TOPSIS using a mixed subjective-objective criteria weights for ABC inventory classification

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Abstract—This paper presents a Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method for ABC inventory classification problems where the inventory are classified - based on multiple criteria - into three groups: A the most important items, B the moderately important ones and C the least important ones. The objective of this classification is to manage and control the inventories in an efficient way based on their weighted scores. To do this, two TOPSIS models using two different distance metrics (first order and second order metrics) and a mixture of subjective-objective criteria weights are proposed. More precisely, this paper addresses the problem of optimizing a set of weights. The objective weights are generated by using the continuous Variable Neighborhood Search (VNS) and the subjective weights are generated by using the Analytic Hierarchy Process (AHP). To test the performance of the proposed models in terms of inventory cost, a benchmark data set commonly used in the relevant literature is exploited.

Keywords—ABC inventory classification; TOPSIS; subjective weights; objective weights;

I. INTRODUCTION

A. ABC inventory classification background

ABC inventory classification is a well known classification method, used by companies to manage a huge number of inventory items. It is worth underlining, in this respect, that items couldn’t be managed with equal attention. Hence, the process of ABC analysis consists in categorizing the items into three predefined and ordered categories: category A contains the most valuables items and needs a tight and rigorous control, category B contains the moderately valuable items and the category C includes the least valuable ones. The classical ABC analysis is based on the Pareto principle or the 80/20 rule where the items are categorized according to a single criterion which is the Annual Dollar Usage (ADU). The ABC analysis is criticized for its exclusive focus on just one criterion (the ADU) because in real inventory problems there are many other criteria that are important for the inventory classification such as: Lead Time (LT), Average Unit Cost (AUC), Critical Factor (CF), Durability. Indeed, the ABC inventory management is a multi criteria inventory classification (MCIC) technique. In order to accommodate MCIC problems, many authors from the literature have proposed many techniques to categorize inventory items based on their weighted scores. The score of an item is the result of an aggregation function that combines the item evaluation on the different criteria and the criteria weights. Based on their weighted scores, the inventory items are then ranked. Then the ABC analysis categorizes the items as follows: the first items in the top of the list (20% of total items) are classified in category A (very important items), items in the bottom of the list (50% of total items) are classified in category C (less important items) and the items in between (30% of total items) are classified in category B (moderately important items).

The computation of the items scores by using an aggregation model and the determination of the parameters of the aggregation model, are two subjects that should be solved for any ABC MCIC technique. Many methodologies such as Mathematical Programming (MP), Artificial Intelligence (AI) and Multi Criteria Decision Making (MCDM) techniques are proposed to deal with a classification of inventory items. Weighted optimization models such as the R-model [13], the ZF-model [12] which is an extended version of the R-model, the Ng-model [16] and the H-model [2] are considered as a MP field. The main objective of these models is to obtain a set of optimal weights which maximizes the score of each item. The criteria weights are generated by means of a Data Envelopment Analysis (DEA) optimization technique whereas the weighted scores are expressed by a weighted additive function. Some drawbacks may be addressed to the above MP models such as: an inventory item with a high evaluation on an irrelevant criterion may be considered as an important item.

To reduce the conflict in the classification models based on MP techniques and to manage the misclassified items, Ladhari et al. (2015) [15] have developed a new hybrid MCIC model which combines the ZF-model [12] and the Ng-model [16].

The models proposed by Flores, Olson and Dorai (1992)
Partovi and Burton (1993) [7] and Battacharya, Sakar and Mukherjee (2007) [1] are considered as typical MCDM classification models. Flores, Olson and Doraí (1992) introduced a classification method based on the AHP technique to determine the criteria weights and a simple additive weighting rule to compute the weighted scores for each inventory item. Battacharya, Sakar and Mukherjee (2007) proposed a TOPSIS model to compute the scores and the AHP to determine the parameter (weights) of the TOPSIS. These models are criticized because they focus on the AHP technique to determine the criteria weights.

AI approaches have also been applied to address the MCIC problem. An algorithm that estimates the criteria weights in order to establish a classification of the inventory items, and that optimizes an objective function (e.g. inventory cost function, misclassified items rate, correct classified item rate, etc.), is proposed. The criteria weights are estimated by some well-known metaheuristic such as Genetic Algorithm (GA) [9], Particle Swarm Optimization (PSO) [4] and Simulated Annealing (SA) [6]. Once the criteria weights are determined, a score is computed for each item by using an aggregation rule (e.g. weighted sum). Partovi and Anandarajan (2002) [8] have developed an Artificial Neural Network (ANN) for inventory classification. Two learning methods were utilized in the ANNs, namely Back Propagation (BP) and Genetic Algorithms (GA). Analogously, Yu (2010) [10] have compared the Support Vector Machines (SVMs), Backpropagation Networks (BPNs), and the k-Nearest Neighbor (k-NN) algorithm with traditional multiple discriminant analysis (MDA) technique.

