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Application of the modified similarity-based method for multi-criteria inventory classification

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A B S T R A C T

In the era of digital manufacturing and highly competitive environment, it is desirable to deliver the right item, right quantity at right time at minimal cost. Under this volatile market environment, the inventory should be readily available at the manufacturing level at the lowest possible cost. Many industries have been conventionally employing traditional ABC analyses based on a single criterion of annual consumption cost for classification of inventory items in spite of other criteria such as unit cost, consumption rate, average inventory cost that may be important in inventory classification. To address such problems, incorporation of Multi-criteria decision making (MCDM) methods is considered an advantage. The present article focuses on a new approach to categorize inventory items using Modified similarity-based method. The proposed method is applied to the inventory data of raw materials from a renowned conveyor belt manufacturing company of West Bengal, India. By using Modified similarity-based method, the items are classified in A, B and C categories. Results obtained from the said method using R program are compared with those of well recognized TOPSIS and AHP methodologies to validate the application of this method for inventory classification.

1. Introduction

Inventories are defined as idle resources of any kind having economic values. Appropriate inventory control is necessary because both its surplus and deficit efficiency largely affects the cost of its operation. Thus inventory control is essential to determine the item(s) to indent (i.e., to order) along with with its quantity, time to indent and the optimum stock to maintain so that purchase and storage costs are minimized (Mallick et al., 2012). Hence, the management of an organization put substantial attention on the planning and control of inventory.

Although ABC analysis can be employed to almost all aspects of materials management, traditional ABC analysis considers the cost of annual consumption of inventory items. Consumption costs are arranged in descending order. The cumulative percentage is calculated based on cumulative consumption cost, and correspondingly, A, B and C classifications are made. The choice of breakpoint percentages to classify the inventories by the management can be done on the basis of a number of effectively managed items under each category (Flores et al., 1992).

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A number of researchers have questioned the focus on the consumption value as a single criterion. Cohen and Ernst (1988) opined that many other criteria may be significant to evaluate the importance of inventory items. In these cases, multiple criteria decision-making methods are helpful.

Keeping the above background in view, the objective of this paper based on case-study is to classify inventory items using the Modified similarity-based method with R-programming. Results obtained from this approach are compared with that of TOPSIS model and the AHP (Analytic Hierarchy Process) separately to validate this method.

2. Review of the literature

In the past, some investigators have worked on multi-criteria inventory classification (MCIC). This approach was brought in by Flores and Whybark (1986, 1987). Their approach became increasingly complicated if more than two criteria were considered. Flores et al. (1992) applied the AHP for MCIC, while various products of a company were classified using a fuzzy method by Puente et al. (2002). Their study reported how fuzzy set theory allows uncertainty to be incorporated into the classification model which also reflects the business reality of the market accurately. Guvenir and Erel (1998) used the Genetic Algorithm (GA) fruitfully to find the solution of MCIC problem naming the method - GAMIC. On the other hand, Braglia et al. (2004) used the AHP for identification of the outstanding control strategy to manage the inventory of spare parts. A weighted linear optimization model for MCIC was introduced by Ramanathan (2006). Data Envelopment Analysis (DEA) was used for obtaining the Performance score for each item. Limitation of this model was detected to be the possibility of misclassifying some items. Zhou and Fan (2007) rectified this problem by incorporating balancing features for MCIC by using the highest and lowest favorable score for each item. In another work, Bhattacharya et al. (2007) utilized the concept of the TOPSIS model for ABC classification. Cakir and Canbolat (2008) proposed an MCIC by integrating fuzzy logic, when demand, lead time, payment terms, unit cost, and substitutability were taken for classifying inventory components using fuzzy AHP by Çebi et al. (2010). A modified DEA-like model was applied by Torabi et al. (2012) for ABC classification considering both the quantitative and qualitative criteria, while Kabir and Hasin (2013) developed an MCIC model by integrating Fuzzy-AHP and Neural Networks. Soylu and Akyol (2014) suggested an MCIC in terms of reference items into each class by taking preferences of the decision maker. A method known as EDAS (Evaluation based on Distance from Average Solution) was introduced by Ghorabaee et al. (2015) for solving some MCIC problems to find stability of the proposed method, whereas Liu et al. (2016) made a new classification approach using an outranking model that required consideration of non-compensation in ABC analysis. Mallick et al. (2017) integrated Graph Theory (GT) and the AHP as a decision analysis tool for MCIC. Mallick et al. (2016) also presented a multi-criteria inventory classification (MCIC) system by MOORA (Multi-Objective Optimization on the basis of Ratio Analysis) for hospital inventory management.

3. The proposed methodology

The modified similarity-based method used in this study is adapted from the TOPSIS methodology, which uses the notion of an ideal solution to compare a pair of alternatives. The lowest and the highest similarity to the negative and positive ideal solutions respectively are identified to be the most preferred alternative.

The modified similarity-based method has been applied by a number of researchers to solve several problems. This method has an added advantage of ranking alternatives for deciphering discrete multi-criteria issues (Deng, 2007), ranking banks (Safari et al., 2013), personnel selection (Chaghooshi et al., 2014), ranking countries with respect to human development index (Safari & Ebrahimi, 2014), ranking of organizations with regard to the measure taken for corporate governance (Moradi & Ebrahimi, 2014), multi-objective optimization in drilling operation (Sonkar et al., 2014), cutting fluid selection (Prasad & Chakraborty, 2018) etc.

