P-ISSN 2586-9000
E-ISSN 2586-9027
Homepage : *https://tci-thaijo.org/index.php/SciTechAsia* Science & Technology Asia
Vol.25 No.1 January - March 2020 Page: [62-71]
Original research article

Selection of Inventory Policy under Pythogrean Fuzzy Environment

Prabjot Kaur*, Anjali Priya

Department of Mathematics, Birla Institute of Technology, Jharkhand-835215, India

Received 23 September 2019; Received in revised form 15 January 2020
Accepted 16 January 2020; Available online 26 March 2020

ABSTRACT

This paper is an application of inventory policy selection using Grey Relational Analysis (GRA) under Pythagorean Fuzzy Environment. Ranking of inventory policy is a complex multiple criteria decision making (MCDM) problem. The multi-criteria problem comprises qualitative and quantitative factors that are uncertain and contradictory. These factors are not always crisp and are some of the times subjected to vagueness because of the unreliable nature of the data collected. Hence, they are considered in the Pythagorean fuzzy environment which removes this vagueness by assigning membership and non-membership functions to these factors. A comparison of GRA method is made with VIKOR for determining the rank of the best inventory policy. A numerical example is depicted to outline the application of these two algorithms. The first rank of one of the inventory policies is the same by both these methods. Spearman Rank Correlation is utilized to compare the results of both the methods; a high correlation value illustrates the validity of the methods used for comparison of the results.

Keywords: Grey relational analysis; Inventory; Pythagorean fuzzy sets; VIKOR

1. Introduction

In the present world, knowledge assumes a noteworthy role in an organization. For any organization, it is significant for them to have profound information about their operations. Inventory policy selection and evaluation include a procedure that can be thought about, checked after some time and ideally improved through certain measures. Determination of the right inventory control policy is a challenge in the dynamic business environment as it enables organizations to gain an upper hand in terms of cost, quality, and service, which in turn provides a vital step in fulfilling the requirements of the customer. Inventory control policies in firms are typically worried about the essential capacity of keeping a trade-off

***Corresponding author:** prabjotkaur@bitmesra.ac.in **doi:** 10.14456/scitechasia.2020.7

between excess inventories and maintaining a strategic distance from deficiency of materials. The inventory policy selection process is complex because of various criteria, some of which are perhaps cost, demand, lead time, etc. Arcelus and Srinivasan (1988) [1] investigated the cost structures of an inventory system and their implication on inventory policy. Jansse and Kok (1999) [2], Tekin et al. (2001) [3] inspected how the policy parameters were tactful concerning the system parameters. Mohammaditabar et al. (2012) [4] gave an integrated model to order the things and locate the best approach at the same time. They considered the ordering and inventory holding costs as the noteworthy criteria for studies. Lolli et al. (2014) [5] presented a novel technique of AHP and k-mean for multicriteria inventory classification methods. The criteria utilized for the study were annual dollar usage, critical factor and lead time. Eraslan and Tansel (2019) [6] gave an upgraded decision support system for the ABC inventory classification. Lolli et al. (2019) [7] categorized criteria into two groups; the first group included parameters for setting demand generation and the second group included cost security factors.

