Advances in Mathematical Finance & Applications, 6(4), (2021), 789-800
DOI: 10.22034/AMFA.2020.1878440.1290

Published by IA University of Arak, Iran
Homepage: www.amfa.iau-arak.ac.ir

A CRITIC-Based Improved Version for Multiple Criteria ABC Inventory Classification

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ARTICLE INFO
Article history:
Received 09 September 2019
Accepted 08 January 2020

Keywords:
Multi-criteria ABC inventory classification;
Linear programming;
The CRITIC approach.

ABSTRACT
In this paper, we present an improved version of Ramanathan model [R. Ramanathan, ABC inventory classification with multiple-criteria using weight linear optimization, Computer and Operations Research 33 (2006) 695-700] and Zhou and Fan model [P. Zhou & L. Fan, A note on multi-criteria ABC inventory classification (MCABCIC) using weighted linear optimization, European Journal of Operation Research, 182 (2007) 1488-1491]. The model that Ramanathan [1] offered, hereafter called the R-model, in spite of its advantages may lead to a situation in which the weights of some criteria in relation to an item would not play any role in determining the its overall score. Thus, for the R inventory items, the Zhou and Fan [2] approach, hereafter called the ZF-model, may lead to a situation where an item with a high value for an unimportant criterion is inappropriately classified as class A. Furthermore, none of the above studies take into account the ranking order of the criteria. Therefore, in order to remove drawbacks of both approaches, an integrated model based on criteria importance through inter-criteria correlation (CRITIC) is applied. The proposed approach determines the objective weights associated with all criteria rankings. At last, the results obtained from implementing the proposed model on an illustrative example are compared with other models.

1 Introduction

Determination of the appropriate ordering policies based on the priority of each item among others is the most usual approach for minimizing inventory costs. The multi-criteria ABC inventory classification (MCABCIC) is base of this technique where items are divided into 3 classes, namely, A (very important), B (moderately) and C (least important) and then the appropriate ordering policies are selected for each item. In Traditional ABC (TABC), there is only one criterion i.e. Annual dollar usage, however, there are many criteria that can affect the items rankings. In recent years, some papers have applied the weighted linear optimization (data envelopment analysis (DEA)) models [1-3] for MCABCIC classification. Ramanathan [1] proposed a weighted linear optimization model (hereafter the R-model) for MCABCIC where performance score of each item obtains using a DEA-like model. Unfortunately, it cannot take into account the ranking order (*RO*) of criteria. Also, the weights of some criteria in relation to an item may not play any role in determining its overall score. Zhou and Fan [2] (hereafter the ZF-model) extended the R-model by obtaining most favorable and least favorable scores for preventing zeroing the weight of an item against an unimportant criterion. Then, a composite index was constructed to combine these two scores. However, it does not consider *RO* of criteria. In real

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world, since the decision-making process is a collective activity; it is the better to adopt the considerations of different experts. In order to exploit the advantages of both models and removal of their weaknesses, the aim of this paper is to offer an optimization model based on criteria importance through inter-criteria correlation (CRITIC) for considering the different *ROs*. Reminder of paper is as follows. In section 2, R and ZF's models are explained summarily. The proposed model is presented in section 3. In section 4, a real illustrative example is shown to validate the more rational results of our model and finally the prioritizing differences of the proposed method with others models are stated in section 5.

2 R and ZF Models

2.1 R-Model

Let there are R $(r = 1,2,...R)$ items in warehouse which they are to be classified into classes A, B and C based on C $(c = 1,2,...C)$ criteria. Also, let x_{rc} and w_{rc} denote the measure and the weight of *r*th item against *c*th criterion, respectively. Furthermore, assume that all criteria are positive related to the score of the inventory items. If isn't such a case, transformations such as taking negative can be applied. The main target is to aggregate the performance of an inventory item in terms of different criteria to a single score, called the optimal inventory score of an item. Thus, the most favorable scores for each item *i* obtain by solving iteratively the following weighted linear optimization model (1):

$$\begin{aligned} gI_i = \max \; & \sum_{c=1}^{C} w_{ic}\, x_{ic}, \\ s.t. \; & \sum_{c=1}^{C} w_{ic}\, x_{rc} \leq 1, \qquad r = 1,...,R, \\ & w_{ic} \geq 0, \end{aligned} \tag{1}$$

