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Research Article

A Bi-objective Non -Linear Approach for Determining Ordering Strategies for Group B in ABC Analysis

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Abstract

The main aim of this research is to find the best inventory review policy for different types of items in group B in ABC analysis through minimizing the total cost of the system and maximizing the service level. Moreover, this study has considered several operational constraints such as limitations on storage space, number of orders, and mean shortage. To solve this problem, first, an individual optimization method is utilized to obtain optimal solutions. Afterward, two classic and novel multi-objective optimization methods have been used to convert the bi-objective problem to a single-objective and then achieve near-optimal solutions for both objectives simultaneously. Finally, the proposed methods are compared in terms of objective function values and computational time to find the better method.

***Keywords*:** Bi-objective problem; Chance constraints; Ordering strategy; Statistical analysis

1. Introduction and Background

Inventory management is a critical issue on the effective performance of manufacturing firms and contains a large part of financial interactions (Keshavarz-Ghorbani and Pasandideh, 2021). Hence, applying an appropriate inventory review policy has a significant impact on the volume of selling, gaining profits, and enhancing system position in the current competitive world. Through analysis of inventory systems, it can be found that various products are not of the same importance. To distinguish the importance of different items, inventory control policies should be performed, by which products could fall under less or precise control policies. ABC analysis is a traditional method used to classify various inventory items on the basis of their values (Hajiagha et al., 2021). This method divides items into three groups with the most similar features (Abdolazimi et al., 2021). Wherein, items with a high price and low demand volume are referred to the group ‘A’; conversely, items with a low price and high demand volume are referred to the group ‘C’. Moreover, group ‘B’ items, which are notable in our investigation, are moderate in demand volume and sales price. The group ‘A’ items have drawn the attention of inventory control managers, due to high inventory holding and shortage costs. In these cases, managers often choose a continuous review policy to prevent products from being in overstock or stockout situations. On the contrary, the group ‘C’ items are negligible and need less control. The group ‘B’ items fall between the two other groups. Although they may require moderate attention, they are not as important as the group ‘A’ items. In this regard, Mohammaditabar et al. (2012) sought different types of classification methods like ABC analysis to find the best performing method that can significantly minimize inventory holding costs. They attempted to achieve better inventory control policies via minimizing the dissimilar items in each category. Soylu and Akyol (2014) used a multi-criteria ABC method to manage the inventory of the huge number of items based on the decision maker’s preference for each criterion. Yang et al. (2017) attempted to discover the link between inventory classification and its impact on system performance. According to their investigation in a real case study, a multi-criteria inventory classification method raises efficiency in an inventory system.

The current research seeks to determine appropriate inventory review policies for the group ‘B’ items, which has never been investigated. For this purpose, we have considered that the inventory level could be inspected continuously or periodically.

In a continuous review policy (r, Q), an order of size Q is placed when an inventory level drops r or below that. However, in a periodic review policy (R, T), the inventory level is inspected at fixed time intervals (T), and orders up to level R. The choice of inventory control policy remarkably affects the performance of systems. For instance, Rao (2003) proved that periodically reviewing an inventory system with a continuous demand rate incurs approximately 41.42% additional cost to the system. Johansen (2013) investigated an inventory system under the assumption of lost sale and a continuous review policy to suggest a modified based-stock policy. Massonnet et al. (2014) introduced a cost balancing technique for periodic review models and applied it in a continuous-time version, in which both demand and cost are time-based. They also proposed a modified algorithm for inventory lot-sizing problems that can notably raise worst-case bound.

Continuous review policy is more common for cases with uncertain demand and lead time. This policy provides

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accurate inventory quantity but couldn't work well for plenty of items. In this respect, the continuous review policy has been investigated for many single-product inventory problems (e.g., Axsäter, 2007; Lau and Lau, 2008; Mattsson, 2010; Qi, 2013). However, most of real inventory systems encounter with multi-product warehouses that have been reviewed under (*r, Q*) policy (e.g., Ghalebsaz-Jeddi et al., 2004; Betts and Johnston, 2005; Berk and Gürler, 2008; Pasandideh et al., 2011; Hajiaghaei-Keshteli et al., 2011; Zhao et al., 2012; Kundu and Chakrabarti, 2012; Poormoaied and Atan, 2020; M'Hallah et al., 2020).

In classical practices, continuous review policies have been commonly used for multi-item single-period non-perishable problems. Saracoglu et al. (2014) formulated a multi-period continuous review model considering some constraints such as limited budget and warehouse space. Genetic algorithm has been performed to solve the problem and achieve near-optimal solutions in large-sized instances. Cobb et al. (2015) considered continuous review inventory systems with uncertain demand and lead time. In their research, a mixture of polynomial distribution and a mixture of truncated exponentials distribution have been proposed to enhance efficiency. Then, these methods were compared together. Priyan and Uthayakumar (2015) considered a continuous review policy with allowable shortages. They attempted to analyze system behavior under uncertainty in order quantities. Tamjidzad and Mirmohammadi (2015) proposed an optimal (*r, Q*) policy considering resource constraint and a quantity discount to make attraction in selling products. In their model, customers' demand could be satisfied by renting extra quantity in face of deficiency. Horng and Lin (2017) applied an assemble-to-order system under (*r, Q*) policy which is an Np-hard problem, therefore they utilized an ordinal optimization problem based on a metaheuristic algorithm to find near-optimal solutions. Fattahi et al. (2015) investigated a multi-product (*r, Q*) inventory system with the aim of minimizing the total cost of the system and maximizing the service level, simultaneously. In their investigation, there are limitations on warehouse space and budget, and unsatisfied demand is backlogged.

