Inventory classification using hybrid approaches: a comparative study

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Abstract

The ABC classification is one of the most frequently analysis used in production and inventory management domains, in order to classify a set of elements in three predefined classes A, B and C, where each class follows a specific management and control policies, in order to generate companies financial well-being. This paper introduces new approches for the multicriteria inventory classification based on the hybridization of the Differential Evolution algorithm (DE) with three multicriteria decision making methods namely Topsis, Electre III and Vikor. The evolutionary algorithm (DE) attends to optimize the input (criteria weights) of MCDM methods. MCDM methods generate a score for each item using an aggregation function that combines the item evaluations on the different criteria and the criteria weights. Once the items ranked using the score of each item, The first 20% items with higher score are classified in class A, The next 30% items are classified in class B and the remaining items (50% of total items) are classified in class C. An inventory cost function is used thereafter to evaluate each established classification. This inventory cost function is based on different inventory costs (ordering cost, holding cost, shortage cost) and service level measurement(cycle service level, fill rate) and also represents the objective function of our model, which consist of minimizing the inventory cost. The

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highlight of the three proposed hybridization approches (DE-Topsis, DE-Electre III and DE-Vikor) is the exploitation of the robustness and usefulness of both DE and MCDM techniques. To test the performance of the proposed three hybridation approches with respect to some others ABC inventory classification models, a benchmark data set of 47 items from an Hospital Respiratory Therapy Unit is used. Based on results generated, a comparative study was conducted to compare our three hybrid models with other ABC classification models of the literature. The 3 models provided encouraging results, outperforming the most common classification algorithms.

Keywords: ABC inventory classification, Diffenrential Evolution, Topsis, Electre III, Vikor

1. Introduction

The classification of inventory is a way or more explicitly a strategy in how that inventory will be managed. The most popular and a widely used approach for the inventory classification problem is the ABC analysis, which consists of classifying each inventory item to one group among A, B, or C groups. Each group has an appropriate levels of control. This distribution of inventory items into three classes is done according to the annual dollar usage of an inventory item. However, in practice it was demonstrated that obtaining a good inventory classification is not guaranteed with the traditional one dimensional ABC analysis [2, 3]. Thereby, many enterprises have taken seriously the task of replacing the conventional ABC classification by the multi-criteria inventory classification (MCIC), by including others criteria in order to fit in with constantly and rapid changes.

To deal with MCIC problems, various methodologies have been used in the literature to categorize inventory items by taking into account their computed scores, such as Artificial Intelligence, Multi-Criteria Decision Making and the Mathematical Programming.

The main contribution of this paper is the development of a new hybrid approaches based on of Differential Evolution method (DE) [13, 14] with three Multi-Criteria Decision Making methods, namely Topsis [15, 16], Electre III [17, 18, 19] and Vikor [20, 21, 22], to tackle the ABC inventory classification problem. The contribution of this paper led to the proposal of three hybridization models DE-Topsis, DE-Electre III and DE-Vikor, which attempt to combine the main advantages of each method. In other words, we use the Differential Evolution method to generate solutions within the constraints of the problem. These solutions represent the weights of the criteria and serve as input parameters to the Multi-Criteria Decision Making methods, which have the task to generate an items ranking, based on score. An ABC distribution will be subsequently applied to these items to dispatch them between the A, B and C classes, in order to obtain an ABC classification of the solution. This classification is evaluated by using an inventory cost function, which also represents an objective function of our problem. The aim of the proposed models is especially to reduce the inventory cost compared to existing models in the literature, respecting the standard norms of the ABC classification.

The remainder of this paper is organized as follows. In section 2, we present a general review of the literature regarding the main approaches that have been implemented to generate ABC classifications. The four used methods of our hybrid models (DE, Topsis, Electre III and Vikor) are briefly presented in section 3. In section 4, the three proposed hybrid optimization models is described. Section 5 presents the dataset, the experimental results, and comparative numerical studies with some models from the literature. The paper ends with conclusions and discussion regarding future research.

2. Literature review

ABC analysis has been widely studied in the literature and especially in the area of inventory management. The MCIC problem was discussed for the first time by Flores and Whybark [8, 23], who emphasized the importance to integrate several criteria in order to generate adequate inventory classficiation, given the global market requirements, and introduce the matrix-based methodology for the multi-criteria ABC classification.

