International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249-8958 (Online), Volume-12 Issue-4, April 2023

Modified Ordering Policy for Items of Imperfect Quality with Allowable Proportionate Discount using Cross Selling Effects and Datamining Techniques

Bhawani Sankar Panigrahi, Sanjay Kumar, Pabitra Kumar Tripathy

***Abstract:** Model of Economic Order Quantity (EOQ) in which cross-selling effects are taken into account and proportional discounts are allowed for products of lesser quality. Here, we introduce cross-selling impact as a means of establishing the ordering policy. To account for the benefits of upselling and cross-selling, we treat groups of frequently purchased items as discrete units for the purposes of calculating EOQ. Furthermore, the cross-selling impacts remain more pronounced when things are defective in nature. Initially, a number of data mining approaches are investigated in order to determine the best approach for establishing the necessary link among the item sets. By factoring in the cross-selling implications, we are able to have a better idea of the EOQ and move the project further. As it is anticipated that every lot contains some level of flaw, the work involves thorough lot-by-lot inspection. The faulty products eventually reached a total profit after varying discounts were applied. Finally, the results of the proposed model are shown through numerical examples.*

***Keywords:** Economic Order Quantity (EOQ), Discounts, Datamining, Techniques.*

I. INTRODUCTION

The acquisition, availability, and processing of data in order to retrieve the needed information has become an expanding field of research due to the rising demand in a wide variety of vibrant application domains. These application domains include industries, social sectors, and commercial enterprises. For these businesses, the use of an appropriate data mining technique aids in development, growth, and strategic decision-making. Data mining's primary purpose is to extract useful information from massive amounts of raw data. With this newfound understanding of the data's interconnectedness, companies can create innovative promotional plans that better predict their products' market success. Modern marketing has seen an increase in the use of computerised resources, which has resulted in the establishment of a vital connection between consumers and upper management. It's useful for gaining an edge over other businesses. Data mining can benefit from the fresh perspectives provided by such easily accessible materials. The further exploration leads to an effective management of data mining tools by augmenting the conventional approaches. The authors are inspired to take this step because the efficient management of production and inventories requires the use of innovative data mining techniques.

Data mining refers to the practise of gaining insight from databases containing vast volumes of data. Association rule mining is a key subfield of data mining that tracks and analyses business transactions and massive datasets in search of significant connections. Once again, clustering is the process of categorising a set of transactions into groups based on their shared characteristics. Finding the Economic Order Quantity (EOQ) of each item might be difficult when dealing with a large inventory. Classification, the process by which inventory is organised into categories, will make this process much simpler. Inventory EOQ modelling with the aid of association rule mining, clustering, and classification approaches helps with efficient stock control. In the real world, the sales of one item might affect the sales of another due to the underlying interdependencies between them. The cross-selling effect describes the possibility of a drop in sales if two businesses are poorly connected. Opportunity cost refers to the amount of money that was lost as a result of this consequence.

Even with careful planning, stringent quality assurance measures, and cutting-edge production techniques, a small percentage of manufactured goods in today's highly competitive market will inevitably have flaws. Items of less-than-perfect quality may not always be flawed, and they may have other uses in the warehouse. The electronics sector is a prime illustration of this phenomenon. Unreliable goods have been shown to have a direct impact on stock control. Defective products must be detected and removed at every stage of the distribution chain. Many scholars have proposed various models for estimating the EOQ of low-quality inventory in order to deal with this kind of stock-out scenario.

Manuscript received on 18 March 2023 | Revised Manuscript received on 22 March 2023 | Manuscript Accepted on 15 April 2023 | Manuscript published on 30 April 2023.

*Correspondence Author(s)

Bhawani Sankar Panigrahi*, Research Scholar, Kalinga University, Naya Raipur (Chhattisgarh), India. ORCID ID: https://orcid.org/0000-0002-1109-4108

Dr. Sanjay Kumar, Associate Professor, Department of CSE, Kalinga University, Raipur (Chhattisgarh), India. ORCID ID: https://orcid.org/0000-0001-5820-7715

Dr. Pabitra Kumar Tripathy*, Associate Professor, Department of Computer Science and Engineering, Kalam Institute of Technology, Berhampur (Odisha), India. E-mail: pabitratripathy81@gmail.com, ORCID ID: https://orcid.org/0000-0002-4870-8476

The first EOQ model was developed to calculate the potential damage caused by defective goods (Porteus [4]). Data miners are now interested in this topic, and several EOQ models that focus on flawed products have been developed as a result. Salemeh et al. provided a typical EOQ method in which, once 100 percent screening is complete, the defective goods are sold at a predetermined discount as a single batch. Jaggi et al[2]. have made improvements to the traditional EOQ method that have benefited businesses and organisations for the past two decades.

