

Multi-Criteria Inventory Classification: A Hybrid GRA-DFA Approach Using Relative Closeness Synthesis

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تصنيف بنود المخزون متعدد المعايير: النهج الهجين GRA-DFA باستخدام توليف التقارب النسبي

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Abstract:

Objectives: This research aims to capitalize their beneficial aspects through proposing a structural classification approach based on DFA and GRA to the MCIC problem. Precisely, both models will simultaneously run to provide combined compensatory and non-compensatory evaluations of inventory items for ABC classifications.

Methods: The proposed approach assigns weights to each criterion using different methods. Results are assessed and validated through an inventory dataset on a total of sixty-three stocking units and four numerical criteria. Empirically, the proposed approach is examined through the inventory cost and service performance indicators compared with that of six existing research studies in the MCIC literature.

Results: The study findings revealed that the proposed approach can offer an adequate representation of solving the MCIC problem, decrease the total inventory cost and foster the total order fill rate.

Conclusions: In this study, a structural classification approach based on GRA and DFA was proposed to adequately improve the MCIC problem. The proposed approach was named the GRA-DFA.

Keywords: Inventory management; inventory cost-service analysis; multi-criteria inventory classification; GRA; DFA; MCDM.

الملخص:

الأهداف: تهدف هذه الدراسة البحثية إلى الاستفادة من مزايا هذين النموذجين من خلال اقتراح منهجية تصنيف هيكلية تعتمد على (GRA) و (DFA) لحل مشكلة تصنيف بنود المخزون متعدد المعايير (MCIC). وبلمحة أدق، سيعمل كلا النموذجين معاً لتقديم تقييمات مدمجة (تعويضية وغير تعويضية) لعناصر المخزون لتصنيفات من أجل تصنيفها ABC.

المنهجية: عُمِدَت المنهجية المقترحة إلى تعيين أوزاناً لكل معيار باستخدام طرق مختلفة (نماذج اشتقاق أوزان المعايير). وقد تم تقييم النتائج والتحقق من صحتها من خلال مجموعة بيانات مخزون تضم 63 عنصراً و أربعة معايير رقمية. علاوة على ذلك، تم التحقق من صحة النتائج تجريبياً من خلال مؤشرات تكلفة المخزون وأداء الخدمة، وذلك بمقارنتها بست دراساتٍ بحثيةٍ سابقةٍ في مجال إدارة وتصنيف بنود المخزون.

النتائج: أظهرت نتائج الدراسة أن المنهج المقترح يقدم تمثيلاً مناسباً لحل مشكلة إدارة وتصنيف عناصر المخزون مع خفض إجمالي تكلفة المخزون ورفع إجمالي معدل اتمام الطلب.

الخلاصة: في هذه الدراسة، تم اقتراح نهج تصنيف بنيوي قائم على طريقتي التحليل العلائقي الرمادي (GRA) وتحليل التمييز الخطي (DFA) من أجل تحسين مشكلة MCIC بشكل فعال. وقد أُطلق على هذا النهج المقترح اسم GRA-DFA.

الكلمات المفتاحية: إدارة المخزون؛ تحليل تكلفة خدمة المخزون؛ تقنية تصنيف المخزون متعدد المعايير؛ نموذج تحليل العلاقات الرمادية؛ نموذج تحليل دالة الرغبة؛ أساليب اتخاذ القرارات متعددة المعايير.

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1 Introduction

Typically, all business organizations have increasing numbers of inventory items that need strict management for supply chain control. These stock-keeping units (SKUs) take various forms: stockpiles of raw materials, supplies, parts, components, partially manufactured objects, and completed objects. For effective inventory management, inventory units should be segmented, sorted, and tracked for better control and to gain many advantages like boosting service level. The extant inventory literature has presented a well-known technique for managing inventory through the classification of the on-hand products. This technique of inventory classification is known as ABC analysis (always, better, control) and was pioneered in early 1950s by Dickie (1951). ABC analysis categorizes stock inventories into three manageable and meaningful classes depending on a money value criterion, which is called an annual value use (annual demand multiplied by unit cost): Class A comprise highly important inventory items, Class B comprises middle important inventory items, and Class C comprises least important inventory items. This categorization enables the creation of an inventory boundary framework where Class A includes a small percentage of the overall inventory items (5–20%) that represent the highest value use (55–65%); Class B contains 20–30% of the total inventory items, representing the inventory value use of 20–40%; and Class C typically contains the largest portion (about 50–75% of total inventory items), but represent only 5–25% of inventory value use (Chu et al., 2008). General Electric Company successfully implemented ABC analysis to streamline their inventories. Later, the classical ABC inventory analysis became widely employed by other business companies and remains in use. This task maintains inventory items in a certain ABC ordering according to their importance and enables appropriate reviewing of each class of SKUs to take place (Ernst & Cohen, 1990). Silver et al. (1998) have proposed some inventory control methods that can be applied to each class of inventory items. At present, multicriteria inventory ABC classification (MCIC) is a trendy technique that has gained high attention in academic and practices. It enables considering more criteria in evaluating the inventory. Flores and Whybark (1986) have detailed a combination of criteria measurements that provide a logical evaluation of the inventory classification. Thereafter, many research studies from various scientific methodologies have been developed to provide a good inventory classification, as well as mitigate drawbacks that have been discovered during the use of the MCIC technique. The MCIC framework shows that there are still some major challenges that need to be addressed, for instance, generating inaccurate inventory ABC classification, which is due to the use of the Pareto distribution rule (80/20). Additionally, different classification models provide different ABC inventory classifications that may not put the inventory in the right class, leading to a contradiction in inventory performance when compared to other models, unless a sophisticated consensus approach is proposed and applied (Yang et al., 2017). Another shortcoming is determining the preferences of criteria weight to evaluate each inventory item and knowing how to differentiate their evaluation scores from each other. Research from Zowid et al. (2026), Khanorkar and Kane (2023), Kaabi et al. (2018), Guvenir and Erel (1998), and Simos (1990) have fairly succeeded in overcoming the MCIC problems. However, some of these models were found to rely on the decision-maker's subjective judgment, which may lead to results that are difficult to generalize and/or result in somewhat complicated models, requiring a high decision-maker knowledge to implement. Certainly, the literature is still rich with methods of weighting and classifying that can be effective and simple to use by a decision-maker. Hence, this article presents our proposed approach to accurate inventory classification through capitalizing on the beneficial aspects of the desirability function analysis (DFA) and grey relational analysis (GRA) models, thereby mitigating hidden critical risks (e.g., compensatory bias) and providing satisfactory scores of SKUs, thus adequately treating the MCIC problem. In addition, the proposed approach uses combined weighting models as a suggested solution in determining objective criteria weights for the MCIC. It therefore contributes to the existing MCIC literature by proposing the structural classification approach, depending on the DFA and GRA models for efficiently evaluating and ranking inventory items to advance the MCIC technique. The reason for using both DFA and GRA for the MCIC is extensive testing in which they consistently demonstrated their effectiveness and efficiency in several practical and academic domains. These methods have been widely examined by various studies, specifically within the supply chain domain, including supplier selection, inventory systems, and demand management, as shown by Shivade and Sapkal (2024), Karande and Chatterjee (2018), and Wang et al. (2017).

