Optimizing Inventory Carrying Cost Using Rank Order Clustering Approach for Small and Medium Enterprises (SMES)

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Abstract: *For any company, whether big enterprises or small and medium-sized enterprises (SMEs), inventory is one of the key assets. Therefore, inventory-related decisions directly influence the revenue generated by the firm. This work aims to find a sufficient degree of control over each inventory item and to mitigate the inventory management problems of SMEs. Rank Order Clustering (ROC) algorithm is used in this study for multi-item inventory item aggregation. The proposed framework is tested on a medium-sized gearmanufacturing firm that manufactures 40 different types of planetary and customized gear-boxes. The results demonstrate 47.64 % of cost-saving through the proposed methodology of cluster formation using ROC and quantity discounts. This approach helps to identify different assemblies to aggregate the component requirements and to formulate a particular inventory strategy to minimize inventory carrying costs for each component.*

Keywords:*Small and Medium Enterprises (SMEs), Inventory Management (IM), Rank Order Clustering (ROC) algorithm.*

1. Introduction

Over the last five decades, the Small and Medium Enterprises (SME) sector has emerged as a highly vibrant and competitive sector of the Indian economy. It can make a major contribution to the country's economic and social growth by creating the greatest job opportunities at a comparatively lower cost of capital, apart from agriculture. SMEs, as ancillary units, are complementary to large industries and this sector has a strong potential to make a significant contribution to the country's growth. In order to meet the demands of domestic and global markets, SMEs are expanding their domain across sectors of the economy, but MSMEs are still lagging in inventory management[1]. The growth in the output and productivity of SMEs was slower than that of large enterprises, based on the World Bank report (2011). Nevertheless, SMEs have become the hub for underutilised and rising labour forces to generate jobs[2].In the manufacturing sector, SMEs implement either job order or batch order production system to fulfill the requirements of their customers[3]. Therefore, the number of components to be handled varies significantly and therefore inventory management becomes very complex. Inventory products that are mismanaged can lead to a major financial problem for the company that results in either excessive inventory or shortage[4].

Small and medium enterprises are small in size, but they contribute significantly to the growth of the economy [5]. India's MSMEs play a crucial role by providing large employment opportunities at relatively lower capital costs than large industries. According to the 73rd round of the National Sample Survey (NSS) conducted by the National Sample Survey Office, the Ministry of Statistics & Program Implementation, there were 633.88 lakh MSMEs in India engaged in various economic activities during the period 2015-16.[1]. Recently, many researchers have been paying their attention to Inventory management in SMEs. Inventory management helps enterprises to formulate policies to control inventories [6][7][8]. ABC, XYZ, HML & VED analysis are standard approaches for inventory item classification[9].

In group technology, the Rank Order Clustering algorithm is commonly used[10]. Traditionally, group technology strategy is used to characterize machine groups with an appropriate group layout to make it easier to manufacture components with specific characteristics and similar operations[11]. Iteratively, the ROC algorithm modifies rows and columns, creating a matrix in which both columns and rows are structured in order of decreasing value. The key advantage claimed by ROC over the other strategies lies simply in its ability to effectively cope with the issues of exceptional components and bottleneck machines that often occur in practical problems.

Despite the considerable number of papers addressing inventory management issues in supply chains, many research issues in the area are still neglected. One of the main research gaps in this field concerns the use of simple and effective inventory management technique that SMEs can adopt very easily. This paper addresses this research gap by developing a method to optimize inventory carrying cost by quantity agreegation using rank order clustering approach.

2. Literature review

The clustering algorithm known as rank order clustering was first invented by J.R King [12]. Examples of exceptional elements and the case of bottleneck machines were also seen by King. In conclusion, the study presented the ROC algorithm's unique advantages against single clustering algorithms and the method of bond energy. Clustering or group technology aims to characterize unlabeled data sets into object groups [13]. Each category is called a "cluster" which according to specific metrics, consists of similarity to each other and different from other groups [14]. ROC has been implemented in many manufacturing firms to form machines cell formation to react as quickly as possible to meet altering customer demands and to enhance their productivity [15]M.P.Chandrasekharan implemented an upgraded version of the well-known rank order clustering method technique[16].The author introduced the block and slide ROC algorithm and it was intended to significantly reduce the shortcomings, such as the identification of bottleneck machines. Ernst(1990) suggested the Operations Based Groups (ORGs) clustering procedure for inventory systems[17]. Abdul et. al. addressed the use of the analytical hierarchy system for ABC analysis and stressed the multiple criteria inventory item classification on multiple parameters[18].