Inventories are fundamental assets of the manufacturing sector and hence they need to follow an inventory policy that helps them to keep pace with the dynamic business scenario. As of now, there are numerous approaches to solve multiple attribute decision-making problems, such as TOPSIS, VIKOR, AHP/DEA, and ELECTRE algorithms [8]. Inventory problems are inclusive and complex in nature. So no particular model can portray all the inventory situations; therefore, for any organization to survive, it is necessary to choose an optimum inventory policy that gives it an edge over the contenders. Four inventory policies EOQ, JIT, VMI, and Monthly Policy are considered in this paper and are broadly studied in inventory literature (Wilson (1934) [9], Xiao and Xu (2013) [10], Relph and Newton (2014) [11]). The inventory policy selection process would have been simpler if just a single criterion was considered all the while, but the circumstances, in reality, are exactly the inverse where the management needs to consider several criterions before taking an effective decision. Bai and Li (2008) [12] in their work determined an optimal inventory policy and that endeavours towards progression from the conventional to the fuzzy way of dealing with the optimal inventory problems. Huang et al. (2010) [13] built an integrated inventory model to determine the optimal inventory policy for order-processing, cost diminution and allowable delay in payments. Mohammaditabar et al. (2012) [4] proposed the Inventory Control System Design by unified Inventory Classification and Policy Selection. Gupta et al. (2013) [14] proposed a multicriteria strategy for ranking inventory policies using a fuzzy-based distance approach. Balaji and Kumar (2014) [15] gave a multicriteria inventory ABC classification in an automobile rubber components manufacturing industry. Fu et al. (2016) [16] used a distance-based decision-making method to enhance multiple criteria ABC inventory classification. Arikan and Citak (2017) [17] used a Topsis-ABC approach to solve a multiple criteria inventory classification problem in an electronics firm. Zheng et al. (2017) [18] made an improvement to multiple criteria ABC inventory classification using Shannon entropy. Wu et al. (2018) [19] proposed a weighted least-square dissimilarity way for multiple criteria ABC inventory classification. There are very few applications of MADM methods in inventory problems under the Pythagorean fuzzy environment. Our application is a novel and new approach of applying Pythagorean fuzzy sets to the inventory problem. Pythagorean VIKOR finds a compromising solution to rank various alternatives in conflicting criteria [20]. While GRA in Pythagorean environment deals with opinions given by decision maker's w.r.to criteria. The advantage of this methodology is its quick mathematical computation which is helpful in making effective, efficient and easy decisions.

In this research paper, an attempt has been undertaken using the Pythagorean fuzzy method and VIKOR algorithm for evaluation and ranking of the inventory ordering policies. The structure of the paper is as follows: Section 1 introduces the problem of inventory policy selection. Section 2 explains the basic concepts of Pythagorean fuzzy sets used in the paper. Section 3 describes the methodology for solving the problem by VIKOR and GRA. Section 4 illustrates a numerical example. Section 5 gives the conclusions and results of best inventory policy selection.

2. Materials and Methods

2.1 Pythagorean Fuzzy Sets

Pythagorean fuzzy sets were pioneered by Yager [21] to deal with vagueness with the membership grades as pairs satisfying the conditions of membership and non-membership degree.

Let a set X be a universal set. Then the Pythagorean fuzzy set P is defined as:

$$\begin{aligned} P &= \Big\{\big\langle x, P\left(\mu_p(x), \nu_p(x)\right)\big\rangle \,\big|\, x \in X, \\ &\quad 0 \le \left(\mu_p(x)\right)^2 + \left(\nu_p(x)\right)^2 \le 1\Big\}, \end{aligned}$$

where μ_p denotes the degree of membership, ν_p denotes the degree of non-membership function of elements x to P. The notation $P\left(\mu_p(x), \nu_p(x)\right)$ can be represented as $\beta = P\left(\mu_p, \nu_p\right)$. Also, the square sum of μ and ν is not more than one, i.e. $\mu_\beta^2 + \nu_\beta^2 \le 1$, where $\mu_\beta, \nu_\beta \in [0,1]$. Some of the operations defined on PFS are as below [22]:

$$\begin{aligned} \beta_1 \oplus \beta_2 &= P\left(\sqrt{\mu_{\beta 1}^2 + \mu_{\beta 2}^2 - \mu_{\beta 1}^2 \nu_{\beta 2}^2}, \nu_{\beta 1}\nu_{\beta 2}\right), \\ \beta_1 \otimes \beta_2 &= P\left(\mu_{\beta 1}\mu_{\beta 2}, \sqrt{\nu_{\beta 1}^2 + \nu_{\beta 2}^2 - \nu_{\beta 1}^2 \nu_{\beta 2}^2}\right), \\ \lambda\beta &= P\left(\sqrt{1-\left(1-\mu_\beta^2\right)^2}, \nu_\beta^2\right), \lambda > 0, \\ \beta^\lambda &= P\left(\left(\mu_\beta\right)^\lambda, \sqrt{1-\left(1-\nu_\beta^2\right)^2}\right), \lambda > 0. \end{aligned}$$

2.2 The basic principle of VIKOR algorithm

The VIKOR algorithm was proposed by Opricovic (1998) [20], as a multi-attribute decision-making method for complex framework dependent on an ideal point technique. Finding a positive ideal solution and a negative ideal solution gives the higher and the lower value of alternatives under assessment criteria, respectively. In the comprehensive evaluation, VIKOR adopted L_p-metric aggregate function:

$$L_{pj} = \left\{\sum_{i=1}^{n}\left[w_i\left(f_i^* - f_{ij}\right)/\left(f_i^* - f_i^-\right)p\right]\right\}^{1/2}$$

In the function, $1 \le p \le \infty$; $j = 1, 2, \ldots, J$, the variable J depicts the number of alternatives. Each alternative is represented as a_j, f_{ij} is the evaluation value of the i^{th} criterion of the alternative a_i the measure L_{pj} means the distance between alternative a_j and the positive ideal solution.

