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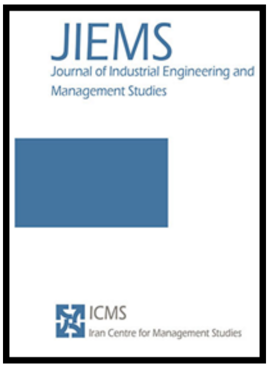

Bi-objective robust optimization model for configuring cellular manufacturing system with variable machine reliability and parts demand: A real case study

Hiwa Farughi[1,*], Sobhan Mostafayi[1], Ahmadreza Afrasiabi[1]

Abstract

In this paper, a bi-objective mixed-integer mathematical model is presented for configuration of a dynamic cellular manufacturing system. In this model, dynamic changes and uncertainty in parts demand and machines reliability are considered. The first objective function minimizes total costs and the second one maximizes the machines reliability through minimizing machines failure. In addition, some routes are considered to produce each part based on operational requirements. An appropriate route is selected respect to the costs and operational time. Some parameters are considered under uncertainty in two categories. The first category such as demand is dependent on market condition and the uncontrolled competitive environment. The second one includes some parameters for production system and machines that are directly related to plans organized by production management. A robust optimization approach is used to deal with parameters uncertainty to produce feasible and optimal solutions. Furthermore, for validation and implementation of results in real world, a case study is investigated. Computational results show that the robust model reports better values for objective functions compared to the scenario-based model. In fact, Pareto-front which are resulted by robust model are dominated by scenario-based models' Pareto front. Sensitivity analyses on main parameters of the problem are performed to drive some managerial insights that help corresponding decision makers to provide suitable and homogenous decisions in a production system.

Keywords: Dynamic cellular manufacturing system; Bi-objective mathematical model; Machine reliability; Robust optimization.

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1. Introduction

Cellular manufacturing system (CMS) is a well-known approach for improving a manufacturers' productivity and competitiveness by providing low-cost, high-quality, customized products with small lot sizes within the shortest possible lead time. (Askin & Estrada, 1999; Wemmerlöv & Hyer, 1989; Wemmerlov & Johnson, 1997) identify advantages of CMS and explain how it can improve a manufacturing organization's in overall system performance. While the benefits of CMS implementation are well documented, such systems

* Corresponding author; h.farughi@uok.ac.ir
[1] University of Kurdistan, Department of Industrial Engineering, Sanandaj, Iran.

are not without drawbacks (Agarwal & Sarkis, 1998). The main problems are machine breakdown and reliability issues. Dedicating machines and part families to specific manufacturing cells in CMSs provides reductions in setup time. However, ultimately decreases planning flexibility – especially in the case of machine breakdowns (Seifoddini & Djassemi, 2001). Machines are an essential component in a CMS and delays due to machine breakdowns affect the production rate and lead to scheduling problems and finally decrease in the manufacturing operation's overall productivity. Hence, it is very critical to consider explicit of machine reliability when making cell formation decisions and during the operation allocation process. However, ignoring expenses is caused by these disturbances lead to increased production costs. Therefore, we should utilize an approach that considers both costs and reliability simultaneously. Machines are subjected to deterioration caused by usage and age in any dynamic manufacturing environment (H. Wang, 2002). Actually, machines reliability in dynamic manufacturing environments is changed in different production periods with regard to increase in age and running time. Also, with consideration of market condition and customer need within the different periods amount and type of parts demand are different. While organizations perform preventive maintenance to restrict or slow down machine deterioration, decreasing in machine reliability with increasing age and running time are inevitable. On the other hand, data related to one period is not useful for future periods. To achieve the expected performance levels for present and future periods, these dynamic changes must be considered for designing and formation of CMS. Another important point in designing the manufacturing environment and dynamic marketing is the fluctuation in part demand and part mixing. A manufacturing system that does not such considerations in design eventually needs a redesign and reconfiguration. On the other hand, relocating machines to adjust cells configuration is difficult and inefficient (Bedworth, Henderson, & Wolfe, 1991). Therefore, it is ideal to design a robust manufacturing cell for consideration of expected changes in parts demand in long periods. So, operational cost and costs result from installing machines is reached to at minimum level.

Based on the above discussion, fluctuations consideration in parts demand and reliability and dynamic changes from each period to another period has a notable impact in total cost and appropriate performance of CMS. In this research, a mixed integer bi-objective model is represented for configuration of CMS which considers dynamic predictable changes in machines reliability and parts demand within different periods of time. The goals of problem include minimizing system overall costs and maximizing machines reliability through minimizing their failures. Also, for manufacturing of each part some routes are considered according to its operational requirement. Which based on cost and operation time, the appropriate rout is selected.

One of the most important problems in manufacturing system design, is lack of capability to appropriate prediction of necessary parameters in manufacturing. These changes sometimes cause a lot of disruptions for managers and affect system efficiency. Therefore, using robust programming approach to deal with uncertainty leads the system has lowest risk in planning. To achieve this goal and proper planning by means of decision makers, in this study some of most effective manufacturing parameters are proposed under uncertainty conditions, and a robust optimization approach is used.

The structure of this research is proposed in 7 sections. In section 2 previous studies are investigate in the form of literature review. In section 3 machines reliability calculation is presented. Problem definition and mathematical model formulation are presented in section 4. In section 5, robust programming approach is described. In section 6 computational results of PISHGAMAN PICH PARS Company are investigated as case study. Finally, the conclusion and the future suggestions are represented in section 7.

2. Literature review

The majority of research done in cellular manufacturing systems in last two decades focus on configuration development of effective cell with consideration of improving productivity and competitiveness. Also, the number of studies that discuses the dynamic changes in machine reliability on cellular manufacturing system are limited. Some of the most important researches in these field are including (Vakharia & Kaku, 1993) that proposed a mixed integer mathematical model for designing CMS that consider parts reallocation problem with dynamic changes in parts demand and part mixing in multi period planning horizon. Moreover, (Wicks & Reasor, 1999) proposed a mixed integer programming model for designing CMS with consideration dynamic changes in parts demand and part mixing in multi period planning horizon. (Safaei, Saidi-Mehrabad, Tavakkoli-Moghaddam, & Sassani, 2008) proposed a new mathematical model which part demand and facility availability are considered as fuzzy parameters. They developed a new method based on fuzzy programming for solving extend mixed integer model to solve dynamic cell formation. (Safaei & Tavakkoli-Moghaddam, 2009) proposed an extended fuzzy parametric programming approach to solve dynamic cell formation with considering uncertainty in parts demand and machines capacity. (X. Wang, Tang, & Yung, 2009) proposed a nonlinear multi objective mathematical model for dynamic cell formation through assigning weights into three conflicting goals which including minimizing moving costs in reconfiguration cells, maximizing machine capacity utilization rate and minimizing intracellular movement within planning horizon. (Mahdavi, Aalaei, Paydar, & Solimanpur, 2010) present an integer programming model for designing cellular manufacturing system in a dynamic environment. The advantage of their model is considering multi-period production planning, reconfiguration of dynamic system, duplicate machinery, machine capacity, labor availability time and assigning labor. (Reza Kia et al., 2012) investigate a non-linear mixed integer programming model for designing layout of dynamic CMS which product mix and parts demand are different within multi-period planning horizon. They considered three important decisions in designing cellular manufacturing system including: 1) Cell formation, 2) Group layout and 3) Group scheduling. Also, (R Kia, Khaksar-Haghani, Javadian, & Tavakkoli-Moghaddam, 2014) introduce a mixed integer model for layout designing for multiple classes of cellular manufacturing systems in a dynamic environment. Novelties of their model is determining cell configuration simultaneously and group layout as related decisions in CMS which their objective is to achieve optimal scheme in multi period planning horizon. (Erenay, Suer, Huang, & Maddisetty, 2015) proposed a mathematical programming method to design a multi-layered cellular system in environment with uncertain demand. Their research goal is to extend a mathematical model to minimize manufacturing cells cost. (Renna & Ambrico, 2015) proposed a dynamic CMS with reconfiguration machines for controlling market disturb condition which present an approach including three mathematical model for designing, reconfiguration and manufacturing system scheduling. (Yılmaz & Erol, 2015) represented a programming model for reconfiguration of flexible manufacturing cells. They considered different factors such as demand changes, part mix, part diversity, existed routes and operation times. (Han, Zhang, Sun, & Xu, 2006) analysed reliability in flexible cellular manufacturing by using fuzzy error tree so that their basis is triangular membership function. (K Das, Lashkari, & Sengupta, 2007) introduced a preventive maintenance model for developing CMS performance with consideration of machines reliability and utilization of resource, the proposed model is based on combining cost and reliability approach. Also in the following (Das & Abdul-Kader, 2011) represented an integer multi objective programming model with the purpose of designing a cellular manufacturing system. So that within a multi - period planning horizon with consideration of dynamic changes in machine reliability and part demand remains optimal. (Ameli & Arkat, 2008) developed a pure linear integer programming model for machine cells configuration with production amount and process scheduling of parts. Also, they considered In addition to alternative process routes for different parts, machine's reliability. In the following (Ameli, Arkat, & Barzinpour, 2008) presented a pure multi-objective linear programming model for cell formation problem with alternative process routes and machine reliability. Such that, their objectives are included simultaneously minimizing costs and maximizing reliability. (Arkat, Naseri, & Ahmadizar, 2011) represented a stochastic model for an extended cell formation problem with consideration of machine reliability. They investigated two main topics: 1) selecting best process plan for each part and assigning machines in cells. 2) Selecting the most reliable plan to minimizing moving costs. (Nodem, Kenné, & Gharbi, 2011) represented a method for diagnosing optimal manufacturing, repair/replace policies and also preventive maintenance for critical manufacturing systems. Some of formulation of robust and its application were introduced by (Ben-Tal & Nemirovski, 1998, 1999, 2000; El Ghaoui & Lebret, 1997). They developed a robust framework in linear optimization. In the context of cellular manufacturing system, (Cao & Chen*, 2005) considered system configuration with commodity demand in number of stochastic scenarios. They developed an integrated cell formation optimization model and assigning part for creating robust system configuration with the objective of minimizing machine costs and material controlling costs between cells. (Pillai & Subbarao, 2008) proposed a robust approach in cells formation for parts and machines family, so that controlled demand changes and product mix without any movement. (Ghezavati & Saidi-Mehrabad, 2011) represented integrated strategies and tactical decisions for designing robust CMS under uncertainty in processing time and demand in supply chain network. (Tavakkoli-Moghaddam, Sakhaii, & Vatani, 2014) develop a robust optimization method for a dynamic CMS combined with production planning, so that processing time of parts is under uncertainty. Their model is included concepts of cell formation, inter-cell layout and production planning in a dynamic environment. (Paydar, Saidi-Mehrabad, & Teimoury, 2014) proposed a linear mixed integer model for integrating purchasing and production planning in supply chain and cell configuration simultaneously. Because of existent of uncertainty in some problem parameters like costumer demand and machines capacity they used the robust optimization approach for solving model. (Deep & Singh, 2015) represented a comprehensive mathematical model for robust designing of machine cells for manufacturing of dynamic part. Such that combines machine cell configuration design problem with assigning machine problem, the dynamic manufacturing problem and also part route problem. (Sakhaii, Tavakkoli-Moghaddam, Bagheri, & Vatani, 2016) represent a robust optimization approach for dynamic integrate cellular manufacturing and also a production planning problem with unreliable machines. Their objectives include minimizing deterioration costs a movement cost, education and employing operators, parts circulation in cells, shortage and inventory costs. (Imran, Kang, Lee, Jahanzaib, & Aziz, 2017) presented a cell formation problem that would minimize the value-added work in process. To achieve the objective they formulated a mathematical model and solved it by using discrete event simulation and a hybrid genetic algorithm. (Hazarika & Laha, 2018) proposed a genetic algorithm heuristic for the cell formation problem with multiple process routes, sequence of processes and parts volume. The results demonstrate that the performance of the proposed approach in terms of total intracellular movements of parts and best route selection is either better or competitive with the well-known existing methods. (Kumar & Singh, 2019) proposed a novel modified simulated annealing approach to solving bi-objective robust stochastic cellular facility layout problem. The objectives include minimizing material handling cost and maximizing similarity score for multi-periods and provides a robust layout design considering stochastic demand for multi-periods. In the following a brief description of some researches in topics of cellular manufacturing systems are represented in Table 1.