In recent studies, some authors have focused on the periodic review policy on various topics. For instance, Chand et al. (2016) investigated a periodic review policy for an inventory system in which unfulfilled demand is backordered. In their model, if an urgent condition occurs, delivery lead-time is zero. In the regular condition, lead-time should be less than the length of each period. Xu et al. (2017) considered a periodic review policy with finite horizon planning and stochastic demand. If stochastic demand exceeds up on-hand inventory, it is backlogged and met by future orders. Ahmadzadeh and Vahdani (2017) introduced a periodic review policy for a multi-level supply chain, in which shortages are allowed. They presented a location inventory model, thereby finding the appropriate number and location of warehouses. Besides, a metaheuristic algorithm is applied to solve the problem due to its complexity. Dillon et al. (2017) presented a multi-period multi-product lot-sizing problem, dealing with demand uncertainty and product perishability. In their model, blood inventory control is dependent on three distinct periodic review policies. The first policy is the current hospital policy. The second policy is to find the optimal amount of replenishment interval and maximum inventory position. The third policy has to determine the optimal amount of reorder points, considering daily replenishment. Tao et al. (2017) considered an inventory system with stochastic demand and backlogged shortage. In their study, the inventory level is reviewed regularly through a periodic review policy. Moreover, in emergency conditions, orders are with extra freight unit cost and shorter lead time. Taleizadeh et al. (2020) proposed a vendor-managed inventory contract in both (*r, Q*) and (*R, T*) systems. Their model investigates the effects of some parameters, such as ordering costs, inventory holding costs, and shortage costs, on inventory review policy selection. However, they have not proposed a mathematical model to simultaneously analyze inventory systems. Kong et al. (2020) proposed a periodic review policy to periodically control single-product non-stationary inventory systems over a finite horizon.

In many inventory systems, firms may face overstock or stockout situations due to uncertain customer demand. In the face of shortages, backordering helps the companies to manage their inventories and deliver orders later. Therefore, many researchers and practitioners offer backordering in inventory management problems (e.g., Niknamfar and Pasandideh, 2014; Poorbagheri and Akhavan, Niaki, 2015; Ahmadi et al., 2016; Fatehi Kivi et al., 2018). In this study, demand for each product is uncertain and follows a continuous uniform distribution, and shortages are backlogged. In addition, the gaps are identified by reviewing the related literature and shown in Table 1.

In this paper, we formulate a bi-objective multi-product inventory model as a mixed-binary non-linear programming (MBNLP) problem in order to determine optimal inventory review policies for group 'B' items, with the aim of minimizing total cost and maximizing service level under the assumptions of uncertain demand and stochastic constraints. Simultaneously optimization of the objective functions leads to a reduction in system cost and an increase in customers' satisfaction. To solve the MBNLP problem, first, three multi-objective decision making (MODM) methods are proposed, individual optimization method, LP-metric method, and multi-choice goal programming with utility function method. Afterward, numerical test problems are introduced to analyze the behavior of the model. We use general algebraic modeling system (GAMS) software to solve this problem. By using a one-way analysis of variance (ANOVA), we compare the results to select the best-performing method in terms of objective function values and required CPU-time.

The rest of this paper is organized as follows: in section 2, problem definition and notations are defined. In section 3, a bi-objective multi-product problem is formulated. In section 4, several MODM methods are provided to convert the bi-objective model to a single-objective. Then, the results of numerical examples are analyzed in section 5. Finally, the conclusion and future directions are given in section 6.

Table 1
Literature review

Authors	Inventory review policy	Variety of products	Horizon	Budget constraint	Storage constraint	Number of orders constraint	Demand	Shortage
Saracoglu et al., (2014)	*(r, Q)*	Multiple	Finite	*	*	-	D	L
Cobb et al., (2015)	*(r, Q)*	Single	Infinite	-	-	-	ND	-
Priyan and Uthayakumar, (2015)	*(r, Q)*	Single	Infinite	-	-	-	ND	B
Tamjidzad and Mirmohammadi, (2015)	*(r, Q)*	Single	Infinite	*	-	-	ND	B
rng and Lin, (2017)	*(r, Q)*	Multiple	Finite	-	*	-	ND	L
Fattahi et al., (2015)	*(r, Q)*	Multiple	Infinite	*	*	-	ND	B
Chand et al., (2016)	*(R,T)*	Single	Finite	-	-	-	ND	B
Xu et al., (2017)	*(R,T)*	Single	Finite	-	-	-	ND	B
Ahmadzadeh and Vahdani, (2017)	*(R,T)*	Single	Infinite	-	*	-	ND	B
Dillon et al., (2017)	*(R,T)*	Multiple	Finite	-	*	-	ND	L
Tao et al., (2017)	*(R,T)*	Single	Finite	-	-	-	ND	B
Current study	***(r, Q), (R,T)***	**Multiple**	**Infinite**	-	*	*	**ND**	**B**

ND: Nondeterministic; D: Deterministic 1; B: Backlogged; L: Lost-sale

2. Problem Definition and Assumptions

In this paper, we propose a multi-product inventory control problem with uncertainty in customers' demand. In this respect, unsatisfied demand is backlogged and fulfilled at the next interval. Besides, limitations on the storage space, number of orders, and mean shortage are considered to adapt to real situations.

In many studies, researchers have classified the inventory items to facilitate the process of inventory management. ABC analysis is a classification method based on differences in value and volume of products. Accordingly, high-value and low-volume items are categorized into group 'A', needing the continuous review policy. Conversely, low-value and high-volume items are categorized into group 'C', needing less control. The group 'B' items are moderate in both value and volume, and the issue of selecting the optimal review policy is ahead. This paper has investigated two commonly inventory review policies to model a MBNLP problem, (r, Q) and (R, T).

The goal is to select an appropriate inventory review policy for each product; consequently, determining the reorder point and order quantity in (r, Q) policy, or the maximum inventory position and optimal length of the period in (R, T) policy. This model aims to minimize the total cost, including the ordering cost, inventory holding cost, and shortage cost, and simultaneously maximize the cumulative distribution of demand.

Besides, some of the assumptions of the problem are presented as follows:

- Only one warehouse is available.
- Limitations on storage space and number of orders are chance constraints with normal distribution.
- Demand for each type of product is uncertain and follows a continuous uniform distribution.
- Shortages are backlogged.
- The planning horizon is infinite.

