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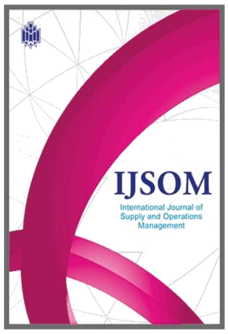

A Multi-stage Stochastic Programming Approach in a Dynamic Cell Formation Problem with Uncertain Demand: A Case Study

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Abstract
This paper addresses a dynamic cell formation problem (DCFP) including a multi-period planning horizon in which demands for each product in each period are different and uncertain. Because the demand uncertainty is considered as stochastic data by discrete scenarios on a scenario tree, a multi-stage nonlinear mixed-integer stochastic programming is applied so that the objective function minimizes machine purchase costs, the operating costs, both inter and intra-cell material handling costs, and the machine relocation costs over the planning horizon. The main goal of the current study is to determine the optimal cell configuration in each period in order to achieve the total minimum expected costs under the given constraints. The nonlinear model is transformed into a linear form. That is why GAMS can provide global optimal solutions in linear models. In order to find the optimal solutions, by using the GAMS for small and medium-sized problems, the optimal solutions are obtained. They applied in two bounds, namely the Sum of Pairs Expected Values (SPEV) and the Expectation of Pairs Expected Value (EPEV). Also, according to the scenario-based model, the efficiency of two suggested bounds is shown in terms of the computational time. Finally, a practical case study is presented in detail to illustrate the application of the proposed model and it's solving method. The results show the efficiency of using SPEV and EPEV for several random examples as well as the proposed case study.

Keywords: Dynamic cell formation problem; Multi-stage stochastic programming; Expectation of pair expected value; Sum of pair expected values.

1. Introduction

Due to a competitive global market, the manufacturing firms are shifting from traditional configurations, such as flow shop and job shop to new configurations, such as a cellular manufacturing system (CMS) in the design of manufacturing systems. CMS is an industrial application group technology (GT) concept which includes not only the advantages of production volume and efficiency of flow shop, but also product variety and flexibility of a job shop.In a CMS, machines are divided into distinctive cells and similar parts in terms of manufacturing and design. However, CMS lead to several significant benefits, such as reduction in work-in-process inventory, set-up times, throughput times, material handling costs, simplified scheduling, and improved quality (Wemmerlöv, U. & Hyer, N. L., 1987; Shishebori, D. & Ghaderi, A., 2015).

In the literature, the designing of CMS is classified into four main problems and consists of 1) cell formation problems (CFP), 2) intra-cell and inter-cell layout problem, 3) group scheduling problem, and 4) resource allocation problem. As the first stage in a CMS problem, the CFP is to construct a set of machine cell and their corresponding part families so that the objective function could be optimized. In the preliminary studies associated with the CMS area known as classical CMS, it was assumed that product mix and part demand are constant over the planning horizon. While in a dynamic real-life environment, a planning horizon can be divided into several smaller periods, where each period has various product mix and/or part demand. However, in a current period, the optimal solution for CFP may not be efficient and optimal for the next period (Safaei, N., et al., 2008; Shishebori, D., et al., 2015).

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As a result, Rheault, M., et al., (1996) introduced the concept of the dynamic cellular manufacturing system (DCMS) to develop the optimal solution for each period concerned with the demand of the cell and overcome the disadvantages of classical CMS. In DCMS, the optimal solution of the CFP can be obtained by reconfigurations of a manufacturing cell for each period. Indeed, reconfiguration consists of a relocation of existing machines in the cellular system, adding new machines to cells, and removing of existing machines from cells. An example of reconfiguration of manufacturing cells at two successive periods is represented in Figure1.

The structure of this paper is as follow. Section 2 includes a review of the literature of DCMS. A theoretical framework for multi-stage stochastic programming (MSP) is provided in Section 3. In Section 4, a mathematical model, based on various scenarios, is developed and in order to investigate the efficiency and accuracy of the proposed model, some test problems are presented in Section 5. Our conclusions remarks are given in Section 6.

2. Literature of the review

In this section, a brief description of the work done by previous authors about DCFP is presented. In general, they are classified the DCFP based on deterministic demands and uncertain demands. Then, the research gap and the motivation of the current study are clarified.

2.1. DCFP with deterministic demands

Chen, M., (1998) proposed an integer mathematical model for DCFP in which the objective function was minimizing the material handling cost, the machine costs, as well as the cell reconfiguration costs. Askin, R. G., et al., (1997) designed flexible cells by an interactive cell formation method. In principle, they tried to design a robust cell formation in terms of responsiveness to part demand and product mix as well as routing by four proposed phases. In other words, instead of presenting several optimal solutions for DCFP, they developed only one optimal solution which was sustainable against variation of demands. Taboun, S., M., et al., (1998) considered that a part can be subcontracted toward suppliers besides that can be produced within the given shop. Balakrishnan, J., & Hung Cheng, C., (2005) used two stages, where the first stage obtained the optimal cell configuration in a static environment and the second stage applied the dynamic programming using the optimal material handling cost of the first stage. They indicated that by increasing of reconfiguration costs, the job shop may be preferred to CMS. Tavakkoli-Moghaddam, R., et al., (2005) presented a mathematical model for DCFP, where the demands were dynamic, but they were deterministic. The alternative process plans and the variable number of cells were new concepts added into DCFP. In a relatively more comprehensive study, Defersha, F. M., & Chen, M., (2006) considered a model incorporating dynamic cell configuration, alternative routing, sequence of operations, multiple units of identical machines, machine capacity, workload balancing among cells, operation costs, subcontracting costs, tool consumption costs, set-up cost, and other practical constraints. Saidi-Mehrabad, M., & Safaei, N., (2007) also considered a DCFP with this assumption that the number of formed cells is as a decision variable. A neural network approach (NNA) was applied to solve a NP-hard problem. NNA can be very efficient for the large-sized problems compared with commercial software GAMS. This was a remark conclusion for this study. Aryanezhad M. B., et al., (2009) developed a model to deal with simultaneous DCFP and worker assignment problem. They grouped the workers to worker levels concerning abilities to work with different machines, and machines to machine levels with regard to the properties of each machine. Moreover, promotion for workers was allowed. It means that each worker could be transferred to upper-level skill by training. With these assumptions and others common in DCFP, they formulated a single objective nonlinear integer programming model. After linearization of the model, it was solved by GAMS.

Wang, X., et al., (2009) is the first study which considers the three-objective model. The objectives are minimizing the relocation costs, maximizing the utilization rate of machine capacity, and minimizing the total number of inter-cells moves. Bulgak, A. A., & Bektas, T., (2009) inserted a production planning into DCFP. Safaei, N., & Tavakkoli-Moghaddam, R., (2009) also developed a simultaneous production planning and DCFP. Their model considered inter-cell and intra-cell material handling, operation sequence, partial subcontracting, and lead time for ordered items. Two numerical examples were presented to verify the performance of the model. The results represented that inventory, subcontracting, and backorder can significantly affect the cell configuration over the horizon planning. Bajestani, M., et al., (2009) developed a two-objective model, where the first objective is minimizing operational costs like machine depreciation, inter-cell material handling and machine relocation costs, and the second objective is minimizing total cell load variation. A comprehensive model including DCFP, production planning, and worker assignment problem is seen in Mahdavi, I., et al., (2010). To illustrative the validity of the proposed model, two examples were solved by branch-and-bound method using Lingo 8.0 Software. CPU time required to reach the optimal solution for relatively large-sized problems was computationally intractable. Further, Ghotboddini, M. M., et al., (2011) developed a two-objective model consisting of minimizing the sum of miscellaneous costs and maximizing the sum of minimum labor ratio for entire periods. Javadian, N., et al., (2011) developed a two objective model, where the total cells load variation and sum of the miscellaneous costs were to be minimized simultaneously. The miscellaneous costs consist of machine cost, internal part production, inter-cell and intra-cell material handling, backorder, inventory holding, and subcontracting. Saxena, L.K. & Jain, P.K., (2012) proposed an integrated model of DCFP and supplied chain design with consideration of different issues, such as multi-plant locations, multiple markets, multi-time periods, reconfiguration, etc. They added other costs, such as facility/plant to market transportation cost, machine procurement cost, machine maintenance overhead cost, machine repair cost, and production loss cost due to machine breakdown to the objective function of the model. Kia, R., et al., (2012) developed a group layout design model of DCMS with assumptions of alternative process routing, lot splitting, and flexible reconfiguration. An intra-cell layout for machines within manufacturing cells was investigated in this paper. Bagheri, M., & Bashiri, M., (2014) also considered a DCFP with inter-cell layout problem and worker assignment in a dynamic environment. They assumed that there are some candidate locations to be a manufacturing cell. Kia, R., et al., (2014) present a mixed-integer programming model for multi-floor layout design of cellular manufacturing systems in a dynamic environment. Zohrevand et al. (2016) considered a multi-objective DCFP with respect to human-related issues and stochastic nature of this problem. Recently, researchers have focused on the sustainable DCFP, where the total production waste (e.g., energy, chemical material, row material, CO_2 emissions, etc.) plays a critical role in addressing the problems. As an example, Niakan, F., et al., (2016) proposed a bi-objective mathematical model of DCFP in which the first objective in this model is to both production and labor costs and the second objective is to minimize the total production waste. Mahmoodian, V., et al., (2017) presented a novel intelligent particle swarm optimization algorithm for the cell formation problem. Rabbani, M., et al., (2019) provided a new multi-objective mathematical model for DCMS with regard to machine reliability and alternative process routes. It is remaindered that optimization techniques have been used in a wide variety of applications, e.g., oil and gas (Shakhsi-Niaei, M., et al., 2013), facility location and network design (Shishebori, D., 2014; Rabbani, M., et al., 2017; Esmaeilbeigi, R., 2017), risk management (Rezaei, K., et al., 2009), performance measurement, and productivity management (Koushki, F., 2018).

2.2. DCFP with uncertain demands

Arzi, Y., et al., (2001) proposed a model of DCFP so as the demand of part types is uncertain. They tried to reduce the planned capacity of each cell for coping with the lumpiness of demands. For this reason, they used the mean, variance, and covariance of demands in capacity-time of machines constraint. Safaei, N., et al., (2008) developed a model of DCFP in which demand of part types and capacity of machines are uncertain. These two uncertain parameters have been assumed that follow piecewise fuzzy numbers as coefficients in the objective function and the technological matrix. Farughi, H., & Mostafayi, S., (2016) presented a robust optimization in a DCFP considering the labor utilization. Egilmez, G., et al., (2017) also formulated a stochastic cell formation problem with a newly proposed stochastic genetic algorithm (SGA) approach considering stochastic demand and processing times, thus capacity requirements. Other studies related to DCFP with uncertain demands can be found in Moslemipour, G., (2018), and Wang, T., & Tang, J., (2018).

