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Manufacturing Cell Configuration Considering Worker Interest Concept Applying a Bi-Objective Programming Approach

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KEYWORDS

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Product mix variation;
Worker interest;
Bi-objective programing;
ε-constraint method

ABSTRACT

Generally, human resources play an important role in manufacturing systems as they can affect the work environment. One of the most important factors impressing on worker performance is there being an interactional interest between workers in workshops. In this paper, we deal with this new concept in cellular manufacturing systems (CMS). Besides the existence of interactional interest, workers could be able to work with machines in their cells. In an ideal situation, all workers could be able to work with all machines in their cells, while there would be an interactional interest between each pair of them in the cells. Two matrices named "Task matrix" and "Interest matrix" are used to model the proposed problem. By minimizing the voids of these two matrices in a diagonal form simultaneously, we seek the ideal situation above. Because of nonhemogeneus matrices, a bi-objective mathematical model is developed. The ε-constraint method is applied as an optimization tool to solve the bi-objective model. Finally some numerical examples are solved to exhibit the capability of the presented problem.

1. Introduction

Cellular manufacturing is a practical aspect of grouping technology (GT) philosophy by Mitrifanov (1966), in where similar parts and dissimilar machines are grouped into cells to exploit the cost-effectiveness of mass production and flexibility of job shop manufacturing to succeed in the recent competitive market (Mahdavi et al. 2009). Some advantages of cellular manufacturing are reported in the literature as: better quality and production control, increase in system flexibility, reduction in setup time, throughput time, work-in-process inventories, and material handling costs (Wemmerlov and Hyer 1989; Heragu 1994). Design of cellular manufacturing systems (CMS) is interpreted as the cell formation problem.

In the last three decades of research, many solution methods have mainly used zero–one machine component incidence matrix as the input data for the cell formation problem, such as hierarchical methods, non-hierarchical methods, production flow analysis, genetic algorithms, simulated annealing, neural networks, mathematical models, meta-heuristic algorithms, etc. (Paydar and Saidi-Mehrabad 2013). Comprehensive summaries and taxonomies can be found in Mansouri et al. (2000), Yin and Yasuda (2006), Ghosh et al. (2010 a, b) and Papaioannou and Wilson (2010). Some works on the cell formation problem can be reviewed as the following:

Mahdavi et al. (2009) developed a mathematical model based on cell utilization concept in a CMS. An efficient algorithm based on genetic algorithm was designed to

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solve the mathematical model. Wu et al. (2009) proposed a hybrid heuristic algorithm employing both the Boltzmann function from the simulated annealing and the mutation operator from the genetic algorithm to explore the unvisited solution region and expedite the solution searching process for the cell formation problem, so that grouping efficacy was maximized. Mahdavi et al (2010a) addressed a mathematical model for the joint problem of the cell formation problem and the machine layout. Their objective was to minimize the total cost of inter- and intra-cell (forward and backward) movements and the investment cost of machines. This model also considered the minimum utilization level of each cell to achieve the higher performance of cell utilization.

Noktehdan et al. (2010) proposed a grouping version of differential evolution algorithm and its hybridized version with a local search algorithm to solve benchmarked instances of cell formation problem posing as a grouping problem. Díaz et al. (2010) proposed a greedy randomized adaptive search procedure (GRASP) heuristic to obtain lower bounds for the optimal solution of the cell formation problem. Their method consists of two phases. In the first phase, an initial partition of machines into machine-cells or parts into part families is obtained, while in the second phase, the assignment of parts to machine cells or machines to part-families is considered. Paydar et al. (2010) formulated the cell formation problem as a single depot multiple travelling salesman problem (SDmTSP). Li et al. (2010) proposed an ant colony optimization metaheuristic (ACO-CF) to solve the machine-part cell formation problem.

Arkat et al. (2011) presented a multi-objective programming model with the aim of minimizing the number of exceptional elements and voids, simultaneously. They also developed a bi-objective genetic algorithm for large-scale problems. Egilmez et al. (2012) considered a nonlinear mathematical model to solve the stochastic CMS design problem. The problem was observed in both machine and labor-intensive cells, where the operation times were probabilistic in addition to the uncertain customer demands. They assumed that processing times and customer demands were normally distributed. The objective was to design a CMS with product families that are formed with most similar products and minimum number of cells and machines for a specified risk level. Paydar and Saidi-Mehrabad (2013) presented a hybrid metaheuristic algorithm in which genetic algorithm and variable neighborhood search were combined. Using the grouping efficacy measure, they also compared the performance of the proposed algorithm on a set of 35 test problems from the literature. The results have shown that the proposed GA-VNS method outperforms the state-of-the-art algorithms.

All of these researches consider the cell formation problem for a single time period with known and constant product mix and demand. The concept of dynamic cellular manufacturing systems (DCMS) was a new aspect of cellular manufacturing (CM), which was proposed by Rheault et al (1995) for the first time. In a dynamic environment, a multi-period planning horizon is considered where each period has different demand requirements. For a comprehensive review on DCMS studies, we refer the reader to Balakrishnan & Cheng (2007).

Tavakkoli-Moghaddam et al. (2005) solved the cell formation problem in dynamic condition by using some traditional metaheuristic methods such as genetic algorithm (GA), simulated annealing (SA) and tabu search (TS). Safaei et al. (2008) developed an extended model of DCMS in where the objective was to minimize the sum of the machine constant and variable costs, inter- and intra-cell material handling, and reconfiguration costs. Then, an efficient hybrid meta-heuristic based on mean field annealing (MFA) and simulated annealing (SA) so-called MFA–SA was used to solve the proposed model. Defersha and Chen (2008) addressed a dynamic cell formation problem incorporating several design factors such as cell reconfiguration, alternative routings, sequence of operations, duplicate machines, machine capacity, workload balancing, production cost as well as other realistic constraints.

