



# Journal of Turkish Operations Management

## Classification of inventory items by group decisions protocol

Orhan Gerdan \*

OSTİM Technical University, Ankara

e-mail: orhan.gerdan@ostimteknik.edu.tr, ORCID No: <https://orcid.org/0000-0003-1117-6995>

### Article Info

#### Article History:

Received: 22.01.2024  
Revised: 20.07.2024  
Accepted: 23.07.2024

### Keywords

ABC inventory classification,  
Multiple criteria analysis,  
Group decisions analysis.

### Abstract

Companies classify inventory items using multiple-criteria via ABC analysis principles and then apply inventory management policies in accordance with the assigned classes' characteristics.

Different kinds of models, such as; linear programming, analytic hierarchy process (AHP), cluster analysis, and etc. are used in those analysis. In the results obtained in the models used, the scores and classes of the stock items differ.

Each author has proven that their model works better than other models on some stock items. The question that managers will have difficulty answering is which of the existing models to choose and use. In order to eliminate this problem faced by managers, in this study, a new ranking and classification, which is a combination of all the models, was obtained by using the Group Decision Making technique.

## 1. Introduction

ABC analysis, firstly pronounced by Dickie (1951), is based on 80/20 principle posed by Italian economist and sociologist Vilfredo Pareto. ABC analysis contributes to efficiency of stock management policies of companies through classification of their inventories comprising more than thousands of items. Traditional ABC analysis is based on classifying items as A (Very Important), B (Important) and C (Less Important) by taking into account only single measurement such as annual dollar usage.

Flores and others (1992), considering multi-criteria, put the inventory items in order and classified them with certain proportions by using AHP. Ramanathan (2006) applied R-model, a Data Envelopment Analysis (DEA) like weighted linear optimization. Zhou and Fan (2007) developed a model (ZF Model), where for preventing any item always locate in A group and have better value than others considering only one criterion, to rank and classify inventory items by using least favorable and most favorable values. Ng (2007) obtained the largest value of inventory items and listed them by ranking criteria according to their weights, using a proper transformation and without using any linear optimizer (Ng Model). Chen Y. et al. proposed a case-based distance model for multiple criteria ABC analysis. Hadi-Vencheh (2010) extended NG-Model by using a non-linear programming (Hadi-Vencheh-Model). His model maintains the effect of weights in the final solution. Chen J. (2011) developed the ZF model. Yu M. (2011) used artificial-intelligence-based classification (Chen-Model). Torabi S.A. et al. (2012) classified items in the presence of both quantitative and qualitative criteria. Mohammaditabar D. et al. (2012) developed simulated annealing is used to find appropriate solutions. Douissa M. R., and Jabeur K. (2016) proposed PROAFTN method for multi-criteria ABC inventory classification. Park J. et al. (2014) used Cross-evaluation-based weighted linear optimization for multi-criteria ABC inventory classification (Park-Model). Kaabi H. et al. (2015) proposed Automatic Learning Method (ALM). Zowid F.M. et al. (2019) proposed Gaussian Mixture Model. Khanorkar Y., and Kane P.V. (2023) analyzed machine learning models in inventory classification.

In the results obtained in these models, the scores and classes of the stock items differ. This situation is challenging for decision makers. Each author has proven that their model works better than other models on some stock items. The question that managers will have difficulty answering is which of the existing models to choose and use. In order to eliminate this problem faced by managers, in this study, a new ranking and classification, which is a combination of all the models, was obtained by using the scores and rankings of the existing models and BC Rule, which is a Group Decision Making technique. Managers will be able to make better decisions by sorting and grouping the models they choose, giving them the weight they want.

In this paper, a group decisions protocol, Borda–Condorcet rule (proposed by Herrero C, and Villar A., 2021) is applied to unify the results obtained using multiple models. The Borda–Condorcet rule is briefly presented in Section 2. In Section 3, application of this model to the Classification of Inventory Items is analyzed and it was revealed statistically whether there was a significance difference between the rankings. In Section 4 the results are compared. Short conclusions and recommendations are given in Section 5.

