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Abstract:
The literature is abundant with research studies that have been developed to provide an efficient model which has never been studied for multicriteria inventory classification MCIC problems. Therefore, this study proposes two hybrid inventory classification systems. Recently, the TOPSIS model has been widely developed, initially examined, and found very efficient to the (MCIC) due to its advantages and simplicity of use. In contrast, to the best of our knowledge, the PROMETHEE II and COPRAS models for determining (criteria weights) parameter values and classification, resulting in low/or competitive inventory cost and high service level. The proposed models utilize two sets of weights of CRITIC and Spearman's rho (SR) tools for learning and optimizing PROMETHEE II and COPARS. In addition, a performance analysis is validated using a real-world dataset composed of 63 stock-keeping units (SKUs). The performance is compared to existing six MCIC classification models. The results reflect performances of the proposed models. Additionally, the comparative analysis indicates that the COPRAS model is the most preferred. Finally, the performance of the proposed models can be a great support for the overall supply chain system and decisions.

Keywords: *Supply Chain; ABC inventory analysis; multi-criteria inventory classification; PROMETHEE II; COPRAS.*

الملخص:

الأدبيات وفيرة بالدراسات البحثية التي تم تطويرها لتوفير نظام فعال لعملية تصنيف بنود المخزون. في الآونة الأخيرة، فقد تم تطوير نموذج TOPSIS على نطاق واسع، وتم اختباره بشكل مبدئي، ووجد أنه فعال للغاية في عملية تصنيف بنود المخزون متعدد المعايير (MCIC) نظرًا لمزاياه وبساطة استخدامه. في المقابل، وعلى حد علمنا، إنه لم يتم اجراء دراسة نماذج PROMETHEE II و COPRAS في إطار عملية تنصيف المخزون MCIC. لذلك تقترح هذه الدراسة نموذجين هجينين لتحديد أوزان المعايير والتصنيف لبنود المخزون، بما يعزز تخفيض تكلفة المخزون ورفع مستوى الخدمة. تستخدم النماذج المقترحة مجموعتين من أدوات تحديد الأوزان CRITIC و Spearman's rho (SR) لتعلم وتحسين PROMETHEE II و COPARS في إطار تصنيف المخزون متعدد المعايير (MCIC). بالإضافة إلى ذلك، يتم التحقق من صحة تحليل الأداء باستخدام مجموعة بيانات حقيقية تتكون من 63 وحدة تخزين (SKU). تتم مقارنة الأداء مع ستة نماذج تصنيف MCIC حالية. بالتالي سوف عكس النتائج أداء النماذج المقترحة. بالإضافة إلى ذلك، يشير التحليل المقارن إلى أن نموذج COPRAS هو الأكثر تفضيلًا. أخيرًا ، يمكن أن يكون أداء نماذجنا المقترحة دعمًا كبيرًا لنظام وقرارات سلسلة التوريد بشكل عام.

الكلمات المفتاحية: *سلسلة التوريد؛ تحليل بنود مخزون ABC؛ تصنيف بنود المخزون متعدد المعايير ؛ PROMETHEE II؛ COPRAS.*