3. Methods

Grey relational analysis (GRA) is part of grey system theory, which is appropriate for unraveling problems with convoluted interrelationships between multiple factors and variables (Mora´n et al. (2006)) [23]. The process of grey relational analysis is best described in (Kuo et al. (2008) [24]):

3.1 Algorithm of steps for inventory policy selection method in Pythagorean Fuzzy Environment

Step 1: Given the data set, calculate the value of M for each inventory policy concerning the criteria

$$M = \mu_\beta^2 - \nu_\beta^2. \tag{3.1}$$

Step 2: Determine the positive ideal solution (PIS) and the negative ideal solution (NIS) of the criteria as:

$$\begin{aligned} m_j^+ &= \left(m_1^+, m_2^+, ..., m_n^+\right), \\ m_j^- &= \left(m_1^-, m_2^-, ..., m_n^-\right). \end{aligned}$$

for all $j = 1, 2, 3, \ldots, n$.

Step 3: Calculate PIS and NIS of the criterion C_j that can be derived by:

$$\begin{aligned} m_j^+ &= \left\{m_{ij} \mid M\left(m_{ij}\right) = \max_i \left\{M\left(m_{ij}\right)\right\}\right\}, \\ m_j^- &= \left\{m_{ij} \mid M\left(m_{ij}\right) = \min_i \left\{M\left(m_{ij}\right)\right\}\right\} \end{aligned}$$

for all $j = 1, 2, 3, \ldots, n$.

Step 4: The distance of each inventory policy to PIS and NIS is given by Eq. (3.2) and Eq. (3.3), respectively, as:

$$\begin{aligned} d_{ij}^+ &= d\left(m_{ij}, m_j^+\right) \\ &= \frac{1}{2}\left(\left|\left(p_{ij}\right)^2 - \left(p_j^+\right)^2\right| \right. \\ &\quad + \left|\left(q_{ij}\right)^2 - \left(q_j^+\right)^2\right| \\ &\quad + \left|\left(1 - \left(p_{ij}\right)^2 - \left(q_{ij}\right)^2\right) \right. \\ &\quad \left.\left. - \left(1 - \left(p_j^+\right)^2 - \left(q_j^+\right)^2\right)\right|\right), \end{aligned} \tag{3.2}$$

$$\begin{aligned} d_{ij}^- &= d\left(m_{ij}, m_j^-\right) \\ &= \frac{1}{2}\left(\left|\left(p_{ij}\right)^2 - \left(p_j^-\right)^2\right| \right. \\ &\quad + \left|\left(q_{ij}\right)^2 - \left(q_j^-\right)^2\right| \\ &\quad + \left|\left(1 - \left(p_{ij}\right)^2 - \left(q_{ij}\right)^2\right) \right. \\ &\quad \left.\left. - \left(1 - \left(p_j^-\right)^2 - \left(q_j^-\right)^2\right)\right|\right). \end{aligned} \tag{3.3}$$

Step 5: Evaluate the grey relational coefficient of each inventory policy which can be obtained by Eq. (3.4) and Eq. (3.5), respectively, as:

$$\phi_{ij}^+ = \frac{\min_i \min_j d_{ij}^+ + \lambda \max_i \max_j d_{ij}^+}{d_{ij}^+ + \lambda \max_i \max_j d_{ij}^+}, \tag{3.4}$$

$$\phi_{ij}^- = \frac{\min_i \min_j d_{ij}^- + \lambda \max_i \max_j d_{ij}^-}{d_{ij}^- + \lambda \max_i \max_j d_{ij}^-}. \tag{3.5}$$

Where λ is the identification coefficient, we take $\lambda = 0.3$.

Step 6: The weighted grey relational coefficient of each inventory policy from PIS and NIS is obtained by:

$$\delta_i^+ = \sum_{j=1}^{n} w_j \times \phi_{ij}^+, \tag{3.6}$$

$$\delta_i^- = \sum_{j=1}^{n} w_j \times \phi_{ij}^-, \tag{3.7}$$

for all $i = 1, 2, \ldots, n$, where $w_j = \mu_\beta + \nu_\beta$.

