Robust optimisation to design a dynamic cellular manufacturing system integrating group layout and workers' assignment

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Abstract: In this paper, a robust optimisation approach is proposed to solve a mathematical model integrating cell formation, group layout and operators assignment decisions under a dynamic situation. The main aim of applying a robust approach is to obtain an optimal design of a cellular manufacturing system that is robust with respect to encountered uncertainties in part demands and processing times. The integrated model incorporates several design attributes including operations sequence, group layout, equal-area facilities multi-rows layout, flexible cell reconfiguration, operators hiring/firing and training, operator available time, limitations of cell size and uncertain processing times and part demands. Two illustrative numerical examples are solved to investigate the validity of the robust model. Regarding the

NP-hardness of the proposed model, an efficient simulated annealing algorithm is implemented. Some test problems either generated randomly or taken from the literature are solved and the results are compared with the ones obtained using CPLEX. [Received: 31 May 2019; Accepted: 3 May 2020]

Keywords: dynamic cellular manufacturing system; robust optimisation; group layout; worker assignment; mixed-integer nonlinear program; simulated annealing.

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1 Introduction

Today, industrial technology advancement is happening more rapidly and this issue brings about the industrial world getting more advanced, dynamic and evolving. Some factors such as the short product life cycle, the short product supply cycle to market and various demands of the customers have urged the manufacturers to improve their activities and manufacturing process efficiency and productivity. In fact, in order to survive under the current competitive conditions, the manufacturers have to deliver their products at lower price, with higher quality in the due time to the customers and reach the potential to react appropriately to the changes due to the products design and demand. The traditional manufacturing systems such as job shop and flow shop manufacturing are not able to meet these requirements since the manufacturing systems have to possess alterability and re-planning capability to respond to the variations in the product design and demand. As a result, cellular manufacturing (CM) as an advanced application of group technology (GT) in the manufacturing field has developed as an encouraging and effective manufacturing system.

Through identifying and exploiting the parts similarity and operation processes in design and manufacturing, CM system leads to manufacturing efficiency increase. Thus, it is one of the most effective manufacturing systems drawing the attention of worldwide manufacturing firms. The most significant advantages of CM compared with the other manufacturing systems have been summarised as the following; decreasing material handling amount and cost, lowering setup time, production rate increase, reducing lot size, decreasing work in process, lowering demand for manufacturing equipment and tools, decreasing the required space, improving products quality, more specialisation, lowering delivery time, better controlling the entire operation and decreasing equipment requirements (Wemmerlöv and Hyer, 1989; Heragu, 1994).

Cellular manufacturing system (CMS) has been evolved and transformed to meet needs of various leading global manufacturers such as Panasonic, Fujitsu, NEC, Sharp, Sanyo, Yamaha, Hitachi, and Canon in Japan as well as Samsung and LG in South Korea (Kim and Lim, 2019).

Generally, there are four steps in designing a CMS:

1 cell formation (CF) (i.e., the most significant step in CM design undertaking three tasks namely clustering parts family and machines cells and then allocating the parts family to the related machines cells)

2 group layout (GL) (i.e., making decision about the layout of cells in shop floor, called inter-cell layout, and the layout of machines in each cell, called intra-cell layout)

3 group scheduling (GS) (i.e., scheduling the parts family in order that the manufacturing operations are finished at the shortest possible time)

4 resource allocation (i.e., allocation of equipment and human resources to the machines in order that incur the least equipping cost).

Wu et al. (2007) clarified that the aforementioned four steps are interrelated and the solution for each step influences the other one. Consequently, a simultaneous solution approach has to be applied to these problems that is the matter not being paid attention enough. However, due to the complexity of integrating CF, GL, and GS decisions, most studies have addressed these decisions sequentially or independently. For each design step of CMS, some exact methods have been proposed to solve the problems separately. For instance, Meziani et al. (2018) proposed a hybrid algorithm combining particle swarm optimisation with the simulated annealing (PSO-SA) to solve the two-machine flowshop scheduling problem which could be applied for cell scheduling as well. As another example, Merchichi and Boulif (2015) presented exact branch and bound algorithms to solve CF problems, considering the actual production constraints.

Nevertheless, the benefits which could be achieved from CMS implementation are enormously affected in what manner these decisions have been made in collaboration with each other.

Further, often fluctuations occurring in product demands and product mixes lead to a dynamic production situation due to increasing the variety of customers' products and decreasing the life cycles of products. It is necessary to reconfigure cells efficiently for consecutive periods in a dynamic situation where the product mixes and parts demands change throughout a multi-period planning horizon. This type of CM was presented as the dynamic cellular manufacturing system (DCMS) by Rheault et al. (1995).

Most models designed for DCMSs have assumed the input parameters as deterministic and certain values. Conversely, in real-world situations many parameters reveal uncertain and imprecise nature. As a result, DCMS design should be implemented in many situations based on some parameters with uncertain values. Therefore, the robust approach is applied to lessen the effects of fluctuations of the uncertain parameters with respect to all probable future scenarios. However, the number of studies on designing CMSs under dynamic and uncertain conditions is limited. These approaches could be categorised into four classes as fuzzy programming, stochastic programming, scenario-based programming, and robust optimisation in terms of uncertainty representation. Recently, different robust optimisation approaches have been designed to manage the uncertainty of the data. In this study, an interval-based robust optimisation approach is applied in order to tackle the uncertainty and to find a solution which is robust with respect to uncertainties in part demands and processing times.

Three targets are aimed at this study. First, formulating an integrated mathematical model with an extensive coverage of important manufacturing features. Those include uncertain process times, uncertain part demands, operation sequence, group layout, equal-area facilities multi-rows layout, flexible reconfiguration, operators hiring/firing and training, operator capacity and cell size limits. Second, developing three robust models built upon the proposed deterministic model and robust optimisation approach. The crucial task of the adjusted robust methodology is to obtain an optimal design of a DCMS which is robust as much as possible with respect to uncertainties in part demands and process times. Third, developing an efficient simulated annealing (SA) algorithm.

The cost components of the objective function to be minimised are intra/intercellular material handling, relocation and installation/uninstallation of machines, and hiring/firing, training and salary of operators. Furthermore, to convert the proposed mixed-integer nonlinear program into a linearised counterpart, linearisation procedures are used. The main constraints are machine-location assignment, operator-machine-cell assignment, cell size limits, operator capacity and training operator.

Kia et al. (2012) formulated a mathematical model to integrate CF and GL decisions in a dynamic environment. They incorporated some advantageous features including:

1. flexible configuration of cells
2. relocation cost calculation based on the machines locations
3. calculation of intra- and inter-cell movements costs based on travelled distance
4. equal-sized facilities multi-rows layout.

One drawback in their study was ignoring the assignment of operators to machines. Bagheri and Bashiri (2014) explored the simultaneous integration of the CF problem with inter-cell layout and operator assignment problems in a dynamic environment. They formulated a mathematical model to minimise inter/intra cell part movements, relocation cost and operator cost. A main shortcoming issue in both cited studies was considering all parameters as deterministic despite the fact some of them should have been forecasted for the future periods, especially in a dynamic environment with high levels of uncertainty and fluctuation.

In overall, the current study designs an interval-based robust optimisation approach to solve a mathematical model developed based on the previous studies (Kia et al., 2012; Bagheri and Bashiri, 2014) to integrate the CF, GL and worker assignment with data uncertainties in part demands and process times.

To investigate the effect of turbulence in the values of part demands and processing times separately and simultaneously on the performance of the model and the values obtained for solutions, three robust models are developed. Then, two illustrative examples are solved to prove the validity of the designed robust models. Furthermore, in order to evaluate the effects and significance of integration of GL and operator assignment in designing a DCMS, two approaches, sequentially and concurrently are considered and the achievement to be reached from a concurrent approach is shown.

An efficient simulated annealing (SA) algorithm is also designed with a matrix-based solution representation with explorative mutation operators for solving the presented mathematical model. Additionally, several test problems are solved using the extended SA and the obtained solutions are compared with those obtained using CPLEX solver to verify the efficiency of the developed SA in terms of both the objective function value (OFV) and computational time. The results show the efficiency of SA in achieving satisfactory solutions.

The rest of this paper is planned as follows. In Section 2, the literature review is carried out. A mathematical model integrating CF, GL and worker assignment decisions is formulated in Section 3 followed using some linearisation procedures. In addition, three robust models are developed in this section. The development of the designed SA is discussed in Section 4. Section 5 presents the test problems that are applied to examine the features of the proposed model and assess the performance of the developed robust models and SA algorithm. Finally, conclusions and directions for future studies are given in Section 6.

2 Literature review

In this section, we review the studies integrating decisions of either layout or workers assignment in designing DCMSs under uncertain environments. Since there have been numerous studies performed in this field, the focus is made on the recent and relevant studies. Many models have been designed for DCMS incorporating some design features simultaneously. A list of some most-commonly considered and significant features is given in Table 1. We explored 16 recently published papers considering the majority of those design features addressed in Table 1. Since Kia et al. (2015) conducted a comprehensive literature review in the field of DCMSs, we summarise recent studies of DCMS addressing layout or worker assignments issues in Table 2. Regarding the papers reviewed in Table 2, it is realised that some of the papers studied other important aspects such as machine capacity, multi-skilled workers assignments, part operations scheduling, resource allocation, machine reliability and supply chain issues that have not been addressed in our study. Nevertheless, it could be argued that the model in the current study offers a large coverage of the design characteristics. This is another advantage of the presented model. By considering the previous works summarised in Table 1, it could be concluded that no study has been performed on simultaneous integrating of three problems as CF, GL and operator assigning under uncertain conditions so far.