The Analytic Hierarchy Process (AHP) method, developed by Saaty [24], is among the most used methods in multi-criteria inventory classification. Since, several studies e.g. [25, 26, 27, 28, 29] have been used the AHP method to solve the MCIC problem in different manners. Other studies are based on fuzzy AHP (FAHP) in order to incorporate the decisions of the decision makers and find the criteria weights [30, 31, 32].

The metaheuristics have also been applied to address the MCIC problem. Guvenir and Erel [2] implement a method that uses the generic algorithm in order to learn criteria weight, and have established cut-off points between the classes A-B and B-C. Tsai and Yeh [34] use the particle swarm optimization technique and presents an inventory classification algorithm that simultaneously search the optimum number of inventory classes and perform classification. Mohammaditabar et al. use the simulating annealing method [35] and developed an integrated model that simultaneously categorizes the items and find the best policy.

Yu [36] propose different artificial intelligence-based techniques including support vector machines (SVMs), backpropagation networks, and the k-nearest neighbor (kNN) algorithm in order to classify inventory items. As for Partovi and Anandarajan [3], they applied an artificial neural network (ANN) for ABC classification inventory items, using back propagation and GA as learning methods.

Linear and nonlinear optimization models have been proposed in the literature in order to generate a weight vector that optimizes the weighted score of each item. Ramanathan [10] has developed a weighted linear optimization model (called R model) that uses a weighted additive function in order to generate a set of optimal weights. Zhou and Fan [11] proposed a ZF-model to address deficiencies and subjectivity of R model. Ng [9] developed a linear optimization model (called NG model) that converts all evaluations of an inventory item into a score without using a linear optimizer. Same as the R model, H model was improved by Hadi-Vencheh [32], by implementing a nonlinear optimization model, which compute the optimal items score by keeping the weight effects. Chen provides a peer-estimation approach based on two weighted linear optimization models R and ZF [37], which aggregates two performances scores generated from R model and ZF model.

To the best of our knowledge, very little researchers has been proposed so far to combine MCIC methods in order to improve the task of inventory managers. To this end, Bhattacharya et al. [38] proposed a model which combines the AHP method with Topsis method. This hybridization consist that the AHP method determines the criteria weights while Topsis method recovers these weights as input parameters in order to calculate the score for each item and finally generate a classification. Lolli et al. [39] have established a multi-criteria classification model called AHP-K-Veto, based on the AHP method and the K-means algorithm. This hybridization arranges the items according to each criterion and aggregates these rankings to an overall ranking based on a veto system.

This literature deficiency compared to multi-criteria inventory classification hybridization methods has led us to focus in this paper on combination of different techniques from different families of methods and develop new hybrid models to better evaluate the inventory classification.

3. Basic concepts

3.1. Differential Evolution

The differential evolution method [13, 14] is probably one of the most powerful stochastic optimization algorithms. This evolutionary algorithm use NP vectors of D dimensions as the population at each generation G. The steps of DE method are as follows:

- **Initialization :** The vectors of the initial population are randomly generated and cover the entire search space :

$$x_{i,G} = [x_{1,i,G}, x_{2,i,G}, x_{3,i,G}, ..., x_{D,i,G}] \tag{1}$$

Where each parameter of the initial vector is generated from the following equation:

$$x_{j,i,0} = x_{j,min} + rand_{i,j}[0,1](x_{j,max} - x_{j,min}) \tag{2}$$

Where $x_{j,min}$ and $x_{j,max}$ are respectively the lower and upper bounds of the search space and $rand_{i,j}[0,1]$ is a uniformly distributed random number $\in [0,1]$.

- **Mutation :** a mutant vector $v_{i,G}$ is generated for each target vector $x_{i,G}$, according to:

$$v_{i,G+1} = x_{r1,G} + F(x_{r2,G} - x_{r3,G}) \tag{3}$$

$r1$, $r2$ and $r3$ are randomly chosen indexes, belonging to the interval $\{1, 2, ..., NP\}$, mutually different and must be different from the current index i. F represent a real in $\in [0,2]$ which has an effect on the differential variation amplification $(x_{r2,G} - x_{r3,G})$. By convention, the factor F will be set to the value 0.5.

