Computers & Industrial Engineering 104 (2017) 219–223

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

Short Communication

Evaluating discriminating power of single-criteria and multi-criteria models towards inventory classification

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ARTICLE INFO

Article history:
Received 14 August 2016
Received in revised form 30 November 2016
Accepted 7 December 2016
Available online 16 December 2016

Keywords:
Inventory classification
Single-criteria
Multi-criteria
Discriminating power

ABSTRACT

Single-criteria and multi-criteria models both are used with regards to inventory classification. In this paper, we evaluated single-criteria and multi-criteria models in terms of their feasibility in classifying inventory items for a given dataset. We introduced discriminating power test. We used two datasets with lead time as the first criterion. We compared the scores of the models. We also modified ZF model and used descending ranking order criteria constraint to address the infeasibilities. Results show that using criteria in descending order reduces the classification infeasibility. Later, we proposed a probability distribution to find the probability of infeasibility for a given dataset against a number of identical scoring items.

1. Introduction

Items are classified into class A, B, or C based on the scores they receive from the model. Class A is the smallest class which contains highest scoring items, followed by class B and then class C. Following Pareto analysis, class A contains 15–20% items, class B contains 30–35%, and class C contains 45–55% items.

Ramanathan (2006) used a Data Envelopment Analysis (DEA) approach for inventory classification. He presented a weighted additive model for more than one criterion in the model that generates the best possible score for each item. Later, scores of the items are ranked in a descending order and then items are classified into class A, B, or C. The model is named as R model in the literature.

After the R model, several other models have been developed. In general, they can be categorized into two classes: First, models that do not assign unequal weights to multiple criteria (Ramanathan, 2006; Zhou & Fan, 2007). Second, models that assign unequal weights to the criteria (Hadi-Vencheh, 2010; Ng, 2007) using descending ranking order criteria constraint. Park, Bae, and Bae (2014) model is an exception. They used a different approach which they called cross-evaluation weighted linear optimization. Items are cross evaluated by each other. Then the cross evaluation scores for a given item is averaged to get the final score of that item.

A good multi-criteria optimization model should provide non-identical scores for each inventory item. For example, if 10 items are to be classified into A, B, or C with 20% in class A, 30% in class B, and 50% in class C. Then, a model which gives an identical score to more than 2 highest scoring items, it becomes infeasible to classify those items because class A cannot contain more than two items. Previous studies have not addressed this issue.

The contribution of this paper is twofold. First, provide a test to evaluate the ability of the multi-criteria models in giving identical scores to multiple inventory items. This is measured in terms of classification infeasibility. When models are compared with respect to classification infeasibility, a user would know which model results in less infeasibility so he can make an intelligent decision in selecting the model for inventory classification. The test is termed as discriminating power test. Second, the probability distribution of infeasibility at different levels of identical scoring items is developed and shown in a graphical format. This gives an insight to the user about the probability of having infeasibility in classifying inventory items when number of identical scoring items goes up or down. This assists in comparison of models for classification infeasibility.

2. Discriminating power test

Model fitness or discriminating power test is a test to judge the ability of a model to classify inventory items without resulting in infeasibility for a given dataset. We applied model fitness test on single-criteria and multi-criteria optimization models. We used two datasets that are discussed in next section.

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http://dx.doi.org/10.1016/j.cie.2016.12.007
0360-8352/

2.1. Sample dataset 1

We considered 10 items dataset used in Park et al. (2014). We used three criteria namely lead time, annual demand, and average unit cost as the first criterion, the second criterion, and the third criterion respectively. The dataset is shown in Table 1.

We need to evaluate how models behave when values of the first criterion for multiple items are identical. This will highlight the shortcomings of single-criteria and multi-criteria models. We selected lead time as the first criterion for this reason. We ran each model for above inventory items using Lingo software. Final scores from the models are summarized in Table 2.

In single-criteria model, lead time is the only criterion that is used to classify inventory in class A, B, and C. We find that items 9, 6, 7, 2 all have same lead time. But all four items cannot be classified into Class B thereby resulting in classification infeasibility. This makes further classification of items infeasible. In the single-criteria method, we find four infeasibilities.