The notations throughout the paper are defined as follows:

Indices
i: index of products ($i = 1,2, \ldots, n$)
Parameters
D_i: demand rate of product i
SH: maximum allowable shortage for all products
m_i: mean demand of product i
π_i: shortage cost of product i
h_i: holding cost of product i
f_i: required storage space for product i
F: available storage space for all products
a_i: fixed ordering cost of product i

M: big number
N: maximum number of orders
Decision variables
y_i: binary variable; 1 if continuous review policy is selected for product i, otherwise, products should be controlled under the periodic review policy
Q_i: order quantity of product i
L_i: maximum inventory level of product i
T_i: time interval to review the inventory level of product i
r_i: reorder point of product i
Tc: total cost of inventory system
Sl: service level of inventory system
$F(r_i)$: cumulative distribution of demands for product i under the continuous review policy
$F(L_i)$: cumulative distribution of demands for product i under the periodic review policy
$\overline{b}(r_i)$: mean shortage of product i under the continuous review policy
$\overline{b}(L_i)$: mean shortage of product i under the periodic review policy

3. Model Description

This research aims to maximize customer satisfaction by supplying their demand as much as possible and minimize system costs simultaneously. To this aim, we proposed a multi-product MBNLP problem based on the notations and assumptions as follow:

$$Min\ Tc = \sum_i^n y_i \left\{A_i \frac{D_i}{Q_i} + h_i \left(\frac{Q_i}{2} + r_i - m_i\right) + \pi_i \frac{D_i}{Q_i} \overline{b}(r_i))\right\} + \sum_i^n (1 - y_i) \left\{\frac{A_i}{T_i} + h_i \frac{D_i T_i}{2} + h_i (L_i - m_i) + \frac{\pi_i}{T_i} \overline{b}(L_i)\right\} \tag{1}$$

$$Max\ Sl = \frac{\sum_i^n y_i F(r_i) + \sum_i^n (1 - y_i) F(L_i)}{n} \tag{2}$$

Subject to

$$p\left\{\sum_i^n \left(y_i \frac{D_i}{Q_i} + (1 - y_i)\frac{1}{T_i}\right) \le N\right\} \ge \beta \tag{3}$$

$$p\left\{\sum_i^n f_i \left(y_i \left(\frac{Q_i}{2} + r_i - m\right) + (1 - y_i)\left(\frac{D_i T_i}{2} + L_i - m\right)\right) \le F\right\} \ge \beta \tag{4}$$

$$\sum_i^n \left(y_i \frac{D_i}{Q_i} \overline{b}(r_i) + (1 - y_i)\frac{1}{T_i} \overline{b}(L_i)\right) \le SH \tag{5}$$

$$T_i \le M\ (1 - y_i)\ \forall i \tag{6}$$

$$L_i \le M\ \ (1 - y_i)\ \forall i \tag{7}$$

$$Q_i \le M\ y_i \quad \forall i \tag{8}$$

$$r_i \le M\ y_i \quad \forall i \tag{9}$$

$$Q_i, r_i, T_i, L_i \ge 0;\ y_i = 0\ or\ 1 \tag{10}$$

The first objective function (1) aims to minimize system cost consisting of holding cost, ordering cost, and shortage cost for all products. The first term is the average cost when products are under (r, Q) policy ($y_i = 1$), and the second term is the average cost when products are under (R, T) policy ($y_i = 0$). The second objective function (2) maximizes the cumulative distribution of demand.
Constraint (3) ensures the average number of orders, whether the inventory review policy is continuously or periodically, should be less than N. This constraint should be met with a probability of at least β. In this constraint, if y_i equals 1, the average number of orders is calculated based on the continuous review policy; otherwise, it is based on the periodic review policy. Constraint (4) represents a limitation on storage space which should not exceed the available storage space. This constraint should be met with a probability of at least β. In this constraint, the first term in the left hand refers to storage space of products under the continuous review policy, and the second term refers to the periodic review policy. Constraint (5) avoids the average number of shortages for all products exceeding a certain limit. Constraints (6) – (9) are developed for the MBNLP model and assert if the inventory level is reviewed continuously, the model determines the optimal order quantity and reorder point, otherwise, the inventory level is reviewed periodically, and the model determines the maximum inventory

position and interval time. Constraint (10) denotes the type of variables.
In order to make the model solvable, first, constraints (3)-(5) should be transformed into a deterministic problem. To this purpose, stochastic constrained programming has been applied as follows:

$$\sum_i^n \left(y_i \frac{D_i}{Q_i} + (1 - y_i)\frac{1}{T_i} \right) + \sigma_N Z_\beta \le \mu_N \tag{11}$$

$$\sum_i^n f_i \left(y_i \left(\frac{Q_i}{2} + r_i - m \right) + (1 - y_i)\left(\frac{D_i T_i}{2} + L_i - m \right) \right) + \sigma_F Z_\beta \le \mu_F \tag{12}$$

where μ_N is the mean allowable number of orders, σ_N is the standard deviation of the allowable number of orders, μ_F the mean storage capacity, and σ_F is the standard deviation of storage capacity. Z_β is the cumulative standard normal distribution ($\beta = 0.95$).

4. Solution Methods

In this paper, we presented a MBNLP problem with two conflicting objectives. In such models, an ideal solution cannot simultaneously optimize both objective functions. Hence, we propose two MODM methods to reformulate a bi-objective optimization problem to a single one, using the GAMS software to solve the problem. The MODM methods are classified into four groups based on getting information from decision-makers. The first group works without preliminary information from decision-makers, including individual optimization, LP-metric/global criteria, Max-Min, and filtering/displaced ideal solution methods. The second group needs primitive information from decision-makers that lexicography/preemptive optimization method, goal attainment method, goal programming method, utility function method are placed in this group. The third group needs to get information from decision-makers during the solution procedure, including the Geoffrion method, satisfactory goal programming method, and Zionts-Wallenius method. The fourth group of this category gets information from decision-makers after the solution procedure, including the multi-criteria simplex method, minimum deviation method, and Denovo programming method.
In this paper, first, ideal solutions are obtained through individual optimization method. Each objective function has to be optimized separately with respect to the constraints. To this end, basic open-source nonlinear mixed-integer programming (BONMIN) is used to solve mixed-integer nonlinear models. The BONMIN solver implements various algorithms such as a nonlinear-based branch-and-bound algorithm, outer-approximation decomposition algorithm, Quesada and Grossmann's branch-and-cut algorithm, and hybrid outer-approximation based branch-and-cut algorithm. The BONMIN employs a proper algorithm to improve the quality of solutions that can reach the optimal solutions for convex problems (Bonami et al., 2009).
After obtaining optimal solutions for each objective function, MODM methods are used to convert the bi-objective problem to a single one. One of the applied MODM methods in this paper is LP-metric, which is easy to implement and used to solve many multi-objective optimization problems (e.g., Yousefi-Babadi et al., 2017; Mardan et al., 2019; Hemmati and Pasandideh, 2020; Nemati-Lafmejani and Davari-Ardakani, 2020). Another MODM method to use in this paper is multi-choice goal programming with utility function (MCGPU) introduced by Chang (2011). This method falls into the second group of MODM and is the extension of classical goal programming (GP). GP has been widely used to solve multi-objective optimization problems (e.g., Pasandideh et al., 2015; Hafezalkotob et al., 2016; Maleki et al., 2017; Mirkhorsandi and Pasandideh, 2020). The proposed methods are described in detail as follows:

4.1. LP-metric/global criteria method

The aim of this method is to minimize the sum of relative deviations between objective functions (f_c; c = 1, 2, …, C) and their ideal solutions (f_c^*; $c=1,2, \ldots, C$). The ideal solution of each objective function is obtained through the individual optimization method. LP-metric is calculated for a maximization problem as follows:

$$Min\ d = \left(\sum_c^C \left(\frac{f_c^* - f_c}{f_c^*} \right)^p \right)^{\frac{1}{p}}, \tag{13}$$

It is worth noting that minimization problems should be converted to maximization, and also p is 1, in this paper.