Step 7: The relative relational degree of each inventory policy from PIS can be calculated by:

$$RCD_i = \frac{\delta_i^+}{\delta_i^+ + \delta_i^-}. \tag{3.8}$$

Then the inventory policy can be ranked in the descending order according to the relative relational degree.

3.2 VIKOR algorithm

Step 1: Calculate the value of M and w_i, respectively, as:

$$M = \mu_\beta^2 - \nu_\beta^2, \quad w_i = \mu_\beta + \nu_\beta. \tag{3.9}$$

Step 2: Calculate the positive ideal solution $\left(f_i^*\right)$ and the negative ideal solution $\left(f_1^-\right)$, $i = 1, 2, ..., n$ as:

$$f_1^* = \max\left(f_{ij} \,|i = 1, 2, ..., n\right), \tag{3.10}$$

$$f_1^- = \min\left(f_{ij} \,|i = 1, 2, ..., n\right). \tag{3.11}$$

Step 3: Calculate the value of S_i and R_i with the following two equations:

$$S_i = \frac{\sum\limits_{i=1}^{n} w_i\left(f_1^* - f_{ij}\right)}{\left(f_1^* - f_1^-\right)}, \tag{3.12}$$

$$R_i = \max\left[\frac{w_i\left(f_1^* - f_{ij}\right)}{\left(f_1^* - f_1^-\right)}\right], \tag{3.13}$$

where S_i is the optimal solution from the schemes' comprehensive evaluation, R_i is the most pessimistic solution from the schemes' comprehensive evaluation, and w_i are the weights.

Step 4: Calculate Q, the value of the interest ratio brought by the scheme

$$Q_j = v\frac{(S_i - S^*)}{(S^- - S^*)} + (1 - v)\frac{\left(R_j - R^*\right)}{(R^- - R^*)} \tag{3.14}$$

for all $j = 1, 2, \ldots, J$, where $S^* = \min_j S_j$, $S^- = \max_j S_j$, $R^* = \min_j R_j$, $R^- = \max_j R_j$ and v represents the weights of "the majority of criteria strategy" or the largest group's utility value; here we take the value of $v = 0.3$. The minimum value of Q in the ranking is considered the optimal compromise scheme.

Condition 1: The acceptable advantage is given as:

$$Q\left(A1\right) - Q\left(A2\right) \geq \frac{1}{(m-1)},$$

where $A1$ the suboptimal scheme in the rank tables. $A2$ Is the optimal solution in S or R rank tables with Q ranking have been set simultaneously.

Condition 2: Is acceptable stability in decision making. Inventory policy with the first ranking considered as the best.

If this inventory policy could not be satisfied with those conditions, then other compromise solutions are offered including:

- If Condition 2 is not satisfied, then $A1$ and $A2$are considered.
- If Condition 1 is not satisfied, then $A1, A2, \ldots, An$ is considered. Then $A1$and An is determined by the equation:

$$Q\left(A1\right) - Q\left(A2\right) \geq \frac{1}{(m-1)}.$$

3.3 Using the Spearman Rank Order Correlation Coefficient formula

The Spearman's Correlation Coefficient [25] is a nonparametric test of the firmness and control of the association that exists between two ranked variables. The formula for the Spearman Rank Correlation is given by:

$$r_k = 1 - \frac{6\sum\limits_i d_i^2}{n\left(n^2 - 1\right)}, \tag{3.15}$$

where n is the number of data points of the two variables and d_i is the difference in the ranks of the i^{th} element of each random variable considered. The Spearman correlation coefficient ρ can take values from $+1$ to -1.

4. Numerical Example

Some MSME is located in North India and is considered which practice inventory control policies (alternatives) like

Heuristics (heu), JIT, EOQ, and VMI. These policies were evaluated on the following criteria: raw material ordering frequency (x_1), stock verification frequency (x_2), production types (x_3), inventory cost (x_4), capital investment(x_5), and demand (x_6). Using proficient opinion, the membership degree μ_{ij}, and non-membership degree ν_{ij} of the inventory policy concerning the criteria is expressed with the intuitionistic fuzzy decision matrix in Table 1.