Mittal et al. have used association rule mining to develop an EOQ model for defective inventory items that have cross-selling consequences. Mittal et al. provide a better model for imperfect stock items that takes into account the impact of upselling, downselling, clustering, and association rule mining. Mittal et al. model EOQ by using a novel categorization technique called ABC and the cross-selling impact, which affects the inventory policy for multi-item inventory. New ground has been set in this regard through the application of the learning effect to the development of an economic inventory model that offers a proportional discount for items of faulty quality Patro et al.[2].

Literature review demonstrates how cross-selling effects can be used to create EOQ models that include a fixed discount for the percentage of defectives even when screening all products. The EOQ inventory model seeks to find the percentage of screening present in each lot in order to calculate the profit made by paying proper attention to the ideal order or lot size. Yet, new avenues for study are opened up by the fact that the cross-selling impacts with different data mining techniques in modelling the inventory do not account for the percentage of defective items.

II. PROPOSED WORK

In this paper, we present a novel approach to conceptualising the development of an EOQ inventory model for low-quality goods by taking cross-selling effects into account across three distinct cases: the presence of few association rules; the presence of association rule mining; and the presence of clustering and ABC classification. It establishes a permitted proportionate discount wherein each lot is presumed to have some percentage of flaws. The overall profit is calculated by performing a full inspection of the lot in question and deducting an appropriate percentage for any flaws found. Its goal is to provide workable solutions to actual business issues by contrasting new and old inventory practises in light of cross-selling effects within a Support-Confidence framework Wang et al[3]. Additionally, we present a new estimation strategy for computing the inventory models of defective goods in a group of frequently used items, by incorporating the opportunity cost into the baseline of the association rules. This paper then investigates a novel opportunity cost as a means of adapting the often item inventory model to a set of items rather than a single one. The study includes a numerical example to demonstrate the suggested method and support its veracity.

III. MODEL OF PROPOSED WORK

This study compares the order quantities for faulty quality items when a proportionate discount is applied to a collection of frequently purchased items, shedding light on the effects of cross-selling when combined with different data mining techniques.

When two products are so intertwined that one's success or failure in the market depends on the other, we say that their sales are correlated. Let us consider the given item set f containing items $r_1, r_2, r_3, \ldots r_n$. In this, the “Support” of an item means it’s frequency of occurrence in the whole transactions. For item r_1, it can be expressed as:

$$Support(r_1) = Frequency(r_1)/Total\ number\ of\ transactions \quad (1.1)$$

The relationships between items can be specified by “Confidence” or the conditional probability.

$conf(r_1 \rightarrow r_2)$ refers to frequency at which r_2 is purchased while r_1 is purchased.

$$Conf(r_1 \rightarrow r_2) = Support(r_1 U r_2)/Support(r_1) \quad (1.2)$$

A common item-set can be determined using a support confidence framework and an apriori method. For created items with higher levels of confidence and support than the user-defined minimum, this value is displayed as the association rules for those items. Using the Apriori technique, we may determine the minimum support and confidence required to build association rules based on a threshold confidence in a given set of items, known as a frequent itemset.

Important stages for realising the presented algorithm in this direction are as follows (Agrawal et al.).

Step 1*:* It scans all the transactions to count occurrences of each item to find set of frequent 1-item set.

Step 2: It is made up of two subcomponents, namely, as apriori creation and candidate counting assistance. This process involves using to generate a candidate item-set, searching the database, and comparing the count of items for which each candidate has support to the minimal support count necessary to satisfy the condition. The operations of joining and pruning are accomplished with the help of an apriori generating function. In the join stage, we do a join of with to generate candidates, while in the prune step, we employ the Apriori property to get rid of things that have rare subsets. In the present work's research, we also took into account a different example involving the clustering of transactions (Wang et al. In this context, "big items" refers to goods that appear in just a small number of transactions inside a given cluster on the basis of their similarities. A product's popularity in cluster is defined by the sum of its sales there.