Table 1 List of significant features in the CMS design

1	Alternative routing	
	1.1	Selecting the best route from the user-specified routings
	1.2	Selecting from all possible options based on operation and machine type
2	Material handling cost	
	2.1	Inter-cell material handling cost
	2.2	Intra-cell material handling cost
3	Group layout	
	3.1	Inter-cell layout
	3.2	Intra-cell layout
4	Data type	
	4.1	Deterministic
	4.2	Stochastic
5	Cell size limitation	
6	Cell reconfiguration	
7	Workers training	
8	Workers hiring/firing/salary costs	
9	Multi-period production planning	
10	Operations process time	
11	Workforces planning issues	
12	Machine operation cost	
13	Machines relocation	
14	Machine capacity	
15	Demand requirement	
16	Outsourcing	
17	Inventory holding	
18	Supplier and supply chain issues	

Table 2 Important features in the CM design used in this research and other recent studies

Articles/authors	*1*		*2*		*3*		*4*		*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*	*17*	*18*	*Solution approach**
	1.1	*1.2*	*2.1*	*2.2*	*3.1*	*3.2*	*4.1*	*4.2*															
Current research			x	x	x	x		x	x	x	x	x		x	x		x		x				SA and RO
Kia et al. (2012)		x	x	x	x	x	x		x	x			x	x		x	x	x	x				SA
Delgoshaei et al. (2016)		x	x	x				x	x				x			x		x	x	x			GA
Shafigh et al. (2017)		x	x	x	x	x	x						x	x		x	x	x	x	x	x		Integrated LP-SA
Sakhaii et al. (2016)	x		x	x	x			x	x		x	x	x	x	x		x	x	x		x		RO
Zohrevand et al. (2016)		x	x					x	x	x		x		x	x		x	x	x				Hybrid TS-GA
Raoofpanah et al. (2019)				x		x	x		x				x	x			x	x	x	x	x	x	BD
Liu et al. (2016)							x				x		x		x				x		x		Hybrid BFA
Nouri (2016)		x	x	x			x		x	x		x		x	x	x	x	x	x	x	x		BFA and NSGA-II
Azadeh et al. (2016)		x	x	x				x	x	x					x		x		x				NSGA-II and MOPSO
Bagheri and Bashiri (2014)		x	x	x	x		x		x		x	x		x	x				x				LP-metric
Rafiei and Ghodsi (2013)		x	x	x			x		x	x			x	x	x	x	x	x	x				ACO
Feng et al. (2018)	x		x		x	x	x		x					x		x		x	x	x			LP-SA and LP-GA
Mehdizadeh et al. (2016)		x	x	x			x		x	x		x	x	x	x	x	x	x	x	x	x		MOVDO and NSGA-II
Paydar et al. (2014)		x	x	x	x	x		x	x					x				x	x		x	x	RO
Niakan et al. (2016)		x	x	x			x		x	x	x	x		x	x	x	x	x	x				MOSA and NSGA-II
Aalaei and Davoudpour (2017)		x	x					x	x			x	x	x				x	x		x	x	RO

Note: *SA – simulated annealing; RO – robust optimisation; GA – genetic algorithm; LP – linear programming; TS – tabu search; BD – Benders decomposition; BFA – bacteria foraging algorithm; NSGA-II – non-dominated sorting genetic algorithm-II; MOPSO – multi-objective particle swarm optimisation; ACO – ant colony optimisation; MOVDO – multi-objective vibration damping optimisation; MOSA – multi-objective simulated annealing.

3 Mathematical model and problem statement

3.1 Model assumptions

The model presented in this study deals with cell formation, group layout, and operator assigning simultaneously. We assume that the shop floor has been divided into the same-size locations that their distance from each other is given and every machine has to be assigned to one of these locations. In addition, as the cell layouts are determined, simultaneously operators are assigned to the cells and it is defined which machines are served by them. This model aims to minimise total costs of intracellular and intercellular material handling, machines relocation, operators training, hiring/firing and salary. The problem assumptions are as the following:

1. Each part has a processing route specified with respect to its route sheet.
2. Demand and processing time for each part is given in an uncertain interval.
3. There is no barrier or physical partition between the cells and the costs related to the cell reconfiguration only includes uninstalling/installing and intercellular machines movement.
4. The number of the candidate locations and the distance between them is determined in advance and it is fixed during the planning horizon.
5. The number of the formed cells in each period is specified by the system designer.
6. The cells upper and lower limit has been specified in advance and it remains constant during the planning horizon.
7. The movement time of parts and machines has been taken zero.
8. Each machine can process only one operation at each time.
9. The intracellular and intercellular material handling cost depends on the travelled distance. Also, the distance between two machines depends on the assigned locations distance from each other.
10. All the machines and locations are equal-area with the same dimensions. Actually, we design a multi-row layout of equal-area facilities in a CMS along with the operator assignment.
11. The material handling unit cost is determined. This cost differs for intracellular and intercellular movements. However, due to the intercellular movements being more important, the cost of each intercellular movements unit is more than that of the intracellular movement unit.
12. Each operator is assigned only to one cell and in fact, is not allowed to move among the cells in a period. However, an operator could be assigned to more than one machine if there is enough time capacity for him or her.
13. If an operator is not able to work on a machine, he or she can be trained to work with the machine.
14. Training operators happens between the periods and its time is considered zero.

15 Each operator can be hired or fired independently.

Indices

$m, m' = \{1, 2, \ldots, M\}$	Machine indices.
$i, i' = \{1, 2, \ldots, I\}$	Part indices.
$j, j' = \{1, 2, \ldots, u_i^h\}$	Part operations indices.
$l, l' = \{1, 2, \ldots, L\}$	Location indices.
$k = \{1, 2, \ldots, K\}$	Operator index.
$h = \{1, 2, \ldots, H\}$	Time period index.
$c = \{1, 2, \ldots, C\}$	Cells index.

Parameters

a_{km}	Training cost for operator k to work with machine type m.
t_{ijm}	Process time of operation j of part i by machine type m.
$\tilde{t}_{ijm}$	Uncertain process time of operation j of part i by machine type m.
$\hat{t}_{ijm}$	Interval of uncertain processing time of operation j of part i by machine type m.
D_{ij}	Demand of part type i in period h.
$\tilde{D}_{ih}$	Uncertain demand of part type i in period h.
$\hat{D}_{ih}$	Interval of uncertain demand of part type i in period h.
$d_{ll'}$	Distance between locations l and l'.
H_k	Cost of hiring operator k.
F_k	Cost of firing operator k.
pp_{ijmh}	1 if operation j of part i should be processed by machine type m in period h; 0 otherwise.
sa_{km}	Salary cost of operator k to work with machine type m per hour.
IA_i	Intra-cell movement cost for part type i per distance unit.
IE_i	Inter-cell movement cost for part type i per distance unit.
IM_m	Movement cost of machine type m per distance unit.
σ_m	Installation/uninstallation cost of machine type m.
WT_{kh}	Available time capacity of operator k in period h.
b_u	Upper cell size limit.
b_l	Lower cell size limit.

z_{kmh} 1 if operator k is able to work with machine type m in period h; 0 otherwise.

I_{m*h} Number of parts processed by machine type m in period h.

G_{m*h} Number of parts operations processed by machine type m in period h.

Decision variables

h_{kh} 1 if operator k is hired in period h; 0 otherwise.

SS_{kch} 1 if operator k is assigned to cell c in period h; 0 otherwise.

Z_{kmh} 1 if operator k is not able to work by machine m in period $h > 1$; 0 otherwise.

w_{mlch} 1 if machine type m is located in location l and assigned to cell c in period h, 0 otherwise.

r_{kmh} 1 if operator k is assigned to machine m in period h; 0 otherwise.

α_{kmh} Portion of time capacity of operator k used for working by machine m in period h.

3.2 Mathematical model

The integrated model is formulated as a mixed-integer nonlinear program:

$$\sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{l=1}^{L}\sum_{m'=1}^{M}\sum_{l'\neq l}^{L}\sum_{i=1}^{I}\sum_{j=1}^{u_i^h-1}\left(D_{ih} * w_{mlch} * w_{m'l'ch} * pp_{ijmh} * pp_{i(j+1)m'h} * d_{ll'} * IA_i\right) \quad (1.1)$$

$$+\sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{c'\neq c}^{C}\sum_{m=1}^{M}\sum_{l=1}^{L}\sum_{m'=1}^{M}\sum_{l'\neq l}^{L}\sum_{i=1}^{I}\sum_{j=1}^{u_i^h-1}\left(D_{ih} * w_{mlch} * w_{m'l'c'h} * pp_{ijmh} * pp_{i(j+1)m'h} * d_{ll'} * IE_p\right) \quad (1.2)$$

$$+\sum_{h=1}^{H-1}\sum_{l=1}^{L}\sum_{m=1}^{M}\delta_m * \left|\sum_{c=1}^{C} w_{mlch} - \sum_{c=1}^{C} w_{mlch+1}\right|$$
$$+\sum_{h=1}^{H-1}\sum_{m=1}^{M}\sum_{l=1}^{L}\sum_{l'\neq l=1}^{L}\sum_{c=1}^{C}\sum_{c'=1}^{C} IM_m * w_{mlch} * w_{ml'c'h+1} * d_{ll'} \quad (1.3)$$

$$+\sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{k=1}^{K} h_{kh} ss_{kch} z_{kmh} * r_{kmh}\left(\sum_{l=1}^{L} w_{mlch}\right) * a_{km} \quad (1.4)$$

$$+\sum_{h=1}^{H}\sum_{k=1}^{K}\left(h_{kh} * H_k + (1-h_{kh}) * F_k\right) \quad (1.5)$$