2.1 ZF-Model

The main target is to determine the most favorable scores and the least favorable scores of an item and transform them into a single score such that items can be appropriately classified with respect to different criteria. Their model was exercised for not placing an item with high measure for an unimportant criterion as well as low measure for an important criterion as class A in R-model [1]. The most favorable scores for each item *i* obtain by solving iteratively the following weighted linear optimization model (2) which it, in real, is the same R-model:

$$\begin{aligned} gI_i = \max \; & \sum_{c=1}^{C} w_{ic}^{\,g}\, x_{ic}, \\ s.t. \; & \sum_{c=1}^{C} w_{ic}^{\,g}\, x_{rc} \leq 1, \qquad r = 1,...,R, \\ & w_{ic}^{\,g} \geq 0, \end{aligned} \tag{2}$$

Also, the least favorable scores for each item *i* are calculated by the following model (3):

$$
\begin{aligned}
bI_i = \min\ & \sum_{c=1}^{C} w_{ic}{}^{b} x_{ic}, \\
s.t.\ & \sum_{c=1}^{C} w_{ic}{}^{b} x_{rc} \geq 1, \qquad r = 1,\dots,R, \\
& w_{ic}{}^{b} \geq 0,
\end{aligned} \tag{3}
$$

Then a single score obtains by following composite index:

$$
nI_r(o) = o.\frac{gI_r - gI^0}{gI^* - gI^0} + (1-o).\frac{bI_r - bI^0}{bI^* - bI^0}, \tag{4}
$$

where, $gI^* = \max\{gI_r, r=1,2,...R\}$, $gI^0 = \min\{gI_r, r=1,,2,...R\}$, $bI^* = \max\{bI_r, r=1,2,...R\}$, $bI^0 = \min\{bI_r, i=1,2,..., R\}$, o is a control parameter that it is equal to 0.5 in Eq. (4). By sorting the composite scores $nI_r(o)$'s in descending order, the items are classified based on ABC classification analysis.

3 The Proposed Model

In this section, an improved version of CRITIC-based R and ZF models is introduced to take into account the different ranking of criteria. The CRITIC approach was first presented by Diakoulaki et al. [4]. It is a suitable method when determining the weights based on the decision maker preferences are not possible. The weight determined by this method is named as objective weight. It is based on contrast intensity of each criterion and conflict between criteria measuring based on the standard deviation and the correlation coefficient, respectively. Suppose that the crisp decision matrix be as $D = [x_{rc}]_{R \times C}$ for a MCABCIC problem where there are R items A_R $(r = 1,..., R)$ under C criteria C_C $(c = 1,..., C)$ and x_{rc} represents the assessment measure of item r with respect to criterion c . Also, let w_{rc} and $\mathrm{x}_c = (x_{1c}, x_{2c},..., x_{Rc})$ be the weight of item r with respect to criterion c and vector of c-th criterion, respectively. The above MCABCIC problem can be also showed in matrix format as follows:

$$
D = \left[x_{ij}\right]_{R \times C} =
\begin{array}{c}
 \\ A_1 \\ A_2 \\ A_3 \\ \vdots \\ A_R
\end{array}
\begin{array}{c}
\begin{array}{ccccc}
\overset{w_{i1}}{C_1} & \overset{w_{i2}}{C_2} & \overset{w_{i3}}{C_3} & \dots & \overset{w_{iC}}{C_C}
\end{array} \\
\begin{bmatrix}
x_{11} & x_{12} & x_{13} & \cdots & x_{1C} \\
x_{21} & x_{22} & x_{23} & \cdots & x_{2C} \\
x_{31} & x_{32} & x_{33} & \cdots & x_{3C} \\
\vdots & \vdots & \vdots & \dots & \vdots \\
x_{R1} & x_{R2} & x_{R3} & \cdots & x_{RC}
\end{bmatrix}
\end{array}, \tag{5}
$$

The following steps represent the CRITIC weight based on objective weights:

1. Normalize the performance measures of the above matrix to obtain the project outcomes as follows:

$$n_{rc} \cong \frac{x_{rc}\ 0 \min_{r \cong 1,2....,R}\{x_{rc}\}}{\max_{r \cong 1,2....,R}\{x_{rc}\} - \min_{r \cong 1,2....,R}\{x_{rc}\}}, \tag{6}$$