So, large items present in a cluster are homogeneous, and support is at least equal to, where is user-defined minimum support; otherwise, the items present are small and heterogeneous. The goal of this clustering is to reduce expenses. In addition, the intra-cluster cost, which is determined by all tiny things, and the inter-cluster cost, which is the alias of large items in all clusters, are both used to determine the final, minimised cost. Clusters are formed and dissolved dynamically in this clustering method, all in the name of optimising costs.

This clustering algorithm is specified in terms of two phases as:

1. Allocation phase: sequentially each transaction is read and assigned to a cluster, either existing one or new.
2. Refinement phase: cost is minimized.

In the third scenario, an ABC categorization strategy is considered for adjusting multi-item EOQ inventory policies Dye et al[2]. The purpose is to examine the impact of the cross-selling factor on the products in their respective categories. This methodology initially sorts the list of goods in a given inventory database into three groups, A, B, and C, based on the Pareto principle, which asserts that a small percentage of items in transaction for higher percentage of total dollar consumption (product of unit price and annual demand of item). The letter A stands for the relatively few and the letter C for the inconsequentially numerous. Finally, using a standard data mining approach—specifically, association rule mining in all three domains—the cross-selling effect is achieved.

The confidence between things is a measure of the influence of cross on those items. In frequent item-set, the effect of an out-of-stock item rk on another item *i* i.e, $f(r_1,r_2,r_3 \ldots\ldots r_n)$ can be represented as a probability

$$prob_{k,i} = \sum_{i=1}^{n} conf(k \to f(k,i)) \tag{1.3}$$

where, $k = 1,2,3,\ldots\ldots n$ denotes the items present in a frequent item-set and $f(k,i)$ represents the subset of item i not including number of items. For $i = k$, $f_{i,i} = i$, that gives $conf(i \to i) = 1$.

The opportunity cost of an item *k* can be described by the lost cost of that item on account of the effect of cross selling. It can be represented by the relation

$$OC_k = \sum u_i . prob_{k,i} \tag{1.4}$$

where, $u_i =$ cost of each unit item *i*. In this regard the Probabilistic index I_{ndk} is defined as:

$$I_{ndk} = \frac{OC_k + H_k}{OC_k} \tag{1.5}$$

where, H_k = cost of holding item *k* per unit. I_{ndk} will be used later to modify order policy along with opportunity cost.

The present work analyzed mathematically in modeling of EOQ with imperfect items by considering some assumptions which are closer to realistic situations. Now, let us consider the items of frequent item set are delivered instantaneously with the order size of L_s.

The number of items of good quality= the size of lot - the items of defective quality.

$$L_s - pL_s = (1-p)L_s \tag{1.6}$$

To ignore shortages of good items, $(1-p)L_s$ is at least equal to the demand at the time of screening t (Salameh and Jaber [?]), i.e,

$$(1-p)L_s \geq Dt \tag{1.7}$$

$$p \leq 1 - \frac{D}{r} \tag{1.8}$$

The total cost per cycle for the proposed economic order quantity model is:

$$TC(L_s) = O_c + P_c L_s + S_c L_s + H_c\left[\frac{L_s(1-p)T}{2} + \frac{pL_s^{\,2}}{r}\right] \tag{1.9}$$

The cycle wise total revenue is defined as:

$TR(L_s) =$ Total sales with regard to good quality items + total sales with regard to defective items

$$TR(L_s) = 2SL_s^{\,2} + \frac{\left\{O_c + P_c L_s + S_c L_s + H_c\left(\frac{L_s(1-p)T}{2} + \frac{pL_s^{\,2}}{r}\right)\right\}(L_s p + 1)}{2L_s + L_s p + 1} \tag{1.10}$$

The cycle wise total profit =

$$TP(L_s) = TR(L_s) - TC(L_s) \tag{1.11}$$

$$TP(L_s) = \left[\frac{2SL_s^{\,2} + \left\{O_c + P_c L_s + S_c L_s + H_c\left(\frac{L_s(1-p)T}{2} + \frac{pL_s^{\,2}}{r}\right)\right\}(L_s p + 1)}{2L_s + L_s p + 1}\right] - \left[O_c + P_c L_s + S_c L_s + H_r\left(\frac{L_s(1-p)T}{2} + \frac{pL_s^{\,2}}{r}\right)\right] \tag{1.12}$$

Total profit $TPU(L_s)$ unit wise formulated by:

$$TPU(L_s) = TP(L_s)/T \tag{1.13}$$

where, $T = \frac{L_s(1-p)}{D}$

$$TPU(L_s) = \frac{2D(SL_s - O_c - P_c L_s - S_c L_s)}{2L_s + L_s p + 1}\left(\frac{1}{1-p}\right) - \frac{H_c L_s^{\,2}}{2L_s + L_s p + 1}(1+p) \tag{1.14}$$

