

Designing robust layout in cellular manufacturing systems with uncertain demands**Kamran Forghani^a, Mohammad Mohammadi^{b*} and Vahidreza Ghezavati^c**^a*M.S. Student of Department of Industrial Engineering, Faculty of Engineering, Kharazmi University, Karaj, Iran*^b*Assistant Professor, Department of Industrial Engineering, Faculty of Engineering, Kharazmi University, Karaj, Iran*^c*Assistant Professor, Islamic Azad University, South Tehran Branch, Tehran, Iran***CHRONICLE****ABSTRACT***Article history:*

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In this paper, a new robust approach is presented to handle demand uncertainty in cell formation and layout design process. Unlike the scenario based approaches, which use predefined scenarios to represent data uncertainty, in this paper, an interval approach is implemented to address data uncertainty for the part demands, which is more realistic and practical. The objective is to minimize the total inter- and intra-cell material handling cost. The proposed model gives machine cells and determines inter-and intra-cell layouts in such a way that the decision maker can control the robustness of the layout against the level of conservatism. An illustrative example is solved by CPLEX 10 to demonstrate the performance of the proposed method. The results reveal that when the level of conservatism is changed the optimal layout can vary, significantly.

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1. Introduction

Group technology (GT) is a manufacturing theory, which attempts to increase production efficiency by grouping products having similar attributes and manufacturing processes. Similar parts are classified into part families and manufactured by clusters of dissimilar machines. Cellular Manufacturing system (CMS) is a practical application of GT, which determines part families and machine cells known as cell formation (CF) problem, to attain some manufacturing characteristics. In CMSs, the flexibility of job shop manufacturing for producing different products is considered to the efficiency of flow line manufacturing to increase production outputs (Mungwattana, 2000). According to Wemmerlöv and Hyer (1989), the main improvements derived from cellular manufacturing (CM) are reductions in throughput time, in material handling, in setup time and improvement in the production quality.

Classical CF problems minimize the number of inter-cellular movements of parts (Chiang & Lee, 2004). However, during the past two decades, other issues such as production planning (Kioon et al., 2009; Khaksar-Haghani et al., 2011), scheduling (Solimanpur et al., 2004; Wu et al., 2007b), layout

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(Chiang & Lee, 2004; Wu et al., 2007; Jolai et al., 2012), uncertainty (Mungwattana, 2000; Saidi-Mehrabad & Ghezavati, 2009), etc. have been incorporated in the CM design. Survey papers by Yin and Yasuda (2006), Papaioannou and Wilson (2010) and Ghosh et al. (2011) summarized good reviews on current approaches, solution procedures and directions for future researches.

Facilities layout is one of the key areas in a manufacturing system, which has a direct influence on the operational performance, as measured by manufacturing lead time, throughput rate and work-in-process (Benjaafar, 2002). Tompkins et al. (2003) estimated that 20–50% of the manufacturing costs are due to the handling parts and an efficient arrangement of facilities could reduce expenditures up to 30%. The interaction among various cells due to exceptional elements, parts require processing on machines in two or more cells, is a major barrier to maintain the benefits of CMS (Arıkan & Güngör, 2009). Therefore, the layout problem in CMSs should be designed, efficiency. In the context of layout problem in designing CMSs, Aktürk and Turkcan (2000) developed a heuristic algorithm with three main stages to form machine cells and obtain the layout of machines. The first two stages are to form independent machine cells, completely and to obtain intra-cell layout. In the third stage, we decrease additional machine investment expenditures by allowing inter-cell movements of parts.

Chiang and Lee (2004) addressed the joint problem of manufacturing CF and its layout assignment, where machine cells are located along the bi-directional linear layout. The primary objective is to minimize the inter-cell flow cost, instead of minimizing the number of inter-cell movements. Simulated annealing (SA) (Haddad et al., 2012; Kazemipoor et al., 2012) approach is combined with dynamic programming algorithm to solve the resulted problem. Chan et al. (2006) proposed a two-stage method to solve CF problem as well as cell layout problem. The first stage was to detect machine cells and part families and the second stage is to arrange the layout sequence of machine cells, formed in the first stage. Both problems, presented in the first and second stages were solved by genetic algorithm (GA).

Wu et al. (2007) presented an approach to concurrently make the CF, group layout and group scheduling decisions. A hierarchical GA was developed to solve the proposed problem. Mahdavi et al. (2008) proposed a matrix based heuristic to design an efficient CF and layout. Ahi et al. (2009) implemented the multiple attribute decision making concept and proposed a two-stage technique to determine CF, inter-and intra-cell layouts. Khaksar-Haghani et al. (2011) presented a mathematical model to integrate CF, group layout and group scheduling decisions in designing multi-floor CM.