- **Crossover :** this step is useful for diversification of vector parameters. For this, the trial vector $u_{i,G+1}$ is generated as follows:

$$u_{i,G+1} = (u_{1i,G+1}, u_{2i,G+1}, ..., u_{Di,G+1}) \tag{4}$$

is formed, where

$$u_{ji,G+1} = \begin{cases} v_{ji,G+1} & \text{if } (rand(j) \leq P_{CR}) \; or \; j = rnbr(i) \\ x_{ji,G} & \text{if } (rand(j) > P_{CR}) \; and \; j \neq rnbr(i) \end{cases} \tag{5}$$

With $j \in [1, D]$, $rand(j)$ is a random number generated in $[0,1]$, P_{CR} is the crossover probability $\in [0,1]$. For ensure that the trial vector $u_{i,G+1}$ receives at least one parameter from the mutant vector $v_{i,G+1}$, we choose a random index $rnbr(i)$ between 1 and D.

- **Selection :** This step indicates if the target vector will be maintained in the next generation or to be replaced by the trial vector.

$$x_{i,G+1} = \begin{cases} u_{i,G} & \text{if } f(u_{i,G}) \leq f(x_{i,G}) \\ x_{i,G} & \text{if } f(u_{i,G}) > f(x_{i,G} \end{cases} \tag{6}$$

where $f(x)$ represents the objective function to be minimized.

3.2. Topsis

The basic concept of the MCDM method Topsis is that the choosen solution must have the shortest distance to the Positive Ideal Solution (PIS) and the farthest distance from the Negative Ideal Solution (NIS) [15, 16]. To understand the problem, we consider N alternatives A_i $(i = 1, ..., N)$ evaluated by M criteria C_j $(j = 1, ..., M)$. Here the approach of the Topsis method, step by step :

- Construct the performance matrix $X = (x_{ij})_{N,M}$, where each alternative $A_i(i = 1, ..., N)$ is evaluated on the criterion $C_j(j = 1, ..., M)$.
- Obtain the weight of each criterion $w_j(j = 1, ..., M)$, such that :

$$\sum_{j=1}^{M} w_j = 1 \tag{7}$$

- Compute the normalized decision matrix $R = (x^n_{ij})$:

$$x^n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{k=1}^{N} x^2_{kj}}} \qquad j = 1, ..., M \ \ and \ \ i = 1, ..., N. \tag{8}$$

- Compute the normalized weighted decision matrix $V = (v_{ij})_{N,M}$:

$$v_{ij} = w_j x^n_{ij} \qquad j = 1, ..., M \ \ and \ \ i = 1, ..., N. \tag{9}$$

- Compute the Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS) :

$$PIS = A^+_i = \{V^+_1, V^+_2, ..., V^+_m\} = \{(max\{v_{ij}\}|j \in B, min\{v_{ij}\}|j \in C)\} \tag{10}$$

$$NIS = A^-_i = \{V^-_1, V^-_2, ..., V^-_m\} = \{(min\{v_{ij}\}|j \in B, max\{v_{ij}\}|j \in C)\} \tag{11}$$

Where B and C represent respectively the sets of benefit and cost criteria and A_i^+ (respectively A_i^-) is the maximum (respectively the minimum) value of v_{ij} among all inventory. items..

- Compute the euclidean distance S_i^+ (respectively S_i^-) between each alternative A_i and PIS (respectively NIS) :

$$S_i^+ = \sqrt{\sum_{j=1}^{M} (v_{ij} - V_j^+)^2} \qquad i = 1, ..., N. \tag{12}$$

$$S_i^- = \sqrt{\sum_{j=1}^{M} (v_{ij} - V_j^-)^2} \qquad i = 1, ..., N. \tag{13}$$

- Compute the score of each alternative A_i :

$$SM_i = \frac{S_i^-}{S_i^+ + S_i^-} \qquad i = 1, ..., N. \tag{14}$$

3.3. Electre III

Electre III is a MCDM method [17, 18, 19] that uses the pairwise comparison in order to categorize a collection of items, with taking into account an immeasurable and conflicting criteria. To measure the degree of credibility of the statement "a outranks b", denoted by $\sigma(a, b)$, four steps must be followed:

- **Step 1 :** computation of partial concordance indices for each pair of items a and b:

$$avec \quad C_j(a,b) = \begin{cases} 0 & \text{if } g_j(b) - g_j(a) \geq pj \\ 1 & \text{if } g_j(b) - g_j(a) \leq qj \\ \frac{pj + g_j(a) - g_j(b)}{pj - qj} & \text{otherwise.} \end{cases} \tag{15}$$

  Where $g_j(a)$ represent the evaluation of the item a according to the criterion j, q_j is the indifference threshold and pj represents the preference threshold.