Table 1. Intuitionistic Fuzzy Decision Matrix of inventory policy

	x_1	x_2	x_3	x_4	x_5	x_6
heu	0.6, 0.25	0.8, 0.2	0.75, 0.1	0.45, 0.5	0.6, 0.3	0.75, 0.05
jit	0.8, 0.15	0.6, 0.3	0.7, 0.25	0.8, 0.1	0.75, 0.2	0.72, 0.23
eoq	0.4, 0.45	0.68, 0.2	0.78, 0.08	0.65, 0.25	0.7, 0.2	0.82, 0.1
vmi	0.75, 0.5	0.45, 0.5	0.65, 0.25	0.4, 0.45	0.8, 0.15	0.45, 0.5

Similarly, the weights of the attributes are given as:

$$W = \{(0.30, 0.65), (0.35, 0.40), (0.25, 0.25), (0.50, 0.35), (0.60, 0.30), (0.55, 0.25)\}$$

4.1 Calculations by GRA in Pythagorean Fuzzy environment

Step 1: Calculating the value of M function of each inventory policy with respect to the criteria using Eq. (3.1) is given in Table 2.

Table 2. Value of M function of each inventory policy with respect to the criteria

	x_1	x_2	x_3	x_4	x_5	x_6
heu	0.297	0.600	0.553	0.048	0.270	0.560
jit	0.618	0.270	0.427	0.630	0.522	0.466
eoq	0.042	0.422	0.602	0.360	0.450	0.662
vmi	0.560	0.048	0.360	0.042	0.618	−0.048

Step 2: Obtaining the table by calculating the value of PIS and NIS is given in Table 3:

Table 3. Value of PIS and NIS

	x_1	x_2	x_3	x_4	x_5	x_6
PIS	0.8, 0.15	0.8, 0.2	0.78, 0.08	0.8, 0.1	0.8, 0.15	0.82, 0.1
NIS	0.4, 0.45	0.45, 0.5	0.65, 0.25	0.4, 0.45	0.6, 0.3	0.45, 0.5

Step 3: Calculating distance of each inventory policy from PIS using Eq. (3.2) we get the Table 4:

Table 4. The distance of each inventory policy from PIS

	x_1	x_2	x_3	x_4	x_5	x_6
heu	0.280	0.000	0.046	0.438	0.280	0.117
jit	0.000	0.280	0.118	0.000	0.078	0.154
eoq	0.480	0.178	0.000	0.218	0.150	0.000
vmi	0.098	0.438	0.186	0.480	0.000	0.470

Step 4: Calculating distance of each inventory policy from NIS using Eq. (3.3), we get the Table 5:

Table 5. The distance of each alternative from NIS

	x_1	x_2	x_3	x_4	x_5	x_6
heu	0.200	0.438	0.140	0.090	0.000	0.360
jit	0.480	0.160	0.068	0.480	0.202	0.316
eoq	0.000	0.260	0.186	0.262	0.130	0.470
vmi	0.402	0.000	0.000	0.000	0.280	0.000

Step 5: Calculating the grey relational coefficient of each inventory policy from PIS using Eq. (3.4) is given in Table 6.

Table 6. The grey relational coefficient of each inventory policy from PIS

	x_1	x_2	x_3	x_4	x_5	x_6
heu	0.340	1.000	0.741	0.247	0.319	0.547
jit	1.000	0.319	0.416	1.000	0.519	0.478
eoq	0.231	0.447	1.000	0.398	0.490	1.000
vmi	0.595.	0.247	0.436	0.231	1.000	0.235

Step 6: Calculating the grey relational coefficient of each inventory policy

from NIS using Eq. (3.5) is given in Table 7.

Table 7. The grey relational coefficient of each inventory policy from NIS

	x_1	x_2	x_3	x_4	x_5	x_6
heu	0.419	0.231	0.484	0.615	1.000	0.281
jit	0.231	0.474	0.679	0.231	0.416	0.313
eoq	1.000	0.352	0.481	0.355	0.520	0.231
vmi	0.264.	1.000	1.000	1.000	0.481	1.000

Step 7: Calculating the weighted grey relational coefficient of each inventory policy concerning each criterion from PIS is given in Table 8.