Ahkioon et al. (2009) developed a preliminary CM model that integrated several manufacturing attributes considering multi-period planning, dynamic system reconfiguration, and production planning and alternate routings. Safaei and Tavakkoli-Moghaddam (2009) extended the original model proposed by Safaei et al. (2008) with a new contribution on the outsourcing by considering the carrying inventory, backorder, partial subcontracting and production planning in a dynamic environment. Khaksar-Haghani et al. (2011) developed Such an integrated DCMS model with an extensive coverage of important design features, which had not been proposed before, and incorporated several manufacturing attributes including alternative process routings, operation sequence, processing time, production volume of parts, purchasing machines, duplicate machines, machine depot, machine capacity, lot splitting, material flow conservation equations, inflation coefficient, cell workload balancing, budget constraints for cell construction and machine procurement, varying number of formed cells, worker capacity constraint, holding inventories and backorders, outsourcing part-operations, warehouse capacity, and cell reconfiguration.

With increased global competition and shorter product life cycles, there is a shift to demands for mid-volume and mid-variety product mixes (Ahkioon et al. 2009). Thus, not only product demand but also product mix can be periodically variable. In the previous researches, even in DCMS, a CM is designed to perform best for a specific product mix. Product mix variations affect the structure of the machine-part incidence matrix, so the performance of the CM will change as well. It is desirable to modify the cellular manufacturing system to meet the new processing requirements effectively. However, for all practical purposes (heavy machines) such a modification is not feasible (Seifoddini and Djassemi 1996). Therefore, it is necessary to primarily configure manufacturing cells just by presence of workers and machines (working teams). Then by appearing the received product mix in each time period, part families can be assigned to the formed working teams. Figure 1 shows the flowchart of the proposed two-phase approach toward cell configuration in presence of product mix variation.

This paper focuses on developing new criteria to configure manufacturing cells just by presence of workers and machines in order to overcome product mix variation difficulties, besides presenting a human resource point of view.

Worker is a self-aware component in industrial systems. Environmental elements can intensively affect the performance of workers. Workshops should be transformed to a friendly environment instead of a strict working one.

In most of the researches on CM, workers are not considered or just assumed as a working element like parts, machines, tools and etc., without any emotion and personality (Min and Shin 1993, Parkin and Li 1997, Li 2003, Mahdavi et al. 2010b, Mahdavi et al. 2012, Rafiei and Ghodsi 2013). Some researchers have considered human aspects of workers in manufacturing systems. Askin and Huang (2001) formulated an integer programming model for an aggregate worker assignment and training problem for use in converting a functionally organized manufacturing environment into a CM arrangement. Suresh and Slomp (2001) also provided a cross-training model and linked team formation to the cell formation problem. Bidanda et al (2005) studied an overview and evaluation of the diverse range of human issues involved in CM based on an extensive literature review. They enumerated eight different and important human issues in cellular manufacturing as: worker assignment strategies, skill identification, training, communication, autonomy, reward/compensation systems, teamwork, and conflict management.

Othman et al. (2012) considered a workforce planning (WP) model including some human aspects such as skills, training, and workers' personalities and motivation. They presented a multi-objective non-linear programming model to minimize the hiring, firing, training, and overtime costs and minimize the number of fired most productive workers. The purpose was to determine the number of workers for each worker type, the number of workers trained, and the number of overtime hours.

The reminder of the paper is organized as the following. In section 2, the proposed problem and assumptions are described in detail. In section 3, the mathematical notations and proposed bi-objective mathematical model are presented. In section 4, the exact ε-constraint method, as a solution method for bi-objective combinatorial problems, has been described. In section 5, some numerical examples are generated randomly in medium scale to show the performance of the proposed bi-objective mathematical model. Finally we conclude this paper in section 6.

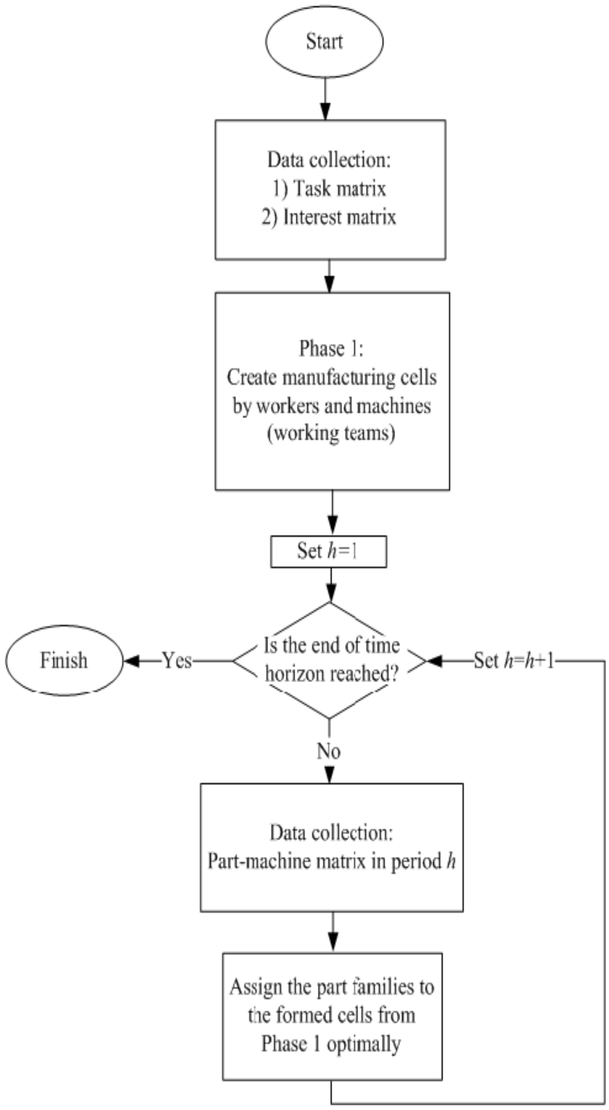


Fig. 1. Flow chart of the proposed method toward cell formation with product mix variation

2. Problem Description

In this paper the relationship between workers and machines is represented by a binary $W \times M$ matrix called *task matrix*, where W is the number of workers and M is the number of machines. The task matrix shows the capability of workers in work with various machines. Moreover, the relations between workers are represented by a binary $W \times W$ matrix called *interest matrix*. The interest matrix shows which pair of workers have interactional interest.