1. Introduction

At present, industrial companies of different sizes have thousands of inventories with diversified characteristics and demand patterns, which require an effective supply chain system and stock control. Inventory management is quite a complex function that entails the development of intelligent systems to support decisions (Boylan, Syntetos, & Karakostas, 2008). Inventory classification methods depend heavily on a mono criterion (annual consumption cost) or multicriteria to divide SKUs into three classes: A (highly important), B (moderately important), and C (relatively unimportant). Accordingly, each class has approximate percentages in terms of quantity and value for better stock control. Recently, multicriteria inventory classification MCIC has become a substitutional technique that considers further criteria for evaluating inventories. It aims to arrange items in a specific manner that reflects the level at which inventory is to be held, so that an appropriate inventory control policy is applied. In addition, the purpose of classifying inventories is to establish effective system leads to greater cost-effectiveness and business success. This has confirmed by (Liu, Liao, Zhao, & Yang, 2016) where they have indicated that ABC classification of inventory would have a significant impact on the overall inventory cost and policy of inventory control (Vukasović, Gligović, Terzić, Stević, & Macura, 2021). In the MCIC literature, many studies have been conducted using various approaches (e.g., machine learning) to overcome shortcomings of the MCIC. One of these shortcomings is determining the criteria weights for evaluating inventory items. For instance, the analytic hierarchy process (AHP) model has been widely used to provide weights in subjective estimations; however, it may lead to outcomes that cannot be generalized. Furthermore, artificial intelligence technologies, such as a genetic algorithm (GA) have been proposed to infer the objective weights for the MCIC. However, their implementations have been somewhat complicated, whereas other available statistical tools are simpler and more efficient. Indeed, the literature is abundant with diversified tools for extracting criteria weights but give contradictory results that could be difficult to validate, thus making decision-making a perplexing problem that affects the entire inventory classification system. Due to the issues associated with the determination of criteria weights, besides the few investigations of other advantageous MCDM models for the MCIC problem, this motivates our research work to fill the gap stated in above. As it should be noted that most of the existing MCIC models such as (R-model, ZF-model, Ng-model, H-model, Lui-model and Lolli-model) considered in this current research work only focused on developing a classification method and comparative classification results without looking at costs and services of the inventory system (i.e. total holding inventory cost, cycle service level and fill rate of satisfied demand) that is a significant factor in showing the overall inventory performance. Thus, this study could adequately address the stated problem by using CRITIC and SR models that can efficiently estimate weights and operate ranking models with respect to MCIC. While the main advantage of the CRITIC and SR is extracting weights by measuring the mean, standard deviation and correlation coefficient, the main advantage of the preference ranking organization method for enrichment evaluation (PROMETHEE II) and complex proportional assessment (COPRAS) models is the completeness of ranking order prudently, thus avoiding errors in decision-making and providing proportional dependencies of significance and utility degree of the available items. Thus, to fill the gap in the extant literature, this study proposes new hybrid models as alternatives to the existing MCIC solutions. The advantage of the proposed models shows a comprehensive analysis of inventory ABC classification when compared under the PROMETHEEII that has been built in original to provide overall estimate based on measuring shortest and farthest distances among inventory items (i.e. Squared Euclidean Distance), and the COPRAS that has been built on the nature of providing an overall estimate based on measuring (maximum and minimum weights) among a set of inventory items. Hence, the contributions of this study are twofold. First, it presents new combined set of weights. The weights follow a simple combination methodology with balanced estimations that is conducted for the first time. The obtained weights operate the two classification models to generate the final inventory evaluations. Second, it evaluates the performance of the inventory systems with respect to inventory costs and services by using a comparative analysis method of Babai, Ladhari, and Lajili (2015). Besides, considering further models of (Lolli, Ishizaka, & Gamberini, 2014; Liu, Liao, Zhao, & Yang, 2016) in terms of inventory cost and services evaluation.

The remainder of this manuscript is as follows. In the next section, related literature is reviewed. The materials and methods section describe the research problem and formulate the proposed models. It is followed by the results section that describes the findings and the validation approach. In the final section, we discuss and summarize the conclusions of this study.

2. Related Literature

In the past few decades, many studies have been conducted to address MCIC problems. The most relevant ones to this research study employ two techniques: mathematical programming (MP) and multicriteria decision making (MCDM).

Ramanathan (2006) developed a linear optimization model, which is referred to as the R-model for SKUs classifications. The R-model is equivalent to a data envelopment analysis (DEA) and aims to obtain a set of weights which maximizes an item score. It employs a weighted additive function that automatically estimates the optimally weighted scores.

Zhou and Fan (2007) proposed a linear optimization model, referred to as the ZF-model, aimed at alleviating some shortcomings of the R-model. It incorporates two balancing features that estimate the maximum and minimum favorable weights. The model offers a control value that can be subjectively determined by a decision-maker for preferences.

Ng (2007) presented an alternative mathematical solution using weighted linear programming technique, called the Ng-model for the MCIC. The model aims to simplify the estimation procedures to provide scalar score for inventory classification without a linear optimizer.

The AHP model based-MCDM technique was developed by (Saaty, 1980) and initially used for MCIC by (Flores, Olson, & Dorai, 1992; Gajpal, Ganesh, & Rajendran, 1994; Partovi & Hopton, 1994). Typically, AHP is used to infer weights and assess inventory performance. Although it has been broadly and differently applied to MCIC problems; it has been criticized because it involves a significant amount of subjectivity in pair-wise comparisons of criteria preferences and ranking levels of items associated with weights. Nonetheless, it is still utilized owing to its usefulness, particularly with the TOPSIS model.

Using a small sample of a real-world dataset from the Indian pharmaceutical industry, Bhattacharya, Sarkar, and Mukherjee (2007) were the first to employ a hybrid TOPSIS model for MCIC. First, they used AHP to specify the values of criteria weights, then implemented the TOPSIS scheme to generate the final evaluation of SKUs for ABC classification. Their research work conducted by considering various criteria such as (LT, unit cost, consumption rate, perishability of items and cost of storing items. In addition, the model's stability and performance were validated by using the ANOVA statistical analysis and showed that it provides a low average investment.

Arikan and Citak (2017) developed AHP-TOPSIS integrated interactive framework to determine the criteria weights of TOPSIS and to generate inventory scores using TOPSIS. A large dataset of 2444 SKUs obtained from an electronic company has been considered for a real-life case.

