A Genetic Programming Methodology for the Solution of the Multiobjective Cell - Formation Problem

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Abstract

This article introduces a genetic programming algorithm for the solution of the multiobjective cell-formation problem. This problem is related to the design of a cellular manufacturing production system. A well-known evolutionary multiobjective technique guides the algorithm in its search for the Pareto set of solutions. The framework is tested on an industrial case study taken from the literature. Results illustrate that, unlike traditional techniques, the proposed framework has the ability to provide the designer of the system with a wealth of potential solutions.

Keywords: Genetic Programming, multiobjective optimization, cellular manufacturing, cell-formation.

1. Introduction

The cell-formation problem is a typical example of a difficult grouping problem encountered in production research. While numerous heuristic solution methodologies have been proposed for the single objective version of this problem, there has been relatively little research on the multiobjective version of the problem, despite the fact that practical considerations during the design of a manufacturing system are most likely to consider multiple conflicting objectives [1].

Multiobjective Evolutionary Algorithms, (MOEAs) have been reported to provide efficient solutions to non-trivial multiobjective optimization problems (see [2] for an excellent review of MOEA research). The methodology presented in this article introduces a Genetic Programming-based MOEA that evolves a set of solutions for multiobjective cell-formation problems. It combines the powerful evolutionary heuristic GP-SLCA [3] with NSGA-II [4], a state-of-the-art evolutionary technique for multiobjective optimization. A typical example taken from the literature is used to illustrate the benefits gained from the proposed methodology.

2. The Multiobjective Cell-Formation Problem

Cellular Manufacturing (CM) is the application of the organizational approach called Group Technology (GT) [5] at the shop floor production level. It states that there are considerable benefits to be gained by grouping machines into cells that process similar parts.

The general multiobjective cell-formation problem can be defined as follows: A grouping of machines into cells and parts into associated families needs to be identified that will simultaneously optimize a number of objectives. A single solution that simultaneously optimizes all objectives considered does not generally exist for this problem. Instead, there exists a set of solutions, in which no solution is better than the other (non-dominated) with respect to all objectives considered. This set is known as the Pareto set of solutions.

The cell-formation problem is a difficult NP-hard grouping problem that has attracted considerable research attention, at least for the single objective case. By comparison, there has been little research on the solution of the multiobjective version of this problem. Recent reviews by Mansouri [1] and Dimopoulos [6] illustrate the inefficiency of existing solution methodologies. The computational intractability of the problem leads the majority of researchers to utilize heuristic aggregating techniques that result in a single compromise solution for the problem considered. For this reason both reviewers propose the use of non-aggregating techniques that will help on the simultaneous identification of multiple non-dominated solutions. The methodology proposed in this paper follows on these guidelines and introduces a robust multiobjective optimization methodology for the cell-formation problem that attempts to provide the decision maker with a good approximation of the Pareto set of solutions. This methodology is described in the following section.

3. The Multiobjective GP-SLCA Methodology

GP-SLCA was originally designed as a methodology for solving single-objective cell-formation problems [3]. Its efficiency has been illustrated on a wide range of simple cell-formation problems that have been published in the literature [3]. The main idea of the algorithm is the incorporation of the Single Linkage Cluster Analysis (SLCA) technique, a traditional hierarchical clustering algorithm introduced by McAuley [7], within an evolutionary framework accommodated by a Genetic Programming machine.

SLCA employs Jaccard's similarity coefficient in order to calculate a similarity value between all pairs of machines in the plant. A set of machine groupings are subsequently generated based on these values. GP-SLCA replaces Jaccard's coefficient with similarity coefficients evolved through a genetic programming machine. Similarity inputs similar to the ones used by traditional man-made similarity coefficients are employed by genetic programming for the evolution of coefficients.

The SCLA process is applied to each evolved coefficient and a corresponding set of machine groupings is generated. The best solution found in each set with respect to the optimization objective considered is assigned as the fitness of the corresponding genetically evolved coefficient. The evolutionary process continues in the same manner for the specified number of generations. Interested readers can find a detailed description of the GP-SLCA algorithm, examples of evolved coefficients, and a comprehensive experimental analysis of GP-SLCA performance in [3].

Multiobjective GP-SLCA uses the same mechanism for the generation of machine groupings. However, both the evolutionary mechanism of the algorithm and its fitness assignment process have been suitably modified in order to accommodate the need for the multiobjective search:

Multiobjective GP-SLCA employs the NSGA-II evolutionary multiobjective technique as the driving force of the evolutionary algorithm [4]. NSGA-II promotes the evolution of a set of solutions that is ideally a close approximation of the Pareto-set of solutions for the problem considered.