Shorter product life-cycle, higher product variety, unpredictable demand, and shorter delivery times have caused manufacturing systems to operate under dynamic and uncertain environments (Mungwattana, 2000). In practice, costs, demands, processing times, set-up times and other inputs for manufacturing systems may be highly uncertain so that these could significantly influence the production processes in the manufacturing systems. Manufacturing systems ought to be able to adapt/respond to such changes and uncertainties quickly with reasonable investment and operating costs. Addressing data uncertainty in designing CMSs is relatively new class of CMS problems. In this way, Mungwattana (2000) developed a model for designing CMSs by assuming dynamic and stochastic production requirements and employing routing flexibility and simulated annealing (SA) was used to solve the proposed model. Tavakkoli-Moghaddam et al. (2007) presented a mathematical model to solve a facility layout problem in CMSs with stochastic demands by assuming that CF is first completed and known a priori. In this model, depending on the level of uncertainty, the optimal layout in CMSs can change, significantly.

Ghezavati and Saidi-Mehrabad (2009) addressed a mathematical model for CMS integrated with group scheduling in an uncertain space. Discrete scenarios were used to describe stochastic processing time of parts on machines by assuming that all parts in a part family could be processed in the same cell and no inter-cellular transfer is required. This model aims to minimize the total expected cost consisting maximum tardiness cost among all parts, cost of subcontracting for exceptional elements and the cost

of resource underutilization. A hybrid method based on combination of GA and SA was implemented to solve such a stochastic model. Arıkan and Güngör (2009) presented a multi-objective fuzzy mathematical model with fuzzy part demand, machine capacity and the EEs' elimination costs. The objective functions were minimization of the cost of EE elimination, minimization of the number of inter-cell operations and maximization of the utilized machine capacity. The proposed model gives the decision maker alternative decision plans for various grades of precision. Kia et al. (2011) presented a mathematical model for the layout design of dynamic CMSs with fuzzy uncertain demands and machine time-capacities. The disadvantage of this method was that it gives only one decision plan for the fuzzy parameters in various risk levels. Ghezavati and Saidi-Mehrabad (2011) implemented queuing system theory to formulate data uncertainty in designing CMSs with exponentially distributed inter-arrival and processing times. A hybrid method based on GA and SA was employed to solve the problem.

As was mentioned, the efficiency of CMSs depends on the structure of cells and arrangement of machines within the cells, significantly. In this paper, a new mathematical model is developed to form machine cells and determine inter-and intra-cell layouts under an uncertain environment while designing CMSs, concurrently. The uncertainty stems from part demands. Unlike the scenario based approaches, which use predefined scenarios to represent uncertainty, the proposed model of this paper uses an interval approach to address data uncertainty for part demands, which is more realistic and practical. The problem is formulated as a mixed-integer non-linear programming model to minimize the total inter-and intra-cell material handling cost, and then linearization methods are used to transform the resulted problem into a linear mathematical model. Sim's (2004) approach is applied to handle the uncertainty for the problem formulation and control the robustness of the layout against the level of conservatism. Finally, an illustrative example is solved by CPLEX 10 to demonstrate the efficiency of the proposed approach.

2. Robust optimization

In recent years, a body of literature has been developed under the name of robust optimization, in which we seek a solution, which remains feasible and near-optimal under the perturbation of parameters for the optimization problem. To address data uncertainty, Mulvey et al. (1995) presented an approach, which integrates goal optimization formulations with scenario-based description of the problem data. Kouvelis and Yu (1997) proposed a framework for robust discrete optimization, which seeks to find a solution, which minimizes the worst case performance under a set of scenarios for the data. Unfortunately, under their approach, the robust counterpart of many polynomially solvable discrete optimization problems becomes NP-hard; moreover, the scenario-based approaches may not be practical for some real-world cases. Soyster (1973) proposed a linear optimization model to obtain a solution, which is feasible for all data belonging to a convex set. The Soyster's method produces solutions, which are too conservative in the sense that we give up too much optimality for the nominal problem to ensure robustness. To overcome such problem, Ben-Tal and Nemirovski (2000) presented a non-linear robust model under ellipsoidal uncertainty sets, that is less conservative than the Soyster's model. However, A practical drawback of Ben-Tal and Nemirovski's approach is that it leads to non-linear, although convex, models and consequently the difficulty of the robust problem increases.