The study shows the application practicability of the modified similarity method towards Multi-Criteria Inventory Classification and related decision making in real time manufacturing atmosphere. The proposed methodology pursues steps listed below following Rao (2007), Safari et al. (2014) and Prasada et al. (2018)

Step 1: To identify the inventory attributes or criterion for the decision matrix.

Step 2: To generate the decision matrix based on the raw inventory data after suitable normalization.

A decision matrix can be represented as shown in Eq. (1). This reflects the performance of different alternatives related to varying attributes.

$$D = [x_{ij}]_{i=1,\dots,m,\ \ j=1,\dots,n} \tag{1}$$

when,

x_{ij} : Measure of the performance of the i^{th} alternative over j^{it} criteria
m: Number of alternatives
n: Number of criteria Information stored in a decision matrix.

Step 3: To construct the relative importance matrix

A relative importance matrix (Saaty, 1986, 1990) (Eq. 2) is the pair-wise comparison matrix made using the values taken from the 9-point scale (from 1 to 9) as proposed by (Saaty, 1980, 1994). If there are N numbers of criteria, the pair-wise comparison of the i^{th} criterion with respect to the j^{th} one gives rise to a square matrix. In this, $a_{ij} = 1$ when $i = j$ and $a_{ji} = 1/a_{ij}$. a_{ij} is the comparative importance of i^{th} criterion with respect to the j^{th} one). The AHP using geometric mean method is employed (Rao, 2007) here for calculating weighting vector in Step 4 of the considered criteria:

$$M = [a_{ij}] = \begin{bmatrix} a_{11} & a_{12} \dots & a_{1n} \\ a_{21} & a_{22} \dots & a_{2n} \\ \vdots & & \vdots \\ a_{i1} & a_{i2} \dots & a_{nn} \end{bmatrix} \tag{2}$$

Step 4: To determine the weighting vector using Eq. (3).

$$W = (w_1, w_2, \dots, w_m) \tag{3}$$

Step 5: Normalized matrix is made using Eq. (4).

$$X' = \begin{bmatrix} x'_{11} & x'_{12} & \dots & x'_{1m} \\ x'_{21} & x'_{22} & \dots & x'_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x'_{n1} & x'_{n2} & \dots & x'_{nm} \end{bmatrix};\ x'_{ij} = \frac{x_{ij}}{\sqrt{\sum_{k=1}^{n} x_{kj}}} \tag{4}$$

where, x_{ij} is the normalized performance of i^{th} alternative related to j^{it} criteria and it is a dimensionless quantity lying within the interval [0, 1].

Step 6: To compute performance matrix as given in Eq. (5).

$$Y = \begin{bmatrix} w_1 x'_{11} & w_2 x'_{12} & \dots & w_m x'_{1m} \\ w_1 x'_{21} & w_2 x'_{22} & \dots & w_m x'_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ w_1 x'_{n1} & w_2 x'_{n2} & \dots & w_m x'_{nm} \end{bmatrix} = \begin{bmatrix} y_{11} & y_{12} & \dots & y_{1m} \\ y_{21} & y_{22} & \dots & y_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ y_{n1} & y_{n2} & \dots & y_{nm} \end{bmatrix} \tag{5}$$

Step 7: To find out positive and negative ideal solutions from Eq. (6) and Eq. (7).

$$A^{+} = (y_1^{+}, y_2^{+}, \dots, y_m^{+}) \tag{6}$$

$$A^{-} = (y_1^{-}, y_2^{-}, \dots, y_m^{-})' \tag{7}$$

where $\begin{cases} y_j^{+} = \max\limits_{i=1,2,\dots,n} y_{ij} \\ y_j^{-} = \min\limits_{i=1,2,\dots,n} y_{ij} \end{cases}$

Step 8: Calculate of the degree of conflict between each alternative to obtain positive and negative ideal solutions using Eq. (8) and Eq. (9).

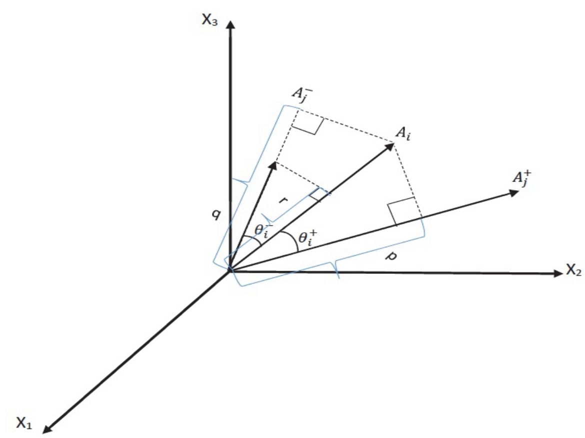

Fig. 1. The degree of conflict between alternatives and Ai

$$\cos\theta_i^{+} = \frac{\sum_{j=1}^{m} y_{ij} y_j^{+}}{\sqrt{\sum_{j=1}^{m} y_{ij}^2} \times \sqrt{\sum_{j=1}^{m} \left(y_j^{+}\right)^2}} \tag{8}$$

$$\cos\theta_i^{+} = \frac{\sum_{j=1}^{m} y_{ij} y_j^{+}}{\sqrt{\sum_{j=1}^{m} y_{ij}^2} \times \sqrt{\sum_{j=1}^{m} \left(y_j^{+}\right)^2}} \tag{9}$$