Using a benchmark inventory dataset, Kaabi, Jabeur, and Ladhari (2018) proposed a GA hybrid approach for TOPSIS and SAW to carry out ABC inventory classification. The performance of their models was tested with respect to some existing MCIC classification models.

Douissa and & Jabeur (2020) proposed a new ABC classification approach which involves a non-compensatory aggregation procedure, based on a simplified ELECTRE III model, to compute the score of each inventory item where a non-compensatory scheme assumes that a poor score of an item under a specific criterion cannot be compensated by its scores on the remaining criteria used. Their research work conducted by utilizing two datasets to validate their obtained results that demonstrated low inventory cost when the total relevant cost criterion is estimated.

Thereafter, except for COPRAS and PROMETHEE II, several other MCDM models, such as AHP, Fuzzy TOPSIS, VIKOR, and PROAFTEN were tested for MCIC.

3. Methods and Materials

3.1. Description of the MCIC problem and dataset

We consider a sample inventory dataset composed of variables with respect to J criteria measurements that needs to be classified into different classes for preferences as A, B, or C. Let $x_{ij}=1, 2,\ldots, N$, $j=1, 2, \ldots, J$ provides the performance of SKU_i with respect to criterion j. A common practice requires specifying criteria weights and then proposing certain aggregation plans to find the overall SKUs scores. Inventory ABC rank is then assigned. This study uses a dataset detailed in (Liu, Liao, Zhao, & Yang, 2016). It contains 63 SKUs with respect to four criteria: average unit cost (AUC), annual RMB usage (ARMBU), lead time (LT), and turnover rate (TOR). The distribution of items is pre-specified as 10 %–20% for class A items, 20 %–50% for class B items, and at least 50% for class C items.

3.2. Methodology

In the sequel, this research work consists of two basic stages. Each stage is composed of a set of tasks that need to be estimated and followed. Therefore, with assuming that all criteria are positively related to the importance level of an inventory item, the first stage is concerned about the weight schemes that is proposed in this work to be derived from the proposed inventory dataset by using algorithmic tools which should give meaningful weights for preferences. The use of CRITIC and SR models are examples. The second task is concerned about evaluating each inventory item that should be estimated by a classifier model to generate the overall performance score for further ABC analysis and ranking. For this task, PROMETHEE II or COPRAS is utilized. By this, all the items are estimated with the same group of weight schemes, and consequently, their performance scores are comparable and lead to more appropriate inventory classification decisions. For the hybridized models proposed in this study, the next section is devoted for the algorithmic steps.

3.3. Formulation of proposed models

In this study, the proposed models are named CRITIC-SR-PROMETHEE II and CRITIC-SR-COPRAS. First, we use the CRITIC and SR tools to estimate the criteria weights that are extracted from the nature of the dataset used. Second, the MCDM ranking models are applied to provide the final evaluations each SKU in a single score that is so called "optimal score". To apply the proposed models, five main phases are completed, as described in the next section.

Phase 1: CRITIC algorithm

The CRITIC is a method based-MCDM, which was developed by (Diakoulaki, Mavrotas, & Papayannakis, 1995). It is mainly used to determine the weights of attributes through a decision matrix. The CRITIC steps are as follows.

1.1 A decision matrix is linearly normalized using the following equation:

$$\beta_{ij} = \frac{z_{ij} - min\{z_{ij}\}}{max\{z_{ij}\} - min\{z_{ij}\}}, \text{ for all } i = 1, ..., I. \text{ and } j = 1, ..., J. \tag{1}$$

1.2 We determine the amount of information contained in the jth criterion response:

$$\delta_{ij} = \sigma_j \sum_{j=1}^{J} (1 - r_{ij}), \quad 2)$$

Where, σ_j represents the standard deviation of jth response and r_{ij} denotes the correlation coefficient between two criteria.

1.3 We compute the normalized objective weights using the following equation:

$$\rho_j = \frac{\delta_{ij}}{\sum_{j=1}^{J} \delta_{ij}} \tag{3}$$

Noting that the CRITIC method gives greater weight value to the criterion which has high σ_j and low correlation to other criteria.

Phase 2: Spearman's rho algorithm

The SR tool was developed to measure the correlation coefficient between bivariate data and the mean of normal distribution analysis. There are various ways to extend SR to a multivariate measure of the association between d variables $X_1,\ldots,X_d$ (Schmid & Schmidt, 2007). The model uses simple arithmetical mean and variance. Thus, it is reformulated to fit the MCIC problem as follows:

2.1 We calculate non-normalized mean μ_j expressed as:

$$U_j = \frac{1}{J} \sum_{j=1}^{J} \mu_j \tag{4}$$

2.2 We calculate the SR variance as:

$$SR_{ij} = \sum_{j=1}^{j} (S_{ij} - \mu_j)^2 \tag{5}$$

2.3 A normalized criteria weight for the SR is computed as:

$$g_j^* = \frac{SR_{ij}}{\sum_{j=1}^{J} SR_{ij}} \tag{6}$$

Phase 3: Combination of weights

The combination of set of weights is stored in a matrix which is called the "weight matrix" to find the final criteria weights. To do so, the weighting matrix W=$(w_{ij})m*n$ is computed as:

$$w_j = \frac{1}{J} \sum_{j=1}^{J} \rho_j g_j^* \tag{7}$$

Phase 4: COPRAS

The COPRAS model was developed by (Zavadskas, Kaklauskas, & Sarka, 1994). It is an effective MCDM model that has the unique property of focusing on evaluating and ranking alternatives by maximizing and minimizing weighting indices (Podvezko, 2011). The COPRAS steps can be explained as enlisted below:

4.1 For a constructed decision matrix, we assign the criteria weights w_j for all (j=1, …, J) values such that is:

$$\sum_{j=1}^{J} w_j = 1 \tag{8}$$

4.2 We calculate the normalized matrix $R = (y_{ij})$:

$$y_{ij} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{M} (x_{ij})^{\wedge 2}}} \tag{9}$$

4.3 We calculate the weighted normalized matrix $V = (V_{ij})\ I, J$:

$$V_{ij} = w_j \, x_{ij} \tag{10}$$

4.4 We calculate the maximization and minimization weighted solution as:

$$max_i = \sum_{j=1}^{J} u_{ij}$$

$$min_i = \textstyle\sum_{j=k+1}^{J} u_{ij} \tag{11}$$

4.5 We calculate the relative weight Q_i of A_i as:

$$Q_i = max_i + \frac{min_i \sum_{i=1}^{N} min_i}{min_i \sum_{i=1}^{N} \frac{min_i}{min_i}} \tag{12}$$

4.6 We determine the highest value (max_{Q_i}) among candidates of A_i as:

$$A^* = \{A_i | max_{Q_i}\} \tag{13}$$

4.7 We calculate the weighted performance degree (U_i) as:

$$U_i = \frac{Q_i}{max_{Q_i}} .100\% \tag{14}$$

Phase 5: PROMETHEE II

The PROMETHEE model was first developed by Brans in 1982. It is characterized by many types of preference functions that are used to assess the differences between alternatives in judgments. PROMETHEE II aims to provide a full ranking of alternatives. The preference function describes how one alternative is to be ranked and interprets the deviation among samples on a single parameter into a preference degree. That is, the preference degree exemplifies the deviation function. Hence, deviations result in weaker or stronger preference degrees (Makan, Malamis, Assobhei, Loizidou, & Mountadar, 2012). The PROMETHEE II follows the below seven stepwise procedures:

5.1 For a constructed decision matrix of a dataset, we assign weights and normalize decision matrix $R = (y_{ij})$ for beneficial criteria expressed as:

$$y_{ij} = \frac{x_{ij} - min\{x_{ij}\}}{max\{x_{ij}\} - min\{x_{ij}\}} \tag{15}$$

5.2 We calculate the evaluative differences (deviations) of each *i*th alternative with respect to the other alternatives as:

$$D = (M_a - M_b) = \left(y_{(ij)_a} - y_{(ij)_b}\right) \tag{16}$$

5.3 We calculate the preference function K_j as given:

$$K_j(M_a, M_b) = 0 \ if \ y_{(ij)_a} \le y_{(ij)_b} \rightarrow \mathrm{D}\,(M_a - M_b) \le 0$$

$$K_j(M_a, M_b) = \left(y_{(ij)_a} - y_{(ij)_b}\right) if \ y_{(ij)_a} > y_{(ij)_b} \rightarrow \mathrm{D}\,(M_a - M_b) > 0 \tag{17}$$

5.4 We calculate the aggregated preference $\pi(M_a, M_b)$:

$$\pi(M_a, M_b) = \frac{\left[\sum_{j=1}^{J} w_j K_j(M_a, M_b)\right]}{\sum_{j=1}^{J} w_j} \tag{18}$$

5.5 We create an aggregate $R = (y_{ij})$. Depending on the number of alternatives A_i, $A_i \times A_i$ matrix is formed.