$$\sum_{h=1}^{H}\sum_{k=1}^{K}\sum_{m=1}^{M}\alpha_{kmh} WT_k * sa_{km} \quad (1.6)$$

s.t.:

$$\sum_{m=1}^{M}\sum_{c=1}^{C} w_{mlch} \leq 1 \qquad \forall l, h \tag{2}$$

$$\sum_{m=1}^{M}\sum_{l=1}^{L} w_{mlch} \leq b_u \qquad \forall c, h \tag{3}$$

$$\sum_{m=1}^{M}\sum_{l=1}^{L} w_{mlch} \geq b_l \qquad \forall c, h \tag{4}$$

$$\sum_{c=1}^{C}\sum_{l=1}^{L} w_{mlch} = 1 \qquad \forall m, h \tag{5}$$

$$\sum_{c=1}^{C} s_{kch} = h_{kh} \qquad \forall k, h \tag{6}$$

$$r_{kmh} \leq \sum_{c=1}^{C}\left[\left(\sum_{l=1}^{L} w_{mlch}\right) S_{kch}\right] \qquad \forall m, k, h \tag{7}$$

$$\sum_{i}^{I}\sum_{j}^{u_i^h} D_{ih}\, pp_{ijmh} t_{ijm} \leq \sum_{k}^{K} \alpha_{kmh} WT_k \qquad \forall m, h \tag{8}$$

$$\sum_{m=1}^{M} \alpha_{kmh} \leq 1 \qquad \forall k, h \tag{9}$$

$$\alpha_{kmh} \leq r_{kmh} \qquad \forall k, m, h \tag{10}$$

$$Z_{km(h+1)} = \left(1 - r_{kmh}\right) Z_{kmh} \qquad \forall k, m, h \in 1 \ldots h-1 \tag{11}$$

$$r_{kmh}, Z_{kmh}, h_{kh}, w_{mlch}, s_{kch} \in 0, 1 \text{ and } a_{km} \in [0, 1] \tag{12}$$

The objective function consists of six constituents. Terms (1.1) and (1.2) are the intracellular and intercellular parts movement cost. To give a detailed explanation about equations (1.1) and (1.2), we decompose them in some terms as described in the following. Firstly, we clarify in which situations the intracellular or intercellular parts movement will happen and result in corresponding either intracellular or intercellular handling cost. It is obvious that if two consecutive operations of a part are processed by the same machine, there will not be any handling cost, as there will not be neither intracellular nor intercellular movement for handling those two operations. However, if two consecutive operations of a part are processed by different machines, a material handling cost is incurred, either for intracellular or intercellular movement. Hence, the term $pp_{ijmh} \times pp_{i(j+1)m'h}$ in both equations (1.1) and (1.2) determines whether two consecutive operations j and $j + 1$ of part i are processed by the same machine m or different machines m and m'. If m and m' are equal, it means that they are the same machines located in the same locations, so the travelled distance $d_{ll'}$ for handling operations j and $j + 1$ is 0 which brings no handling cost. If m and m' are different, it means they should be located in different locations $l \neq l'$. Consequently, a handling cost is incurred either for intracellular or intercellular movement. Now, the usage of two terms $w_{mlch} \times w_{m'l'ch}$ and $w_{mlch} \times w_{m'l'c'h}$ are explained. In the situation that processing of two consecutive operations j and $j + 1$ of part i are processed by different machines m and m' located in different locations $l \neq l'$; only one of terms $w_{mlch} \times w_{m'l'ch}$ and $w_{mlch} \times w_{m'l'c'h}$ will take 1 and the other one take 0. In case $w_{mlch} \times w_{m'l'ch} = 1$, it means that machines m and m' are assigned to same cell c and the handling cost should be calculated by multiplying the amount of flow, D_{ih}, by travelled distance between two locations $l \neq l'$, $d_{ll'}$, and the corresponding intra-cell movement cost per part per distance unit, IA_i.

Similarly, In case $w_{mlch} \times w_{m'l'c'h} = 1$, $(c \neq c')$ it means that machines m and m' are assigned to different cells c and c'; therefore, the handling cost should be calculated by multiplying the amount of flow, D_{ih}, by travelled distance between two locations $l \neq l'$, $d_{ll'}$, and the corresponding inter-cell movement cost per part per distance unit, IE_i.

Term (1.3) is the cost of the machines movement that the first part is related to the machines installation/uninstallation and the second part belongs to the intercellular machines movement. Equations (1.4), (1.5) and (1.6) are for the operators costs where equation (1.4) is training cost, equation (1.5) is hiring/firing cost and equation (1.6) is the salaries paid to operators.

Constraint (2) guarantees that in each location in each period, only one machine can be located at most. Constraints (3) and (4) specify the max/min machines number in each cell. Constraint (5) states that each machine in each period has to be placed in one location. Constraint (6) assures that when an operator is hired, the operator has to be assigned to one of the cells. Constraint (7) states that an operator can be assigned to one machine provided that both the operator and the machine have been placed in the same cell. Constraint (8) states that the total portions of time capacity of different operators utilised for working by machine m in period h has to be more than or equal to total processing times of different parts processed by machine m. Constraint (9) states that the total percentage of the times spent by an operator on various machines in one period must be less than 1. Constraint (10) expresses that an operator serves a machine by spending a portion of its time capacity if that operator is assigned to that machine. Constraint (11) states that an operator is trained for working with a machine in a period when that operator has not been assigned to that machine in the previous periods and also has not been trained to work with that machine until that period. Constraint (12) expresses the variable type where the first five ones are binary and the last one takes a value in interval [0, 1].

3.3 Model linearisation

The model proposed in Section 3.2 is nonlinear due to using the multiplication terms and absolute function. In fact, the presented model is nonlinear because of equations (1.1) to (1.4) in the objective function and the constraints (7) and (11). Since solving nonlinear models is usually more difficult than the linear ones, in this part, we rewrite the model as linear using the procedures available in the literature.

The equations (1.1), (1.2) and the second part of term (1.3) in the objective function are nonlinear due to two variables getting multiplied and are linearised by defining an auxiliary variable and adding two constraints that is a homogenous linearisation. Then, for linearising these equations, the variables $ww_{mm'll'ch}$, $wwc_{mm'll'ch}$ and $wwh_{mll'cc'h}$ are defined as the following:

$$\begin{aligned} & ww_{mm'll'ch} = w_{mlch} * w_{m'l'ch} \\ & wwc_{mm'll'cc'h} = w_{mlch} * w_{m'l'c'h} \\ & wwh_{mll'cc'h} = w_{mlch} * w_{ml'c'h+1} \end{aligned} \tag{13}$$

where the following constraints should be added to the main model:

$$\begin{aligned} & ww_{mm'll'ch} - w_{mlch} - w_{m'l'ch} + 1.5 \ge 0 \\ & 1.5 * ww_{mm'll'ch} - w_{mlch} - w_{m'l'ch} \le 0 \\ & wwc_{mm'll'cc'h} - w_{mlch} - w_{m'l'c'h} + 1.5 \ge 0 \\ & 1.5 * wwc_{mm'll'cc'h} - w_{mlch} - w_{m'l'c'h} \le 0 \qquad \forall l \ne l', c \ne c', m < m' \\ & wwh_{mll'cc'h} - w_{mlch} - w_{ml'c'h+1} + 1.5 \ge 0 \\ & 1.5 * wwh_{mll'cc'h} - w_{mlch} - w_{ml'c'h+1} \le 0 \end{aligned} \tag{14}$$

Linearisation of term (1.4) is similar to that of terms (1.1)–(1.3). The only difference is that four variables are multiplied in term (1.4) and then auxiliary variable q_{mkch}, rz_{kmh} and xs_{mkch} are defined as the following:

$$\begin{aligned} & xs_{mkch} = \sum_{l=1}^{L} w_{mlch} ** ss_{kch} \\ & rz_{kmh} = r_{kmh} * z_{kmh} \\ & q_{mkch} = h_{kh} * xs_{mkch} * rz_{kmh} \end{aligned} \tag{15}$$

where the following constraints should be added to the main model:

$$\begin{aligned} & xs_{mkch} \le \sum_{l=1}^{L} w_{mlch} && \forall m, k, c, h \\ & xs_{mkch} \le ss_{kch} && \forall m, k, c, h \\ & xs_{mkch} \ge \sum_{l=1}^{L} w_{mlch} + ss_{kch} - 1 && \forall m, k, c, h \\ & rz_{kmh} \le z_{kmh} && \forall k, m, h \\ & rz_{kmh} \le r_{kmh} && \forall k, m, h \\ & rz_{kmh} \ge r_{kmh} + z_{kmh} - 1 && \forall k, m, h \\ & q_{mkch} \le h_{kh} && \forall m, k, c, h \\ & q_{mkch} \le xs_{mkch} && \forall m, k, c, h \\ & q_{mkch} \le rz_{kmh} && \forall m, k, c, h \\ & q_{mkch} \ge h_{kh} + xs_{mkch} + rz_{kmh} - 2 && \forall m, k, c, h \end{aligned} \tag{16}$$

To linearise the first part of term (1.3), a commonly-used linearisation procedure is employed. Auxiliary variables qw_{mlh} and pw_{mlh} are introduced and the absolute term is transformed as follows:

$$\left|\sum_{c=1}^{C} w_{mlch} - \sum_{c=1}^{C} w_{mlch+1}\right| = pw_{mlh} + qw_{mlh} \tag{17}$$

Where the following constraint is added to the main model:

$$\sum_{c=1}^{C} w_{mlch} - \sum_{c=1}^{C} w_{mlch+1} = pw_{mlh} - qw_{mlh} \qquad \forall m, l, h \in 1, 2, \dots, h-1 \tag{18}$$