1.1 Research inspiration

This research study was inspired by some previous research. A study conducted by Syntetos et al. (2009) confirms that inventory ABC classification should be given more academic attention because of its important

implications in its decision-making. Another study by Zhou and Fan (2007) provides an inventory classification scheme with the concept of incorporating some balancing features through two sets of weights, which identifies the most and least favorable status for each item. Consequently, performance is aggregated. Third, research studies by Prakash et al. (2022) and Yaser and Shunmugesh (2019) have built two or more integrated MCDM approaches, that is, Grey-TOPSIS for evaluation and ranking purposes in different business fields; however, such approaches have never been examined for the MCIC field. Last, Douissa and Jabeur (2020) use a non-compensatory strategy based on the ELECTRE III model and explicitly suggest that the future research could involve considering other inventory performance measures such as the cost of on-hand inventory to provide more effective inventory classification. Accordingly, we wanted to develop these concepts in our proposed approach in this article.

1.2 Research objectives

Primarily, we aim to suggest a structuring approach that offers a balanced compensation and non-compensation evaluation, capitalizing on the usefulness of hybridization of criteria weights and hybridization of MCDM models, as a proposed solution for advancing the MCIC system. Additionally, the proposed approach aims to provide efficient ABC classification results reducing significantly inventory costs and enhancing the service level compared with other models.

2 Literature Studies

2.1 MCIC-based mathematical programming models

Ramanathan (2006) has developed a simple mathematical programming scheme, referred to as an R-model, for addressing inventory classification, whereby each item can choose a set of favorable weights for maximizing its score. To extend the R-model, Zhou and Fan (2007) have suggested a mathematical method that uses two sets of weights and a composite index where each item can show its most favorable and least favorable indices. Their method is referred to as the ZF model. Ng (2007) has presented a mathematical programming method (hereafter, the Ng model) that uses a scalar measure for the criteria used and generates inventory scores of items. Hadi-Vencheh (2010) has introduced an MCIC method using a generalized reduced gradient nonlinear mathematical programming that generates an inventory classification. To further extend the R, Ng, ZF, and Hadi-Vencheh models, Jeddou (2013) has presented two classification methods, referred to as the R* model and M-Ng models, that consider a pre-processing step for the data transformation to mitigate criteria dominance when ordered. Chen et al. (2008) have proposed a weighted Euclidean distance and a quadratic linear optimization aiming to alleviate the misclassifications and the impact of outliers of the MCIC. Fu et al. (2016) have presented a modified Ng classification model that uses a distance-based MCDM methodology. The model resolves the criteria weights with their ordering; thereby, each inventory item is evaluated based on aggregated performance scores. For the same purpose, Zheng et al. (2017) have developed a linear mathematical method that uses a Shannon entropy model to sum all criteria sequences, thereby providing a scoring scheme for inventory classification. Hatefi et al. (2014) have proposed a mathematical programming method that enables classifying inventory items so that quantitative and qualitative criteria are coexistent. An et al. (2019) have developed an improved classification method based on a weighted DEA where both quantitative and qualitative criteria can be considered to provide a comprehensive evaluation of the inventory system. Abdolazimi et al. (2021) have proposed an inter-mathematical programming method that enables a decision-maker to consider a multiple-level supply chain and optimizes the number of items at each ABC class. Heuristic and meta-heuristic methods are then used for a comparative analysis.

2.2 MCIC-based MCDM models

The analytic hierarchy process (known as AHP) is an MCDM model that has been widely used to advance the MCIC. Flores et al. (1992) have developed a study that generates a univariate and consistent measure for a simple inventory classification by a joint criteria matrix and AHP model. Partovi and Burton (1993) have introduced a study that uses AHP approach for advancing the MCIC system. Their AHP approach assessed inventory items through qualitative and quantitative criteria and validated them by a series of extensive simulation experiments. Braglia et al. (2004) have designed a classification model that uses the AHP and decision tree for efficient classification of spare part inventories. A study by Mallick et al. (2017) has proposed a classification model using systematic graph theory and AHP to provide more precise inventory of ABC

classifications. Despite the wide use and usefulness of AHP, it involves subjectivity judgment in pair-wise comparisons for criteria preferences and ranks (Hatefi et al., 2014).

TOPSIS is another great MCDM technique that has been widely used for advancing the MCIC. Bhattacharya et al. (2007) presented an inventory classification model that uses both AHP (for determining criteria weights) and TOPSIS (Euclidean distance is applied to evaluate items and offer their satisfied scores for ABC classification) for the MCIC. Chen (2012) has developed an alternative classification method that uses two virtual items and incorporates the TOPSIS without any subjective judgment in inventory classification. Arikan and Citak (2017) have conducted AHP-TOPSIS for the MCIC problem using a large inventory dataset obtained from a Turkish firm. Cherif and Ladhari (2016) have developed a hybridized model that uses a differential evolution and TOPSIS to optimize the criteria weights parameters and generate a score to each item in the ABC ranking. Kheybari et al. (2019) have proposed hybrid methodologies that involve Shannon's entropy, TOPSIS, and goal programming for criteria weights determination and an effective inventory classification. Kaabi et al. (2018) and Kaabi (2022) have developed a hybridized classification model that uses a genetic algorithm (GA), TOPSIS, and weighted sum (WS) to optimize criteria weights and advance the ABC classification. Hadi-Vencheh et al. (2023) have introduced a model that uses TOPSIS and alternative factor extraction (referred to as TOPSIS-AFEA) to optimally rank each item in stock. In addition, their study uses information entropy and GRA to differentiate itself from other existing ABC methods. Khanorkar and Kane (2023) have conducted a study using three different classification models for the MCIC. They have used the classical ABC analysis, k-means, and the MCDM model proposed by Hadi-Vencheh et al. (2023). Results reveal that the k-means is very helpful in addressing the MCDM problem. Sarkar (2024) has developed a combination of directional distance function and TOPSIS models to select a pair of ideal points for categorizing inventory items with an underlying assumption of convexity. Other MCDM models have also been applied to the MCIC. For example, Kartal et al. (2016) have introduced a hybrid method in which some MCDM models integrated with machine learning methods classify items and evaluate obtained classification accuracy. To aim at minimizing inventory cost and thereby enhancing service level, Douissa and Jabeur (2020) have developed a hybridized classification model that involves C-VNS and ELECTRE III to provide a non-compensatory classification and weighted scores of items for an effective ABC inventory classification. Zowid (2023) has conducted a study that uses two classification models (PROMETHEE II and COPARS) to advance the criteria weights and inventory classifications. In addition, he conducted a comparative analysis by considering some existing mathematical programming and MCDM models for a study validation. Nipu and Mahatab (2024) have developed classification models that use EDAS, TODIM, and standard deviation for providing an ABC inventory classification. Their study resulted in determining the best-contributing product to prevent stock-outs.