4.2. Multi-choice goal programming with utility function

Charnes et al. (1955) proposed the classical GP that aims to minimize undesirable deviations between objective functions and aspiration levels of decision-makers to solve multi-objective problems. The formulation of GP is given by

$$Min\ Z = \sum_c h_c(d_c^+, d_c^-)$$

Subject to

$$f_c - d_c^+ + d_c^- = f_c^* \qquad \forall c = 1,2, \ldots, C \tag{14}$$

$$d_c^+, d_c^- \ge 0 \qquad \forall c = 1,2, \ldots, C$$

where d_c^+ and d_c^- are over and under expected values of the goals. If the objective function is the maximization type, GP minimizes d_c^-, otherwise, GP minimizes d_c^+. In addition, f_c^* is the expected value of the objective function determined by decision-makers.

In this method, aspiration levels are determined by decision-makers as a parameter that may be far from reality. Therefore, Chang (2007) introduced a multi-choice goal programming method to achieve multiple vector aspiration levels instead of being a parameter. This method avoids decision-makers setting the unrealistic value of aspiration level for each goal. The mathematical formulation of multi-choice goal programming is written as follows:

$$Min\ z = \sum_c^C \{w_c(d_c^+ + d_c^-) + \alpha_c(e_c^+ + e_c^-)\}$$

Subject to

$$\begin{aligned} & f_c - d_c^+ + d_c^- = y_c && \forall\, c = 1,2,\dots,C \\ & y_c - e_c^+ + e_c^- = g_{c,max}\ or\ g_{c,min} && \forall\, c = 1,2,\dots,C \\ & g_{c,min} \le y_c \le g_{c,max} && \forall c = 1,2,\dots,C \\ & d_c^+, d_c^-, e_c^+, e_c^- \ge 0 && \forall\, c = 1,2,\dots,C \end{aligned} \tag{15}$$

where y_c is a continuous variable within an interval $[g_{c,min}, g_{c,max}]$, and e_c^+ and e_c^- are over and under expected values of $|y_c - g_{c,max}|$ or $|y_c - g_{c,min}|$, and α_c is weight for each of them. w_c is the weight for deviations from aspiration levels. This method can be easily performed as a linear form of the mathematical model, however, it has not considered the decision maker's preference value. According to decision maker's preferences, Chang (2011) improved a multi-choice goal programming method considering a utility function. In this case, decision-makers would like to increase or decrease the utility as much as possible. The following explanation shows how to add utility functions to increase or decrease the utility values.

Case 1. Decision-maker's preference to decrease the utility value in MCGPU method

$$Min\ z = \sum_{c=1}^C \{w_c(d_c^+ + d_c^-) + \beta_c f_c^-\}$$

Subject to

$$\begin{aligned} & \lambda_c \le \frac{g_{c,max} - y_c}{g_{c,max} - g_{c,min}} && \forall\, c = 1,2,\dots,C \\ & f_c - d_c^+ + d_c^- = y_c && \forall\, c = 1,2,\dots,C \\ & \lambda_c + f_c^- = 1 && \forall\, c = 1,2,\dots,C \\ & g_{c,min} \le y_c \le g_{c,max} && \forall\, c = 1,2,\dots,C \\ & d_c^+, d_c^-, \lambda_c, f_c^- \ge 0 && \forall\, c = 1,2,\dots,C \end{aligned} \tag{16}$$

where β_c is a weight for f_c^-, indicating the preference based on the utility function (λ_c). This mathematical formulation is used for the minimization problem, in which f_c^- would like to become 0, and consequently λ_c tries to become 1. This formulation forces y_c to become close to its lower bound $g_{c,min}$. Interested readers can refer to Kettani et al. (2004) for further information.

Case 2. Decision-maker's preference to increase the utility value in MCGPU method

$$Min\ z = \sum_{c=1}^C \{w_c(d_c^+ + d_c^-) + \beta_c f_c^-\}$$

Subject to

$$\begin{aligned} & \lambda_c \le \frac{y_c - g_{c,min}}{g_{c,max} - g_{c,min}} && \forall\, c = 1,2,\dots,C \\ & f_c - d_c^+ + d_c^- = y_c && \forall\, c = 1,2,\dots,C \\ & \lambda_c + f_c^- = 1 && \forall\, c = 1,2,\dots,C \\ & g_{c,min} \le y_c \le g_{c,max} && \forall\, c = 1,2,\dots,C \\ & d_c^+, d_c^-, \lambda_c, f_c^- \ge 0 && \forall\, c = 1,2,\dots,C \end{aligned} \tag{17}$$

In this case, as λ_c approaches 1, y_c tends to get its upper bound for the maximization problem.

5. Numerical analysis

The parameters are generated in predefined ranges according to Table 2. All parameters are considered for five independent types of products, having the features of group B in ABC analysis. In addition, the range of parameters changes for each instance to analyze the system cost and its effects on the inventory review policy selection.

In this section, various test problems are executed in order to evaluate the application of the aforementioned MODM methods and compare them in terms of both objective function values and computational time. As seen in Table 1, there are thirty numerical examples, where $U(a,b)$ are the parameters generated based on uniform distribution between a and b, and $N(\mu,\sigma)$ are the parameters following a normal distribution with mean μ and variance σ, and mean capacity of shortage is deterministic.

To sum up, we have used two classic and novel MODM methods to simultaneously optimize both objective functions. We coded the model in GAMS 24.1.3 and solved it via BONMIN solver, using a computer with Intel@ Core ™ i7-CPU 2.20 GHz, RAM 8.00 GB. Table 3 represents the objective function values and computational time.