Table 1. some researches in context of cellular manufacturing systems

Ref.	Problem conditions				Objectives		Alternative routing		Machine reliability
	Deterministic	Uncertainty							
		Robust	Fuzzy	Stochastic	SO	MO	Machine require	Best rout	
(Cao & Chen*, 2005)		✓			✓		✓		
(Yin, Yasuda, & Hu, 2005)	✓				✓			✓	
Nsakanda, Diaby, & Price,) (2006	✓				✓			✓	
Tavakkoli-Moghaddam,) Javadian, Javadi, & Safaei, (2007				✓	✓		✓		
(K Das et al., 2007)	✓					✓		✓	✓
(Ameli & Arkat, 2008)	✓				✓			✓	✓
(Ameli et al., 2008)	✓					✓		✓	✓
(Safaei et al., 2008)			✓		✓		✓		
Safaei & Tavakkoli-) (Moghaddam, 2009			✓		✓		✓		
(Arıkan & Güngör, 2009)			✓			✓	✓		
Paydar, Mahdavi, Sharafuddin,) (& Solimanpur, 2010	✓				✓		✓		
Solimanpur, Saeedi, &) (Mahdavi, 2010	✓						✓		
(Chung, Wu, & Chang, 2011)	✓				✓			✓	✓
(Das & Abdul-Kader, 2011)	✓					✓		✓	✓
(Arkat et al., 2011)				✓	✓			✓	✓
Ghezavati & Saidi-Mehrabad,) (2011				✓	✓		✓		
Tavakkoli-Moghaddam,) Ranjbar-Bourani, Amin, & (Siadat, 2012	✓					✓	✓		
Tavakkoli-Moghaddam,) (Sakhaii, & Vatani, 2013		✓			✓			✓	
(Paydar et al., 2014)		✓			✓		✓		
(Deep & Singh, 2015)		✓			✓			✓	
)Farughi & Mostafayi, 2016(		✓				✓	✓		
(Sakhaii et al., 2016)		✓			✓			✓	✓
(Imran et al., 2017)	✓				✓		✓		✓
(Hazarika & Laha, 2018)	✓				✓			✓	
(Kumar & Singh, 2019)		✓		✓		✓			
This paper		✓				✓		✓	✓

Based on the investigated studies, design and reconfiguration of CMS under uncertainty conditions are presented by many researchers. This topic is important because appropriate forecasting of effective parameters in designing of manufacturing system is difficult and always has lack of enough accuracy. Also, with regard to nature of manufacturing systems and probability of occurring machines deterioration, designing of robust system to deal with changes in related parameters is an essential issue in manufacturing. Which yet did not have been investigated comprehensively. Actually, with regard to literature review, this paper design a robust multi objective model for planning of manufacturing parts for the first time with consideration of machines reliability that in is described completely section 1.

3. Machines reliability analysis in cellular manufacturing systems

3.1. Machines availability

Each machine in a predefined time, is in one of two situations: failed (under repair) or in working mode. By utilizing Markovian approach in this system, the moment and time interval that machines are available calculated by following formula in research of (Das & Abdul-Kader, 2011):

j machine index
t time period index

$$A_j(T) = \frac{r_{jt}}{r_{jt} + \lambda_{jt}} + \frac{\lambda_{jt}}{r_{jt} + \lambda_{jt}} e^{-(r_{jt}+\lambda_{jt})T} \quad (1)$$

$$A_j(\hat{T}_2 - \hat{T}_1) = \frac{r_{jt}}{r_{jt} + \lambda_{jt}} + \frac{\lambda_{jt}}{(r_{jt} + \lambda_{jt})^2(\hat{T}_2 - \hat{T}_1)} [e^{-(r_{jt}+\lambda_{jt})\hat{T}_1} - e^{-(r_{jt}+\lambda_{jt})\hat{T}_2}] \quad (2)$$

$$r_{jt} = \frac{1}{MTTR_{jt}}, \lambda_{jt} = \frac{1}{MTBF_{jt}} \quad (3)$$

Which T is the time that machine j in time t is available. $A_j(T)$ Means the probability that machine j in time T is working. $A_j(\hat{T}_2 - \hat{T}_1)$ Is availability interval of machine j in interval time of $\hat{T}_2 \leftrightarrow \hat{T}_1$ in time period t. And r_{jt} , λ_{jt} are repair rate and machine j deterioration rate within the interval time of t. The approach used in this article is such that machine effective capacity estimated by consideration of total capacity (total given time) within an interval and relate availability interval.

3.2 machines reliability model in a cellular manufacturing system

For explaining related problem in this article with regard to an example in research of (K Das et al., 2007) according table 2 information, manufacturing route for processing four part types on five machines are depicted. In this example, each part type may be manufactured by one of two possible process plans.