5.6 We determine the leaving (or positive) and entering (or negative) outranking flow of the alternatives as given:

Leaving flow ($\emptyset^+$):

$$\frac{1}{n-1} \sum_{b=1}^{N} \pi(a, b)$$

Entering flow ($\emptyset^-$):

$$\frac{1}{n-1} \textstyle\sum_{b=1}^{N} \pi(a, b) \tag{19}$$

5.7 We compute the final ranking flow of each alternative as:

$$\{\emptyset(a)\} = \{\emptyset^+(a)\} - \{\emptyset^-(a)\} \tag{20}$$

4. Results

To examine the performance of the proposed models, the real dataset of 63 SKUs was evaluated in terms of four criteria: AUC, ARMBU, LT, and TOR. Once the criteria weights were estimated, the PROMETHEE II and COPRAS models were implemented to generate the final optimal score of each SKU. After running the models in an Excel sheet, the obtained weights are (W_{AUC}=0.008, W_{ARMBU}=0.999, W_{LT}=0.0001, W_{TOR}=0.0000). Table (1) presents the detailed weights obtained. Depending on the nature of the inventory data used in this research study, the ARMBU was found to be a significant criterion in accordance with Zhou and Fan (2007) they have stated that annual usage value as the most important criterion. Moreover, this has affirmed in a recent study by (Karagiannis & Paleologou, 2021) who have stated that their empirical results showed the importance of the three classification criteria, namely that annual value usage is at least as important as average unit cost, which in turn is at least as important as lead time. The weights were estimated in an objective manner as combined and based on mean, which should lead to more accurate items classifications when operating PROMETHEE II and COPRAS. Thus, table (2) presents the results obtained, compared to some other existing models.

Table (1): Extracted criteria weight matrix of the dataset used

Dataset 63 SKUs	W_{AUC}	W_{ARMBU}	W_{LT}	W_{TOR}
CRITIC	0.0008	0.9991	0.0001	0.0000
SR	0.0003	0.9997	0.0000	0.0000
Combined (CRITIC-SR)	0.0005	0.9994	0.0000	0.0000

Table (2): Classification results of the 63 inventory items of the MCIC models.

SKUs	AUC	ARAMU	LT	TOR	CRITIC-SR-PROMETHEE II	CRITIC-SR-COPRAS	R[a]	ZF[a]	Ng[a]	H[a]	Lolli[a]	Liu[a]
1	210.39	413692.2	18	0.487	B	B	B	A	B	B	B	B
2	70.92	363303.1	29	1.87	B	B	B	B	C	B	B	B
3	125.24	452711.6	12	1.653	A	A	C	B	B	B	A	A
4	26.72	391531.3	16	2.548	C	B	C	C	C	B	C	C
5	81.98	164125.6	24	1.204	C	C	C	C	C	C	C	C
6	164.18	101627	12	0.162	C	C	B	C	B	C	C	C
7	219.19	327849.6	5	2.994	B	B	B	A	A	A	B	B
8	190.53	55345.3	18	0.13	C	C	B	C	B	C	C	B
9	202.96	443096.1	18	0.378	B	B	A	B	B	B	B	B
10	119.58	294066.8	25	1.374	B	C	B	B	C	B	C	B
11	71.21	390861.5	30	2.407	A	B	B	B	B	A	B	B
12	113.36	298718.7	11	1.211	C	B	C	C	C	C	C	C
13	71.83	88071.9	1	2.264	C	C	C	C	C	C	C	C
14	89.35	41150.6	2	1.019	C	C	C	C	C	C	C	C
15	153.28	414547.2	14	1.032	B	B	C	B	B	B	B	B
16	103.63	77582	30	1.836	C	C	C	B	C	B	C	C
17	230.34	31681.6	2	2.822	C	C	A	C	A	B	B	B
18	80.27	295351.8	11	0.531	C	C	C	C	C	C	C	C
19	187.75	233313.8	6	0.353	C	C	B	B	B	C	C	C
20	51.35	231721.6	26	1.376	C	C	B	C	C	C	C	C
21	75.92	454758.8	20	2.929	A	A	B	B	B	A	A	A
22	67.16	80559.6	27	2.381	C	C	B	C	C	C	C	C
23	173.29	397196.1	23	0.471	B	B	B	B	B	B	B	B
24	41.71	336693	15	2.37	B	B	B	C	C	B	C	C
25	132.89	459578.7	3	2.152	A	A	C	B	B	B	B	B
26	50.33	281313.1	16	0.917	C	C	C	C	C	C	C	C
27	39.29	101493.5	13	0.431	C	C	C	C	C	C	C	C
28	189.24	128298.4	18	2.979	C	C	B	B	B	B	B	B
29	228.69	311478.1	29	2.319	B	B	A	A	A	A	A	A
30	54.94	188630.7	29	1.54	C	C	C	B	C	C	B	C
31	42.17	180117	30	1.135	C	C	B	B	C	C	C	C
32	199.8	15296.7	16	0.799	C	C	A	C	B	C	B	B
33	152.85	383919.9	22	1.79	B	B	A	B	B	B	A	A
34	193.37	119454.6	5	0.324	C	C	C	B	B	C	C	C
35	138.47	333290.6	6	2.05	B	B	C	B	C	B	C	C
36	73.4	374496.8	8	0.619	B	B	B	C	C	C	C	C
37	147.65	364491.1	28	2.665	A	B	A	A	B	A	A	A
38	40.93	407329.5	3	1.856	B	B	C	C	C	C	C	C
39	92.86	370301.3	21	0.107	B	B	B	C	C	C	B	B
40	225.49	322614	6	2.548	B	B	B	A	A	B	B	B
41	10261	50402.1	25	0.42	C	C	C	C	C	C	C	C
42	207.53	499699.9	10	0.692	A	A	C	B	A	B	B	B
43	243.36	209629.8	25	1.127	C	C	B	A	A	A	A	A
44	140.26	38914.1	25	0.609	C	C	C	C	C	C	C	C
45	170.96	370885.2	10	2.002	B	B	B	B	B	B	B	B
46	136.45	499854.8	7	0.376	B	A	C	B	B	B	B	B
47	187.27	274935.6	5	2.512	C	C	C	B	B	B	B	B
48	160.84	296976.8	28	2.108	B	B	B	A	B	A	A	A
49	36.47	78051.4	22	0.882	C	C	C	C	C	C	C	C
50	209.5	318688.5	4	2.259	B	B	B	B	B	B	B	B
51	32.53	273490.9	20	2.507	B	C	C	B	C	B	C	C
52	17164	142923	5	0.815	C	C	C	C	B	C	C	C
53	235.08	329205.1	3	1.574	B	B	B	B	A	B	B	B
54	113.84	497119.6	23	0.03	A	A	C	B	B	B	B	B
55	27.85	255434	6	2.227	C	C	B	C	C	C	C	C
56	15.4	103414	1	2.902	C	C	C	C	C	C	C	C
57	194.05	316586	1	2.928	B	B	B	C	B	B	B	B
58	0.68	341859.6	13	1.991	B	B	C	C	C	C	C	C
59	151.69	228109	18	1.259	C	C	C	C	C	C	C	B
60	89.23	43136.7	2	0.025	C	C	C	C	C	C	C	C
61	98.65	495254.8	1	1.089	B	A	A	C	B	C	A	B
62	99.15	20635.4	18	2.069	C	C	C	C	C	C	C	C
63	104.84	370919.4	11	1.214	B	B	C	C	C	C	C	C

