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Revised multi-choice goal programming for integrated supply chain design and dynamic virtual cell formation with fuzzy parameters

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Cell formation, as one of the most important decision problems in designing a cellular manufacturing system, includes grouping machines in cells and the parts as part families. In a dynamic environment, the part demand/mix change is considered over a planning horizon divided to several periods. So, the cell formation for one period may no longer be effective for future periods and hence reconfiguration of cells is essential. Due to the variation of demand and necessity of cells reconfiguration, virtual cell formation concept is introduced by researchers to take the advantage of cell formation without reconfiguration charges. On the other hand, Simultaneous consideration of supply chain and cell formation results in lower distribution and procurement costs and faster response to customers. In this paper, a new bi-objective possibilistic optimisation mathematical model is developed for integrating procurement, production and distribution planning considering various conflicting objectives simultaneously as well as the imprecise nature of some critical parameters such as customer demands and machine capacities. Then, a revised multi-choice goal programming approach is applied to solve the proposed mathematical model and to find a preferred compromise solution. Moreover, a real-world industrial case is provided to validate how the proposed model works.

Keywords: virtual cell formation; supply chain; multi-choice goal programming

1. Introduction

In today’s world, for a business in order to survive, it is crucial to pay extra attention to customers’ explicit and implicit needs and interests. Customers demand goods and products with higher quality at a lower price. Customer care and continuous improvement in processes and products are the keys to survival of businesses in competitive world. In such environment, many businesses focus on agility and fast respond to their customers’ demands. Group technology (GT) can help the companies to achieve this goal by focusing on cellular manufacturing (CM). GT was first introduced by Mitrofanov (1966) and was propagated by Burbidge (1971) who extended the methods appropriate for hand computation. CM is an industrial application of GT concept. According to the literature, the chief advantages of CM are reduction in set-up time, reduction in throughput time, reduction in work-in-process inventories, reduction in material handling costs, better quality and production control, increment in flexibility, etc. (Wemmerlov and Hyer 1989; Heragu 1994). One of the major issues encountered in the implementation of a CM system is the cell formation problem (CFP). In the design of cells, similar parts are grouped into part families and dissimilar machines into machine groups (also known as manufacturing cells) so that one or more part families can be processed within a single machine group. CFP in a given 0–1 machine–part incidence matrix involves a rearrangement of rows and columns of the matrix to create part families and machine cells (Paydar and Saidi-Mehrabad 2013).

Because of increasing variety of customer goods and decreasing product life cycles, manufacturers often face fluctuations in product demand and product mix leading to a dynamic production environment (Rheault, Drolet, and Abdulnour 1995). In most research papers, however, CFP has been considered under static conditions in which cells are formed for a single time period with known and constant product mix and demand. In contrast, for a more realistic dynamic situation, a multi-period planning horizon in which the product mix and demand in each period is different is addressed in this paper. As a result, a cell configuration in one period may not be optimal in another period. To overcome this problem, several researchers recently proposed models and solution procedures by considering dynamic cell reconfigurations over multiple time periods (e.g. Defersha and Chen 2006; Safaei, Saidi-Mehrabad, and Jabal-Ameli 2008; Aramoon Bajestani et al. 2009; Safaei and Tavakkoli-Moghaddam 2009; Deljoo et al. 2010, Ghotbodini, Rabbani, and Rahimian 2011; Kia et al. 2012). These studies assume that the production quantity is equal to demand in each planning period. In actuality, production quantity may not be equal to the demand as it may be satisfied through inventory or by outsourcing. Therefore, production
quantity should be determined through production planning decisions based on which the number and type of machines to be installed in the manufacturing system are determined. Few papers (e.g., Defersha and Chen 2008; Akhkoon, Bulgak, and Bektaş 2009; Mahdavi et al. 2010; Rafiee et al. 2011) have addressed the aforementioned condition in CFP.

The relocation of the machines for dynamic production requirements has some disadvantages. The reconfiguration of cells is associated with reconfiguration cost. Reconfiguration ceases the production, thus there will be loss of profit and customer dissatisfaction, which in turn may cause severe problems for any company. In the aforementioned papers, the cost of moving the machines as a consequence of cells reconfiguration is considered. But, in their design methodology the time for reconfiguration is taken as zero meaning that in no time, relocation has to be done; however, this is not possible in reality (Pillai and Subbarao 2008). On the other hand, relocation of machines in a physical proximity may not be possible or economic. To surmount this obstacle, virtual cellular manufacturing (VCM) is proposed.

In a VCM system, machines and parts are temporarily grouped for one period during which machines of a cell dedicatedly serve the parts assigned to that cell. The only difference of VCM with a real CM is that machines are not necessarily brought to a physical proximity in VCM. The virtual cells are formed periodically depending on changes in demand volumes and mix as new part families and machine groups during a planning horizon. In a particular time period, when a part needs an operation, it is routed to the machines dedicated to the corresponding part family. Machines in the virtual cell are set up for that part family. If the demand pattern changes from one period to another, the machines in any virtual cell may be reassigned to another part family. Since no machine relocation is needed, there will be no rearrangement cost and time. This means that the output of VCM is the dynamic assignment of machines to cells and period-by-period assignment of parts to part families over the planning horizon. Actually, VCM provides a dynamic environment by forming dynamic configuration without actual relocation. This is the most important advantage of VCM (Balakrishnan and Cheng 2007).