## 2. Borda–Condorcet Rule

Borda–Condorcet Rule is an evaluation protocol that transforms a collection of rankings, defined over a set of alternatives, into a complete, transitive, and cardinal assessment. It unifies the ideas of Borda and Condorcet by computing the support that each alternative receives on average when confronted with any other. The protocol evaluates those alternatives in terms of pairwise comparisons but weighs the outcomes differently depending on how each alternative fares with respect to the others (Herrero C, and Villar A., 2021). Hereafter the protocol will be referred to as the BC rule.

The implementation processes of the BC rule for multi-criteria decision problems can be summarized in the following steps.

STEP 1: Identify the Borda–Condorcet matrix.

STEP 2: Find the largest eigenvalue and its eigenvector of the Borda–Condorcet matrix, then normalize eigenvector's elements and multiply by 100 to get the BC values.

STEP 3: Sort the BC values in the descending order.

In STEP 1, the Borda–Condorcet matrix, the rows and columns of the matrix consist of the option set. Values in cells,  $c_{ij}$ , denote the number of people who prefer  $i$  over  $j$ . Those  $c_{ij}$  are the Condorcet numbers.

$$c_{ij} = n_{ij} + \frac{e_{ij}}{2} \quad (1)$$

In equation (1);

$n_{ij}$ ; number of individuals who prefer alternative  $i$  to alternative  $j$ , and

$e_{ij} = e_{ji}$  the number of individuals who are indifferent between both alternative.

The Borda score (That is the number of individuals that prefer alternative  $i$  to any other) of alternative  $i$  is thus given by:

$$B(i) = \sum_{j \neq i} c_{ij} \quad (2)$$

## 3. Classification of Inventory Items by BC Rule

This part will represent classification of inventory items by BC rule using different multi criteria ABC inventory classification models' results. The scores of six models in the literature, detailed information of which are presented in Table 1, were used. The reason for choosing these models is that all of them are classified using the same common criteria (Annual Dollar Usage, (ADU), Unit Cost, (AUC), and Lead Time, (LT)). The scores are in the columns; (4), (7), (10), (13), (16), and (19). The differences in the classification of stock items (Columns; (5),

(8), (11), (14), (17), and (20)) are obvious in the Table 1. The difficult question to be asked then are, as a decision maker, the classification obtained by which method should be chosen?

The purpose of this study is to answer that difficult question, unification of different multi criteria ABC inventory classification models using BC rule, which is a group decision making method. In this paper, the weights for the results obtained with each model are considered equally. The final classifications obtained according to different weight values will obviously be different.

Unification of different multi-criteria ABC inventory classification models using BC rule can be explained in the following steps.

STEP 1: Rank the inventory items for each model in order of scores in descending order. Number them in this order, starting with 1. Give the same number to those with the same score. Instead of numbering in this way, score values can also be used.

STEP 2: Identify the Borda–Condorcet matrix.

STEP 3: Find the largest eigenvalue and its eigenvector of the Borda–Condorcet matrix, then normalize eigenvector's elements and multiply by 100 to get the BC values.

STEP 4: Sort the BC values in the descending order. Assign the inventory items to class A, B, and C.

The application of these steps to reclassify 47 inventory items using the outputs of six different models is summarized below.

- In Step 1, the scores of the six models are ordered in descending order and numbered starting from 1. Inventory items with the same score are given the same number (See Table 1: Columns; (6), (9), (12), (15), (18), and (21)).
- In the second step, the Borda–Condorcet matrix was obtained for 47 stock items using the ranking of the six models (Table 2).
- Step 3 involves finding the eigenvector with the largest eigenvalue of the Borda Condorcet matrix (Table 3: BC Valuation column). Since the size of the matrix is 47 by 47, the eigenvalue and eigenvector are found by calculator in the link [https://www.arndt-bruenner.de/mathe/scripts/engl\\_eigenwert2.htm](https://www.arndt-bruenner.de/mathe/scripts/engl_eigenwert2.htm).
- In the last step, BC values are ordered from largest to smallest, and the first 10 inventory items are assigned to A, the next 14 inventory items to B, and the remaining 23 inventory items to C (Table 3: Class column).