2. Assume that for C criteria, there are K ranking orders (RO) as follows [5]:

$$RO_k \cong \{RO_1, RO_2, ..., RO_K\}$$

3. Obtain the most favorable and the least favorable scores for each item r and ranking order k in the following matrices (using model (2) and model (3)), respectively:

$$S^g \cong \left[\bar{s}_{rc}^g\right]_{R \partial C} \cong \begin{array}{c} \begin{matrix} w_1^{og} & w_2^{go} & w_3^{og} & & w_K^{og} \\ RO_1 & RO_2 & RO_3 & \ldots & RO_K \end{matrix} \\ \begin{bmatrix} s_{11}^g & s_{12}^g & s_{13}^g & \cdots & s_{1K}^g \\ s_{21}^g & s_{22}^g & s_{23}^g & \cdots & s_{2K}^g \\ s_{31}^g & s_{33}^g & s_{33}^g & \cdots & s_{3K}^g \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ s_{R1}^g & s_{R2}^g & s_{R3}^g & \cdots & s_{RK}^g \end{bmatrix} \end{array}, \tag{7}$$

and

$$S^b \cong \left[\bar{s}_{rc}^b\right]_{R \partial C} \cong \begin{array}{c} \begin{matrix} w_1^{ob} & w_2^{gb} & w_3^{ob} & & w_K^{ob} \\ RO_1 & RO_2 & RO_3 & \ldots & RO_K \end{matrix} \\ \begin{bmatrix} s_{11}^b & s_{12}^b & s_{13}^b & \cdots & s_{1K}^b \\ s_{21}^b & s_{22}^b & s_{23}^b & \cdots & s_{2K}^b \\ s_{31}^b & s_{33}^b & s_{33}^b & \cdots & s_{3K}^b \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ s_{R1}^b & s_{R2}^b & s_{R3}^b & \cdots & s_{RK}^b \end{bmatrix} \end{array}, \tag{8}$$

where s_{rk}^g, s_{rk}^b, w_k^{og}, and w_k^{ob} are the most favorable score of item r with respect to ranking order k, the least favorable score of item r with respect to ranking order k, the most favorable objective weight with respect to ranking order k, and the least favorable objective weight with respect to ranking order k, respectively.

4. Normalize measures s_{rk}^g and s_{rk}^b as $s_{rk}^{ng} \cong \frac{s_{rk}^g}{\sum_{r \cong 1}^{R} s_{rk}^g}$ and $s_{rk}^{nb} \cong \frac{s_{rk}^b}{\sum_{r \cong 1}^{R} s_{rk}^b}$, respectively:

5. Compute the standard deviation s_k for the vector of k-th RO.

$$s_k^g \cong \sqrt{\frac{\sum_{r \cong 1}^{R} (s_{rk}^{ng}\ 0\ \bar{s}_k^{ng})^2}{R\ 0\ 1}}, \qquad k \cong 1, ..., K, \tag{9}$$

$$s_k^b \cong \sqrt{\frac{\sum_{r \cong 1}^{R} (s_{rk}^{nb}\ 0\ \bar{s}_k^{nb})^2}{R\ 0\ 1}}, \qquad k \cong 1, ..., K, \tag{10}$$

where

$$\bar{s}_k^{ng} = \frac{\sum_{r=1}^{R} s_{rk}^{ng}}{R}, \qquad k = 1,\dots,K, \tag{11}$$

$$\bar{s}_k^{nb} = \frac{\sum_{r=1}^{R} s_{rk}^{nb}}{R}, \qquad k = 1,\dots,K, \tag{12}$$

6. Construct the most favorable correlation matrix $C_{K\times K}^{g} = \rho_{kk'}^{g}$ ($k' = 1,\dots,K$) and the least favorable correlation matrix $C_{K\times K}^{b} = \rho_{kk'}^{b}$ ($k' = 1,\dots,K$) where each element of this matrix is the linear correlation coefficient between vector of *k*-th *RO* and vector of k'-th *RO*. It is worth that the more discordant the scores of the items in *ROs* *k* and k', the lower the value $\rho_{kk'}$.