Sim (2004) proposed methodologies in robust optimization, which cover a broad range of mathematical optimization problems, including linear optimization, quadratic constrained quadratic optimization, general conic optimization including second order cone programming and semidefinite optimization, mixed integer optimization, network flows and 0-1 discrete optimization. Sim's approach retains the same complexity class as the original model and allows the decision maker to vary the level of conservatism of the robust solutions in terms of probabilistic bounds of constraint violations, while keeping the problem tractable.

In this section, we present a robust approach developed by Sim (2004) for discrete optimization problems with uncertain parameters in the objective function. This approach allows to control the degree of conservatism of the solution. Let c be n -vector and X be the feasible space. Without loss of generality, it is assumed that data uncertainty influences only the elements on the matrix c . Each entity c_j , $j \in N$ independently takes values in $[c_j, c_j + d_j]$, where d_j represents the deviation from the nominal coefficient c_j . Consider the following nominal mixed-integer programming (MIP) problem on a set of n variables:

$$\begin{aligned} \min c'x \\ \text{Subject to: } x \in X \end{aligned} \quad (1)$$

In practice, it is unlikely that all of the c_j , $j \in N$ will change. The goal is to be protected against all cases in which up to Γ_0 of these coefficients are allowed to change. Therefore, we are interested in finding an optimal solution, which optimizes against all scenarios under which a number Γ_0 of the c_j , $j \in N$ can vary in such a way that maximally influences the objective function. Let $J = \{j | d_j > 0\}$; therefore the robust counterpart of problem (1) can be written as follows:

$$\begin{aligned} \min c'x + \max_{\{S | S \subseteq J, |S| \leq \Gamma_0\}} \left\{ \sum_{j \in S} d_j |x_j| \right\} \\ \text{Subject to: } x \in X \end{aligned} \quad (2)$$

In model (2), parameter Γ_0 takes value in the interval $[0, |J|]$ and adjusts the level of robustness in the objective function. If $\Gamma_0 = 0$, the influence of the deviations are completely ignored and the problem becomes the same as the nominal problem, while if $\Gamma_0 = |J|$, all possible deviations are considered, which is indeed more conservative. Sim (2004) showed that problem (2) is equivalent to the following MIP model:

$$\begin{aligned} \min c'x + z_0 \Gamma_0 + \sum_{j \in J} p_j \\ \text{Subject to: } x \in X \\ z_0 + p_j \geq d_j x_j, \quad \forall j \in J \\ p_j \geq 0, \quad \forall j \in J \\ z_0 \geq 0 \end{aligned} \quad (3)$$

As it can be seen, no auxiliary integral variable has been used in problem (3); thus, if the nominal problem can be solved in a polynomial time, its robust problem can also be solved, polynomially. This robust framework is used as the basis of this research to formulate our problem and it has been used in other areas, significantly (Roghalian & Foroughi, 2010; Moghadam, & Seyedhosseini, 2010)

3. Problem statement and formulation

The single line (flow line) facility layout problem is considered when multi-products with various production volume and different process routings need to be manufactured (El-Baz, 2004). It is a common layout type implemented in the layout design of CMSs; see Chiang and Lee (2004), Chan et al. (2006) and Jolai et al. (2012). In this paper, we assume that machines, within each cell, are arranged along a linear flow line on the equally spaced locations by considering cell size limit. In addition, machine cells are sequentially placed in multiple rows. Furthermore, it is assumed that cell locations are approximately equally spaced. The proposed layout approach is demonstrated in Fig. 1. In this approach, each row represents a machine cell and each column represents machine locations. Parts are transferred among machines based on their operation sequences.

Sets

- i parts index $i = 1, \dots, P$ (P is the total number of parts)
- o operations index $j = 1, \dots, Op_i$ (Op_i is the number of operations of part i)
- k, k' machines index $k, k' = 1, \dots, M$ (M is the total number of machines)
- l, l' cells index $l = 1, \dots, C^{max}$ (C^{max} is the maximum number of cells allowed)
- m location index $m = 1, \dots, NM$ (NM is the maximum number of machines permissible in a cell)

Parameters

- d_i nominal demand of part i
- dv_i deviation from the nominal demand of part i
- $c_{ikk'}^{Intra}$ unit intra-cell material handling cost for transporting part i between machines k and k'
- $c_{ikk'}^{Inter}$ unit inter-cell material handling cost for transporting part i between machines k and k'
- a_{ijk} 1 if j -th operation of part i needs to machine k ; 0 otherwise
- $f_{ikk'}$ number of times that an operation at machine k immediately follows an operation at machine k' , or vice-versa, for part i
- w_m width of the center of location m
- h_l height of the center of cell l
- $TMHC$ the total material handling cost
- BM an arbitrary large number