- **Step 2 :** computation of the global concordance index $C(a,b)$ for each pair of items a and b:

$$C(a,b) = \frac{\sum_{j=1}^{n} w_j \times C_j(a,b)}{\sum_{j=1}^{n} w_j} \tag{16}$$

  With w_j represent le weight of criterion j. The global concordance index $C(a,b)$ is a measure of the strength of arguments that associate with the statement "a outranks b".

- **Step 3 :** computation of partial discordance indices $D(a,b)$ for each pair of items a and b :

$$D_j(a,b) = \begin{cases} 0 & \text{if } g_j(b) - g_j(a) \leq pj \\ 1 & \text{if } g_j(b) - g_j(a) \geq vj \\ \frac{g_j(b)-g_j(a)-pj}{vj-pj} & \text{otherwise.} \end{cases} \tag{17}$$

  Where v_j is the veto threshold which represents the tolerance limit that can accept makers for compensation. The partial discordance indice $D(a,b)$ represent the measure of the strength of arguments that disagree with the statement "a outranks b" according to the criterion j.

- **Step 4 :** computation of the credibility index of the statement "a outranks b":

$$\sigma(a,b) = \begin{cases} C(a,b) & \text{if } D_j(a,b) \leq C(a,b)\ \forall j \\ C(a,b) \times \prod_{D_j(a,b) > C(a,b)} \frac{1 - D_j(a,b)}{1 - C(a,b)} & \text{otherwise.} \end{cases} \tag{18}$$

  The credibility index corresponds to the concordance index weakened by the possible effects of veto.

  Since the exploitation of the outranking relation by Electre III is difficult to understand by decision-makers because of its complexity (Preorder construction, distillation phase and intersection of preorders), we will use the exploitation of the outranking relation of PROMETHEE II method [44] in order to generate the global score of each element, using the degree of credibility $\sigma(a, b)$ calculated in the previous step. Therefore, to calculate the overall score of each item we proceed in these steps:

- **Step 5 :** computation of the positive and negative outranking flow:

$$\Phi^{+}(a) = \frac{1}{m-1} \sum_{x \neq a} \sigma(a, x) \tag{19}$$

$$\Phi^{-}(a) = \frac{1}{m-1} \sum_{x \neq a} \sigma(x, a) \tag{20}$$

  m is the number of total items. The positive outranking flow $\Phi^{+}(a)$ expresses how an item outperforms all other elements, in other words, it represents the power of an element. While the negative outranking flow $\Phi^{-}(a)$ represents how an item is preceded by all other elements. It is considered the weakness of an item.

- **Step 6 :** computation of the net outranking flow:

$$\Phi(a) = \Phi^{+}(a) - \Phi^{-}(a) \tag{21}$$

  The net outranking flow is used to generate a complete ranking of the items.

  Note that the Electre III method requires the following input parameters (n is the number of criteria):

  - The weight vector $w = (w_1; ...; w_n) \geq 0$.
  - The indifference threshold vector $q = (q_1; ...; q_n) \geq 0$.
  - The preference threshold vector $p = (p_1; ...; p_n) \geq 0$.
  - The veto threshold vector $v = (v_1; ...; v_n) \geq 0$.

3.4. Vikor

The VIKOR method has been implemented to address the multi-criteria optimization problems. Starting with criteria weights, the method operates in order to obtain a compromise ranking-list, as well as the compromise solution, and determines the weight stability intervals for preference stability of the compromise solution. This method focuses on the ranking and selection from a collection of items, with taking into account an immeasurable and conflicting criteria. The basic idea of MCDM method is that the multi-criteria ranking is based on an index, computed from the measure of "closeness" to the "ideal" solution [20, 21, 22].