Montreuil, Drolet, and Lefrançois (1992) presented the idea of separating the logical system from the physical system. Vakharia, Moily, and Huang (1999) compared the performance of virtual cells and multi-stage flow shops through analytical approximations. Sarker and Li (2001) addressed an approach for VCM with special emphasis on job routing and scheduling rather than on cell sharing. Slomp, Chowdary, and Suresh (2005) proposed a framework for the design of VCMS, specifically accounting for the limited availability of workers and worker skills. They propose a goal programming (GP) formulation that first groups jobs and machines and then assigns workers to the groups to form VCMS. The objective is to use the capacity as efficiently as possible and also to have VCMS as independent as possible. Nomden, Slomp, and Suresh (2006) surveyed the existing researches in the area of VCMS. They presented several definitions of virtual cells offered by various researchers and addressed the potential issues for future researches. Mak, Peng, and Lau (2007) presented a methodology to solve the manufacturing cell formation and the production scheduling problems for designing virtual cellular manufacturing systems (VCMS). This methodology involves (1) a mathematical model, describing the characteristics of a VCMS, with the objective of minimising the total materials/components travelling distance considering constraints such as delivery due dates of products, maximum capacities of resources, critical tools limitation, and (2) an ant colony optimisation algorithm for manufacturing cell formation and production scheduling. Kesen et al. (2009) examined the behaviours of VCMS, process layout and cellular layout. They addressed the VCMS by using family-based scheduling rules. They compared these systems through simulation and developed an ant colony optimisation-based meta-model to reflect the systems’ behaviour. Liang, Fung, and Jiang (2011) reviewed manufacturing resource modelling approaches with a focus on resource element approach. They introduced a function-clustering-degree concept, representing the trade-off between the quantity and granularity of virtual cells, to evaluate the reconfiguration performance of manufacturing systems for supporting virtual cell formation. Mahdavi et al. (2011) presented a fuzzy GP-based approach for solving a multi-objective mathematical model of CFP and production planning in a dynamic VCMS. The aim of their study was to minimise holding and backorder costs and exceptional elements in a cubic space of machine–part–worker incidence matrix.

In traditional manufacturing systems, first the supply chain is designed, the number of production facilities is determined and the facilities are assigned to support each market for each goods. Then, the organisation of the processes (product line, process or cell formation) within factory is decided. Rao and Mohanty (2003) introduced the requirement for the integration of CM and supply chain design. Simultaneous consideration of supply chain decisions and CM concepts help in getting lower distribution and procurement costs and faster response to customers. Therefore, the integrated approach to CM design with supply chain design takes trade-off and yields quick response, lower production costs and lower distribution costs to companies (Schaller 2008). A supply chain network is supposed to be in use for a long period of time during which many parameters may change. Naturally, strategic decisions have long-lasting effects. Nevertheless, it may be important to consider the possibility of making
future adjustments in the network configuration to allow gradual changes in the supply chain structure and/or in the capacities of the facilities. In this case, the planning horizon is divided into several time periods and strategic decisions are made for each period (Melo, Nickel, and Saldanha-da-Gama 2009).

Schaller (2008) presented a mathematical model used to integrate the design of CM systems with the design of a production network. The objective of his model was to minimise the total production and supply-chain costs by selecting production locations and forming cells in the selected locations. He proposed a tabu search procedure to generate solutions to the model. Saxena and Jain (2012) proposed an integrated model of dynamic CM and supply chain design considering multi-plant locations, multiple markets, multi-time periods, and reconfiguration. The aim of objective was to minimise the sum of costs such as transportation cost, holding and outsourcing cost and machine costs for the entire planning time horizon. Hybrid artificial immune system algorithm was applied for solving the model. Paydar, Saidi-Mehrabad, and Teimoury (2013) proposed a mixed integer linear programming model for integrating procurement and production planning in supply chain and design of cell formation considering the imprecise nature of some critical parameters such as customer demands and machine capacities. They utilised a robust optimisation model to solve their proposed model whose aim is to minimise the total costs including intercellular and intracellular material handling cost, investment cost of machine, inventory cost and procurement cost.

Most cell formation and supply chain models assume that the input parameters are deterministic and certain. However, in practice, many parameters such as parts demands and processing times and machine capacities are uncertain and imprecise. Ho (1989) categorised the uncertainty affecting the real-world manufacturing systems into two groups: (1) environmental uncertainty (Pan and Nagi 2010) and (2) system uncertainty (Sakiani, FatemiGhomi, and Zandieh 2012). In the context of our problem, environmental uncertainty includes the uncertainties in demand and the capacity of suppliers for providing raw materials. The uncertainties in actual available time of machines in each period lead to system uncertainty.

Three main reasons exist for considering uncertainty: (1) substantial time gap between design and implementation; (2) high cost of acquiring those figures with precision; and (3) lack of statistical observations at the design stage. Since sufficient data are not always available for predicting uncertain parameters, fuzzy approach is presented as a strong tool for expressing this uncertainty through the expert’s knowledge. Customer demands, machine capacities and suppliers capacities are the critical parameters which are imprecise (fuzzy) in nature due to incompleteness and/or unavailability of required data over the mid-term decision horizon. Hence, we have to estimate the problem parameters subjectively based on current insufficient data.

In this study, a bi-objective possibilistic optimisation model for simultaneous supply chain design and virtual cell formation considering multi-period production planning under uncertain demands and capacities is proposed. The remainder of this paper is organised as follows. In Section 2, the assumptions and notations are provided and a new bi-objective possibilistic mixed integer linear programming for the proposed problem is presented. To solve the model, a two-phase approach is proposed in Section 3. The proposed model solution method is validated by means of an industrial case study in Section 4. Conclusions and further research directions are the matter of Section 5.

2. Problem description

2.1. Problem definition

The integration of virtual cell formation and supply chain design in this paper is shown in Figure 1. In this study, a novel model considering multiple suppliers, one manufacturer and multiple customers with the aim of integrating the procurement, production and distribution planning decisions considering two conflicting objectives simultaneously is proposed. In addition, the imprecise nature of

![Figure 1. The integration structure of virtual cell formation and supply chain design.](image-url)
some critical parameters, e.g. customer demands, capacity of suppliers for providing raw material and available time of machines in each period is taken into account. As it can be seen in Figure 1, the considered network in this study has a general structure which is able to support both virtual cell formation and supply chain decisions and hence can be applied to different kinds of industries.

A manufacturer may produce different part types using a common set of input raw materials which can be supplied from a pre-determined set of qualified suppliers. The part types are produced in the virtual cells in order to satisfy their associated customer dynamic demands and then delivered to customers based on a distribution plan. The aim of this research is to achieve the best planning decisions over a multi-period, in an integrated and coordinated manner, for the following issues:

1. Procurement planning: The quantity for each type of raw material purchased from each supplier in each period.
2. Production planning: The design of virtual cell formation and the production quantity for each part type in each period.
3. Distribution planning: The number of each part type to be delivered to each customer in each period.