7. Calculate the amount of information by composing the measures quantifying the two notions through the following multiplicative aggregation formula:

$$C_k^{g} = s_k^{g} \sum_{k'=1}^{K} (1 - \rho_{kk'}^{g}), \qquad k = 1,\dots,K, \tag{13}$$

and

$$C_k^{b} = s_k^{b} \sum_{k'=1}^{K} (1 - \rho_{kk'}^{g}), \qquad k = 1,\dots,K, \tag{14}$$

The higher the measure C_k, the larger the measure of information for RO_k.

8. Obtain the normalized objective weights w_k^{og} and w_k^{ob} using the following equation:

$$w_k^{og} = \frac{C_k^{g}}{\sum_{k=1}^{K} C_k^{g}}, \qquad k = 1,\dots,K, \tag{15}$$

$$w_k^{ob} = \frac{C_k^{b}}{\sum_{k=1}^{K} C_k^{b}}, \qquad k = 1,\dots,K, \tag{16}$$

9. Calculate the total score (*TS*) of item *r* as follows:

$$TS_r(o) = o.\frac{gI_r - gI^0}{gI^* - gI^0} + (1 - o).\frac{bI_r - bI^0}{bI^* - bI^0}, \qquad k = 1,\dots,K, \tag{17}$$

where $gI_r = \sum_{k=1}^{K} w_k^{og} s_{rk}^{g}$, $bI_r = \sum_{k=1}^{K} w_k^{ob} s_{rk}^{b}$, $gI^* = \max\{gI_r, r = 1,2,\dots R\}$, $gI^0 = \min\{gI_r, r = 1,2,\dots R\}$, $bI^* = \max\{bI_r, r = 1,2,\dots R\}$, and $bI^0 = \min\{bI_r, i = 1,2,\dots, R\}$. Then, sort the composite scores $TS_r(o)$'s in descending order.

4 An Illustrative Example

In order to compare the proposed model with results of R and ZF models, we apply the data in [2]. All 47 inventory items under three criteria: annual dollar usage, average unit cost and lead time are shown in Table 1. Also the converted measures into interval [0-1] using Eq. (6) have been presented in Table 1.

Table 1: The measures of items and the transformed values with respect to criteria

Item number	Annual dollar usage($)	Average unit cost($)	Lead time(day)	Annual dollar usage (Transformed)	Average unit cost (Transformed)	Lead time (Transformed)
1	5840.64	49.92	2	1.0000	0.2187	0.1667
2	5670	210	5	0.9707	1.0000	0.6667
3	5037.12	23.76	4	0.8619	0.0910	0.5000
4	4769.56	27.73	1	0.8159	0.1104	0.0000
5	3478.8	57.98	3	0.5939	0.2580	0.3333
6	2936.67	31.24	3	0.5007	0.1275	0.3333
7	2820	28.2	3	0.4806	0.1127	0.3333
8	2640	55	4	0.4497	0.2435	0.5000
9	2423.52	73.44	6	0.4124	0.3335	0.8333
10	2407.5	160.5	4	0.4097	0.7584	0.5000
11	1075.2	5.12	2	0.1806	0.0000	0.1667
12	1043.5	20.87	5	0.1751	0.0769	0.6667
13	1038	86.5	7	0.1742	0.3972	1.0000
14	883.2	110.4	5	0.1476	0.5139	0.6667
15	854.4	71.2	3	0.1426	0.3225	0.3333
16	810	45	3	0.1350	0.1947	0.3333
17	703.68	14.66	4	0.1167	0.0466	0.5000
18	594	49.5	6	0.0978	0.2166	0.8333
19	570	47.5	5	0.0937	0.2069	0.6667
20	467.6	58.45	4	0.0761	0.2603	0.5000
21	463.6	24.4	4	0.0754	0.0941	0.5000
22	455	65	4	0.0739	0.2923	0.5000
23	432.5	86.5	4	0.0701	0.3972	0.5000
24	398.4	33.2	3	0.0642	0.1371	0.3333
25	370.5	37.05	1	0.0594	0.1558	0.0000
26	338.4	33.84	3	0.0539	0.1402	0.3333
27	336.12	84.03	1	0.0535	0.3852	0.0000
28	313.6	78.4	6	0.0496	0.3577	0.8333
29	268.68	134.34	7	0.0419	0.6307	1.0000
30	224	56	1	0.0342	0.2483	0.0000
31	216	72	5	0.0328	0.3264	0.6667
32	212.08	53.02	2	0.0322	0.2338	0.1667
33	197.92	49.48	5	0.0297	0.2165	0.6667
34	190.89	7.07	7	0.0285	0.0095	1.0000