2.3. Research gap and the motivation

The previous researchers have considered the effect of demand uncertainties in DCFP at the same time. In other words, the decisions associated with the problem in order to deal with uncertainties have been made simultaneously before the uncertain demands are met (at one stage). On the other hand, it is sometimes necessary that some decisions in each stage are made after visiting the uncertain demands. In such conditions, some decisions should be made before and others after determining the uncertain demands (at several stage).

In this paper, a multi-stage stochastic programming is proposed for the multi-objective integrated model of DCFP and production planning with uncertain demand. The uncertain demand brought up as a discrete time stochastic process during the planning horizon with finite support. This information structure can be interpreted as a scenario tree. The goal of multi-stage stochastic programming is to determine a solution for the proposed model which can be implemented in a production environment that takes into account the possible demand scenarios and minimizes the expected costs associated to DCFP and production planning.

3. Multi-stage stochastic programming

A multi-stage stochastic programming (MSP) approach (Kall, P., & Wallace, W., 1994, Birge, R., & Louveaux, F., 1997, Kall, P., & Mayer, J., 2005) was proposed to address multi-period optimization models with dynamic stochastic data during the time. In MSP, the decisions are made in several decision stages. The decision maker takes some action in the first stage, after which a random event occurs that affects the outcome of the first-stage decision. Afterwards, a recourse decision can be made in the second stage to compensate for any negative effect that might have been experienced as a result of the first-stage decision. When the uncertain parameter has a discrete time stochastic process with finite probability space, the uncertainty can be represented with a scenario tree as shown in Figure1. For each uncertain parameter, each scenario tree has five specifications. The first specification is a *stage* which denotes the stage of the time when new information is available to the decision maker. Thus, the stages do not necessarily correspond to time periods. The second is *nodes* which represent a possible state of scenario, associated with a set of uncertain parameter in the corresponding stage.

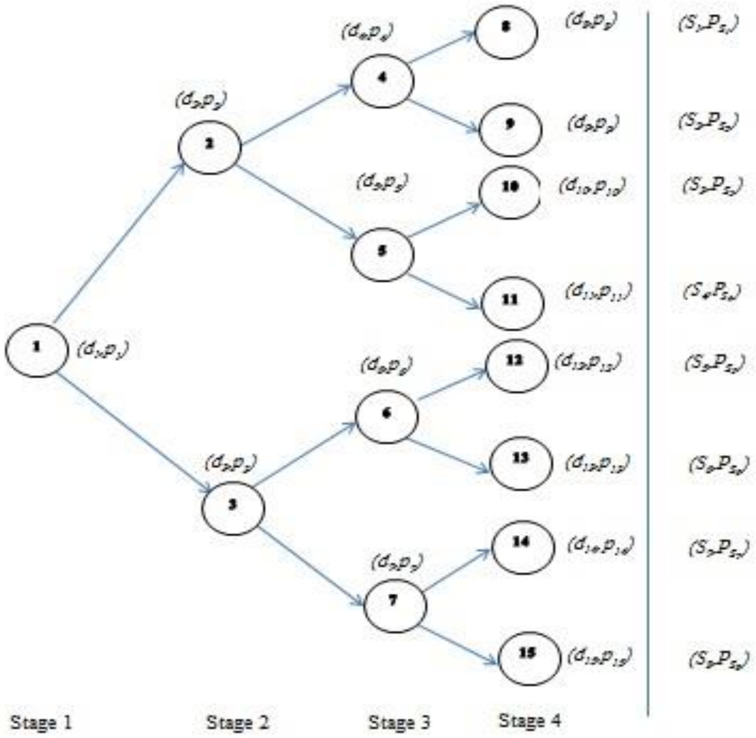

Figure 1. An example for scenario tree

The first node as *root node* of the tree is the current state of the scenario, and the node in the last stage as *leaf node* is the final state of the scenario. The third is the *branches for scenario tree* denoting the scenarios for the next stage. The fourth is the *value of that uncertain parameter* and the last is the *probability of realization* for that value of an uncertain parameter. A scenario is a path starting from the root node and ending at a leaf node. The scenario tree represented in Fig. 1 has 15 nodes. Node 1 is as root node and nodes 8-15 are as leaves nodes. Furthermore, the value and the probability of realizing uncertain parameter are given in parentheses. There are 8 different scenarios $S_1 - S_8$ (8 different paths from root node to leaf nodes). Each of scenarios occurs with a probability equal to the product of probabilities for nodes existing in that path. For example, the probability for the first possible scenario is equal to product of probabilities of nodes 1, 2, 4, and 8 ($P_{s_1} = p_1 \times p_2 \times p_4 \times p_8$). A review of the approaches for generating the scenario trees for MSP, based on the underlying random data processes has been developed in Dupačová, J, et al., (2000).

4. Model development

In this section, an integrated model of DCFP and production planning with two objectives is proposed. It is assumed that uncertain demand is brought up as a discrete time stochastic process during the planning horizon with a finite support. This problem is formulated under the following assumptions: (1) Each part type includes a number of operations that must be processed as numbered, respectively, (2) The processing time for all operations of a part type on different machine types are known and deterministic in advance, (3) Each machine has known and stable capabilities and time-capacity throughout the planning horizon, (4) The constant cost of each machine is known. This cost includes maintenance, other over-head, rent, and overall service cost for each machine. Thus, the buying or selling cost is not considered. (5) The variable cost of each machine type is known in advance. This cost is dependent on the workload allocated to the machine. (6) The demand for each part type in each period is discrete data with known value and probability in advance. In other words, there is a scenario tree for each part type. (7) The relocation cost for each machine type from one cell to another is known. All of the machines are able to be moved toward any cell. This cost is the sum of uninstalling, shifting, and installing costs. The time needed for relocation is assumed to be zero. (8) The decision stages correspond to periods. It is assumed that information about the demand of each period becomes available at the beginning of the period. (9) Parts are moved in a batch between and within cells. Moreover, inter and intra-cell batches related to the part types have different sizes and costs. It is assumed that the distance between each pair of cells and each pair of machines at each cell is the same. (10) All machine types are multi-purposed. Likewise, each operation of part can be performed on various machine types with different processing times. (11) The maximum number of cells can be formed in each period is known in advance. (12) The maximal and minimal cell size is known in advance. (13) Holding and backorders inventories are allowed between periods with known costs. (14) Partial subcontracting is allowed. In other words, the total or portion of the demand of the part types can be subcontracted at each period. Also, the time-gap between releasing and receiving orders (lead time) is fixed and known in advance.

4.1. Notation

Indices:

i Index for part types ($i=1,\dots,I$)

j Index for operations which belong to part i ($j=1,\dots,O_i$)

m Index for machine types ($m=1,\dots, M$)

c Index for manufacturing cells ($c=1,\dots,C$)

s Index for scenarios ($s=1,\dots, S$)

t Index for time periods ($t=1,\dots,H$)

4.2. Input parameters

I Number of part types

O_i Number of operations for part i

M Number of machine types

C Number of cells which are formed

D_{its} Demand for part i in period t in scenario s

B_i^{inter} Batch size for inter-cell movement of part i

B_i^{intra} Batch size for intra-cell movement of part i

γ^{inter} Inter-cell movement cost per batch

γ^{intra} Intra-cell movement cost per batch. To justify the CMS, it is assumed that $\left(\frac{\gamma^{intra}}{B_i^{intra}}\right) < \left(\frac{\gamma^{inter}}{B_i^{inter}}\right)$.

α_m Constant cost of machine type m in each period ($)

β_m Variable cost of machine type m for each unit time ($)

δ_m Relocation cost of each machine type m ($)

T_m Time-capacity of machine type m in each period (hour)

pr_s Probability of occurrence of scenario s

UB Maximal cell size

LB Minimal cell size

pt_{jim} Processing time required to perform operation j of part type i on machine type m (hour)

a_{jim} If operation j of part type i can be done on machine type m equals to 1; otherwise 0

λ_i Unit cost of subcontracting part type i ($)

η_i Inventory carrying cost per unit part type i during each period ($)

ρ_i Backorder cost per unit part type i during each period ($)

l Lead time where $l \leq H-1$

Z Large positive number

4.3. Decision variables

N_{mcts} Number of machine type m assigned to cell c in period t for scenario s

K_{mcts}^{+} Number of machine type m added in cell c in period t for scenario s

K_{mcts}^{-} Number of machine type m removed from cell c in period t for scenario s

x_{jimcts} If operation j of part type i is done on machine type m in cell c in period t for scenario s equals to 1; otherwise 0

P_{its} Number of part type i produced in period t for scenario s

y_{its} If $P_{its}>0$ equals to 1; otherwise 0

S_{its} Number of part type i subcontracted in period t for scenario s

In_{its}^{+} Inventory level of part type i at the end of period t for scenario s

In_{its}^{-} Backorder level of part type i at the end of period t for scenario s

4.4. Mathematical model

By using the above notations, the proposed model (I) can be written as follows:

model (I):

$$\min \quad Z=\sum_{s=1}^{S} pr_s [\sum_{t=1}^{H}\sum_{m=1}^{M}\sum_{c=1}^{C} N_{mcts}\alpha_m \tag{1a}$$

$$+\sum_{t=1}^{H}\sum_{c=1}^{C}\sum_{i=1}^{I}\sum_{j=1}^{O_i}\sum_{m=1}^{M}\beta_m P_{its} pt_{jim} x_{jimcts} \tag{1b}$$

$$+{}^{1}/_{2}\sum_{t=1}^{H}\sum_{i=1}^{I}\sum_{j=1}^{O_i-1}\sum_{c=1}^{C}\left\lceil\frac{P_{its}}{B_i^{inter}}\right\rceil \gamma^{inter}\left|\sum_{m=1}^{M} x_{(j+1)imcts}-\sum_{m=1}^{M} x_{jimcts}\right| \tag{1c}$$

$$+{}^{1}/_{2}\sum_{t=1}^{H}\sum_{i=1}^{I}\sum_{j=1}^{O_i-1}\sum_{c=1}^{C}\left\lceil\frac{P_{its}}{B_i^{intra}}\right\rceil \gamma^{intra}\left(\sum_{m=1}^{M}\left|x_{(j+1)imcts}-x_{jimcts}\right| - \left|\sum_{m=1}^{M} x_{(j+1)imcts}-\sum_{m=1}^{M} x_{jimcts}\right|\right) \tag{1d}$$

$$+{}^{1}/_{2}\sum_{t=1}^{H}\sum_{c=1}^{C}\sum_{m=1}^{M}\delta_m(K_{mcts}^{+}+K_{mcts}^{-}) \tag{1e}$$

$$+\sum_{t=1}^{H}\sum_{i=1}^{I}(\eta_i In_{its}^{+}+\rho_i In_{its}^{-}+\lambda_i S_{its}) \tag{1f}$$