The main assumptions and characteristics of the problem are as follows:

- The customers’ dynamic demands for part types are uncertain over a given planning horizon
- The production system of the manufacturer is dynamic virtual cell formation.
- The customers’ demands may not be postponed for future periods; i.e. no backorders are allowed.
- Each supplier may consider a minimum acceptable utilised capacity for each type of raw material in each period; i.e. each supplier only accepts orders for which the utilised capacity would be equal or greater than an economic pre-specified value. On the other hand, each supplier has a maximum capacity for each type of raw material in each period.

2.2. Problem formulation

2.2.1. Notations

The indices, parameters and decision variables used to formulate the proposed model are presented below.

Indices

- \( r \) raw material type index; \( r = 1,2,\ldots, R \)
- \( i \) part index; \( i = 1, 2,\ldots, P \)
- \( m \) machine index; \( m = 1,2,\ldots, M \)
- \( k \) virtual cell index; \( k = 1, 2,\ldots, K \)
- \( c \) costumer index; \( c = 1,2,\ldots, C \)
- \( j \) supplier index; \( j = 1,2,\ldots, J \)
- \( t \) period index; \( t = 1,2,\ldots, T \)

Parameters

- \( HP_{it} \) Unit inventory holding cost for part \( i \) in period \( t \)
- \( HR_{rt} \) Unit inventory holding cost for raw material type \( r \) in period \( t \)
- \( CLS_{ict} \) Unit lost sale cost of part \( i \) for customer \( c \) in period \( t \)
- \( CB_{rjt} \) Cost of buying one unit of raw material type \( r \) from supplier \( j \) in period \( t \)
- \( CP_{at} \) Unit production cost of part \( i \) manufactured in period \( t \)
- \( D_{ict} \) Demand of customer \( c \) for part \( i \) in period \( t \)
- \( CTR_{rjt} \) The cost of transporting one unit of raw material type \( r \) in period \( t \) from supplier \( j \)
- \( CTP_{ict} \) The cost of transporting one unit of part \( i \) in period \( t \) to customer \( c \)
- \( MAC_{rj} \) Minimum acceptable capacity utilisation of supplier \( j \) for raw material type \( r \) in each period
- \( SP_{jr} \) 1 if supplier \( j \) can be provided the raw material type \( r \); 0 otherwise
- \( a_{im} \) 1 if part \( i \) should be processed on machine \( m \); 0 otherwise
- \( \lambda_{ri} \) Amount of raw material types \( r \) needed for producing one unit of part \( i \)
- \( T_{mt} \) Available time of machine \( m \) in period \( t \)
- \( MT_{im} \) Processing time of part \( i \) on machine \( m \)
- \( CRM_{r} \) The volume of one unit of raw material type \( r \)
- \( CRM \) Raw material storage capacity for storehouse factory
- \( NP \) Part type storage capacity at storehouse factory

Decision variables

- \( S_{ict} \) The amount of part \( i \) shipped to customer \( c \) in period \( t \)
- \( B_{rjt} \) The amount of raw material type \( r \) bought from supplier \( j \) in period \( t \)
- \( Z_{it} \) Number of part type \( i \) produced during period \( t \)
- \( L_{ict} \) The amount of lost sale for part \( i \) and customer \( c \) in period \( t \)
- \( IP_{it} \) Inventory of part \( i \) at the end of period \( t \)
- \( IR_{rt} \) Inventory of raw material type \( r \) at the end of period \( t \)
- \( RM_{rjt} \) 1 if raw material type \( r \) is bought from supplier \( j \) in the period \( t \); 0 otherwise
- \( X_{mk} \) 1 if machine \( m \) is assigned to virtual cell \( k \) in period \( t \); 0 otherwise
- \( Y_{ikt} \) 1 if part \( i \) is assigned for virtual cell \( k \) in period \( t \); 0 otherwise

It should be noted that symbols with a tilde indicate parameters which are subject to uncertainty. These
parameters are estimated by appropriate possibility distributions. In terms of above notations, the concerned objective functions and constraints can be described as follows.

2.2.2. Objective functions

Two important objectives in the proposed problem are considered: the total costs (\(TC\)) and the total value of grouping efficacy (\(TVGE\)).

The total costs are the most practical decision objective usually used in supply chain models. The total costs include the costs of procurement, production and delivery activities and could be calculated as follows:

\[
\text{Min } TC = \text{Procurement Cost} + \text{Holding Cost} + \text{Production Cost} + \text{Delivery Cost} \tag{1-1}
\]

\[
\text{Procurement Cost} = \sum_t \sum_r \sum_j (CB_{rjt}B_{rjt} + CTR_{rjt}B_{rjt}) + \tag{1-2}
\]

\[
\text{Holding Cost} = \sum_t \sum_i \left( \sum_j (HP_jIP_{it}) + \sum_r (HR_rIR_t) \right) + \tag{1-3}
\]

\[
\text{Production Cost} = \sum_t \sum_i \left( \sum_j (CP_{ijt}Z_{it}) \right) + \tag{1-4}
\]

\[
\text{Delivery Cost} = \sum_t \sum_i \sum_c (CTP_{icit}S_{ict} + CLS_{ict}L_{ict}) \tag{1-5}
\]

The main focus of supply chain is on the efficient material flow among suppliers, factory and customers so that the total cost in the supply chain is minimised. The first objective function integrates different functions (e.g. procurement, production and distribution) in the supply chain. The first term of Equation (1-1) computes the cost of buying for all raw material types from suppliers in the planning horizon. The second term of Equation (1-1) calculates the transportation cost of raw material types incurred by the manufacturer. The terms of Equation (1-2) consider the inventory holding cost of parts and raw materials, respectively. Equation (1-3) denotes the production cost of parts in the factory. The first term of Equation (1-4) represents the transportation of shipping the finished products to customers and the second term is the lost sale cost of parts in the system.