Table 2. manufacturing routes based on machines

Part types	Process plan	Operations 1	Operations 2	Operations 3
1	1	M_3, M_2	M_4, M_5	M_4
	2	M_2, M_4	M_3	M_1, M_4
2	1	M_2	M_4, M_5	M_3
	2	M_1, M_3	M_2	M_5
3	1	M_1, M_4	M_3, M_2	M_2
	2	M_4, M_5	M_2, M_4	M_1, M_3
4	1	M_1, M_3	M_2, M_4	M_5
	2	M_4, M_5	M_1	M_4

According to table 2 each operation could be done on multiple machines which shows that each part can be processed in multiple process or in multiple machine routes. For example, part type 1, following process plan 1 has the options of performing operation 1 either on machine M3, or M2 and operation 2 either on M4 or M5. If we suppose one of the part type 1 process route in the form of rout1 {1, 2, 3} which that set {1, 2, 3} represents machines 1, 2, 3 in manufacturing route. The System reliability in this situation is as follows:

$$R_s(T) = R_1(T) \times R_2(T) \times R_3(T) \quad (4)$$

Here $R_j(T)$ is the reliability of machine j at time T, it means the probability that machine j is working within time t, or $R_j(T) = Pr(T' \geq T)$. Where T' is continuous random variable defined as time to failure? Although equations 1 and 2 defined machines availability in terms of failure and repair rate for machines that are repairable. In this research we consider $R_j(T)$ for non-repairable machines. In this step we consider $R_j(T)$ as a reliability performance metric for selecting machines in cell configuration process. In next steps equation 4 convert to equation 5 to express system failure rate. Where is applicable to calculating reliability for repairable machines? We assume that machine failure time follow an exponential distribution. The reliability equality for machine j may be represented as:

$R_j(T) = e^{-\lambda_{jt}T}$ Where λ_{jt} is the failure rate of machine j in time period t, when $T \geq 0$ represents time period number as 1, 2, etc. and T is the time duration in hours for the period number t). Then the system reliability equation 4 becomes: $R_{rout1\{1,2,3\}}(T) = e^{-\sum_{j\in 1,2,3}\lambda_{jt}T}$. Since T is planned time period of time and is the same for all considered machines. Hence the equation will be below:

$$\frac{1}{\ln\{R_{rout1\{1,2,3\}}(T)\}} \times \frac{1}{T} = \sum_{j\in 1,2,3} \lambda_{jt}T = LIR_{rout1\{1,2,3\}t} \quad (5)$$

Where $LIR_{rout1\{1,2,3\}t}$ is the system failure rate for machines {M_1,M_2,M_3} along the part process route rout1{1, 2, 3} for a combined plan in {1, 2} at time period t. similarly LIR_{ipt} represent all combination of parts process plans in time period t. minimizing LIR_{ipt} improved overall machines reliability in selected process plans for part types.

4. Problem definition

In this research a mixed integer programming bi-objective model represented for configuration of cellular manufacturing systems with alternative routes with consideration of machines reliability. The objectives of this model are included minimizing overall cost of system as first objective and minimizing the amount of machines failure as second objective. One of the notable points in this model is capable of dividing necessary operations for manufacturing one type part of various machines that can do it. Also, idle time of machines and cell is considered. It means that for assigning parts and machines to cells in order to we consider the costs related to movements and operations on parts, costs related to cells idle time with regard to reliability of machines are considered. This model chooses an appropriate machine in different process part routes and increase machine reliability and decrease system costs. Also, it is required new machines are purchased. More accurately we assume machines set $j = 1,2, \dots, m$ for processing parts type $i = 1,2, \dots, n$ or forecasting demand for periods $t = 1,2, \dots$, is existed. T_t Denotes time duration for period t. reliability parameters for machine j in period t are included: $MTBF_{jt}$ and $MTTR_{jt}$. Current machines reliability parameters at period $t = 1$ are according to available data in each machine maintenance file. Based on manufacturer's data and the maintenance history of machines, the reliability parameters for the next period can be estimated. Part type i can be processed under any plans. A part-type process plan combination is denoted as (ip) and machines that can do operations O related to (ip) represented by j_{ipo}. Operation and readjust costs for operation O of (ip) on machine j are denoted as $CO_{oj}(ip)$ and $CR_{oj}(ip)$ and readjusting time is represented by $TO_{oj}(ip)$ and $TR_{oj}(ip)$ these costs and times within through planning horizon are known and constant. Based on available total capacity b_{it} (in hours) and availability $A_j(T_t)$, effective capacity of each machine (in hours) designated in each period t. if the effective capacity of machine j at period it is not able to meet all operations assigned to it, then new machine is purchased with similar capacity and reliability rate. When a new capacity is purchased in each period, it becomes available for the next periods without any extra cost. The binary variable $x_{ojc}(ipt)$ equals 1 if at time period t operation o related to (ip) have been done on machine j in cell c, otherwise it equals zero. The goal is grouping machine in some cells where number of parts assigned to one or more cells to minimize overall costs. While system reliability maximized within planning horizon. Since in real world manufacturing parameters are influenced by environmental factors. We can't designate exact value for them. In this model for considering this issue, we use uncertain parameters. Actually, different parameters value with regard to scenarios with specified probability are available. For solving model, we use robust optimization approach. Also presented model is a bi-objective model that we use LP-metric approach to solve it (Farughi & Mostafayi, 2016).

4.1. Mathematical model

Indices

c	Cells indices
i	Parts indices
p	Process plan indices
ip	Alternative routing for part *i* in process plan *p*
m	Machines indices
j_{ipo}	Set of machines that can perform operation o on ip route
o	Operation indices
h	Time period indices
s	Scenarios indices

Parameters

$A(T_h)_{ms}$	Availability of machine *j* at time *T* in the period number *h* under scenario *s*
α_{mhs}	Machine *m* holding cost at period *h* under scenario *s*
$CO(ip)_{oms}$	Operation *o* process cost of ip on machine m under scenario *s*
$CR(ip)_{oms}$	readjusting cost of process *o* of ip on machine *m* under scenario *s*
δ_{mhs}	cost of installation and uninstallation machine *m* at period *h* under scenario *s*
T_{hs}	Duration of period *h* under scenario *s*
ϑ_{mhs}	Cell idle time cost for machine m at period h under scenario *s*
CP_{mhs}	cost of idle time of machine m at period h under scenario *s*
$TO(ip)_{mohs}$	Time needed to processing operation *o* of ip by machine *m* in period *h* under scenario s
$TR(ip)_{mohs}$	Time needed to adjusting operation o of ip by machine m in period *h* under scenario s
CM_{mhs}	cost of purchasing new capacity for machine *m* in period *h* under scenario *s*
λ_{mhs}	Failure coefficient for machine *m* in period *h* under scenario *s*
Av_{mhs}	Number of available machines type *m* in period *h* under scenario *s*
UM	Upper bound for cells capacity
LM	Lower bound for cells capacity
$r(ip)_{oms}$	equals 1 if operation *o* needed machine *m* of ip under scenario *s*
D_{ihs}	Demand of part i in period *h* under scenario *s*
b_{mhs}	Available time for machine *m* in period *h* under scenario *s*

Decision variables

M_{mcs}	Binary variable will equal 1 if machine *m* assigned to cell *c* under scenario *s* otherwise will be equal zero
N_{mchs}	Number of machine type *m* assigned to cell *c* in period *h* under scenario *s*
$Z(ip)_{omchs}$	Number of part type *i* manufactured under plan *p* by operation *o* on machine *m* in cell *c* at period *h* under scenario *s*
K^{+}_{mchs}	Number of added machine type m to cell c in period h under scenario s

K^{-}_{mchs}	Number of removed machines type *m* from cell *c* in period *h* under scenario *s*
$TOTNM_{mchs}$	aggregated added capacities to machine *m* in cell *c* at period *h* under scenario *s*
$X(ip)_{omchs}$	Binary variable will be equal 1 if part type *i* under plan *p* by operation *o* on machine *m* in cell *c* at period *h* under scenario *s* manufactured. Otherwise will equal to zero

$$Min\ Z1 = \sum_{i=1}^{7} Z_i$$

$S.T$

$$Z_1 = \sum_{m=1}^{M}\sum_{c=1}^{C}\sum_{h=1}^{H}\sum_{s=1}^{} N_{mchs}\alpha_{mhs} \quad (6)$$

$$Z_2 = \sum_{o=1}^{O(ip)}\sum_{i=1}^{n}\sum_{p=1}^{P(i)}\sum_{m\epsilon m(ipo)}^{M}\sum_{c=1}^{C}\sum_{h=1}^{H}\sum_{s=1}^{} Z(ip)_{omchs}TR(ip)_{mhs}\{CO(ip)_{oms} + CR(ip)_{om}\} \quad (7)$$

$$Z_3 = \left(\frac{1}{2}\right)\sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{i=1}^{n}\sum_{\substack{o=1\\ o<OP}}^{O}\sum_{s=1}^{}\sum_{p=1}^{P(i)}\left|\sum_{m=1}^{M} Z(ip)_{(o+1)mchs} - Z(ip)_{omchs}\right| \quad (8)$$

$$Z_4 = \sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{s=1}^{S}\delta_{mhs}(K^{+}_{mchs} + K^{-}_{mchs}) \quad (9)$$

$$Z_5 \geq \sum_{h=1}^{H}\sum_{m=1}^{M}\sum_{s=1}^{S}\left(\left(T_{hs}N_{mchs} - \sum_{p=1}^{p(i)}\sum_{k=1}^{OP}\sum_{i=1}^{n} Z(ip)_{omchs}\,TR(ip)_{mhs}\right)\vartheta_{mhs}\right) \quad (10)$$

$$Z_6 = \sum_{h=1}^{H}\sum_{m=1}^{M} CP_{mhs}\left(1 - MUT_{mhs} + \sum_{c=1}^{C} TOTNM_{mchs}\right) \quad (11)$$

$$MUT_{mh} = \sum_{i=1}^{n}\sum_{p=1}^{P(i)}\sum_{o=1}^{O(ip)}\sum_{c=1}^{C}\left\{\frac{TO(ip)_{mhs} + TR(ip)_{mhs}}{A_j(T_h)b_{mhs}}\right\} Z(ip)_{omchs} \qquad \forall\ m,h,s \quad (12)$$

$$Z_7 = \sum_{m=1}^{M}\sum_{c=1}^{C}\sum_{h=1}^{H}\sum_{s=1}^{S} CM_{mhs}N_{mchs} \quad (13)$$

$$Min\ Z2 = \sum_{h=1}^{H}\sum_{i=1}^{n}\sum_{p=1}^{P(i)}\sum_{o=1}^{O(ip)}\sum_{m\epsilon m(ipo)}^{M}\sum_{c=1}^{C}\sum_{s=1}^{S} LIR_{iphs}\,X(ip)_{omchs} \quad (14)$$