Table 2
Fixed and uncertain parameters of the model

Instances	$D_i \sim U(a, b)$	$f_i \sim U(a, b)$	$a_i \sim U(a, b)$	$h_i \sim U(a, b)$	$\pi_i \sim U(a, b)$	$N \sim N(\mu, \delta^2)$	$F \sim N(\mu, \delta^2)$	*SH*
1	[180,328]	[1,10]	[10,25]	[5,30]	[36,48]	[550,144]	[2500,625]	300
2	[50,100]	[5,15]	[20,45]	[15,39]	[25,45]	[120,64]	[750,441]	50
3	[10,25]	[2,12]	[5,25]	[20,100]	[15,30]	[45,9]	[142,49]	13
4	[5,11]	[10,45]	[50,100]	[10,35]	[60,105]	[46,16]	[259,81]	17
5	[10,49]	[30,90]	[90,110]	[90,120]	[95,130]	[96,16]	[1880,441]	75
6	[20,55]	[20,55]	[80,100]	[20,38]	[18,40]	[96,36]	[2800,1618]	45
7	[20,85]	[10,15]	[5,15]	[15,24]	[15,30]	[87,49]	[1865,961]	19
8	[12,64]	[5,14]	[19,31]	[10,18]	[25,35]	[47,16]	[948,144]	19
9	[180,328]	[1,5]	[20,45]	[10,20]	[35,50]	[550,144]	[450,121]	300
10	[240,360]	[1,6]	[5,10]	[1,5]	[10,20]	[350,100]	[650,225]	450
11	[5,15]	[20,30]	[50,85]	[30,45]	[65,95]	[56,25]	[350,64]	17
12	[10,35]	[35,50]	[10,16]	[5,17]	[15,30]	[66,25]	[1750,960]	18
13	[100,180]	[10,40]	[20,95]	[30,60]	[55,100]	[396,121]	[4750,1225]	589
14	[18,46]	[25,45]	[20,60]	[10,20]	[40,65]	[106,64]	[1500,360]	75
15	[4,24]	[5,16]	[16,38]	[9,23]	[20,30]	[26,9]	[448,121]	14
16	[30,50]	[5,18]	[30,90]	[10,40]	[60,85]	[186,64]	[198,49]	98
17	[5,14]	[20,28]	[10,25]	[4,20]	[20,32]	[86,9]	[298,81]	48
18	[5,15]	[15,30]	[40,65]	[8,27]	[45,70]	[96,25]	[408,196]	35
19	[30,90]	[4,18]	[20,33]	[4,12]	[25,35]	[165,49]	[843,122]	98
20	[5,18]	[4,9]	[20,30]	[9,18]	[25,35]	[15,9]	[193,81]	5
21	[10,40]	[10,20]	[20,33]	[4,12]	[25,42]	[69,16]	[689,81]	14
22	[10,27]	[15,30]	[20,33]	[4,12]	[25,35]	[172,25]	[659,169]	87
23	[30,130]	[10,25]	[100,150]	[60,90]	[115,150]	[180,64]	[2959,1089]	295
24	[50,170]	[10,25]	[100,120]	[60,90]	[100,125]	[90,49]	[5056,1156]	50
25	[40,90]	[10,25]	[50,114]	[60,90]	[50,85]	[189,64]	[1259,576]	160
26	[100,200]	[20,45]	[50,84]	[60,90]	[60,95]	[269,81]	[3995,1681]	244
27	[10,20]	[12,18]	[20,44]	[20,35]	[25,50]	[89,36]	[365,121]	10
28	[30,70]	[12,18]	[20,44]	[20,35]	[35,60]	[89,25]	[895,256]	71
29	[180,328]	[10,25]	[30,45]	[20,35]	[35,50]	[550,144]	[1950,625]	300
30	[180,328]	[20,35]	[10,55]	[10,45]	[35,50]	[550,144]	[5050,625]	300

In this section, various test problems are executed in order to evaluate the application of the aforementioned MODM methods and compare them in terms of both objective function values and computational time. As seen in Table 1, there are thirty numerical examples, where $U(a,b)$ are the parameters generated based on uniform distribution between a and b, and $N(\mu,\sigma)$ are the parameters following a normal distribution with mean μ and variance σ, and mean capacity of shortage is deterministic.

To sum up, we have used two classic and novel MODM methods to simultaneously optimize both objective functions. We coded the model in GAMS 24.1.3 and solved it via BONMIN solver, using a computer with Intel@ Core ™ i7-CPU 2.20 GHz, RAM 8.00 GB. Table 3 represents the objective function values and computational time.

Table 3
Results of applying the MODM methods

Instances	**Individual Optimization method (A)**			**LP-metric method (B)**			**MCGPU (C)**		
	TC	SI	CPU time	TC	SI	CPU time	TC	SI	CPU time
1	17142	0.845	16.256	17941	0.63	8.07	18065	0.636	9.989
2	5407	0.724	8.567	5569	0.657	6.662	5528	0.657	10.013
3	1865	0.795	3.779	1994	0.699	1.903	1920	0.658	1.370
4	1347	0.825	8.664	1530	0.515	0.663	1641	0.57	0.646
5	4641	0.902	2.024	4917	0.711	2.096	4904	0.708	1.996
6	4294	0.985	1.888	4480	0.781	0.803	4517	0.789	2.203
7	2761	0.945	2.838	3139	0.892	1.535	3198	0.907	3.334
8	2243	0.939	2.185	2400	0.831	1.575	2401	0.832	2.316
9	14789	0.922	16.720	15366	0.683	10.144	15683	0.7	27.857
10	3831	0.96	16.42	3936	0.723	16.046	3939	0.723	16.760
11	1750	0.745	2.333	1971	0.524	0.633	2050	0.499	0.781
12	1017	0.761	9.327	1078	0.66	1.052	1114	0.682	5.978
13	13296	0.96	1.239	13750	0.782	7.481	13797	0.785	6.179
14	2890	0.83	5.093	3075	0.642	0.634	3104	0.65	6.381
15	1388	0.766	7.322	1439	0.687	1.066	1451	0.693	2.108
16	5309	0.659	4.295	5964	0.422	0.740	5948	0.42	5.105
17	479	0.78	2.467	530	0.549	0.906	537	0.561	1.630
18	881	0.843	5.266	941	0.652	0.992	965	0.673	3.192
19	3020	0.819	5.859	3179	0.657	0.852	3233	0.67	1.575
20	716	0.715	3.425	724	0.714	2.073	724	0.714	4.331
21	1246	0.669	2.043	1299	0.634	3.632	1342	0.652	4.997
22	812	0.715	1.641	1154	0.463	1.739	871	0.672	4.302
23	22745	0.815	1.619	23957	0.677	1.886	23787	0.67	5.45
24	23048	0.929	2.027	24099	0.857	1.848	24129	0.858	2.61
25	10548	0.878	1.892	11520	0.681	4.561	11614	0.688	3.535
26	20212	0.806	4.787	21636	0.675	2.031	21598	0.673	7.945
27	1148	0.924	1.508	1250	0.697	1.660	1318	0.741	3.644
28	3407	0.756	6.377	3653	0.622	1.970	3641	0.619	1.012
29	20512	0.714	15.007	22194	0.57	8.588	21999	0.563	23.382
30	18652	0.781	8.163	19927	0.645	5.282	19661	0.633	6.877