Table 1 shows an instance of task matrix for 7 workers and 5 machines. For example, worker 4 can work with machines 3, 4 and 5. Table 2 presents an interest matrix for 7 proposed workers. Because of interactional consideration for interests, interest matrix becomes an upper-triangular matrix. For example, workers 4 and 6 have an interactional interest, but workers 4 and 5 don't. Making the task and interest matrix is done by filling in a questionnaire by workers about their experts and relations with the others.

Tab. 1. An instance of task matrix

		Machines				
		1	2	3	4	5
Workers	1	1	1	0	0	1
	2	1	1	1	0	0
	3	1	1	0	1	1
	4	0	0	1	1	1
	5	0	0	0	1	1
	6	0	1	1	1	1
	7	1	0	1	1	0

Tab. 2. An instance of interest matrix

		Workers						
		1	2	3	4	5	6	7
Workers	1	1	1	1	1	0	0	1
	2		1	0	0	1	0	0
	3			1	0	1	1	0
	4				1	0	1	1
	5					1	1	0
	6						1	1
	7							1

In an ideal situation and in each cell, all of workers both could be able to work with all of their machines and have interactional interest between each pair of themselves. The first objective (Z_1) is related to the number of voids corresponding to the task matrix and the second one (Z_2) is related to the number of voids corresponding to the interest matrix.

By clustering the workers and machines into the cell as a diagonal form, the voids of both matrices can be calculated. Tables 3 and 4 represent the assignment of workers and machines to the cells for the previous example with the objective functions $Z_1 = 2$ and $Z_2 = 3$.

Minimizing the voids of task matrix causes workers can be capable to work with all machines in their cells, leading the following outcomes:

- Reduce in inter-cell movements of workers between manufacturing cells, which is a time consuming phenomenon.
- Independence of manufacturing cells because of no need for workers from other manufacturing cells.
- Increase in reliability of manufacturing cells in result of their independence. Because in an uncalled for worker absence, his/her left jobs could be continued by other coworkers.

Also minimizing the voids of interest matrix causes all workers in each cell have interactional interest with all coworkers, in where we will expect the following outcomes in long time horizon:

- Making a friendly working environment in each manufacturing cell.
- Increase in worker's cooperation and coordination in each manufacturing cell.
- Exchange of experiments between workers of each manufacturing cell and self-training between them during the time horizon.
- Increase in synergy of manufacturing cells, and finally increase in the system efficiency.

At the end of this section some of the summarized hypotheses of this paper are listed as follows:

- Our attention is restricted to configuration of working teams without part family grouping.
- All workers and machines are unique, so terms "worker type" and "machine type" are not used.
- Workers' interests and skills are assumed to be unchanged during time periods, so interest and task matrices are constant.

Tab. 3. A diagonal form for worker-machine assignment

		Machines				
		1	2	3	4	5
Workers	1	1	1			
	2	1	1			
	3	1	1			
	4			1	1	1
	5			0	1	1
	6			1	1	1
	7			1	1	0

Tab. 4. A diagonal form for worker-worker assignment

		Workers						
		1	2	3	4	5	6	7
Workers	1	1	1	1				
	2		1	0				
	3			1				
	4				1	0	1	1
	5					1	1	0
	6						1	1
	7							1

3. Problem Formulation

3-1. Indices

W : Number of workers
M : Number of machines
K : Number of cells
i : Index of workers $(i = 1,2,..., W)$
j : Index of machines $(j = 1,2,..., M)$
k : Index of cells $(k = 1,2..., K)$

3-2. Parameters

a_{ij} =1 if worker i can work on machine j ; 0 otherwise
$b_{ii'}$ =1 if worker i and i' have interactional interest; 0 otherwise
LB_W : Lower bound for workers to be assigned to each cell
LB_M : Lower bound for machines to be assigned to each cell

3-3. Decision Variables

X_{ik} : 1 if worker i is assigned to cell k ; 0 otherwise
Y_{jk} : 1 if machine j is assigned to cell k ; 0 otherwise

In this section, a bi-objective mathematical model is developed, which the first objective function computes the total number of voids corresponding to task matrix and the second objective function computes the total number of voids corresponding to interest matrix. The nonlinear programming model is proposed below.

3-4. Mathematical Model

$$\text{Min } Z_1 = \sum_{k=1}^{K}\sum_{i=1}^{W}\sum_{j=1}^{M} X_{ik} Y_{jk} (1 - a_{ij}) \tag{1-1}$$

$$\text{Min } Z_2 = \sum_{k=1}^{K}\sum_{i=1}^{W-1}\sum_{i'=i+1}^{W} X_{ik} X_{i'k} (1 - b_{ii'}) \tag{1-2}$$

Subject to:

$$\sum_{k=1}^{K} X_{ik} = 1 \qquad \forall i; \tag{2}$$

$$\sum_{k=1}^{K} Y_{jk} = 1 \qquad \forall j; \tag{3}$$

$$\sum_{i=1}^{W} X_{ik} \geq LB_W \qquad \forall k; \tag{4}$$

$$\sum_{j=1}^{M} Y_{jk} \geq LB_M \qquad \forall k; \tag{5}$$

$$\sum_{k=1}^{K}\sum_{j=1}^{M} X_{ik} Y_{jk} a_{ij} \geq 1 \qquad \forall i; \tag{6}$$

$$X_{ik}, Y_{jk} \in \{0,1\} \qquad \forall i, j, k. \tag{7}$$

The first objective function corresponds to the total number of cases in where a worker cannot work with a machine, and the second objective function represents the total number of cases in where a pair of workers has no interactional interest. Constraint (2) ensures that each worker is assigned to only one cell. Constraint (3) guarantees that each worker is assigned to only one cell. Constraint (4) enforces the lower bound on the number of workers to be assigned to each cell. Constraint (5) enforces the lower bound on the number of machines to be assigned to each cell. Constraint (6) ensures that each worker be able to work with at least one machine on his/ her cell. Constraint (7) specifies that decision variables are binary.

