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Sensitive Analysis of the ZF Model for ABC Multi Criteria Inventory Classification

Makram Ben Jeddou

***Abstract*—**ABC classification is widely used by managers for inventory control. The classical ABC classification is based on Pareto principle and according to the criterion of the annual use value only. Single criterion classification is often insufficient for a closely inventory control. Multi-criteria inventory classification models have been proposed by researchers in order to consider other important criteria. From these models, we will consider a specific model in order to make a sensitive analysis on the composite score calculated for each item. In fact, this score, based on a normalized average between a good and a bad optimized index, can affect the ABC-item classification. We will focus on items differently assigned to classes and then propose a classification compromise.

***Keywords*—**ABC classification, Multi criteria inventory classification models, ZF-model.

I. Introduction

THE control and inventory tracking is one of the important tasks for managers. This task is more difficult when the number of items is important. Managers should establish a priority rule for this monitoring. The ABC classification is one of the most used item segmentation method. This three class hierarchy is based on Pareto principle. Under this approach, class A is composed of 10 to 20% of items between 70 and 80 % of the value of total annual use. Articles of this class are very important and must be managed and monitored carefully. The second class B includes between 30 and 40% of all items representing 15-20 % of the value of total annual use. Control sections of this class can be less flexible than the previous category. Finally, class C may contain up to 50 % of items in stock, but only 5 to 10% of the value of total annual use. Control standards and monitoring may be reduced for the last category of items.

II. Literature Review

The classical ABC classification is only based on one criterion. However, inventory managers often need to consider, simultaneously, many criteria in the classification of stocks such as the unit price, delivery time, criticality of article, number of orders, number of clients interested by the item, etc.

Several models [1] have been presented in literature for multi-criteria inventory classification (MCIC). We will focus more on linear and nonlinear optimization models.

Ramanathan [2] proposed a model for the MCIC noted as the R model. The latter uses a weighed additive function to calculate a score called optimal score, for each item i, ∀ i = 1, ..., n, according to different criteria j, ∀ j = 1, ... J. The weights wij of yij values (evaluation of item i on criterion j) are identified by solving, for all items, a linear optimization model. This model is shown as:

$$S_i = Max \sum_{j=1}^{J} w_{ij} y_{ij} \tag{1}$$

$$Subject\ to:$$

$$\sum_{j=1}^{J} w_{ij} y_{nj} \leq 1, \quad n = 1,2,\ldots,N \tag{2}$$

$$w_{ij} \geq 0, \quad j = 1,2,\ldots,J \tag{3}$$

To get the optimal score for each article, the R model should be solved by repeatedly changing each time the objective function. These scores can then be used to classify items into three categories A, B and C.

Zhou & Fan [3] proposed another model for MCIC noted ZF model. It uses a different approach for calculating the score. Indeed, this model uses two sets of weights that are most favorable and less favorable weight for each item. Assume that R model provides the maximum possible score for each item i noted Gi (Good index). Gi is generated using the most favorable element i weight because they derive from a maximization function. By analogy the ZF model provides the minimum score for each element i noted Bi (Bad index) based on the least favorable weight. These weights are obtained by a linear optimization model with an objective function to minimize. Then, the new final score of an article will combine the corresponding Gi and Bi scores. The ZF model is formulated as:

$$G_i = Max \sum_{j=1}^{J} w_{ij} y_{ij} \tag{4}$$

$$Subject\ to:$$

$$\sum_{j=1}^{J} w_{ij} y_{ij} \leq 1, \quad i = 1,2,\ldots,N \tag{5}$$

$$w_{ij} \geq 0, \quad j = 1,2,\ldots,J \tag{6}$$

$$B_i = Min \sum_{j=1}^{J} w_{ij} y_{ij} \tag{7}$$

Makram Ben Jeddou is with the Higher Institute of Technological Studies, Rades, 2040 Tunisia (phone: 216 98 248 688; e-mail: makram.benjeddou@isetr.rnu.tn).