Step 9: To calculate the degree of similarity between alternatives and the positive and negative-ideal solution by Eq. (10) and Eq. (11)

$$S_i^{+} = \frac{|C_i^{+}|}{|A^{+}|} = \frac{\cos\theta_i^{+} \times |A_i|}{|A^{+}|} = \frac{\cos\theta_i^{+} \times \sqrt{\sum_{j=1}^{m} y_{ij}^2}}{\sqrt{\sum_{j=1}^{m} \left(y_j^{+}\right)^2}} \tag{10}$$

$$S_i^{-} = \frac{|A^{-}|}{|C_i^{-}|} = \frac{|A^{-}|}{\cos\theta_i^{-} \times |A_i|} = \frac{\sqrt{\sum_{j=1}^{m} \left(y_j^{-}\right)^2}}{\cos\theta_i^{-} \times \sqrt{\sum_{j=1}^{m} y_{ij}^2}} \tag{11}$$

Step 10: To calculate the overall performance index for each alternative across all criteria by Eq. (12).

$$P_i = \frac{S_i^+}{S_i^+ + S_i^-}. \tag{12}$$

Step 11: In this step, all inventory items are ranked according to their overall performance index value arranged in descending order.

Fig. 2 indicates the procedure of the modified similarity-based method applied classifying inventory items as A, B or C.