B. Motivation of the proposed work

This paper focuses on determining the criteria weights of the TOPSIS model under two different distance metrics ($\ell_2$ and $\ell_1$). These criteria weights combine two sets of weights: the subjective and the objective weights. The objective criteria weights did not take into account the decision maker’s judgments and opinions in classifying the items. However, human assessment on the criteria weights is always subjective and thus imprecise. Hence, a compromise solution between incorporating explicitly human judgments and reducing the amount of subjectivity should be treated. In order to retain the presence of the decision maker judgment and to make the classification problem more objective, we present a mixture of subjective and objective criteria weights.

C. Contribution of the paper

The proposed research work has some characteristics that distinguish it from previous works for MCIC. In this paper, we:

1) propose two TOPSIS methods using two different distance metrics ($\ell_2$ and $\ell_1$) and the criteria weights are a combination of the subjective and objective weights.

2) propose the Analytic Hierarchy Process (AHP) technique to generate the subjective weights and the continuous variable neighborhood search (VNS) to generate the objective weights.

3) provide optimal results in terms of inventory cost. The aim of the proposed models is not solely to classify the items based on subjective-objective weights, but especially to reduce the inventory cost.

D. Outline of the paper

The remainder of this paper is organized as follows. Section 2 presents a description of the proposed methods for ABC inventory classification. In section 3, computational results of the proposed model are discussed and compared with those obtained by other classification models from the literature. Finally, concluding remarks and suggestions for further research are reported in section 4.

II. THE PROPOSED WORK

In order to address the assignment of inventory items to a category, this research work proposes a TOPSIS method as an aggregation function to compute the weighted scores and a combination of subjective and objectives criteria weights. In this section, the details of TOPSIS using the mixture of subjective-objective weights are proposed.

A. TOPSIS steps

TOPSIS is used as an aggregation function to compute the weighted scores. TOPSIS is a well known MCDM method to rank a set of alternatives evaluated on a collection of conflicting and non-commensurable criteria. Its basic principle is that the chosen alternative should have the shortest distance from the positive ideal solution (PIS) and the farthest distance from the negative ideal solution (NIS) [1]. Formally, for a problem with $n$ alternatives $A_i (i=1,...,N)$ that are evaluated by $m$ attributes (criteria) $C_j (j=1,...,M)$, the idea of TOPSIS can be expressed in a series of steps as follows [1]:

- **Step1.** Construct the performance matrix $X=(x_{ij})_{N,M}$ in which each alternative $A_i (i=1,...,N)$ is evaluated on the criterion $C_j (j=1,...,M)$.

- **Step2.** Determine the criteria weights $w_j (j=1,...,M)$ such that:

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

where

$$w_j = \alpha w_j^{objective} + (1 - \alpha) w_j^{subjective} \quad (2)$$

and $0 \leq \alpha \leq 1$. 

weights are illustrated as follows: the main steps to generate the subjective criteria
al. [3], we have computed the vector of subjective criteria on the pairwise comparison matrix provided by Flores et
its ease of use and it can incorporate many criteria. Based
MCDM based classification models and has been praised for
B. Determining the subjective weights with AHP

• Step1: Assign a degree of importance to each criterion
• Step2: Apply a pairwise comparison for each pair of
criteria
• Step3: Convert the subjective judgments into a set of
weights
C. Determining the objective weights with continuous VNS

To offset the impact of subjectivity resulting from the
AHP, a continuous VNS (CVNS) algorithm is used to
generate the objective criteria weights. The basic idea of
the continuous VNS introduced by Mladenovic and
Hansen in 1997 [11], consists in combining local search
with systematic neighborhood changes both in the descent
to the local minima and in the escape from the valleys
which contain them [11]. The solution (i.e. the estimated
parameter) of the CVNS algorithm is a real criteria weights
vector which combines the subjective and objective weights.
The basic steps of the CVNS are as follows:

• Step1: Initialization : generate the neighborhood structure
• Step2: Shaking: generate a random solution
• Step3: Apply local search: The Best Improvement
method
• Step4: Apply neighborhood change
• Step5: Keep the best solution

While termination condition is met do

End while.

To find the best solution, in CVNS algorithm, a set of
neighborhoods (N_k) for each solution x is defined as follows:
N_k(x) = \{ y \in S : \rho(x, y) \leq r_k \}, where r_k is the radius of
N_k monotonically increasing with k and \rho is any metric
function (i.e.Euclidean, rectangular, etc.). In this work, the
following metric \( \rho(x, y) = (\sum_{i=1}^{n} |x_i - y_i|^p)^{1/p} \) will
be used [11]. To guide the process of the algorithm and
to evaluate each inventory classification, we have used the
inventory cost function proposed by Mohammaditabar et al.
[6]. This function computes the Inventory Cost (IC) of the
obtained ABC classification as follows:

\[
IC = \sum_g \left( \frac{\sum_{i \in \text{group}(g)} S_i}{T_g} + 2 \frac{T_g}{\sum_{i \in \text{category}(g)} D_i h_i} \right)
\]

where \( T_g \) is the optimal joint replenishment cycle of item
category g ( g = A, B or C)

S_i : set up cost of item i, \( D_i \) : demand per unit time of item
i, \( h_i \) : holding cost per unit of time of item i.