$$Subject\ to: \quad (8)$$

$$\sum_{j=1}^{J} w_{ij} y_{ij} \geq 1\ , \qquad i = 1,2,\dots,N$$

$$w_{ij}\ \geq 0, \qquad j = 1,2,\dots,J \quad (9)$$

Therefore, the final score of each element i is obtained by combining the two extreme scores Gi and Bi. It is formulated as:

$$S_i = \lambda . \frac{G_i - G^-}{G^+ - G^-} + (1-\lambda) . \frac{B_i - B^-}{B^+ - B^-} \quad (10)$$

with:

$$G^+ = Max\{G_i, i = 1,2,\dots,N\} \quad (11)$$

$$G^- = Min\{G_i, i = 1,2,\dots,N\} \quad (12)$$

$$B^+ = Max\{B_i, i = 1,2,\dots,N\} \quad (13)$$

$$B^- = Min\{B_i, i = 1,2,\dots,N\} \quad (14)$$

λ is a control parameter, between 0 and 1, that can reflect the preference of the decision maker for Gi and Bi. Then, obtained scores will be used to classify items into three categories A, B and C.

Ng [4] presented a new model for MCIC. It retains the objective function of the model R, but introduces other constraints. Ng model assumes that the criteria are ranked in descending order of importance. This is reflected in the relationship between all the weights of criteria: wi1 ≥ wi2 ≥ ... ≥ wij for any item i. A linear optimization model is constructed for each item i.

$$Max \quad \sum_{j=1}^{J} w_{ij} y_{ij} \quad (15)$$

$$Subject\ to:$$

$$\sum_{j=1}^{J} w_{ij} = 1 \quad (16)$$

$$w_{ij} - w_{i(j+1)} \geq 0, \qquad j = 1,2,\dots,(\mathrm{J}-1) \quad (17)$$

$$w_{ij}\ \geq 0, \qquad j = 1,2,\dots,J \quad (18)$$

Hadi-Vencheh [5] proposed a new variant of Ng model considering the weights of factors in quadratic form. Thus, in the proposed model, noted H model, we find the same Ng model logic except for the constraint on the sum of the weight factors. It was replaced by a squared sum of weight factors. Hence, H model becomes a non-linear optimization model as:

$$Max \quad \sum_{j=1}^{J} w_{ij} y_{ij} \quad (19)$$

$$Subject\ to:$$

$$\sum_{j=1}^{J} w^2{}_{ij} = 1 \quad (20)$$

$$w_{ij} \geq w_{i(j+1)} \geq 0, \quad j = 1,2,\dots,(\mathrm{J}-1) \quad (21)$$

$$w_{ij}\ \geq 0, \qquad j = 1,2,\dots,J \quad (22)$$

Chen [6] proposed a peer-estimation model for multi-criteria ABC inventory classification. The approach is based on five steps of calculation procedures and optimizations. The performance of each inventory item is estimated by criteria weights not only most favorable and least favorable themselves but also to its peers. The proposed approach determines two common sets of criteria weights for the performance estimation of all items in the most favorable and least favorable senses. The resulting two performance scores in both senses are aggregated by weight coefficients derived from using the maximizing deviations method.

In this article, we will focus on ZF model in order to undergo a sensitive analysis for control parameter λ and then see the effect on the ABC multi-criteria classification.

III. Methodology

For this sensitive analysis we will consider the same multi-criteria inventory classification problem (Table I) used for ZF model. This database was originally provided by [7], for multi-criteria inventory classification. In this original database, 47 items were provided and the inventory classification was based on three criteria:

- Average unit cost, measured in dollars.
- Annual dollar usage, also measured in dollars
- Lead time, measured in days.

Our methodology for sensitive analysis for the control parameter λ in the ZF model, will be based on seven steps as below:

- Calculate good index G_i for all the items according to ZF optimization approach.
- Calculate bad index B_i for all the items according to ZF optimization approach.
- Normalize all good and bad indexes using the normalization rule considered in ZF model.
- Calculate composite score S_i for all items for different λ value between 0 and 1. We will consider 9 different λ values for this sensitive analysis from 0.1 to 0.9. Then we will have 9 different distributions of composite scores that can be used to undergo various ABC multi-criteria classifications.
- For this classification, we will consider the following segmentation: 20% articles belonging to class A, 30% to B and 50% to class C.
- Analyze all 9 classifications and separate items assigned to the same classes by all of them and those assigned differently. For the first category this will be the final class assignment and for the second range of items we will calculate the belonging probability to each class.
- According to the missing items in each class and the probability calculated above, we will assign the remaining items to the different classes A, B and C.