We consider that the alternatives are denoted $a_1, a_2, ..., a_J$. f_{ij} reprensents the evaluation of the i^{th} alternative on the j^{th} criterion, with n as the total of evaluations and J as the total of criteria. The metrics of Vikor method $L_{1,j}$ and $L_{\infty,j}$ are used to generate a measure of classification. [45, 46]:

$$L_{p,j} = \left\{ \sum_{i=1}^{n} [(w_j(f_i^* - f_{ij})/(f_i^* - f_i^-)]^p \right\}^{\frac{1}{p}} \qquad 1 \leq p \leq \infty; j = 1, 2, ..., J. \quad (22)$$

The obtained solutions $min_j S_j$ and $min_j R_j$ in the following equations represent the maximum utility measure (majority rule) and the minimum regret measure (individual regret of the oppposant). The Vikor method determines the best f_i^* and the worst f_i^- values of all criterion functions, $i = 1, 2, ..., n$ and B and C represent respectively the sets of benefit and cost criteria:

$$f_i^* = \{(max_j\{f_{ij}\}|j \in B, min_j\{f_{ij}\}|j \in C)\} \quad (23)$$

$$f_i^- = \{(min_j\{f_{ij}\}|j \in B, max_j\{f_{ij}\}|j \in C)\} \quad (24)$$

The next step consists of calculating the three measures S, R and Q (Vikor Index) of compromise ranking method VIKOR and sort all the alternatives according to these three ordered lists:

$$S_j = \sum_{i=1}^{n} w_j(f_i^* - f_{ij})/(f_i^* - f_i^-) \quad (25)$$

$$R_j = max_i \Big[(w_j(f_i^* - f_{ij})/(f_i^* - f_i^-)\Big] \quad (26)$$

$$Q_j = v(S_j - S^*)/(S^- - S^*) + (1 - v)(R_j - R^*)/(R^- - R^*) \quad (27)$$

$$S^* = min_j\, S_j, \qquad S^- = max_j\, S_j, \qquad R^* = min_j\, R_j, \qquad R^- = max_j\, R_j.$$

w_i are the criteria weights and v represents a factor used by the decision maker and reflect the weight of the strategy of "the maximum group utility". By convention, this factor v is set to 0.5.

Once the Vikor indexes Q_j, S_j and R_j are calculated, it only remains to sort the all the alternatives in decreasing order of the values S, R and Q, in order to obtain three ranking lists.

the alternative (a') is considered as the best ranked solution by Vikor method (The alternative (a') having the smallest Q value) if the following two conditions are respected:

- **C1 ("acceptable advantage")** : $Q(a'') - Q(a') > \Delta_Q$
  where:
  - a'' is ranked second by Q order;
  - $\Delta_Q = 1/(n-1)$ ($\Delta_Q = 0.25 \;\; if \;\; n \leq 4$) and n is the total of alternatives.
- **C2 ("acceptable stability in decision making")** : the alternative a' also has to be the best ranked by S or by R, or both, as well.

If only the first condition is respected, then the alternatives a' and a'' represents a set of compromise solutions. Whereas if only the second condition is verified, the alternatives $a', a'', ..., a^{(k)}$ belong to the set of compromise solutions, with $a^{(k)}$ is calculated by the relation $Q(a^{(k)}) - Q(a') \simeq \Delta_Q$

4. A new hybrid models for ABC MCIC

The three proposed hybridization models Topsis DE-Topsis, DE-Electre III and DE-Vikor attempt to combine the main advantages of each method. To better understand our three hybrid models for the ABC MCIC problem, we explained the different steps of our approaches in the following algorithm 1.

Algorithm 1 ED-MCDM models

Notation :

s_0 : First initial solution, s : Current solution, s^* : Best solution

$E(s)$: Set of solutions

$DE(s)$: Solution generated by DE method from solution s

$MCDM(s)$: Classification generated by MCDM method from solution s

f : Objective function, f^* : Best value of the objective function

Initialization :

Generate the intial solutions $s \in E(s)$;

$s^* = s_0$; $f^* = f(MCDM(s_0))$;

```
for s ∈ E(s) do
    if f(MCDM(s)) < f* then
        s* = s;
        f* = f(MCDM(s));
    end
end
repeat
    for each s ∈ E(s) do
        s_DE = DE(s);
        f(MCDM(s)) = Cost of the solution s
        f(MCDM(s_DE)) = Cost of the solution s_DE
        if f(MCDM(s_DE)) < f(MCDM(s)) then
            s = s_DE;
            if f(MCDM(s)) < f* then
                s* = s;
                f* = f(MCDM(s));
            end
        end
    end
until termination condition is reached;
return s*
```

To compare objectively all the performance of the optimization models, an estimation function based on the inventory cost and the fill rate service level is used [47], in order to evaluate the item classifications of each model. By setting the specified service level for each class (0.99 for class A, 0.95 for class B and 0.9 for class C), this inventory performance evaluation method estimates two important measures: the total holding inventory cost for all items and the achieved overall service level of the system. To present this performance evaluation method, we use the same notation as in [47].