3-5. Linearization of the Proposed Model

Here, we linearize the objective functions and constraint (6) of the mathematical model proposed in section 3.The nonlinear terms are multiplication of binary variables which can be linearized using the auxiliary binary variables H_{ijk} and $G_{ii'k}$. The validity of each linearization is established by lemmas.

Lemma1. First nonlinear part of the objective function and constraint (6) can be linearized with $H_{ijk} = X_{ik} Y_{jk}$, under the following set of constraints:

$$H_{ijk} - X_{ik} - Y_{jk} + 1.5 \geq 0 \qquad \forall i, j, k; \tag{8}$$

$$1.5 H_{ijk} - X_{ik} - Y_{jk} \leq 0 \qquad \forall i, j, k. \tag{9}$$

Proof1. Consider the following two cases:
Case1. $X_{ik} Y_{jk} = 1$, $\forall i, j, k.$
Such a situation arises when $X_{ik} = Y_{jk} = 1$. So, constraint (8) implies $H_{ijk} \geq 0.5$, ensuring that $H_{ijk} = 1$.
Case2. $X_{ik} Y_{jk} = 0$, $\forall i, j, k.$
Such a situation arises under one of the following three subcases:

(a) $X_{ik} = 1$ and $Y_{jk} = 0$ $\forall i, j, k;$
(b) $X_{ik} = 0$ and $Y_{jk} = 1$ $\forall i, j, k;$
(c) $X_{ik} = 0$ and $Y_{jk} = 0$ $\forall i, j, k.$

In all of these subcases, we have $H_{ijk} = 0$, because constraint (9) implies $1.5 H_{ijk} \leq 0\, or 1$, to ensure that $H_{ijk} = 0$.
Since H_{ijk} does not have a strictly positive cost coefficient, the minimizing objective function does not ensure that $H_{ijk} = 0$. Thus, constraint (9) should be added to the mathematical model.

Lemma2. Second nonlinear part of the objective function can be linearized with $G_{ii'k} = X_{ik} X_{i'k}$, under the following set of constraints:

$$G_{ii'k} - X_{ik} - X_{i'k} + 1.5 \geq 0 \qquad \forall i, i', k,\ i < i'; \qquad (10)$$

$$1.5G_{ii'k} - X_{ik} - X_{i'k} \leq 0 \qquad \forall i, i', k,\ i < i'. \qquad (11)$$

Proof2. The proof is similar to proof1.

3-6. Linearized Model

Now, we present the linear mathematical model as follows:

$$\text{Min } Z_1 = f(x) = \sum_{k=1}^{K}\sum_{i=1}^{W}\sum_{j=1}^{M} H_{ijk}(1 - a_{ij}) \qquad (12\text{-}1)$$

$$\text{Min } Z_2 = g(x) = \sum_{k=1}^{K}\sum_{i=1}^{W-1}\sum_{i'=i+1}^{W} G_{ii'k}(1 - b_{ii'}) \qquad (12\text{-}2)$$

Subject to:
(2) – (5), (8)-(11) and

$$\sum_{k=1}^{K}\sum_{j=1}^{M} a_{ij} H_{ijk} \geq 1 \qquad \forall i; \qquad (13)$$

$$X_{ik}, Y_{jk}, H_{ijk}, G_{ii'k} \in \{0,1\} \qquad \forall i, i', k,\ i < i'. \qquad (14)$$

4. Solution Method

Bi-objective combinatorial optimization (BOCO) problems are a special case of the multi-objective optimization problems (MOPs). There has been variety range of methods tackling with the MOPs in the literature. Collette and Siarry (2003) have classified these methods into five sets: scalar methods, interactive methods, fuzzy methods, methods using metaheuristics, decision aid methods. Rezaei-Sadrabadi and Sadjadi (2009) believe MOPs can be divided into four different categories as: scalarization methods, utility functions, Pareto solution set approaches, and interactive methods.

General BOCO problems are formulated as:

$$\begin{aligned}&\text{Min } h(x) = (f(x), g(x))\\ &\text{such that } x \in X,\end{aligned} \qquad (15)$$

where X is the set of feasible solutions, or the solution space. The reader is referred to Ehrgott and Gandibleux (2002) for a review of the literature on MOPs. Among the methods to find the Pareto front of MOPs, weighted sum scalarization is the most popular according to Ehrgott and Gandibleux (2002). This method solves different single objective sub problems generated by a linear scalarization of the objectives. By varying the weights of this linear function, all supported non-dominated points can be found. Besides weighting sum algorithms, the ε-constraint method is the best known approach for solving MOPs, according to Ehrgott and Gandibleux (2002). This method generates single objective sub problems, called ε-constraint problems, by transforming all but one objectives into constraints. The upper bounds of these constraints are given by the ε-vector and, by varying it; the exact Pareto front can theoretically be generated. In practice, because of the high number of sub problems and the difficulty to establish an efficient variation scheme for the ε-vector, this approach has mostly been integrated within heuristic and interactive schemes. It can however generate the exact Pareto front in particular situations.