Subject to:

$$\sum_{c=1}^{C}\sum_{m=1}^{M} a_{jim}x_{jimcts}= y_{its} \qquad \forall j,i,t,s \tag{3}$$

$$\sum_{i=1}^{I}\sum_{j=1}^{O_i} P_{its} pt_{jim} x_{jimcts} \le T_m N_{mcts} \qquad \forall m,c,t,s \tag{4}$$

$$\sum_{m=1}^{M} N_{mcts} \le UB \qquad \forall c,t,s \tag{5}$$

$$\sum_{m=1}^{M} N_{mcts} \ge LB \qquad \forall c,t,s \tag{6}$$

$$N_{mc(t-1)s}+K_{mcts}^{+}-K_{mcts}^{-}= N_{mcts} \qquad \forall m,c,t,s \tag{7}$$

$$In_{its}^{+}-In_{its}^{-}= In_{i(t-1)s}^{+}-In_{i(t-1)s}^{-}+P_{its}+S_{i(t-l)s}-D_{its} \qquad \forall i,t,s \tag{8}$$

$$In_{iHs}^{+}= 0 \qquad \forall i,s \tag{9}$$

$$In_{iHs}^{-}= 0 \qquad \forall i,s \tag{10}$$

$$P_{its} \le Zy_{its} \qquad \forall i,t,s \tag{11}$$

$$P_{its} \ge y_{its} \qquad \forall i,t,s \tag{12}$$

$$y_{its},\ x_{jimcts} \in\{0,1\},\ N_{mcts},K_{mcts}^{+},K_{mcts}^{-},\ P_{its},\ S_{its},In_{its}^{+},In_{its}^{-},\ W_{micts},A_{micts}\ge 0 \qquad \forall i,j,m,c,t,s \tag{13}$$

The objective function of the model (I) consists of six terms. Term (1a) is the constant cost for all of the machines used in all cells over the planning horizon in all scenarios. This cost is obtained by the product of the number of machine type

m allocated to cell c in period t and their associated costs. Term (1b) is the variable cost of machines used in all cells during the planning horizon in all scenarios. This cost is the sum of the product of the workload assigned to each machine type in each cell and their associated cost. Term (1c) is the inter-cell material handling costs for all scenarios. This term is the sum of the product of the number of inter-cell transfers resulting from two consecutive operations which have to be processed in two distinctive cells and cost of transferring an inter-cell batch of each part type (γ^{inter}). Term (1d) computes the total intra-cell material handling cost for all scenarios. It is the sum of the product of the number of intra-cell transfers resulting from two subsequent operations, which should be processed in only one cell and cost of transferring an intra-cell batch of each part type (γ^{intra}). Because each inter/intra-cell movement is calculated twice, the coefficients *1/2* are embedded in terms (1c) and (1d) (Safaei, Saidi-Mehrabad, and Jabal-Ameli 2008). Term (1e) is associated with cell reconfiguration cost for all scenarios. Likewise, it is the sum of the number of product of relocated, added, or removed machines and their costs. The coefficient *1/2* is also embedded in relocation cost because it is taken into account twice in calculations (Safaei, N., et al., 2008). Term (1f) is the production planning costs including inventory carrying, backorder, and subcontracting costs in all scenarios. The first, second, and third part is the sum of the product inventory level for each part type at the end of the given period and associated cost, backorder level for each part type at the end of the given period and related costs, and the number of subcontracted parts and associated cost, respectively. Eq. (3) assures that each operation in each period for each scenario is assigned to only one machine and one cell, if a portion of the part demand should be produced in the period. Eq. (4) guarantees that machine capacities are not exceeded. Eq. (5) and Eq. (6) state that the maximum and minimum cell size should not be violated. Eq. (7) generates a balance for the number of machines in the current period. It means that the number of machines in the current period is equal to the number of machines in the previous period, plus the number of machines being moved in, and minus the number of machines moved out. Eq. (8) is a known constrain in production planning problems called balance inventory constraint. This constraint means that the inventory level minus backorder level of each part at the end of each period for each scenario is equal to the inventory level of the part at the end of the previous period plus the quantity of production and subcontracting minus the part demand and backorder level in the current period for the same scenario. Eqs. (9) and (10) state that the inventory and backorder level for each part type in each scenario for the last period of planning horizon is equal to zero. Eqs. (11) and (12) ensure that if a portion of the demand for part type i in scenario s is produced in the given period, the binary variable y_{its} is equal to 1 and otherwise it is 0. Non-negativity and binary definitions of variables have been given in Eq. (13).

4.5. Linearization

As it can be seen, the proposed mathematical model includes several nonlinear terms. Because the nonlinear models are usually harder to be solved to optimality, a linearization method is used to transform the nonlinear model to linear ones. Our proposed model is nonlinear due to the existing absolute terms $(1c)$ $(1d)$, and the product of decision variables in terms $(1b)$, $(1c)$ $(1d)$, and Eq. (4). For each stage, a limited number of demand scenarios are taken into account (e.g., high, average, low). In each state, the amount of demand is known. In order to linearize the absolute term$(1c)$, two auxiliary variables, such as W^1_{jict} and W^2_{jict} are needed. Consequently, the absolute term $(1c)$ is transformed as follows:

$$1/2\sum_{t=1}^{H}\sum_{c=1}^{C}\sum_{i=1}^{I}\sum_{j=1}^{O_i-1}\left[\frac{P_{its}}{B_i^{inter}}\right]\gamma^{inter}\left|\sum_{m=1}^{M}x_{(j+1)imcts}-\sum_{m=1}^{M}x_{jimcts}\right|=$$

$$1/2\sum_{t=1}^{H}\sum_{c=1}^{C}\sum_{i=1}^{I}\sum_{j=1}^{O_i-1}\left[\frac{P_{it}}{B_i^{inter}}\right]\gamma^{inter}\left(W^1_{jicts}+W^2_{jicts}\right) \tag{1c'}$$

In addition, constraint (16) must be added to the model as follows:

$$\sum_{m=1}^{M}x_{(j+1)imcts}-\sum_{m=1}^{M}x_{jimcts}=W^1_{jicts}-W^2_{jicts} \qquad \forall j,i,c,t,s \tag{16}$$

Despite the above technique, Eq. (16) is nonlinear because there is the product of two variables P_{its} and $W^1_{jicts}+W^2_{jicts}$. For this purpose, we should define another auxiliary variable, such as φ^1_{jicts} as follows:

$$1/2\sum_{t=1}^{H}\sum_{c=1}^{C}\sum_{i=1}^{I}\sum_{j=1}^{O_i-1}\left[\frac{P_{its}}{B_i^{inter}}\right]\gamma^{inter}\left(W^1_{jicts}+W^2_{jicts}\right)=1/2\sum_{t=1}^{H}\sum_{c=1}^{C}\sum_{i=1}^{I}\sum_{j=1}^{O_i-1}\left[\frac{\varphi^1_{jicts}}{B_i^{inter}}\right]\gamma^{inter} \tag{1c''}$$

The following constraints (17) and (18) must be added to the model (I):

$$\varphi^1_{jicts}\geq P_{its}-Z\left(1-W^1_{jicts}-W^2_{jicts}\right) \qquad \forall j,i,c,t,s \tag{17}$$

$$\varphi^1_{jicts} \leq P_{its}+Z\left(1\text{-}W^1_{jicts}\text{-}W^2_{jicts}\right) \qquad \forall j,i,c,t,s \tag{18}$$

In order to linearize the integer part function in term (1c''), the integer variable L^1_{jicts} defined in term (1c''') and two constraints (19) and (20) are required as follows:

$$1/2\sum_{t=1}^{H}\sum_{c=1}^{C}\sum_{i=1}^{I}\sum_{j=1}^{O_i-1}\left[\frac{\varphi^1_{jicts}}{B_i^{inter}}\right]\gamma^{inter} = 1/2\sum_{t=1}^{H}\sum_{c=1}^{C}\sum_{i=1}^{I}\sum_{j=1}^{O_i-1} L^1_{jicts}\,\gamma^{inter} \quad (1c''')$$

$$L^1_{jicts} \leq \frac{\varphi^1_{jicts}}{B_i^{inter}} \qquad \forall j,i,c,t,s \tag{19}$$

$$L^1_{jicts} \geq \frac{\varphi^1_{jicts}}{B_i^{inter}}\text{-}1 \qquad \forall j,i,c,t,s \tag{20}$$

Similar to the above calculation, for linearizing the term (1d), two auxiliary variables O^1_{jimcts} and O^2_{jimcts} are defined. The transformed term (1d') is as follows:

$$1/2\sum_{t=1}^{H}\sum_{c=1}^{C}\sum_{i=1}^{I}\sum_{j=1}^{O_i-1}\left[\frac{P_{its}}{B_i^{intra}}\right]\gamma^{intra}\left(\sum_{m=1}^{M}\left|x_{(j+1)imcts}\text{-}x_{jimcts}\right| - \left|\sum_{m=1}^{M}x_{(j+1)imcts}\text{-}\sum_{m=1}^{M}x_{jimcts}\right|\right) =$$

$$1/2\sum_{t=1}^{H}\sum_{c=1}^{C}\sum_{i=1}^{I}\sum_{j=1}^{O_i-1}\left[\frac{P_{its}}{B_i^{intra}}\right]\gamma^{intra}\left\{\sum_{m=1}^{M}\left(O^1_{jimcts}+O^2_{jimcts}\right)\text{-}\left(W^1_{jicts}+W^2_{jicts}\right)\right\} \quad (1d')$$

Where the following constraint should be inserted into the model:

$$O^1_{jimcts}+O^2_{jimcts}= x_{(j+1)imcts}\text{-}x_{jimcts} \qquad \forall j,i,m,c,t,s \tag{21}$$

Now, we define φ^2_{jicts} as an auxiliary variable and use in following term:

$$1/2\sum_{t=1}^{H}\sum_{c=1}^{C}\sum_{i=1}^{I}\sum_{j=1}^{O_i-1}\left[\frac{P_{its}}{B_i^{intra}}\right]\gamma^{intra}\left\{\sum_{m=1}^{M}\left(O^1_{jimcts}+O^2_{jimcts}\right)\text{-}\left(W^1_{jicts}+W^2_{jicts}\right)\right\}$$

$$= 1/2\sum_{t=1}^{H}\sum_{c=1}^{C}\sum_{i=1}^{I}\sum_{j=1}^{O_i-1}\left[\frac{\varphi^2_{jicts}}{B_i^{intra}}\right]\gamma^{intra} \quad (1d'')$$

Where the following constraints must be added to the model (I):

$$\varphi^2_{jicts} \geq P_{its}\text{-}Z\left(1\text{-}\sum_{m=1}^{M}\left(O^1_{jimcts}+O^2_{jimcts}\right)+\left(W^1_{jicts}+W^2_{jicts}\right)\right) \forall j,i,c,t,s \tag{22}$$

$$\varphi^2_{jicts} \leq P_{its}+Z\left(1\text{-}\sum_{m=1}^{M}\left(O^1_{jimcts}+O^2_{jimcts}\right)+\left(W^1_{jicts}+W^2_{jicts}\right)\right) \forall j,i,c,t,s \tag{23}$$