3 Research Materials

3.1 Problem definition

From the prior description of inventory management, as well as MCIC challenges in dealing with massive stock materials, this article seeks to tackle the MCIC problem via proposing an alternative structural classification approach. To begin, two main problems are identified. First, most diverse MCDM models previously applied to the MCIC problem have been fully compensatory aggregation schemes, which may lead to a poor performance of an inventory item under an impactful criterion and subsequently be compensated by its high performance on other criteria. This can be called hidden critical risks.

Second, studies by Babai et al. (2015) and Zowid et al. (2026) assume that a set of collected inventory items are formed of variables of entities and criteria measurements and must be evaluated (e.g., by aggregated performance), and then stratified into three different classes for ABC classification. Douissa and Jabeur (2020) have presented a table showing different MCIC methods with compensation levels used to provide inventory classifications. Our proposed model differs from previous hybrid models in the literature. We suggest a move from a classification of items to a functional decision support by incorporating dynamic inventory control policies (e.g., cycle service level [CSL] versus order fill rate) as suggested in Babai et al. (2015) and Zowid et al. (2026). Very few research studies have considered a non-compensatory model or even combinations thereof. Therefore, the proposed approach would offer a compensatory bias evaluation of inventory items. This research work proposes a structural classification approach aiming to provide an effective classification method and results as compared to the relevant existing models in the MCIC literature.

3.2 Collected inventory dataset

This research work uses the real-life inventory dataset reported in Liu et al. (2016) obtained from a Chinese sports apparatus company. The dataset consists of 63 SKUs that are characterized by different numerical criteria: RMB use (¥), stocking unit cost (¥), turnover (ratio), and lead time (days). For that inventory dataset, a manager aims to prioritize the three categories of the SKUs by allocating approximately 11%, 32%, and 57% for Classes A, B, and C, respectively (Liu et al., 2016).

4 Model development

This section presents our structural classification approach for a real inventory dataset as well as how we improve the MCIC problem. We therefore evaluate a combination of different weights to derive the optimal weights for all the criteria, giving a weight value to every criterion measure. The proposed approach also conducts a combination of a full compensatory and non-compensatory aggregation scheme based on MCDM models (GRA and DFA) to provide an overall and compensatory bias evaluation of each item as a satisfied score for ABC classification. Subsequently, our model can be called hereafter the *GRA-DFA model*. To perform the proposed approach, algorithms are formulated and presented in two principal stages: In the first stage, the satisfied criteria weights are searched by combining the outcomes of the criteria weight derived from the CRITIC (Diakoulaki et al., 1995), C-VNS (Mladenović & Hansen, 1997), and EW (Wang et al., 2009) methods. In the second stage, both the DFA (Harrington, 1965) and GRA (Ju-Long, 1982) models are applied to evaluate each inventory item with respect to the multiple criteria given. In other words, GRA and DFA generate an inventory score separately to indicate how well each item meets the inventory's limits and how closely each item's pattern matches the ideal inventory reference sequence. Last, one further mandatory step aggregates outputs of GRA and DFA by using the global relative closeness (RC), which generates the satisfied score for each item. It is worth noting that the use of RC provides not only the items' scores and ranks but also maps them for multidimensional performance logic and enhances the discrimination of inventory item similarity (e.g., score and rank). Components of the GRA-DFA approach are depicted in Figure 1.

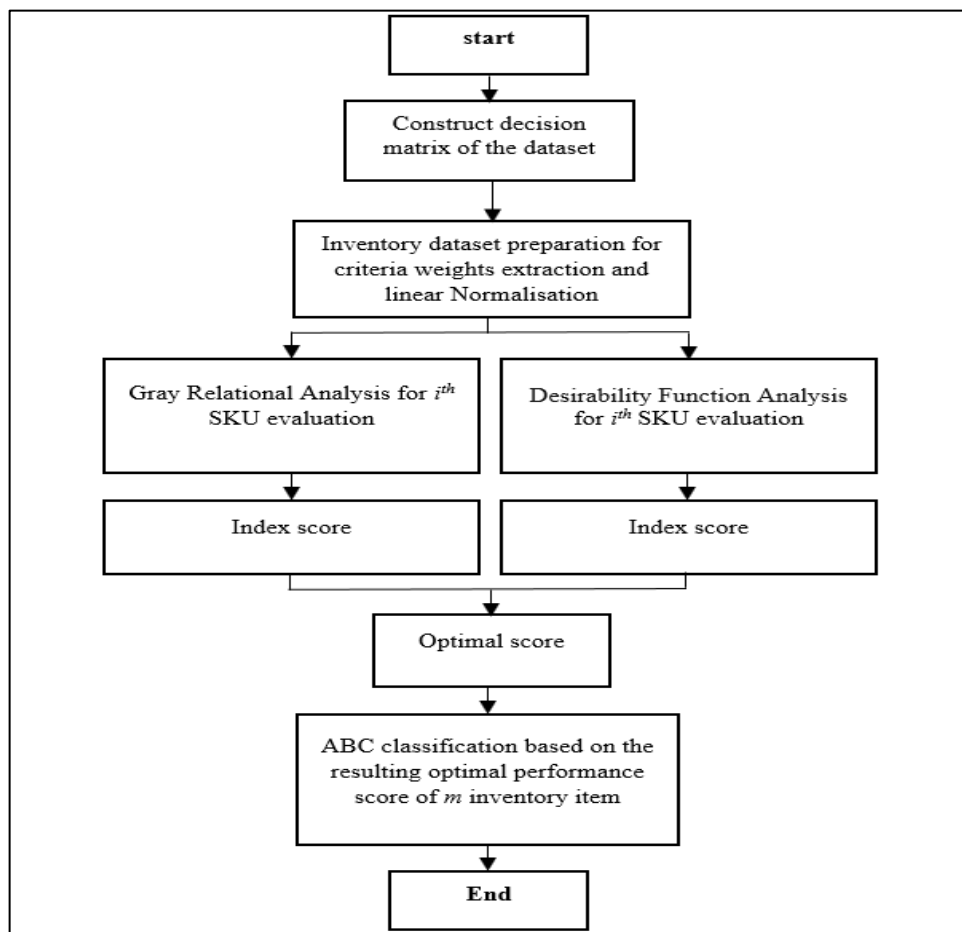


Figure 1: Proposed approach. (Elaborated by the author)

4.1 Extraction of the criteria weights:

The MCIC technique seeks to classify inventories in the presence of multicriteria. All criteria, therefore, would be examined in terms of their reordered internal impact and each criterion's relative impact. In other words, weights are then given to the criteria to indicate their relative impact and preferences (Wang et al., 2009). Different weights would influence the decision-making and outcomes of the inventory classification and the MCIC system. Consequently, reaching objective and rational results of the criteria weights is necessary. Three sets of criteria weights are proposed to generate optimal weights. They are detailed in the following four stages.

Stage 4.1.1 CRITIC

The CRITIC is an MCDM method, aiming to determine criteria weights with respect to importance/preference. In CRITIC, contrast intensity and conflict of decision criteria are two principal dimensions, used for measuring criteria weights objectively (Diakoulaki et al. 1995). The key procedural steps are as follows.