$S.T$

$$LIR_{iph} = \sum_{m\epsilon m(ipo)}^{M}\lambda_{mhs} \qquad \forall\ i,p,h,s \quad (15)$$

$$\sum_{m=1}^{M}\sum_{i=1}^{Q} Z(ip)_{omchs}\ TR(ip)_{mhs}\ P_{ihs} \leq N_{mchs}T_{hs} \qquad \forall\ m,c,h,s \quad (16)$$

$\sum_{c=1}^{C} N_{mchs} \le Av_{mhs}$	$\forall\, m,h,s$	(17)
$\sum_{m=1}^{M} N_{mchs} \le UM$	$\forall\, c,h,s$	(18)
$\sum_{m=1}^{M} N_{mchs} \ge LM$	$\forall\, c,h,s$	(19)
$\sum_{c=1}^{C} Z(ip)_{omchs} \le M.r(ip)_{oms}$	$\forall\, m,c,h,s$	(20)
$N_{mc,h-1,s} + K^{+}_{mchs} - K^{-}_{mchs} = N_{mchs}$	$\forall\, m,c,h,s$	(21)
$\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{o=1}^{O}\sum_{p=1}^{P} Z(ip)_{omchs} = D_{ihs}$	$\forall\, i,h,s$	(22)
$TOTNM_{mchs} = TOTNM_{mc(h-1)s} + N_{mchs}$	$\forall\, m,c,h,s$	(23)
$\sum_{i=1}^{n}\sum_{p=1}^{P(i)}\sum_{o=1}^{O(ip)} Z(ip)_{omchs}\{TO(ip)_{oms} + TR(ip)_{oms}\} \le\ b_{mhs}A(T_h)_{js}(M_{mcs} + TOTNM_{mchs})$	$\forall\, m,c,h,s$	(24)
$X(ip)_{omchs} \le Z(ip)_{omchs}$	$\forall\, i,p,o,m,c,h,s$	(25)
$Z(ip)_{omchs} \le M.X(ip)_{omchs}$	$\forall\, i,p,o,m,c,h,s$	(26)
$K^{+}_{m,c,1,s} = N_{m,c,1,s}$	$\forall\, m,c,s$	(27)
$N_{mchs}, K^{+}_{mchs}\ , K^{-}_{mchs}\ , Z(ip)_{omchs}$	$\forall\, i,p,o,m,c,h,s$	(28)

The first objective function minimizes total system costs and have seven terms. The first term is calculated holding cost of the system with regard to number of machines. The second term calculates performing operation costs and readjusting cost of machine with regard to time elapsed to do them. The third term calculated parts movement costs. In fourth term extra costs and removing machine costs are calculated. In dynamic manufacturing model, the best design for cell formation for one period, maybe not optimal for all periods. With the redesign of industrial cells, cell formation can be converted to efficient performance even we have mix production and variable demands. However, there are some problems with innovation of manufacturing cells. Actually, machines movement between cells needs labor and costs which may cause damages to machines. Therefore, with changes in demand we have to change the machine between cells, which this movement resulted cost in the system. Fifth term calculates idle time of cells costs in the system and sixth terms calculates machines idle time costs, and finally seventh term calculates costs for purchasing new capacity for machines. The second objective minimizes failure rate of machines clearly this objective is activated when considered machine assigned to cells. Actually the second objective function optimizes system reliability index (SRI) over the set of entire part process plan (ip) combinations in time period h. equation (15) generates a combined term by summation of the system failure rate along all feasible processing routes in each period. Constraint (16) ensures that the total processing time of parts will not be more than maximum availability time of the machines. Constrain (17) also ensures that number of machines used type m in cell c not be more than maximum available machines. Constraints (18) and (19) defines lower and upper bounds of allowable machines in each cell. Constraint (20) represents required operations for manufacturing each part is done by machines that are capable to do it. Constraint (21) calculates number of added or removed machine in each cell at each period. Constraint (22) ensures that number of manufactured parts equal to total demands. Constraint (23) calculates the amount of added capacity to each machine. Constraint (24) ensures that number of operations assigned to each machine not be more than its maximum capacity. Constraints (25)-(28) define controlling constraints for decision variables of the model.

5. Robust optimization model framework

Robust optimization obtains a set of solutions that are robust against parameters (input data) fluctuations. The robust optimization approach represented by (Mulvey, Vanderbei, & Zenios, 1995). Robust optimization approach has much applications in operation research studies (Noorossana, Niaki, & Ershadi, 2014), (Babaee Tirkolaee, Alinaghian, Bakhshi Sasi, & Seyyed Esfahani, 2016), (Hejazi & Soleimanmeigouni, 2014). In this approach two types of robustness introduced. Solution robustness (near optimal solution in all scenarios) and model robustness (solution near to feasibility in all scenarios) the solution that obtain from the robust optimization model is called robust. If input data have changed so it remains near optimal, they called it solution robustness. A solution called robust if for little changes in input data it is almost feasible. This case is called model robustness. Robust optimization is included two specific constraints: 1) structural constraint, 2) controlling constraints. While Structural constraints are in the form of auxiliary constraints and formulated which influenced by uncertain data. In the following the framework of robust optimization explained briefly. At first $x \epsilon R^{n_1}$ are designing variables vector and $y \epsilon R^{n_2}$ is control variables vector. Robust optimization model form is as follows:

$Min\ c^T x + d^T y$	(29)
$Ax = b$	(30)
$Bx + Cy = e$	(31)
$x\ , y \geq 0$	(32)

Constraint (30) is a structural constraint and its coefficient is constant and determine. Constraint (31) is controlling constraint which its coefficient is influenced by scenario and is non-deterministic. Constraint (32) ensures variables are non-negative. The formulation of robust optimization model is included a set of scenarios$\tau = \{1,2, \dots S\}$. Under each scenario $\tau \epsilon S$ the coefficients relate to controlling constraints are equal to $\{d_s, B_s, C_s, e_s\}$ with a constant probability. Which P_s represents the probability of occurring each scenario and $\sum_s P_s = 1$. The optimal solution of this model is robust if for each specific scenario $S \epsilon \tau$ is still near optimal. This case is called model robustness. There are conditions that maybe the solutions that obtain for above model aren't both feasible and optimal for all scenarios $S \epsilon \tau$. At this point the relationship between solution robustness and model robustness are determined by multi criteria decision making concepts. For measuring this relationship robust optimization model is formulated. First of all control variable Y_s that for each scenario $S \epsilon \tau$ and error vector δ_s measured allowable infeasibility in control constraints under scenario s is introduced. Because of uncertain parameters the solution obtained by model maybe be infeasible for some scenarios therefore δ_s represents infeasibility of model under scenario s. if model be feasible δ_s will equal zero. Otherwise δ_s will equal to a positive value according to constraint (35). Actually, the robustness measures unsatisfied demand model for manufacturing part. The robust optimization model based on mathematical programming (29) to (32) formulated as follows:

$Min\ \sigma(x, y_1, \dots, y_s) + \omega\ \rho(\delta_1, \delta_2, \dots, \delta_s)$	(33)
$AX = b$	(34)
$B_s x + C_s y_s + \delta_s = e_s$	(35)
$x \geq 0\ , y \geq 0$	(36)