Decision variables

- z_{kl}^y =1 if machine k is assigned to cell (row) l ; 0 otherwise
- z_{km}^x =1 if machine k is assigned to location (column) m ; 0 otherwise

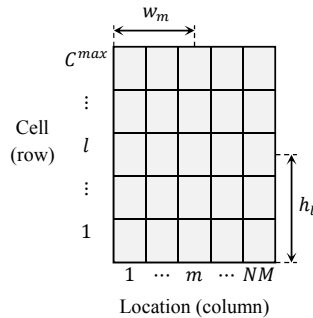


Fig. 1. Proposed approach for arrangement of machines within the cells

In order to approximate w_m and h_l for the problem we can use the following equations:

$$w_m = (m - 1)(\bar{w} + ld^{intra}) + \frac{\bar{w}}{2}, \quad \forall m, \tag{4}$$

$$h_l = (l - 1)(\bar{h} + ld^{inter}) + \frac{\bar{h}}{2}, \quad \forall l, \tag{5}$$

where \bar{w} and \bar{h} are the average width and height of machines respectively, ld^{intra} is the spacing between machines and ld^{inter} is the spacing between cells.

3.1. Mathematical model

According to the descriptions given above, the problem can be formulated as the following mixed-integer non-linear programming model:

$$\begin{aligned}
\min TMHC = & \sum_{\substack{i \\ k' > k}} d_i \cdot f_{ikk'} \cdot c_{ikk'}^{Intra} \left| \sum_m w_m (z_{km}^x - z_{k'm}^x) \right| \left(\sum_l z_{kl}^y \cdot z_{k'l}^y \right) \\
& + \sum_i d_i \cdot f_{ikk'} \cdot c_{ikk'}^{Inter} \left| \sum_m w_m (z_{km}^x - z_{k'm}^x) \right| \left(1 - \sum_l z_{kl}^y \cdot z_{k'l}^y \right) \\
& + \sum_{\substack{i \\ k' > k \\ l' > l}} d_i \cdot f_{ikk'} \cdot c_{ikk'}^{Inter} (h_{l'} - h_l) (z_{kl}^y \cdot z_{k'l'}^y + z_{k'l}^y \cdot z_{kl'}^y)
\end{aligned} \tag{6}$$

subject to:

$$\sum_l z_{kl}^y = 1, \quad \forall k, \tag{7}$$

$$\sum_m z_{km}^x = 1, \quad \forall k, \tag{8}$$

$$\sum_k z_{kl}^y \cdot z_{km}^x \leq 1, \quad \forall l, m, \tag{9}$$

$$z_{km}^x \in \{0,1\}, \quad \forall k, m, \tag{10}$$

$$z_{kl}^y \in \{0,1\}, \quad \forall k, l, \tag{11}$$

where $f_{ikk'}$ is calculated as follows:

$$f_{ikk'} = \sum_{j=1}^{op_{i-1}} (a_{ijk} \cdot a_{ij+1k'} + a_{ijk'} \cdot a_{ij+1k}), \quad \forall i, k' > k, \tag{12}$$

Objective function (6) minimizes the total material handling cost, where the first term is the total intra-cell handling cost and the remaining terms are correspond to the total inter-cell handling cost. Constraints (7) and (8) enforce that each machine is assigned to one cell and one location respectively. In addition, constraint (9) ensures that each location is occupied by at most one machine. Finally, the binary restriction on the decision variables is given in constraints (10) and (11).

3.2. Model linearization

Since the proposed model is non-linear (due to the presence of the absolute and product terms in objective function (6) and constraint (9)), and non-linear models are usually much harder to solve for optimality than linear models, thus in this section we reformulate the problem as a MIP model. In order to linearize objective function (6) we introduce new sets of variables $dx_{kk'}$ to $Z_{kk'l}^y$ to replace as $|\sum_m w_m (z_{km}^x - z_{k'm}^x)|$ and $z_{kl}^y \cdot z_{k'l}^y$, respectively, also constraints (17)–(21) are added to the model. So, objective function (6) can be written as follows:

$$\begin{aligned}
\min TMHC = & \sum_{\substack{i \\ k' > k}} d_i \cdot f_{ikk'} \cdot dx_{kk'} \left(c_{ikk'}^{Intra} \left(\sum_l Z_{kk'l}^y \right) + c_{ikk'}^{Inter} \left(1 - \sum_l Z_{kk'l}^y \right) \right) \\
& + \sum_{\substack{i \\ k' > k \\ l' > l}} d_i \cdot f_{ikk'} \cdot c_{ikk'}^{Inter} (h_{l'} - h_l) (z_{kl}^y \cdot z_{k'l'}^y + z_{k'l}^y \cdot z_{kl'}^y)
\end{aligned} \tag{13}$$