- I. For a constructed decision matrix, a membership matrix x_i mapping the value of every C_j criterion for $[0,1]$ interval is defined. This step estimates the ideal value f_j^* (favorable performance of j criterion), and the anti-ideal value f_j^- (least favorable performance of j criterion).

$$x_{aj} = \frac{c_j - f_j^-}{f_j^* - f_j^-} \quad (1)$$

- II. The σ_j standard deviation of each criterion measure (x_j) is calculated.
- III. Establish a symmetric matrix decision of the correlation coefficient for x_j and x_j , which is as r_{jj} .
- IV. Measure the conflict of criterion that is expressed as.

$$\sum_{j'=1}^n (1 - r_{jj'}) \quad (2)$$

- V. Conflict of decision and contrast intensity criteria are calculated using equation (3):

$$C_j = \sigma_j \sum_{j'=1}^n (1 - r_{jj'}) \quad (3)$$

- VI. Find a normalized weights result of each criterion, using equation (4).

$$CRITIC_j = \frac{C_j}{\sum_{j=1}^n C_j} \quad (4)$$

Stage 4.1.2 C-VNS

The continuous variable neighborhood search (referred to as C-VNS) is a method that aims to solve and optimize discrete, continuous, and combinatorial problems (Mladenović & Hansen, 1997). It relies on two main processes. First, a local search algorithm is used to promote the current incumbent outcome. Second, a shaking process is performed to extend the space of explored outcomes (Douissa & Jabeur, 2020). The C-VNS is presented in algorithm 1 and detailed next.

Algorithm 1; Pseudocode Continuous Variable Neighborhood Search

1. **Initialization step:** Choose a set of neighborhood structure N_k , $k=1, \dots, k_{max}$ to generate a random initial solution.
 2. **frequently execute** the subsequent steps until a (stop condition) is attained:
 3. **Set** $k \leftarrow 1$
 4. **frequently execute** the succeeding steps until $k > k_{max}$:
 5. (i) **For shaking process:** Randomly, propose a point y from the (k_{th}) neighborhood $N_k(x)$;
 6. (ii) **For local search process:** Perform some local search method y to get a local minimum (y')
 7. (iii) **For neighborhood change:** In case of the local minimum (y') is higher than the current best solution, move there ($x \leftarrow y'$); and keep searching with N_1 ($k=1$); otherwise,
 8. step to line 3 (Set $k \leftarrow k + 1$);
 9. **End**
 10. **Stop condition, is reached the approximate solution of iterations**
-

Source: Mladenović et al. (2008).

The main procedural steps from initialization to the stop condition are as follows:

Step 1. Initialization, a different set of neighborhood structures N_k , $k=\{1, \dots, k_{max}\}$ must be established to generate the criteria weight as non-negative solution spaces S . This requires randomly picking the value of each criterion C_j as:

$$\begin{aligned} & \min_{i, ki \neq k} (|g_i(a_i) - g_j(a_k)|) \\ & \max_{i, ki \neq k} (|g_i(a_i) - g_j(a_k)|) \end{aligned} \quad (5)$$

subject to: $\sum_{j=1}^N w_j = 1 \quad (6)$

Step 2. Compute a normalization of the obtained weights as:

$$w_j^N = \frac{w_j}{\sum_{j=1}^n w_j} \quad j=1, 2, \dots, J \quad (7)$$

Step 3. Identify the neighborhood $N_k(x)$ that represents the solutions in the K^{th} neighborhood of (x) as:

$$N_k(x) \{y \in S | p_k(x, y) \leq r_k\} \quad (8)$$

where for both r_k as a radius (size) of the neighborhood $N_k(x)$ and p_k represent any metric equation (i.e., Euclidean distance). Note that the following metric equation (9) is commonly used:

$$p_k(x, y) = (\sum_{i=1}^n |x_i - y_i|^p)^{1/p} \quad \text{where } (1 \leq p \leq \infty) \quad (9)$$

Step 4. Five key parameters must be identified through the following:

- Determine the minimum or maximum number of iterations to search for the solution S .
- Specify the quantum of neighborhood structures k_{max} considered for the search.
- Determine the geometry of neighborhood structures N_k identified through the choice of indices.
- Consider the distributions implemented $N_k(x)$ in the shaking step for obtaining the random point y .
- Consider the local optimizer (the objective function) employed in the local search step.

It is important to note that numerical values can be assigned to fixing some key parameters directly by the user or any calculating values.

Step 5. Perform a shaking process, which requires picking a random point y from the (k_{th}) neighborhood $N_k(x)$.

Step 6. Conduct a local search that requires proposing the output y as the initial output to find a local optimum (y') .

Step 7. Create a neighborhood change that requires checking two conditions:

if $f(y') < f(x)$, set x to $(x \leftarrow y')$ to update and search with $N_1 (k=1)$;

otherwise,

if $f(y') \geq f(x)$, go $k \leftarrow k + 1$ to search further away

where $f(y')$ denotes the obtained local minimum and $f(x)$ denotes the best solution.

Step 8. Create a stopping condition to accept the reached solution; otherwise, update steps 5, 6, and 7.

Stage 4.1.3 Equal Weight

The equal weighting (EW) of an MCDM method is aimed at solving various decision-making problems (Wang et al., 2009). It has been indicated that the EW is capable of offering effective results as good as other weighting methods (Dawes & Corrigan, 1974). The method primarily was developed to serve a given dataset so as to infer values of criteria weight whereby a decision-maker distributes the same importance to all criteria. Thus, preferences among the criteria do not need to be articulated. It is simply formulated as:

$$EW_j = \frac{1}{J} \quad j=1, \dots, J \quad (10)$$

Stage 4.1.4 Combination Weighting Method

This subsection considers the mathematical combination of three methods of criteria weighting as shown in Table 1, where the weighted matrix elicits combined weights as final criteria weights. It requires constructing a weighting matrix $W = (w_{ij})_{m \times n}$ for extracting the mean values as:

$$w_j = \sum_{i=1}^J [CRITIC_j CVNS_j EW_j] / J \quad j=1, \dots, J \quad (11)$$

Subject to

$$\sum_{j=1}^J w_j = 1$$

where w_j denotes a single output of weighted values under each criterion j^{th} , and J denotes a total number of weights/observations of the data. It should be noted that all criteria weights must be 1.

Table 1: Description of main methods of criteria weigh utilized to the MCIC problem.