Now, the linearised model is presented by adding new auxiliary variables and constraints as follows:

$$\sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{l=1}^{L}\sum_{m'=1}^{M}\sum_{l'\neq l}^{L}\sum_{i=1}^{I}\sum_{j=1}^{u^{h}_{i}-1}\left(D_{ih} * ww_{mm'll'ch} * pp_{ijmh} * pp_{i(j+1)m'h} * d_{ll'} * IA_i\right) \tag{1.7}$$

$$+\sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{c'\neq c}^{C}\sum_{m=1}^{M}\sum_{l=1}^{L}\sum_{m'=1}^{M}\sum_{l'\neq l}^{L}\sum_{i=1}^{I}\sum_{j=1}^{u_i^h-1}\left(D_{ih} * wwc_{mm'll'cc'h} * pp_{ijmh} * pp_{i(j+1)m'h} * d_{ll'} * IE_i\right) \tag{1.8}$$

$$+\sum_{h=1}^{H-1}\sum_{l=1}^{L}\sum_{m=1}^{M}\delta_m *\left(pw_{mlh} + qw_{mlh}\right) + \sum_{h=1}^{H-1}\sum_{m=1}^{M}\sum_{l=1}^{L}\sum_{l'\neq l=1}^{L}\sum_{c=1}^{C}\sum_{c'=1}^{C} wwh_{mll'cc'h} * d_{ll'} \tag{1.9}$$

$$+\sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{k=1}^{K} q_{mkch} * a_{km} \tag{1.10}$$

$$+\sum_{h=1}^{H}\sum_{k=1}^{K}\left(h_{kh} * H_k + (1-h_{kh}) * F_k\right) \tag{1.11}$$

$$+\sum_{h=1}^{H}\sum_{k=1}^{K}\sum_{m=1}^{M} \alpha_{kmh} WT_k * sa_{km} \tag{1.12}$$

The constraints of the linearised model include change-free ones (2), (6), (8)–(10), new constraints (13), (14), and constraints (15) are substituted with the constraints (7), (11) and (12), respectively.

S.t.:

$$\begin{aligned}
& r_{kmh} \le \sum_{c=1}^{C}\left(xs_{mkch}\right) && \forall m, k, h \\
& z_{km(h+1)} = \left(z_{kmh} - rz_{kmh}\right) && \forall k, m, h \in 1 \dots, h-1 \\
& r_{kmh}, Z_{kmh}, h_{kh}, w_{mlch}, s_{kch}, q_{mkch}, rz_{kmh}, xs_{mkch}, pw_{mlh}, \\
& qw_{mlh}, ww_{mm'll'cc'h}, ww_{mm'll'ch} \in \{0, 1\}, \alpha_{kmh} \in (0, 1)
\end{aligned} \tag{19}$$

3.4 Mathematical modelling under uncertain conditions

In the previous section, the problem integrating cell formation, group layout and operator assignment has been addressed with certain parameters while the majority of the manufacturing systems are operating under uncertain conditions. In a manufacturing system, uncertainty can stem from parameters such as demand, processing times, machine capacity, costs and etc.

Of the most significant and influencing parameters whose variations can have a great role in CM designing are the processing time and the parts demand, thus it is necessary to pay attention to these parameters while designing. Using a robust optimisation approach in this section, three robust models are developed based on the deterministic model to investigate the turbulence effect of part demand and processing times on model performance separately and simultaneously. In these three models, the objective is to form cells, find intracellular machines layout, locate the cells and assign operators to the machines so that the obtained solution remains optimal or close to optimal through keeping a confidence level respect to the changes in demand and the processing time. Unlike the scenario-based approaches where scenarios with certain occurrence probability are employed, in this study interval-based approach is used in order to cope with uncertainty.

3.4.1 Robust optimisation approach

In recent years, handling uncertain data has been a major challenge in optimisation. One approach developed to address data uncertainty is robust optimisation to find a solution that can cope with all possible realisations of the uncertain data. Various approaches of robust optimisation have been developed by Ben-Tal and Nemirovski (1998, 1999, 2000), El Ghaoui et al. (2003) and Bertsimas and Sim, (2003).

In this paper, we employed the approach permitting to control the conservatism level of the solution (Bertsimas and Sim, 2003). Solutions obtained by a robust optimisation approach are expected to guarantee more situations, even the worst one. The important concern of the robust methodology used in this paper is to obtain an optimal CM design that is robust respect to uncertainty of part demands and process times. The deterministic compact form of a mathematical model can be presented as follows:

$$\begin{aligned} & Min\ c^T \cdot x \\ & s.t. \\ & \quad Ax \le b \\ & \quad lb \le x \le ub \end{aligned} \tag{20}$$

Assume that only elements of matrix $A = (a_{nj})$ are subjected to data uncertainty. Then, robust optimisation approaches model data uncertainties through bounded intervals. Therefore, the uncertain elements of matrix A can be defined using the mean value and interval of each uncertain element as follows:

$$\tilde{a}_{n,j} = \left[a_{n,j} - \hat{a}_{n,j}, a_{n,j} + \hat{a}_{n,j}\right] \qquad \tilde{a}_{n,j} \in A \tag{21}$$

A number named conservatism level (CL), symbolised by Γ_n ($n = 1, \ldots, CN$) and introduced in Bertsimas et al. (2004) is used for robustness purposes and fine-tuning the robustness level which takes changed values in the interval $[0, |J_n|]$, where J_n is a set encompassing uncertain elements of the n^{th} equation $J_n = \{j \mid \hat{a}_{n,j} > 0\}$. As a result, the nonlinear robust counterpart of equation (20) can be written as follows:

$$
\begin{aligned}
& Min\ c^T \cdot x \\
& s.t. \\
& \quad \sum_j a_{n,j} \cdot x_j + \max_{\{S_n \cup \{t_n\} S_n \subseteq J_n, |S_n| = \lfloor \Gamma_n \rfloor, t_n \subseteq J_n \setminus S_n\}} \left\{ \sum_{j \in s_n} \hat{a}_{n,j} \cdot |x_j| \right. \\
& \quad \left. + \left(\Gamma_n - \lfloor \Gamma_n \rfloor\right) \cdot \hat{a}_{n,t_n} \cdot |x_{t_n}| \right\} \le b_n \quad \forall n \\
& \quad lb \le x \le ub
\end{aligned} \tag{22}
$$

Using a linearisation technique for nonlinear equation (22), we have:

$$
\begin{aligned}
& Min\ c^T \cdot x \\
& s.t. \\
& \quad \sum_j a_{n,j} \cdot x_j + z_n \cdot \Gamma_n + \sum_{j \in J_n} p_{n,j} \le b_n && \forall n \\
& \quad z_n + p_{n,j} \ge \hat{a}_{n,j} \cdot y_j && \forall n,\ j \in J_n \\
& \quad -y_j \le x_j \le y_j && \forall j \\
& \quad lb_j \le x_j \le ub_j && \forall j \\
& \quad z_n \ge 0 && \forall n \\
& \quad p_{n,j} \ge 0 && \forall n,\ j \in J_n \\
& \quad y_j \ge 0 && \forall j
\end{aligned} \tag{23}
$$

3.4.2 *Robust modelling for integrated CMS under demand uncertainty conditions*

The model presented in Section 3.2 has been formulated in terms of the parts nominal demand. In this section, in order to formulate the robust model regarding demand variations, the approach introduced by Bertsimas and Sim (2004) and described in Section 3.4.1 has been employed. Assuming that demand value of part i is uncertain and placed in symmetrical interval $\tilde{D}_{ih} \in [D_{ih} - \hat{D}_{ih}, D_{ih} + \hat{D}_{ih}]\ \forall i, h,$ the robust model is formulated as the following:

$$Min\ \text{RO}^1$$

s.t:

(2)−(6), (9)−(10), (14), (16), (19)

$$
\underbrace{\sum_{h=1}^{H} \sum_{c=1}^{C} \sum_{m=1}^{M} \sum_{l=1}^{L} \sum_{m'=1}^{M} \sum_{l' \neq l}^{L} \sum_{i=1}^{I} \sum_{j=1}^{u_i^h - 1} \left(\tilde{D}_{ih} * ww_{mm'll'ch} * pp_{ijmh} * pp_{i(j+1)m'h} * d_{ll'} * IA_i \right)}_{(1-7)}
$$

$$
+ \underbrace{\sum_{h=1}^{H} \sum_{c=1}^{C} \sum_{c' \neq c}^{C} \sum_{m=1}^{M} \sum_{l=1}^{L} \sum_{m'=1}^{M} \sum_{l' \neq l}^{L} \sum_{i=1}^{I} \sum_{j=1}^{u_i^h - 1} \left(\tilde{D}_{ih} * wwc_{mm'll'cc'h} * pp_{ijmh} * pp_{i(j+1)m'h} * d_{ll'} * IE_i \right)}_{(1-8)}
$$

$$+\underbrace{\sum_{h=1}^{H-1}\sum_{l=1}^{L}\sum_{m=1}^{M}\delta_m*(pw_{mlh}+qw_{mlh})+\sum_{h=1}^{H-1}\sum_{m=1}^{M}\sum_{l=1}^{L}\sum_{l'\neq l=1}^{L}\sum_{c=1}^{C}\sum_{c'=1}^{C}wwh_{mll'cc'h}*d_{ll'}}_{(1-9)} \tag{24}$$

$$+\underbrace{\sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{k=1}^{K}q_{mkch}*a_{km}}_{(1-10)}+\underbrace{\sum_{h=1}^{H}\sum_{k=1}^{K}(h_{kh}*H_k+(1-h_{kh})*F_k)}_{(1-11)}$$