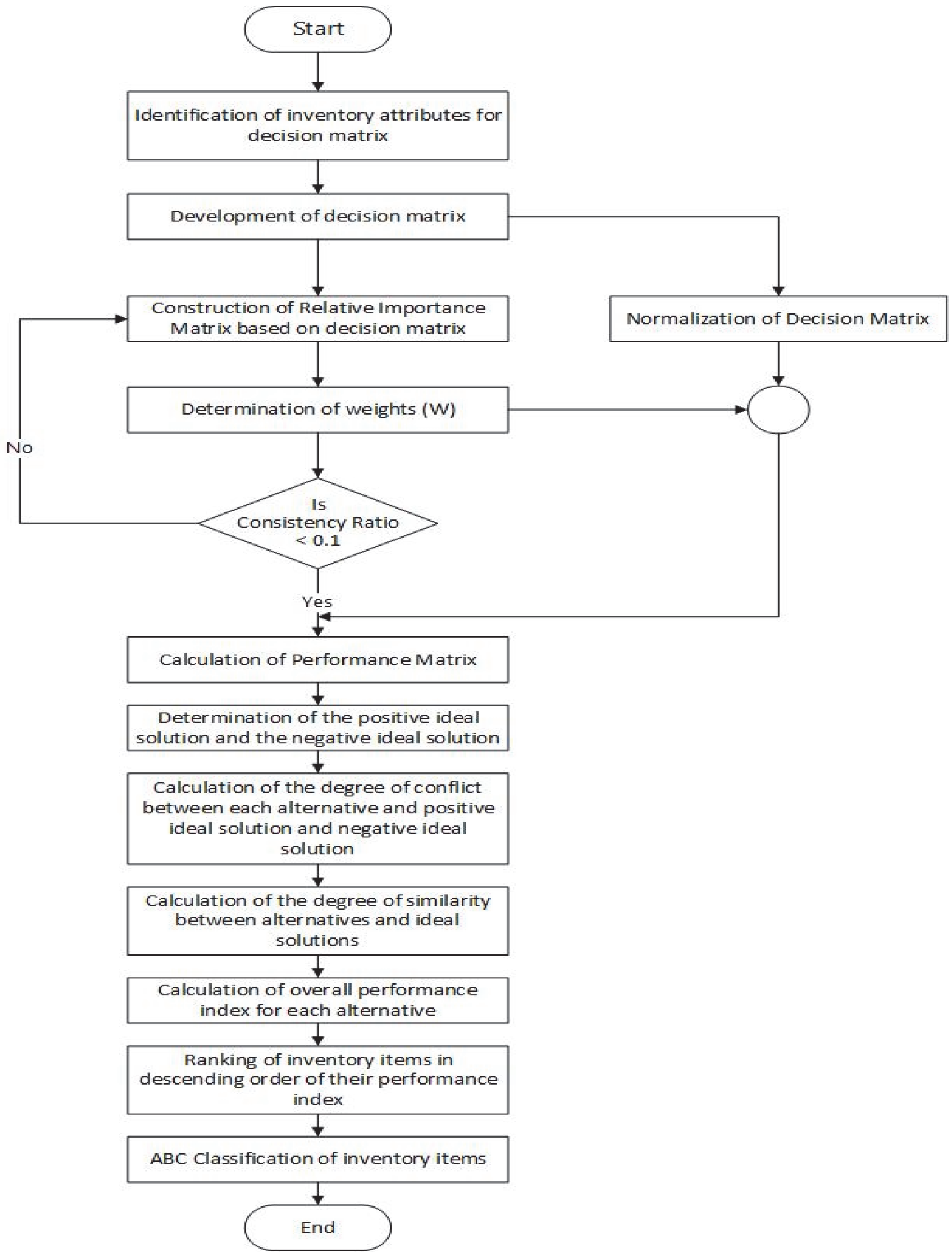

Fig. 2. Procedure for ABC classification by the modified similarity-based method

4. Case study

The paper envisaged to test the modified similarity-based method using inventory data of raw materials from a well-known conveyor belt manufacturing company, located in the state of West Bengal, India. To acquire the preliminary knowledge about the company, feedback through questionnaire was collected. Upon interpretation of the data thus obtained, the inventory practice prevalent in that company was found to be inadequate as reported in (Mallick et al., 2012). In the context of total inventory, it has been found from the analyses of organizational data that Raw Materials (RWM) occupies the major share. RWM are further sub-grouped into seven categories. Of these, almost 70% of RWM inventory is shared by four categories. In the first of inventory analysis, a monthly variation of Total RWM Inventory Cost was estimated and presented in Fig. 3. Next, a monthly variation of total inventory for four categories stated for the paper exhibited in Fig. 4, was prepared. The similar pattern of curves in Fig. 3 and Fig. 4 strengthen the assumption that four categories of materials have been appropriately selected for multi-criteria inventory classification.

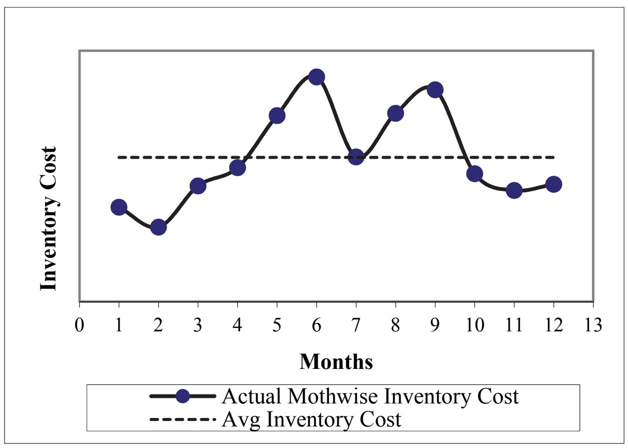

Fig. 3. Monthly variation of Total RWM Inventory Cost (Mallick et al., 2012)

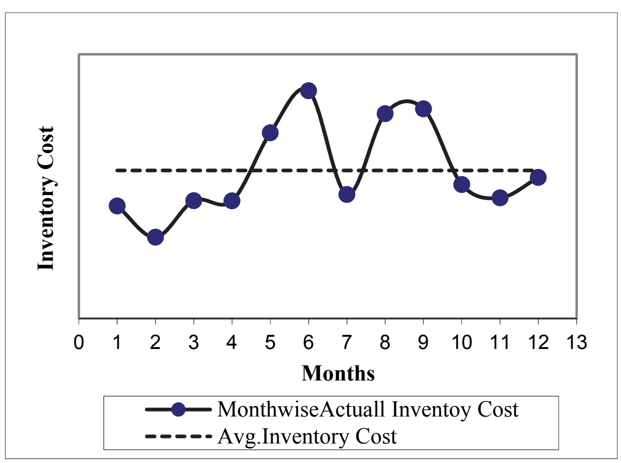

Fig. 4. Monthly variation of Total Inventory Cost for 4 categories stated for the paper (Mallick et al., 2012)

In this paper, analyses using the modified similarity-based method of the above-mentioned four categories of RWM of 90 items are presented. Items are codified as RWM01, RWM02 ….. to maintain the confidentiality of the company. The four criteria - Unit Cost (INR), Annual Consumption Cost

(INR), Annual Consumption Rate (No. of issues/year), and Average Inventory Cost (INR) were decided as very significant for classification of inventory items by these authors and management personnel of the concerned company. The modified similarity-based method has been applied for the ABC analysis to identify those items having a major financial impact with high demand in the shop floor.

The procedure of applying the methodology for the multi-criteria inventory classification, given in Section 3, is described below:

1. With all the values related to the chosen criteria for each item considered in this case study, a decision matrix is formulated as shown in Appendix A.
2. The Relative Importance Relation Matrix (table 1) is made following the expert opinion of the said company. The AHP using geometric mean method is employed (Rao, 2007) here for computing priority weights of criteria. The weight (w_i) of each criteria is calculated as: unit cost: 0.105; annual consumption cost: 0.395; consumption rate: 0.314; and average inventory cost: 0.187. The last row of Appendix A contains these weights.

Table 1
Relative Importance Relation Matrix

	Unit cost	Annual Consumption Cost	Yearly Issue	Annual Inventory Cost
Unit cost	1	1/5	1/2	1/2
Annual Consumption Cost	5	1	1	2
Yearly Issue	2	1	1	2
Annual Inventory Cost	2	1/2	1/2	1

3. A simulation model using spreadsheets and R program (Appendix B) is created to determine the effect of using modified similarity-based method for inventory classification and a comparison of the proposed modified similarity-based ABC classification with that of the well documented TOPSIS (Bhattacharya et al., 2007; Hwang & Yoon, 1981) and AHP (Rao, 2007; Saaty, 1980, 1994) classification techniques.

A comparison amongst the outcomes of the three methodologies in the form of rankings of the alternatives in descending order of their performance scores is presented in Appendix C.

Table 2 presents that 75% of the total annual consumption cost is considered as the single criterion attributable to 12 % of the total number of items under category A as per traditional ABC analysis; 4% is from more than 59 % of total items under category C and 21% is from nearly 29% of the overall items under category B.

For fruitful comparison, all the three MCDM methods (Modified similarity-based method, TOPSIS and AHP method) have also been considered utilizing the same allocation pattern of the traditional ABC classification of 11, 25 and 54 items under class A, B, and C respectively. Comparative analysis of annual consumption cost percentage of A, B and C type of items obtained from all 3 MCDM types of ABC analyses is depicted in Table 2.