There are several measures of goodness for CFP machine–part groups in the literature. One of the frequently used measures is grouping efficacy and that is because they are simple to implement and generate block diagonal matrices which take advantage of grouping efficacy measure (Paydar and Saidi-Mehrabad 2013). Grouping efficacy was proposed by Kumar and Chandrasekharan (1990) and is calculated through

\[
\mu = \frac{e - e_0}{e + e_0}
\]

where \(e\) is the total number of 1s in the given machine–part incidence matrix, \(e_0\) is the number of voids and \(e_0\) is the number of exceptional elements.

\[
\text{Max } TVGE = \sum_{t} \sum_{j} Z_{it} \left( \sum_{m} a_{im} - \sum_{m} \sum_{m} a_{im} (1 - Y_{ikt}X_{ikt}) \right) \tag{2}
\]

The above equation is the second objective function used to maximise the grouping efficacy of produced parts in virtual cells in the planning horizon.

2.2.3. Constraints

\[
IR_{r(t-1)} + \sum_j B_{rjt} - \sum_i \lambda_{rt}Z_{it} = IR_{rt} \quad \forall r, t \tag{3}
\]

\[
IP_{it(t-1)} + Z_{it} - \sum_c S_{ict} = IP_{it} \quad \forall i, t \tag{4}
\]

\[
S_{ict} + L_{ict} = D_{ict} \quad \forall i, c, t \tag{5}
\]

\[
B_{rjt} \leq CAP_{rij} \times SP_{jr} \times RM_{rjt} \quad \forall r, j, t \tag{6}
\]

\[
B_{rjt} \geq MAC_{rij} \times SP_{jr} \times RM_{rjt} \quad \forall r, j, t \tag{7}
\]

\[
\sum_i MT_{im} \times Z_{it} \leq T_{it} \quad \forall m, t \tag{8}
\]

\[
\sum_r VRM_r \times IR_{rt} \leq CRM \quad \forall t \tag{9}
\]

\[
\sum_i IP_{it} \leq NP \quad \forall t \tag{10}
\]

\[
\sum_k X_{mk_t} = 1 \quad \forall m, t \tag{11}
\]

\[
\sum_k Y_{ikt} = \min(1, Z_{it}) \quad \forall i, t \tag{12}
\]

\[
Y_{ikt}, X_{mk_t}, RM_{rjt}, B_{rjt}, L_{ict} \in \{0, 1\} \quad \forall r, i, m, k, j, t \tag{13}
\]

\[
Z_{it}, IP_{it}, IR_{rt}, S_{ict}, B_{rjt}, L_{ict} \geq 0 \text{ and integer } \forall r, i, c, j, t \tag{14}
\]

Equations (3) and (4) are relevant inventory balancing constraints for the raw material types and parts at the manufacturer’s warehouses, respectively. The term \(\sum_j \lambda_{rt}Z_{it}\) represents the sum of required raw material type \(r\) needed for production of part type \(i\) in period \(t\) according to the bill of material. The term \(\sum_j B_{rjt}\) indicates the amount of purchasing raw material type \(r\) from all suppliers in period \(t\). The term \(\sum_c S_{ict}\) is the amount of part \(i\) sold to all customers in each period.
Equation (5) calculates the amount of lost sales for part $i$ and customer $c$ in each period. Inequality (6) limits the maximum capacity of each supplier for each raw material type. Constraint (7) guarantees that the manufacturer takes into accounts the suppliers’ minimum acceptable utilised capacity requirements for each raw material type. Constraint (8) guarantees that the capacity limitation of each machine in each period is considered. Constraints (9) and (10) limit the raw material and part types inventory levels to the related inventory storage capacities. Equation (11) guarantees that each machine must be assigned to only one virtual cell in each period. Constraint (12) ensures that each part type is either assigned to only one virtual cell or is not assigned to any virtual cell in period $t$. Relations (13) and (14) denote the type of decision variables.

### 2.2.4. Linearisation

Obviously, the second objective of proposed model is non-linear because of the multiplication and division of variables. Here, an attempt is made to linearise the numerator and denominator of objective function by introducing auxiliary variables and adding some additional constraints. Let us define the following new variable:

$$F_{imkt} = Y_{ik} \times X_{mkt}$$

Adding the following constraints to the original mathematical model linearises the multiplication terms:

$$F_{imkt} - Y_{ik} - X_{mkt} + \Delta \geq 0 \quad \forall i, m, k, t \quad (15)$$

$$\Delta \times F_{imkt} - Y_{ik} - X_{mkt} \leq 0 \quad \forall i, m, k, t \quad (16)$$

$$F_{imkt} \in \{0, 1\} \quad \forall i, m, k, t \quad (17)$$

where $\Delta$ is a constant, $\Delta \in \mathbb{R}$ and $1 < \Delta < 2$.

Proof 1. The decision variable $F_{imkt}$ may have different values depending on the values of $Y_{ik}$ and $X_{mkt}$ assuming $\Delta = 1.5$:

(i) If $Y_{ik} = 0$ and $X_{mkt} = 0$ then $F_{imkt} = 0$

(ii) If $Y_{ik} = 0$ and $X_{mkt} = 1$ then $F_{imkt} = 0$

(iii) If $Y_{ik} = 1$ and $X_{mkt} = 0$ then $F_{imkt} = 0$

So that

$$F_{imkt} - 0 - 0 + 1.5 \geq 0 \Rightarrow F_{imkt} + 1.5 \geq 0$$

$$1.5 \times F_{imkt} - 0 - 0 \leq 0 \Rightarrow 1.5 \times F_{imkt} \leq 0$$

Since, $F_{imkt}$ is a binary variable, it certainly takes zero.

(iv) If $Y_{ik} = 1$ and $X_{mkt} = 1$ then $F_{imkt} = 1$

So that

$$F_{imkt} - 1 - 1 + 1.5 \geq 0 \Rightarrow F_{imkt} \geq 0.5$$

$$1.5 \times F_{imkt} - 1 - 1 \leq 0 \Rightarrow 1.5 \times F_{imkt} \leq 2$$

Since, $F_{imkt}$ is a binary variable, it certainly takes one.