We must notice that because robust optimization model consider various scenarios, the first term in objective function is for selecting a unit for objective in previous objective function (33), $\Delta_s = c^T x + d^T y$ is a random variable with a random value equal to $\Delta_s = c^T x + {d_s}^T y_s$ with probability of P_s under scenario$S \epsilon \tau$. In random linear programming formulation, we used average value of $\sigma(0) = \sum_s \Delta_s \; P_s$ and actually the first term represents solution robustness. The second term in objective function $\rho(\delta_1, \delta_2, \dots, \delta_s)$ is feasible penalty function which penalties violation of control constraints under some scenarios. Controlling constraint violation means infeasible solution obtained under some scenarios of problem. By using of weight ω relationship between solution robustness which measured by first term $\sigma(0)$ and model robustness which measured by penalty function $\rho(0)$ we can model that under multi criteria decision making. Since our goal is minimizing $\sigma(0)$, it may be the solution be infeasible. If ω increased enough, the term $\rho(0)$ dominated and caused more cost. Studies about selecting appropriate $\rho(0)$ and $\sigma(0)$ could find with checking (Mulvey et al., 1995; Yu & Li, 2000). The term $\sigma(x, y_1, \dots, y_s)$ represented by (Mulvey et al., 1995) as follows:

$$\sigma(0) = \sum_s^S \Delta_s \, p_s + \lambda \sum_s^S p_s \left(\Delta_s - \sum_{s'}^S \Delta_{s'} \, p_{s'} \right)^2 \tag{37}$$

To show the robustness of the solution, the variance of the equation (33) represents that decision has high risk. In other words, a little variation in parameters with uncertainty can cause huge changes in value of measurement function. λ Is assigned weight for solution variance. Viewed as a quadratic term exit in equation (34). (Yu & Li, 2000) used an absolute value instead of a quadratic term_because of decreasing computational time which explained as follows:

$$\sigma(0) = \sum_s^S \Delta_s \, p_s + \lambda \sum_s^S p_s \left| \Delta_s - \sum_{s'}^S \Delta_{s'} \, p_{s'} \right| \tag{38}$$

5.1 The proposed model for robust optimization

In this study some parameters including cost of purchasing a machine, the variable cost of machine, cost of movement between cells in each category, cost of intra-cell movement, machine movement cost, holding cost of part and part demand parameter considered as uncertain and under scenarios. Based on the case study environment, production managers and some other experts cannot reach to an agreement for the exact amount of cost parameters. In fact, each expert presents cost parameters based on his calculations a experiences. Therefore, there are some different values for one parameter. In other word, there are some scenarios with certain probability for each value of parameters. Based on the nature of mentioned uncertainty of parameters, in this paper scenario based robust in used in order to handle the uncertainty of the parameters.

Like robust optimization approach explained in section 5, the robust model is represented as follows:

$$TC_s = \sum_{i=1}^{7} Z_{is} \tag{39}$$

$S.T$

$$Z_{1s} = \sum_{m=1}^{M}\sum_{c=1}^{C}\sum_{h=1}^{H} N_{mchs}\alpha_{mhs} \tag{40}$$

$$Z_{2s} = \sum_{o=1}^{O(ip)}\sum_{i=1}^{n}\sum_{p=1}^{P(i)}\sum_{m\epsilon m(ipo)}^{M}\sum_{c=1}^{C}\sum_{h=1}^{H} Z(ip)_{omchs}t_{oims}\{CO(ip)_{oms} + CR(ip)_{oms}\} \tag{41}$$

$$Z_{3s} = \left(\frac{1}{2}\right)\sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{i=1}^{n}\sum_{\substack{o=1\\o<OP}}^{O}\sum_{p=1}^{P(i)}\left|\sum_{m=1}^{M} Z(ip)_{(o+1)mchs} - Z(ip)_{omchs}\right| \tag{42}$$

$$Z_{4s} = \sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{m=1}^{M} \delta_{mhs}(K^{+}_{mchs} + K^{-}_{mchs}) \tag{43}$$

$$Z_{5s} \geq \sum_{m=1}^{M}((T_{ms}N_{mchs} - \sum_{p=1}^{p(i)}\sum_{k=1}^{OP}\sum_{i=1}^{n} Z(ip)_{omchs}\, t_{oims})\vartheta_{mhs}) \tag{44}$$

$$Z_{6s} = \sum_{h=1}^{H}\sum_{m=1}^{M} CP_{mhs}\left(1 - MUT_{mhs} + \sum_{c=1}^{C} TOTNM_{mchs}\right) \tag{45}$$

$$MUT_{mhs} = \sum_{i=1}^{n}\sum_{p=1}^{P(i)}\sum_{o=1}^{O(ip)}\sum_{c=1}^{C}\left\{\frac{TO(ip)_{mhs} + TR(ip)_{mhs}}{A_{js}(T_h)b_{mhs}}\right\} Z(ip)_{omchs} \qquad \forall\, m,h \tag{46}$$

$$Z_{7s} = \sum_{m=1}^{M}\sum_{c=1}^{C}\sum_{h=1}^{H} CM_{mhs}N_{mchs} \tag{47}$$

$$R_{2s} = \sum_{h=1}^{H}\sum_{i=1}^{n}\sum_{p=1}^{P(i)}\sum_{o=1}^{O(ip)}\sum_{m\epsilon m(ipo)}^{M}\sum_{c=1}^{C} LIR_{iphs}\, X(ip)_{omchs} \tag{48}$$

$$LIR_{iphs} = \sum_{m\epsilon m(ipo)}^{M} \lambda_{mhs} \tag{49}$$

Therefore, the robust optimization model for dynamic cell formation is depicted below, which in its only objective functions (50) and (51) an also constraint (52) has changed and other constraint are the same as pervious model.

$$Min\, W_1 = \sum_{s} P_s\, TC_s + \lambda_1 \sum_{s} P_s \left|TC_s - \sum_{s\prime} P_{s\prime}\, TC_{s\prime}\right| + \omega \sum_{s}\sum_{i}\sum_{h} P_s\, \delta_{ihs} \tag{50}$$

$$Min\, W_2 = \sum_{s} P_s\, R_s + \lambda_1 \sum_{s} P_s \left|R_s - \sum_{s\prime} P_{s\prime}\, R_{s\prime}\right| + \omega \sum_{s}\sum_{i}\sum_{h} P_s\, \delta_{ihs} \tag{51}$$

$s.t$

$$\left(\sum_{c=1}^{C}\sum_{m=1}^{M} Z(ip)_{omchs}\right) + \delta_{ihs} = D_{ihs} \qquad \forall\, i,h,s \qquad (52)$$

Constraints 15-28

First and second term of first objective function are average and variance of total costs. Actually, these two terms measured the robustness of the solution. The third term of first objective measured model robustness with regard to control constraint infeasibility under scenario s.

The first objective function is nonlinear because has absolute value. And the problem will convert to a linear problem by introducing two new variables q_{1s}, p_{1s}. The constraint $q_{1s} - p_{1s} = TC_s - \sum_{s'} P_{s'} TC_{s'}$ added to main model. Also, the second objective function is nonlinear because having absolute value term. And problem converting to a linear programming model with introducing two new variables q_{2s}, p_{2s}. Constraint $q_{2s} - p_{2s} = R_s - \sum_{s'} P_{s'} R_{s'}$ added to main model therefor the objective function of robust optimization model retyping as follows:

$$Min\ W_1 = \sum_{s} P_s\, TC_s + \lambda_1 \sum_{s} P_s\,(q_{1s} + p_{1s}) + \omega \sum_{s}\sum_{i}\sum_{h} P_s\, \delta_{ihs} \qquad (53)$$

$$Min\ W_2 = \sum_{s} P_s\, R_s + \lambda_1 \sum_{s} P_s\,(q_{2s} + p_{2s}) + \omega \sum_{s}\sum_{i}\sum_{h} P_s\, \delta_{ihs} \qquad (54)$$

5.2 proposed process for solving model

The robust model presented in the previous section is a bi-objective programming problem. First of all, we must convert the problem to a single objective problem. For this purpose, with using of LP-metric we can do that (Lee, 1980). And replace the bi-objective problem with a single objective problem. Because two objectives are not in same scale at first, we normalize them by using equation (55) which W_i^* is the optimal value for each objective. For the optimal model the two objectives are replaced by equation below and lead the problem to a single objective. In this study we assume that two objectives named by *W1*, *W2* .Based on LP-metric method the robust optimization model for dynamic cell formation problem for each objective function solved separately. The objective function LP-metric model formulated as follows:

$$Min\ W_3 = \left[a \times \frac{w_1 - w_1^*}{w_1^*}\right] + \left[(1-a) \times \frac{w_2 - w_2^*}{w_2^*}\right] \qquad (55)$$

Where $0 \le \alpha \le 1$, w_1^* is optimal value of first objective and w_2^* is optima value of second objective. The coefficients are the weights for objective function in above equation. By using above equation, the bi-objective problem converts to a single objective problem and solved by CPLEX 12.1 solver in GAMS software.

