by GA as a random integer variable chosen in the interval [2, m/2], being m the total number of matrix tools.

The metric given by equation (6) will be applied to the set of solutions generated by the GA.

3.4 Tabu Search

The heuristic method Tabu Search (TS) was originally proposed by Glover in 1986 (Glover, 1986) for various combinatorial optimization problems. The main ideas of TS are to avoid recently visited area of the solution space and to guide the search towards new and promising areas (Glover, 1986). Non-improving moves are allowed to escape from the local optima, and attributes of recently performed moves are stored in a tabu list and may be forbidden for a number of iterations to avoid cycling (Glover, 1986).

The initial solution is obtained by a random method, which draws random values for the clusters of machines and parts. The neighbourhood structure consists of two movements. The first movement remove a machine or part from its cluster and inserts it in another, since in the removed cluster remains, at least, one machine or part. The second movement swaps two machines or parts from different clusters. A list of the five best solutions found is stored in a candidate list. The intensification is applied every 20 consecutive iterations without improvement and consists of taking the best solution of the candidate list and generating a larger number of neighbours, providing a robust search in a promising area. Every time a candidate solution is used, it's removed from the candidate list. The tabu list applied in this paper stores the machine or part moved and its origin cluster for 20 iterations. Even so, a tabu movement can be used since the objective function is improved. The objective function used to evaluate the solutions is the group efficacy, shown in section 2. The stopping criterion applied is the maximum iteration number without improvement (nbmax) and its size is 200.

4 ARCHITECTURE

To demonstrate the performance of each implemented algorithm in the MCFP, we generated 300 random incidence matrices with a uniform distribution. 100 instances size 10 x 10 and magazine size limited to 4 tools, 100 instances size 40 x 20 and magazine size limited to 6 tools, and 50 instances size 100 x 100 and magazine size limited to 6 tools. The magazine limitation means that a Part will not have more tools than its limitations.

The tests occur in two phases. In the first phase it will be used two exact methods, ROC and SLC, and two metaheuristics, TS and GA, to test their group efficacy in random matrices. The second phase will compare the group efficacy of the 4 techniques in a set of 35 problems found in literature. Finally, the results of GA and TS will be compared with the best result found with the source problems. The tests were run on a personal computer with a Core 2 Duo processor and 2 GB of RAM Memory. Figure 3 shows the model architecture.

In this model, it can be observed that the ROC obtains the solutions by the diagonalizing of the matrices and the SLC obtains the solutions by the similarity coefficient. These two techniques do not see the problem as a whole at every stage of their solution procedures. However, TS and GA consider, for each solution, the whole problem of obtaining better solutions. In the TS solutions are evaluated using group effectiveness, maximizing the number of 1s in the diagonal blocks, while in GA the fitness function tries to reduce the exceptional items.

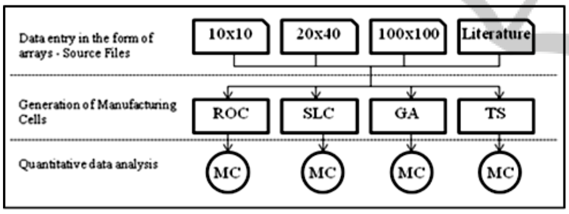

Figure 3: Model architecture.

5 COMPUTACIONAL EXPERIMENTS AND RESULTS

Initially, the ROC, SLC, GA and TS were applied in 3 types of matrices, 10x10, 20x40 and 100x100. The Table 1 below shows the matrices size and for each technique, ROC, SLC, GA and TS, shows the group efficacy presented in section 2, and its standard deviation.

Table 1: Random matrices analysis.

Size	ROC	δ	SLC	δ	GA	δ	TS	δ
10x10	20,21	3,50	24,36	4,44	37,10	4,87	54,37	5,68
20x40	13,98	0,99	25,00	1,74	26,88	7,65	38,69	8,27
100x100	25,81	0,29	22,73	0,79	26,89	27,69	33,95	13,55

The group efficacy of the 4 techniques studied in this paper was compared with a set of 35 problems from the literature. These problems were presented in James et. al. (2007) and the results were obtained directly from the original article they appeared.

The Table 2 below presents an ID to identify the problem, the source problem and the group efficacy obtained using ROC and SLC. The values shown by the GA and TS are the average group efficacy, they are obtained in 100 executions of each matrix, and their standard deviation.

Table 2: Comparing studied techniques.