Now, we introduce new sets of variables $\gamma_{ikk'}$ and $\delta_{kk'll'}$ to replace the $dx_{kk'} \left(c_{ikk'}^{Intra} (\sum_l Z_{kk'l}^y) + c_{ikk'}^{Inter} (1 - \sum_l Z_{kk'l}^y) \right)$ and $z_{kl}^y \cdot z_{k'l'}^y + z_{k'l}^y \cdot z_{kl}^y$ product terms respectively; also, constraints (15), (16) and (21)–(23) are added to the model, in order to linearize Eq. (13). Finally, constraint (9) is linearized by introducing a new set of variables Z_{klm}^{xy} to replace the $z_{kl}^y \cdot z_{km}^x$ product term, and adding constraints (24) and (25) to the model. The linearized model is shown below.

$$\min TMHC = \sum_{\substack{i \\ k' > k}} d_i \cdot f_{ikk'} \cdot \gamma_{ikk'} + \sum_{\substack{i \\ k' > k \\ l' > l}} d_i \cdot f_{ikk'} \cdot c_{ikk'}^{Inter} (h_{l'} - h_l) \delta_{kk'll'} \tag{14}$$

subject to: (7), (8), (10) and (11)

$$\gamma_{ikk'} \geq c_{ikk'}^{Intra} \cdot dx_{kk'} - BM \left(1 - \sum_l Z_{kk'l}^y \right), \quad \forall i, k' > k, \tag{15}$$

$$\gamma_{ikk'} \geq c_{ikk'}^{Inter} \cdot dx_{kk'} - BM \sum_l Z_{kk'l}^y, \quad \forall i, k' > k, \tag{16}$$

$$dx_{kk'} \geq \sum_m w_m (z_{km}^x - z_{k'm}^x), \quad \forall k' > k, \tag{17}$$

$$dx_{kk'} \geq \sum_m w_m (z_{k'm}^x - z_{km}^x), \quad \forall k' > k, \tag{18}$$

$$Z_{kk'l}^y \geq z_{kl}^y, \quad \forall k' > k, l, \tag{19}$$

$$Z_{kk'l}^y \geq z_{k'l}^y, \quad \forall k' > k, l, \tag{20}$$

$$Z_{kk'l}^y \geq z_{kl}^y + z_{k'l}^y - 1, \quad \forall k' > k, l, \tag{21}$$

$$\delta_{kk'll'} \geq z_{kl}^y + z_{k'l'}^y - 1, \quad \forall k' > k, l' > l, \tag{22}$$

$$\delta_{kk'll'} \geq z_{k'l}^y + z_{kl'}^y - 1, \quad \forall k' > k, l' > l, \tag{23}$$

$$\sum_k Z_{klm}^{xy} \leq 1, \quad \forall l, m, \tag{24}$$

$$Z_{klm}^{xy} \geq z_{km}^x + z_{kl}^y - 1, \quad \forall k, l, m, \tag{25}$$

$$dx_{kk'} \geq 0, \quad \forall k' > k, \tag{26}$$

$$\gamma_{ikk'} \geq 0, \quad \forall i, k' > k, \tag{27}$$

$$\delta_{kk'll'} \geq 0, \quad \forall k' > k, l' > l, \tag{28}$$

$$Z_{kk'}^y \geq 0, \quad \forall k' > k, \tag{29}$$

$$Z_{klm}^{xy} \geq 0, \quad \forall k, l, m, \tag{30}$$

3.3. Robust model

In this section, we present a mathematical model, which is robust to demand changes. It is assumed that the uncertainty only affects the demand of parts in which the uncertain demand of each part takes values in the interval $[d_i, d_i + dv_i]$. According to the robust framework presented in Section 2, the robust counterpart of the problem presented in Subsection 3.2, is as follows:

$$\min TMHC = \sum_i d_i \cdot g_i + Z_0 \cdot \Gamma_0 + \sum_i p_i \tag{31}$$

subject to: (7), (9), (10), (11) and (15)–(30)

$$g_i = \sum_{\substack{i \\ k' > k}} f_{ikk'} \left(\gamma_{ikk'} + \sum_{l' > l} c_{ikk'}^{Inter} (h_{l'} - h_l) \delta_{kk' ll'} \right), \quad \forall i, \quad (32)$$

$$Z_0 + p_i \geq dv_i g_i, \quad \forall i, \quad (33)$$

$$Z_0, \Gamma_0 \geq 0 \quad (34)$$

$$p_i \geq 0 \quad (35)$$

In the above model, parameter Γ_0 takes values in the interval $[0, |i| = P]$ and adjusts the level of robustness in the objective function. In general, a higher values of Γ_0 increases the level of robustness at the expense of higher nominal cost.