IV. Results

For the 47 items, good and bed indexes and also their normalized values are depicted in Table II.

Calculation of the composite scores $S_{i\lambda}$ for each λ value is shown in Table III.

TABLE I
MULTI-CRITERIA INVENTORY DATABASE

Item no	Average unit cost ($)	Annual dollar usage ($)	Lead time
1	49,92	5840,64	2
2	210	5670	5
3	23,76	5037,12	4
4	27,73	4769,56	1
5	57,98	3478,8	3
6	31,24	2936,67	3
7	28,2	2820	3
8	55	2640	4
9	73,44	2423,52	6
10	160,5	2407,5	4
11	5,12	1075,2	2
12	20,87	1043,5	5
13	86,5	1038	7
14	110,4	883,2	5
15	71,2	854,4	3
16	45	810	3
17	14,66	703,68	4
18	49,5	594	6
19	47,5	570	5
20	58,45	467,6	4
21	24,4	463,6	4
22	65	455	4
23	86,5	432,5	4
24	33,2	398,4	3
25	37,05	370,5	1
26	33,84	338,4	3
27	84,03	336,12	1
28	78,4	313,6	6
29	134,34	268,68	7
30	56	224	1
31	72	216	5
32	53,02	212,08	2
33	49,48	197,92	5
34	7,07	190,89	7
35	60,6	181,8	3
36	40,82	163,28	3
37	30	150	5
38	67,4	134,8	3
39	59,6	119,2	5
40	51,68	103,36	6
41	19,8	79,2	2
42	37,7	75,4	2
43	29,89	59,78	5
44	48,3	48,3	3
45	34,4	34,4	7
46	28,8	28,8	3
47	8,46	25,38	5

TABLE II
GOOD AND BED INDEXES

Item no	Gi	Bi	Gi standardized	Bi standardized
1	1	1,8	1,00	0,20
2	1	5	1,00	1,00
3	1	2,27	0,85	0,32
4	1	1	0,78	0,00
5	1	2,29	0,52	0,32
6	1	1,89	0,47	0,22
7	1	1,84	0,47	0,21
8	1	2,67	0,62	0,42
9	1	3,72	0,94	0,68
10	1	4	0,73	0,75
11	0	1	0,17	0,00
12	1	1,94	0,67	0,24
13	1	3,94	1,00	0,74
14	1	3,57	0,69	0,64
15	0	2,32	0,35	0,33
16	0	1,9	0,32	0,23
17	1	1,42	0,48	0,11
18	1	2,84	0,83	0,46
19	1	2,55	0,64	0,39
20	1	2,37	0,47	0,34
21	1	1,63	0,47	0,16
22	1	2,46	0,48	0,37
23	1	2,59	0,51	0,40
24	0	1,62	0,30	0,16
25	0	1	0,00	0,00
26	0	1,62	0,30	0,16
27	0	1	0,26	0,00
28	1	3,21	0,83	0,55
29	1	3,51	1,00	0,63
30	0	1	0,10	0,00
31	1	2,56	0,64	0,39
32	0	1,36	0,16	0,09
33	1	2,5	0,64	0,38
34	1	1	1,00	0,00
35	0	1,68	0,31	0,17
36	0	1,62	0,30	0,16
37	1	1,8	0,64	0,20
38	0	1,56	0,32	0,14
39	1	2,08	0,64	0,27
40	1	2,17	0,83	0,29
41	0	1	0,12	0,00
42	0	1	0,12	0,00
43	1	1,48	0,64	0,12
44	0	1,12	0,30	0,03
45	1	1,36	1,00	0,09
46	0	1	0,30	0,00
47	1	1	0,64	0,00