A classification system for multi-criteria stock items using weighted linear optimization was proposed by Ramanathan (2006)[19]. There are many circumstances where many other factors become significant in deciding the importance of an inventory item, apart from the annual use-value. The researcher also discussed the topic of multi-criteria inventory classification. Bhattacharya (2007) suggested a technique for classifying inventory products using the TOPSIS method that takes into account the distances between the ideal and negative-ideal solutions of each alternative[20]. Many researchershave stressed the use of various inventory classification criteria[21][22]. Few studies provide a thorough comparison between traditional ABC inventory classifications and advanced multiple criteria inventory classification. K.Zalik (2008) brings in k`-means algorithm which is a modification of k-means algorithm where pre-assigning the exact number of clusters is not required. Simulated tests were also revealed by the author to validate the efficacy of the proposed algorithm[23].

Wan Lung Ng (2007) provided a study that transforms an inventory item's multiple criteria measures into a scalar ranking where ranking is based on the measured results using the ABC theory[24]. Peter et al., (2013) identified different mathematical tools for various methods of cluster analysis[25]. The author also studied hierarchical & non-hierarchical cluster analysis and compared them in detail. A thorough comparison of three inventory classification techniques was proposed by Tomislav Saric et al., (2014): multi-criteria ABC analysis, neural networks, and cluster analysis (K-means algorithm)[26]. For multi-criteria inventory classification, Mehdi et. Al., (2015) suggested an inventory classification system known as EDAS, wherein positive and negative outcomes, called positive distance from average and negative distance from average, are addressed[27]. It is used for testing alternative units for stock-keeping. Raja et.al., (2016) suggested clustering classification of spare parts to carry out inventory classification, actual data consisting of 612 spare parts wereused[28]. As a basis for the classification, 11 variables were identified with the aid of software. Different hierarchical clustering approaches were analyzed by Danijela Pezer (2017), namely single linkage, maximum linkage, weighted linkage, and ward method. Ward's approach was selected to interpret results by the dendrogram, as it helps to define clusters for the classification of inventory objects. The author concluded that hierarchical approaches are successful in determining the optimum number of clusters. The k-algorithm was used to verify the results[29]. E. Balugani et. al., (2018) introduced the method of clustering inventory objects into homogeneous groups to be handled with unique inventory policies by K-algorithm and ward. The study concluded that there is no need for computationally expensive inventory system management simulations by clustering inventory objects[30].

Literature survey reveals that many researchers have paid their attention in developing inventory policies for large enterprises and these studies lack of simple and cost effective strategies that SMEs can adopt very easilily. In addressing this gap, we propose a novel approach that addressesinventory management issues of SMEs. Our approach applies ROC method in conjuction with quantity discounts to optimize inventory levels to cut the total cost.

3. Methodology

In this proposed work, the ROC algorithm is aimed to categorize inventory items for aggregation of inventory items. Rank Order Clustering is traditionally used for grouping of machines but here it is used for cluster formation of inventory items for aggregation of the requirement to optimize inventory carrying cost and ordering cost.

Extensive numerical analysis is conducted on a medium-sized firm that manufactures planetary gearboxes and customized gearboxes to validate the results of the proposed solution. There are multiple components in each gearbox assembly, which range from 14 to 55. Some pieces are made in-house and some of them are bought from suppliers. The range of inventory products to be managed by the company is therefore very broad and difficult, particularly when the demand for gearbox assemblies differs over a period of time. The firm under the organization does not follow any technique to classify inventory items. The procurement process of required goods is carried out when the requirement arises, resulting in shortages or excess inventories. Details of purchased parts for every gearbox assembly are collected to gain control over the procurement procedure. For each gearbox assembly, Table 1 shows the number of components required per assembly.