In the next step, non-negative variable $L_{imkt} = Z_{it} \times F_{imkt}$ is introduced and the following constraints are added to the original model:

$$L_{imkt} \geq Z_{it} - A \times (1 - F_{imkt}) \quad \forall i, m, k, t \quad (18)$$

$$L_{imkt} \leq Z_{it} + A \times (1 - F_{imkt}) \quad \forall i, m, k, t \quad (19)$$

$$L_{imkt} \leq A \times F_{imkt} \quad \forall i, m, k, t \quad (20)$$

$$L_{imkt} \geq 0 \text{ and integer } \forall i, m, k, t \quad (21)$$

in which $A$ is a large positive number.

Proof 2. For decision variable $L_{imkt}$ two situations are imaginable:

(i) If $F_{imkt} = 0$ then $L_{imkt} = 0$. So that

$$L_{imkt} \geq Z_{it} - A$$

$$L_{imkt} \leq Z_{it} + A$$

$$L_{imkt} \leq A \times 0$$

Since, $A$ is a large positive number, the value of $Z_{it}$ has no effect and therefore,

$$L_{imkt} \geq -A$$

$$L_{imkt} \leq A$$

$$L_{imkt} \leq 0$$

Since, $A$ is a positive integer variable, it certainly takes zero.

(ii) If $F_{imkt} = 1$ then $L_{imkt} = Z_{it}$. So that

$$L_{imkt} \geq Z_{it}$$

$$L_{imkt} \leq Z_{it}$$

$$L_{imkt} \leq A$$

In this situation, $L_{imkt} = Z_{it}$.
Now, the linear fractional form of the second objective function is as follows:

$$\text{Max TVGE} = \sum_i \sum_t \left( \frac{Z_{it} \sum_m a_{im} - \sum_k \sum_m a_{im} \times (Z_{it} - L_{inki})}{\sum_m a_{im} + \sum_k \left( \sum_m F_{inki} - \sum_m F_{inkt} \times a_{im} \right)} \right)$$

(22)

Moreover, the term of $\min(1, Z_{it})$ in constraint (12) is nonlinear and can be replaced with the following linear constraints:

$$\sum_k Y_{ikt} \leq 1 \quad \forall i, t \quad (23)$$

$$Z_{it} \leq A \times \sum_k Y_{ikt} \quad \forall i, t \quad (24)$$

$$Z_{it} \geq \sum_k Y_{ikt} \quad \forall i, t \quad (25)$$

Constraint (12) may have two conditions:

(i) If $Z_{it} = 0$ then

$$\sum_k Y_{ikt} = \min(1, 0) = 0$$

This means that, if in period $t$, part type $i$ is not produced ($Z_{it} = 0$) then, any machine type is not used for processing of part type $i$.

(ii) If $Z_{it} > 0$ (suppose that $Z_{it} = 50$), then

$$\sum_k Y_{ikt} = \min(1, 50) = 1$$

This means that, part type $i$ in period $t$ should be processed on required machine types.

Proof 3. Constraints (23) to (25) are to ensure the control of Equation (12). For these linear constraints two conditions could be arisen:

(i) If $Z_{it} = 0$ then

$$\sum_k Y_{ikt} \leq 1$$

$$0 \leq A \times \sum_k Y_{ikt}$$

Since, $Y_{ikt}$ is a binary variable, we have $\sum_k Y_{ikt} = 0$.

(ii) If $Z_{it} > 0$ (suppose that $Z_{it} = 50$) then

$$\sum_k Y_{ikt} \leq 1$$

$$50 \leq A \times \sum_k Y_{ikt}$$

$$50 \geq \sum_k Y_{ikt}$$

Since, $Y_{ikt}$ is a binary variable, $\sum_k Y_{ikt} = 1$.

3. Solution procedure

Uncertainty can be categorised as (1) flexible programming, (2) uncertainty in input parameters (Inuguchi and Ramik 2000; Dubois, Fargier, and Fortemps 2003). Flexibility is related to flexible target values of objective functions and constraints; and flexible mathematical programming models are used to cope with flexible target values. In flexible programming methods, the membership functions of fuzzy goals and constraints are commonly preference-based and determined by the decision-maker (DM; Mula, Poler, and Garcia 2006; Kumar, Vrat, and Shankar 2006). The uncertainty in input parameters, in turn, can be categorised into two classes (Pishvaee and Razmi 2012): (1) randomness, that comes from the random nature of data and generally stochastic programming methods are applied to handle this category of uncertainty; (2) epistemic uncertainty with ambiguous coefficients in goals and constraints is generally handled by possibilistic programming methods (Pishvae and Torabi 2010; Kabak and Ülengin 2011). Possibilistic programming approach is utilised to deal with the uncertain data in the proposed model because of parameters in the right-hand sides in some constraints are ambiguous in nature.

To solve this model, a two-phase approach is applied. In the first phase, the proposed model is converted into an equivalent auxiliary crisp model. In the second phase, a revised multi-choice goal programming method (RMCGP) is applied for finding a preferred compromise solution. It is noticeable that few studies have applied this method for the industry problems (Liao and Kao 2010; Paksoy and Chang 2010; Da Silva, Silva Marins, and Barra Montevechi 2013).

3.1. Phase 1: An auxiliary crisp model

Several methods have been developed for obtaining compromise solutions to deal with possibilistic programming
models (Tanaka and Asai 1984; Luhandjula 1989; Lai and Hwang 1992; Jimenez et al. 2007). The method proposed by Lai and Hwang (1992) is utilised to transform the proposed model into an auxiliary crisp model. The weighted average method (Lai and Hwang 1992) is applied for the defuzzification of the four fuzzy parameters in the right-hand sides of constrains (5)–(8).