Table 1: Continue

Item number	Annual dollar usage($)	Average unit cost($)	Lead time(day)	Annual dollar usage (Transformed)	Average unit cost (Transformed)	Lead time (Transformed)
35	181.8	60.6	3	0.0269	0.2708	0.3333
36	163.28	40.82	3	0.0238	0.1742	0.3333
37	150	30	5	0.0215	0.1214	0.6667
38	134.8	67.4	3	0.0189	0.3040	0.3333
39	119.2	59.6	5	0.0162	0.2659	0.6667
40	103.36	51.68	6	0.0135	0.2273	0.8333
41	79.2	19.8	2	0.0093	0.0717	0.1667
42	75.4	37.7	2	0.0087	0.1590	0.1667
43	59.78	29.89	5	0.0060	0.1209	0.6667
44	48.3	48.3	3	0.0040	0.2108	0.3333
45	34.4	34.4	7	0.0016	0.1429	1.0000
46	28.8	28.8	3	0.0006	0.1156	0.3333
47	25.38	8.46	5	0.0000	0.0163	0.6667
Min	25.38	5.12	1			
Max	5840.64	210	7			

Since there are three criteria in this example, the following six *RO* can be generated to calculate scores:

$RO_1 \cong$ Lead time A Average unit cost A Annual dollar usage ,

$RO_2 \cong$ Lead time A Annual dollar usage A Average unit cost ,

$RO_3 \cong$ Average unit cost A Lead time A Annual dollar usage

$RO_4 \cong$ Average unit cost A Annual dollar usage A Lead time

$RO_5 \cong$ Annual dollar usage A Average unit cost A Lead time

$RO_6 \cong$ Annual dollar usage A Lead time A Average unit cost

Table 2: The most favourable correlation coefficients of between *ROs* ($\upsilon^{g}_{kk'}$)

		RO_1	RO_2	RO_3	RO_4	RO_5	RO_6
	RO_1	1.0000	0.9687	0.8719	0.7917	0.7935	0.9034
	RO_2	-	1.0000	0.8947	0.7463	0.6909	0.8311
	RO_3	-	-	1.0000	0.8770	0.6987	0.7421
	RO_4	-	-	-	1.0000	0.8921	0.8652
	RO_5	-	-	-	-	1.0000	0.9550
	RO_6	-	-	-	-	-	1.0000

By calculating the most favourable scores (model (2)), the least favourable scores (model (3)) for each of items, their correlation coefficients ($\upsilon^{g}_{kk'}$ and $\upsilon^{b}_{kk'}$), the standard deviation (s^{g}_{k} and s^{b}_{k} by Eq. (9-10), respectively), and the normalized objective weights (w_k^{og} and w_k^{ob} by Eq. (15-16), respectively) are determined (as represented in Tables 2-4). Fig. 1 and 2 show the graphical representation of data in Table 4. The classification results using our model, ZF, and R models have been compared together with in Table 5 as well. To this end, we remain the number of items in classes A, B and C according to the same number of items in TABC method, i.e. 10 items for class A, 14 items for class B and 23 items for class C.

Table 3: The least favourable correlation coefficients of between *ROs* ($\upsilon_{kk'}^{b}$)

			C_1				
		RO_1	RO_2	RO_3	RO_4	RO_5	RO_6
	RO_1	1.0000	0.9139	0.9698	0.8719	0.7991	0.8161
	RO_2	-	1.0000	0.9169	0.9312	0.9335	0.9488
	RO_3	-	-	1.0000	0.9262	0.8513	0.8455
	RO_4	-	-	-	1.0000	0.9631	0.9249
	RO_5	-	-	-	-	1.0000	0.9840
	RO_6	-	-	-	-	-	1.0000

Table 4: The Most Favourable and Least Favourable Standard Deviation (s_k^g And s_k^b) and the Normalized Objective Weights (w_k^{og} And w_k^{ob}) for Different *Ros*

		RO_1	RO_2	RO_3	RO_4	RO_5
	s_k^g	0.3852	0.3955	0.3098	0.2129	0.2085
	w_k^{og}	0.0353	0.0469	0.0387	0.0240	0.0276
*	s_k^b	3.0008	2.7936	2.5280	2.5004	2.2773
	w_k^{ob}	0.2579	0.1357	0.1692	0.1307	0.1458