4. Illustrative example

In this section, to validate the proposed model and illustrate its various features, an example is solved by CPLEX 10.0 on a PC with 2.4 GHz CPU and 1 GB RAM. The example consists of 20 part types and 10 machine types. The main inputs, including operation sequences, uncertain demand of parts and unit inter- and intra-cell handling costs have been included in Table 1. The machines are to be grouped into 3 cells with the capacity of 4 machines in each cell (i.e. $C^{max} = 3$ and $NM = 4$). The average width and height of machines (\bar{w} and \bar{h}) are assumed to be 2 and 1.5 units respectively. Also the spacing between machines in the same cell (ld^{Intra}) and the spacing between cells (ld^{Inter}) are assumed to be 1.5 and 3 units respectively. Eq. (4) and Eq. (5) are used to calculate w_m and h_l for the problem.

Table 1

Input parameter for numerical example

Part	Operation sequences					Nominal demand (d_i)	Deviation from nominal demand (dv_i)	Unit intra-cell handling cost ($c_{i,k,k'}^{Intra}, \forall k' > k$)	Unit inter-cell handling cost ($c_{i,k,k'}^{Inter}, \forall k' > k$)
1	9	10	4			0	10	6.6	8.9
2	2	3	9	7		10	5	3.9	6.0
3	3	1	10	2		15	15	3.9	6.9
4	3	9	10	7	4	15	5	5.6	8.5
5	10	8	6	1	9	20	10	3.3	6.0
6	5	7	3	9		5	15	5.1	7.7
7	9	10	8			0	20	6.7	9.4
8	3	4	2			20	5	4.1	6.7
9	6	1	9	10		5	10	5.7	8.3
10	8	9	3	6		10	15	3.8	5.9
11	3	5	9	4		15	5	3.4	6.2
12	1	3	7	2		5	15	6.4	8.7
13	9	10	1			0	10	6.1	8.9
14	9	4	10	3		5	5	6.4	8.7
15	1	9	6	10		10	5	4.4	7.2
16	1	8	10	2	7	5	15	6.6	8.9
17	1	9	2	10		20	10	4.7	6.9
18	10	8	1	2		0	25	6.8	9.8
19	1	10	8			10	15	4.5	7.0
20	3	1	4	2		15	15	4.2	6.6

This example was investigated by considering various values of conservatism (i.e. $\Gamma_0 \in [0,20]$), to verify the behavior of the model. The problem was solved optimally within 14,348 seconds for all values of Γ_0 (on average 683 seconds for each level of Γ_0). The relationship between the total material handling cost and level of conservatism has been plotted in Fig. 2. In addition, the machine cells as well as arrangement of machines within the cells for various values of Γ_0 has been illustrated in Fig. 3. The results show that 7 different solutions can be produced for this problem when we change the level of conservatism. In addition, from Fig. 3 we figure out that depending on the level of conservation, the optimal solution is changed, significantly.