The BC rule provides the decision maker with the opportunity to unify the classifications obtained from different models.

Table 1: Scores, Class, and Rank of the Stock Items According to the Models.

Table with 21 columns: Item No., Criteria (1) ADU, (2) AUC, (3) LT, R-Model (4) Score, (5) Class, (6) Rank, NG-Model (7) Score, (8) Class, (9) Rank, ZF-Model (10) Score, (11) Class, (12) Rank, Hadi-VENEH-Model (13) Score, (14) Class, (15) Rank, Chen-Model (16) Score, (17) Class, (18) Rank, Park-Model (19) Score, (20) Class, (21) Rank. The table lists 47 stock items with their respective scores and classifications across five different models.

Table 2: Borda-Condorcet Matrix of the Ranked Items According to the Models.

A large matrix table showing the Borda-Condorcet matrix for 47 ranked items. Each row and column represents an item, and the cells contain numerical values representing the pairwise comparisons between items according to the models. The matrix is symmetric along the diagonal.

Table 3: BC Rule Rank, Scores, and Class.

Item No.	Rank of Items by Scores						BC Rule		
	R-Model	NG-Model	ZF-Model	HADI-VENCEH-Model	CHEN-Model	PARK-Model	Rank	BC Valuation	Class
1	24	1	9	2	7	29	9	5,04	A
2	29	2	1	1	1	3	1	14,50	A
3	46	3	10	5	4	12	10	3,76	A
4	1	4	25	8	24	40	13	2,43	B
5	39	5	21	10	15	27	16	1,67	B
6	32	10	27	17	19	28	21	1,09	B
7	38	11	28	19	20	30	26	0,87	C
8	42	12	13	12	13	21	19	1,57	B
9	43	8	3	6	2	6	6	5,25	A
10	37	6	5	3	6	11	8	5,14	A
11	44	37	43	43	41	42	47	0,07	C
12	47	23	19	23	16	15	30	0,70	C
13	45	9	2	6	3	2	5	5,66	A
14	1	13	7	9	12	10	4	6,05	A
15	7	27	28	29	32	31	28	0,76	C
16	8	31	33	33	33	32	32	0,61	C
17	12	31	32	31	30	25	29	0,71	C
18	1	15	8	13	11	8	7	5,15	A
19	20	20	13	20	17	14	14	1,75	B
20	21	26	24	26	29	24	27	0,86	C
21	22	31	30	31	31	26	31	0,63	C
22	15	25	21	25	28	23	23	1,02	B
23	25	20	19	20	26	22	22	1,09	B
24	36	37	35	38	36	35	45	0,21	C
25	26	45	47	46	47	47	44	0,24	C
26	23	37	35	39	37	37	38	0,40	C
27	9	31	41	37	45	45	36	0,42	C
28	1	14	6	11	10	7	3	6,78	A
29	31	7	3	4	5	1	2	8,38	A
30	13	43	46	44	46	46	41	0,32	C
31	35	19	13	18	18	13	20	1,28	B
32	14	43	41	42	42	41	40	0,36	C
33	5	24	16	24	22	17	17	1,61	B
34	28	18	17	16	9	5	12	2,65	B
35	30	36	34	35	35	34	43	0,31	C
36	16	37	35	39	38	38	37	0,42	C
37	27	27	21	27	23	18	24	0,93	B
38	16	31	35	34	34	33	34	0,51	C
39	11	20	18	22	21	16	18	1,60	B
40	40	17	11	15	14	9	15	1,69	B
41	41	47	44	47	44	44	46	0,08	C
42	16	45	44	45	43	43	42	0,31	C
43	32	29	26	28	25	19	33	0,59	C
44	5	37	39	36	39	36	35	0,49	C
45	32	15	12	14	8	4	11	2,84	B
46	16	42	40	41	40	39	39	0,38	C
47	10	30	30	30	27	20	25	0,89	C

Wilcoxon Signed Ranks Test Statistics, Friedman's ANOVA on Ranked Data and Spearman's Rank Correlation techniques were used to investigate whether there was a difference between the ranks obtained from all models given in Table-3 and to investigate the correlation.