$$\underbrace{\sum_{h=1}^{H}\sum_{k}^{K}\sum_{m=1}^{M}\alpha_{kmh}WT_k*sa_{km}}_{(1-12)}+Z^0\Gamma^0+\sum_{i}^{I}\sum_{h}^{H}p_{ih}^1+\sum_{i}^{I}\sum_{h}^{H}p_{ih}^2\leq RO^1$$

$$\sum_{i}^{I}\sum_{j}^{u^h{}_i}\tilde{D}_{ih}pp_{ijmh}t_{ijm}+Z^1{}_{mh}\Gamma^1{}_{mh}+\sum_{i}^{I}\sum_{h}^{H}p_{ih}^3\leq\sum_{k}^{K}\alpha_{kmh}WT_k \quad \forall m,h \tag{25}$$

$$Z^0+p_{ih}^1\geq\hat{D}_{ih}ww_{mm'll'ch}*pp_{ijmh}*pp_{i(j+1)m'h}*d_{ll'}*IA_i \quad \forall i,j,m,m',l,l',c,c',h$$

$$Z^0+p^2{}_{ih}\geq\hat{D}_{ih}wwc_{mm'll'cc'h}*pp_{ijmh}*pp_{i(j+1)m'h}*d_{ll'}*IE_i \quad \forall i,j,m,m',l,l',c,c',h$$

$$Z_{mh}^1+p_{ih}^3\geq\hat{D}_{ih}pp_{ijmh}t_{ijm} \quad \forall i,j,m,h \tag{26}$$

$$Z^0\geq 0$$

$$Z_{mh}^1\geq 0 \qquad \forall m,h$$

$$p_{ih}^1,p_{ih}^2,p_{ih}^3\geq 0 \qquad \forall i,h$$

Concerning the demand dimension is I×H, thus the total number of uncertain demand variables equals to $I*H$. Given $\tilde{D}_{ih}\in[D_{ih}-\hat{D}_{ih},D_{ih}+\hat{D}_{ih}]\,\forall i,h$ and equation (25), it is determined that $n = m * h$ and $\Gamma_1^1,\Gamma_2^1,\Gamma_3^1,\ldots,\Gamma_{m*h}^1$. Also, in equation (25) since the total uncertain set equals the total number of the parts processed in period h, thus we have $J_n = [0, |J_n|] = [0, |I_{m*h}|]$ and in addition, because the total number of uncertain variables in the objective function equals $2 * I_{m*h}$, the maximum value of Γ^0 equals $2 * I_{m*h}$. Then, we have $J_n = [0, |J_n|] = [0, |2*I_{m*h}|]$.

3.4.3 Robust modelling for integrated CMS under processing time uncertainty conditions

Assuming that the processing time of the part i is uncertain and placed in the symmetric interval $\tilde{t}_{ijm}\in[t_{ijm}-\hat{t}_{ijm},t_{ijm}+\hat{t}_{ijm}]\,\forall i,j,m,$ the robust model of the integrated problem is formulated as the following:

Min RO^2

s.t.

(2)−(6), (9)−(10), (14), (16), (19)

$$\underbrace{\sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{l=1}^{L}\sum_{m'=1}^{M}\sum_{l'\neq l}^{L}\sum_{i=1}^{I}\sum_{j=1}^{u_i^h-1}\left(D_{ih} * ww_{mm'll'ch} * pp_{ijmh} * pp_{i(j+1)m'h} * d_{ll'} * IA_i\right)}_{(1-7)}$$

$$+\underbrace{\sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{c'\neq c}^{C}\sum_{m=1}^{M}\sum_{l=1}^{L}\sum_{m'=1}^{M}\sum_{l'\neq l}^{L}\sum_{i=1}^{I}\sum_{j=1}^{u^h{}_i-1}\left(D_{ih} * wwc_{mm'll'cc'h} * pp_{ijmh} * pp_{i(j+1)m'h} * d_{ll'} * IE_i\right)}_{(1-8)}$$

$$+\underbrace{\sum_{h=1}^{H-1}\sum_{l=1}^{L}\sum_{m=1}^{M}\delta_m * \left(pw_{mlh} + qw_{mlh}\right) + \sum_{h=1}^{H-1}\sum_{m=1}^{M}\sum_{l=1}^{L}\sum_{l'\neq l=1}^{L}\sum_{c=1}^{C}\sum_{c'=1}^{C} wwh_{mll'cc'h} * d_{ll'}}_{(1-9)} \quad (27)$$

$$+\underbrace{\sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{k=1}^{K} q_{mkch} * a_{km}}_{(1-10)} + \underbrace{\sum_{h=1}^{H}\sum_{k=1}^{K}\left(h_{kh} * H_k + (1-h_{kh}) * F_k\right)}_{(1-11)}$$

$$+\underbrace{\sum_{h=1}^{H}\sum_{k}^{K}\sum_{m=1}^{M}\alpha_{kmh} WT_k * sa_{km}}_{(1-12)} + Z^0\Gamma^0 + \sum_{i=1}^{I}\sum_{h=1}^{H} p_{ih}^1 + \sum_{i}^{I}\sum_{h=1}^{H} p_{ih}^2 \leq RO^2$$

$$\sum_{i}^{I}\sum_{j}^{u_i^h} D_{ih} pp_{ijmh}\tilde{t}_{ijm} + Z_{mh}^2\Gamma_{mh}^2 + \sum_{i}\sum_{j} p^4{}_{ijm} \leq \sum_{k}^{K}\alpha_{kmh} WT_k \quad \forall m, h \quad (28)$$

$$Z_{mh}^2 + p_{ijm}^4 \geq D_{ih} pp_{ijmh}\hat{t}_{ijm} \qquad \forall i, j, m, h$$

$$Z_{mh}^2 \geq 0 \qquad \forall m, h \quad (29)$$

$$p_{ijm}^4 \geq 0 \qquad \forall i, j, m$$

Regarding the processing time dimension equals $I * J * M$, then the total number of uncertain variables equals $I * J * M$. In addition, considering $\tilde{t}_{ijm} \in [t_{ijm} - \hat{t}_{ijm}, t_{ijm} + \hat{t}_{ijm}]$ $\forall i, j, m$ and also equation (28), it is set that $n = m * h$ and $\Gamma_1, \Gamma_2, \Gamma_3, \ldots, \Gamma_{m*h}$. Also, in equation (28), since the total number of uncertain set equals the total number of the operations of the parts processed by machine m in period h (e.g., $J_n = [0, |J_n|] = [0, |G_{m*h}|]$, G_{m*h} is the operation number of the parts processed by machine m in period h.

3.4.4 Robust modelling for integrated CMS under demand and processing time uncertainty conditions

$$Min\ RO^3$$

s.t:

(2)–(6), (9)–(10), (14), (16), (19)

$$\underbrace{\sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{l=1}^{L}\sum_{m'=1}^{M}\sum_{l'\neq l}^{L}\sum_{i=1}^{I}\sum_{j=1}^{u^h{}_i-1}\left(\tilde{D}_{ih} * ww_{mm'll'ch} * pp_{ijmh} * pp_{i(j+1)m'h} * d_{ll'} * IA_i\right)}_{(1-7)}$$

$$+\underbrace{\sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{c'\neq c}^{C}\sum_{m=1}^{M}\sum_{l=1}^{L}\sum_{m'=1}^{M}\sum_{l'\neq l}^{L}\sum_{i=1}^{I}\sum_{j=1}^{u^h{}_i-1}\left(\tilde{D}_{ih} * wwc_{mm'll'cc'h} * pp_{ijmh} * pp_{i(j+1)m'h} * d_{ll'} * IE_i\right)}_{(1-8)}$$

$$+\underbrace{\sum_{h=1}^{H-1}\sum_{l=1}^{L}\sum_{m=1}^{M}\delta_m * \left(pw_{mlh} + qw_{mlh}\right) + \sum_{h=1}^{H-1}\sum_{m=1}^{M}\sum_{l=1}^{L}\sum_{l'\neq l=1}^{L}\sum_{c=1}^{C}\sum_{c'=1}^{C} wwh_{mll'cc'h} * d_{ll'}}_{(1-9)} \tag{30}$$

$$+\underbrace{\sum_{h=1}^{H}\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{k=1}^{K} q_{mkch} * a_{km}}_{(1-10)} + \underbrace{\sum_{h=1}^{H}\sum_{k=1}^{K}\left(h_{kh} * H_k + (1-h_{kh}) * F_k\right)}_{(1-11)}$$

$$\underbrace{\sum_{h=1}^{H}\sum_{k}^{K}\sum_{m=1}^{M}\alpha_{kmh}WT_k * sa_{km}}_{(1-12)} + Z^0\Gamma^0 + \sum_{i=1}^{I}\sum_{h=1}^{H} p_{ih}^1 + \sum_{i}^{I}\sum_{h=1}^{H} p_{ih}^2 \le RO^3$$

$$\sum_{i}^{I}\sum_{j}^{u_i^h}\tilde{D}_{ih}pp_{ijmh}\tilde{t}_{ijm} + Z_{mh}^1\Gamma_{mh}^1$$

$$+\sum_{i=1}^{I}\sum_{h=1}^{H} p_{ih}^3 + \sum_{i=1}^{I}\sum_{j=1}^{u^h{}_i}\sum_{m=1}^{M} p_{ijm}^4 \le \sum_{k}^{K}\alpha_{kmh}WT_k \qquad \forall m, h$$

$$Z^0 + p_{ih}^1 \ge \hat{D}_{ih}ww_{mm'll'ch} * pp_{ijmh} * pp_{i(j+1)m'h} * d_{ll'} * IA_i \quad \forall i, j, m, m', l, l', c, c', h$$

$$Z^0 + p^2{}_{ih} \ge \hat{D}_{ih}wwc_{mm'll'cc'h} * pp_{ijmh} * pp_{i(j+1)m'h} * d_{ll'} * IE_i \quad \forall i, j, m, m', l, l', c, c', h$$

$$Z_{mh}^1 + p_{ih}^3 \ge \hat{D}_{ih}pp_{ijmh}t_{ijm} \qquad \forall i, j, m, h \tag{31}$$

$$Z_{mh}^1 + p_{ijm}^4 \ge D_{ih}pp_{ijmh}\hat{t}_{ijm} \qquad \forall i, j, m, h$$

$$Z^0 \ge 0$$

$$Z_{mh}^1 \ge 0 \qquad \forall m, h$$

$$p_{ih}^1, p_{ih}^2, p_{ih}^3, p_{ijm}^4 \ge 0 \qquad \forall i, h$$

In this section, similar to the other two ones, the value $|J_n|$ is defined for Γ^0 and Γ^1, where we have $\Gamma^0 = 2 * I_{m*h}$ and $\Gamma^1 = G_{m*h} + I_{m*h}$.