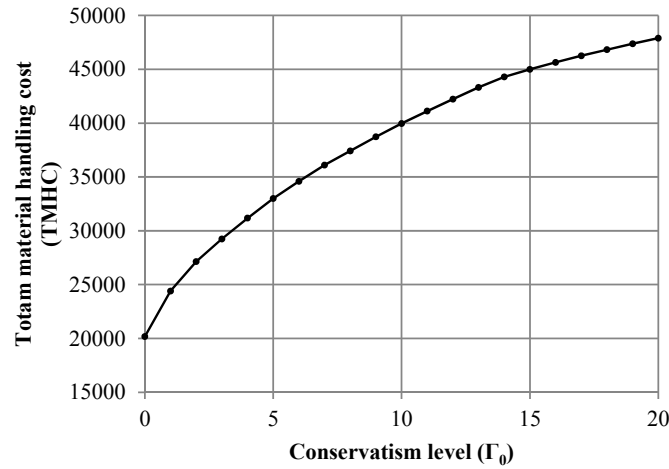


Fig. 2. Behavior of the objective function in terms of various values of Γ_0

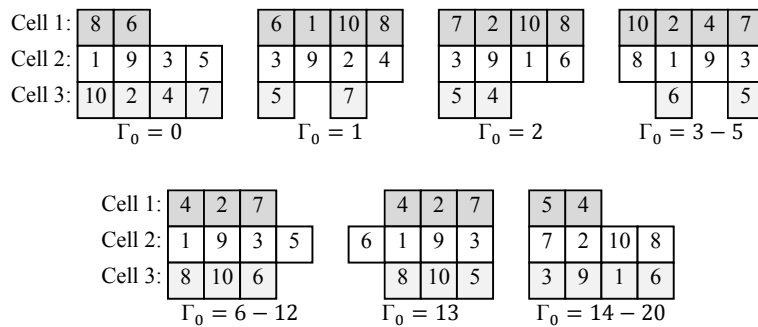


Fig. 3. Obtained solutions for various values of Γ_0

5. Conclusion

In this study, a new approach was presented to design CMSs with uncertain demands. The primary objective of this paper was to form machine cells and obtain inter-and intra-cell layouts, in such a way that the decision maker was able to control the robustness of the solution against the level of conservatism. The problem was formulated as a mixed-integer non-linear programming model to minimize total material handling costs, and then the linearization procedures were applied to linearize it. To illustrate the proposed approach, a numerical example was solved for various grades of conservatism. The results revealed that depending on the attitude of the decision maker towards conservatism the optimal solution can change, significantly.

For the proposed approach of this paper, it was assumed that the uncertainty only arises from part demands; however, in real-world problems, other parameters such as processing times, capacity of machines, etc. may be uncertain and can be considered along alternative processing routings in the problem formulation. In addition, employing metaheuristics such as GA, SA, etc. for efficiently solving large-scale problems in a reasonable computational time is a suitable research area for interested researchers.

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References

- Ahi, A., Aryanezhad, M.B., Ashtiani, B., & Makui, A. (2009). A novel approach to determine cell formation, intracellular machine layout and cell layout in the CMS problem based on TOPSIS method. *Computers and Operations Research*, 36, 1478–1496.
- Aktür, M.S., & Turkcan, A. (2000). Cellular manufacturing system design using a holonistic approach. *International Journal of Production Research*, 38, 2327–2347.
- Arikan, F., & Güngör, Z. (2009). Modeling of a manufacturing cell design problem with fuzzy multi-objective parametric programming. *Mathematical and Computer Modelling*, 50, 407–420.
- Benjaafar, S. (2002). Modeling and analysis of congestion in the design of facility layouts. *Management Science*, 48, 679–704.
- Ben-Tal, A., & Nemirovski, A. (2000). Robust solutions of Linear Programming problems contaminated with uncertain data. *Mathematical Programming*, 88, 411–424.
- Chan, F.T.S., Lau, K.W., Chan, P.L.Y., & Choy, K.L. (2006). Two-stage approach for machine-part grouping and cell layout problems. *Robotics and Computer-Integrated Manufacturing*, 22, 217–238.
- Chiang, C.P. & Lee, S.D. (2004). Joint determination of machine cells and linear intercell layout. *Computers and Operations Research*, 31, 1603–1619.
- El-Baz, M.A. (2004). A genetic algorithm for facility layout problems of different manufacturing environments. *Computers & Industrial Engineering*, 47, 233–246.
- Ghezavati, V.R., & Saidi-Mehrabad, M. (2011). An efficient hybrid self-learning method for stochastic cellular manufacturing problem: A queuing-based analysis. *Expert Systems with Applications*, 38, 1326–1335.
- Ghezavati, V.R., & Saidi-Mehrabad, M. (2010). Designing integrated cellular manufacturing systems with scheduling considering stochastic processing time. *International Journal of Advanced Manufacturing Technology*, 48(5-8), 701-717.
- Ghosh, T., Sengupta, S., Chattopadhyay, M., & Dan, P.K. (2011). Meta-heuristics in cellular manufacturing: A state-of-the-art review. *International Journal of Industrial Engineering Computations*, 2, 87–122.
- Haddad, H., Mohammadi, H., & Pooladkhan, H. (2012). Two models for the generalized assignment problem in uncertain environment. *Management Science Letters*, 2(2), 623–630.
- Jolai, F., Tavakkoli-Moghaddam, R., Golmohammadi, A., & Javadi, B. (2012). An Electromagnetism-like algorithm for cell formation and layout problem. *Expert Systems with Applications*, 39, 2172–2182.