4-1. The Exact ε-Constraint Method for BOCO problems

The ε-constraint is probably the best known technique to solve multi-objective discrete optimization problems. It guarantees the exact set of the efficient solutions. It solves ε-constraint problems $P_k(\varepsilon)$ obtained by transforming one of the objectives into a constraint. This method was introduced by Haimes et al. (1971), and an extensive discussion can be found in Chankong and Haimes (1983). For the bi-objective case, the problems $P_1(\varepsilon_2)$ and $P_2(\varepsilon_1)$ are:

$$\begin{aligned}&\text{Min } f(x)\\ &\text{Such that } x \in X \qquad P_1(\varepsilon_2)\\ &g(x) \leq \varepsilon_2\end{aligned} \qquad (16)$$

$$\begin{aligned}&\text{Min } g(x)\\ &\text{Such that } x \in X \qquad P_2(\varepsilon_1)\\ &f(x) \leq \varepsilon_1.\end{aligned} \qquad (17)$$

Theorem3. x^* is an efficient solution of a BOCO problem if and only if $\exists \varepsilon_2$ such that x^* solves $P_1(\varepsilon_2)$ or $\exists \varepsilon_1$ such that x^* solves $P_2(\varepsilon_1)$.

Throrem4. If x^* solves $P_1(\varepsilon_2)$ or $P_2(\varepsilon_1)$ and if the solution is unique, then, x^* is an efficient solution of a BOCO problem.

Theorems 1 and 2 have been proved for general multi-objective problems (see Chankong and Haimes 1983; Miettinen1999) and are therefore valid for the BOCO problems. These theorems mean that efficient solutions can always be found by solving ε-constraint problems, as long as ε_2 is such that $P_1(\varepsilon_2)$ is feasible or ε_1 is such that $P_2(\varepsilon_1)$ is feasible. Let the objective space be defined by $Z = \{(Z_1, Z_2) : Z_1 = f(x), Z_2 = g(x), \forall x \in X\}$ and $Z^I = \{(Z_1^I, Z_2^I) : Z_1^I = \min Z_1, Z_2^I = \min Z_2\}$ being the ideal points and $Z^N = (Z_1^N, Z_2^N)$: $Z_1^N = \min\{Z_1 : Z_2 = Z_2^I\}$, $Z_2^N = \min\{Z_2 : Z_1 = Z_1^I\}$ being the nadir points defining the lower and upper bounds on the value of efficient solutions, respectively.

Algorithm 1 below finds the Pareto front of BOCO problems with integer objective values through a sequence of ε-constraint problems. In the algorithm, ε_j is decreased by a constant value Δ (here set to 1). As explained later, Δ may sometimes be larger to strengthen the ε-constraint method.

Algorithm1. Exact Pareto front of BOCO problems with integer objective values.

1. Set $i=1, j=2$ or $i=2, j=1$.
2. Compute the ideal and nadir points.
3. Set $F=(Z_i^I, Z_j^N)$ and $\varepsilon_j = Z_j^N - \Delta(\Delta=1)$.
4. While $\varepsilon_j \geq Z_j^I$ do
   a. Solve $P_i(\varepsilon_j)$ by branch-and-cut and add the optimal solution (Z_i^*, Z_j^*) to F.
   b. Set $\varepsilon_j = Z_j^* - \Delta$.
5. Remove dominated points from F if required.

5. Computational Results

In this section four numerical examples are presented to illustrate the proposed bi-objective model using branch-and-bound method by the Lingo 9 software package on an Intel® Core (TM) i52.4 GHz Personal Computer with 4 GB RAM, and windows 7 Professional Operating System.

Input data for task and interest matrices are shown in Tables 5-8. The minimum size of each cell for workers and machines is assumed to be 1. After performing Algorithm 1, computational results and Pareto solution set obtained, are presented in Table 9. W, M and K represent the number of workers, machines and cells, respectively. CPU time for each example is calculated by summation of CPU times where Lingo software package is executed for various iterations. In ε-constraint method the number of iterations for each example is more than points in Pareto solution set. Also Figure 2 presents a schematic for Pareto frontier of the examples.

For each point in Pareto solution set, there is a specific assignment of workers and machines to cells. Due to the large volume of computational results, we restrict our attention to Example 2. The Pareto optimal solutions are found to be:

1. The first Pareto point is $Z_1^*=0$ and $Z_2^*=10$ with the assignment as shown in Table10.
2. The second Pareto point is $Z_1^*=1$ and $Z_2^*=6$ with the assignment as shown in Table11.
3. The third Pareto point is $Z_1^*=2$ and $Z_2^*=4$ with the assignment as shown in Table12.
4. The forth Pareto point is $Z_1^*=3$ and $Z_2^*=3$ with the assignment as shown in Table13.
5. The final Pareto point is $Z_1^*=7$ and $Z_2^*=2$ with the assignment as shown in Table14.

One of drawbacks of ε-constraint method is generating dominated points in some of iterations. Figure 3 shows the primal solutions generated form steps (1)-(4) of Algorithm 1, and then according to step (5), dominated points are removed in Figure 4.

Every point in Pareto solution set can be applied by the decision maker (DM). In other words Pareto based multi-objective solution approaches provide a set of efficient solutions in which DM has an opportunity to choose his preferred solution among the efficient ones.

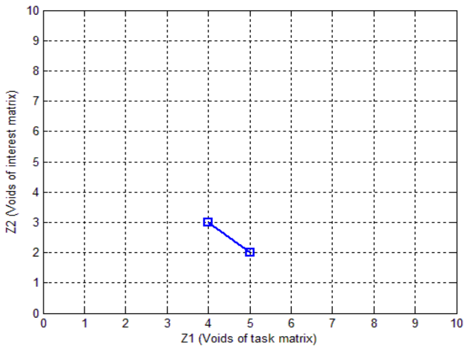
As discussed in section 4, the ε-constraint method is an exact approach to solve the bi-objective problems and in some cases, finds the efficient Pareto solution set. In this method Δ plays an important role in convergence of the obtained Pareto set to the optimal Pareto set and more Δ decreases, more the Pareto set converges at the optimal Pareto one.

In this paper, two objective functions have a discrete solution space and integer values because of their non-fractional variable coefficients (all variable coefficients are one), so we are confident about setting $\Delta=1$ leads to the optimal Pareto solution set, because the upper bound of the second function decreases one by one, and thus all the solution space points can be reached. Instead, setting $\Delta=1$ causes more iteration for ε-constraint method and on the other hand most of iterations lead a dominated point. So for large scale examples, a balance between Pareto front with high quality and low iteration must be designed.

