A multi-objective approach for cell formation problem

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1. Introduction

Objectives such as due date satisfaction, product customization, high quality and economic strategy are important in achieving success for manufacturing firms that want to increase both their market share and profits. Group technology (GT) is a manufacturing philosophy that can be used to achieve these objectives. It attempts to improve production efficiency and manufacturing flexibility in mass production systems by dividing the manufacturing system into a number of independent subsystems (Erozan et *al*, 2015). Cellular manufacturing is one of the major applications of GT. Cell formation problem is the main issue in designing Cellular Manufacturing System (CMS). In contrast to existing mathematical model, we present a multi-objective mathematical model to simultaneously minimize the imbalanced workload, the number of voids and minimize the number of exceptional elements with variable number of cells. ε-constraint method joined with lexicographic optimization are then applied to solve the sub-models in order to generate the optimal Pareto solutions. In order to show the relationship between the selected criteria, a three combination of two objectives simultaneously is presented. The remainder of this paper is organized as follows: Section 2 contains the problem description. Section 3 contains the provided epsilon constraint method. Numerical results showing its performance is presented in section 4.

2. Problem Description

In designing Cellular Manufacturing System (CMS), precisely in cell formation problem, the main objective is to obtain a perfect clustering of parts families and machine cells. For this, it is necessary to take into account the needs of the manufacturing system, facing the constraints of the problem. Then, the goal is to optimize the functions to form well-structured cells. In this context, we can cite a number of performance criteria concerning the cell formation; the cost of maintenance, capacity, quality, makespan, setup, machine and system utilization.

Based on the literature we notice that the major criteria that effect the design and implementation of CMS are the number of exceptional elements, the number of voids (Saxena and Jain, 2011) and the unbalanced of workload between cells since it directly affects various operational issues (intercell movement, intracell movement, demand satisfaction, due date, machine and system utilization). The resolution of CMS should take into account these criteria. Therefore, our resolution methodology included the implementation of subsystems in which grouping a set a set of machines to process the parts is performed to maximise the system utilization and to balance the workload between cells with optimal number of cells. Thus, we present a model, which is inspired from the research work of Triki et *al*, (2017). This model allows us to have any number of cells in the optimal solution, then the model will be linearized and solved using CPLEX considering these objectives function simultaneously.

3. Lexicographic optimization and ε −constraint methods: triple objective problem

The Lexicographic optimization and ε-constraint methods are considered to solve multi-objective discrete optimization problem. They provides the exact set of efficient solutions. They don't aggregate criteria, i.e. only one of the original objective functions is selected to be optimized while the other(s) are added as additional constraints (Mavrotas, 2009). The resolution method can be summarized in the following algorithm:

Input: *f_1, f_2, f_3 and Δ*
Output: *The Pareto front P.*

1. *$P := \varnothing$*
2. *Solve the problem with lexicographic optimization Lex min $f_k(x)$ $for\ k = 1,2,3$*
3. *$x := opt(f_1, f_2, f_3)$*
4. *$P := \{x\}$*
5. *Set the Set lower and upper bound: $\underline{f}$ and $\overline{f}$ $for\ k = 2,3$*
6. *$\varepsilon_2 := \overline{f}_2$, $\varepsilon_3 := \overline{f}_3$*
7. *while $\varepsilon_2 \geq \underline{f}_2$ do*
8.   *while $\varepsilon_3 \geq \overline{f}_3$ do*
9.   *$x := opt(f_1, f_2, f_3, \varepsilon)$*
10.   *$P := P \cup \{x\}$*
11.   *$\varepsilon_3 := \varepsilon_3 - \Delta$*
12.   *end while*
13. *$\varepsilon_2 := \varepsilon_2 - \Delta$*
14. *end while*
15. *Remove the dominated solution from P (some dominated points might found throughout this procedure).*

To calculate the range of objective function value over the efficient solutions, we need to construct the payoff table by applying the lexicographic optimization of the objectives functions (Mavrotas, 2009). Objective functions bounds, $f \in \mathbb{R}$ are the Ideal and Nadir points. *Δ is* a positive constant for reducing *ε* at each iteration. *Δ* is considered equal to 1 since the difference between two integer objective values is at least equal to 1. This parameter setting ensures the sequence of ε-constraint problems generating one feasible solution for each point of the Pareto front *P* (Grandinetti et *al.* 2013).

4. Experimental results

In order to experiment the proposed method, a well-known instance was selected from literature (Adil et *al.*1996). In addition, we adapted it to our model by adding parameters according to the normal distribution based on the same rules provided in (Wang et *al.* 2009). Table 1 defines the proprieties of the instance are as follow: six machines with capacity 228 1473 1281 793 929 2361 for each machine. Six parts with according demands 132 69 362 75 38 47 and the following matrix define the processing time for each part in each machine was defined by a matrix in which the values are in [0...1].