#### Wilcoxon Signed Ranks Test Statistics

$H_0$ : There is no significant difference between the medians of two methods (Ordinal Matched Pairs) at the level of  $\alpha=0.05$

$H_1$ : There is a significant difference between the medians of two methods (Ordinal Matched Pairs) at the level of  $\alpha=0.05$

Table 4: Wilcoxon Signed Ranks Test Statistics

	R-Model/ BC-Rule	NG-Model/ BC-Rule	ZF-Model/ BC-Rule	HADI-VENCEH-Model/ BC-Rule	CHEN-Model/ BC-Rule	PARK-Model/ BC-Rule
Z	-0.275	-0.221	-0.471	-0.025	-0.228	-0.498
p	0.783	0.825	0.638	0.980	0.820	0.618
Result	$H_0$ accepted	$H_0$ accepted	$H_0$ accepted	$H_0$ accepted	$H_0$ accepted	$H_0$ accepted

As a result, there is no significant difference between the medians of BC Rule and other methods at the level of  $\alpha=0.05$

### Friedman's ANOVA on Ranked Data

H<sub>0</sub>: There is no significant difference between the mean ranks of two methods at the level of  $\alpha=0.05$

H<sub>1</sub>: There is a significant difference between the mean ranks of two methods at the level of  $\alpha=0.05$

Table 5: Friedman's Test Statistics

	R-Model/ BC-Rule	NG-Model/ BC-Rule	ZF-Model/ BC-Rule	HADI-VENCEH-Model/ BC-Rule	CHEN-Model/ BC-Rule	PARK-Model/ BC-Rule
Chi-Square	1.723	0.200	0.000	2.381	0.091	0.000
p	0.189	0.655	1.000	0.123	0.763	1.000
Result	H <sub>0</sub> accepted	H <sub>0</sub> accepted	H <sub>0</sub> accepted	H <sub>0</sub> accepted	H <sub>0</sub> accepted	H <sub>0</sub> accepted

As a result, there is no significant difference between the mean of BC Rule and other methods at the level of  $\alpha=0.05$

Correlation analysis results also support the results obtained in both methods. Because there is a strong positive correlation between other models except R-Model.

### Spearman's Rank Correlation (Correlation coefficient for ordinal variables)

H<sub>0</sub>: The correlation coefficient is not significant at the level of  $\alpha=0.05$

H<sub>1</sub>: The correlation coefficient is significant at the level of  $\alpha=0.05$

Table 6: Spearman's Rank Correlation

	BC Rule	R-Model	NG-Model	ZF-Model	HADI_VENCEH-Model	CHEN-Model	PARK-Model
BC Rule	1.000						
R-Model	-0.034	1.000					
NG-Model	0.910*	-0.251	1.000				
ZF-Model	0.950*	-0.206	0.878*	1.000			
HADI VENCEH-Model	0.952*	-0.223	0.983*	0.938*	1.000		
CHEN-Model	0.935*	-0.325*	0.922*	0.964*	0.958*	1.000	
PARK-Model	0.858*	-0.224	0.717*	0.924*	0.799*	0.904*	1.000

(\*) Correlation is significant at the level of  $\alpha=0.05$ .

There is strong positive correlation between BC Rule end other methods (Except R-Model, negative correlation)

It was stated that there was no significant difference between the rankings of BC Rule and other models. However, when the classes of stock items in the BC Model are examined, it is observed that there is a transition between classes compared to other models. Observation results are given numerically and percentage in Table 7.

## 4. Results

In this study, a ranking and classification was made with BC Rule, a group decision-making technique, using the rankings made with six different Stock Classification models, assuming the weight of each of the six models is equal.

Table-3 gives the BC values, rank, and class of inventory items.

In pairs comparisons of ranking BC Rule with other methods, It was determined that there is no significant difference between the medians and means of BC Rule and other methods at the level of  $\alpha=0.05$ , and a strong positive correlation between other models except R-Model.

Table 7: Class Transitions from Models to BC Rule as Numerically and Percentage.