In addition, in the case of multiple conflicting objectives, the set of SLCA-generated solutions for a particular coefficient may contain multiple equally 'good' non-dominated solutions. Since only a single set of objective values can be associated with each coefficient, there is a need to relate only one of these solutions with the evolved coefficient. For this reason GP-SLCA associates a random similarity threshold value with each coefficient evolved. This threshold value is used by the SLCA algorithm for the generation of a single corresponding machine-cell grouping. McAuley [7] provides an in-depth discussion of the similarity threshold concept. The objective values that correspond to this configuration constitute the objective values of the coefficient and are subsequently used by the NSGA-II evolutionary technique in order to rank solutions according to their Pareto efficiency. The operation of GP-SLCA in pseudo code form is as follows:

Procedure Main

```
initialize population of randomly created similarity
    coefficients
run procedure SLCA for each coefficient
rank solutions using the NSGA-II process based on the
    objective values
loop
        loop
                select individuals for crossover or
                                mutation
                apply genetic operators and form
                                new coefficients
        until a new generation has been formed
        run procedure SLCA for each coefficient
        rank solutions using the NSGA-II process based
            on the objective values
until termination criterion is true
```

Procedure SLCA

```
compute similarity matrix
create machine cells for the associated random similarity
    threshold value
assign parts to machine cells
calculate the objective values for the cell configuration
```

Note that since NSGA-II is an elitist multiobjective strategy, the final generation of solutions contains all non-dominated solutions that have been found during the evolutionary process.

4. Experimental Analysis

In this article we present the application of multiobjective GP-SLCA on an industrial test case described in the article of Lin *et al.* [8]. The size of the problem (22 machines and 62 parts) is much larger than the average size of the cell-formation problems employed in the literature [1].

The aim of the problem is to simultaneously optimize the following objectives:

- Minimization of total intercell moves of parts. These moves are present when the production of a part requires an operation in a cell of machines other than its associated cell.
- Minimization of total intracell moves of parts. These are the moves required for the

processing of parts within their associated cells.

- Minimization of within-cell load variation. The processing load induced by parts in their associated machine cells should be as balanced as possible in order to achieve a steadier operating pace.

The optimization of these objectives has been reported to provide significant reductions in transportation costs, setup costs, rework, and Work-In-Progress inventory. However, a single solution that simultaneously optimizes all three objectives does not exist.

Lin *et al.* used a minimum spanning tree algorithm to generate a solution for this problem. Their mathematical model provides a weighting mechanism for aggregating the objectives considered into a single objective. The algorithm of Lin *et al.* generated the solution depicted in Table 1, based on a particular set of weighting assignments:

Balance Delay Cost	Intercell Moves Cost	Intracell Moves Cost	Total Cost
198.2	31	425	617.1

Tab. 1: Solution generated by the minimum spanning tree algorithm of Lin *et al.* (1996)

Twenty runs of the multiobjective GP-SLCA algorithm were conducted on the same problem. A population size of 500 coefficients was used in all experimental runs. Table 2 illustrates the objective values of the non-dominated solutions that were evolved, together with the associated total cost generated based on the cost model and weighting weight assignments of Lin *et al.*. The total number of non-dominated solutions evolved during all experimental runs was 200. However, due to space limitations only the solutions that were found in more than 50% of the experimental runs are illustrated in the table. Due to space constraints it is also not possible to present in this article the machine-cell and part-family assignments that result in these objective values, except for the solution illustrated in the Appendix. However, all evolved configurations and their corresponding values can be made available by the author to any interested reader

As expected, multiobjective GP-SLCA provided a wealth of potential solutions to the decision maker. By contrast, the typical minimum spanning tree algorithm generates a single compromise solution. This solution is dominated by 3 solutions (solutions 38-40) of multiobjective GP-SLCA with respect to all objectives considered. In addition, multiobjective GP-SLCA generated 6 solutions with a lower aggregate cost value based on the cost model and weighting assignments of Lin *et al.*. The multiobjective GP-SLCA solution that generated the best aggregate cost value (solution 37) is illustrated in Figure 1 of the Appendix. It should be noted that this result is not the significant outcome of this approach. The main benefit is that any cost model can be recursively applied to all evolved solutions.