Table 1. Components required per Gearbox Assembly

Assembly Number	*Components per assembly*	*Assembly Number*	*Components per assembly*	*Assembly Number*	*Components per assembly*	*Assembly Number*	*Components per assembly*
1095	15	2130	26	3095	20	4095	13
1130	24	2160	25	3130	28	4130	25
1160	21	2190	25	3160	31	4160	30
1190	20	2230	25	3190	31	4190	27
1240	23	2240	32	3240	43	4240	27
1260	20	2260	40	3260	34	4260	26
1280	20	2280	39	3280	38	4280	29
1300	14	2300	29	3300	41	4300	34
1340	16	2340	28	3340	54	4340	43
2095	18	2380	37	3380	52	4380	41

ROC has been studied by many manufacturing firms in order to respond as quickly as possible to meet demand variations as well as to boost their productivity. To the best of our knowledge, this is the first time in which ROC is aimed to form clusters of gearbox assemblies in which similar components are being used. The purpose of applying ROC is to aggregate the total required quantity for reducing the total cost by optimizing ordering and inventory carrying cost. The incidence matrix has been formulated by considering the type of gearbox assembly in the column and bought out parts in a row. The incidence matrix for 40 gearboxes and 180 components is constructed by filling the binary values '0 'or' 1. If a specific purchased-out part is needed, binary value '1' is assigned for specific gearbox assembly, otherwise binary value '0' is assigned. MS Excel builds the initial incidence matrix consisting of gearbox assemblies in columns and their components in rows. The initial components-assemblies matrix is shown in Fig. 1, but as the whole matrix cannot be shown, only a few components-assemblies matrix is considered to explain the ROC process.

Assembly Number. ⇩	**Allen Bolt 10x30**	**Allen Bolt 10x80**	**Allen Bolt 10x70**	**Allen Bolt 10x80**	**Ball Brg. 6212**	**Ball Brg. 6214**	**Ball Brg. 6216**	**Ball Brg. 6217**	**Ball Brg. 6218**	**Barrel Nipple 1/4" BSP**	**Breather Plug 1/2" BSP**	**Breather Plug 1/4" BSP**	**Copper Washer M 8**	**Drain Plug 1/2" BSP**	**External Circlip A 20**
1095							1			1			1		
1130	1			1				1		1		1		1	
1160										1					
1190						1									
1240		1	1						1				1		
1260		1	1								1				
1280	1			1											
1300	1					1				1					
1340					1										
2095										1					1
2130		1										1	1		
2160												1			
2190									1						1
2230	1		1			1					1				
2240			1										1		

Figure1. Initial Components Vs Assemblies matrix

Finally, the ROC algorithm is used on the incidence matrix to get the grouping of gearbox assemblies and bought out parts. This approach is illustrated with a stepwise procedure as given below.

- Step-1 is carried out on the initial matrix, by assigning binary weight to each column. In the column, 180 components are given, so binary values are allocated from 2^179 to 2^0 from right to left.
- Step-2 is then carried out as per the formula, by computing the decimal equivalent for each row.
- Step-3 The rows are now rearranged with their decimal equivalent values in descending order.
- Step-4 In the next step, binary values ranging from 2^39 to 2^0 are given to rows from bottom to up as per step-4 of the algorithm.
- Step-5 Each column's decimal equivalent is determined.
- Step-6 The columns are rearranged with their decimal equivalent values in descending order. Since there is a column rearrangement, the second iteration of the algorithm will occur.

Steps 1 to 6 are replicated until there is no rearrangement in either rows or columns. Finally, the algorithm stopped after the third iteration. Finally, after the third iteration, the algorithm stopped. Once the Rank Order Clustering algorithm stops, the next step is to classify final iteration groups or clusters.

Figure 2 shows the matrix after exchanging selected rows and columns with the application of ROC.

Assembly No ⇩	Allen Bolt 10x80	Ball Brg. 6212	Ball Brg. 6214	Allen Bolt 10x80	Copper Washer M 8	Allen Bolt 10x70	Ball Brg. 6218	Ball Brg. 6216	Allen Bolt 10x30	Breather Plug 1/4" BSP	Drain Plug 1/2" BSP	Ball Brg. 6217	External Circlip A 20	Barrel nipple 1/4" BSP	Breather Plug 1/2" BSP
1240				1	1	1	1								
1260				1		1				1					1
1095	1				1			1						1	
2240			1			1									
1340		1													
2095															
2190					1		1								
2130			1												
2160	1														
1300									1				1	1	
1160										1				1	1
2230				1		1			1		1				1
1280									1				1		
1130									1			1		1	1
1190			1								1				

Figure2. Final Matrix

As shown in fig.2, the final matrix helpsto purchase managers to identify the common components used in various assemblies and aggregate the quantity needed to order in larger amounts rather than more frequently ordering. The major objective is to identify the common components and to aggregate customer's demands.

4. Results and discussion

The matrix manipulation results in two different clusters with few outliers for all the 180 components and 40 assemblies, as shown in table 2.