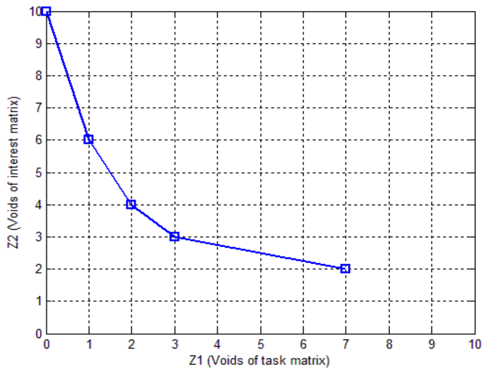
Tab. 5. Input data for example No. 1 (Left: Task matrix, Right: Interest matrix)

	Machine					
Worker	1	0	0	1	1	0
	0	0	0	1	1	1
	1	1	0	1	0	0
	1	0	1	0	0	1
	0	1	1	0	1	0
	0	1	1	0	0	1

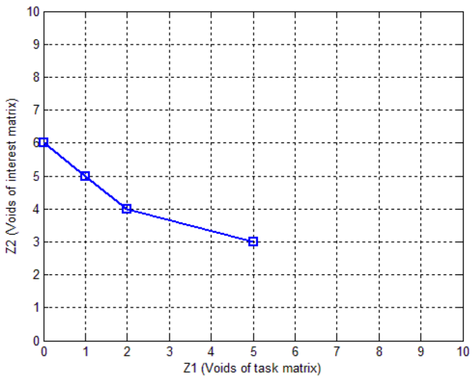
	Worker					
Worker	1	0	1	1	0	0
	0	1	0	0	1	1
	1	0	1	0	1	0
	1	0	0	1	0	1
	0	1	1	0	1	0
	0	1	0	1	0	1



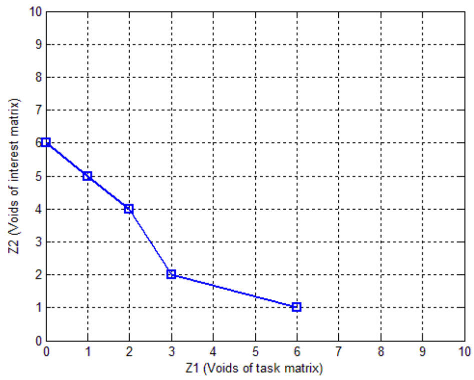
(a). Example No.1



(b). Example No.2



(c). Example No.3



(d). Example No.4

Fig. 2. Obtained Pareto solution set by ε-constraint method for the examples

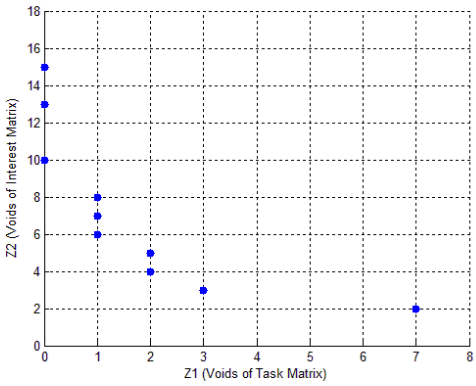


Fig. 3. The primal solutions for Example 2

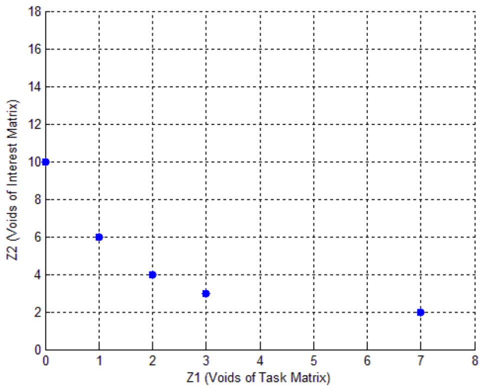


Fig. 4. The final Pareto frontier for Example 2

Tab. 6. Input data for example No. 2 (Left: Task matrix, Right: Interest matrix)

	Machine								
	1	1	1	0	1	0	0	1	1
	1	0	1	1	0	0	0	1	0
	0	1	1	0	1	1	1	1	1
	1	1	0	1	0	1	0	1	0
Worker	1	0	1	0	0	1	1	0	0
	0	1	1	0	0	0	0	0	0
	0	0	1	0	1	1	1	0	1
	1	0	1	0	1	1	0	1	0
	1	1	1	1	0	0	1	0	0

	Worker								
	1	0	0	1	0	0	0	0	1
	0	1	0	1	0	0	1	1	0
	0	0	1	0	0	0	1	0	0
	1	1	0	1	0	1	0	0	0
Worker	0	0	0	0	1	0	0	1	1
	0	0	0	1	0	1	0	0	0
	0	1	1	0	0	0	1	0	0
	0	1	0	0	1	0	0	1	1
	1	0	0	0	1	0	0	1	1

Tab. 7. Input data for example No. 3 (Left: Task matrix, Right: Interest matrix)

Left: Task matrix (rows: Worker; columns: Machine)

1	0	0	1	0	1	1	0	1	0	0	1
1	0	1	0	1	1	0	0	0	1	0	0
0	0	0	0	1	0	1	1	1	1	1	0
1	1	1	0	0	1	1	1	0	0	0	0
0	1	1	1	0	0	1	1	0	0	1	0
1	1	1	1	0	1	0	0	0	1	1	1
0	0	1	1	1	0	0	1	1	1	1	1
1	1	1	0	1	0	0	1	0	1	1	0
0	1	0	1	1	1	0	0	0	0	0	0
1	1	1	1	0	1	1	1	1	0	0	0
1	1	1	1	1	0	1	0	1	0	1	0
1	0	1	1	0	1	1	0	1	0	0	0

Right: Interest matrix (rows: Worker; columns: Worker)

