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New AHP-based approaches for multi-criteria inventory classification

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ABSTRACT

Multi-Criteria Inventory Classification (MCIC) groups inventory items with respect to several criteria, in order to facilitate their management. This paper introduces a new hybrid method based on AHP and the K-means algorithm. On benchmarking data, it provides a clearly higher clustering validity index than previous sorting methods. However, as with previous methods, it is a full compensatory method. This means that an item scoring badly on one or more key criteria may still be placed in the best class because these bad scores are compensated. In order to prevent these hidden bad scores, a new variant method is introduced: AHP-K-Veto. The sorting is performed on each single criterion, where a veto system prevents an item evaluated as high/bad on at least one criterion to be top/bottom ranked in the global aggregation. This veto system is an assurance against hidden problems but slightly worsens the clustering validity index.

1. Introduction

Inventory management may lead to significant savings (Johnson and Montgomery, 1974; Nahmias, 1997; Ghiani et al., 2004; Manzini and Gamberini, 2008). However, when there are a large number of items, the associated administrative effort and unused economy of scale of transportation and storage handling, may exceed the aforementioned savings. One solution to facilitate the management of the inventory is to group similar items in order to have a single policy for the bundle instead of a different policy for each item. For instance, the same target service level, which is the probability of not incurring in a stock-out during a replenishment cycle, could be associated to all the items of the same cluster. The critical issue in this process is how clusters are built. This question has been explored in depth in the literature since the development of the ABC inventory classification by Dickie (1951).

Traditionally, the ABC inventory is based on a single criterion, which is generally the annual usage value given by the product of the annual demand and the average unit price. Nevertheless, a single classifying criterion cannot generally represent the whole criticality of an item. Therefore, Multi-Criteria Inventory Classification (MCIC) methods, which include several other criteria, e.g., unit cost, lead time and availability, have been proposed (Flores and Whybark, 1986; Chen et al., 2008). The criteria to adopt depend on the aim of the classification and normally not on the classification technique. Therefore, last decade has provided several papers on how to improve these classification techniques. In this paper, a new hybrid AHP method with the K-Means algorithm, referred to as AHP-K, is proposed. This method provides a less subjective and more precise MCIC. A veto system is subsequently introduced in AHP-K-Veto, which is available when judged necessary by the decision maker, to prevent an item evaluated as high/low on at least one criterion to be bottom/top ranked, when an aggregation is made on all criteria. In this paper, the second approach is used to solve a real case study. Then, the dataset of Reid (1987) is adopted as a benchmark for the comparison of the performance of the new methods against the previous ones.

The paper has been organised as follows: Section 2 briefly describes the notation used in the paper. In Section 3, the main contributions in the literature on ABC clustering are briefly reviewed. Section 4 presents the AHP-K and AHP-K-Veto methods for MCIC and Section 5 shows the application of the presented methodologies through the real case study. Section 6 compares the proposed sorting approaches with the existing ones. Finally, Section 7 concludes the paper.

2. Notation

I	total number of criteria;
J	total number of items;
N	number of classes;
i	criterion, with $i=1,\ldots,I$;

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a_j item, with $j=1,\dots,J$;
$v_{i,j}$ value of item a_j on the criterion i, with $i=1,\dots,I$ and $j=1,\dots,J$;
$w_{i,j}$ weight on the criterion i for the item a_j;
$C_{n,i}$ class n on criterion i, with $i=1,\dots,I$ and $n=1,\dots,N$;
C_n class n on the final score, with $n=1,\dots,N$.

3. Literature review

The literature on MCIC is extensive. As the benchmarking in our paper is based on the dataset provided by Reid (1987), we have mainly concentrated our review on the published papers that used this dataset. The last section presents some other approaches from artificial intelligence and explains why they are not suitable for our case.

3.1. ABC clustering approach

A pioneering approach in inventory classification is the ABC analysis on a single criterion, which is one of the most widely used techniques in organisations. According to this approach, resources spent on inventory control should be related to the importance of each item. Therefore, class A contains few items but constitutes the largest amount of annual usage value, whilst class C holds a large number of items but forms a small amount of annual usage value. Items that fall in between these two classes are assigned to class B. Several authors recognise that the traditional ABC analysis on a single criterion does not provide a satisfactory classification of inventory items (Guvenir and Erel, 1998; Huiskonen, 2001; Partovi and Anandarajan, 2002). Therefore, alternative MCICs are applied to take into account the multi-criteria structure of the problem and Flores and Whybark (1986; 1987) proposed the first step in this direction. They developed a joint criteria matrix with two criteria: capital usage and lead time, in order to enrich the ABC grouping approach. However, the methodology becomes difficult to implement, as more criteria have to be considered. Ernst and Cohen (1986) suggested using a multi-criteria classification named Operations Related Groups (ORG) and stock control policies and then demonstrated through different case studies (Cohen and Ernst, 1988; Ernst and Cohen, 1990) that the ORG outperforms the ABC method in terms of both operational and statistical performance. After these contributions, MCIC has mainly been focused on three other approaches: AHP, DEA (Data Envelopment Analysis) and AI (Artificial Intelligence), which are reviewed in Sections 3.2–3.4.