Criteria Weighting methods	Reference
CRITIC	Diakoulaki et al. (1995)
C-VNS	Mladenović et al. (2008)
Equal weighting (EW)	Wang et al. (2009)

4.2. Methods of scoring inventory items:

Stage 4.2.1 DFA

DFA is a non-compensatory MCDM method developed by Harrington in 1965. It aims to estimate the overall performance of i^{th} alternative for a single desirability function (N_{ij}), and thereby is summed into a composite index (Dg). This function is a mean value for maximization or minimization objective. A DFA method could be useful for the MCIC problem by changing multiple responses to a normalized single-response function so that the results can be employed in intricate production and supply chain processes for multilevel optimization (Fajdek-Bieda, 2022; Mobin et al., 2018). For example:

1. For a developed decision matrix where $T = (\tau_{ij})$, I, J denotes each item A_i ($i=1, 2, \dots, I$) and is evaluated depending on the criterion C_j ($j=1, 2, \dots, J$), the criteria weights w_j values as:

$$\sum_{j=1}^J w_j = 1 \quad \text{for } j = (1, 2, \dots, J) \quad (12)$$

2. For a pre-processing of data, compute a max-min normalization and weighted normalized decision matrix $R = (N_{ij})$:

$$N_{ij} = \frac{\tau_{ij} - \min\{\tau_{ij}\}}{\max\{\tau_{ij}\} - \min\{\tau_{ij}\}} w_j \quad (13)$$

where $\max\{\tau_{ij}\}$ values and $\min\{\tau_{ij}\}$ values are the output response. Also, w_j

3. Compute the desirability function D_g as:

$$D_g = (N_{ij1} N_{ij2} \dots N_{ijn})^{1/J} \quad (14)$$

where J denotes the total number of criteria $j=1, 2, \dots, J$

Stage 4.2.2 GRA

GRA is a fully compensatory MCDM method aiming at addressing an ambiguous situation or discrete or incomplete data problems (Ju-Long, 1982) because it can be used effectively for problems with multiple criteria (Geum et al., 2011). It focuses on decision-making in situations where some of the information is known and the rest is unknown. By this, the unknown information is in a “grey relation”. If there are high relationships among various variables, the grey relation would be certain; otherwise, the relationships are uncertain and in question (Özomay et al., 2022). Accordingly, the steps of the GRA is presented as:

- i. Suppose that $X = (X_{ij})$, I, J denotes that each item A_i ($i=1, \dots, I$) should be assessed in terms of the attribute C_j ($j=1, \dots, J$), so the determination of the weights w_j ($j=1, \dots, J$) is:

$$\sum_{j=1}^J w_j = 1 \quad (15)$$

- ii. To pre-process data, the liner or max-min transformed decision matrix $R = (\beta_{ij})$ is expressed as:

$$\beta_{ij} = \frac{x_{ij} - \min\{x_{ij}\}}{\max\{x_{ij}\} - \min\{x_{ij}\}} \quad (16)$$

where β_{ij} is a normalized value, x_{ij} , $i = 1, 2, \dots, I$ and $j = 1, 2, \dots, J$ indicates the i^{th} item value in related to j^{th} attribute.

- iii. Calculate the coefficient of the GRA to find the maximum normalized value of the data sequence using the following equation:

$$Y_{max} = \max(x_{ij}) \quad (17)$$

- iv. Compute the derivational reference sequence (∂_{ij}):

$$\partial_{ij} = Y_{max} - x_{ij} \quad (18)$$

- v. Compute the grey relational coefficient δ :

$$\delta(x_{ij}) = \frac{\min\{\gamma_{ij}\} + \max\{\gamma_{ij}\}\beta}{\gamma_{ij} + \max\{\gamma_{ij}\}\beta} \{\gamma_{ij}, j = 1, 2, \dots, J\} \quad (19)$$

where the deviation sequence $\delta(x_{ij})$ is calculated using:

$$\gamma_{ij} = |Y_{max} - x_{ij}| \quad (20)$$

where β denotes a distinguishing coefficient, $\beta \in (0, 1)$. β value is assumed as 0.5. It should be pointed out that the 0.5 takes variation into account instead of reflecting a decision-maker's preferences.

- vi. Compute the GRA using the following equation:

$$r_{ij} = \frac{1}{J} \sum_{j=1}^J w_j \delta(x_{ij}) \quad (21)$$

Stage 4.2.3. Aggregate performance and ABC rank

- i. Global relative closeness index of the GRE-DFA is expressed as:

$$RC = \frac{r_{ij}}{r_{ij} + D_g} \quad (22)$$

- ii. Finally, rank inventory items for using ABC principle.

5 Computational results and discussions

To illustrate the proposed approach and examine its performance compared to some opted models, a real-life dataset of 63 items presented in Liu et al. (2016) is used for a comparative analysis. It is worth pointing out that our proposed approach does not require imposing any order among criteria measurements up to the final solution. At the first stage, the proposed classification approach is applied to elicit a criteria weight vector using the CRITIC, C-VNS, and EW methods. The acquired criteria weights for CRITIC are $W_{AUC} = 0.143$, $W_{ARMBU} = 0.276$, $W_{LT} = 0.301$, and $W_{TOR} = 0.279$; for C-VNS they are $W_{AUC} = 0.200$, $W_{ARMBU} = 0.230$, $W_{LT} = 0.300$, and $W_{TOR} = 0.270$; and for EW they are $W_{AUC} = 0.250$, $W_{ARMBU} = 0.250$, $W_{LT} = 0.250$, and $W_{TOR} = 0.250$. One additional stage is added by combining the obtained values of the criteria weights, calculated through the average of each criterion for all criteria weighting models. For example, the corresponding optimal weight of the average unit cost (AUC) is $W_{AUC} 0.143 + W_{AUC} 0.200 + W_{AUC} 0.250 / 3 = 0.198$. The optimal criteria weights are presented in Table 2, which shows that $W_{AUC} = 0.198$, $W_{ARMBU} = 0.252$, and $W_{LT} = 0.284$, $W_{TOR} = 0.266$. Note that the criteria weights appear to have reasonable values even before conducting the combining function, meaning that they are close to each other with respect to importance. And, if there are outlier values, the combining function could mitigate them and interpret the reason for reaching the relative importance level of criteria. Our study found that lead time is the most important criterion. This finding is supported by Douissa and Jabeur (2020).

Table 2: Calculation results of the optimal criteria weight for the 63 SKUs.

63 SKUs	W_{AUC}	W_{ARMBU}	W_{LT}	W_{TOR}	Total
CRITIC	0.143	0.276	0.301	0.279	1.000
C-VNS	0.200	0.230	0.300	0.270	1.000
EW	0.250	0.250	0.250	0.250	1.000
Combined weights (Optimal weights)	0.198	0.252	0.284	0.266	1.000

Once the weights of criteria are computed, the GRA and DFA models are then jointly implemented to generate grade indices of each inventory item. At this point, the inventory dataset should be linearly normalized for a comparability sequence. This is because the data comprises different inventory items and different criteria measurements. The results obtained by the GRA demonstrate a reflection of the identification rate of the comparability and the reference sequences, whereas the results obtained by the DFA indicate the maximum or minimum weighted performance. This gives various assessment perspectives to each inventory item and capitalizes on their usefulness. In Table 3, the first column presents the SKUs in numbers, representing each row and the figures of each attribute for the corresponding inventory item (i.e., SKU_i). Table 3 shows grade indices where the eighth and ninth columns indicate the DFA grade index and the GRA grade index for each inventory item, respectively. Both indices provide non-negative grades. The RC taken from TOPSIS is a function used for aggregating the two indices. We employ it in the current study because of its suitability for providing inventory evaluations that are closest to the positive ideal solution. Chen (2011) use this technique when developing a peer estimation method for inventory classification. Wardana et al. (2021) also proposed using MCDM and fuzzy DEA methods. We then calculated the RC (optimal/satisfied score) to the solution for each SKU item according to the GRA and DFA grade indices. For example, the estimated composite desirability of SKU_5 with respect to the criteria is 0.036 when all responses are combined into a single value, whereas it is 0.235 when GRA is estimated. We then compute the RC function as $0.235 / 0.036 + 0.235 = 0.866$, representing the optimal or satisfied performance. We finally rearrange all the 63 SKUs in descending order based on the obtained maximum scores (i.e., 1.000–0.748), as presented in Table 3.