Table 2 illustrates that 71.35% of the annual consumption cost by using Modified similarity-based method is responsible for ‘A’ type of items as compared to 69.94% by TOPSIS and AHP method. For ‘B’ type of items, 12.00% is accounted for by using Modified similarity-based method, 12.78% by TOPSIS and 12.60% by AHP method. For ‘C’ type of items, 16.65% is for Modified similarity-based method, 17.28% for TOPSIS and 17.46% for the AHP. Therefore, it can be stated that desirable inventory control is possible by managing ‘A’ group items only.

Table 2
A comparison of annual consumption cost percentage of class A, B and C type of items for Traditional ABC classification Modified Similarity-Based Method, TOPSIS, and AHP methodologies

Class of items	No. of items	% of Items	Traditional ABC classification based on Annual Consumption Cost	Annual Consumption Cost		
				Modified Similarity	TOPSIS	AHP
A	11	12	75%	71.35%	69.94%	69.94%
B	25	29	21%	12.00%	12.78%	12.60%
C	54	59	4%	16.65%	17.28%	17.46%

5. Comparative analysis

For comparing the relative performance of modified similarity-based method with that of TOPSIS and AHP while solving this multi-criteria inventory classification problem, the following tests are performed.

(a) Scatterplot Matrix
(b) Kendall's coefficient of concordance,
(c) Spearman's rank correlation coefficient,

First, ranks of items obtained by using Modified similarity-based method, TOPSIS, and AHP are plotted in a scatter plot matrix (Cleveland, 1993; Emerson et al., 2013) (Fig. 5). Each panel of the scatter plot matrix in Fig. 5 represents the scatter plot of one variable against the other revealing ranking similarity amongst them.

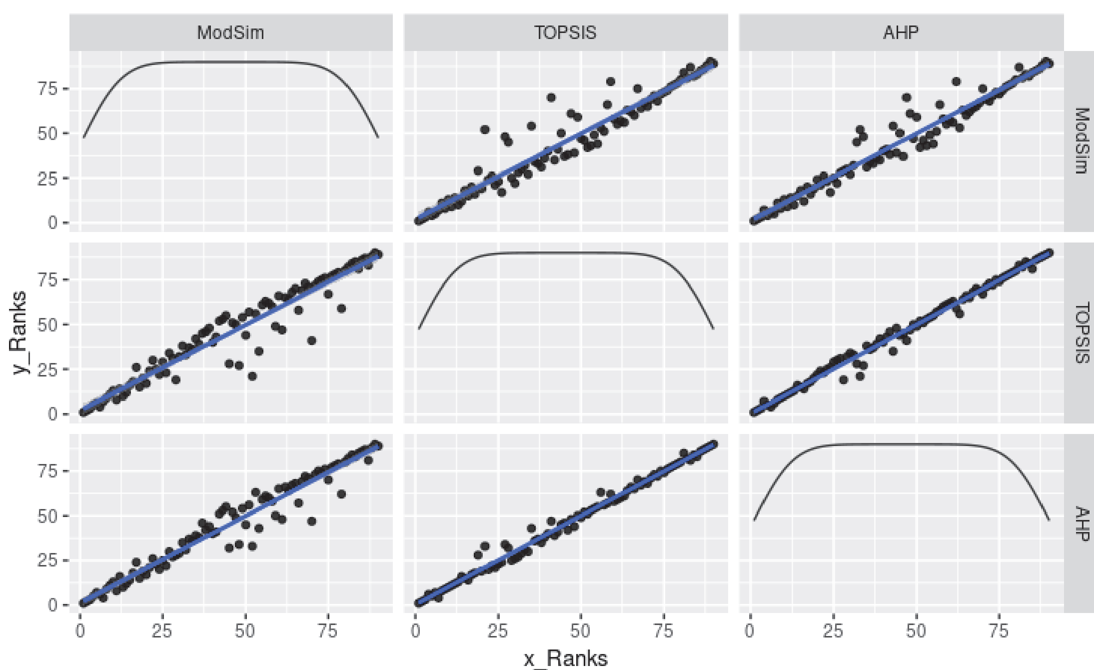

Fig. 5. A scatter plot matrix for ranks of items obtained by using modified similarity method, TOPSIS, and AHP

Overall ranking agreement among the methods considered is next determined using Kendall's coefficient of concordance (z) value (range: 0-1). Value of 1 represents a perfect match (Athawale & Chakraborty, 2011; Hajkowicz & Higgins, 2008). For this multi-criteria inventory classification problem, the z value of 0.98347 is evaluated that is quite close to 1. It indicates close conformity between these MCDM methods.

Spearman's rank correlation coefficient (r_s) is utilized (Athawale & Chakraborty, 2011; Sheskin, 2004) in the third test to compute the similarity between two sets of rankings. +1 value of r_s indicates a perfect match between two rank orders, and in this work, r_s values range from 0.96 to 0.99 (Table 3).