Table 8. The grey relational coefficient of each inventory policy from PIS

	x_1	x_2	x_3	x_4	x_5	x_6
heu	0.323	0.750	0.371	0.209	0.287	0.438
jit	0.950	0.239	0.208	0.850	0.467	0.382
eoq	0.219	0.335	0.500	0.338	0.441	0.800
vmi	0.565.	0.185	0.218	0.196	0.900	0.188

Step 8: Calculating the weighted grey relational coefficient of each inventory policy concerning each criterion from NIS is given in Table 9.

Table 9. Weighted grey relational coefficient of each inventory policy concerning each criteria from PIS

	x_1	x_2	x_3	x_4	x_5	x_6
heu	0.398	0.173	0.242	0.523	0.900	0.225
jit	0.219	0.356	0.339	0.196	0.374	0.250
eoq	0.950	0.264	0.241	0.302	0.468	0.185
vmi	0.251	0.750	0.500	0.850	0.433	0.800

Step 9: Calculating the grey relational coefficient of each inventory policy with respect to each criterion using Eq. (3.6) and Eq. (3.7) we obtain Table 10.

Step 10: Calculating the relative closeness of the degree of each inventory policy from PIS using Eq. (3.8) we obtain Table 11.

Table 10. The grey relational coefficient of each inventory policy concerning each criterion

	heu	jit	eoq	vmi
PIS	2.378	3.096	2.633	2.252
NIS	2.461	1.734	2.410	3.584

Table 11. The relative closeness of the degree of each inventory policy from PIS

heu	jit	eoq	vmi
0.490	0.641	0.522	0.386

Then the inventory policy can be ranked in the descending order according to the relative closeness degree as:

$$jit > eoq > heu > vmi.$$

4.2 Using the VIKOR Algorithm

Step 1: Calculating the value of the M function of each inventory policy concerning the criteria using Eq. (3.1) is given in Table 12.

Table 12. Calculating the value of the M function of each inventory policy concerning the criteria

	x_1	x_2	x_3	x_4	x_5	x_6
heu	0.297	0.600	0.553	−0.048	0.270	0.560
jit	0.618	0.270	0.427	0.630	0.522	0.466
eoq	−0.042	0.422	0.602	0.360	0.450	0.662
vmi	0.560	−0.048	0.360	−0.042	0.618	−0.048

Step 2: Calculating distance of each inventory policy from PIS and NIS using Eq. (3.10) and Eq. (3.11) we get:

$$\begin{aligned} f_1^* &= (0.618, 0.600, 0.602, \\ &\quad 0.630, 0.618, 0.662), \\ f_1^- &= (-0.042, -0.422, 0.360, \end{aligned}$$

$-0.042, 0.270, -0.048)$.

Step 3: Using Eq. (3.12), Eq. (3.13) and Eq. (3.14) we obtain a table as shown below:

Table 13. The S, R and Q value

	heu	jit	eoq	vmi
S	2.591	1.073	1.857	2.700
R	0.900	0.362	0.950	0.850
Q	0.920	0	0.840	0.880

Then the inventory policy can be ranked according to the minimum value of as:

$$jit > eoq > vmi > heu.$$

4.3 Calculating the rank correlation

The above results can be tabulated as in Table 14.

Table 14. Rank Correlation between the two methods

	d_x	d_y	$d = d_x - d_y$	d^2
heu	3	4	-1	1
Jit	1	1	0	0
eoq	2	2	0	0
vmi	4	3	1	1

In here, d_x = ranks of the alternative generated by using Pythagorean Fuzzy method, d_y= ranks of the alternative generated by using VIKOR algorithm. Using Eq. (3.15), we have:

$$n_k = 1 - \frac{6 \times 2}{4\,(4^2 - 1)} = 0.8.$$

The two methods are positively correlated.

5. Conclusions

We presented an application of Grey Relational Analysis (GRA) under Pythagorean Fuzzy Environment for an inventory policy selection problem. We used two methods of GRA and VIKOR for comparing the ranking of inventory policy selection. The first rank of inventory policy selection was of JIT followed by EOQ. There was variation in ranking for Heuristic and VMI inventory policy. A positive and high value of correlation was found between the two methods proving their effectiveness. VIKOR is a consensus based ranking method where the decision-maker provides maximum group efficacy of the majority and a minimum of the individual penitence of the antagonist. The GRA can generate conscientious solutions decisively when they are gauged with the results from the current methodologies. GRA also provides a better acumen among inventory policy selection.The advantage of PFS in both methods is its ability to release the degree of freedom of IFS and provide more loosening expression of fuzziness.