The total safety stock inventory cost is given by:

$$C_T = \sum_{i=1}^{N} h_i k_i \sigma_i \sqrt{L_i} \tag{28}$$

For each inventory item i, the safety factor k_i is calculated as follow:

$$k_i = \Phi^{-1}(CSL_i) \tag{29}$$

The Fill Rate of each item i can be approximated by:

$$FR_i = 1 - \frac{\sigma_i \sqrt{L_i}}{Q_i} G(k_i) \tag{30}$$

Where

$$G(k_i) = \frac{1}{\sqrt{2\pi}} e^{-\frac{k_i^2}{2}} (1 - \Phi(k_i)) \tag{31}$$

The overall FR of the inventory system is calculated as follows:

$$FR_T = \frac{\sum_{i=1}^{N} FR_i D_i}{\sum_{i=1}^{N} D_i} \tag{32}$$

This evaluation function uses a standard cycle service level for each class of items, and consequently the stock-out probability per class. The ultimate goal of this approach is to evaluate Total safety stock cost of the inventory system C_T and the global Fill Rate FR_T for a cycle service level per class. The advantage of this evaluation function is its Cost-Service orientation and we used it as both a performance measure of the multi-criteria classification and an objective function of our hybrid models.

5. Experimental results

To evaluate the performance of our three proposed hybrid models in the ABC inventory classification context, we consider the data set provided by an Hospital Respiratory Therapy Unit (HRTU). Ramanathan [10], Zhou and Fan [11], Ng [9], Vencheh [12], Chen [37], Ladhari et al. [40] and Hadhami et al. [41] use this data set (Table 1) which contains 47 inventory items evaluated on three criteria: Annual Dollar Usage (ADU) ranging from 25.38 to 5840.64, Average Unit Cost (AUC) ranging from 5.12 to 210 and Lead Time (LT) ranging from 1 to 7.

If we take a closer look at the different classifications of the existing models and our new three hybrid models in table 1, we notice that the first conclusion that emerges is our three hybridization models have provided better results than the seven models from literature (the worst proposed model DE-Electre III has an classification cost equal to 833.677, against 927.517 for the best classification cost of the seven literature models).

The best cost classification of our three proposed models belongs to DE-Vikor model (821.365), followed by the DE-Topsis model (821.444) and finally the DE-Electre III model (822.417), with acceptable Fill Rates (all the rates are higher than 0.972), reflecting a good classification and a customer satisfaction.

The ABC classification results of these seven ABC classification models are showed in table 1. Note that for these existing models from the litterature, they respect the same distribution of ABC MCIC, with a percentage of 20% of total items in class A (10 items having the highest score), 30% of total items belonging to class B (14 items) and 50% of total items in class C (23 items having the worst score). We used this distribution (20%-30%-50% or more explicitly 10-14-23 items) in our 3 proposed hybrid models in order to ensure meaningful any comparison of models.

Based on theses results, our three proposed hybrid models for ABC MCIC provides excellent results, outperforming the most common classification algorithms.