Figs. (1)-(3) show the comparison of the total cost, service level, and computational time between MODM and the individual optimization methods for all examples.

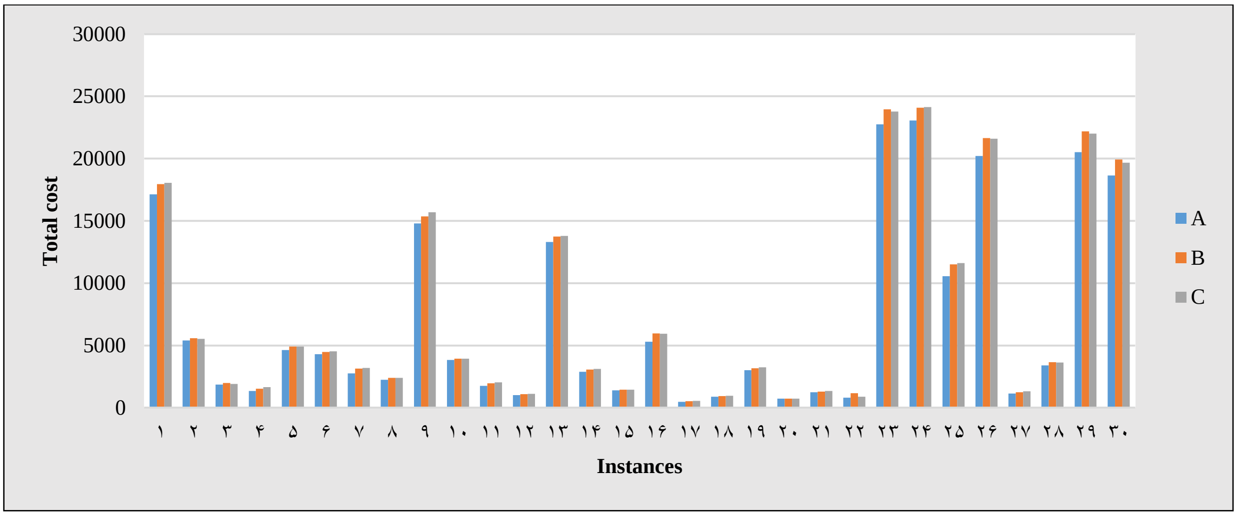

Fig. 1. The graphical representation of the results in terms of the total cost

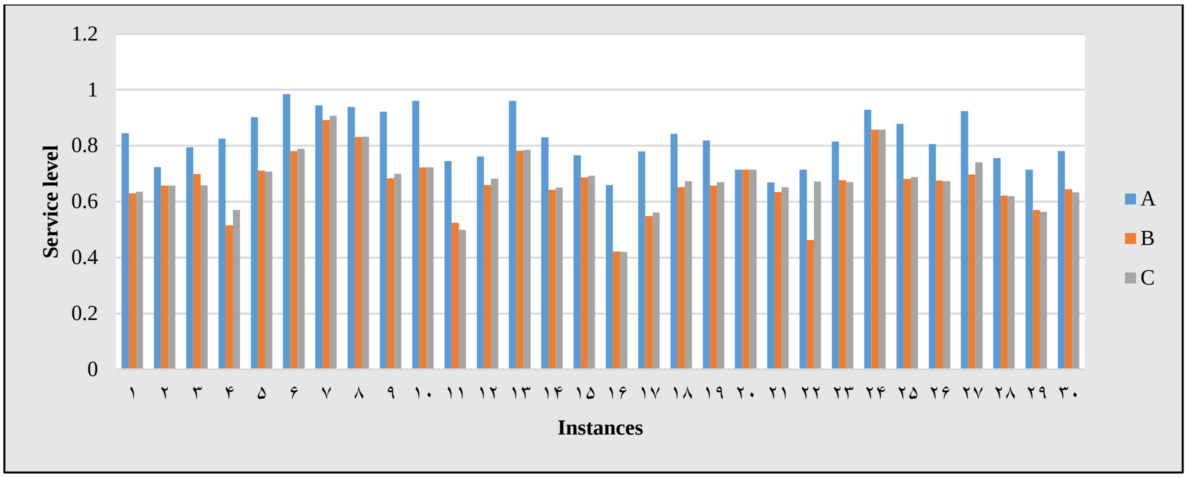

Fig. 2. The graphical representation of the results in terms of the service level