Finally, we define the integer variable L^2_{jicts} and replace in term (1d'') with integer part function as follows:

$$1/2\sum_{t=1}^{H}\sum_{c=1}^{C}\sum_{i=1}^{I}\sum_{j=1}^{O_i-1}\left[\frac{\varphi^2_{jicts}}{B_i^{intra}}\right]\gamma^{intra} = 1/2\sum_{t=1}^{H}\sum_{c=1}^{C}\sum_{i=1}^{I}\sum_{j=1}^{O_i-1} L^2_{jicts}\,\gamma^{intra} \quad (1d''')$$

Also, the following constraints are necessary to be added to the model:

$$L^2_{jicts} \leq \frac{\varphi^2_{jicts}}{B_i^{intra}} \qquad \forall j,i,c,t,s \tag{24}$$

$$L^2_{jicts} \geq \frac{\varphi^2_{jicts}}{B_i^{intra}}\text{-}1 \qquad \forall j,i,c,t,s \tag{25}$$

Term (1b) and Eq. (4) by defining ψ_{jimcts} as an auxiliary variable and two following constraints is linearized:

$$\sum_{t=1}^{H}\sum_{m=1}^{M}\sum_{c=1}^{C}\sum_{i=1}^{I}\sum_{j=1}^{O_i}\beta_m P_{its}\,pt_{jim}x_{jimcts} = \sum_{t=1}^{H}\sum_{m=1}^{M}\sum_{c=1}^{C}\sum_{i=1}^{I}\sum_{j=1}^{O_i}\beta_m\ \psi_{jimcts} \quad (1b')$$

$$\sum_{i=1}^{I}\sum_{j=1}^{O_i} pt_{jim}\psi_{jimcts} \leq T_m N_{mcts} \qquad \forall m,c,t,s \tag{26}$$

$$\psi_{jimcts} \geq P_{its}\text{-}Z\left(1\text{-}x_{jimcts}\right) \qquad \forall j,i,m,c,t,s \tag{27}$$

$$\psi_{jimct} \leq P_{it} + Z\left(1 - x_{jimcts}\right) \qquad \forall j,i,m,c,t,s \tag{28}$$

Now, the linear mathematical model (II) can be written as follows:

Model (II):

$$\min \quad Z = \sum_{s=1}^{S} pr_s \Bigg(\text{(1a)}$$

$$+ \sum_{t=1}^{H}\sum_{m=1}^{M}\sum_{c=1}^{C}\sum_{i=1}^{I}\sum_{j=1}^{O_i} \beta_m \, pt_{jim} \, \psi_{jimcts} + {}^{1}\!/_{2} \sum_{t=1}^{H}\sum_{c=1}^{C}\sum_{i=1}^{I}\sum_{j=1}^{O_i\text{-}1} L^{1}_{jicts} \, \gamma^{inter} + {}^{1}\!/_{2} \sum_{t=1}^{H}\sum_{c=1}^{C}\sum_{i=1}^{I}\sum_{j=1}^{O_i\text{-}1} L^{2}_{jicts} \, \gamma^{intra} + \text{(1e)} + \text{(1f)} \Bigg)$$

Eqs.(3), Eqs.(5)-(28);

It has to be noted that in order to improve the efficiency of the model, in addition to the constraints defined in the developed mathematical model, non-anticipativity constraints are necessary as well. These conditions require the groups of scenarios with identical values for the uncertain parameters up to a certain period must yield the same decisions up to that period. Mathematically, the conditions can be represented via equal flows on a certain set of variables. For example, this condition for variable N_{mcts} is as follows:

$$N_{mcts} = N_{mctr} \tag{29}$$

For scenarios s and r, inheriting an identical past up to time. The conditions stipulate that decision variables must be equal to each other as long as they have a common historical past until the t in the planning horizon {0, 1, …, H-1}. While these constraints are extremely numerous, solution algorithms take advantage of their simple form including a pair of +1 and -1 for each row.

5. Experimental and computational results

Assume a shop with three part types so that each part type has three processes, three machines, two cells, and three periods. The comprehensive information about this shop has been represented in Table 1. In this experience, we assume that the uncertain demand evolves as a discrete time stochastic process during the planning horizon with a finite support. This information can be interpreted as a scenario tree (see Figure2). For each stage, two numbers of demand scenarios are taken into account (high and low). As a result, there are eight scenarios in this example and because it has been assumed that the probability of occurrence of each demand scenario in each stage is 0.5; therefore, the probability of each scenario is equal to 0.5×0.5×0.5=0.125. We know that three variables N_{mcts}, K_{mcts}^{+}, K_{mcts}^{-} are control variables and other variables x_{jimcts}, P_{its} , y_{its}, S_{its} , In_{its}^{+}, In_{its}^{-} are state variables. The control variables are those which should be determined before the occurrence of scenarios while state variables are determined after the occurrence of scenarios in each period. Thus, the non-anticipativity constraints in Table 2 can be added into the model for this example.

Table 1. The comprehensive information for the first example

Machine info.					I_1			I_2			I_3		
T_m (hour)	α_m\$	β_m\$	δ_m\$		1	2	3	1	2	3	1	2	3
500	1800	8	900	M1	0.93	0.55		0.64	0.48		0.71		0.89
500	1400	10	800	M2		0.91	0.56	0.89	0.39	0.76		0.77	
500	2200	6	600	M3	0.89		0.45			0.79	0.85	0.62	0.87
D_{it}		low		Period 1			600			950			450
				Period 2			800			0			300
				Period 3			150			340			0
		high		Period 1			800			1100			550
				Period 2			1000			100			750
				Period 3			550			620			250
B_i^{inter}							35			40			25
B_i^{intra}							6			8			9
λ_i							40			25			51
η_i							13			14			16
ρ_i							18			21			20
I_0							100			100			100
$\gamma^{inter}=50$		$\gamma^{intra}=5$		$l=1$			$UB=4$				$LB=1$		

Table 2. The non-anticipativity constraints associated with computational example

$N_{mc1s}=N_{mc1r}$ $\forall\ 1\leq s<r\leq 8$	$y_{i2s}=y_{i2r}$ $\forall\ 1\leq s<r\leq 2$
$K_{mc1s}^{+}=K_{mc1r}^{+}$ $\forall\ 1\leq s<r\leq 8$	$y_{i2s}=y_{i2r}$ $\forall\ 3\leq s<r\leq 4$
$K_{mc1s}^{-}=K_{mc1r}^{-}$ $\forall\ 1\leq s<r\leq 8$	$y_{i2s}=y_{i2r}$ $\forall\ 5\leq s<r\leq 6$
$x_{jimc1s}=x_{jimc1r}$ $\forall\ 1\leq s<r\leq 4$	$y_{i2s}=y_{i2r}$ $\forall\ 7\leq s<r\leq 8$
$x_{jimc1s}=x_{jimc1r}$ $\forall\ 5\leq s<r\leq 8$	$S_{i2s}=S_{i2r}$ $\forall\ 1\leq s<r\leq 2$
$P_{i1s}=P_{i1r}$ $\forall\ 1\leq s<r\leq 4$	$S_{i2s}=S_{i2r}$ $\forall\ 3\leq s<r\leq 4$
$P_{i1s}=P_{i1r}$ $\forall\ 5\leq s<r\leq 8$	$S_{i2s}=S_{i2r}$ $\forall\ 5\leq s<r\leq 6$
$y_{i1s}=y_{i1r}$ $\forall\ 1\leq s<r\leq 4$	$S_{i2s}=S_{i2r}$ $\forall\ 7\leq s<r\leq 8$
$y_{i1s}=y_{i1r}$ $\forall\ 5\leq s<r\leq 8$	$In_{i2s}^{+}=In_{i2r}^{+}$ $\forall\ 1\leq s<r\leq 2$
$S_{i1s}=S_{i1r}$ $\forall\ 1\leq s<r\leq 4$	$In_{i2s}^{+}=In_{i2r}^{+}$ $\forall\ 3\leq s<r\leq 4$
$S_{i1s}=S_{i1r}$ $\forall\ 5\leq s<r\leq 8$	$In_{i2s}^{+}=In_{i2r}^{+}$ $\forall\ 5\leq s<r\leq 6$
$In_{i1s}^{+}=In_{i1r}^{+}$ $\forall\ 1\leq s<r\leq 4$	$In_{i2s}^{+}=In_{i2r}^{+}$ $\forall\ 7\leq s<r\leq 8$
$In_{i1s}^{+}=In_{i1r}^{+}$ $\forall\ 5\leq s<r\leq 8$	$In_{i2s}^{-}=In_{i2r}^{-}$ $\forall\ 1\leq s<r\leq 2$
$In_{i1s}^{-}=In_{i1r}^{-}$ $\forall\ 1\leq s<r\leq 4$	$In_{i2s}^{-}=In_{i2r}^{-}$ $\forall\ 3\leq s<r\leq 4$
$In_{i1s}^{-}=In_{i1r}^{-}$ $\forall\ 5\leq s<r\leq 8$	$In_{i2s}^{-}=In_{i2r}^{-}$ $\forall\ 5\leq s<r\leq 6$
$N_{mc2s}=N_{mc2r}$ $\forall\ 1\leq s<r\leq 4$	$In_{i2s}^{-}=In_{i2r}^{-}$ $\forall\ 7\leq s<r\leq 8$
$N_{mc2s}=N_{mc2r}$ $\forall\ 5\leq s<r\leq 8$	$N_{mc3s}=N_{mc3r}$ $\forall\ 1\leq s<r\leq 2$
$K_{mc2s}^{+}=K_{mc2s}^{+}$ $\forall\ 1\leq s<r\leq 4$	$N_{mc3s}=N_{mc3r}$ $\forall\ 3\leq s<r\leq 4$
$K_{mc2s}^{+}=K_{mc2s}^{+}$ $\forall\ 5\leq s<r\leq 8$	$N_{mc3s}=N_{mc3r}$ $\forall\ 5\leq s<r\leq 6$
$K_{mc2s}^{-}=K_{mc2s}^{-}$ $\forall\ 1\leq s<r\leq 4$	$N_{mc3s}=N_{mc3r}$ $\forall\ 7\leq s<r\leq 8$
$K_{mc2s}^{-}=K_{mc2s}^{-}$ $\forall\ 5\leq s<r\leq 8$	$K_{mc3s}^{+}=K_{mc3s}^{+}$ $\forall\ 1\leq s<r\leq 2$
$x_{jimc2s}=x_{jimc2r}$ $\forall\ 1\leq s<r\leq 2$	$K_{mc3s}^{+}=K_{mc3s}^{+}$ $\forall\ 3\leq s<r\leq 4$
$x_{jimc2s}=x_{jimc2r}$ $\forall\ 3\leq s<r\leq 4$	$K_{mc3s}^{+}=K_{mc3s}^{+}$ $\forall\ 5\leq s<r\leq 6$
$x_{jimc2s}=x_{jimc2r}$ $\forall\ 5\leq s<r\leq 6$	$K_{mc3s}^{+}=K_{mc3s}^{+}$ $\forall\ 7\leq s<r\leq 8$
$x_{jimc2s}=x_{jimc2r}$ $\forall\ 7\leq s<r\leq 8$	$K_{mc3s}^{-}=K_{mc3s}^{-}$ $\forall\ 1\leq s<r\leq 2$
$P_{i2s}=P_{i2r}$ $\forall\ 1\leq s<r\leq 2$	$K_{mc3s}^{-}=K_{mc3s}^{-}$ $\forall\ 3\leq s<r\leq 4$
$P_{i2s}=P_{i2r}$ $\forall\ 3\leq s<r\leq 4$	$K_{mc3s}^{-}=K_{mc3s}^{-}$ $\forall\ 5\leq s<r\leq 6$
$P_{i2s}=P_{i2r}$ $\forall\ 5\leq s<r\leq 6$	$K_{mc3s}^{-}=K_{mc3s}^{-}$ $\forall\ 7\leq s<r\leq 8$
$P_{i2s}=P_{i2r}$ $\forall\ 7\leq s<r\leq 8$	