Table 1: Proposed classification models vs existing classification models

Item	ADU	AUC	LT	R[10]	ZF[11]	Chen[37]	H[12]	Ng[9]	ZF-NG[40]	ZF-H[41]	DE		
											Topsis	Electre III	Vikor
1	5840,64	49,92	2	A	A	A	A	A	A	C	C	C	C
2	5670	210	5	A	A	A	A	A	A	A	A	A	A
3	5037,12	23,76	4	A	A	A	A	A	A	A	C	C	C
4	4769,56	27,73	1	B	C	B	A	A	B	B	C	C	C
5	3478,8	57,98	3	B	B	B	A	A	A	A	C	C	C
6	2936,67	31,24	3	C	C	B	B	A	B	B	C	C	C
7	2820	28,2	3	C	C	B	B	B	B	B	C	C	C
8	2640	55	4	B	B	B	B	B	B	A	B	B	B
9	2423,52	73,44	6	A	A	A	A	A	A	A	A	A	A
10	2407,5	160,5	4	B	A	A	A	A	A	A	B	B	B
11	1075,2	5,12	2	C	C	C	C	C	C	A	C	C	C
12	1043,5	20,87	5	B	B	B	B	B	B	B	B	B	B
13	1038	86,5	7	A	A	A	A	A	A	A	A	A	A
14	883,2	110,4	5	B	A	B	A	B	A	A	A	A	A
15	854,4	71,2	3	C	C	C	C	C	C	B	C	B	C
16	810	45	3	C	C	C	C	C	C	B	C	C	C
17	703,68	14,66	4	C	C	C	C	C	C	C	C	C	C
18	594	49,5	6	A	A	B	B	B	B	B	A	A	A
19	570	47,5	5	B	B	B	B	B	B	B	B	B	B
20	467,6	58,45	4	C	B	C	C	C	C	B	B	B	B
21	463,6	24,4	4	C	C	C	C	C	C	C	B	C	B
22	455	65	4	C	B	C	C	C	C	B	B	B	B
23	432,5	86,5	4	C	B	C	B	B	B	B	B	B	B
24	398,4	33,2	3	C	C	C	C	C	C	C	C	C	C
25	370,5	37,05	1	C	C	C	C	C	C	C	C	C	C
26	338,4	33,84	3	C	C	C	C	C	C	C	C	C	C
27	336,12	84,03	1	C	C	C	C	C	C	C	C	C	C
28	313,6	78,4	6	A	A	A	B	B	A	B	A	A	A
29	268,68	134,34	7	A	A	A	A	A	A	A	A	A	A
30	224	56	1	C	C	C	C	C	C	C	C	C	C
31	216	72	5	B	B	B	B	B	B	B	B	A	A
32	212,08	53,02	2	C	C	C	C	C	C	C	C	C	C
33	197,92	49,48	5	B	B	B	B	B	B	C	B	B	B
34	190,89	7,07	7	A	B	A	B	B	B	C	A	B	B
35	181,8	60,6	3	C	C	C	C	C	C	C	C	C	C
36	163,28	40,82	3	C	C	C	C	C	C	C	C	C	C
37	150	30	5	B	B	B	C	C	C	C	B	B	B
38	134,8	67,4	3	C	C	C	C	C	C	C	C	C	C
39	119,2	59,6	5	B	B	B	B	B	B	C	B	B	B
40	103,36	51,68	6	B	B	B	B	B	B	C	A	A	A
41	79,2	19,8	2	C	C	C	C	C	C	C	C	C	C
42	75,4	37,7	2	C	C	C	C	C	C	C	C	C	C
43	59,78	29,89	5	B	C	C	C	C	C	C	B	B	B
44	48,3	48,3	3	C	C	C	C	C	C	C	C	C	C
45	34,4	34,4	7	A	B	A	B	B	B	B	A	A	A
46	28,8	28,8	3	C	C	C	C	C	C	C	C	C	C
47	25,38	8,46	5	B	C	C	C	C	C	C	B	B	B
Classification Cost				927,52	945,36	958,14	999,99	1011	985,6	971,02	**821,44**	**822,42**	**821,37**
Fill Rate				0,986	0,984	0,988	0,990	0,991	0,989	0,989	0,972	0,972	0,972

6. Conclusions

The aim of our proposed models is not solely to classify the inventory items based on objective weights, but especially to reduce the inventory cost. The idea of combining the Differential Evolution method and the MCDM methods in our models can be easily applied to general multi-criteria classification problems, not just the ABC MCIC problem. It will help the decision makers to obtain a satisfactory classification for a large-size problem in an efficient way. One of the advantages of the proposed models is that they can be used by an inventory manager as a commercial tool, without the need of an extensive knowledge of MCIC, or understanding the technical details or estimating the input parameters of a method.

To extend this research, it would be interesting to assess the benefits of applying our models empirically using larger datasets. Another avenue for further research consists of hybridization techniques from another different families of methods and compare them with existing models.

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