- Kazemipoor, H., Tavakkoli-Moghaddam, R., & Shahnazari-Shahrezaei, P. (2012). Solving a mixed-integer linear programming model for a multi-skilled project scheduling problem by simulated annealing. *Management Science Letters*, 2(2), 681–688.
- Khaksar-Haghani, F., Kia, R., Javadian, N., Tavakkoli-Moghaddam, R., & Baboli, A. (2011). A comprehensive mathematical model for the design of a dynamic cellular manufacturing system integrated with production planning and several manufacturing attributes. *International Journal of Industrial Engineering & Production Research*, 22, 199–212.
- Khaksar-Haghani, F., Kia, R., Mahdavi, I., Javadian, N., & Kazemi, M. (2011). Multi-floor layout design of cellular manufacturing systems. *International Journal of Management Science and Engineering Management*, 6, 356–365.
- Kia, R., Paydar, M.M., Jondabeh, M.A., Javadian, N., & Nejatbakhsh, Y. (2011). A fuzzy linear programming approach to layout design of dynamic cellular manufacturing systems with route selection and cell reconfiguration. *International Journal of Management Science and Engineering Management*, 6, 219–230.
- Kioon, S.A., Bulgak, A.A., & Bektas, T. (2009). Integrated cellular manufacturing systems design with production planning and dynamic system reconfiguration. *European Journal of Operational Research*, 192, 414–428.
- Kouvelis, P., & Yu, G. (1997). *Robust discrete optimization and its applications*, Kluwer Academic Publishers, Norwell, MA.
- Mahdavi, I., Shirazi, B., & Paydar, M.M. (2008). A flow matrix-based heuristic algorithm for cell formation and layout design in cellular manufacturing system. *International Journal of Advanced Manufacturing Technology*, 39, 943–953.
- Moghadam, B.F., & Seyedhosseini, S.M. (2010). A particle swarm approach to solve vehicle routing problem with uncertain demand: A drug distribution case study. *International Journal of Industrial Engineering Computations*, 1(1), 55-66.
- Mulvey, J., Vanderbei, R., & Zenios, S. (1995). Robust optimization of large-scale systems. *Operations Research*, 43, 264–281.
- Mungwattana, A. (2000). *Design of cellular manufacturing systems for dynamic and uncertain production requirements with presence of routing flexibility*. Ph.D. thesis submitted to the Faculty of the Virginia Polytechnic Institute and State University, Blackburg, VA.
- Papaioannou, G., & Wilson, J.M. (2010). The evolution of cell formation problem methodologies based on recent studies (1997–2008): review and directions for future research. *European Journal of Operational Research*, 206, 509–521.
- Roghianian, E., Foroughi, A. (2010). An empirical study of iranian regional airports using robust data envelopment analysis. *International Journal of Industrial Engineering Computations*, 1(1), 65-72.
- Saidi-Mehrabad, M., & Ghezavati, V.R. (2009). Designing cellular manufacturing systems under uncertainty. *Journal of Uncertain Systems*, 3, 315–320.
- Sim, M. (2004). *Robust Optimization*. Ph.D. thesis submitted to the Sloan School of Management at the Massachusetts Institute of Technology, MA.
- Solimanpur, M., Vrat, P., & Shankar, R. (2004). A heuristic to minimize makespan of cell scheduling problem. *International Journal of Production Economics*, 88, 231–241.
- Soyster, A.L. (1973). Convex programming with set-inclusive constraints and applications to inexact linear programming. *Operations Research*, 21, 1154–1157.

- Tavakkoli-Moghaddam, R., Javadian, N., Javadi, B., & Safaei, N. (2007). Design of a facility layout problem in cellular manufacturing systems with stochastic demands. *Applied Mathematics and Computation*, 184, 721–728.
- Tompkins, J.A., White, J.A., Bozer, Y.A., & Tanchoco, J.M.A. (2003). *Facilities planning*, 3rd Ed, John Wiley and Sons, NY.
- Wemmerlöv, U., & Hyer, N.L. (1989). Cellular manufacturing in the US industry: A survey of users. *International Journal of Production Research*, 27, 1511–1530.
- Wu, X., Chu, C.H., Wang, Y., & Yan, W. (2007). A genetic algorithm for cellular manufacturing design and layout. *European Journal of Operational Research*, 181, 156–167.
- Wu, X., Chu, C.H., Wang, Y., & Yue, D. (2007). Genetic algorithms for integrating cell formation with machine layout and scheduling. *Computers and Industrial Engineering*, 53, 277–289.
- Yin, Y., & Yasuda, K. (2006). Similarity coefficient methods applied to the cell formation problem: a taxonomy and review. *International Journal of Production Economics*, 101, 329–352.