1	1	0	0	1	0	0	1	0	0	0	0
1	1	1	0	0	0	0	0	1	1	1	0
0	1	1	0	0	0	0	0	0	0	1	0
0	0	0	1	0	0	0	0	0	1	0	1
1	0	0	0	1	0	0	0	0	0	1	1
0	0	0	0	0	1	0	0	1	1	0	1
0	0	0	0	0	0	1	0	0	1	0	1
1	0	0	0	0	0	0	1	1	0	0	0
0	1	0	0	0	1	0	1	1	0	1	0
0	1	0	1	0	1	1	0	0	1	0	0
0	1	1	0	1	0	0	0	1	0	1	0
0	0	0	1	1	1	1	0	0	0	0	1

Tab. 8. Input data for example No. 4 (Left: Task matrix, Right: Interest matrix)

Left: Task matrix (rows: Worker; columns: Machine)

1	0	1	0	0	0	1	0	0	0	1	0	0	1	0
1	1	1	0	1	0	1	1	0	0	1	1	1	0	1
0	1	1	0	0	1	0	1	1	1	0	0	0	0	1
1	0	0	0	1	0	0	1	0	1	1	0	0	0	1
1	1	0	0	1	0	1	0	0	1	0	0	1	1	0
0	0	1	0	1	0	1	1	0	0	0	1	1	0	0
0	1	0	1	0	1	0	0	0	0	0	1	1	1	0
1	1	1	1	0	1	1	1	0	1	1	1	0	1	0
1	1	0	1	1	1	0	0	1	0	1	0	1	0	1
0	0	0	0	1	0	1	0	0	1	0	0	0	0	1
0	0	1	0	1	0	1	1	0	1	1	0	0	1	1
1	1	0	0	1	0	0	0	0	1	0	0	0	1	0
1	1	0	1	1	1	0	0	1	1	0	1	1	0	1
1	1	0	0	0	1	1	1	0	1	0	1	1	1	0
1	0	0	1	0	0	1	0	1	0	0	1	0	0	0

Right: Interest matrix (rows: Worker; columns: Worker)

1	0	0	1	1	0	0	1	1	0	1	1	0	1	1
0	1	0	0	1	0	1	1	0	1	0	0	0	1	0
0	0	1	0	1	0	0	1	1	0	1	0	1	0	1
1	0	0	1	0	1	1	0	1	0	0	0	1	1	0
1	1	1	0	1	0	0	0	0	1	1	1	0	1	0
0	0	0	1	0	1	0	0	0	1	0	1	0	0	0
0	1	0	1	0	0	1	0	1	0	1	0	1	0	1
1	1	1	0	0	0	0	1	0	1	0	1	0	0	1
1	0	1	1	0	0	1	0	1	0	0	1	0	0	0
0	1	0	0	1	1	0	1	0	1	0	0	1	1	0
1	0	1	0	1	0	1	0	0	0	1	0	0	1	1
1	0	0	0	1	1	0	1	1	0	0	1	1	0	0
0	0	1	1	0	0	1	0	0	1	0	1	1	1	0
1	1	0	1	1	0	0	0	0	1	1	0	1	1	0
1	0	1	0	0	0	1	1	0	0	1	0	0	0	1

Tab. 9. Obtained numerical results for ε-constraint method

No.	***W***	***M***	***K***	***Constraints***	***Decision variables***	***CPU time** (sec)*	***Pareto solution set*** Z_1	Z_2
1	6	6	2	313	170	7	4	3
							5	2
2	9	9	3	1008	542	458	0	10
							1	6
							2	4
							3	3
							7	2
3	12	12	4	2351	1250	6,316	0	6
							1	5
							2	4
							5	3
4	15	15	5	4558	2402	9,409	0	6
							1	5
							2	4
							3	2
							6	1

To illustrate setting $\Delta > 1$ decreases the quality of Pareto solution set, we execute the ε-constraint method this time with $\Delta = 2$ for Example 2 again. After removing the dominated points, the Pareto solution set is obtained with point set of $\{(0,11),(1,6),(2,4),(7,2)\}$. These points are shown in Figure 5. As we can see, just point set of $\{(1,6),(2,4),(7,2)\}$ are common in two Pareto solution sets. Point (0, 11) is dominated by point (0, 10) and also the Pareto archive in Figure 5 is sparser than what in Figure 4, because of absence of point (3, 3). Thus, it can be concluded that the ε-constraint method with lower amounts of Δ leads to more efficient Pareto solution set, and for our problem with discrete solution space and integer variable coefficients, setting $\Delta = 1$ causes the optimal Pareto frontier.

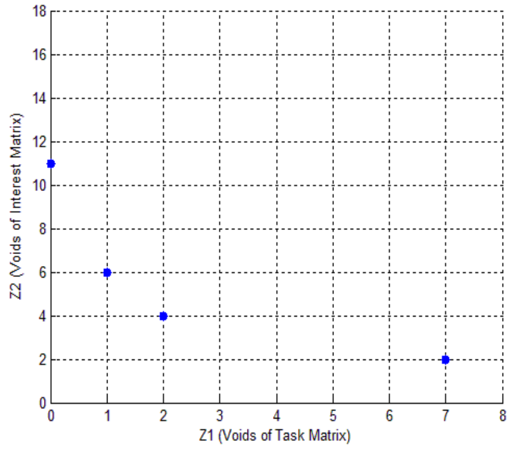


Fig. 5. Pareto points for Example 2 with $\Delta = 2$

Tab. 10. Machine-worker arrangement corresponding to Pareto point (0, 10) for example No. 2

Worker \ Machine	3	1	2	4	8	5	6	7	9
1	1	1	1	0	1	1	0	0	1
2	1	1	0	1	1	0	0	0	0
5	1	1	0	0	0	0	1	1	0
6	1	0	1	0	0	0	0	0	0
8	1	1	0	0	1	1	1	0	0
9	1	1	1	1	0	0	0	1	0
4	0	1	1	1	1	0	1	0	0
3	1	0	1	0	1	1	1	1	1
7	1	0	0	0	0	1	1	1	1