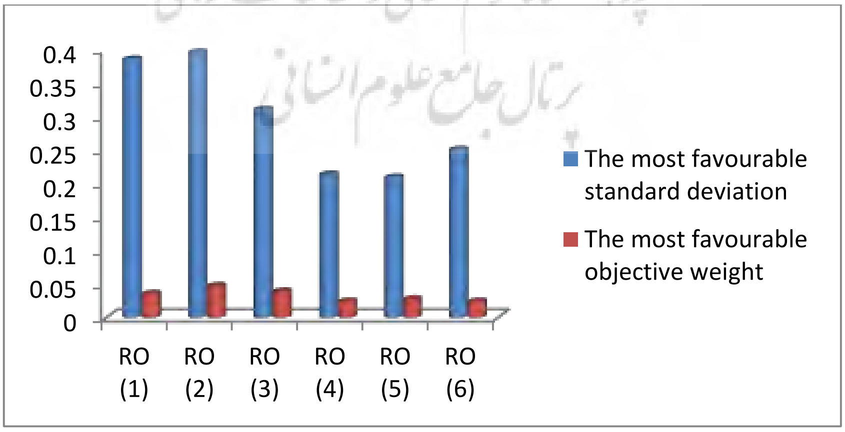

Fig. 1: The Most Favourable Standard Deviation and Objective Weight

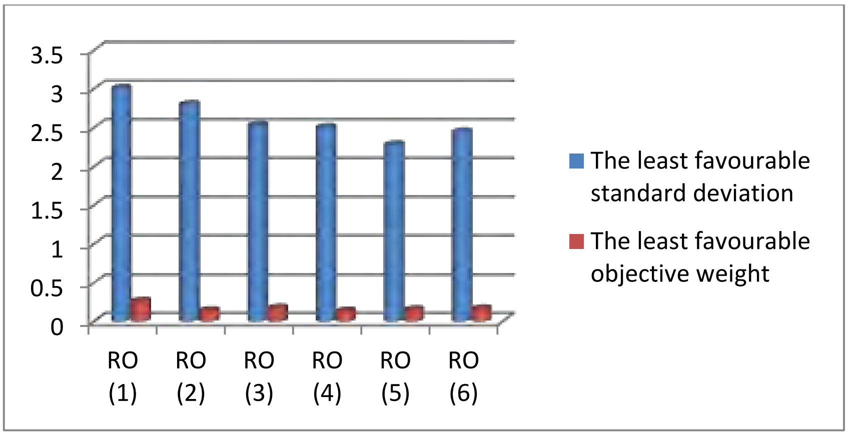

Fig. 2: The Least Favourable Standard Deviation and Objective Weight

Table 5: TS_r And Comparison of the Obtained Results with Other Approaches

Item number	Annual dollar usage($)	Average unit cost($)	Lead time(day)	TS_r	Pro-posed-model	ZF - model	R– model	TABC
2	5670	210	5	1.0000	A	A	A	A
29	268.68	134.34	7	0.7018	A	A	A	A
13	1038	86.5	7	0.6805	A	A	A	B
9	2423.52	73.44	6	0.6500	A	A	A	A
10	2407.5	160.5	4	0.6483	A	A	B	A
3	5037.12	23.76	4	0.5684	A	A	A	A
1	5840.64	49.92	2	0.5595	A	A	A	A
14	883.2	110.4	5	0.5358	A	A	B	B
28	313.6	78.4	6	0.5288	A	A	A	B
45	34.4	34.4	7	0.4917	A	B	A	B
18	594	49.5	6	0.4848	B	A	A	B
34	190.89	7.07	7	0.4564	B	B	A	C
40	103.36	51.68	6	0.4446	B	B	B	B
8	2640	55	4	0.4299	B	B	B	A
5	3478.8	57.98	3	0.4202	B	B	B	A
31	216	72	5	0.4076	B	B	B	C
19	570	47.5	5	0.3858	B	B	B	C
39	119.2	59.6	5	0.3705	B	B	B	C
33	197.92	49.48	5	0.3653	B	B	B	C
4	4769.56	27.73	1	0.3631	B	C	B	A
12	1043.5	20.87	5	0.3615	B	B	B	C
23	432.5	86.5	4	0.3439	B	B	C	C
6	2936.67	31.24	3	0.3263	B	C	C	C
37	150	30	5	0.3194	B	B	B	B
22	455	65	4	0.3161	C	B	C	B
7	2820	28.2	3	0.3109	C	C	C	A