Table 3
Spearman's rank correlation coefficient

Method	TOPSIS	AHP
Modified Similarity	0.96	0.97
TOPSIS		0.99

6. Conclusions

In the present investigation, the modified similarity-based method is used for MCIC. These authors could not find this kind of methodology to have been used earlier to classify inventory items. An inventory management system of raw materials for 90 items of a renowned conveyor belt manufacturing company has been considered for this work. Results acquired using the proposed method are compared with those of TOPSIS and AHP for validation. Following are the inferences observed:

- The outcome of this work is that application of multi-criteria decision-making method i.e. modified similarity-based method to Inventory management, enables one to control 71.35% of the annual consumption cost by controlling only 'A' type of items (12%), but which could be accounted for 69.94% in TOPSIS as well as AHP method. Therefore, it is stated that for any organization, inventory cost-control as well as multi-criteria decision making both can be attained by applying a modified similarity-based method from a materials management point of view.

- The modified similarity-based method may be recommended for practical use in the decision-making method for classification of multi-criteria inventory items.

The present work considers the decision taken under certainty, which is otherwise often highly uncertain and risky for the decision-makers. Therefore, the applicability of this method may be elevated by introducing fuzzy set theory for consideration of uncertainty and vagueness in attribute values. In order to use modified similarity-based method advantageously for solving the classification of inventory items with imprecise and vague data, the fuzzy modified similarity-based method may be proposed for future study.

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Appendix A

Decision Matrix for multi-criteria inventory classification problem.

Code No	Rate (INR)	Annual Consumption Cost (INR)	Yearly Issue (No. of issues/year)	Avg Inventory cost(INR)
RWM01	104189.00	21551494.65	39	738786.80
RWM02	92826.00	1871372.16	9	585292.82
RWM03	95508.00	196493383.80	352	9166366.90
RWM04	99374.00	15229065.50	80	914043.29
RWM05	22446.00	48258.90	4	26569.44
RWM06	86159.00	39519840.92	195	2006615.65
RWM07	79946.00	51391687.18	204	36332913.16
RWM08	90559.00	45609134.76	316	2338003.31
RWM09	183997.00	5952302.95	12	2027805.09
RWM10	143777.00	869850.85	13	139220.43
RWM11	113579.00	2607773.84	18	857554.07
RWM12	84120.00	997663.20	14	275075.94
RWM13	124050.00	440377.50	3	200555.01
RWM14	89651.00	23302984.43	190	1187788.77
RWM15	222310.00	3545844.50	8	401480.33
RWM16	191559.00	2744082.68	25	855005.90
RWM17	130.08	435748.88	7	254982.78
RWM18	40443.00	8412144.00	76	656852.84
RWM19	36103.00	5767454.25	56	231243.55
RWM20	808.00	298960.00	11	309516.93
RWM21	44625.00	35469065.63	242	1131164.81
RWM22	47900.00	94602.50	1	159253.07
RWM23	39693.00	30173626.28	247	815449.04
RWM24	49022.00	145840.45	11	37032.69
RWM25	252.00	1008.00	1	924.00
RWM26	207.97	3161144.00	94	247542.09
RWM27	217.56	1740480.00	53	288733.95
RWM28	502.91	1282420.50	20	143704.58
RWM29	872.02	654015.00	14	188063.02
RWM30	249.17	2846767.25	45	105403.11
RWM31	150.54	4730719.50	160	544032.68
RWM32	929.20	3793322.41	82	426584.31
RWM33	541.86	7721505.00	47	2524225.50
RWM34	69.74	209220.00	62	84230.00
RWM35	16.73	47680.50	6	12657.06
RWM36	63.98	495205.20	18	132829.51
RWM37	78.09	80042.25	13	30178.76
RWM38	100.37	194717.80	32	32524.58
RWM39	192.19	2025682.60	100	517510.92
RWM40	3267.89	32456.68	2	51456.87
RWM41	725.67	1015938.00	13	993045.03
RWM42	193.40	527015.00	99	41008.86
RWM43	125.78	334574.80	53	49851.11
RWM44	187.96	2777109.00	107	88603.17
RWM45	270.75	5027827.50	127	215887.51

Appendix A

Continued.

Code No	Rate (INR)	Annual Consumption Cost (INR)	Yearly Issue (No. of issues/year)	Avg. Inventory cost (INR)
RWM46	359.09	236999.40	25	62905.43
RWM47	269.34	211431.90	32	49864.78
RWM48	1152.70	169446.90	2	128717.46
RWM49	509.93	101986.00	3	15935.31
RWM50	145.13	1846779.25	168	106031.44
RWM51	393.48	5559872.40	180	304699.39
RWM52	292.89	3163212.00	208	200455.38
RWM53	258.55	12604312.50	247	308689.46
RWM54	315.03	190593.15	16	46707.10
RWM55	270.27	1724322.60	111	165419.86
RWM56	338.63	277676.60	14	38325.48
RWM57	149.88	3747000.00	152	175309.40
RWM58	245.00	2982875.00	183	199479.17
RWM59	65.14	141679.50	43	15349.32
RWM60	77.63	2412352.25	189	173247.81
RWM61	62.18	220739.00	31	83698.48
RWM62	144.63	2390010.75	169	150458.85
RWM63	129.42	6471.00	1	2084.00
RWM64	38.81	23286.00	3	21200.69
RWM65	5382.00	80536.25	6	127372.43
RWM66	32.03	2657417.00	54	280588.36
RWM67	23.15	7122190.10	140	221589.10
RWM68	71.42	89560.68	3	12017.50
RWM69	80.73	48438.00	3	68900.00
RWM70	248.55	1714995.00	10	2133363.99
RWM71	19.12	237604.24	97	44509.85
RWM72	78.66	35397.00	6	5875.00
RWM73	47.52	3219480.00	280	142053.33
RWM74	112.41	477742.50	60	79214.47
RWM75	36.57	12388087.50	202	628093.28
RWM76	31.35	2164717.50	300	96165.02
RWM77	801.37	34458.91	2	165479.56
RWM78	1.85	63270.00	34	5647.50
RWM79	2.70	2160.00	3	1598.65
RWM80	9.06	1535488.80	141	43778.75
RWM81	22.29	8693856.43	146	307858.56
RWM82	318.76	14726712.00	176	1110382.43
RWM83	33.68	7350660.00	218	421987.78
RWM84	10.36	814296.00	214	44675.88
RWM85	111.25	2205531.25	145	201868.86
RWM86	100.09	16795102.00	313	739851.23
RWM87	107.03	774897.20	136	126856.74
RWM88	4.70	3760.00	8	1593.75
RWM89	40.74	65184.00	5	33000.39
RWM90	151.53	41670.75	5	2416.67
Weight	0.105	0.395	0.314	0.187