The pattern of triangular fuzzy number is considered to denote each fuzzy parameter. The triangular possibility distribution is the most common tool for modelling the imprecise nature of the ambiguous parameters due to its computational efficiency and simplicity in data acquisition (Torabi and Hassini 2008). Generally, a possibility distribution can be stated as the degree of occurrence of an event with imprecise data. Figure 2 shows the triangular possibility distribution of fuzzy number $A = (A^p, A^m, A^o)$, where $A^p$, $A^m$ and $A^o$ are the most pessimistic value, the most possible value and the most optimistic value of $A$ estimated by a DM, respectively.

The equivalent auxiliary crisp constraints can be represented as follows:

$$S_{ict} - L_{ict} = \left( w_1 D^p_{ict} + w_2 D^m_{ict} + w_3 D^o_{ict} \right) \forall i, c, t \tag{26}$$

$$B_{frt} \leq \left( w_1 CAP^p_{frt} + w_2 CAP^m_{frt} + w_3 CAP^o_{frt} \right) \times W_{frt} \forall r, j, t \tag{27}$$

$$B_{frt} \geq \left( w_1 MAC^p_{frt} + w_2 MAC^m_{frt} + w_3 MAC^o_{frt} \right) \times W_{frt} \forall r, j, t \tag{28}$$

$$\sum_{i} MT_{im} \times Z_{it} \leq \left( w_1 T^p_{im} + w_2 T^m_{im} + w_3 T^o_{im} \right) \forall m, t \tag{29}$$

where $\beta$ is the minimum acceptable possibility and is generally determined by the DM. Moreover, $w_1 + w_2 + w_3 = 1$, and $w_1$, $w_2$ and $w_3$ denote the weights of the most pessimistic, the most possible and the most optimistic value of the fuzzy parameters, respectively. The appropriate values for these weights as well as $\beta$ are usually determined by the DM. However, based on the concept of the most likely values proposed by Lai and Hwang (1992) and considering several relevant papers (Liang 2006; Torabi and Hassini 2008; Noori-Darvish, Mahdavi, and Mahdavi-Amiri 2012), these parameters can be sets as: $\beta = 0.5$, $w_2 = 4/6$, $w_1 = w_3 = 1/6$.

Thus, we would have an auxiliary crisp bi-objective mixed integer programming model as follows:

$$\begin{align*}
\text{Min TC} \\
\text{Max TVGE} \\
\text{s.t.}
\end{align*} \tag{30}$$

(3), (4), (9)–(11), (13), (14), (15)–(21), (23)–(29).

### 3.2. Phase 2: RMCGP

Most of the real-world problems are formulated into a single-objective linear programming model. Researchers and practitioners are more and more aware of the presence of multiple criteria in real-life problems of management and decisions (Tamiz, Jones, and Romero 1998). The GP, introduced by Charnes and Cooper (1961), is a technique for solving decision-making problems with multiple objectives by achieving a set of compromising solutions. GP minimises the deviations between aspiration levels provided by DM for each goal and their achievements. Tamiz, Jones, and Romero (1998) and Aouni, Mertel, and Hassaine (2009) reviewed the developments in GP. With fast growth in computational facilities, both linear and non-linear GP can be solved using well-developed software, such as LINGO software or meta-heuristics (e.g. simulated annealing, genetic algorithms and so on) (Jones, Mirrazavi, and Tamiz 2002). GP is more direct and flexible in manipulating different scenarios by adjusting either target values or weights.

The main idea in GP is to introduce extra auxiliary variables, called deviations, which act not as ‘decision-makers’ but as ‘facilitators’ to formulate the model. These deviations represent the distance between aspiration levels of goals (target values) and the realised results. Two kinds of deviations are considered, under-achievement of the goal, represented by negative deviation ($d^-$), and over-achievement of the goal, represented by positive deviation ($d^+$). Each goal is expressed as a linear equation with deviation(s). As opposed to linear programming, which directly optimises objectives, GP attempts to minimise the unwanted deviations between aspiration level of a goal and the optimal solution. GP model consists of two sets of constraints: system constraints and goal constraints. System constraints are formulated following the LP concepts, while goal constraints are auxiliary constraints, which determine the best possible solution with respect to a set of desired goals. A simple model of GP can be expressed as follows:
Min \( \sum_{i=1}^{n} W_i(d_i^+ + d_i^-) \)

s.t.

\[
h_k(X) = (\leq \text{ or } \geq) 0 \quad k = 1, 2, \ldots, q
\]

\[
f_i(X) - d_i^+ + d_i^- = b_i \quad i = 1, 2, \ldots, n
\]

\[
d_i^+, d_i^- \geq 0 \quad i = 1, 2, \ldots, n
\]

where \( h_k(X) \) represent system constraint \( k \), \( f_i(X) \) is goal constraint \( i \), \( b_i \) is the aspiration level of goal \( i \), \( d_i^+ \) and \( d_i^- \) are positive and negative deviations from the target value of goal \( i \), respectively.

\[
d_i^- = \begin{cases} b_i - f_i(X) & \text{if } f_i(X) < b_i \\ 0 & \text{otherwise} \end{cases}
\]

\[
d_i^+ = \begin{cases} f_i(X) - b_i & \text{if } f_i(X) > b_i \\ 0 & \text{otherwise} \end{cases}
\]

Standard GP approaches emphasise on finding a solution near the aspiration level for each objective and penalise the deviation away from the aspiration level. Nevertheless, in practice, the DMs usually specify a conservative initial aspiration level, based on the available information and resource limitations; however, they may actually prefer higher (or lower) aspiration levels. In order to solve this problem, Chang (2007) proposed a new method for multi-choice goal programming (MCGP) for multi-objective decision problems with multiple aspiration levels. The MCGP allows the DM to set multi-choice aspiration levels for each goal to avoid underestimation of the decision. The MCGP problem is formulated as follows:

Min \( \sum_{i=1}^{n} W_i[f_i(X) - g_{i1} \text{ or } g_{i2} \text{ or } \ldots \text{ or } g_{im}] \)

s.t.

\[
h_k(X) = (\leq \text{ or } \geq) 0 \quad k = 1, 2, \ldots, q
\]

where \( g_j(i = 1, 2, \ldots, n \text{ and } j = 1, 2, \ldots, m) \) is the \( j \)th aspiration level of the \( i \)th goal, \( g_{j+1} \leq g_j \leq g_{j-1} \)

The achievement function of the MCGP can be represented as follows:

Min \( \sum_{i=1}^{n} W_i(d_i^+ + d_i^-) \)

s.t.

\[
h_k(X) = (\leq \text{ or } \geq) 0 \quad k = 1, 2, \ldots, q
\]

\[
f_i(X) - d_i^+ + d_i^- = g_i \quad i = 1, 2, \ldots, n
\]

\[
d_i^+, d_i^- \geq 0 \quad i = 1, 2, \ldots, n
\]

where \( S_p(B) \) represents a function of binary serial numbers.