TABLE III
COMPOSITE SCORES

Item no	$\mathbf{Si_{0,1}}$	$\mathbf{Si_{0,2}}$	$\mathbf{Si_{0,3}}$	$\mathbf{Si_{0,4}}$	$\mathbf{Si_{0,5}}$	$\mathbf{Si_{0,6}}$	$\mathbf{Si_{0,7}}$	$\mathbf{Si_{0,8}}$	$\mathbf{Si_{0,9}}$
1	0,28	0,36	0,44	0,52	0,60	0,68	0,76	0,84	0,92
2	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00
3	0,37	0,42	0,48	0,53	0,58	0,64	0,69	0,74	0,80
4	0,08	0,16	0,23	0,31	0,39	0,47	0,54	0,62	0,70
5	0,34	0,36	0,38	0,40	0,42	0,44	0,46	0,48	0,50
6	0,25	0,27	0,30	0,32	0,35	0,37	0,40	0,42	0,44
7	0,24	0,26	0,29	0,31	0,34	0,37	0,39	0,42	0,44
8	0,44	0,46	0,48	0,50	0,52	0,54	0,56	0,58	0,60
9	0,71	0,73	0,76	0,78	0,81	0,83	0,86	0,89	0,91
10	0,75	0,75	0,74	0,74	0,74	0,74	0,73	0,73	0,73
11	0,02	0,03	0,05	0,07	0,09	0,10	0,12	0,14	0,16
12	0,28	0,32	0,36	0,41	0,45	0,49	0,54	0,58	0,62
13	0,76	0,79	0,81	0,84	0,87	0,89	0,92	0,95	0,97
14	0,65	0,65	0,66	0,66	0,67	0,67	0,68	0,68	0,69
15	0,33	0,33	0,33	0,34	0,34	0,34	0,34	0,34	0,34
16	0,23	0,24	0,25	0,26	0,27	0,28	0,29	0,30	0,31
17	0,14	0,18	0,22	0,26	0,29	0,33	0,37	0,41	0,44
18	0,50	0,53	0,57	0,61	0,64	0,68	0,72	0,75	0,79
19	0,41	0,44	0,46	0,49	0,51	0,54	0,57	0,59	0,62
20	0,36	0,37	0,38	0,39	0,41	0,42	0,43	0,44	0,46
21	0,19	0,22	0,25	0,28	0,31	0,34	0,38	0,41	0,44
22	0,38	0,39	0,40	0,41	0,42	0,43	0,45	0,46	0,47
23	0,41	0,42	0,43	0,44	0,45	0,46	0,47	0,48	0,50
24	0,17	0,18	0,20	0,21	0,23	0,24	0,25	0,27	0,28
25	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
26	0,17	0,18	0,20	0,21	0,23	0,24	0,25	0,27	0,28
27	0,03	0,05	0,08	0,10	0,13	0,16	0,18	0,21	0,23
28	0,58	0,61	0,63	0,66	0,69	0,72	0,74	0,77	0,80
29	0,66	0,70	0,74	0,78	0,81	0,85	0,89	0,93	0,96
30	0,01	0,02	0,03	0,04	0,05	0,06	0,07	0,08	0,09
31	0,42	0,44	0,47	0,49	0,52	0,54	0,57	0,59	0,62
32	0,10	0,10	0,11	0,12	0,13	0,13	0,14	0,15	0,15
33	0,40	0,43	0,46	0,48	0,51	0,54	0,56	0,59	0,62
34	0,10	0,20	0,30	0,40	0,50	0,60	0,70	0,80	0,90
35	0,18	0,20	0,21	0,23	0,24	0,25	0,27	0,28	0,29
36	0,17	0,18	0,20	0,21	0,23	0,24	0,25	0,27	0,28
37	0,24	0,29	0,33	0,38	0,42	0,47	0,51	0,55	0,60
38	0,16	0,18	0,19	0,21	0,23	0,25	0,27	0,28	0,30
39	0,31	0,34	0,38	0,42	0,46	0,49	0,53	0,57	0,60
40	0,35	0,40	0,45	0,51	0,56	0,61	0,67	0,72	0,77
41	0,01	0,02	0,04	0,05	0,06	0,07	0,09	0,10	0,11
42	0,01	0,02	0,04	0,05	0,06	0,07	0,09	0,10	0,11
43	0,17	0,22	0,28	0,33	0,38	0,43	0,49	0,54	0,59
44	0,06	0,08	0,11	0,14	0,16	0,19	0,22	0,24	0,27
45	0,18	0,27	0,36	0,45	0,55	0,64	0,73	0,82	0,91
46	0,03	0,06	0,09	0,12	0,15	0,18	0,21	0,24	0,27
47	0,06	0,13	0,19	0,26	0,32	0,39	0,45	0,51	0,58