Appendix B

R programming for ABC classification by the modified similarity-based method

```
ModifiedSimilarity=function(decision = NULL, weights = NULL, impacts = NULL){
  if(missing(weights))
    stop("'weights' must be a numeric vector")
  if(missing(impacts))
    stop("'impacts' must be a character vector")
  if(! is.matrix(decision) |  is.data.frame(decision))
    stop("'decision' must be a matirx or data frame")
  if(length(weights) != ncol(decision))
    stop("length of 'weights' is not equal to number of columns")
  if(length(impacts) != ncol(decision))
    stop("length of 'impacts' is not equal to number of columns")
  if(! all(weights > 0))
    stop("weights must be positive numbers")
  if(! is.character(impacts))
    stop("impacts must be a character vector of '+' and '-' signs")
  if(! all(impacts == "+" | impacts == "-"))
    stop("impacts must be only '+' or '-' sign")
  weights <- weights/sum(weights)
  N <- matrix(nrow = nrow(decision), ncol = ncol(decision))
  for(i in 1:nrow(decision)){
    for(j in 1:ncol(decision)){
      N[i,j] <- decision[i,j] / sqrt(sum(decision[,j] ^ 2))
    }
  }
  W=diag(weights)
  V=N%*%W
  u <- as.integer(impacts == "+") * apply(V, 2, max) +
    as.integer(impacts == "-") * apply(V, 2, min)
  l <- as.integer(impacts == "-") * apply(V, 2, max) +
    as.integer(impacts == "+") * apply(V, 2, min)
  similarity_u =function(x){
    sum(x * u)/sum(u^2)
  }
  similarity_l =function(x){
    sum(l^2)/sum(x * l)
  }
  du <- apply(V, 1, similarity_u)
  dl <- apply(V, 1, similarity_l)
  score <- du/(dl+du)
  return(data.frame(alt.row = 1:nrow(decision), score = score, rank = rank(-score)))
}
```

Appendix C

Comparison of ABC inventory classification by Modified Similarity-Based Method, TOPSIS, and AHP

Code No	Modified similarity			TOPSIS			AHP		
	Overall performance index(P)	Ranking	Group	Relative closeness to the Ideal solution	Ranking	Group	AHP Score	Ranking	Group
RWM01	0.79639	29	C	0.10975	19	B	0.13103	28	C
RWM02	0.13716	61	C	0.04751	47	C	0.05860	48	C
RWM03	0.99677	1	A	0.72731	1	A	0.80062	1	A
RWM04	0.86626	23	B	0.09689	25	C	0.15351	23	B
RWM05	0.00891	75	C	0.01157	67	C	0.01439	70	C
RWM06	0.97449	6	A	0.21269	4	A	0.30420	6	A
RWM07	0.98929	2	A	0.44318	2	A	0.50944	2	A
RWM08	0.98690	3	A	0.27089	3	A	0.42809	3	A
RWM09	0.37590	48	C	0.09549	27	C	0.11992	34	C
RWM10	0.15973	54	C	0.06988	35	C	0.08192	43	C
RWM11	0.30531	50	C	0.05894	44	C	0.07930	45	C
RWM12	0.14813	59	C	0.04288	49	C	0.05561	50	C
RWM13	0.03257	70	C	0.06036	41	C	0.06314	47	C
RWM14	0.96064	8	A	0.15925	9	A	0.26462	9	A
RWM15	0.20239	52	C	0.10554	21	B	0.12125	33	C
RWM16	0.43307	45	C	0.09363	28	C	0.12261	32	C
RWM17	0.02797	72	C	0.00531	74	C	0.00849	75	C
RWM18	0.78900	31	C	0.06381	38	C	0.10712	35	C
RWM19	0.65273	39	C	0.04683	48	C	0.07974	44	C
RWM20	0.04724	68	C	0.00759	73	C	0.01238	72	C
RWM21	0.97749	4	A	0.21037	5	A	0.31387	5	A
RWM22	0.00460	79	C	0.02414	59	C	0.02451	62	C
RWM23	0.97499	5	A	0.19600	6	A	0.30374	7	A
RWM24	0.05484	66	C	0.02543	58	C	0.03343	57	C
RWM25	0.00017	90	C	0.00013	89	C	0.00102	89	C
RWM26	0.71885	35	C	0.05975	42	C	0.09153	39	C
RWM27	0.45890	43	C	0.03407	53	C	0.05233	53	C
RWM28	0.14719	60	C	0.01358	66	C	0.02138	65	C
RWM29	0.07305	65	C	0.00916	70	C	0.01517	68	C
RWM30	0.44770	44	C	0.03073	55	C	0.04650	55	C
RWM31	0.87684	21	B	0.09883	24	B	0.15502	21	B
RWM32	0.70292	38	C	0.05382	46	C	0.08336	42	C
RWM33	0.70496	37	C	0.05424	45	C	0.07063	46	C
RWM34	0.39239	47	C	0.03841	50	C	0.05616	49	C
RWM35	0.00677	76	C	0.00324	77	C	0.00552	77	C
RWM36	0.08651	64	C	0.01127	68	C	0.01776	67	C
RWM37	0.03016	71	C	0.00775	72	C	0.01194	73	C
RWM38	0.15306	57	C	0.01982	62	C	0.02914	60	C
RWM39	0.71642	36	C	0.06247	39	C	0.09597	38	C
RWM40	0.00179	87	C	0.00190	83	C	0.00366	81	C
RWM41	0.12944	62	C	0.01497	65	C	0.01907	66	C
RWM42	0.62531	40	C	0.06062	40	C	0.08963	40	C
RWM43	0.33195	49	C	0.03292	54	C	0.04824	54	C
RWM44	0.74142	33	C	0.06676	37	C	0.10152	37	C
RWM45	0.83189	27	C	0.08069	34	C	0.12456	30	C