3.2. AHP-based approaches

Flores et al. (1992) apply an AHP-based approach (see Saaty, 1980) that synthesises several weighted criteria (e.g., average unit cost, annual capital usage, criticality and lead time) into a single priority score for each item. AHP is a general-purpose method that can solve a broad range of multi-criteria problems. In particular, MCIC is a specific issue that can be faced with the application of AHP, where the alternatives correspond to the inventory items.

AHP can solve problems with qualitative and quantitative evaluations. These evaluations are entered into a pairwise comparison matrix. The importance of the criteria and ranking of the alternatives are then derived with the eigenvalue method (see Saaty, 1980; Ishizaka and Labib, 2011). Because the value of the items on each criterion in MCIC are often precisely measureable (e.g., lead time, costs, durability), Flores et al. (1992) simply normalised them in order to be commensurable and combinable in a weighted global score. The pairwise comparisons are only adopted to evaluate the importance of criteria with the eigenvalue method. This study demonstrates that AHP is more exhaustive than the ABC approach in supporting the policy development process, because the overall picture is taken into consideration and not just one single criterion. Several modified versions of AHP are applied in MCIC (Partovi and Burton, 1993; Partovi and Hopton, 1994), including a more recent AHP fuzzy version proposed by Cakir and Canbolat (2008).

Despite the specifics of each proposed method, it can be noted that the final sorting step, i.e., the attribution of each item to a criticality class (A, B or C), follows an exogenous rule imposed by the decision maker. For example, Flores et al. (1992) impose that the top 10% of items are assigned to class A, the next 20% to class B and the last 70% to class C. The paradoxical consequence of this rule is that two items having exactly the same score could be assigned to two different classes to satisfy these proportions. This approach, translated into terms of inventory control, leads to the management of these two similar items in different ways. In other words, the proposed methods are strongly affected by the arbitrary nature of the decision maker in the attribution of the items to the critically classes, without providing any objective or justifiable rules for achieving the cardinalities of these classes. It can be noted that such an approach is not always coherent with the aim of defining clusters of items with similar characteristics.

In order to remove this arbitrariness, AHP-K is introduced (see Section 4.1), which integrates AHP with the K-Means algorithm in order to make the clustering more objective. Subsequently, AHP-K-Veto is presented, in order to retain the presence of the decision maker with the faculty of imposing a veto on the final result.

3.3. Weighted linear optimisation approaches

Inspired from the Data Envelopment Analysis (DEA), Ramanathan (2006) introduces a weighted linear model (see Eqs. (1)–(3)), which via a linear optimisation, choose weights that show each item j under its best profile:

$$\max f_j = \sum_{i=1}^{I} w_{i,j} v_{i,j} \tag{1}$$

$$\text{s.t.} \sum_{i=1}^{I} w_{i,j} v_{m,j} \le 1, m=1,2,\dots,J \tag{2}$$

$$w_{i,j} \ge 0, \quad i=1,2,\dots,I \tag{3}$$

This formula is very similar to a simple weighted sum (SWS). The difference is that the weights are auto-generated (i.e., endogenous) and variable, whilst in the SWS, they are attributed by the decision maker (i.e., exogenous) and fixed for all items. The advantage of this method is that we do not require any input from the decision maker. This approach may be useful for new items, where the information on weights importance is not yet available due to the lack of experience. Unlike AHP, it is not compensatory in the sense that bad scores may be totally ignored. In order to limit this problem, Ng (2007) asks the decision maker for an ordinal ranking of the weights. This information is added as a constraint in the linear optimisation model. Later, Hadi-Vencheh (2010) modifies the normalisation constraint on the weights (Eq.(4)). The squared sum of the weights is normalised, in order to increase the distance between them and decrease the likelihood that the weakness of an item is ignored.

$$\sum_{i=1}^{I} w_i^2 = 1 \tag{4}$$

On the same problem, Zhou and Fan (2007) use Eq. (1) to calculate the most favourable weights for each item and then minimise the objective function (Eq. (1)) in order to find the least favourable weights. Based on these weights, good and bad indexes of weights are created. Both indexes are then combined in a weighted sum, where the decision maker subjectively defines the weights of both indexes. Chen (2011) has criticised this approach because only two