Chang (2008) has introduced the revised MCGP (RMCGP) approach in order to solve the problem of multiplicative terms of binary variables used in the MCGP-achievement function. The MCGP-achievement function can then be reformulated as the following two alternative MCGP-achievement functions.

The first case: ‘the more the better’ is formulated as

Min \( \sum_{i=1}^{n} [W_i(d_i^+ + d_i^-) + \alpha_i(e_i^+ + e_i^-)] \)

s.t.

\[
h_k(X) = (\leq \text{ or } \geq) 0 \quad k = 1, 2, \ldots, q
\]

\[
f_i(X) - d_i^+ + d_i^- = y_i \quad i = 1, 2, \ldots, n
\]

\[
y_i - e_i^+ + e_i^- = g_i \text{ max} \quad i = 1, 2, \ldots, n
\]

\[
y_i - e_i^+ + e_i^- \geq 0 \quad i = 1, 2, \ldots, n
\]

The second case: ‘the less the better’ is formulated as

Min \( \sum_{i=1}^{n} [W_i(d_i^+ + d_i^-) + \alpha_i(e_i^+ + e_i^-)] \)

s.t.

\[
h_k(X) = (\leq \text{ or } \geq) 0 \quad k = 1, 2, \ldots, q
\]

\[
f_i(X) - d_i^+ + d_i^- = y_i \quad i = 1, 2, \ldots, n
\]

\[
y_i - e_i^+ + e_i^- = g_i \text{ min} \quad i = 1, 2, \ldots, n
\]
\[\begin{align*}
g_{i, \min} \leq y_i \leq g_{i, \max} & \quad i = 1, 2, \ldots, n \\
d_i^+, d_i^-, e_i^+, e_i^- & \geq 0 \quad i = 1, 2, \ldots, n
\end{align*}\]

where \(g_{i, \max}\) is the upper bound of the \(i\)th aspiration level, \(g_{i, \min}\) is the lower bound of the \(i\)th aspiration level, \(y_i\) is the continuous variable with a range of \(g_{i, \min} \leq y_i \leq g_{i, \max}\), \(d_i^+\) and \(d_i^-\) are positive and negative deviations from \(|f_i(X) - y_i|\) and \(w_i\) is the weight of the \(i\)th goal. For the first case: \(e_i^+\) and \(e_i^-\) are positive and negative deviations from \(|y_i - g_{i, \max}|\) and \(\alpha_i\) is the weight of the sum of deviations of \(|y_i - g_{i, \max}|\). For the second case: \(e_i^+\) and \(e_i^-\) are positive and negative deviations from \(|y_i - g_{i, \min}|\) and \(\alpha_i\) is the weight of the sum of deviations of \(|y_i - g_{i, \min}|\).

4. Case study

The concept of physically dividing the factory into cells is certainly appealing to large manufacturing units from the viewpoint of enhancing their agility. But in the case of small and medium enterprises (SMEs), it may not always be possible to do this physical separation for a variety of reasons (Babu, Nandurkar, and Thomas 2000). However, in SMEs, application of GT/CM may obtain considerable advantages. However, physical separation of the operations into cells can be constrained by practical, technical and organisational limitations. In such situation, these industries may be required to have the advantages that CM affords by a variety of means, but without actually breaking down the factory into cells. To this end, formation of virtual cells could be helpful. To illustrate the practicality and validity of the proposed model, a real industrial case study is presented. First, the case study and data collection procedure is described in what follows and then, it is used to justify the performance of the proposed model.

4.1. Outline of the case study

Case study is conducted for a typical equipment manufacturer in the northern Iran. Hadi Company (HC) was founded in 1982. The company is a type of SME that produces different types of farm equipment. Along with an increment in production rate, the variety of other types of equipment is increased. Thus the factory’s area increased to 1500 m² with the production section in which 80 people including workers and specialist work seven days a week.

The company has contracts with four main suppliers to supply 12 raw material types. Eight part types (farm equipment) consisting of (1) sprinkler, (2) combine blades, (3) cultivator, (4) transplant tray, (5) chisel plough, (6) castration forceps, (7) milking cows and (8) dripper are produced in the company. The manufacturer shop and the nearby two warehouses (for raw materials and part types) constitutes the facility of the company. Six stations, i.e. (1) cutting, (2) bending, (3) welding, (4) machinery, (5) dyeing and (6) assembly are designed in the manufacturing shop. The company sales the part types via three sales agents located in the North, Centre and North West of Iran.

The initial parameters are gathered by considering the documents of sales, manufacturing and procurement departments. The uniform distribution of cost and demand parameters are set according to the dynamic nature of the environment situations and reported in Table 1. Moreover, symmetrical triangular possibility distribution for the fuzzy parameters is used. Therefore, the most possible value of each imprecise parameter is first generated based on a uniform distribution and then the corresponding most pessimistic and optimistic values are determined by multiplying the most possible value by 0.8 and 1.2, respectively (Selim and Ozkarahan 2008; Torabi and Hassini 2008). Each part type has a number of operations that should be processed with the identified processing times summarised in Table 2. Table 3 reports the bill of material in which the entry \((p, r)\) denotes the quantity of raw material type \(r\) required to produce one unit of part type \(p\). Also, the supplier information is explored and reported in Table 4.

The assembly station is required for production of all part types. Therefore, it is considered as one virtual cell in the factory. The HC is applied to the proposed model for the three periods and two virtual cells.