In the mentioned models, parameter Γ takes a value between $(0, |J_n|)$ depending on the designer's opinion and controls the model robustness level (conservativeness level). Generally, the more Γ value is, the higher the model robustness. However, in order to keep this robustness, the objective function will increase. According to the robust model concept developed by Bertsimas et al. (2004), in the first model, the demand of Γ parts should be changed in such a way that maximum incurred cost becomes minimised. Although, how many parts demand can alter simultaneously is the question which has to be answered by the designer. That for the second model, the parts processing time and for the third model, demand and processing time will be similar.

4 Simulated annealing algorithm for the integrated model

The simulated annealing algorithm introduced by Kirkpatrick et al. (1983) is a stochastic neighbourhood search method for solving NP-hard combinatorial optimisation problems. SA imitates the annealing process attempting to enforce a system to its lowest energy level by decreasing the temperature from a satisfactory level to the preferred energy level through a controlled cooling scheme. SA has been employed in many optimisation models in DCMSs (Kia et al., 2012; Niakan et al., 2016; Shafigh et al., 2017; Feng et al., 2018). In this section, the elements of the extended SA are described as follows:

4.1 Solution structure representation

Solution structure shown in Figure 1 indicates a point in the feasible solution space so that its display is important in each meta-heuristic approach. The proposed solution structure represented by separate matrices involves five components as shown in Figure 1.

Figure 1 Solution structure representation

$$\left\langle (L\_TO\_C)_{T\times(L+C-1)} \middle| (M\_TO\_C)_{T\times(M+C)} \middle| (W\_TO\_C)_{C\times(K\times T)} \middle| (Alpha)_{M\times(K\times T)} \middle| Penalty_{(K\times M)} \right\rangle$$

In this figure, M stands for the machines index, C for the cells index, T for the periods index, L for the locations index and K for the operators index. In the continuation, each of these matrices has been explained.

The first part named matrix L_TO_C indicates the locations assignment to the cells and expressed as a matrix $T * (L + C - I)$. Let us give an example with $T = 2$, $C = 2$, $L = 6$. In this example, in the first period, locations 2, 1 and 4 are assigned to cell 1 and locations 6, 3 and 5 are assigned to cell 2.

$$L\_TO\_C = \begin{bmatrix} 2 & 1 & 4 & \| & 6 & 3 & 5 \\ 3 & 6 & 2 & \| & 4 & 1 & 5 \end{bmatrix}$$

The second part named matrix M_TO_C indicates the machines assigned to each location and expressed as a matrix $T * (M + C)$. The rows number equals the periods number and the columns number corresponds with the machines and cells number.

$$M\_TO\_C = \begin{bmatrix} 2 & 4 & \| & 1 & 3 & 5 \\ 3 & 2 & 1 & \| & 5 & 4 \end{bmatrix}$$

In the example above with $T = 2$, $C = 2$, $M = 5$, machine type 1 is located in cell 2 in the first period and in cell 1 in the second period.The third part named matrix W_TO_C indicates the operators assigned to the cells and stated as a 2-dimensional matrix

$C * (K * T)$. The rows number equals the cells number and the columns number equals the operators number in the periods.

$$W\_TO\_C = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & \| & 1 & 1 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 & 1 & \| & 0 & 0 & 0 & 1 & 1 \end{bmatrix}$$

In the example above with $T = 2$, $C = 2$ and $K = 5$ the sixth column's first row's element is 1 implying the first operator in the second period is assigned to the first cell.

The fourth part is a 2-dimensional matrix $M * (K * T)$ named matrix Alpha indicates the portion of time capacity of an operator used for working with a machine in a period, where rows number equals the machines number and columns number correspond with the operators number in the periods. The matrix elements take values in interval [0, 1].

$$Alpha = \begin{bmatrix} 0.6 & 0 & 0 & 0.4 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0.5 & 0 \\ 0.4 & 0 & 0 & 0 & 0.6 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.5 & 0.5 & 0 \end{bmatrix}$$

In the example above with $T = 2$, $M = 5$, $K = 5$, the fifth column's third row element shows that the fifth operator has allocated 60% of the available time to the third machine in the first period as the first five columns is for the first period and the rest is for the second period.

The fifth part is a matrix $K * M$ named penalty indicates whether the operator has been trained to work with a machine or not. For instance in the below matrix, the element in the third column's second row is 1, it means that the second operator has been trained for working with the third machine.

$$Penalty_{K \times M} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

4.2 Initial solution generation

In this study, the initial solution is generated randomly. Regarding the solution structure, the subsequent solutions in the algorithm are generated in each replicate by doing mutation over various parts of the solution. It is worth mentioning that if the generated solution was infeasible regarding the defined constraints, it would be rejected and another initial solution is generated until a feasible one is reached.

4.3 Neighbour solution creation mechanism

For exploring feasible solution space, it is required producing another feasible solution by changing the current solution which refers to the neighbour solution. Then, the solution feasibility has to be investigated. Here, the rejection strategy is used which means if the obtained solution is not feasible, it is omitted and another solution will be produced.

To produce a new feasible solution using the current solution, five different types of mutation operation are performed as follows:

1 Changing machines location assignment to cells: when the assignments of machines location to cells is changed, all matrices of a period should be updated.

2 Changing machines location: for implementing this mutation, two columns are selected randomly from the matrix *M_TO_C* indicating the machines assigned to each location and replaced with each other. In order to keep the obtained solution feasibility, the mentioned positions in all of the subsequent matrices are substituted.

3 Changing locations assignment in cells: for implementing this mutation, two columns are selected randomly from matrix *L_TO_C* indicating the locations assignment to the cells and replaced with each other.

4 Changing operators assignment to cells: For implementing this mutation, once more the operators are assigned to cells randomly in matrix *W_TO_C*.

5 Changing workload of an operator: for implementing this mutation, an operator is chosen randomly in matrix *Alpha* and the value assigned to it is changed.

The developed SA pseudo code, mechanism of acceptance/rejection of neighbourhood solutions, termination condition, cooling scheme comprising initial temperature, Markov chain length (MCL), and cooling rate are considered similar to those defined by Kia et al. (2015).

5 Computational results

5.1 Two illustrative numerical examples

In this section, to validate the presented deterministic model and illustrate the performance of its derived robust models, two numerical examples are solved by branch and bound method using CPLEX solver 23.5 over a PC with specifications 2021 Intel core 5 with 4GB RAM.

5.1.1 The first numerical example

In the first numerical example with two periods, there are four machines and four operators with diverse skills and also three types of parts have to be processed by the machines based on their operation sequence. Table 3 shows the information related to operations sequence of parts, processing times and part demands. The information related to operator-machine including the operator capability of working with various machines are given in Table 6, training cost and time capacity for each operator in Table 5 and the operator hiring/firing and salary cost in Table 4. In the proposed model, it is considered that the process plan of a part could be changed in each period. Also, the salary cost of each operator is changed based on the machine type which the operator is assigned to.

Table 3 Machine/part information for the first example

Parts	*Period 1*			*Period 2*		
	Operations sequence	*Processing time*	*Demand*	*Operations sequence*	*Processing time*	*Demand*
1	1-2	0.75-0.75	150	1-4	0.5-0.4	100
2	4-3	0.25-0.55	100	2-3	0.65-0.7	150
3	2-4	0.9-0.5	200	3-4	0.6-0.3	100

Table 4 Operator capability for the first example

Operators	*Machines*			
	1	*2*	*3*	*4*
1	1	1	0	0
2	0	1	0	0
3	1	0	0	1
4	0	1	1	0

Table 5 Training cost and time capacity of operators for the first example

Operators	*Time capacity*	*Machines*			
		1	*2*	*3*	*4*
1	200	70	60	50	95
2	150	60	80	40	50
3	270	80	70	80	70
4	230	50	50	60	95

Table 6 Hiring/firing and salary cost of operators for the first example

Operator	*Hiring cost*	*Firing cost*	*Machine*			
			1	*2*	*3*	*4*
1	80	60	0.23	0.22	0.19	0.19
2	110	50	0.27	0.20	0.22	0.24
3	100	80	0.20	0.18	0.17	0.21
4	70	40	0.17	0.21	0.20	0.20

The cost of intercellular movement for each part is 3 units and for intracellular movement is 1 unit. Each cell has to include at least one machine and at most two machines. The machine movement cost for each travelled distance unit is 50 cost units as well as the machine installation/uninstallation cost is 50 cost units. In addition, Table 7 shows the distance between the candidate locations.