ID	Problem source	ROC	SLC	GA		TS	
				Av.	δ	Av.	δ
1	King and Nakornchai (1982)	82,35	30,00	82,35	0,00	82,35	0,00
2	Waghodekar and Sahu (1984)	57,14	50,00	49,79	6,74	69,57	0,00
3	Seifoddini (1989)	85,19	40,74	77,36	0,00	79,59	0,00
4	Kusiak and Chow (1992)	45,83	28,21	70,13	7,86	76,92	0,00
5	Kusiak and Chow (1987)	36,51	32,43	42,85	2,47	60,87	0,00
6	Boctor (1991)	27,27	25,00	45,08	1,53	70,83	0,00
7	Seifoddini and Wolfe (1986)	36,46	31,11	45,34	5,88	69,44	0,00
8	Chandrasekharan and Rajagopalan (1986a)	38,13	30,60	49,60	9,69	85,25	0,00
9	Chandrasekharan and Rajagopalan (1986b)	56,88	38,02	40,96	6,17	56,70	7,15
10	Mosier and Taube (1985)	70,59	34,29	39,41	5,72	70,35	5,34
11	Chan and Milner (1982)	92,00	29,21	48,31	7,70	92,00	0,00
12	Askin and Subramanian (1987)	61,46	23,15	25,62	4,98	55,35	6,78
13	Stanfel (1985)	55,45	16,95	26,00	4,32	68,71	3,94
14	McCormick et al. (1972)	26,88	18,45	23,75	2,62	52,75	1,55
15	Srinivasan et al. (1990)	32,07	21,43	24,43	5,35	53,74	6,57
16	King (1980)	28,25	19,23	20,83	2,06	55,78	1,24
17	Carrie (1973)	34,52	17,02	21,80	2,00	51,35	2,12
18	Mosier and Taube(1985)	38,54	15,20	22,69	4,36	38,12	8,61
19	Kumar et al. (1986)	32,65	14,84	21,23	3,36	50,13	2,10
20	Carrie (1980)	85,00	18,53	22,80	3,58	70,19	4,87
21	Boe and Cheng (1991)	24,52	17,62	21,91	2,99	54,95	7,83
22	Chandrasekharan and Rajagopalan (1989)	98,50	13,42	17,68	3,11	100,00	0,00
23	Chandrasekharan and Rajagopalan (1989)	24,53	14,34	16,23	2,91	85,11	0,00
24	Chandrasekharan and Rajagopalan (1989)	14,75	13,64	15,58	1,64	73,51	0,00
25	Chandrasekharan and Rajagopalan (1989)	14,04	17,99	14,86	1,21	53,15	1,06
26	Chandrasekharan and Rajagopala (1989)	15,93	17,71	15,33	1,08	48,55	0,00
28	McCormicket (1972)	35,59	16,10	21,97	3,82	53,41	3,91

Table 2: Comparing studied techniques (Cont.).

29	Carrie (1980)	17,29	15,59	16,97	1,57	45,66	1,98
30	Kumar and Vannelli (1987)	16,71	15,84	44,37	5,86	60,37	4,79
31	Stanfel (1985)	38,50	15,79	11,29	1,36	39,55	13,56
32	Stanfel (1985)	12,42	13,62	12,31	1,40	41,16	10,89
33	King and Nakornchai (1982)	13,87	12,74	9,59	1,53	43,19	3,89
34	McCormick et al. (1972)	50,33	29,37	31,60	8,35	57,67	7,99
35	Chandrasekharan and Rajagopalan (1987)	27,42	10,01	12,01	1,30	83,08	0,91

In Table 2 above it can be observed that in this set of 35 problems, ROC obtained the best solution for the problems 1, 3 and 20, for all the other problems, TS obtained the best average solution.

Finally, the techniques and the results found with the source problem were compiled and analyzed. Table 3 below shows the ID to identify the problem, the technique which obtained the best solution in the source problem articles and the best solutions obtained by GA and TS.

Table 3: Comparing GA and TS with literature.

ID	Resolution Techniques	Best Solution Found	Best GA	Best TS
1	ZODIAC	73,68	82,35	82,35
2	GATSP	68,00	62,50	69,57
3	EA	79,59	77,36	79,59
4	GATSP	76,92	76,92	76,92
5	EA	53,13	46,51	60,87
6	GATSP	70,37	46,34	70,83
7	ZODIAC	68,30	53,70	69,44
8	EA	85,25	60,23	85,25
9	MST	58,72	56,07	58,72
10	GAL	72,79	46,15	75,00
11	ZODIAC	92,00	57,50	92,00
12	EA	69,86	32,76	69,86
13	GP	71,80	35,47	71,83
14	EA	52,58	28,24	52,75
15	ZODIAC	67,83	36,33	68,99
16	GAL	86,25	26,55	57,53
17	EA	54,46	26,24	57,43
18	EA	42,94	31,78	42,74
19	EA	49,65	29,03	50,81
20	GP	76,70	22,80	77,91
21	EA	58,07	21,91	57,98
23	MST	85,11	24,49	85,11
24	GRAFICS	73,51	20,33	73,51
25	GP	53,30	18,18	53,15
26	GP	47,90	19,05	48,55
27	EA	44,75	18,05	46,90
28	EA	54,27	31,36	53,41

Table 3: Comparing GA and TS with literature (Cont.).

29	EA	44,37	20,53	46,78
30	GP	60,70	54,98	62,24
31	GP	59,40	16,16	59,77
32	EA	50,48	16,89	50,83
33	EA	42,12	12,25	44,61
34	MST	56,42	46,38	60,48
35	GATSP	84,03	16,21	84,00

The ZODIAC was obtained from Chandrasekharan and Rajagopalan (1987), GRAFICS was obtained from Srinivasan and Narendran (1991), GA-Genetic Algorithm was obtained from Onwubolu and Mutingi (2001), GP-Genetic Programming Algorithm was obtained from Dimopoulos and Mort (2001). The results for ZODIAC and GRAPHICS were both obtained from Srinivasan and Narendran (1991); otherwise the results were taken from the original citation.

6 CONCLUSIONS

This work presents a study for manufacturing cell formation approach considering setup with the application and analysis of 4 techniques, ROC, SLC, GA and TS in random matrices with different sizes and in a set of 35 known problems. Considering the experiments universe, SLC obtained better solutions in matrices size 10x10 and 20x40, in matrices size 100x100 ROC obtained better solution with a lower standard deviation.

The TS and GA obtained better solutions and a lower standard deviation compared with ROC and SLC. It happened because TS and GA use the search space to look for new solutions while ROC are limited by the sorting technique and SLC are limited by the similarity coefficient. Analysing the techniques, in the set of 35 problems, it can be seen that TS obtained better solutions in about 57% of the 35 problems studied while ROC obtained better solutions in 8% of the 35 problems. Even so, TS proved to be robust obtaining better solutions with a low standard deviation. Finally, using a technique that generates a better group efficacy means that lower number of setups and lower setup time will be needed to process a whole Parts Family, providing a higher production rate.

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