In R model, we see that four items (item 1, 5, 6, and 9) received identical scores that are highest in values. Since class A cannot contain more than two items. It becomes infeasible to classify all four items into class A. For this dataset, we can say R model does not show a good discriminating power among inventory items. ZF model is an extended version of R model to improve the inventory classification of R model. We evaluate if ZF model is able to fix the classification issue of R model. We find that ZF model gives more distinctive scores to items than R model. But after classifying item 5 and item 7 to class B, the next highest scoring items are item 1 and item 9 which are identical in value. We cannot classify both into class B as class B cannot contain more than three items. We cannot proceed further to classify items. This makes the classification of items infeasible. However, ZF model reduces the infeasibilities from four to two. In all other models (Ng model, HV model, and PBB model) we do not find any classification infeasibility although we see items with identical scores in Ng model. Next, we can find if adding descending ranking order criteria constraint in ZF model can improve classification infeasibilities of ZF model. Descending ranking order criteria constraint allows the user to prioritize the criteria based on the importance level. In other words, all criteria are not considered of equal importance.

Table 1
Dataset of sample 1 inventory items.

Item	Lead time (weeks)	Annual demand (units)	Avg unit cost (USD)
1	7	0.483	71.21
2	4	8.000	58.45
3	3	4.000	40.82
4	2	4.004	19.8
5	7	1.200	86.5
6	4	12.000	71.2
7	4	4.000	78.4
8	6	2.000	51.68
9	4	48.000	14.66
10	5	3.000	72

2.1.1. Modified ZF model

Descending ranking order constraint is added in both maximization and minimization model. The models are presented in Eq. (1) and in Eq. (2).

Maximization model:

$$\begin{aligned} & gI_i = max\sum_{n=1}^{N} w_{in}^{g} Y_{in} \\ & s.t. \sum_{n=1}^{N} w_{in}^{g} y_{mn} \leqslant 1, \quad m = 1,2,\ldots,M \\ & w_{in}^{b} - w_{i(n+1)}^{b} \geqslant 0 \quad n = 1,2,\ldots,(n-1) \\ & w_{in}^{g} \geqslant 0 \end{aligned} \tag{1}$$

Minimization model:

$$\begin{aligned} & bI_i = min\sum_{n=1}^{N} w_{in}^{b} y_{in} \\ & s.t. \\ & \sum_{n=1}^{N} w_{in}^{b} y_{mn} \geqslant 1, \quad m = 1,2,\ldots M \\ & w_{in}^{b} - w_{i(n+1)}^{b} \geqslant 0 \quad n = 1,2,\ldots,(n-1) \\ & w_{in}^{b} \geqslant 0 \end{aligned} \tag{2}$$

Constraint number 2 (modified ZF model: $w_{in}^{b} - w_{i(n+1)}^{b} \geqslant 0$) is the descending ranking order criteria constraint. The scores are shown in Table 3.

We observe from Table 3 that infeasibilities from ZF model are removed in modified ZF model. We find that using descending ranking order criteria reduced the infeasibilities of ZF model.

2.2. Sample dataset 2

We tested the discriminating power of the models using second sample dataset. The data contains 47 inventory items used in previous studies (Flores, Olson, & Dorai, 1992; Ng, 2007; Ramanathan, 2006). We classify 7 items in class A (15%), 12 items in class B (25%), and 28 items in class C (60%). The score of the models and classification of items is shown in Table 4.

Table 2
Scores and classification of items for dataset 1.

Items	Lead time (weeks)	Annual demand (units)	Avg unit cost ($)	Single criteria	R model		HV model		ZF model		Modified ZF Model		PBB model		Ng model	
				Score	Score	Class	Score	Class	Score	Class	Score	Class	Score	Class	Score	Class
5	7	1.20	86.50	A	1.000	Infeasible	1.233	A	0.551	B	1.000	A	0.998	A	1.000	A
1	7	0.48	71.21	A	1.000	Infeasible	1.145	A	0.500	Infeasible	0.939	A	0.862	B	1.000	A
8	6	2.00	51.68	B	0.808		0.890	B	0.398		0.719	B	0.647	C	0.800	B
10	5	3.00	72.00	B	0.832		0.849	C	0.458		0.657	B	0.786	C	0.600	B
9	4	48.00	14.66	Infeasible	1.000	Infeasible	0.990	B	0.500	Infeasible	0.835	B	0.921	A	0.700	B
6	4	12.00	71.20	Infeasible	1.000	Infeasible	0.853	B	1.000	A	0.646	C	0.894	B	0.477	C
7	4	4.00	78.40	Infeasible	0.939		0.785	C	0.535	B	0.537	C	0.800	B	0.453	C
2	4	8.00	58.45	Infeasible	0.750		0.676	C	0.653	A	0.535	C	0.688	C	0.400	C
3	3	4.00	40.82		0.419		0.364	C	0.199		0.237	C	0.378	C	0.210	C
4	2	4.00	19.80		0.137		0.081	C	0.000		0.000	C	0.113	C	0.047	C