Worker \ Worker	1	2	5	6	8	9	4	3	7
1	1	0	0	0	0	1	1	0	0
2	0	1	0	0	1	0	1	0	1
5	0	0	1	0	1	1	0	0	0
6	0	0	0	1	0	0	1	0	0
8	0	1	1	0	1	1	0	0	0
9	1	0	1	0	1	1	0	0	0
4	1	1	0	1	0	0	1	0	0
3	0	0	0	0	0	0	0	1	1
7	0	1	0	0	0	0	0	1	1

Tab. 11. Machine-worker arrangement corresponding to Pareto point (1, 6) for example No. 2

Worker \ Machine	1	2	4	8	5	6	7	9	3
2	1	0	1	1	0	0	0	0	1
4	1	1	1	1	0	1	0	0	0
3	0	1	0	1	1	1	1	1	1
7	0	0	0	0	1	1	1	1	1
1	1	1	0	1	1	0	0	1	1
5	1	0	0	0	0	1	1	0	1
6	0	1	0	0	0	0	0	0	1
8	1	0	0	1	1	1	0	0	1
9	1	1	1	0	0	0	1	0	1

Worker \ Worker	2	4	3	7	1	5	6	8	9
2	1	1	0	1	0	0	0	1	0
4	1	1	0	0	1	0	1	0	0
3	0	0	1	1	0	0	0	0	0
7	1	0	1	1	0	0	0	0	0
1	0	1	0	0	1	0	0	0	1
5	0	0	0	0	0	1	0	1	1
6	0	1	0	0	0	0	1	0	0
8	1	0	0	0	0	1	0	1	1
9	0	0	0	0	1	1	0	1	1

Tab. 12. Machine-worker arrangement corresponding to Pareto point (2, 4) for example No. 2

Worker \ Machine	5	6	7	9	1	2	4	8	3
3	1	1	1	1	0	1	0	1	1
7	1	1	1	1	0	0	0	0	1
1	1	0	0	1	1	1	0	1	1
2	0	0	0	0	1	0	1	1	1
4	0	1	0	0	1	1	1	1	0
5	0	1	1	0	1	0	0	0	1
6	0	0	0	0	0	1	0	0	1
8	1	1	0	0	1	0	0	1	1
9	0	0	1	0	1	1	1	0	1

Worker \ Worker	3	7	1	2	4	5	6	8	9
3	1	1	0	0	0	0	0	0	0
7	1	1	0	1	0	0	0	0	0
1	0	0	1	0	1	0	0	0	1
2	0	1	0	1	1	0	0	1	0
4	0	0	1	1	1	0	1	0	0
5	0	0	0	0	0	1	0	1	1
6	0	0	0	0	1	0	1	0	0
8	0	0	0	1	0	1	0	1	1
9	0	0	1	0	0	1	0	1	1

Tab. 13. Machine-worker arrangement corresponding to Pareto point (3, 3) for example No. 2

Worker \ Machine	2	8	1	4	3	5	6	7	9
1	1	1	1	0	1	1	0	0	1
4	1	1	1	1	0	0	1	0	0
6	1	0	0	0	1	0	0	0	0
2	0	1	1	1	1	0	0	0	0
5	0	0	1	0	1	0	1	1	0
8	0	1	1	0	1	1	1	0	0
9	1	0	1	1	1	0	0	1	0
3	1	1	0	0	1	1	1	1	1
7	0	0	0	0	1	1	1	1	1

Worker \ Worker	1	4	6	2	5	8	9	3	7
1	1	1	0	0	0	0	1	0	0
4	1	1	1	1	0	0	0	0	0
6	0	1	1	0	0	0	0	0	0
2	0	1	0	1	0	1	0	0	1
5	0	0	0	0	1	1	1	0	0
8	0	0	0	1	1	1	1	0	0
9	1	0	0	0	1	1	1	0	0
3	0	0	0	0	0	0	0	1	1
7	0	0	0	1	0	0	0	1	1

Tab. 14. Machine-worker arrangement corresponding to Pareto point (7, 2) for example No. 2

Worker \ Machine	4	5	6	9	1	3	7	2	8
2	1	0	0	0	1	1	0	0	1
3	0	1	1	1	0	1	1	1	1
7	0	1	1	1	0	1	1	0	0
5	0	0	1	0	1	1	1	0	0
8	0	1	1	0	1	1	0	0	1
9	1	0	0	0	1	1	1	1	0
1	0	1	0	1	1	1	0	1	1
4	1	0	1	0	1	0	0	1	1
6	0	0	0	0	0	1	0	1	0

Worker \ Worker	2	3	7	5	8	9	1	4	6
2	1	0	1	0	1	0	0	1	0
3	0	1	1	0	0	0	0	0	0
7	1	1	1	0	0	0	0	0	0
5	0	0	0	1	1	1	0	0	0
8	1	0	0	1	1	1	0	0	0
9	0	0	0	1	1	1	1	0	0
1	0	0	0	0	0	1	1	1	0
4	1	0	0	0	0	0	1	1	1
6	0	0	0	0	0	0	0	1	1

6. Conclusions

In this paper, we investigated a new concept of there being an interactional interest between workers in a manufacturing cell besides the ability to work with all machines in their cells, and presented a bi-objective mathematical model to carry out this new point of view in CMS. This bi-objective mathematical model tried to decrease voids of both task and interest matrices in each cell, simultaneously. To find the optimal Pareto frontier, the ε-constraint method was applied for some randomly generated examples. The ε-constraint method is a repetitive algorithm and sometimes causes part of CPU time is consumed to generate dominated points, so this method is not efficient for large scale examples. Hence as the future related works, implementation of alternative solution approaches is much needed. Recently some of extensions of the ε-constraint, such as the augmented ε-constraint method and also multi-objective evolutionary algorithms (MOEA) are efficiently alternative approaches to handle ε-constraint difficulties.

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