In Table IV, we present all the ABC multi-criteria classification for the different λ values. This table shows that 30 items are identically classified (Table V) and the remaining 17 items are differently assigned to the three classes A, B and C (Table VI). By considering and analyzing the nine ABC multi-criteria classifications, we calculate the belonging probability for these items to each class. At the same time we consider the number of missing items to be assigned to each class: 4 for class A, 8 for class B and 5 for class C. By combining these two results, we reached a compromise classification, shown in Table VII, for the remaining 17 items. Items 1, 3, 10 and 14 are assigned to class A with an average assignment probability of 70%. Items 5, 8, 20, 22, 23, 31, 34, and 45 are assigned to class B with an average assignment probability of 67%. Items 4, 6, 15, 43 and 47 are assigned to class C with an average assignment probability of 71%.

TABLE IV
ABC CLASSIFICATIONS

Item no	λ 0,1	λ 0,2	λ 0,3	λ 0,4	λ 0,5	λ 0,6	λ 0,7	λ 0,8	λ 0,9
1	B	B	B	A	A	A	A	A	A
2	A	A	A	A	A	A	A	A	A
3	B	B	A	A	A	A	B	A	A
4	C	C	C	C	C	B	B	B	B
5	B	B	B	B	B	B	B	C	B
6	B	C	C	C	C	C	C	C	C
7	C	C	C	C	C	C	C	C	C
8	A	A	A	B	B	B	B	B	B
9	A	A	A	A	A	A	A	A	A
10	A	A	A	A	A	A	A	B	B
11	C	C	C	C	C	C	C	C	C
12	B	B	B	B	B	B	B	B	B
13	A	A	A	A	A	A	A	A	A
14	A	A	A	A	A	A	B	B	B
15	B	B	B	C	C	C	C	C	C
16	C	C	C	C	C	C	C	C	C
17	C	C	C	C	C	C	C	C	C
18	A	A	A	A	A	A	A	A	A
19	B	B	B	B	B	B	B	B	B
20	B	B	B	B	B	C	C	C	C
21	C	C	C	C	C	C	C	C	C
22	B	B	B	B	B	B	C	C	C
23	B	B	B	B	B	B	B	B	C
24	C	C	C	C	C	C	C	C	C
25	C	C	C	C	C	C	C	C	C
26	C	C	C	C	C	C	C	C	C
27	C	C	C	C	C	C	C	C	C
28	A	A	A	A	A	A	A	A	A
29	A	A	A	A	A	A	A	A	A
30	C	C	C	C	C	C	C	C	C
31	A	A	B	B	B	B	B	B	B
32	C	C	C	C	C	C	C	C	C
33	B	B	B	B	B	B	B	B	B
34	C	C	C	B	B	B	A	A	A
35	C	C	C	C	C	C	C	C	C
36	C	C	C	C	C	C	C	C	C
37	B	B	B	B	B	B	B	B	B
38	C	C	C	C	C	C	C	C	C
39	B	B	B	B	B	B	B	B	B
40	B	B	B	B	B	B	B	B	B
41	C	C	C	C	C	C	C	C	C
42	C	C	C	C	C	C	C	C	C
43	C	C	C	C	C	C	B	B	B
44	C	C	C	C	C	C	C	C	C
45	C	B	B	B	B	B	A	A	A
46	C	C	C	C	C	C	C	C	C
47	C	C	C	C	C	C	C	B	B