6. Case study: A department of PISHGAMAN PICH PARS Co. with regard to available data

PISHGAMAN PICH PARS manufacturing unit has more than 10 years of experience in designing, supplying and manufacturing of different screw and bolts and sells bolts in oil industries like: gas and petrochemical, water and wastewater, building and construction, automobile, mines and metals and electrical, this Co by using of new technical knowledge has succeed and is one of the well-known supplier in Iran. The products of this Co are included:

different types of bolts and washers like hexagon screws, Ajax bolt, hexagon nuts, sealed nuts and different types of washers and specific bolts according to global standards. One of the problems exists in this Co production planning which production managers deal with is cells configuration and assigning machines and parts without regarding to probability of machine breakdown. Actually, the current production planning is based on experience and sometimes caused to manufacturing system be stopped for a while. Which this short time cause to a lot of cost in production system. On the other, hand with regard to some dynamic parameters in planning such as forecasting amount of demand and then cost related to it and parameters related to machines and manufacturing system, planning only based on experience is very difficult. Consequently, experts and production manager of Co with regard to experience and consulting with experts and successful factories decide to plan with mathematical model. For this purpose, in this research a department above Co considered as a case study. Since whole data is not available for ruining model, because of reasons such as lack of appropriate recording of data to increasing confidence in accuracy and efficiency of data with agreeing of experts and experienced supervisors of manufacturing sector we used some data that exist in research of (Das & Abdul-Kader, 2011). This system manufactured 4 types' parts in 3 manufacturing cell by 4 types of machine. And performed for 2 time period with regard to condition of presented model in this article. With considering problems such as price fluctuations in market, customers demand and etc. which manufacturing system always deal with them. The manger decides to optimize such parameters (costs, demand amount and etc.) under some scenarios. Aforementioned parameters under 3 scenarios with occurring probability of 0.2, 0.5 and 0.3 represented in table below:

Table 3. input data related to $MTTR$, $MTBF$, machines idle time cost and purchasing machines capacity

	$MTBF$ (hour)						$MTTR$ (hour)							
	Period1			Period2			Period3			Period4			Idle time cost	Capacity cost
	scenario			scenario			scenario			scenario				
machine	1	2	3	1	2	3	1	2	3	1	2	3		
1	279	247	240	264	261	250	143	150	160	106	113	122	1880	4125
2	121	207	192	211	200	192	62	62	63	72	74	76	1304	4500
3	326	316	310	389	370	358	135	140	144	135	137	140	1376	7450
4	117	111	105	211	200	192	75	76	79	83	84	85	1604	7000

With regard to information in table above, if factory planning horizon considered monthly, based on previous data in work, averagely in month 25 days and daily 10 hours the factory is active, where obviously we can consider the length of planning horizon equals to $(25 \times 10) = 250$ hours. Actually $T_1 = (0 - 250)$ and $T_2 = (250 - 500)$. Therefore, with the help of equation (2) that explained in introduction section we can calculate machines availability. For example, availability of machine 2 in period 1 under scenario 1 is as follows:

$$A_2(T_1) = A_2(T_{12} - T_{11}) = A_2(0 - 250) = \frac{\frac{1}{62}}{\left(\frac{1}{62} + \frac{1}{212}\right)} + \frac{\frac{1}{212}}{\left(\frac{1}{62} + \frac{1}{212}\right)^2 \times (250 - 0)} \times \left\{1 - e^{-\left(\left(\frac{1}{62}+\frac{1}{212}\right)\times 250\right)}\right\} \qquad (56)$$

Where in it for calculating λ_{jt} and r_{jt} we use equations $r_{jt} = \frac{1}{MTTR_{jt}}$ and $\lambda_{jt} = \frac{1}{MTBF_{jt}}$ for example in above formula $r_{21} = \frac{1}{MTTR_{21}} = \frac{1}{62}$ and $\lambda_{21} = \frac{1}{MTBF_{21}} = \frac{1}{212}$. As represented similarly for all machine we can calculate availability probability. Table below depicts operations on parts base on time, cost and machine type required, where actually is manufacturing route. For example, in manufacturing scheme 1 according to scenario 1, part 1 can be manufactured by routes that machines 2 and 3 in it. For other parts also there is a similar explanation.

Table 4. input data related to manufacturing cost and manufacturing time by machine in production plans

part	index	(process) plan 1						Process plan 2					
		Scenario1		Scenario2		Scenario3		Scenario1		Scenario2		Scenario3	
1	machine	3	2	1	4	1	3	3	2	4	3	1	2
	time	6.5	6.5	7.4	5	6.4	4.8	5.7	4.9	6.9	5.7	5	4.1
	cost	1.09	1.06	0.82	0.63	0.87	1.02	0.76	0.73	1.08	0.78	0.98	0.95
2	machine	1	3	4	2	2	3	4	1	3	2	4	3
	time	5.4	7.3	4	6.1	5.5	7.5	4.5	4.6	5.6	7.3	7.3	6.3
	cost	0.66	0.97	0.76	0.7	0.63	0.65	1.13	1.11	0.93	0.65	1.08	0.82
3	machine	2	1	2	3	3	4	3	2	1	4	1	3
	time	7.9	5.2	5.9	6.7	6.5	5.3	6.9	6.7	7.9	5	4.5	7.8
	cost	0.63	1.16	0.74	0.9	1.14	0.9	0.64	0.76	0.78	0.84	0.74	1.16
4	machine	2	4	3	4	2	1	3	2	1	2	3	4
	time	4.5	7.4	6.3	6.3	5.3	6.4	7.3	4.9	4.4	5.6	4.8	7.4
	cost	1.10	1.11	0.98	0.93	0.78	0.66	0.98	0.85	0.88	0.79	0.94	0.91
5	machine	3	2	3	1	4	3	2	3	3	4	2	1
	time	4.6	4.5	5.3	8	7.2	5.8	6.5	6.3	6.9	7	7.7	5.7
	cost	1.08	0.79	1.11	1.01	0.83	0.8	0.89	1.16	0.73	1.06	1.13	0.64
6	machine	4	1	2	3	3	4	1	3	3	2	4	3
	time	5.3	3	7.8	5.8	7.1	5.6	7.3	4.8	4.8	7.9	6.2	6.3
	cost	0.73	0.89	0.61	0.76	1.12	0.98	0.82	0.84	0.68	1.08	1.13	1.03

Table 5. input data related cost information and re-adjusting time in production plans

part	index	Process plan 1						Process plan 2					
		Scenario1		Scenario2		Scenario3		Scenario1		Scenario2		Scenario3	
1	machine	3	2	1	4	1	3	3	2	4	3	1	2
	time	0.42	0.31	0.2	0.44	0.2	0.27	0.39	0.3	0.36	0.45	0.23	0.28
	cost	0.05	0.06	0.05	0.05	0.07	0.06	0.05	0.05	0.07	0.05	0.05	0.06
2	machine	1	3	4	2	2	3	4	1	3	2	4	3
	time	0.32	0.27	0.19	0.37	0.31	0.32	0.31	0.21	0.3	0.23	0.29	0.36
	cost	0.05	0.05	0.07	0.06	0.05	0.07	0.05	0.06	0.05	0.06	0.05	0.07
3	machine	2	1	2	3	3	4	3	2	1	4	1	3
	time	0.15	0.45	0.34	0.21	0.3	0.27	0.05	0.41	0.33	0.34	0.3	0.32
	cost	0.07	0.06	0.07	0.05	0.07	0.07	0.06	0.05	0.05	0.07	0.07	0.06
4	machine	2	4	3	4	2	1	3	2	1	2	3	4
	time	0.35	0.42	0.42	0.2	0.26	0.2	0.32	0.32	0.21	0.23	0.18	0.36
	cost	0.06	0.07	0.07	0.06	0.06	0.05	0.06	0.06	0.06	0.05	0.07	0.06
5	machine	3	2	3	1	4	3	2	3	3	4	2	1
	time	0.32	0.26	0.17	0.15	0.33	0.38	0.4	0.18	0.23	0.37	0.3	0.36
	cost	0.07	0.05	0.07	0.07	0.06	0.06	0.05	0.05	0.06	0.05	0.06	0.05
6	machine	4	1	2	3	3	4	1	3	3	2	4	3
	time	0.3	0.4	0.39	0.19	0.33	0.21	0.42	0.2	0.27	0.15	0.35	0.24
	cost	0.05	0.06	0.05	0.07	0.07	0.05	0.06	0.05	0.05	0.06	0.06	0.07

The amount of parts demand for manufacturing in planning horizon with regard to defines scenarios is according to table below. As observed the change in demand value sometime is significant. This change can be a result of importing external commodity or until seasonal changes and shutting down some construction project and etc. for example after shutting down of PADIDE Co construction projects, many of companies such as SAYBAN SAZEH TOOS which directly and semi-exclusively must manufacture required parts, and faced with serious problem to satisfying demands and orders.

Table 6. input data related to amount of demands

Period1								
Scenario1			Scenario2			Scenario3		
part	plan		part	plan		part	plan	
	1	2		1	2		1	2
1	738	763	1	859	950	1	995	885
2	748	1220	2	860	1100	2	1000	958
3	1095	1200	3	1060	1178	3	989	689
4	1238	1035	4	1145	1155	4	1135	1148
5	1018	1154	5	1150	1249	5	990	1000
6	850	940	6	920	1100	6	1015	985
Period2								
Scenario1			Scenario2			Scenario3		
part	plan		part	plan		part	plan	
	1	2		1	2		1	2
1	913	1197	1	1062	1208	1	1211	1250
2	1106	760	2	962	880	2	742	855
3	825	963	3	772	1011	3	1034	880
4	986	850	4	1196	1188	4	1148	1026
5	1108	895	5	1054	1170	5	1185	1114
6	739	1211	6	1236	1160	6	800	855

Other required information to solve problem also is as follows as table below with regard to scrutiny of previous data in factory planning system.