[a] **Source:** reproduced classifications by (Douissa & Jabeur, 2020)

The obtained results were analytically compared from two aspects as follows: First aspect, in general view, they showed that only 15 out of 63 items were kept in the same classes when compared to other classification models. Specifically, findings reflected that no item is kept matched as class A out of the 7 A-items. Items 23 and 45 and 50 are kept matched as a class B out of 25 B-items. Lastly, items 5, 13, 14, 18, 26, 27, 44, 45, 49, 56, 60 and 62 are in match class of C out of 31 C-items. Second aspect, they reflected brief and overall comparative analysis among both the proposed models and the selected cited ones that are presented in table (3) below.

Table (3): Concordance and discordance approximate rates among models

Dataset 63 SKUs	Proposed models		Selected cited MCIC models	
	Number	Percentage	Number	Percentage
Similarities among items	55	87.30%	21	33.33%
Dissimilarities among items	8	12.70%	42	66.67%
Total	**63**	**100%**	**63**	**100%**

As table (4) and figure (1) present to highlight the numerical values of similarity and dissimilarity among models and classified items in a detailed matrix and visualized indicators. Under the factors of max and min values presented in the table (4), the proposed models showed high concordance rate as (87.302) when compared to each other. The H-model and the ZF-model showed high concordance rate as (80.952) when compared to each other. Both Lui and Lolli models result in high concordance rate that is as (92.063) when compared to each other whereas the ZF-model, the Ng-model, and the H-model result in low concordance rate as (50.794) when compared among themselves under factor of max and min rates. Figure (1) is generated for better sensitivity analysis when all models are considered and shown in group of trends. The figure showed that only the proposed models, Lolli and Liu models, could result in high concordance rates when compared to others. In conclusion, it is important to underline that, the obtained classification results will subject to another significant analysis that reflect their performances in terms of inventory cost and service that is one of the main objectives of conducting this research paper.

Table (4): Detailed concordance rate among classified items and models

	CRITIC-SR-PROMETHEE II	CRITIC-SR-COPRAS	R	ZF	Ng	H	Lolli	Liu
CRITIC-SR-PROMETHEE II	0.000	87.302	55.556	55.556	50.794	69.841	66.667	66.667
CRITIC-SR-COPRAS	87.302	0.000	53.968	50.794	50.794	61.905	65.079	60.317
R	55.556	53.968	0.000	52.381	57.143	52.381	61.905	63.492
ZF	55.556	50.794	52.381	0.000	69.841	80.952	71.429	68.254
Ng	50.794	50.794	57.143	69.841	0.000	63.492	69.841	68.254
H	69.841	61.905	52.381	80.952	63.492	0.000	74.603	77.778
Lolli	66.667	65.079	61.905	71.429	69.841	74.603	0.000	92.063
Liu	66.667	60.317	63.492	68.254	68.254	77.778	92.063	0.000
Max	87.302	87.302	63.492	80.952	69.841	80.952	92.063	92.063
Min	50.794	50.794	52.381	50.794	50.794	52.381	61.905	60.317