Table 3: ABC Classification results by the proposed approach (GRA-DFA)

SKUs	Original and non-normalized main inventory classification data				Original and non-normalized other inventory data		DFA index	GRA index	Satisfied Score
	AUC (¥)	ARAMU (¥)	LT	TOR	Annual Demand	EOQ*			
13	71.83	88071.9	1	2.264	1226	249.266	0.000	0.227	1.000
32	199.8	15296.7	16	0.799	77	37.347	0.000	0.227	1.000
56	15.4	103414	1	2.902	6715	1259.852	0.000	0.231	1.000
57	194.05	316586	1	2.928	1631	174.937	0.000	0.236	1.000
58	0.680	341859.6	13	1.991	502735	51875.903	0.000	0.237	1.000
60	89.23	43136.7	2	0.025	483	140.431	0.000	0.218	1.000
61	98.65	495254.8	1	1.089	5020	430.396	0.000	0.232	1.000
14	89.35	41150.6	2	1.019	461	136.976	0.010	0.222	0.955
54	113.84	497119.6	23	0.03	4367	373.668	0.013	0.238	0.947
17	230.34	31681.6	2	2.822	138	46.621	0.015	0.229	0.937
8	190.53	55345.3	18	0.13	290	74.495	0.016	0.226	0.933
62	99.15	20635.4	18	2.069	208	87.411	0.018	0.233	0.930
27	39.29	101493.5	13	0.431	2583	489.201	0.017	0.225	0.930
6	164.18	101627	12	0.162	619	117.148	0.018	0.224	0.924
34	193.37	119454.6	5	0.324	618	107.836	0.019	0.222	0.922
49	36.47	78051.4	22	0.882	2140	462.174	0.021	0.231	0.915
44	140.26	38914.1	25	0.609	277	84.854	0.022	0.231	0.912
39	92.86	370301.3	21	0.107	3988	395.366	0.023	0.234	0.910
38	40.93	407329.5	3	1.856	9952	940.767	0.023	0.234	0.909
55	27.85	255434	6	2.227	9172	1094.876	0.025	0.233	0.904
19	187.75	233313.8	6	0.353	1243	155.218	0.024	0.225	0.902
36	73.4	374496.8	8	0.619	5102	503.012	0.027	0.230	0.893
18	80.27	295351.8	11	0.531	3679	408.477	0.028	0.229	0.892
46	136.45	499854.8	7	0.376	3663	312.607	0.029	0.232	0.888
26	50.33	281313.1	16	0.917	5589	635.797	0.031	0.233	0.882
31	42.17	180117	30	1.135	4271	607.190	0.033	0.239	0.879
22	67.16	80559.6	27	2.381	1200	254.976	0.034	0.240	0.875
25	132.89	459578.7	3	2.152	3458	307.779	0.034	0.236	0.875
53	235.08	329205.1	3	1.574	1400	147.254	0.033	0.230	0.874
16	103.63	77582	30	1.836	749	162.161	0.036	0.240	0.868
5	81.98	164125.6	24	1.204	2002	298.147	0.036	0.235	0.866
4	26.72	391531.3	16	2.548	14653	1412.855	0.037	0.242	0.866
20	51.35	231721.6	26	1.376	4513	565.579	0.037	0.239	0.865
51	32.53	273490.9	20	2.507	8407	969.925	0.038	0.241	0.865
30	54.94	188630.7	29	1.54	3433	476.945	0.038	0.240	0.863
12	113.36	298718.7	11	1.211	2635	290.885	0.038	0.232	0.860
24	41.71	336693	15	2.37	8072	839.320	0.039	0.239	0.860
50	209.5	318688.5	4	2.259	1521	162.574	0.039	0.234	0.858
63	104.84	370919.4	11	1.214	3538	350.480	0.039	0.233	0.857
35	138.47	333290.6	6	2.05	2407	251.540	0.039	0.234	0.857
47	187.27	274935.6	5	2.512	1468	168.927	0.040	0.234	0.854
9	202.96	443096.1	18	0.378	2183	197.874	0.041	0.236	0.853
42	207.53	499699.9	10	0.692	2408	205.506	0.042	0.234	0.847
23	173.29	397196.1	23	0.471	2292	219.422	0.043	0.237	0.847
1	210.39	413692.2	18	0.487	1966	184.444	0.043	0.235	0.845
59	151.69	228109	18	1.259	1504	189.961	0.043	0.234	0.843
7	219.19	327849.6	5	2.994	1496	157.604	0.045	0.238	0.840
15	153.28	414547.2	14	1.032	2705	253.427	0.045	0.235	0.839
40	225.49	322614	6	2.548	1431	151.973	0.046	0.236	0.836
3	125.24	452711.6	12	1.653	3615	324.129	0.048	0.238	0.833
28	189.24	128298.4	18	2.979	678	114.195	0.049	0.239	0.831
10	119.58	294066.8	25	1.374	2459	273.599	0.049	0.239	0.831
45	170.96	370885.2	10	2.002	2169	214.920	0.049	0.236	0.829
2	70.92	363303.1	29	1.87	5123	512.763	0.051	0.245	0.829
43	243.36	209629.8	25	1.127	861	113.508	0.051	0.237	0.824
11	71.21	390861.5	30	2.407	5489	529.689	0.056	0.249	0.817
21	75.92	454758.8	20	2.929	5990	535.902	0.056	0.248	0.816
33	152.85	383919.9	22	1.79	2512	244.571	0.058	0.242	0.808
48	160.84	296976.8	28	2.108	1846	204.417	0.060	0.244	0.802
37	147.65	364491.1	28	2.665	2469	246.695	0.066	0.249	0.790
41	10261	50402.1	25	0.42	5	1.320	0.065	0.234	0.782
29	228.69	311478.1	29	2.319	1362	147.237	0.069	0.246	0.781
52	17164	142923	5	0.815	8	1.329	0.078	0.231	0.748
Max	17164.0	499854.8	30	2.994	502735	51876	0.078	0.249	1.000
Min	0.680	15296.7	1	0.025	5	1.320	0.000	0.218	0.748

Note: EOQ* refers to economic order quantity.