Acknowledgements

Special thank you to the anonymous referees for their valuable comments and suggestions.

References

[1] Arcelus FJ, Srinivasan G. The sensitivity of optimal inventory policies to model assumptions and parameters, Eng Cost Prod Econ 1989;15:291-298.

[2] Janssen F, Kok TD. A two-supplier inventory model. In: International Journal of Production Economics 1999;59(1-3);395-403.

[3] Tekin E, Gurlur U, Berk E. Age-based vs. stock level control policies for a perishable inventory system, European J Oper Res 2001;134:309-329.

[4] Mohammaditabar D, Ghodsypour SH, O' Brien C. Inventory control system de-

sign by integrating inventory classification and policy selection. Int J Prod Econ 2012;140:655–659.

[5] Lolli F, Ishizaka A, Gamberini R. New AHP based approaches for multicriteria inventory classification, Int J Prod Econ 2014;156:62-74.

[6] Eraslan E, IC YT, An improved decision support for ABC inventory classification. Evol Syst 2019. https://link.springer.com/article/10.1007/s12530-019-09276-7

[7] Lolli F, Balugani AE, Ishizaka A, Gamberini R, Rimini B, Regattieri F. Machine learning for multicriteria inventory classification applied to intermittent demand. Prod Plan Control 2019; 30:1-14.

[8] Hwang CL, Yoon K. Multiple attribute decision making: methods and applications: a state-of-the-art survey. Berlin: Springer-Verlag Berlin Heidelberg; 1981.

[9] Wilson RH., A scientific routine for stock control. Harv Bus Rev 1934;13:116-128.

[10] Xiao T, Xu T. Coordinate price and service level decisions for a supply chain with the deteriorating item under vendor managed inventory. Int J Prod Econ 2013;145:743-752.

[11] Relph G, Newton M, Both Pareto and EOQ have limitations combining them delivers a powerful management tool for MRP and beyond. Int J Prod Econ 2014;157:24-30.

[12] Bai S. Li Y. Study of inventory management based on triangular fuzzy numbers theory. In: 2008 IEEE International Conference on Service Operations and Logistics, and Informatics. Beijing; 2008. p.1648-51.

[13] Huang CK, Tsai DM, Wub JC, Chung KJ. An integrated vendor-buyer inventory model with order- processing cost research reduction and permissible delay in payments, European J Oper Res 2010;202:473-478.

[14] Gupta A, Garg RK, Tewari PC. Multicriteria ranking of inventory ordering policies using fuzzy based-distance based approach for the Indian automotive industry. J Manage 2013;8:41-8.

[15] Balaji K, Kumar VSS. Multicriteria inventory ABC classification in an automobile rubber components manufacturing industry. Procedia CIRP 2014;17:463–468.

[16] Fu Y, Lai KK, Miao Y, Leung JWK. A distance-based decision-making method to improve multiple criteria ABC inventory classification. Int Trans Oper Res 2016;23:969–978.

[17] Arikan F, Citak S. Multiple riteria Inventory classification in an electronics firm, Int J Inf Technol Decis Mak 2017;16:1-17.

[18] Zheng S, Fu Y, Lai KK, Liang L. An improvement to multiple criteria ABC inventory classification using Shannon entropy. J Syst Sci Complex 2017;30:857–65.

[19] Wu S, Fu Y, Lai KK, Leung WKJ. A-weighted least-square dissimilarity approach for multiple criteria ABC inventory classification. Asia-Pac J Oper Res 2018;35:1-12.

[20] Opricovic S. Multicriteria optimization of civil engineering systems [dissertation]. Belgrade: University of Belgrade; 1998.

[21] Yager RR. Pythagorean membership grades in multicriteria decision making. IEEE Trans Fuzzy Syst 2014;22:958-965.

[22] Peng X, Yang Y. Some Results for Pythagorean Fuzzy Sets. Int J Intell Syst 2015;30:1133-60.

[23] Mora´n J, Granada E, Mı´guez JL, Porteiro J. Use of grey relational analysis to assess and optimize small biomass boilers. Fuel Process Technol 2006;87:123–127.

[24] Kuo Y, Yang T, Huang GW. The use of grey relational analysis in solving multiple attribute decision-making problems. Comput Ind Eng 2008;55:80-93.

[25] Gupta SC, Kapoor VK. Fundamentals of mathematical statistics. New Delhi: Sultan Chand and Sons; 1970.