4.2. Results of the case study

The main results of the proposed model are presented below. The proposed model of the HC is implemented by LINGO 9 software package. Recalling the proposed two phase’s solution procedure, we are dealing with a bi-objective mixed integer linear programming model for the HC. According to the phase 1, the proposed model is converted into an equivalent auxiliary crisp model. In the second phase, a RMCGP method is applied for finding a
preferred compromise solution is found for the case study as follows:

\[
\text{Min } W_1(d_1^+ + d_1^-) + a_1(e_1^+ + e_1^-) + W_2(d_2^+ + d_2^-) + a_2(e_2^+ + e_2^-)
\]

\text{s.t. Equations: (3), (4), (9)–(11), (13), (14), (15)–(21), (23)–(29) and}

\[
TC - d_1^+ + d_1^- = y_1
\]

\[
y_1 - e_1^+ + e_1^- = g_1 \min
\]

\[
g_1 \min \leq y_1 \leq g_1 \max
\]

\[
TVGE - d_2^+ + d_2^- = y_2
\]

\[
y_2 - e_2^+ + e_2^- = g_2 \max
\]

\[
g_2 \min \leq y_2 \leq g_2 \max
\]

\[
d_1^+, d_1^-, d_2^+, d_2^-, e_1^+, e_1^-, e_2^+, e_2^- \geq 0
\]

where \(d_1^+\), positive deviation variable of goal \(TC\); \(d_1^-\), negative deviation variable of goal \(TC\); \(d_2^+\), positive deviation variable of goal \(TVGE\); \(d_2^-\), negative deviation variable of goal \(TVGE\); \(e_1^+\), positive deviations from \([y_1 - g_1 \min]\); \(e_1^-\), negative deviations from \([y_1 - g_1 \min]\); \(e_2^+\), positive deviations from \([y_1 - g_2 \max]\); \(e_2^-\), negative deviations from \([y_1 - g_2 \max]\).

In order to clarify that, to obtain, \(g_1 \max\) and \(g_1 \min\), four sub-problems, with individual objectives should be solved. More specifically,

\[
g_1 \min\text{ can be obtained by solving } \text{Min } TC
\]

\[
g_1 \max\text{ can be obtained by solving } \text{Max } TC
\]

\[
g_2 \min\text{ can be obtained by solving } \text{Min } TVGE
\]

\[
g_2 \max\text{ can be obtained by solving } \text{Max } TVGE
\]

The DM is provided by the solutions to these sub-problems. Consulting with experts, she/he makes decisions about these parameters. To implement the proposed approach, the DM specifies \(g_1 \max\) and \(g_1 \min\) for the objective functions as

The obtained solution is as follows:

\[
g_1 \min = 160000, g_1 \max = 175000, g_2 \min = 4700, g_2 \max = 5200
\]

\[
d_1^+ = 0, d_1^- = 0, e_1^+ = 8471.6, e_1^- = 0, TC = y_1 = 168471.6
\]

\[
d_2^+ = 0, d_2^- = 47.6, e_2^+ = 0, e_2^- = 500, TVGE = 4652.4, y_2 = 4700
\]

From the results, it can be realised that the first goal is fully satisfied because its corresponding positive deviations for the first goals are zero. However, the second goal has a negative deviation value \((d_2^-)\) from the aspiration level, 4700, and the solution violates the aspiration interval \(4700 \leq y_2 \leq 5200\) achieving 98.98 % of the goal.

The solution of the model determines the procurement, production and distribution plan and the virtual dynamic cells for three periods. Table 5 presents the production volumes and inventory levels for each part type in each period with fuzzy demands. It can be seen that, in the obtained production plan, there is some quantities of part types in the inventory at the end of periods which are kept for the next periods. Table 6 provides the procurement...
plan in which the amount of each raw material type provided by each supplier and the corresponding inventory level at the end of the planning horizon kept for the next period is determined.

The virtual cell configurations of this case study are presented in Figure 3 in which some of the characteristics and advantages of proposed model can be realised. As mentioned in the ‘Introduction’ section, the actual relocation does not occur. However, the machine assignment in the virtual cells can be changed. Specifically, in period 1, virtual cell 1 contains machinery and bending stations, virtual cell 2 contains cutting, welding and dyeing stations and virtual cell 3 includes assembly station.

In period 2, virtual cell 1 contains machinery, cutting, welding and bending stations, virtual cell 2 contains dyeing station, and virtual cell 3 includes assembly station. In the second period, configuration of virtual cells is changed so that the cutting and welding stations are moved from virtual cell 2 to cell 1, respectively. In period 3, the configuration is same as the first period. Part families, machine groups and exceptional elements are also depicted in Figure 4. For example, the exceptional element and number of voids for period 1 are 3 and 2, respectively, and the \( TVGE \) for this period is 1837.5. Considering the results, it can be seen that the proposed solution procedure can be easily applied to SMEs exploiting the profits of CM and supply chain, simultaneously.

<table>
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<th>( Z_{i2} )</th>
<th>( Z_{i3} )</th>
<th>( IP_{i1} )</th>
<th>( IP_{i2} )</th>
<th>( L_{i3} )</th>
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<td>0</td>
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In this study, a novel bi-objective possibilistic programming model is developed to formulate dynamic virtual cell formation problem and supply chain integrating procurement, production and distribution planning in a multi-echelon, multi-product and multi-period network. To solve the model, a two-phase procedure is developed in which in the first phase, the proposed model is converted into an equivalent auxiliary crisp model and in the second phase, a RMCGP method is applied for finding a preferred compromise solution. Finally, an industrial case study of HC was presented to illustrate the practicality and validity of the proposed model.

The proposed model provides suitable insights for DMs helping them in better comprehension of the variables and essential issues affecting the decisions. The proposed model provides a robust and feasible way for solving bi-objectives decision-making problems which involves either-or-choice/multi-choice of aspirations levels.

This study is still open for incorporating other features such as

- Partial or total subcontracting and workload balancing among the virtual cells.
- Operation sequence of part type for virtual cell formation problem.
- Worker assignments and worker trainings.

References