For this simple example, model (II) without non-anicipativity constraints was coded on GAMS software (Solved by NEOS Website) and the obtained results are represented in Table 3. According to Table 3, the optimal objective function value for this example without non-anicipativity constraints is 112918.745. Notably, the obtained results without respect to non-anicipativity constraints are applicable because the values of the variables are different for scenarios which have the same history. In other words, there are the various values for variables in each scenario without considering the non-anicipativity constraints, and since companies do notknow exactly which scenario will occur so these results are invalid. On the other hand, the non-anicipativity constraints are added to model 2 and results are represented in Table 4. The objective function with non-anicipativity constraints is 119645.645 so that the computational time is about 32 minutes. These results can be performed in practice and they are valid. Also, it is observed that the objective function is increased by applying the non-anicipativity constraints to the model and this is logical. Table 3 and Table 4 represent the effect of non-anicipativity constraints on the obtained optimal variables and objective function.

Certainly, the computational times increase with increasing the number of part types, machine types, cells, periods, and scenarios. In order to investigate the variations of computational times with respect to variations of the number of parts and machine types, cells, periods and scenarios, it is necessary to generate several new examples. These examples are generated based on the above example with new random parameters in Table 5. In this table, the term "U" implicates the uniform distribution. Changes in computational times (minutes) are indicated in Figure 3 for several examples. It can be observed in Fig. 3 that the computational time has an exponential growth than increasing of number of parts, machines, and periods. This growth rate is higher for the number of periods than others. Also, the computational time versus the number of cells has almost a linear growth. Consequently, an efficient approach is needed for solving the large-sized examples in terms of computational time to be optimal or near-optimal solutions.

Table 3. The optimal results obtained for the computational example without considering the non-anicipativity constraints

Scenario		***t*=1**			***t*=2**			***t*=3**		
		***I*1**	***I*2**	***I*3**	***I*1**	***I*2**	***I*3**	***I*1**	***I*2**	***I*3**
	P_{its}	500	850	350	800		300	150	273	340
	S_{its}									
s=1	In_{its}^{+}	(100*)	(100*)	(100*)						
	In_{its}^{-}									
	D_{its}	600	950	450	800	0	300	150	340	0
	P_{its}	554	850	350	746		300	550		250
	S_{its}					620				
s=2	In_{its}^{+}	(100*)	(100*)	(100*)	54					
	In_{its}^{-}									
	D_{its}	600	950	450	800	0	300	550	620	250
s=3	P_{its}	746	850	335	746	100	671	158	340	94
	S_{its}									
	In_{its}^{+}	(100*)	(100*)	(100*)	246					
	In_{its}^{-}			15	8		94			
	D_{its}	600	950	450	1000	100	750	150	340	0
s=4	P_{its}	746	850	335	746	100	671	558	301	335
	S_{its}			9		319				
	In_{its}^{+}	(100*)	(100*)	(100*)	246					
	In_{its}^{-}			15	8		85			
	D_{its}	600	950	450	1000	100	750	550	620	250
s=5	P_{its}	744	1000	463	800		287		340	
	S_{its}				106					
	In_{its}^{+}	(100*)	(100*)	(100*)	44		13			
	In_{its}^{-}									
	D_{its}	800	1100	550	800	0	300	150	340	0

Table 3. Continued

Scenario		*t*=1			*t*=2			*t*=3		
		***I*₁**	***I*₂**	***I*₃**	***I*₁**	***I*₂**	***I*₃**	***I*₁**	***I*₂**	***I*₃**
s=6	P_{its}	700	1000	450	800		300	550	434	250
	S_{its}				186					
	In_{its}^{+}	(100*)	(100*)	(100*)						
	In_{its}^{-}									
	D_{its}	800	1100	550	800	0	300	550	620	250
s=7	P_{its}	746	1000	496	909		704	195		
	S_{its}		100			340				
	In_{its}^{+}	(100*)	(100*)	(100*)	46		46			
	In_{its}^{-}				45					
	D_{its}	800	1100	550	1000	100	750	150	340	0
s=8	P_{its}	746	1000	507	954		669	550	434	274
	S_{its}		100			186				
	In_{its}^{+}	(100*)	(100*)	(100*)	46		57			
	In_{its}^{-}						24			
	D_{its}	800	1100	550	1000	100	750	550	620	250

* The initial inventory

Table 4. The optimal results obtained for the computational example with considering the non-anicipativity constraints

Scenario		*t*=1			*t*=2			*t*=3		
		***I*₁**	***I*₂**	***I*₃**	***I*₁**	***I*₂**	***I*₃**	***I*₁**	***I*₂**	***I*₃**
	P_{its}	502	850	350	798		300	150	154	
	S_{its}					186				
s=1	In_{its}^{+}	(100*)	(100*)	(100*)						
	In_{its}^{-}									
	D_{its}	600	950	450	800	0	300	150	340	0
	P_{its}	502	850	350	798		300	550	434	250
	S_{its}					186				
s=2	In_{its}^{+}	(100*)	(100*)	(100*)						
	In_{its}^{-}									
	D_{its}	600	950	450	800	0	300	550	620	250
s=3	P_{its}	502	850	350	746	100	671	402	136	79
	S_{its}					204				
	In_{its}^{+}	(100*)	(100*)	(100*)						
	In_{its}^{-}				252		79			
	D_{its}	600	950	450	1000	100	750	150	340	0
s=4	P_{its}	502	850	350	746	100	671	802	416	329
	S_{its}					204				
	In_{its}^{+}	(100*)	(100*)	(100*)						
	In_{its}^{-}				252		79			
	D_{its}	600	950	450	1000	100	750	550	620	250
s=5	P_{its}	746	869	450	753	131	300	150	154	
	S_{its}	1				186				
	In_{its}^{+}	(100*)	(100*)	(100*)						
	In_{its}^{-}		131							
	D_{its}	800	1100	550	800	0	300	150	340	0

Table 4. Continued

Scenario		*t*=1			*t*=2			*t*=3		
		***I*₁**	***I*₂**	***I*₃**	***I*₁**	***I*₂**	***I*₃**	***I*₁**	***I*₂**	***I*₃**
s=6	P_{its}	746	869	450	753	131	300	550	434	250
	S_{its}	1				186				
	In_{its}^{+}	(100*)	(100*)	(100*)						
	In_{its}^{-}		131							
	D_{its}	800	1100	550	800	0	300	550	620	250
s=7	P_{its}	746	869	450	746	231	671	346	136	79
	S_{its}	1			11	204				
	In_{its}^{+}	(100*)	(100*)	(100*)						
	In_{its}^{-}		131		207		79			
	D_{its}	800	1100	550	1000	100	750	150	340	0
s=8	P_{its}	746	869	450	746	231	671	746	416	329
	S_{its}	1			11	204				
	In_{its}^{+}	(100*)	(100*)	(100*)						
	In_{its}^{-}		131		207		79			
	D_{its}	800	1100	550	1000	100	750	550	620	250

* The initial inventory

Table 5. The parameter setting for random examples

Parameters	Value	Parameters	Value
T_m	350	λ_i	*U(0,100)*
α_m	*U(1000,2500)*	η_i	*U(10,20)*
β_m	*U(2,14)*	ρ_i	*U(10,50)*
δ_m	*U(500,100)*	γ^{inter}	50
pt_{jim}	*U(0,1)*	γ^{intra}	5
D_{it}(low)	*U(0,1500)*	*l*	1
D_{it}(high)	D_{it}(low)+(0,1000)	*UB*	2
B_i^{inter}	*U(0,50)*	*LB*	1
B_i^{intra}	*U(0,10)*		

In the literature, one approach resolving the computational time problem for large-sized examples is using the known bounds, such as the Sum of Pairs Expected Value (SPEV), the Expected Value of the Reference Scenario (EVRS), and the Expectation of Pairs Expected Value (EPEV). In this context, we use the SPEV and EPEV as a lower and upper bounds, respectively. To study more about these two bounds and their algorithms, the authors refer readers to Birge, J. R., & Louveaux, F., 1(997), Maggioni, F., et al. (2012) , and Maggioni, F., et al. (2014). The comparisons between the optimal objective function and two bounds SPEV and EPEV for several examples are shown in Table 6. The Value of Stochastic Solution (VSS), the Expected Value of Sum of Pair (EVSP), VSS% and EVSP% are calculated as Eqs. (30)-(33):

$$\text{VSS} = \text{EPEV-optimal objective function} \tag{30}$$

$$\text{EVSP} = \text{optimal objective function-SPEV} \tag{31}$$

$$\text{VSS\%} = \frac{\text{VSS}}{\text{EPEV}} \times 100 \tag{32}$$

$$\text{EVSP\%} = \frac{\text{EVSP}}{\text{optimal objective function}} \times 100 \tag{33}$$

In fact, VSS and EVSP show the costs incurred to the system due to simplifying the uncertain problem (model 2 together nonanticipativity constraints) into a problem with several pairs-scenario problems. These two values can help, whether the company should trust to optimal solutions obtained in problems associated with finding two bounds SPEV and EPEV. In other words, the higher values for VSS% and EVSP% means that using the obtained solutions in SPEV and EPEV cannot be reliable and vice versa. In Table 5, the maximum and minimum value for VSS% and EVSP% are 2 and 19 , respectively. We recommend that for large-sized examples where to find the optimal solutions are time-consuming, solutions obtained by two bounds can be utilized if VSS% and EVSP% are less than or equal 10. This range can be logical for every company with respect to the authorities' opinion.

Moreover, the computational times in obtaining two bounds are represented in Figure 4. By comparing the computational times until desirable results for optimal and two bound objective functions in Fig 3 and Fig 4, respectively, it is concluded that the solving times for two bounds are less than the objective function. Also, the quality of bounds is almost suitable for most of the examples. As a result, using two bounds instead of the optimal objective function can be reasonable especially for large-sized problems.