Table 7 Distance between locations for the first example

Locations	*1*	*2*	*3*	*4*	*5*
1	0	1	1	2	2
2	1	0	2	1	3
3	1	2	0	1	1
4	2	1	1	0	2
5	2	3	1	2	0

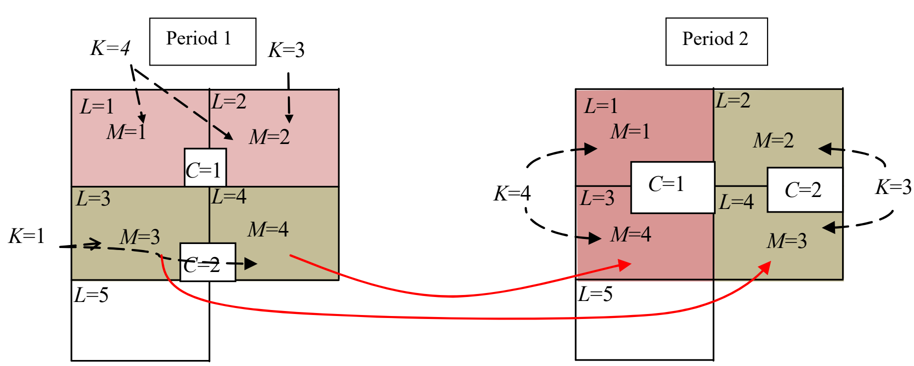
5.1.1.1 Solving deterministic model for the first numerical example

The objective function value derived from solving the first numerical example with a deterministic model is given in Table 8. Also, cell formation, machines layout and operators assignment have been depicted in Figure 2. Regarding the existing literature, it is the first time that a mathematical model integrating CM, GL and operator assignment in a dynamic environment with the proposed objective function and the considered assumptions is formulated. Hence, the obtained solution cannot be compared with the previous studies.

Table 8 Objective function value in solving deterministic model for the first numerical example

Total costs of machine relocations and inter-cell/intra-cell movements of parts	*Total costs of training, hiring/firing and salary of operators*	*Total cost*
1,600	805.75	2,405.75

Figure 2 Cell formation, machines layout and operators assignment in solving deterministic model for the first numerical example (see online version for colours)

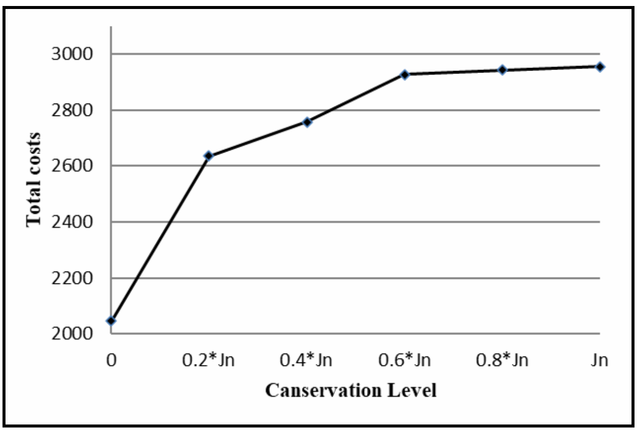


As a result of changes in part demands in successive periods, the locations of machines 3 and 4 have been substituted. In addition, because the fourth operator is assigned to work with the first machine despite the fact that he or she is not able to work with that machine, the training cost of 50 units has been imposed. Also, since the workload in the second period is less than the 1st period, the first operator has been fired in the second period. One of the advantages of this model revealed in the obtained cell configuration in Figure 2 is that the goal behind putting the machines closer to each other is to prevent additional movements inside the cells that brings about cell productivity rise.

5.1.1.2 Solving models RO¹, RO² and RO³ for the first numerical example

In order to demonstrate the results obtained from solving the first numerical example by models RO^1, RO^2 and RO^3, the proposed robust models is solved for different levels of $\Gamma_0 \in [0, |J_n|]$, where $\hat{D}_{ih} = 20\% * \tilde{D}_{ih} \ \forall i, h$ and $\hat{t}_{ijm} = 20\% * \tilde{t}_{ijm} \ \forall i, j, m$. The relation between total costs and conservativeness level Γ_0 have been depicted in Figures 3 for model RO^1. The results illustrate that the robustness level change influences the obtained solution. In addition, as it is predicted while the model robustness increases, total costs go up as well.

Figure 3 The effect of conservativeness level Γ_0 on total costs of model RO^1 for the first numerical example (see online version for colours)



5.1.2 The second numerical example

In the second example with two periods, there are five machines and five operators having different skills and also four types of parts. The information related to the second example is given in Tables 9–13.

Table 9 Machine-part information for the second example

Parts	*Period 1*			*Period 2*		
	Operations sequence	*Processing time*	*Demand*	*Operations sequence*	*Processing time*	*Demand*
1	5-4-1	0.75-0.75-0.75	70	5-2-1	0.75-0.75-0.75	60
2	5-4-3	0.75-0.75-0.75	80	4-1-3	0.75-0.75-0.75	80
3	1-2-3	0.75-0.75-0.75	80	2-5	0.75-0.75-0.75	50
4	1-2	0.75-0.75-0.75	70	1-4	0.75-0.75-0.75	50

Table 10 Operator capability for the second example

Operators	*Machines*				
	1	*2*	*3*	*4*	*5*
1	1	0	1	1	0
2	0	0	1	1	1
3	0	1	1	1	0
4	1	1	0	0	1
5	0	0	1	1	0

Table 11 Training cost and time capacity of operators for the second example

Operators	*Time capacity*	*Machines*				
		1	*2*	*3*	*4*	*5*
1	150	70	100	100	95	35
2	180	60	80	100	100	50
3	180	80	70	110	100	90
4	250	50	95	100	95	70
5	150	90	50	90	110	30

Table 12 Hiring/firing and salary cost of operators for the second example

Operators	*Hiring cost*	*Firing cost*	*Machines*				
			1	*2*	*3*	*4*	*5*
1	110	50	0.23	0.22	0.19	0.19	0.23
2	100	50	0.17	0.17	0.22	0.20	0.21
3	100	50	0.17	0.18	0.17	0.21	0.19
4	99	50	0.19	0.18	0.20	0.20	0.22
5	99	50	0.20	0.19	0.20	0.22	0.18

Table 13 Distance between locations for the second example

Locations	*1*	*2*	*3*	*4*	*5*	*6*
1	0	1	2	1	2	3
2	1	0	1	2	1	2
3	2	1	0	3	2	1
4	1	2	3	0	1	2
5	2	1	2	1	0	1
6	3	2	1	2	1	0

The other parameters are similar to those defined for the first example, except that each cell can include at most three machines.

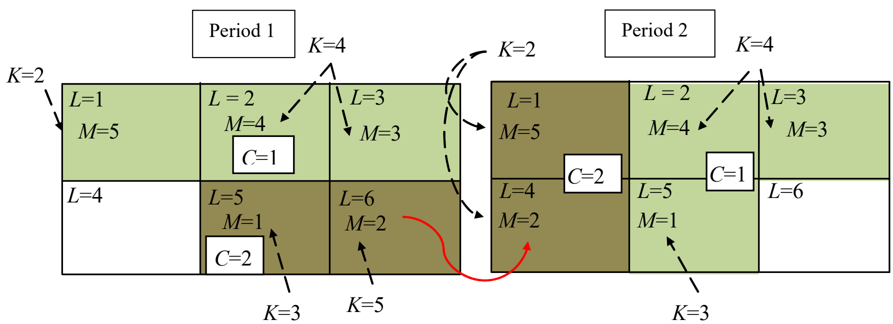
5.1.2.1 Solving deterministic model for the second numerical example

The objective function value derived from solving the second numerical example with a deterministic model is given in Table 14. Also, cell formation, machines layout and operators assignment have been depicted in Figure 4. Now, we interpret the obtained solution as it follows.

Table 14 Objective function value in solving deterministic model for the second numerical example

Total costs of machine relocations and inter-cell/intra-cell movements of parts	*Total costs of training, hiring/firing and salary of operators*	*Total cost*
1,560	1,081.44	2,641.44

Figure 4 Cell formation, machines layout and operators assignment in solving deterministic model for the second numerical example (see online version for colours)



Considering the demand changes in the considered dynamic environment, machine 2 has been displaced from location 6 in the first period to location 4 in the second period.

Considering Table 10, the only operator having the ability to work with machines 3 and 4 and not needing training is operator 4 who is assigned to these two machines so that no operator training cost is imposed on due to training operator 4. Besides, with respect to Tables 8 and 10 operator 1 has the highest hiring cost and the ability to work on machines 2 and 5, while these two machines have been located in two different cells and in the case of hiring this operator, he or she has to be assigned to one of these two machines or be trained for working on other machines. Since the other operators are preferable to operator 1 in terms of cost, he or she is not hired as it is shown in Table 15 representing the hired operators.

Table 15 Hired operators in solving deterministic model for the second numerical example

Operators	*Period 1*	*Period 2*
1		
2	*	*
3	*	*
4	*	*
5	*	

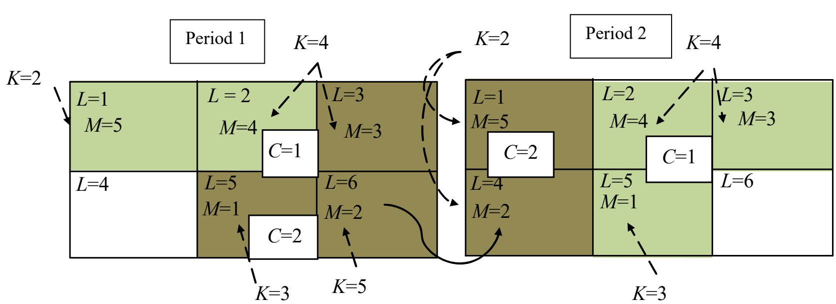
In Table 16, the utilised percentage of the time capacity of operators has been displayed. For example, 0.48% of time capacity of operator 4 is allocated to machine 3 and the other 0.42% to machine 4 in the first period.