Table 2. Cluster details

Clusters	***Number of Components***	***The number of gear-box assemblies per group.***
Group 1	100	24
Group 2	31	16
Outliers	43	-

With the final matrix, assemblies 1280, 1300, and 2380 are identified in which Allen Bolt 10x80 is the common component. Their per periodrequirements are summarized in Table 3.

Table 3. Components required per assembly

Assembly Numbers→	***1280***	***1300***	***2380***
April	10	24	40
May	0	16	8
June	10	48	16
July	10	0	8
August	10	8	24
September	0	0	16
October	10	16	32
November	0	16	88
December	0	0	40
January	10	32	80
February	0	0	24
March	20	16	16

4.1 Existing purchase policy

The purchasing manager applies the lot for lot technique in the current purchase policy and executes separate orders for each assembly in each period. For each product, purchase managers have established more than one supplier, and suppliers offer the same component at differing prices. Therefore, the current order strategy leads to higher costs of ordering and often stock-out conditions. Table 4 presents sample calculations for assembly 1280.

Table 4. Sample calculation to evaluate the assembly-wise cost

Present order quantity per period	***Ordering cost***	***Procurement cost***
10	150	327
0	0	0
10	150	327
10	150	327
10	150	327
0	0	0
10	150	327
0	0	0
0	0	0
10	150	327
0	0	0
20	150	653
	Total: -	3664/-

Similarly, purchasing the required quantity of Allen Bolt 10x80 for assembly numbers 1300 and 2380 respectively costs Rs. 6950/- and 14907/-. Therefore, the total cost needed for the procurement of the total quantity in the current policy is Rs. 25221/-.

4.2 Cost saving through the proposed method

The implementation of the proposed model is demonstrated by the same multi-period, single-item, lot-sizing problem in order to find an optimal solution over the entire one-year planning horizon.

- Item Name: Allen Bolt 10x80.
- The supplier-wise price details are shown in Table 5.

Table 5. Supplier-wise price details

Suppliers of Allen Bolt 10x80	*Price/unit.*
Om Sai Enterprise	17.6
Southern Engineers	25.03
Om Sales Enterprise	32.67

ROC implementation helps purchase managers to identify the assemblies consisting of Allen Bolt 10x80 and aggregate the quantity required in three assemblies. Table 6 gives the aggregate quantity of Allen Bolt 10x80 per period.

Table 6- Aggregated quantity per period

Assembly Number →	*1280*	*1300*	*2380*	*Aggregated quantity per period.*
Apr	10	24	40	74
May	0	16	8	24
Jun	10	48	16	74
Jul	10	0	8	18
Aug	10	8	24	42
Sep	0	0	16	16
Oct	10	16	32	58
Nov	0	16	88	104
Dec	0	0	40	40
Jan	10	32	80	122
Feb	0	0	24	24
Mar	20	16	16	52

Now, instead of ordering three times, procurement managers may order aggregate quantities of three assemblies in a single order. This would help to order the total aggregated quantity at the lowest possible price offered by vendors, resulting in cost advantages, as shown in Table 7.

Table 7. cost benefits of quantity discounts

Total quantity to be ordered	***Ordering cost***	***Purchase cost***
74	150	1302.4
24	150	422.4
74	150	1302.4
18	150	316.8
42	150	739.2
16	150	281.6
58	150	1020.8
104	150	1830.4
40	150	704
122	150	2147.2
24	150	422.4
52	150	915.2
	Total: -	13205

It costs Rs 13205 to buy the same quantity as in the case of the present system after implementing the ROC and quantity discount.To buy the same quantity of Allen Bolt 10x80, this technique will save 47.64 percent of the overall annual cost.To measure the total cost savings per annum, the same method can be extended to the remaining 179 items.

5. Conclusion

The knowledge gained from the above numerical analysis showed potential savings of 47.64 percent for multi-period, single-item, lot-sizing inventory management problems. For an increase in the quantity, this percentage would increase. In the current procurement policy, individual orders were placed with no inventory policy to purchase the required quantity of each gear-box assembly.Different assemblies consisting of similar components were identified with the application of ROC.This results in component aggregation, which further led to a significant decrease in inventory and ordering costs. As quantity increases, more quantity discounts may be requested from suppliers.

This concept can be extended to remaining items, to form inventory strategies for SMEs which will help to scale their inventories up or down and for getting more quantity discounts from suppliers.

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