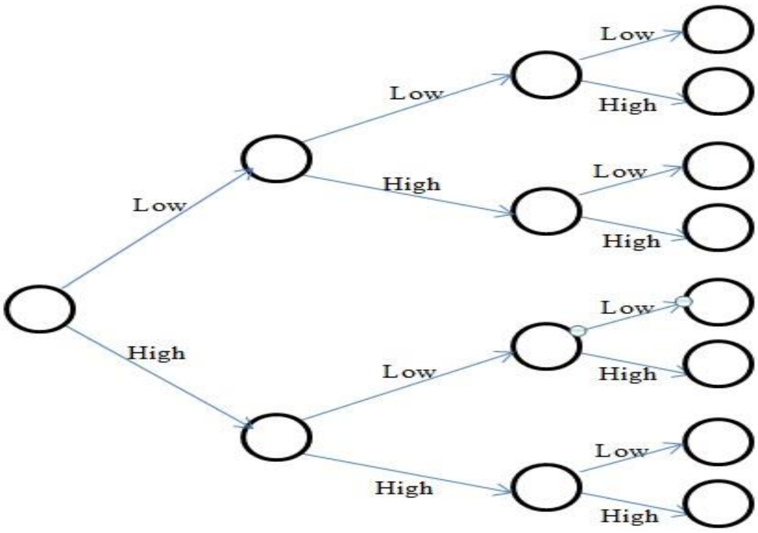

Figure 2. The scenario tree for the computational example

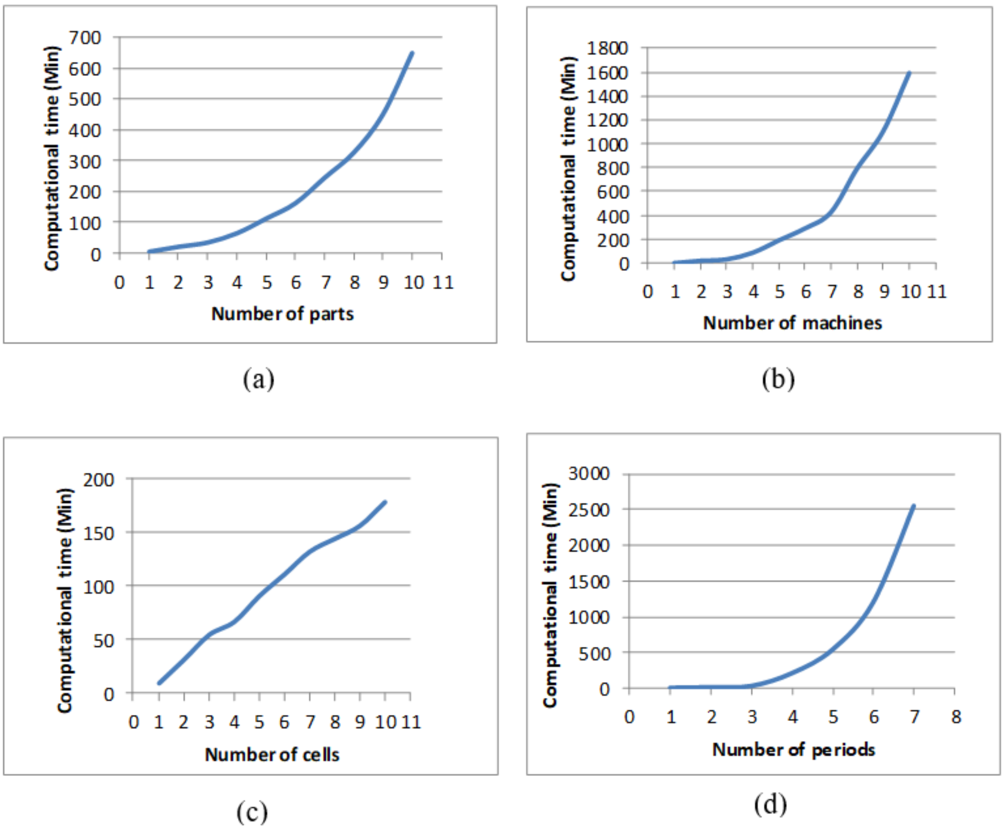

Figure 3. The variations of computational times versus variations of (a) number of part types; (b) number of machine types; (c) number of cells and (d) number of periods

Table 6. The results related to VSS% and EVSP% for the generated random examples

No. of example	I/M/C/S/H	SPEV	Optimal objective function	EPEV	VSS	EVSP	VSS%	EVSP%
1	1/3/2/8/3	52345	56732	59132	2400	4387	4	8
2	2/3/2/8/3	65464	81678	88546	6868	16214	8	19
3	3/3/2/8/3	101230	119645	127617	14699	11688	6	15
4	4/3/2/8/3	115670	123440	129100	5660	7770	4	6
5	5/3/2/8/3	134571	150467	179543	29076	15896	16	10
6	6/3/2/8/3	167789	184534	207685	23151	16745	11	9
7	7/3/2/8/3	169990	196756	201345	4589	26766	2	13
8	3/1/2/8/3	121456	134560	146780	12220	13104	8	10
9	3/2/2/8/3	111398	133451	149876	26425	12053	18	10
10	3/4/2/8/3	93459	104599	119320	14721	11140	12	10
11	3/5/2/8/3	94541	102304	109110	6806	7763	6	8
12	3/6/2/8/3	99345	110345	131964	21619	11000	16	10
13	3/7/2/8/3	103450	112891	115433	2542	9441	2	8
14	3/3/3/8/3	101230	112918	127617	14699	11688	11	10
15	3/3/4/8/3	101230	112918	127617	14699	11688	11	10
16	3/3/5/8/3	101230	112918	127617	14699	11688	11	10
17	3/3/6/8/3	101230	112918	127617	14699	11688	11	10
18	3/3/7/8/3	101230	112918	127617	14699	11688	11	10
19	3/3/2/2/1	29804	36659	38319	1660	6855	4	19
20	3/3/2/4/2	64583	71550	78330	6780	6967	9	10
21	3/3/2/16/4	173473	181226	211334	30108	7753	14	4
22	3/3/2/32/5	191342	234678	290304	55626	43336	19	18
23	3/3/2/64/6	264322	289241	341121	51880	24919	15	9
24	3/3/2/128/7	301231	337674	357890	20216	36443	6	11

6. A practical case study

R-S.Arvin is a manufacturing company located in Robat-Karim, Tehran, Iran. This company produces several parts used in automobiles for Iran-Khodro as the biggest producer of automobile in Iran. Also, this company utilizes a CMS to acquire the essential flexibility for handling the demand uncertainty in different months and to reduce the transportation costs within the company. The number of the used cells in this company is four and the planning horizon is equal to four periods equivalent to four seasons in year. The produced parts (20 parts) together with some other information are presented in Table 7. Further, the current machines in the company together with their information as well as the demand of parts for the low and high state in four different seasons in the year are given in Table 8 and Table 9, respectively. The planning horizon is one year including four seasons that each season has the different demand. Moreover, γ^{inter}, γ^{intra}, l, LB and UB are 10, 2, 1, 1 and 7, respectively.

This company has no information about the demand state of parts at the beginning of each season. But, it should be decided on the number of machines assigned to cells in all periods for all scenarios, the number of machines added in cells in all periods for all scenarios, and number of machines removed from cells in all periods for all scenarios (three variables N_{mcts}, K_{mcts}^{+}, K_{mcts}^{-}) before the demand state is determined. Thus, when the demand state is determined, other variables consisting of variables x_{jimcts}, P_{its} , y_{its}, S_{its} , In_{its}^{+}, In_{its}^{-} should be determined at the end of each season.

Solving the case study problem by the model (Π) together with associated nonanticipativity constraints in GAMS software didn't find even one feasible solution for about three days (4320 minutes). This can be a challenge in solving this case study. Therefore, this problem was solved to obtain VSS% and EVSP% for case study. As an example, the optimal solutions related to cell formation for two bounds SPEV and EPEV for the certain scenario (low, low, low, low) are given in Table 10 and Table 11 respectively.

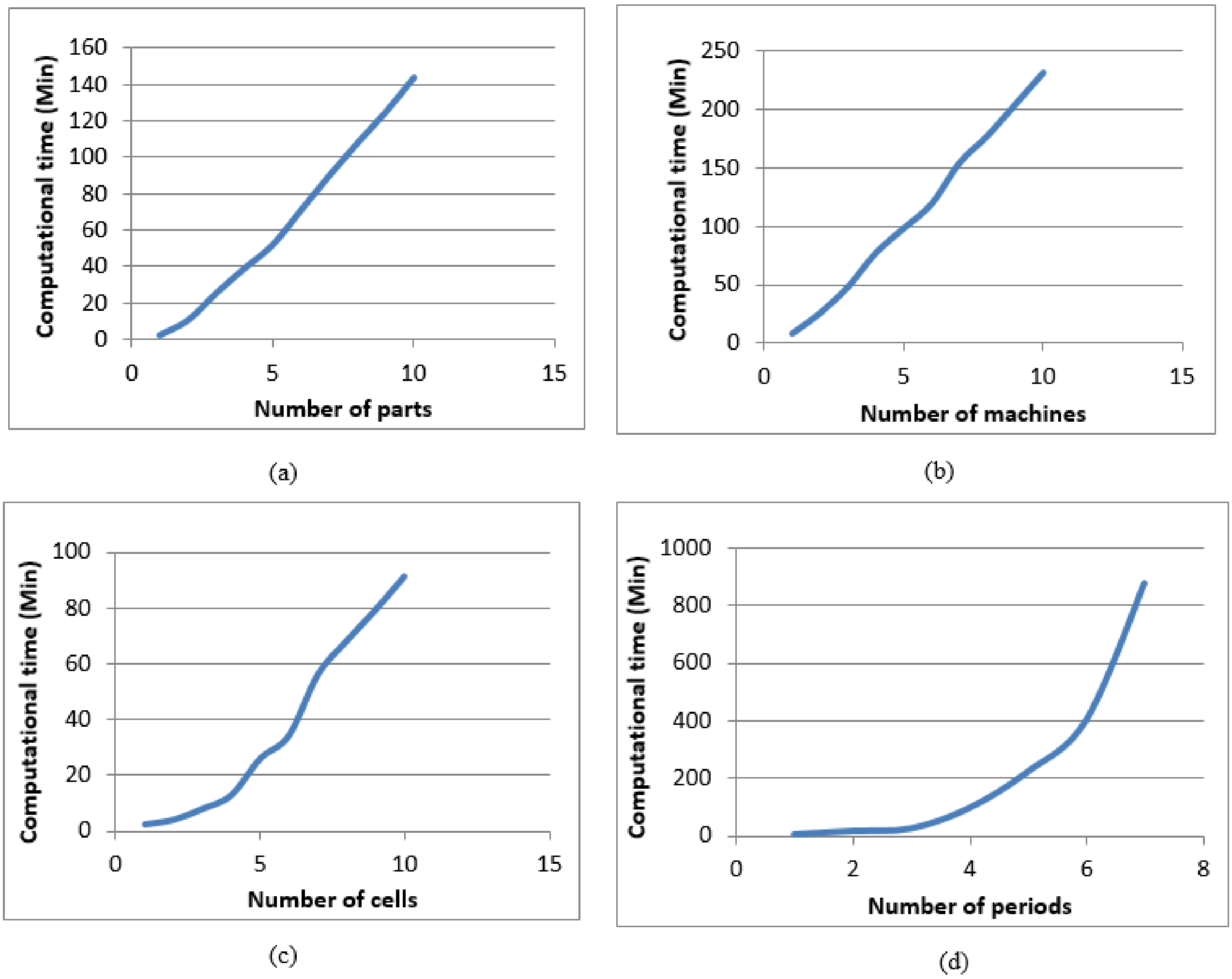

Figure 4. The variations of computational times versus variations of (a) number of part types; (b) number of machine types; (c) number of cells and (d) number of periods; for finding two bounds