Model		BC Rule					
		Class Transition (Numerically)			Class Transition (%)		
		A	B	C	A	B	C
R-Model	A	3	2	5	0,30	0,20	0,50
	B	1	3	10	0,07	0,21	0,71
	C	6	9	8	0,26	0,39	0,35
NG-Model	A	7	3	0	0,70	0,30	0,00
	B	3	9	2	0,21	0,64	0,14
	C	0	2	21	0,00	0,09	0,91
ZF-Model	A	10	0	0	1,00	0,00	0,00
	B	0	12	2	0,00	0,86	0,14
	C	0	2	21	0,00	0,09	0,91
H. VENCHEH-Model	A	8	2	0	0,80	0,20	0,00
	B	2	10	2	0,14	0,71	0,14
	C	0	2	21	0,00	0,09	0,91
CHEN-Model	A	8	2	0	0,80	0,20	0,00
	B	2	10	2	0,14	0,71	0,14
	C	0	2	21	0,00	0,09	0,91
PARK-Model	A	7	3	0	0,70	0,30	0,00
	B	2	8	4	0,14	0,57	0,29
	C	1	3	19	0,04	0,13	0,83

Although there is no significant difference between the rankings, significant changes have been achieved in the ABC classifications. Classification with the BC rule produced different results than classification with the other six models. Detailed results are in Table-7.

If Table-7 is briefly summarized, the classification of 47 inventory items according to six different models and the new classes obtained by the BC rule are compared. The transitions between classes (A, B, and C) are shown numerically and as a percentage. The results were analyzed, starting from the models with low transitions between classes.

ZF-Model ↔ BC Rule: There is no change in 10 A-class inventory items, 2 of the 14 items of class B materials have passed to class C, and 2 of 23 items of Class C materials have passed to Class B.

Hadi-VENCHEH-Model ↔ BC Rule: 2 of the 10 items of class A materials have passed to class B, Of the 14 class B materials, 2 of them passed to class A and 2 of them to class C, and 2 of 23 items of Class C materials have passed to Class B.

Chen-Model ↔ BC Rule: 2 of the 10 items of class A materials have passed to class B, of the 14 class B materials, 2 of them passed to class A and 2 of them to class C, and 2 of 23 items of Class C materials have passed to Class B.

Ng-Model ↔ BC Rule: 3 of the 10 items of class A materials have passed to class B, of the 14 class B materials, 3 of them passed to class A and 2 of them to class C, and 2 of 23 items of Class C materials have passed to Class B.

Park-Model ↔ BC Rule: 3 of the 10 items of class A materials have passed to class B, of the 14 class B materials, 2 of them passed to class A and 4 of them to class C, and of the 23 class C materials, 1 of them passed to class A and 3 of them to class B.

R-Model ↔ BC Rule: Of the 10 class A materials, 2 of them passed to class B and 5 of them to class C, of the 14 class B materials, 1 of them passed to class A and 3 of them to class C, and of the 23 class C materials, 6 of them passed to class A and 9 of them to class B.

## 5. Conclusion and recommendation

ABC analysis of inventory items is very important for inventory managers. In the literature there are lots of technique can be used for this purpose, and they produce different ranking and classification. The question that managers will have difficulty answering is which of the existing models to choose and use. In order to eliminate this problem faced by managers, in this study, a new ranking and classification, which is a combination of all the models, was obtained by using the scores and rankings of the existing models and BC Rule, which is a Group Decision Making technique. Managers will be able to make better decisions by sorting and grouping the models they choose, giving them the weight they want.

In the classification of stock items, better results can be achieved by using the BC rule, which is a group decision-making technique, and by making use of the score points or rankings obtained as a result of the models developed by different authors. From this point of view, the BC rule can be used in any field to combine the outputs obtained using different methods.

For the future research, how BC Rule can be applied to problems, the criterion values have lower and upper limit values, are fuzzy or random instead of deterministic values. Additionally, BC Rule can be used in all sorting problems.