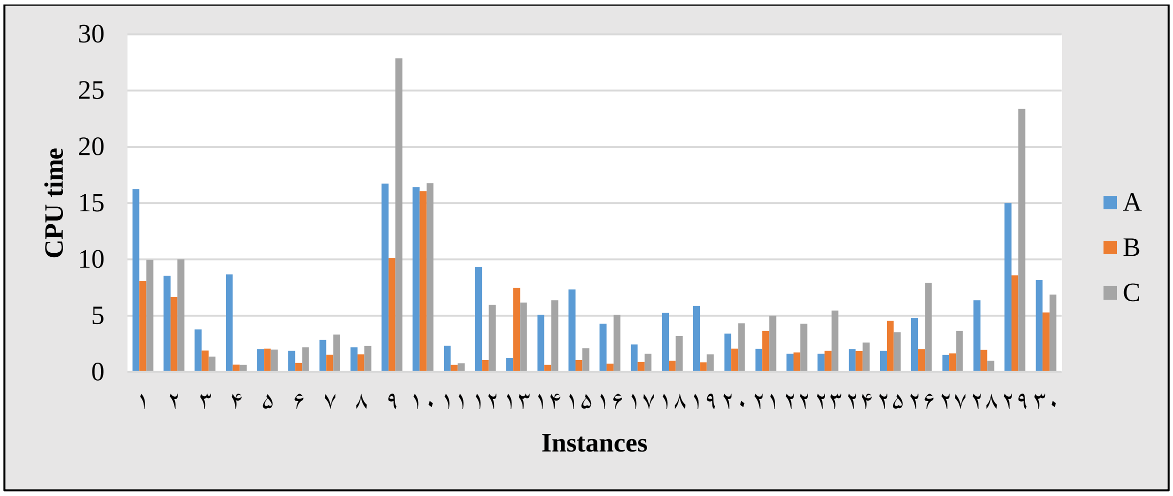

Fig. 3. The graphical comparison of the computational time

ANOVA is carried out to compare the performance of the MODM methods in terms of both objective function values and computational time. Figs. (4)-(6) show the relative interval plots for mean computational time, service level, total cost.

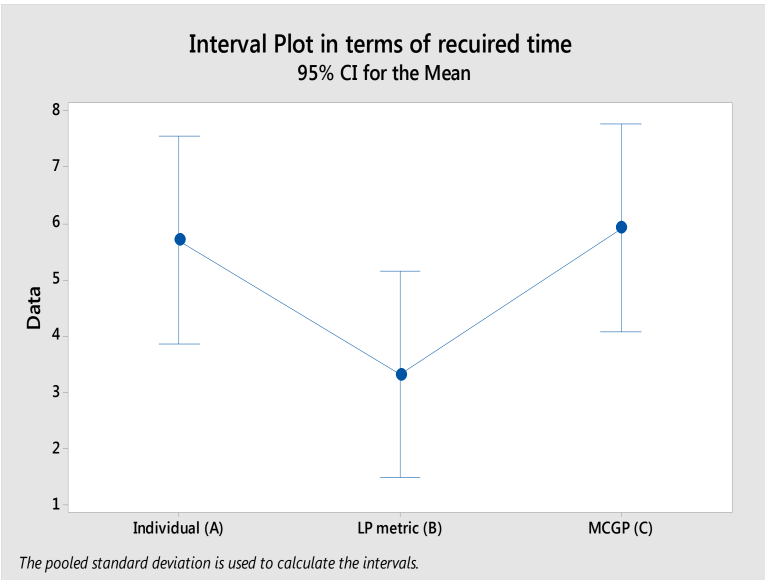

Fig. 4. Interval plots of mean computational time

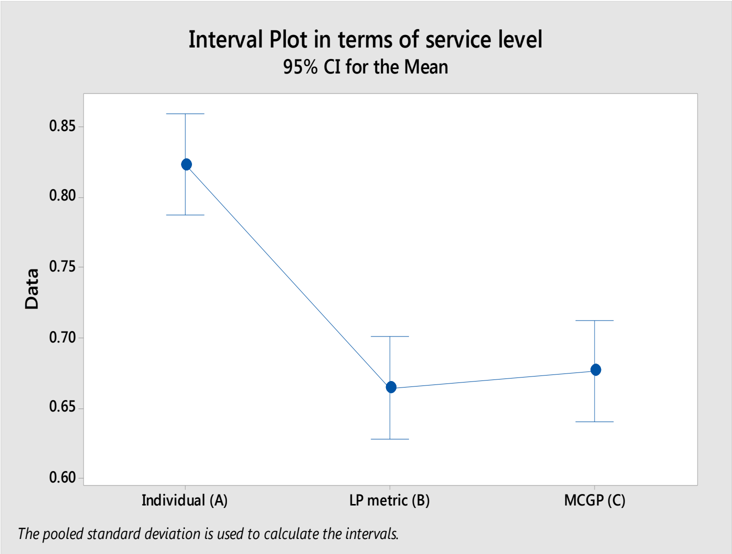

Fig. 5. Interval plots of mean service level

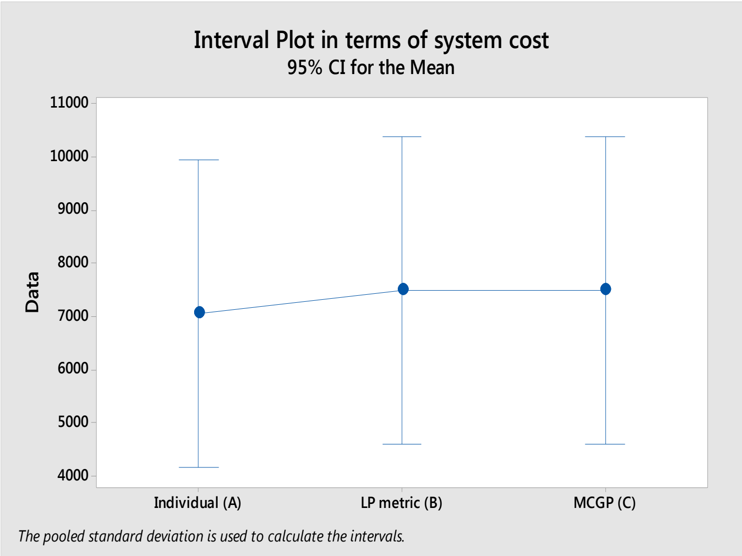

Fig. 6. Interval plots of mean total cost

Based on the results in Table 4, the null hypothesis, which is equality of mean cost in different methods, cannot be rejected at the 95% confidence level because P-Value is more than 0.05. That means there is no significant difference between used MODM methods and their optimal solutions. Moreover, ANOVA is used to examine the equality of the mean computational time of the MODM methods. The results in Table 5 indicate the null hypothesis cannot be rejected at the 95% confidence level, as P-Value becomes more than 0.05.