In this study, we follow the same distribution of inventory items that was already presented in Liu et al. (2016) through allocating the SKUs as 7, 25, and 31 for the classes A, B, and C, respectively. Table 4 presents different classification outcomes when compared with other selected models. The overall comparison among models

showed that 2 out of 63 SKUs have same classification, while the others do not. These two units are 52 and 59. This similarity represents 3.17% out of total SKUs. It should be noted that peer models can also conduct similarity rate and representation for better analysis and appreciation. Therefore, comparing the proposed approach to the Lolli model, 25 units out of 63 SKUs were identical, representing approximately 40% of total SKUs. Comparing the proposed approach to the Liu model, 27 units out of 63 SKUs were identical, representing approximately 43% out of total SKUs. Like the above comparison result, the proposed approach has the same identification percentage compared to the CVNS-ELECTRE III model. Evidently, the proposed approach presents different ABC classification results from those proposed by other models. For instance, some items, on average, moved up or down in terms of ABC classifications. More specifically, both items 13 and 60, which were classified as Class C by different models, jumped up to Class A by the proposed approach. Notably, this is because they carry a very short lead time (i.e., 1–2 days). In fact, most Class A SKUs, such as 56, 57, and 61, which were classified by the proposed approach, have a very low lead time. Class A item 60 has very short lead time (2 days) and very low inventory turnover ratio ($=0.025$) compared to others within the same class. These can be observed through the columns of lead time and inventory turnover ratio in Table 3. Table 3 also shows that item 58 was stratified as Class A through the proposed approach, while it was placed in Class B by other models. This could be attributed to its exceptionally high annual demand ($=502,735$) and economic order quantity (EOQ) ($\approx 51,876$) compared to other items in the dataset.

In addition, the study findings reveal that lead time and inventory turnover are highly significant criteria, but they do not exert dominant influence over other criteria. For example, items 52 and 41, which have high values under the AUC criterion, have the same classification by the proposed approach and others. They were probably classified as Class C due to having a very low annual demand and EOQ. Therefore, it should be noted that such high differences observed in the Tables 3 and 4 are due to the introduction and structural nature of the proposed approach, other MCDM models, and/or the criteria weight used to run classification models. Furthermore, it should be noted that in the current study that the lead time criterion is 0.284, as shown in Table 2, demonstrating its highest significance. Thus, the classification solution obtained could be considered as a proposed solution of data-driven results. Although Liu et al. (2016) are the first to present this real dataset (63 SKUs) for addressing the MCIC, they did not include the actual classification status used by the sports apparatus manufacturer industry. Hence, it is expected that any newly proposed classification method could yield variant analytical results, explaining the variance in our classification results (see Table 4).

Table 4: Items classification result based on the proposed approach and different MCDM models for comparisons.

SKUs	Proposed Approach	Lolli ^a	Liu ^a	CVNS-ELECTRE III ^b	TOPSIS	PROMETHEE II ^c	COPRAS ^c
13	A	C	C	C	C	C	C
32	A	A	A	B	C	C	C
56	A	B	B	B	C	C	C
57	A	C	C	B	B	B	B
58	A	A	A	A	B	B	B
60	A	C	C	C	C	C	C
61	A	B	B	C	C	B	A
14	B	C	C	C	C	C	C
54	B	B	B	B	B	A	A
17	B	B	B	C	C	C	C
8	B	B	B	C	C	C	C
62	B	C	C	C	C	C	C
27	B	A	A	B	C	C	C
6	B	C	C	C	C	C	C
34	B	C	C	C	C	C	C
49	B	C	C	C	C	C	C
44	B	C	C	C	C	C	C
39	B	A	A	A	C	B	B
38	B	C	C	A	C	B	B
55	B	A	A	A	C	C	C
19	B	C	C	C	C	C	C
36	B	B	B	C	C	B	B
18	B	C	B	C	C	C	C
46	B	A	B	C	C	B	A
26	B	A	A	B	C	C	C
31	B	C	C	B	B	C	C
22	B	C	C	C	B	C	C
25	B	C	C	B	B	A	A
53	B	B	B	B	C	B	B
16	B	C	C	B	B	C	C
5	B	B	B	C	B	C	C
4	B	B	B	A	B	C	B

20	C	C	C	C	B	C	C
51	C	B	B	B	B	B	C
30	C	C	C	B	B	C	C
12	C	C	C	C	C	C	B
24	C	C	C	C	B	B	B
50	C	C	B	B	C	B	B
63	C	A	A	A	C	B	B
35	C	B	B	C	C	B	B
47	C	B	B	C	C	C	C
9	C	C	C	B	B	B	B
42	C	B	B	A	C	A	A
23	C	C	C	B	B	B	B
1	C	B	B	C	B	B	B
59	C	C	C	C	C	C	C
7	C	B	B	C	B	B	B
15	C	B	B	C	B	B	B
40	C	B	B	C	B	B	B
3	C	C	C	C	B	A	A
28	C	B	B	C	B	C	C
10	C	B	B	C	B	B	C
45	C	B	B	B	B	B	B
2	C	B	C	B	A	B	B
43	C	C	B	B	B	C	C
11	C	C	C	B	A	A	B
21	C	C	C	C	A	A	A
33	C	C	C	B	A	B	B
48	C	C	C	C	A	B	B
37	C	B	B	C	A	A	B
41	C	C	C	C	B	C	C
29	C	C	C	C	A	B	B
52	C	C	C	C	C	C	C

^a Source: Reproduced classifications by Liu et al. (2016). ^b Source: Reproduced classifications by Douissa and Jabeur (2020).

^c Source: Zowid (2023).

6 Research validation: method and results

The performance of the inventory system could be assessed through some measurable factors of total inventory cost, predefined *CSL* per ABC class, and fill rate. Each factor takes into consideration a different set of criteria to validate a proposed classification model (Teunter et al., 2010). Babai et al. (2015) have recently proposed a mathematical technique for measuring and verifying the performance of inventory systems while classifying the SKUs. Their study has considered different significant inventory criteria (e.g., approximate ordering cost, demand volume, demand value, and lead time) in which inventory cost and service are built to reflect inventory performance. Their study considered different mathematical programming models and became widely used to validate any proposed classification model and result. Hence, the inventory cost and service evaluation technique presented by Babai et al. (2015) is performed to validate our proposed approach. Their technique can be applied using the two key factors that are described next.

First: Total inventory cost

Total inventory cost involves every expense associated with carrying and managing a given level of inventory in stock until its delivery to customers. Total inventory costs (*TIC*) are commonly estimated as a percentage of unit value (Babai et al., 2015; Zowid et al., 2026). Holding/carrying costs usually get greater with the level of inventory, as larger quantity orders cause higher carrying costs (Aziz et al., 2014). Total inventory cost (*TIC*) in the MCIC context is calculated as:

$$TIC = \left[\sum_{i=1}^N H_i F_i \sigma_i \sqrt{LT_i} \right] \quad (23)$$

where H_i denotes the estimation of holding cost i^{th} SKU item, F_i denotes the estimation of the safety factor per i^{th} SKU item, and $\sigma_i \sqrt{LT_i}$ denotes the estimation of the standard deviation of lead-time demand per i^{th} SKU item.