TABLE V
ITEMS IDENTICALLY CLASSIFIED

Item no	λ 0,1	λ 0,2	λ 0,3	λ 0,4	λ 0,5	λ 0,6	λ 0,7	λ 0,8	λ 0,9
2	A	A	A	A	A	A	A	A	A
9	A	A	A	A	A	A	A	A	A
13	A	A	A	A	A	A	A	A	A
18	A	A	A	A	A	A	A	A	A
28	A	A	A	A	A	A	A	A	A
29	A	A	A	A	A	A	A	A	A
12	B	B	B	B	B	B	B	B	B
19	B	B	B	B	B	B	B	B	B
33	B	B	B	B	B	B	B	B	B
37	B	B	B	B	B	B	B	B	B
39	B	B	B	B	B	B	B	B	B
40	B	B	B	B	B	B	B	B	B
7	C	C	C	C	C	C	C	C	C
11	C	C	C	C	C	C	C	C	C
16	C	C	C	C	C	C	C	C	C
17	C	C	C	C	C	C	C	C	C
21	C	C	C	C	C	C	C	C	C
24	C	C	C	C	C	C	C	C	C
25	C	C	C	C	C	C	C	C	C
26	C	C	C	C	C	C	C	C	C
27	C	C	C	C	C	C	C	C	C
30	C	C	C	C	C	C	C	C	C
32	C	C	C	C	C	C	C	C	C
35	C	C	C	C	C	C	C	C	C
36	C	C	C	C	C	C	C	C	C
38	C	C	C	C	C	C	C	C	C
41	C	C	C	C	C	C	C	C	C
42	C	C	C	C	C	C	C	C	C
44	C	C	C	C	C	C	C	C	C
46	C	C	C	C	C	C	C	C	C

TABLE VI
ITEMS CLASSIFIED DIFFERENTLY

Item no	λ 0,1	λ 0,2	λ 0,3	λ 0,4	λ 0,5	λ 0,6	λ 0,7	λ 0,8	λ 0,9
1	B	B	B	A	A	A	A	A	A
3	B	B	A	A	A	A	B	A	A
4	C	C	C	C	C	B	B	B	B
5	B	B	B	B	B	B	B	C	B
6	B	C	C	C	C	C	C	C	C
8	A	A	A	B	B	B	B	B	B
10	A	A	A	A	A	A	A	B	B
14	A	A	A	A	A	A	B	B	B
15	B	B	B	C	C	C	C	C	C
20	B	B	B	B	B	C	C	C	C
22	B	B	B	B	B	B	C	C	C
23	B	B	B	B	B	B	B	B	C
31	A	A	B	B	B	B	B	B	B
34	C	C	C	B	B	B	A	A	A
43	C	C	C	C	C	C	B	B	B
45	C	B	B	B	B	B	A	A	A
47	C	C	C	C	C	C	C	B	B

TABLE VII
COMPROMISE CLASSIFICATION

Item no	A	B	C	Class assignment
1	67%	33%	0%	A
3	67%	33%	0%	A
4	0%	44%	56%	C
5	0%	89%	11%	B
6	0%	11%	89%	C
8	33%	67%	0%	B
10	78%	22%	0%	A
14	67%	33%	0%	A
15	0%	33%	67%	C
20	0%	56%	44%	B
22	0%	67%	33%	B
23	0%	89%	11%	B
31	22%	78%	0%	B
34	33%	33%	33%	B
43	0%	33%	67%	C
45	33%	56%	11%	B
47	0%	22%	78%	C

V. CONCLUSION

We considered a multi-criteria ABC classification using the ZF model for the segmentation of 47 items. This method presents a relative bias due to the choice of lambda parameter in calculating the composite score. We conducted a sensitive analysis in order to neutralize this effect and to reach a compromise classification.

Adopted methodology for this sensitive analysis can be used by managers for inventory classification while changing the classification criteria in order to meet their needs.

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Makram Ben Jeddou was born in Tunis, Tunisia, in March 18, 1972. He got Bachelor in Business and Management at IHEC University, Carthage, Tunisia, 1994; Master in Management and Statistics at ESC university, Tunis, Tunisia, 1996; Aggregation in Management and Statistics, Tunis, 1997. He has been with Higher Institute of Technological Studies, Rades Tunisia since 1997. He works mainly on clustering, multi-criteria classification and their application in management.