Table 4
The one-way ANOVA to compare the MODM methods in terms of the total cost

Source	DF	SS	MS	EMS	P-value
Factor	2	3902497	1951249	0.03	0.970
Error	87	5507037433	63299281		
Total	89	5510939930			

Table 5
The one-way ANOVA to compare the computational time of the MODM methods

Source	DF	SS	MS	EMS	P-value
Factor	2	126.2	63.08	2.47	0.091
Error	87	2225.6	25.58		
Total	89	2351.7			

Table 6
The one-way ANOVA to compare the MODM methods in terms of the service level

Source	DF	SS	MS	EMS	P-value
Factor	2	0.4710	0.235500	23.71	0.000
Error	87	0.8643	0.009935		
Total	89	1.3353			

According to the results in Table 6, the null hypothesis, which is equality of mean service level, cannot be accepted. Indeed the ANOVA test has drawn that P-value is less than 0.05. Therefore, there are significant differences between MODM methods in terms of service level. To exactly demonstrate the differences between these methods, we used Tukey's comparison test in Minitab 17. The results have been presented in Table 7, indicating there are no significant differences between LP-metric and MCGPU. However, there are significant differences between MODM methods comparing to their optimal values. Fig.7 demonstrates the graphical comparison of service level by Tukey's comparison test.

Table 7
The results of Tukey' comparison test related to the service level

Difference of levels	Difference of means	Se of difference	95% CI	T-Value	P-Value
B – A	-0.1592	0.0257	(-0.2205, -0.0978)	-6.18	0.000
C – A	-0.1470	0.0257	(-0.2084, -0.0857)	-5.71	0.000
C – B	0.0121	0.0257	(-0.0492, 0.0735)	0.47	0.885

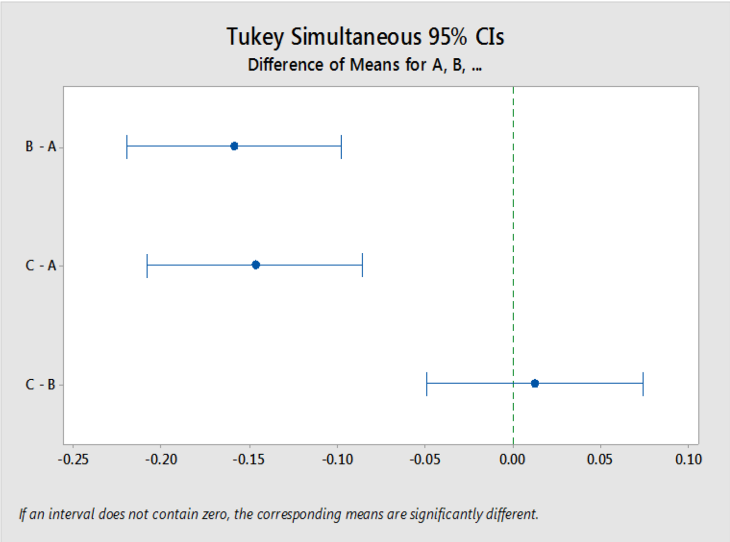

Fig. 7. The results of Tukey's comparison test related to the service level

Fig. 8 illustrates the average percentage of products under the continuous review policy. The results are obtained from solving numerical test problems by MODM methods or the individual optimization problem, indicating the (r, Q) policy is preferred to review inventory levels in most cases.

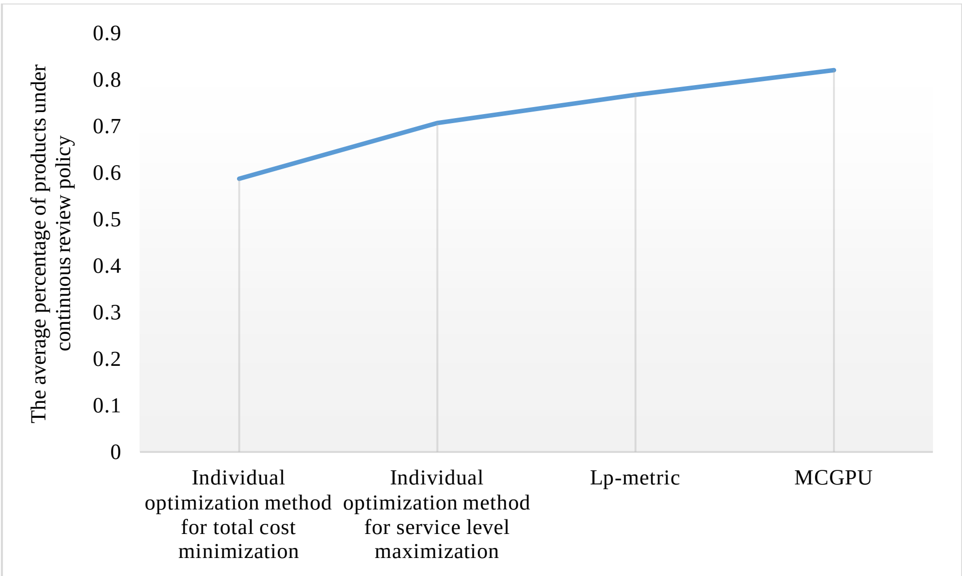

Fig. 8. The average percentage of products under the continuous review policy

6. Conclusion

ABC analysis is a classification method to tackle with the complex management of a large number of items. According to this method, the group ‘A’ items need precise control while the group ‘C’ items need less control. Although a survey on the literature reveals several studies in ABC analysis and inventory control policies, there is a lack of discussion on the group ‘B’ items. This group has moderate features. An appropriate inventory review policy for these items can increase customer satisfaction or avoid wasting resources. Therefore, this study proposed a bi-objective MBNLP model for a multi-product multi-period inventory problem, aiming to determine a proper inventory review policy for the group ‘B’ items. This study considered several functional constraints, storage capacity, number of orders, and maximum allowable shortage. Besides, the number of orders and storage capacity are chance constraints due to uncertainty. The model employs chance-constrained programming to transform the uncertain problem into deterministic.

This study aims to minimize total cost and maximize service level simultaneously. On that account, two classic and novel MODM methods have been proposed to solve the bi-objective problem, namely LP-metric and MCGPU. These methods convert a bi-objective model to a single objective and can reach the exact solutions. Numerical test problems have been executed by MODM methods to compare them in terms of both objective function values and computational time. The results reflect insignificant differences between LP-metric, MCGPU, and the optimal values in terms of the total cost and computational time. However, there are significant differences between LP-metric, MCGPU, and their optimal values in terms of the service level. Moreover, the (r, Q) policy is selected to review the inventory levels in most instances.

For further investigation, the proposed model can be extended in a multi-level supply chain considering lateral transshipments as an effective strategy to cope with the uncertainties. The solution procedure may revisit in large size instances. Moreover, a mixture of backorders and lost sales is considered as another modification.

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