Second: Total order fill rate

The order fill rate is another service factor that has been proposed to support the limitations of *CSL*. It measures the total demand quantity that is ordered over a specified finite period and that is fulfilled from the stock on hand. Also, it translates the lowest ratio of demand satisfaction that can be anticipated on average. It is thus an indication performance, signifying how effective the inventory is with a lower ratio, which indicates a poorer inventory performance and vice versa (Axsäter, 2015; Babai et al., 2015; Babiloni & Guijarro, 2020; Zowid et al., 2026). Therefore, the total order fill rate (*FR*) for a fixed *CSL* per class on the inventory is computed as:

$$Total\ FR = \left[\frac{\sum_{i=1}^N FR_i D_i}{\sum_{i=1}^N D_i} \right] \quad (24)$$

$$FR_i = \frac{\sigma_i \sqrt{L_i}}{EOQ_i} G(k_i) \quad (25)$$

The result obtained is compared with the six MCDM models and is analyzed and validated through the cost and services system obtained from the real-life dataset used in Liu et al. (2016). The estimation of inventory cost and services involves several key criteria measurements, such as constant lead time and standard deviation lead time of demand, which are statistically reported in Table 5. A detailed calculation of the inventory costs and service levels for the proposed approach is reported in the Appendix.

Table 5: Presents the descriptive statistics of the 63 SKUs and key parameters used for the cost and service.

	Daily Demand d_i	Demand D_i	Daily LT LT_i	St. dev of LT demand $\sigma_i \sqrt{LT_i}$	Ordering quantity EOQ_i	Safety factor F_i	Ordering cost (¥)	Holding cost (¥)	Unit cost (¥)
Min	0	5	1	0.488	1,320	1.282	1	0.000	0.680
25th pctile	3.391	1,234.40 0	6	79.752	153.595	1.282	1	0.039	71.520
Mid	29.927	10,893.2 66	14.77	10,893.26 6	1,156.915	1.542	1	0.305	555.637
75th pctile	11.345	4,129.47 5	23	360.265	469.559	1.645	1	0.104	189.885
Max	1,381	502,735	30	47,504	51,876	2.326	1	9.431	17,164.0

Table 6 reports the results of the achieved FR and the TIC when an assigned target CSL is considered for each class across different classification models. It is worth mentioning that the current study presents three scenarios of the targeted CSL . The first target CSL was adopted from Babai et al. (2015) to present inventory performances of the proposed approach along with other models under CSL sets (0.99, 0.95, 0.90). The second and third target CSL sets—0.95, 0.90, and 0.85 and 0.97, 0.93, and 0.88—were respectively adopted from Khan et al. (2025) and Babai et al. (2015) to present an additional scenario, thereby simulating how small changes in demand or lead time affect these service levels. The study findings showed valuable insights into the inventory performance. Notably, according to the first target CSL , our proposed approach results in lower total inventory cost (about 1237 ¥) and achieves a higher FR (0.989%) while the benchmark classification models result in higher inventory costs and either high or very low FR s (e.g., CVNS-ELECTRE III versus Lolli). From Table 6, we find that the second and third target CSL sets result in the same conclusions and affirm that the proposed approach remained at a high level when compared to others. Overall, the proposed approach is the most superior when compared to other benchmark MCIC models (see Table 6). This superiority may be due to the idea used for structuring the inventory classification process, which intends to capitalize on the beneficial aspects of various optimizing methods for advancing criteria weights, inventory performance aggregates (bias compensation evaluation), and the RC index. The outperformance of the proposed approach is due to not imposing a descending ranking order among the criteria used to classify the items, where both the lead time and turnover ratio are the most impactful criteria. This does not influence the total inventory cost (holding cost and unit cost) even if an inventory unit with a substantial unit cost is stratified as lower classes in relation to others with trivial unit costs, thus ensuring a minimization of the total inventory cost. The outperformance of the proposed approach, as well as that of the benchmark classification methods that took into consideration the demand value and the demand volume criteria, is driven by a high ranking of a stock-keeping item with a high unit cost. The CVNS-ELECTRE III (Douissa & Jabeur, 2020) could offer the same reason regarding the descending ranking order among criteria and not enforcing the total inventory cost. Hence, it can then be considered as a second superior model. The underperformance of some other models have been investigated and comparatively analyzed in detail (Babai et al., 2015; Douissa & Jabeur, 2020).

Table 6: Inventory cost and order fill rate results of the GRA-DFA approach compared to other models

	1 st Target CSL for classes ABC (99% _{oA} , 95% _{oB} , 90% _{oC})		2 nd Target CSL for classes ABC (97% _{oA} , 93% _{oB} , 89% _{oC})		3 rd Target CSL for classes ABC (95% _{oA} , 90% _{oB} , 85% _{oC})	
	Costs in (¥)	Achieved FR_T	Costs in (¥)	Achieved FR_T	Costs in (¥)	Achieved FR_T
Lolli ^a	1430.896	0.961	1269.028	0.955	1097.737	0.935
Liu ^a	1427.165	0.961	1268.856	0.955	1095.220	0.934
PROMETEE II ^b	1456.264	0.980	1288.096	0.971	1113.737	0.956
COPRAS ^b	1433.372	0.980	1274.787	0.971	1101.988	0.956
ELECTRE III ^a	1407.900	0.980	1255.549	0.971	1081.057	0.956
TOPSIS	1453.120	0.980	1285.329	0.971	1110.674	0.956
GRA-DFA	1237.405	0.989	1147.013	0.982	980.071	0.971

^a Source: reproduced classifications by (Douissa & Jabeur, 2020), ^b Source: reproduced classifications by (Zowid, 2023).

7 Conclusion

In this study, a structural classification approach based on GRA and DFA is proposed to adequately improve the MCIC problem. The proposed approach is named the GRA-DFA. Three different methods have been used to infer balanced criteria weights so they operate as input parameters of the GRA-DFA, in which the GRA-DFA generates aggregate score of each inventory item (i.e., a satisfied score). A real-world inventory dataset is employed for an efficient ABC inventory classification and comparative investigation. This research work offers an efficient inventory classification approach, exploiting the utility of various algorithms for improving the MCIC in terms of classification, inventory cost, and service efficiency (e.g., enhancing services and lowering cost). The main contribution is the consideration of compensation and non-compensation evaluations to offer a bias-compensated score for each inventory item. The study findings based on classification are compared with six existing classification (MCDM) models. From the inventory classification perspectives, the study findings show that there is some concordance and discordance among the SKUs of the proposed approach and others. From the inventory cost and fill rate perspectives, the study findings show that our proposed approach outperforms others, resulting in a high fill rate and low inventory cost, which are impactful factors in the supply chain system, specifically the MCIC context. At the inventory dataset and classification levels, our suggested approach is validated through the dataset that solely depends on a constant lead time and demand. However, in today's business environment, dynamic criteria like lead time and demand present a significant challenge not only for stratifying inventory effectively but also for the layout and planning of warehouse facilities. Therefore, future research work could conduct additional empirical examinations that incorporate our proposed approach, dynamic lead time, and demand linked with the management of warehouse facilities. At the level of advancing the MCIC system, the work in this article could be extended through incorporating other compensation and non-compensation assessments for the MCIC, for example, synthesizing the association rule learning (ARL) model as a non-compensatory with a fully compensatory machine learning like the multiple linear regression model (MLR). Constructing such models requires searching the criteria weights, the MLR model, or others, and could serve effectively. Last, this synthesizing could provide multi-response variables in which one model validates the other.

8 References

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Appendix (1): Cost and service computation of the GRA-DFA approach for a sample of (63-SKUs).

[illegible]