Table 16 Operators utilisation in solving deterministic model for the second numerical example

		Machines									
		Period 1					*Period 2*				
		1	*2*	*3*	*4*	*5*	*1*	*2*	*3*	*4*	*5*
Operators	2					0.569		0.469			0.422
	3	0.753					0.794				
	4			0.48	0.42				0.22	0.386	
	5		0.92								

Now, to reveal the interrelation between the problems of the cell formation, the machines layout and the operators assignment and the importance of integrating those decisions in a model, we solve the second numerical example in a sequential approach, where at first the cell formation problem is solved, then machines layout problem is solved and finally the operators assignment is solved. The total costs obtained in solving three problems in a sequential approach is 2,790.78 which is 5.6% (i.e., 2,790.78 – 2,641.44/2,641.44 × 100) higher than that obtained in the concurrent approach (i.e., main model). To conclude, OFV has improved about 5.6% by shifting from sequential approach to concurrent approach. This improvement was expectable since simultaneous decisions making about interrelated decisions of cell formation, GL and operators assignment enable the integrated model to optimise all ingredients of the objective function as an optimal strategy in designing a DCMS. Also, the cell formation, machines layout and operators assignment have been depicted in Figure 5.

Figure 5 Cell formation, machines layout and operators assignment in solving deterministic model by a sequential approach for the second numerical example (see online version for colours)



5.1.2.2 *Solving models RO¹, RO² and RO³ for the second numerical example*

Similarly, in order to demonstrate the results obtained from solving the second numerical example by robust models RO^1, RO^2 and RO^3, they are solved for different levels of $\Gamma_0 \in [0, |J_n|]$, where $\hat{D}_{ih} = 20\% * D_{ih} \;\forall i, h$ and $\hat{t}_{ij} = 20\% * D_{ih} \;\forall i, j, m$.

The solutions obtained for models RO^1, RO^2 and RO^3 for robustness level $0.8 \times J_n$ has been depicted in Figures 6–8. As can be seen in these figures, the obtained cell configurations and operators assignment are different in the obtained solutions as a result of turbulence in parameters demand and processing time.

Figure 6 Cell formation, machines layout and operators assignment in solving model RO^1 for the second example with conservativeness level $0.8 \times J_n$ (see online version for colours)

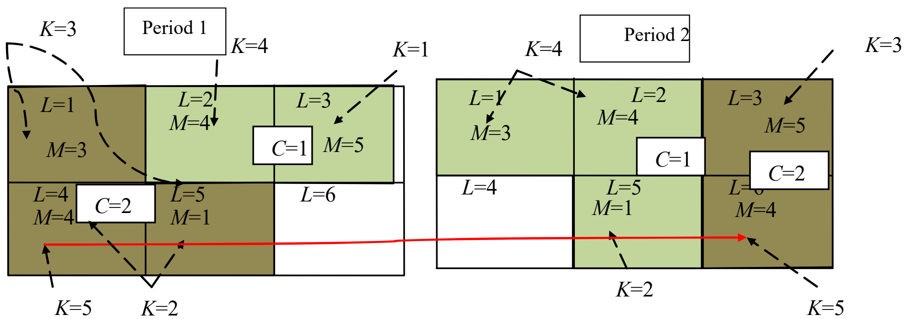


Figure 7 Cell formation, machines layout and operators assignment in solving model RO^2 for the second example with conservativeness level $0.8 \times J_n$ (see online version for colours)

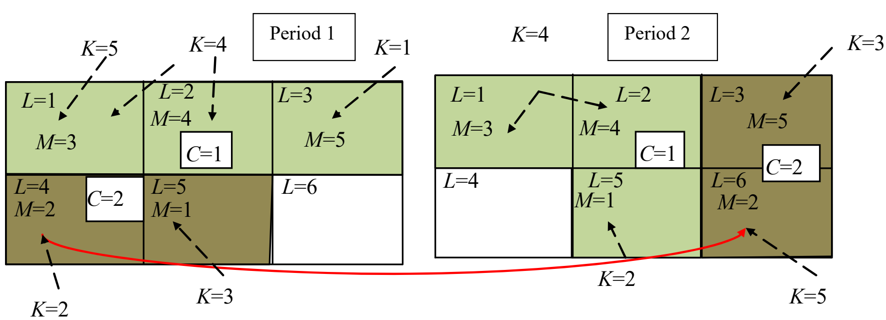


Figure 8 Cell formation, machines layout and operators assignment in solving model RO^3 for the second example with conservativeness level $0.8 \times J_n$ (see online version for colours)

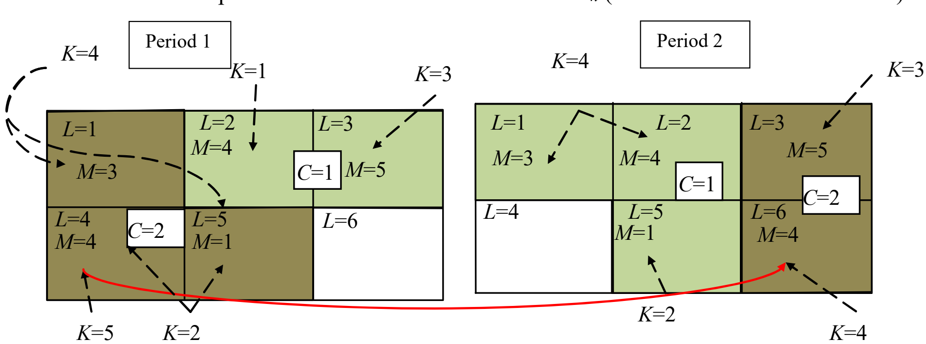


Table 17 Comparison of SA and CPLEX

Problem no.	Problem size							SA parameters				OFV		CPU time		Relative gap (%)
	No. of parts	No. of operations per part	No. of machines	No. of operators	No. of locations	No. of cells	No. of periods	Initial temperature	Final temperature	MCL	Cooling rate	SA	GAMS	SA	GAMS	
1	3	2	4	4	5	2	2	1,000	500	10	0.99	2,465.4	2,405.7	00:00:26	00:46:23	2.4
2	3	3	4	4	5	2	2	1,500	500	15	0.99	3,789.4	3,725.8	00:00:31	01:02:29	1.7
3	3	4	5	5	5	2	2	1,500	500	15	0.99	4,176.4	4,098.5	00:01:09	01:57:19	1.9
4	4	2	3	3	4	2	2	2,000	500	15	0.99	2,170.7	2,126.1	00:01:24	04:27:41	2.1
5	4	3	5	5	6	2	2	3,000	500	20	0.99	2,702.2	2,641.4	00:03:18	13:56:28	2.3
6	4	4	5	5	6	2	2	3,000	500	20	.099	3,417.4	3,297.7	00:04:05	14:51:33	3.6
7	3	2	4	4	5	2	3	8,000	500	15	0.98	3,926.2	3,642	00:14:17	14:42:08	7.8
8	4	3	5	5	6	2	3	8,000	500	20	0.99	4,158.6	-	00:19:52	-	-
9	5	3	5	5	6	2	2	8,000	500	15	0.98	3,028.7	-	00:15:24	-	-
10	7	3	6	7	7	3	3	10,000	500	20	0.98	7,281.3	-	00:27:29	-	-

5.2 Analysis of the computational efficiency

In this section, to evaluate the computational efficiency of the extended SA in terms of objective value and computation time, 10 test problems are solved. The comparison between the solutions obtained by SA and those obtained by CPLEX are shown in Table 17.

Due to the extreme number of decision variables and constraints involved in the proposed model, it is almost impossible to solve large-size problems in a reasonable time using GMAS solver. As reported in Table 17, CPLEX is able to obtain the optimum solutions only in test problems 1–7. For the other test problems 8–10, the solution space is expanded so much that CPLEX even cannot generate a feasible solution before encountering out of memory message. In general, it can be concluded that SA algorithm found near-optimal solutions, in less computational times for example problems 1–7 in a relative gap lower than 7.8% compared to those obtained by GAMS.

6 Conclusions

In this paper, through designing dynamic cell formation as one of the most powerful and widely-implemented manufacturing systems, it has been tried to integrate three interrelated areas as cell configuration, the intracellular/intercellular layout and assigning operators with the objective to minimise the total costs of intra/intercellular material handling, machine relocation and installation/uninstallation, and operator related costs (i.e., hiring/firing, training and salary). Also, by taking the uncertainty over the parts demand and processing time into account, the model is made closer to the real system.

Considering multi-row layout and flexible configuration of cells, computing the machines movement cost, calculating the parts movement cost in terms of the machines distance from each other and considering the operator training and hiring/firing cost are of the features that distinguish the presented model from the other ones in the literature.

Two numerical examples were solved to demonstrate the validity of the designed robust models for investigating the effect of turbulence in the values of part demands and processing times separately and simultaneously on the model performance and obtained solutions.

Furthermore, two approaches, sequentially and concurrently, were investigated in order to assess the effects of integration of group layout and operator assignment in designing a DCMS.

Several numerical examples were solved using the extended SA and the obtained solutions were compared with those gained using CPLEX solver to verify the efficiency of the developed SA in terms of both OFV and computational time. The results show the efficiency of SA in achieving satisfactory solutions.

Besides, for future studies, we can point out the following cases: employing the other meta-heuristic methods for solving the proposed model and comparing the solutions, considering the backorder or inventory holding, taking into account the layout of machines with unequal area, designing multi-objective models for modelling the problem, considering lot splitting feature where each operation of each part can be processed simultaneously by several different machines.

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