The main steps of the proposed algorithm proceeds like so:

• Step1: A new criteria weights vector is generated in
the neighborhood of the current best weight vector by
using CVNS
• Step2: According to the generated weight vector, a
weighted score is computed for each item by using TOPSIS
• Step3: Based on the weighted scores, a classification
of the items are generated and evaluated by using an

\[
\begin{align*}
S_i^+ &= \ell_p \left( \sum_{i=1}^{n} |v_{ij} - V_j^+|^p \right)^{1/p} ; i = 1, ..., N, \\
S_i^- &= \ell_p \left( \sum_{i=1}^{n} |v_{ij} - V_j^-|^p \right)^{1/p} ; i = 1, ..., N, \\
NIS &= A_i^- = \{ V_i^- , V_2^- , ... , V_m^- \} \\
PIS &= A_i^+ = \{ V_i^+ , V_2^+ , ... , V_m^+ \} \\
SM_i &= \frac{S_i^-}{S_i^+ + S_i^-} ; i = 1, ..., N
\end{align*}
\]
To generate the criteria weights and to show the effectiveness of our proposed TOPSIS models, a benchmark data set used in a Hospital Respiratory Theory Unit (HRTU) is then applied in the context of ABC inventory classification. We apply our models to the same data set used by Ramanathan (2007) [17], Zhou and Fan (2007) [16], Ng (2007) [21] and Hedi-Vencheh (2010) [2]. It contains 47 inventory items which are evaluated on three criteria: Annual Dollar Usage (ADU), Average Unit Cost (AUC) and Lead Time (LT). The final ranking of the items verifies the same distribution of ABC MCIC used in the literature, i.e, 10 category A, 14 category B and 23 category C.

For the implementation of the continuous VNS, one should take into account the following parameters: \( (k_{\text{max}}=12, \text{geometry of neighborhood structure } N_k=\ell^2, r_k=k \times r_1 \) with \( r_1 = r_{\text{max}}/k_{\text{max}} \) where \( r_{\text{max}} \) is the maximal value of radius).

Let’s us recall that the continuous VNS solution is a combination of subjective and objective criteria weights \( w_{\text{objective}} = \alpha \) whereas the generated criteria weights vectors are in concordance with those obtained by all the existing inventory classification, i.e. ADU and LT are the most important criteria. We have also tested our models with different values of \( \alpha \) and we can conclude that our models gives better results even when using two different distance metrics.

### III. Computational results

To generate the criteria weights and to show the effectiveness of our proposed TOPSIS models, a benchmark data set used in a Hospital Respiratory Theory Unit (HRTU) is then applied in the context of ABC inventory classification. We apply our models to the same data set used by Ramanathan (2007) [17], Zhou and Fan (2007) [16], Ng (2007) [21] and Hedi-Vencheh (2010) [2]. It contains 47 inventory items which are evaluated on three criteria: Annual Dollar Usage (ADU), Average Unit Cost (AUC) and Lead Time (LT). The final ranking of the items verifies the same distribution of ABC MCIC used in the literature, i.e, 10 category A, 14 category B and 23 category C.

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### IV. Conclusion

In this paper, we present a classification approach based on the TOPSIS method for multiple criteria ABC inventory classification. The first contribution of this research work is to generate two sets of weights for the TOPSIS: the subjective and the objective weights: the AHP is used to generate the subjective weights and the continuous VNS is used to generate the objective weights. The aim of the proposed classification is to take into account both the subjective and objective behaviors in determining weights. We have also used two different distance metrics \( (\ell^2 \text{ and } \ell_1) \) for our proposed TOPSIS models. The second contribution of this paper is to produce a classification which minimizes the cost function.

It should be noted that, the results presented in this paper are based on a benchmark data set of 47 items from the literature. The computational results show that our proposed models have obtained the best inventory cost of all tested classification models.

An interesting avenue for further research would be to (i) combine quantitative and qualitative criteria in the classification model and (ii) to test our proposed models on big data set.

### REFERENCES


Table I

COMPARISON OF ABC CLASSIFICATION BY OTHER TECHNIQUES AND OUR PROPOSED MODELS UNDER THREE CRITERIA

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Inventory Cost (IC) | 1187.7 | 1429.2 | 1424 | 1197.5 | 931.439 | 932.684