Solution	Balance Delay Cost	Intercell Moves Cost	Intracell Moves Cost	Total Cost
1	39.3333	165	289	803.66665
2	39.3333	167	287	807.66665
3	39.3333	168	286	809.66665
4	39.3333	169	285	811.66665
5	39.3333	170	284	813.66665
6	39.3333	171	283	815.66665
7	39.3333	173	281	819.66665
8	39.3333	177	277	827.66665
9	39.3333	178	276	829.66665
10	117.533	99	355	710.7665
11	117.533	100	354	712.7665
12	117.533	102	352	716.7665
13	117.533	103	351	718.7665
14	124	82	372	680
15	124	83	371	682
16	124	84	370	684
17	124	85	369	686
18	124	86	368	688
19	124	87	367	690
20	132.533	96	358	712.2665
21	132.533	97	357	714.2665
22	150.2	47	407	623.1
23	150.2	48	406	625.1
24	150.2	49	405	627.1
25	150.2	50	404	629.1
26	150.2	51	403	631.1
27	150.2	52	402	633.1
28	150.2	53	401	635.1
29	150.2	54	400	637.1
30	153	61	393	652.5
31	178.2	34	420	611.1
32	178.2	35	419	613.1
33	178.2	36	418	615.1
34	178.2	37	417	617.1
35	178.2	38	416	619.1
36	178.2	39	415	621.1
37	193.2	28	426	606.6
38	193.2	29	425	608.6
39	193.2	30	424	610.6
40	193.2	31	423	612.6
41	193.2	32	422	614.6
42	193.2	33	421	616.6
43	323.295	17	437	649.6475
44	323.295	18	436	651.6475
45	323.295	19	435	653.6475
46	323.295	20	434	655.6475
47	377.755	14	440	670.8775
48	551.533	0	454	729.7665

Tab. 2: A subset of non-dominated solutions generated by the multiobjective GP-SLCA algorithm

5. Conclusions

This article presented the application of the GP-SLCA evolutionary multiobjective optimization algorithm for the solution of the multiobjective cell-formation problem. To the best of the author's knowledge, this is the first time that an approximation of the Pareto set of solutions is attempted for the multiobjective cell-formation problem. A large-sized industrial case study was employed to illustrate the efficiency of the proposed methodology.

Multiobjective GP-SLCA not only provided the decision maker with a considerable number of alternative non-dominated solutions, but it was able to evolve solutions that dominated the single aggregate solution generated by a minimum spanning tree algorithm. However, further experimentation needs to be conducted on mathematical models that consider alternative optimization objectives and input data in order to further evaluate its performance.

6. References

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7. Appendix

The illustrated matrix in Figure 1 constitutes a typical way of describing cell-formation problems. The rows of the matrix correspond to machines and the columns to parts that need to be produced. The value of a non-zero entry indicates the workload (demand rate × processing time) induced by a part on a corresponding machine. The borders that have been drawn illustrate the machine and part groupings that were identified by the multiobjective GP-SLCA in this particular solution.

	1	2	3	4	5	6	7	8	9	10	11	12	13	59	60	61	62
1	3	3	3	2	2												
2	3	3	3	2	2												
4	4	4	4	2	2												
16	3	3	3	2	2												
18	2	2	2	1	1												
21	2	2	2	1	1												
3						4	4										
5						4	4			4	4	2	2				
9						3	3	3	3								
10								5	5								
11						3	3	3	3	3	3	2	2				
6														4	4		
20														3	3	3	3
7																	
8																	
15																	
13			5	3	3												
14																	
17																	
12																	
19																	
22																	

	33	34	35	45	46	47	48	49	50	51	24	25	26	27	28	29	30	31	32
1																			
2																			
4																			
16																			
18																			
21																			
3																			
5																			
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10																			
11																			
6																			
20																			
7	6	5	5	9	9	6	5	5	9	9									
8				9	9	6	5	5	9	9									
15				3	3	2	2	2	3	3									
13	4	3	3								4	3	3	4	3	3	4	3	3
14																			
17																			
12																			
19																			
22																			

	36	37	38	39	40	41	42	43	44	52	53	54	55	56	57	58	14	15	16	17	18	19	20	21	22	23
1																										
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6							3	2	2																	
20																										
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8																										
15																										
13	4	3	3	4	3	3	4	3	3																	
14										3	3	2	2	2												
17										2	2	1	1	1	2	2										
12																	3	3	3	3	3	3	3	3	3	3
19																	1	1	1	1						
22																	2	2	2	2						

Fig.1: Solution no.37 found by the multiobjective GP-SLCA algorithm (total cost=606.6 units)