The resolution approach is implemented using IBM CPLEX Optimization Studio 12.5 (concert technology) and run on PC with windows 10 platform, Intel® Core™ i5 CPU @ 3.20 GHZ and 4 Go of RAM. Afterward, for illustration, we presented the result of the instance in three-dimensional (3-D) Pareto plots

After the execution of the solving method, we find nine feasible solutions as shown in the Figure 1 in which the set of efficient solutions i.e. non-dominated or non-improvable solutions that are displayed with red circle are summarized in Table 1 (NC: optimal number of cells).

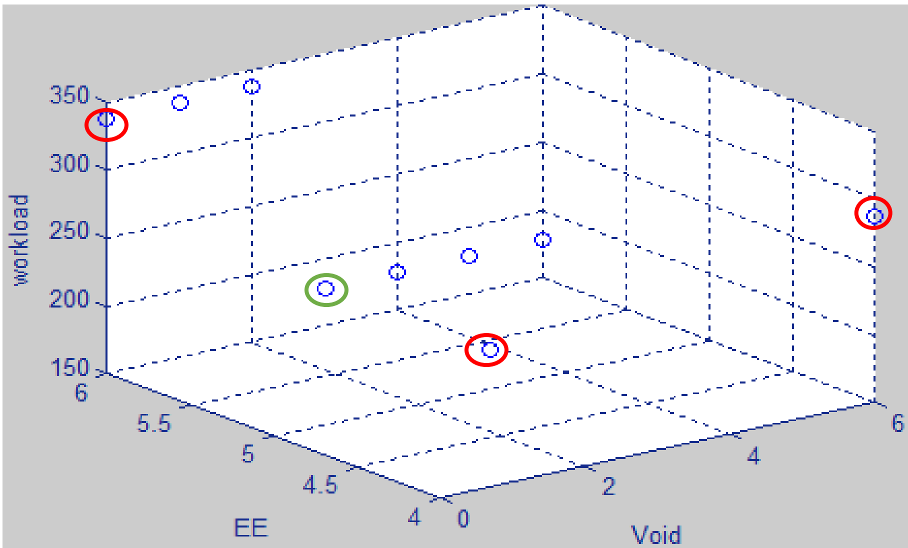

Figure 1 Multi-objective feasible solutions for workload-EE-Void: Pareto-curve (red circles)

	f_1	f_2	f_3	NC
Solution1	177.85	3	5	2
Solution2	388.09	0	6	3
Solution3	286.839	6	4	2

Table 1 the set of efficient solutions

In addition, by using a bi-objective ε-constraint and in order to show the relationship between the selected criteria's, a three combination of two objectives simultaneously (Workload-Void, Workload-Exceptional Elements, Void-Exceptional Elements) detailed in the following figures 2, 3 and 4.

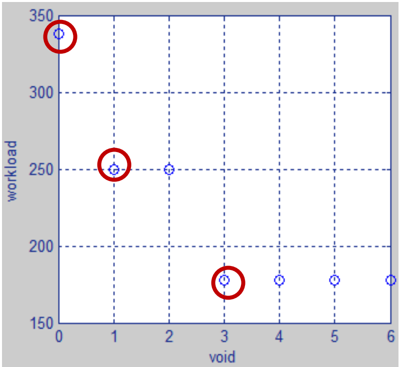

Figure 2 Multi-objective feasible solutions for workload-Void: Pareto-curve (red circles)

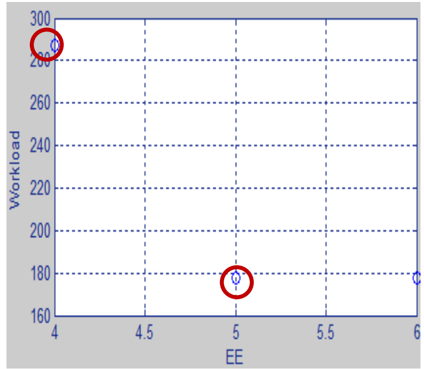

Figure 3 Multi-objective feasible solutions for workload-EE: Pareto-curve (red circles)

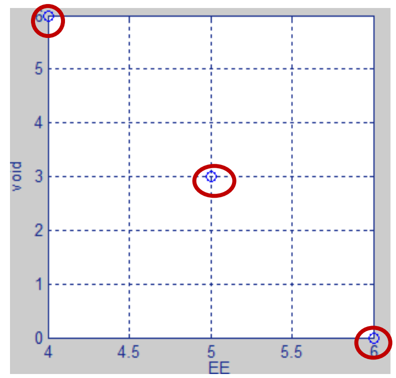

Figure 4 Multi-objective feasible solutions for Void-EE : Pareto-curve (red circles)

These figures show a direct trade-off between the total imblanced workload, the number of voids and the number of Exceptional Elements (EE) also they assured the efficient solutions founded in table1. In addition, from figure1; we show a solution presented by green circle with minimum unbalanced workload = 177.850, number of voids =3 and number of EE=6 which dominates three feasible solutions but in reality it is dominated by a solution which has the value and in the number of voids but a better number of EE.

5. Conclusion

The obtained computational results indicate that the proposed approach can solve cell formation problem with optimal number of cells and provide promising solutions (see. Table1). Therefore, it can be concluded that the proposed approach provides good starting point for multi-objective cell formation problem. For further study, we are planning to develop other scalarization method to make the decision support more useful.

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