Table 7. information related to machines

		α_{mhs}			δ_{mhs}			ϑ_{mhs}			CP_{mhs}		
		scenario			scenario			scenario			scenario		
	machines	1	2	3	1	2	3	1	2	3	1	2	3
Period 1	1	5510	5200	5400	6670	6300	6400	3400	3600	3800	1030	1050	1000
	2	5340	5000	5200	6100	6500	6350	3600	3800	3700	1050	900	800
	3	5600	5500	5100	6500	6200	6100	3700	4100	3500	900	1070	1100
	4	5150	5000	5250	6350	6300	660	3400	3700	4000	1000	1100	900
Period 2	1	5400	5150	5400	6400	6500	6300	4000	3400	3600	850	950	1000
	2	5350	5250	5200	6500	6100	6100	3600	3800	3700	1000	1100	1200
	3	5100	5300	5300	6300	6800	6200	3600	4100	3500	1100	850	900
	4	5050	5200	5150	6400	6300	6300	3700	3600	3700	1000	950	1100

		CM_{mhs}			Av_{mhs}			b_{mhs}			$T_{hs}(Day \times Hour \times min)$		
		scenario			scenario			scenario			scenario		
	machine	1	2	3	1	2	3	1	2	3	1	2	3
Period 1	1	2500	2100	2300	7	8	9	1600	1800	1500	3360	4800	5760
	2	2700	2500	2050	10	12	15	2000	2500	2700			
	3	2100	2000	2400	6	5	8	1800	1700	2000			
	4	2700	2800	2400	10	10	10	1400	2000	1800			
Period 2	1	2700	2100	2500	7	8	9	1600	1800	1500	3360	4800	5760
	2	2050	2000	2100	10	12	15	2000	2500	2700			
	3	2450	2500	2600	6	5	8	1800	1700	2000			
	4	2700	2500	2600	10	10	10	1400	2000	1800			

It is noteworthy that the probability of boom scenario is 0.45 medium scenario is 0.35 and low scenario: 0.2

Because of important of two objective function: total costs objective and summation of failure rate of machines, simultaneously three model for sensitivity analysis is represented:

Model W_1: is including total system cost

Model W_2: is including summation of failure rates in different periods and under different scenarios and related constraints

Model W_3: LP-metric Model is a combined from models W_1 and W_2 with related constraints.

Therefore, some solutions obtain by different value of α . These solutions are recorded in set named Pareto-front. Actually, is a Pareto-front that a set of non-dominated solutions resulted from problem for different amount of α. Which caused mangers selected final solution with regard to significant of objectives. For this purpose, based on the expert's opinion number of 60 different value of α according table below is proposed.

These values obtained through interviewing with factory senior executives and with scrutiny past data (about amount of significance between manufacturing costs and production planning machine deterioration) which recorded periodically.

Table 8. Different weights for parameter α

0.431	0.295	0.364	0.344	0.296	0.166	0.429	0.317	0.164	0.387	0.418	0.323	0.263	0.255	0.437
0.123	0.396	0.168	0.25	0.244	0.281	0.302	0.179	0.172	0.326	0.254	0.227	0.205	0.233	0.341
0.258	0.178	0.235	0.192	0.219	0.304	0.164	0.143	0.219	0.336	0.437	0.414	0.332	0.317	0.348
0.159	257	0.411	0.424	0.286	0.394	0.336	0.369	0.415	0.201	0.404	0.154	0.351	0.367	0.396

After solving model with GAMS software, by a computer with configuration 4GBRAM, CPU 3200 GHz – Core i5. The Pareto-front is according below:

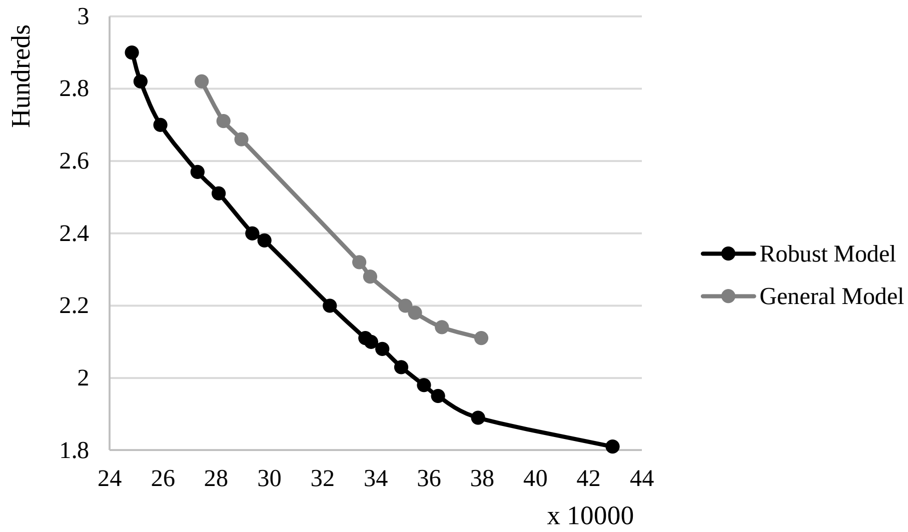


Figure 1. Pareto fronts of the Robust Model and General Model

As observed the difference between solutions resulted from solving main problem and solution for solving robust model is absolutely tangible. Of course, we should mention that some solutions are dominated other solutions and don't exist in any Pareto-front. Actually, above chart according to the definition of Pareto-front only represents non-dominated points. It is notable that in solving the problem we used $\omega = 300$, this value is calculated through checking robust problem represented in the next section.

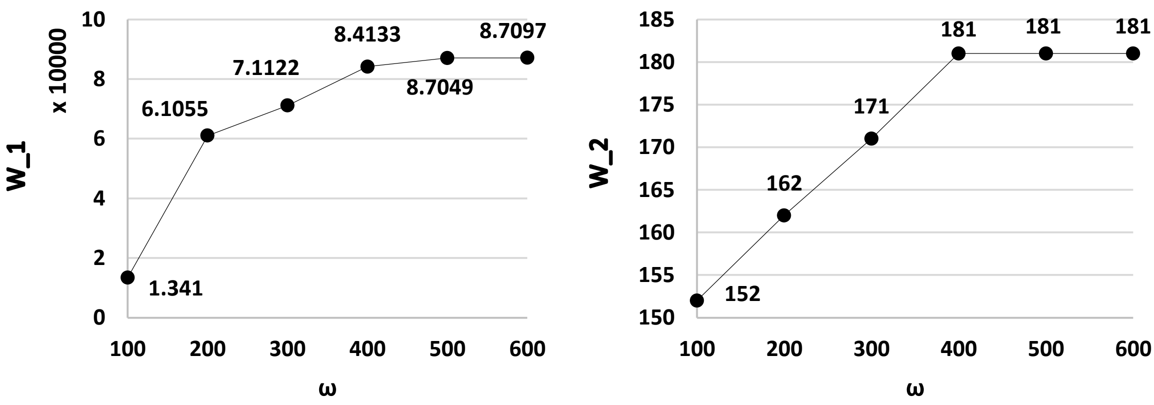
6.1 analysis of problem robustness

In this section we investigate the relationship between model robustness and objective functions W_1 and W_2. Actually, in this scrutiny we specified model feasibility. If it isn't feasible this amount of violation how impact on the objective function. As before mentioned, robustness means lack of sensitivity to changes in model input parameters. Also, we can cell a model is robust when for each scenario is almost feasible. According equations (53) and (54) model robustness is calculated by the third part of these equations. Actually variable δ_{ihs} is an error vector which represents amount of infeasibility of model. Since this variable is always non-negative and sufficient ω is also positive, always the third part of the equations (53) and (54) is non-negative. Therefore, if for one specified value of ω (without changing other parameters) there is no change in objective functions, we can say the error vector of model has a value of zero ($\delta_{ihs} = 0$) and model is feasible for all scenarios. For a specific value of α which is selected based on proposed weights as the final solution for implementing in a factory. We solve the problem for different value of ω and changes in the objective function value is checked. This action continues until the difference between objective function values become zero. (The model becomes feasible for all scenarios) the table below showed solution resulted from solving problem for each objective function and for different value of ω .

Table 9. robustness checking according to objective function W_1 and W_2

ω	W_1			W_2		
	W_1	W_2	W_3	W_1	W_2	W_3
100	13410	0	0	653845	152	17.978
200	61055	341	8.362	710902	162	18.109
300	71122	358	9.084	823975	171	18.908
400	84133	399	10.935	865701	181	19.659
500	87049	412	11.202	912587	181	20.711
600	87097	446	11.489	987278	181	21.108

We observed that for the first objective function, for the value of $\omega = 600$ the third part of the equation (53) is zero and model is feasible. Also, for second objective function the third part of the equation (54) in $\omega = 500$ equals zero and model is feasible for all scenarios. This case can be seen in the figure 2.