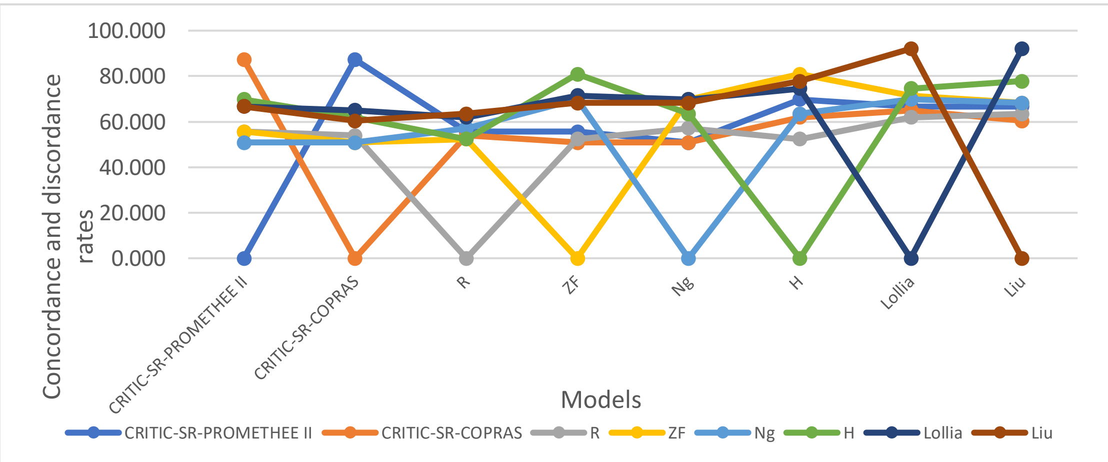

Figure (1): Sensitivity analysis of concordance rates among classified items and models

5. Validation: approach and results

Lajili, Babai and Ladhari, (2012) and Babai, Ladhari, and Lajili (2015) developed a general approach to evaluate the performance of any MCIC model as "inventory system" using two main coefficients: holding inventory cost and achieved fill rate. Thus far, this is the most modern approach and has become the benchmark for validation because it entails additional features such as ordering cost, and inventory review policy (s, *Q*), which reflect the possible degree of fulfilling customer demand that is directly satisfied from the on-hand stock. **First**, the aggregate achieved fill rate based on the mean demand D_i per item is computed as:

$$FR_T = \frac{\sum_{i=1}^{N} FR_i D_i}{\sum_{i=1}^{N} D_i} \tag{21}$$

Second, the total inventory cost including holding cost (H_i), safety factor (SF_i), and lead time (L_i) is expressed as:

$$C_T = \sum_{i=1}^{N} H_i\, SF_i\, \sigma_i \sqrt{L_i}, \tag{22}$$

For the proposed dataset used, both the inventory cost and achieved fill rate were calculated to evaluate the proposed models. Table (5) shows their performances under three targets for *CSLs*. Babai, Ladhari, and Lajili (2015) have affirmed that an increase in the fill rates leads to an increase in costs. Hence, the analysis showed that the proposed models resulted in high cost and fill rate. Furthermore, an additional analysis that combines the cost and fill rate in the curves was performed to provide more comprehensive comparisons. Following the researchers' instructions for explicating the curves and their functions, the efficiency curves in figure (2) showed that all models were adjacent with some variations. The proposed models showed competitive performance within the three targets of *CSLs*. The curve of the CRITIC-SR-COPRAS appeared on the top with demonstrating its high performance, followed by the CRITIC-SR-PROMETHEE II. In contrast, the others showed low efficiencies. The superiority of the CRITIC-SR-COPRAS model may be attributed to the nature of the items' classification process. For instance, COPRAS simultaneously measures the maximum and minimum weighted scores per item, whereas others compute the weights' contributions of an item among a set of items using either maximization or minimization weighted functions. The poor performance of the cited models has been extensively discussed in (Babai et al., 2015). Based on the limitations of this analytical study, the comparative analysis showed that CRITIC-SR-COPRAS tends to be the most preferred.