Appendix C

Continued.

Code No	Modified similarity: Overall performance index(P)	Ranking	Group	TOPSIS: Relative closeness to the Ideal solution	Ranking	Group	AHP: AHP Score	Ranking	Group
RWM46	0.11018	63	C	0.01544	64	C	0.02326	64	C
RWM47	0.15688	55	C	0.01984	61	C	0.02934	59	C
RWM48	0.00346	81	C	0.00193	82	C	0.00333	82	C
RWM49	0.00283	83	C	0.00141	85	C	0.00320	83	C
RWM50	0.84475	26	C	0.10035	23	B	0.15411	22	B
RWM51	0.89871	16	B	0.11027	18	B	0.17340	18	B
RWM52	0.90108	15	B	0.12268	16	B	0.19297	14	B
RWM53	0.95497	9	A	0.15417	11	A	0.24724	11	A
RWM54	0.05097	67	C	0.00971	69	C	0.01504	69	C
RWM55	0.72568	34	C	0.06829	36	C	0.10340	36	C
RWM56	0.04475	69	C	0.00848	71	C	0.01340	71	C
RWM57	0.85102	25	C	0.09310	29	C	0.14402	25	C
RWM58	0.87823	19	B	0.10932	20	B	0.17029	19	B
RWM59	0.23081	51	C	0.02668	57	C	0.03873	56	C
RWM60	0.87775	20	B	0.11208	17	B	0.17428	17	B
RWM61	0.15404	56	C	0.01923	63	C	0.02854	61	C
RWM62	0.85478	24	B	0.10128	22	B	0.15632	20	B
RWM63	0.00019	89	C	0.00007	90	C	0.00098	90	C
RWM64	0.00194	86	C	0.00132	87	C	0.00285	87	C
RWM65	0.01307	73	C	0.00453	75	C	0.00871	74	C
RWM66	0.51381	42	C	0.03580	52	C	0.05494	51	C
RWM67	0.87239	22	B	0.09081	30	C	0.14027	26	C
RWM68	0.00255	85	C	0.00136	86	C	0.00295	86	C
RWM69	0.00302	82	C	0.00155	84	C	0.00316	84	C
RWM70	0.17289	53	C	0.02739	56	C	0.02343	63	C
RWM71	0.60023	41	C	0.05935	43	C	0.08720	41	C
RWM72	0.00630	77	C	0.00324	78	C	0.00549	78	C
RWM73	0.93830	13	B	0.15871	10	A	0.25686	10	A
RWM74	0.39996	46	C	0.03727	51	C	0.05491	52	C
RWM75	0.94184	10	A	0.13222	13	B	0.20822	13	B
RWM76	0.94087	11	A	0.16737	8	A	0.27233	8	A
RWM77	0.00279	84	C	0.00215	81	C	0.00308	85	C
RWM78	0.15258	58	C	0.02105	60	C	0.03047	58	C
RWM79	0.00138	88	C	0.00130	88	C	0.00269	88	C
RWM80	0.79121	30	C	0.08520	32	C	0.12902	29	C
RWM81	0.89128	17	B	0.09670	26	C	0.14922	24	B
RWM82	0.93931	12	B	0.12504	14	B	0.19235	16	B
RWM83	0.93142	14	B	0.13230	12	B	0.21131	12	B
RWM84	0.88207	18	B	0.12415	15	B	0.19267	15	B
RWM85	0.81736	28	C	0.08796	31	C	0.13480	27	C
RWM86	0.97270	7	A	0.19217	7	A	0.31664	4	A
RWM87	0.76339	32	C	0.08204	33	C	0.12351	31	C
RWM88	0.00955	74	C	0.00452	76	C	0.00715	76	C
RWM89	0.00580	78	C	0.00263	79	C	0.00478	79	C
RWM90	0.00457	80	C	0.00260	80	C	0.00463	80	C