After solving the case study modal by two bounds, the values of SPEV and EPEV are equal to 14245674 and 15437903. Because the optimal objective function obtained by the model (II) and non-anticipativity constraints, could not be found in a logical computational time, thus the calculation of VSS% and EVSP% is impossible. But, we can obtain a range for VSS% and EVSP%. The maximum and minimum values for optimal objective function are obtained by model (II) and non-anticipativity constraints are equal to SPEV and EPEV (14245674 and 15437903). Therefore, the range for VSS and EVSP can be obtained as follows. The minimum value for VSS is equal to VSS_{min}= 15437903-15437903=0 and the maximum one is equal to VSS_{max}= 15437903-14245674=1192229. Also, the minimum and maximum values for EVSP are equal to $EVSP_{min}$=14245674-14245674=0 and $EVSP_{max}$= 15437903-14245674=1192229. Thus, the ranges for VSS% and EVSP% are found (0, 7) and (0, 8) respectively. Since the error values are under 10 percent, we can conclude that using the two bounds models can be useful for solving this certain proposed case study. The obtained results mean that the company can incur maximum 1192229 errors in the objective function value in order to obtain the near-optimal solutions in a justifiable computational time.

Table 7. The parts list together with some information about parts for R-S.Arvin company

No. of parts	Name	Processing routes (processing times (min))	B_i^{inter}	B_i^{intra}	λ_i	η_i	ρ_i
1	Multi-way mounting bracket	M1-M4-M9-M5 (0.7-0.65-0.3-0.5)	100	10	8	1.0	2.0
2	Bumper Bracket	M2-M8-M4-M5 (0.3-0.9-0.5-0.2)	150	10	6	1.0	3.0
3	Closed dome	M1-M12-M4-M5 (0.5-0.4-0.3-0.4)	300	50	3	0.5	1.0
4	Split clamp	M1-M12-M5 (0.5-0.9-0.4)	500	100	3	0.5	3.0
5	Polk Hub	M1-M6-M3 (0.2-0.5-0.4)	1000	100	2	0.4	0.5
6	Foundation type 1	M2-M3-M10-M12-M5 (1.5-0.8-0.2-0.5-0.7)	50	5	10	2.0	4.0
7	Differential Handle	M1-M3 –M7 (0.3-0.3-0.2)	1000	100	3	0.5	0.5
8	Fastener	M2-M3-M5 (0.2-0.4-0.3)	500	100	2	0.2	0.5
9	Dyaq shock	M2-M3-M9-M11-M5 (2-0.7-0.7-0.3-0.4)	50	5	12	3.0	5.0
10	Nissan Ram	M2-M4-M8-M12 (1.4-0.4-0.6-0.7)	40	2	15	5.0	7.0
11	Valve	M2-M7-M5 (0.2-0.8-1.5)	2000	500	2	0.2	0.3
12	Oil-consuming	M1-M3-M5-M11 (0.4-0.4-2.6-0.3-0.2)	1000	100	4	1.0	1.0
13	Copley Duster	M2-M7-M4 (0.7-0.7-0.5)	1000	50	5	2.0	2.5
14	In-box Metal	M1-M3-M5 (0.4-0.4-0.5)	500	20	3	0.2	0.5
15	Sealing Washer	M2-M12 (1.3-0.6)	200	10	10	3.0	3.0
16	Semi-Crust	M1-M4-M5 (0.4-0.6-0.8)	1000	100	3	1.0	1.0
17	Lachaki	M2-M7-M11-M9 (0.8-1.2-1-0.5)	100	5	11	1.0	5.0
18	Domical	M2-M12 (0.9-1.8)	100	5	15	1.0	5.0
19	Paulus Washer	M2-M4-M3-M5 (0.5-0.4-0.3-0.4)	1000	200	2	0.2	1.0
20	Piniom washer	M1-M3-M5 (0.4-0.7-0.3)	1000	100	2	0.1	3.0

Table 8. The machines list together with some information about machines for R S.Arvin company

No. of machines	Name	T_m (hour)	α_m\$	β_m\$	δ_m\$	Corresponding cell	Current volume
1	Guillotine 4 mm	350	100	2.0	200	1	1
2	Guillotine 6 mm	350	110	3.5	250	1	1
3	Press 15 tone	350	80	2.5	180	2	1
4	Press 30 tone	350	90	3.0	280	2	1
5	Magnetic drill	350	40	1.5	80	3	1
6	Press 60 tone	350	100	1.8	410	2	1
7	Press 100 tone	350	115	2.2	580	2	1
8	Press 180 tone	350	140	2.4	730	4	1
9	Column drill	350	35	2.0	120	3	1
10	Milling machine	350	60	2.5	400	3	1
11	Press 250 tone	350	180	3.5	900	4	1
12	Press 400 tone	350	200	4.0	1250	4	1

Table 9. The demand information in the different seasons in year for R-S.Arvin company

No. of parts	Low demand				High demand			
	Spring	Summer	Autumn	Winter	Spring	Summer	Autumn	Winter
1	9000	10400	5600	8700	12500	15000	7800	11300
2	18500	14600	27900	22400	27400	23400	35600	30300
3	11200	9400	18700	19200	15200	12300	24500	25400
4	32500	26700	39000	36700	48900	32500	56800	51100
5	17500	16700	23400	19900	30400	23800	30200	27600
6	5900	3300	8800	7100	11800	7800	16700	13400
7	4700	3000	8000	6700	6300	4100	9600	8800
8	50000	39900	67400	70900	90000	68200	82300	85600
9	21600	16700	33300	26700	29400	24600	46800	35000
10	8200	8600	6600	4900	10700	11800	8700	6300
11	100000	83500	113600	125900	141000	115700	167800	180000
12	32100	23400	35800	31200	39400	28500	47100	45500
13	16200	11300	16700	15000	22300	19100	24600	23900
14	48300	40300	43700	30000	61300	50100	58900	41200
15	12300	13900	5700	3200	15900	17500	11300	6700
16	18900	12800	23700	28900	24300	18900	35600	36100
17	12500	9000	15900	13400	19400	15600	22300	20100
18	12600	10600	16700	14000	19500	17800	29900	25600
19	39000	40000	44500	40300	53000	57200	63100	59800
20	76000	81000	80300	83400	91000	100900	93400	120100

Table 10. The optimal cell formation obtained for case study for the model relevant to SPEV in scenario (low, low, low, low)

Period	No. of cells	The assigned machine types (the optimal number of machines)
Spring	1	M1(1)- M2(2)- M5(2)- M12(2)
	2	M3(2)-M7(2)- M9(1)- M10(1)
	3	M1(1)- M2(1)- M4(3)- M12(1)
	4	M11(2)- M5(1)- M6(1)- M8(1)
Summer	1	M1(2)- M2(1)- M7(2)
	2	M3(2)- M5(3)- M10(2)
	3	M1(2)- M2(1)- M9(1)- M12(1)
	4	M4(2)- M6(1)-M8(1)- M11(2)
Autumn	1	M1(1)- M2(3)- M7(2)
	2	M3(2)- M9(2)- M10(2)- M11(1)
	3	M1(2)- M2(1)- M5(2)- M12(2)
	4	M4(2)- M5(1)- M6(1)-M8(1)
Winter	1	M2(3)- M7(2)- M10(1) - M11(1)
	2	M3(2)- M9(2)- M7(2)
	3	M1(2)- M5(3)- M12(2)
	4	M4(2)- M6(1)-M8(2)

Table 11. The optimal cell formation obtained for case study for the model relevant to EPEV in scenario (low, low, low, low)

Period	No. of cells	The assigned machine types (the optimal number of machines)
Spring	1	M1(2)- M2(2)- M5(3)
	2	M3(3)-M8(2)- M9(1)- M10(1)
	3	M1(2)- M7(2)- M12(2)
	4	M4(3)- M6(1)- M11(3)
Summer	1	M1(1)- M2(1)- M4(2)- M5(3)
	2	M3(2)- M8(1)- M7(2)- M10(2)
	3	M1(2)- M2(2)- M9(1)- M12(1)
	4	M3(1)- M4(1)- M6(2)- M11(2)
Autumn	1	M1(2)- M2(3)- M5(2)
	2	M3(3)- M7(2)- M10(2)
	3	M1(1)- M2(2)- M9(1)- M12(2)
	4	M4(2)- M5(2)- M6(1)-M8(1)- M11(1)
Winter	1	M1(2)- M2(2)- M5(2)- M7(1)
	2	M3(2)- M9(2)- M5(2)- M7(1)
	3	M1(1)- M2(2)- M12(2)- M8(2)
	4	M4(2)- M6(2)-M11(2)- M10(1)

7. Conclusions

This paper develops a dynamic cell formation problem (DCFP), where there are several periods with the different quantity of uncertain demand in each period. In other terms, the demand is both dynamic and uncertain for each period. Also, because some companies have deficient information thought historical data about the demand in each period so they can determine several scenarios for demands. However, to determine the optimal cell configuration in each period in order to achieve the total minimum expected costs is the goal. A mixed-integer nonlinear mathematical model, despite the scenario-based and dynamic demand of parts, has been developed. Further, a multi-stage stochastic programming (MSP) is used to cope with uncertainty of demand. The nonlinear model is transformed into a linear model and it is solved by GAMS software for small and medium-sized examples. The validation of model is proved in a random computational example with considering several conditions, such as with and without the non-anticipativity constraints and theirs results in Tables 3 and 4. In order to solve the large-sized examples, we recommended using the generated plans by two bounds SPEV and EPEV when two error values VSS% and EVSP% are less than or equal to 10 percent. In addition, we proved that the computational time for solving the two models associated with SPEV and EPEV were much less than the multi-stage stochastic model together with nonanticipativity constraints. Finally, a practical case study as a large-sized example was presented. The recommended method was used and the maximum error equal to 7% and 8% were obtained for VSS% and EVSP% respectively. In this case, in order to decrease the computational time, using the two bound plan instead of the multi-stage stochastic plan, the maximum cost was incurred equal to 1192229 for R-S-Arvin company. This can be a managerial implication for authorities in manufacturing companies. For further studies, to develop an efficient solving method for large-sized scenario-based DCFP examples, such as benders decomposition method (exact method) or meta-heuristic methods (approximate methods like GA, ACO, SA, TS and etc.) can be as a future research. In additions, considering the distribution functions for demands can be an open work for the future.

References

Aryanezhad, M. B., Deljoo, V. and Mirzapour Al-e-Hashem. S. M. J. (2009). Dynamic Cell Formation and the Worker Assignment Problem: A New Model. *The International Journal of Advanced Manufacturing Technology*, Vol. 41(3-4), pp. 329–42.