Model Robustness according to W_1 objective function

Model Robustness according to W_2 objective function

Figure 2. Model robustness for objective functions

In the following, for the purpose, analyzing problem the value of ω=300 considered and according to this value output result represented in table below. In this Table, we can see unsatisfied demands. As determined the value of error vector for part 1 under "high scenario'' for the period 1 is a positive value. For this art demand is equal to 738 which optimal value of that is 579 units and the amount of unsatisfied demand is 159 units. For part 3 under '''high'' scenario also observed in period 1 where the amount of demand is equal to 1059 units, the optimal manufactured is 951 and amount of unsatisfied demand is 108 units. In period 3 under "high" scenario some of parts has unsatisfied demands. This case showed that in value of $\omega = 300$ some scenarios are infeasible model:

Table 10. Unsatisfied demands under different scenarios

δ_{phs}	Scenarios	P_1	P_2	P_3	P_4	P_5	P_6
h_1	boom	159	0	108	0	0	0
	medium	0	0	0	0	0	0
	low	0	0	0	0	0	0
h_2	boom	0	102	0	298	0	351
	medium	0	0	0	0	0	0
	low	0	0	0	0	0	0

Total costs of system under different scenarios are as follows:

Table 11. System costs under scenarios

Scenario	Machines holding cost	Performing operations cost	Parts movement costs between cells	Purchasing and removing cost of machine	Cell idle time cost	Machines idle time costs	Cost of purchasing new capacity	Total costs	Total failure rates
Boom	83916	59168	34051	61000	32896	72470	47143	390644	227
Middle	62168	68145	28413	47500	28642	49201	35697	319766	202
Fair	50157	49328	21176	31000	18726	28613	22593	221593	194

According to table above, we can observe system total cost from the scenario "high" to the scenario "low" is increased. The reason for this event is increasing trend of demand parameters and system cost. Of course, because of unsatisfied demand under scenario "high" for some parts, the performing operation cost doesn't have increasing trend. The main structure of cell formation and also assigning machines to cells and also assigning parts to machines depicted in the table below:

Table 12. Output data related to assigning machines to cells and parts to machines

		Machine1							Machine2						
		quantity	P1	P2	P3	P4	P5	P6	quantity	P1	P2	P3	P4	P5	P6
Period1	Cell1	1	■			■			2			■	■		■
	Cell2	2		■			■		1		■				■
	Cell3	1				■			1	■			■		
		Machine3							Machine4						
		quantity	P1	P2	P3	P4	P5	P6	quantity	P1	P2	P3	P4	P5	P6
	Cell1	1			■			■	1	■					■
	Cell2	1		■			■		1						
	Cell3	0							3		■		■	■	
		Machine1							Machine2						
		quantity	P1	P2	P3	P4	P5	P6	quantity	P1	P2	P3	P4	P5	P6
Period2	Cell1	2		■	■		■		1			■			
	Cell2	1	■			■			1		■				■
	Cell3	1				■			2	■			■	■	
		Machine3							Machine4						
		quantity	P1	P2	P3	P4	P5	P6	quantity	P1	P2	P3	P4	P5	P6
	Cell1	1					■		1			■		■	
	Cell2	3	■		■	■		■	1	■			■		
	Cell3	1				■			1		■				■

According to the table above, we observed that assigning machines to cells and also assigning parts to machines based on manufacturing routes is usable for performing the operation. For example, at period 1 in cell 3 we used only machines 2, 1 and 4. Also parts 4, 3,1and 6 for performing manufacturing operations transferred to this cell. Actually, with regard to possible manufacturing plan for each part, machines assigned to cell 3 which manufacturing cost and along with considering manufacturing time as a cost, manufacturing time is also minimized. Also, we can specify each part's route according to the table. For example, part (1) with regard to table (3) data according to scenario 1 used machines 2, 3 and based on scenario 2 used machines 1and 4 and finally based on scenario 3 used machines 1, 3 and for manufacturing using plan 1, also for using manufacturing plan2 could use the machine 2, 3 based on scenario 1, based on scenario 2 machines 3, 4 and finally based on scenario 3 machines 1, 2. However, according to the result, part 1 is manufactured based on scenario 2 of plan1 in cell 1, for this reason machine 1, 4 is in this cell. For other parts and machines, we can analyze similarly. The table below represents the duration of manufacturing operation for each part with regard to problem data and probability of each scenario.

Table 13. Output data related to assigning machines to cells and parts to machines

		Machine1							Machine2						
		quantity	P1	P2	P3	P4	P5	P6	quantity	P1	P2	P3	P4	P5	P6
Period1	Cell 1	1	0.42			0.27			2			0.58	0.62		0.53
	Cell 2	2		0.67			0.37		1		0.18				0.36
	Cell 3	1				0.21			1	0.24			0.47		
		Machine3													
		quantity	P1	P2	P3	P4	P5	P6	quantity	P1	P2	P3	P4	P5	P6
	Cell 1	1			0.66			0.23	1	0.37					0.51
	Cell 2	1		0.29			0.42		1						
	Cell 3	0							3		0.45		0.68	0.41	
Period2		Machine1													
		quantity	P1	P2	P3	P4	P5	P6	quantity	P1	P2	P3	P4	P5	P6
	Cell 1	2		0.62	0.47		0.28		1			0.46			
	Cell 2	1	0.28			0.53			1		0.53				0.026
	Cell 3	1				0.71			2	0.47			0.49	0.64	
		Machine3													
		quantity	P1	P2	P3	P4	P5	P6	quantity	P1	P2	P3	P4	P5	P6
	Cell 1	1					0.22		1			0.47		0.39	
	Cell 2	3	0.28		0.37	0.45		0.84	1	0.27			0.54		
	Cell 3	1				0.61			1		0.31				0.47

6.2 Effective implications of the results and managerial insights

In this section, the managerial implications are investigated as follows.

Cellular manufacturing configuration is a technical planning because in factories, fluctuations in costs are so frequent and major. Therefore, optimization tools are helpful for making managerial decisions in practice and also their computational time in obtaining a good solution is an important issue. To provide a good situation for managing the production system, we defined two objective functions including cost minimization and reliability maximizing through failure rate minimizing. In the case study and several problem instances, it is showed the derived cell formations from the presented robust and general models satisfied these main objectives. The proposed robust approach can be used as powerful managerial tools in a production system to provide better and more effective cellular manufacturing systems.

The computational results from the case study shows that the use of our proposed robust optimization approach led to minimize total cost and minimize the failure rate. Moreover, the solutions reduced the number of machines which are used in the system.
This study presented a scenario based robust approach to hedge against the uncertainty for the costs and so it enables a decision maker to obtain robust cell configuration decisions. The robust solution showed in better values for the first and the second objective functions.

7. Conclusion

Cellular manufacturing system (CMS) reconfiguration is a well-known method for improving productivity and competitiveness among manufactures. CMS tries to improve the whole system output and shorten the lead time by grouping specific products in small batches to be produced in a low cost and high-quality manufacturing cell. Despite all advantages of CMS, the shortcomings of such systems cannot be ignored. One of the most important disadvantages is the pause in the manufacturing process resulted from machine breakdowns. This issue is one of the most important concerns of planning managers. In this research, a bi-objective mixed integer mathematical model is presented for the reconfiguration of cellular manufacturing systems with alternative routes based on machines reliability. The objectives of this model include the minimization of the overall cost and minimization of the machine fails. Usually due to changes in the recorded data, to determine the exact amount for parameter used is difficult. Thus, to achieve better result and stay close to real world condition, the parameters are considered with uncertainty. To deal with such uncertainties and achieve promising results, the Mulvey robust programming is employed. To the best of the authors' knowledge, in this research the CMS configuration is performed for the first time considering simultaneously both of the objective functions, namely the minimization of the overall cost and the minimization of machine failure under uncertainty condition in parameters. One significant advantage of the presented model is the sharing of operations required for manufacturing a part of machines in different cells that are capable to do those operations and have idle time. It means for assigning parts to machine and cells in addition to considering costs related to movement and operations on parts, cost related to cells idle time with regard to calculating machine reliability are considered. Due to the existence of two conflicting objective function in presenting a model, to have a better choice in selecting the final solution, solutions are represented as a Pareto - front. Also, to show the impact of using robust planning, set of non-dominated solution resulted from main problem and robust problem are compared with each other. Finally, decisions are compared to the opinion of the production planning experts at the PISHGAMAN PARS PICH Company as a case study. The Pareto-front and results are reported in detail. According to the results, using a robust programming method leads to improvement in objective function's values. This research can be used as a base for future research to extend the current model and to use Meta-heuristic algorithms to solve such complex models. Furthermore, using a fuzzy robust optimization approach might make this model to become more efficient and more useful to implement in manufacturing environments.

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