Table 5: Continue

Item number	Annual dollar usage($)	Average unit cost($)	Lead time(day)	TS_r	Pro-posed-model	ZF - model	R– model	TABC
20	467.6	58.45	4	0.3067	C	B	C	B
43	59.78	29.89	5	0.3055	C	C	B	B
15	854.4	71.2	3	0.2623	C	C	C	B
47	25.38	8.46	5	0.2560	C	C	B	B
21	463.6	24.4	4	0.2368	C	C	C	B
17	703.68	14.66	4	0.2325	C	C	C	B
38	134.8	67.4	3	0.2073	C	C	C	C
16	810	45	3	0.2054	C	C	C	C
35	181.8	60.6	3	0.1977	C	C	C	C
36	163.28	40.82	3	0.1566	C	C	C	C
26	338.4	33.84	3	0.1542	C	C	C	C
44	48.3	48.3	3	0.1497	C	C	C	C
24	398.4	33.2	3	0.1388	C	C	C	C
27	336.12	84.03	1	0.1236	C	C	C	C
46	28.8	28.8	3	0.1154	C	C	C	C
32	212.08	53.02	2	0.0985	C	C	C	C
11	1075.2	5.12	2	0.0523	C	C	C	C
42	75.4	37.7	2	0.0506	C	C	C	C
30	224	56	1	0.0400	C	C	C	C
41	79.2	19.8	2	0.0166	C	C	C	C
25	370.5	37.05	1	0.0000	C	C	C	C

when comparing the results with the TABC, only 24 items of the suggested model remained in the same classes. In other words, by implementing our model, 6 of the 10 in class A based on the TABC classification were reclassified in the same class, 3 items were moved to B and other 1 item to class C. of 14 items in class B, 3 items remained in the same class B and 4 items were transferred into A and 7 items into class C. Moreover, 15 of 23 items of class C remained in the same class C based on the TABC classification and 8 items were transferred into class B.

On the other hand, by comparing the R's model were the proposed approach, only 39 of 47 items kept in the same classes. 8 of 10 items of class A based on R's model are reclassified in the same class while the reminder 2 items were moved to class B. 10 of 14 in class B were reclassified in it, 1 item was grouped to class A and 2 items to class C. Also, of 23 items of class C based on the approach of R's model, 21 stayed in the same class C and 2 items were transferred into class B. Finally, when comparison with ZF-approach, by reason of similarity the methods of ranking, 41 items remained in the same classes. 9 of 10 items class A based on the ZF-model were reclassified in the same class, and other 1 item was reclassified in class B. 11 of 14 items in class B remained in the class B, 2 items were transferred into class A and 2 items into class C. Furthermore, of the 23 items of class C in the Ng-model, 21 items remained in the same class C and other 2 items were moved to class B.

5 Conclusions

In real world, experts usually have the different point of views with respect to *RO* of criteria. However, it is impossible to consider conflict *RO* in optimization models. Thus, in this paper, we presented the improved version of R and ZF models for MCABIC in which the aim was utilization of the advantages of R and ZF models by removing their drawbacks. To this end, the CRITIC approach was used to determine the objective weights from the different *ROs*. In other words, in order to prevent zeroing the weight of an item against an unimportant criterion, we used the ZF method where the CRITIC approach was applied to determine the different *ROs*. The results obtained from the CRITIC approach demonstrated that RO_2 and RO_1 have the highest measure with respect to the most favourable standard deviation and objective weight and also the least favourable standard deviation and objective weight, respectively (see Fig.1 and 2). Hence, the criterion of lead time has the greatest effect in our proposed approach. Trivially, unavailability of the items in due time can impose a lot of stock-out costs on the inventory system. The results showed that by applying the proposed model, only 6 items were classified in a class different from results of the ZF-model. This slight difference is due to the similarity of the used models for acquiring the most favourable scores and the least favourable scores and then converting these into a single score. However, there are many differences between scores of items in a class due to usage of the objective weights.

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