## Conflict of Interest

The authors whose names are listed above, certify that they have no affiliations with or involvement in any organization or entity with any financial interest, or non-financial interest in the subject matter or materials discussed in this article.



## References

- Chen, Y. et al. (2008). A case-based distance model for multiple criteria ABC analysis. *Computer and Operations Research*, 35, 2008, 776-796. <https://doi.org/10.1016/j.cor.2006.03.024>
- Chen, J., (2011). "Peer Estimation for Multiple Criteria ABC Inventory Classification" *Computer and Operations Research*, 38, 2011, 1784-1791. <https://doi.org/10.1016/j.cor.2011.02.015>
- Dickie, H.F., (1951), "ABC Inventory Analysis Shoots for Dollars", *Factory Management and Maintenance*, 109, 1951, 92-94.
- Douissa M. R., and Jabeur K. (2016). A New Model for Multi-criteria ABC Inventory Classification: PROAFTN Method. *Procedia Computer Science*, 96, 2016, 550-559. <https://doi.org/10.1016/j.procs.2016.08.233>
- Flores, B.E., et al., (1992), "Management of Multicriteria Inventory Classification", *Mathematical and Computer Modeling*, 16, 12, 1992, 71-82. [https://doi.org/10.1016/0895-7177\(92\)90021-C](https://doi.org/10.1016/0895-7177(92)90021-C)
- Hadi-Vencheh, A. (2010), "An Improvement to Multiple Criteria ABC Inventory Classification", *European Journal of Operations Research*, 201, 2010, 962-965. <https://doi.org/10.1016/j.ejor.2009.04.013>
- Kaabi H. et al. (2015). Learning criteria weights with TOPSIS method and continuous VNS for multi-criteria inventory classification. *Electronic Notes in Discrete Mathematics*, 47 (2015), 197-204. <https://doi.org/10.1016/j.endm.2014.11.026>
- Khanorkar Y., and Kane P.V. (2023). Selective inventory classification using ABC classification, multi-criteria decision making techniques, and machine learning techniques. *Materials Today: Proceedings*, 72 (2023) 1270–1274. <https://doi.org/10.1016/j.matpr.2022.09.298>
- Mohammaditabar D. et al. (2012). Inventory control system design by integrating inventory classification and policy selection. *Int. J. Production Economics*, 140, 2012, 655-659. <https://doi.org/10.1016/j.ijpe.2011.03.012>
- Ng, W.L., (2007), "A Simple Classifier for Multiple Criteria ABC Analysis", *European Journal of Operations Research*, 177, 2007, 344-353. <https://doi.org/10.1016/j.ejor.2005.11.018>
- Ramanathan, R. (2006), "ABC Inventory Classification with Multiple-Criteria Using Weighted Linear Optimization", *Computer and Operations Research*, 33, 2006, 695-700. <https://doi.org/10.1016/j.cor.2004.07.014>
- Park J. et al. (2014). Cross-evaluation-based weighted linear optimization for multi-criteria ABC inventory classification. *Computers & Industrial Engineering*, 76, 2014, 40-48. <https://doi.org/10.1016/j.cie.2014.07.020>
- Torabi S.A. et al. (2012). ABC inventory classification in the presence of both quantitative and qualitative criteria. *Computers & Industrial Engineering*, 63, 2012, 530-537. <https://doi.org/10.1016/j.cie.2012.04.011>
- Yu M. (2011). Multi-criteria ABC analysis using artificial-intelligence-based classification techniques. *Expert Systems with Applications*, 38, 2011, 3416-3421. <https://doi.org/10.1016/j.eswa.2010.08.127>
- Zhou P., Fan L., (2007), "A Note on Multiple Criteria ABC Inventory Classification Using Weighted Linear Optimisation", *European Journal of Operations Research*, 182, 2007, 1488-1491. <https://ideas.repec.org/a/eee/ejores/v182y2007i3p1488-1491.html>
- Zowid F.M. et al. (2019). Multi-criteria inventory ABC classification using Gaussian Mixture Model. *IFAC PapersOnLine* 52-13, 2019, 1925–1930. <https://doi.org/10.1016/j.ifacol.2019.11.484>