Table (5): Results of the proposed models compared to selected MCIC models

Targets *CSL* for classes ABC	1st Target *CSL* 99%, 95%, 90%		2nd Target *CSL* 95%, 90%, 85%		3rd Target *CSL* 90%, 85%, 80%	
Models	Cost	Fill Rate	Cost	Fill Rate	Cost	Fill Rate
CRITIC-SR-PROMETEE II	1456.264	0.980	1113.737	0.956	892.823	0.928
CRITIC-SR-COPRAS	1433.372	0.980	1101.988	0.956	885.156	0.929
ZF	1414.104	0.961	1089.360	0.934	875.288	0.904
R	1368.041	0.961	1060.527	0.934	853.388	0.904
Ng	1352.324	0.960	1051.929	0.933	847.461	0.902
H	1432.135	0.962	1099.261	0.935	882.134	0.905
Lolli	1430.896	0.961	1097.737	0.935	880.612	0.905
Liu	1427.165	0.961	1095.220	0.934	878.611	0.904

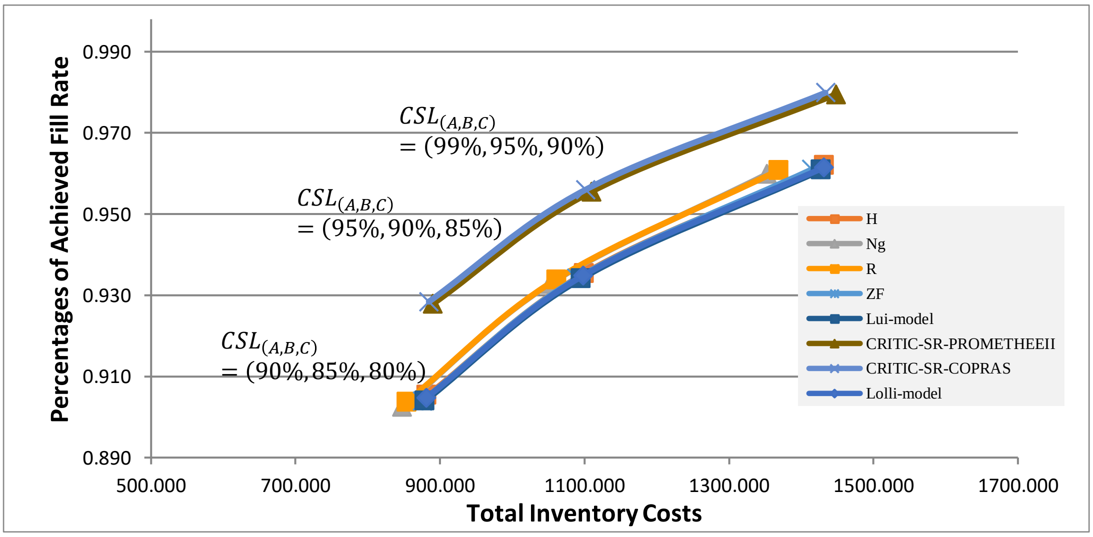

Figure (2): Sensitivity analysis of models for a combined service-cost

6. Discussion and conclusions

In this study, we developed new hybrid classification models for MCIC. The combined CRITIC and SR tools were utilized for unbiased weights estimation, and efficiently operate the MCDM ranking models to generate optimal solutions. The proposed models have named as (CRITIC-SR-PROMETHEE II and CRITIC-SR-COPRAS). The most focused proposing the hybrid classification models is not only to provide a classification scheme and comparative classification results, but rather to provide models that resulted in increasing the service level and decreasing inventory cost. To perform the proposed models, the study used a small real dataset, and the results of which were compared to other existing MCIC models concerning classification, inventory cost, and service. The sensitivity analysis generated to empirically investigate the concordance and discordance rate of classification, holding inventory cost, service level and fill rate of satisfied demand as well as to inferring insights towards the stability and performance of the proposed models and other cited models.

The empirical results showed that the proposed models resulted in high concordance rate when compared to all other cited MCIC models. This could be due to the weights' values generated by CRITIC and SR tools as well as the characteristic of the MCDM models utilized to give the final scores of the SKUs. Additionally, it could be due to the prespecified items quantity on each inventory class. The empirical results based on the combined inventory cost-service factor showed that the proposed models achieved high inventory performance. Precisely, the CRITIC-SR-COPRAS curve is on top, followed by the CRITIC-SR-PROMETHEEII model whereas the other cited MCIC models showed low performances. By this, the paper concludes that the CRITIC-SR-COPRAS is the most preferred because it achieved a promising outcome, that is, resulted in a high performance of service and cost inventory when combined. To generalize the proposed models, researchers could use a large real-life dataset that includes other important criteria, and other inventory control policies such as (R, S) or (s, S) since this study was utilized the (s, Q) policy. Finally, this study does not account for the impact of pandemics such as the current COVID-19 pandemic. Thus, future research should use a real case to investigate the impact of the Covid-19 pandemic on the inventory classification system, inventory behavior (i.e on-hand stock), lean and just-in-time systems which are widely used by companies.

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Declaration of interest:

The author declares that he has no conflict of interest.

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