Arzi, Y., Bukchin, J., and Masin, M. (2001). An efficiency frontier approach for the design of cellular manufacturing systems in a lumpy demand environment. *European Journal of Operational Research*, Vol.134 (2), pp. 346-364.

Askin, R. G., Selim, H. M., and Vakharia, A. J. (1997). A methodology for designing flexible cellular manufacturing systems. *IIE transactions*, Vol. 29(7), pp. 599-610.

Bagheri, M., and Bashiri, M. (2014). A new mathematical model towards the integration of cell formation with operator assignment and inter-cell layout problems in a dynamic environment. *Applied Mathematical Modelling*, Vol. 38(4), pp. 1237-1254.

Bajestani, M. A., Rabbani, M., Rahimi-Vahed, A. R., and Khoshkhou, G. B. (2009). A multi-objective scatter search for a dynamic cell formation problem. *Computers & operations research*, Vol. 36(3), pp. 777-794.

Balakrishnan, J., and Hung Cheng, C. (2005). Dynamic cellular manufacturing under multiperiod planning horizons. *Journal of manufacturing technology management*, Vol. 16(5), pp. 516-530.

Birge, J R, and F Louveaux. (1997). Introduction to Stochastic Programming. Series in Operations Research and Financial Engineering.

Bulgak, A. A., and Bektas, T. (2009). Integrated cellular manufacturing systems design with production planning and dynamic system reconfiguration. *European journal of operational research*, Vol. 192(2), pp. 414-428.

Chen, M. (1998). A mathematical programming model for system reconfiguration in a dynamic cellular manufacturing environment. *Annals of Operations Research*, Vol. 77, pp. 109-128.

Defersha, F. M., and Chen, M. (2006). Machine cell formation using a mathematical model and a genetic-algorithm-based heuristic. *International Journal of Production Research*, Vol. 44(12), pp. 2421-2444.

Dupačová, J., Consigli, G., and Wallace, S. W. (2000). Scenarios for multistage stochastic programs. *Annals of operations research*, Vol. 100(1-4), pp. 25-53.

Farunghi, H., and Mostafayi, S. (2016). Robust Optimization Approach for Design for a Dynamic Cell Formation Considering Labor Utilization: Bi-objective Mathematical Model. *International Journal of Supply and Operations Management*, Vol. 3(1), pp. 1143-1167.

Ghotboddini, M. M., Rabbani, M., and Rahimian, H. (2011). A comprehensive dynamic cell formation design: Benders' decomposition approach. *Expert Systems with Applications*, Vol. 38(3), pp. 2478-2488.

Egilmez, G., Singh, S., and Ozguner, O. (2017). Cell formation in a cellular manufacturing system under uncertain demand and processing times: a stochastic genetic algorithm approach. *International Journal of Services and Operations Management*, Vol. 26(2), pp. 162-185.

Esmaeilbeigi, R., Naderi, B., Arshadikhamseh, A., and Loni, P. (2017). An Estimated Formulation for the Capacitated Single Allocation p-hub Median Problem with Fixed Costs of Opening Facilities. *International Journal of Supply and Operations Management*, Vol. 4(1), pp. 63-72.

Javadian, N., Aghajani, A., Rezaeian, J., and Sebdani, M. J. G. (2011). A multi-objective integrated cellular manufacturing systems design with dynamic system reconfiguration. *The International Journal of Advanced Manufacturing Technology*, Vol. 56(1-4), pp. 307-317.

Kall, PETER, S, and W Wallace. (1994). "Stochastic Programming." *Jonh Wiley & Sons, Chichester*.

Kall, P., & Mayer, J. (1976). Stochastic linear programming (Vol. 7). Berlin: Springer-Verlag.

Kia, R., Khaksar-Haghani, F., Javadian, N., and Tavakkoli-Moghaddam, R. (2014). Solving a multi-floor layout design model of a dynamic cellular manufacturing system by an efficient genetic algorithm. *Journal of Manufacturing Systems*, Vol. 33(1), pp. 218-232.

Kia, R., Baboli, A., Javadian, N., Tavakkoli-Moghaddam, R., Kazemi, M., and Khorrami, J. (2012). Solving a group layout design model of a dynamic cellular manufacturing system with alternative process routings, lot splitting and flexible reconfiguration by simulated annealing. *Computers & operations research*, Vol. 39(11), pp. 2642-2658.

Koushki, F. (2018). "Performance Measurement and Productivity Management in Production Units with Network

Structure by Identification of the Most Productive Scale Size Pattern." *International Journal of Supply and Operations Management*, Vol. 5(4), pp. 379-395.

Maggioni, Francesca, Elisabetta Allevi, and Marida Bertocchi. (2012). Measures of information in multistage stochastic programming. In STOPROG-2012-Stochastic Programming for Implementation and Advanced Applications (pp. 78-82). The Association of Lithuanian Serials.

Maggioni, F., Allevi, E., and Bertocchi, M. (2014). Bounds in multistage linear stochastic programming. *Journal of Optimization Theory and Applications*, Vol. 163(1), pp. 200-229.

Mahdavi, I., Aalaei, A., Paydar, M. M., and Solimanpur, M. (2010). Designing a mathematical model for dynamic cellular manufacturing systems considering production planning and worker assignment. *Computers & Mathematics with Applications*, Vol. 60(4), pp. 1014-1025.

Mahmoodian, V., Jabbarzadeh, A., Rezazadeh, H., and Barzinpour, F. (2017). A novel intelligent particle swarm optimization algorithm for solving cell formation problem. *Neural Computing and Applications*, pp. 1-15.

Moslemipour, G. (2018). A hybrid CS-SA intelligent approach to solve uncertain dynamic facility layout problems considering dependency of demands. *Journal of Industrial Engineering International*, Vol. 14(2), pp. 429-442.

Niakan, F., Baboli, A., Moyaux, T., and Botta-Genoulaz, V. (2016). A bi-objective model in sustainable dynamic cell formation problem with skill-based worker assignment. *Journal of Manufacturing Systems*, Vol. 38, pp. 46-62.

Rabbani, M., Farrokhi-Asl, H., and Ravanbakhsh, M. (2019). Dynamic cellular manufacturing system considering machine failure and workload balance. *Journal of Industrial Engineering International*, Vol. 15(1), pp. 25-40.

Rabbani, M., Ravanbakhsh, M., Farrokhi-Asl, H., and Taheri, M. (2017). Using metaheuristic algorithms for solving a hub location problem: application in passive optical network planning. *International Journal of Supply and Operations Management*, Vol. 4(1), pp. 15-32.

Rezaie, K., Gereie, A., Ostadi, B., and Shakhseniaee, M. (2009). Safety interval analysis: A risk-based approach to specify low-risk quantities of uncertainties for contractor's bid proposals. *Computers & Industrial Engineering*, Vol. 56(1), pp. 152-156.

Rheault, M., Drolet, J. R., and Abdulnour, G. (1996). Dynamic cellular manufacturing system (DCMS). *Computers & Industrial Engineering*, Vol. 31(1-2), pp. 143-146.

Safaei, N., Saidi-Mehrabad, M., and Jabal-Ameli, M. S. (2008). A hybrid simulated annealing for solving an extended model of dynamic cellular manufacturing system. *European Journal of Operational Research*, Vol. 185(2), pp. 563-592.

Safaei, N., Saidi-Mehrabad, M., Tavakkoli-Moghaddam, R., and Sassani, F. (2008). A fuzzy programming approach for a cell formation problem with dynamic and uncertain conditions. *Fuzzy Sets and Systems*, Vol. 159(2), pp. 215-236.

Safaei, N., and Tavakkoli-Moghaddam, R. (2009). Integrated multi-period cell formation and subcontracting production planning in dynamic cellular manufacturing systems. *International Journal of Production Economics*, Vol. 120(2), pp. 301-314.

Saidi-Mehrabad, M., and Safaei, N. (2007). A new model of dynamic cell formation by a neural approach. *The International Journal of Advanced Manufacturing Technology*, Vol. 33(9-10), pp. 1001-1009.

Saxena, L. K., and Jain, P. K. (2012). An integrated model of dynamic cellular manufacturing and supply chain system design. *The International Journal of Advanced Manufacturing Technology*, Vol. 62(1-4), pp. 385-404.

Shakhsi-Niaei, M. , Iranmanesh, S. H., and Torabi, S. A. (2013). A review of mathematical optimization applications in oil-and-gas upstream & midstream management. *International Journal of Energy and Statistics*, Vol. 1(02), pp. 143-154.

Shishebori, D. (2014). Study of facility location-network design problem in presence of facility disruptions: A case study (research note). *International Journal of Engineering-Transactions A: Basics*, Vol. 28(1), pp. 97-108.

Shishebori, D., Akhgari, M. J., Noorossana, R., and Khaleghi, G. H. (2015). An efficient integrated approach to reduce scraps of industrial manufacturing processes: a case study from gauge measurement tool production firm. *The International Journal of Advanced Manufacturing Technology*, Vol. 76(5-8), pp. 831-855.

Shishebori, Davood, and Abdolsalam Ghaderi. (2015). "An integrated approach for reliable facility location/network design problem with link disruption." *International Journal of Supply and Operations Management*, Vol. 2(1), pp. 633-640.

Taboun, S. M., Merchawi, N. S., and Ulger, T. (1998). Part family and machine cell formation in multiperiod planning horizons of cellular manufacturing systems. *Production Planning & Control*, Vol. 9(6), pp. 561-571.

Tavakkoli-Moghaddam, R., Aryanezhad, M. B., Safaei, N., and Azaron, A. (2005). Solving a dynamic cell formation problem using metaheuristics. *Applied Mathematics and Computation*, Vol. 170(2), pp. 761-780.

Wang, X., Tang, J., and Yung, K. L. (2009). Optimization of the multi-objective dynamic cell formation problem using a scatter search approach. *The International Journal of Advanced Manufacturing Technology*, Vol. 44(3-4), pp. 318-329.

Wang, Y., and Tang, J. (2018). Cost and Service-Level-Based Model for a Seru Production System Formation Problem with Uncertain Demand. *Journal of Systems Science and Systems Engineering*, Vol. 27(4), pp. 519-537.

Wemmerlöv, U., and Hyer, N. L. (1987). Research issues in cellular manufacturing. *International Journal of Production Research*, Vol. 25(3), pp. 413-431.

Zarrinpoor, N. (2018). An Exploration of Evolutionary Algorithms for a Bi-Objective Competitive Facility Location Problem in Congested Systems. *International Journal of Supply and Operations Management*, Vol. 5(3), pp. 266-282.

Zohrevand, A.M., H. Rafiei, and A. H. Zohrevand. (2016). Multi-Objective Dynamic Cell Formation Problem: A Stochastic Programming Approach. *Computers & Industrial Engineering*, Vol. 98, pp. 323-332.

s://www.deprem.afad.gov.tr/deprem-bolgeleri-haritasi?lang=en.