As percentage of imperfect items p is random in nature having a known probability density function $f(p)$, the expected value of $TPU(L_s)$ can be found as:

$$ETPU(L_s) = \frac{2D(SL_s - O_c - P_cL_s - S_cL_s)}{2L_s + L_sE[p] + 1}E\left(\frac{1}{1-p}\right) - \frac{H_cL_s^2}{2L_s + L_sE[p] + 1}(1 + E[p]) \quad (1.15)$$

Here, the optimality condition signifies the concavity of the expected total profit with respect to unit time and is computed using the first derivative of Equation 3.15

$$ETPU'(L_s) = \left(\frac{1}{(2L_s + L_sE[p] + 1)^2}\right)\begin{bmatrix} 2DS - 2DP_c - 2DC_s + 4DO_c \\ + 2DO_cE[p]E\left(\frac{1}{1-p}\right) - 2H_cL_s^2 \\ - H_cL_s^2(E[p])^2 - 3H_cL_s^2E[p] \\ - 2H_cL_s - 2H_cL_sE[p] \end{bmatrix} \quad (1.16)$$

The second derivative of Equation 3.15

$$ETPU''(L_s) = -\left(\frac{2}{(2L_s + L_sE[p] + 1)^3}\right)(2 + E[p]) \begin{pmatrix} 2DS - 2DP_c - 2DC_s + 4DO_c \\ + 2DO_cE[p]E\left(\frac{1}{1-p}\right) + H_c + H_cE[p] \end{pmatrix} \quad (1.17)$$

The 2^{nd} derivative of $ETPU(L_s)$ gives negative result for all values of L_s, that implies existence of a distinct value of L_smax which maximizes Equation 3.13, is given as follows:

$$L_smax = \sqrt{\frac{(2DS - 2DP_c - 2DC_s + 4DO_c + 2DO_cE[p])E\left(\frac{1}{1-p}\right)}{2H_c + 3H_cE[p] + H_c(E[p])^2 + \frac{2H_c}{L_s} + \frac{2H_c}{L_s}(E[p])}} \quad (1.18)$$

For large value of L_s, $\frac{1}{L_s} \to 0$

$$L_smax = \sqrt{\frac{(2DS - 2DP_c - 2DC_s + 4DO_c + 2DO_cE[p])E\left(\frac{1}{1-p}\right)}{2H_c + 3H_cE[p] + H_c(E[p])^2}} \quad (1.19)$$

The amount to order of a particular set of goods is equal to their worth in. This work adjusts the optimal order quantity by including the impact of cross-selling. Equation 3.5 is modified as follows to determine the new order quantity for a set of imperfectly frequent items:

$$EOQ = L_smax\sqrt{I_{nd}} \quad (1.20)$$

IV. NUMERICAL EXAMPLE

Cost, selling price, annual demand, etc. are only few of the factors that must be taken into account in order to complete the task at hand. In order to verify the present work, we looked at three numerical cases. Apriori is an association rule mining with clustering and classification method, and the data come from the works of Mittal et al.[1], and Patro et al[2]. We have analysed the mentioned methods side by side. We have solved the equations with Mathematica 5.1 and run the algorithms on the MATLAB platform. In each case, an assumption is taken that the defective proportion p is uniformly distributed with probability density function. The expected values are given as follows: $E[p] = 0.02$ and $E[1/(1-p)] = 1.02055$.

4.1. Case-I: Apriori

To illustrate the developed model, we adopt the values of the parameters as shown in Table 3.1 according to Mittal et al., and analyze the inventory situation.

Table 1: Set Parameters of Inventory Situation

Minimum support or min_sup	50%
Minimum confidence or min_conf	60%
O_c	100 per cycle
H_c	\$10 per unit per year
C_s	\$1 per unit
S	\$60 per unit
w	131400 units/year

Suppose the inventory item-set is $I = \{r_1, r_2, r_3, r_4, r_5, r_6\}$, then the inventory transaction set can be given by TID={1500, 2500, 3500, 4500, 5500} as shown in Table 3.2. The inventory transactions are provided in the rows of this Table. The Support-Confidence framework can be used to identify the association rule of these inventory transactions. The apriori algorithm is used to determine the detailed frequent itemsets available in the transaction data base as follows:

$$\{r_1\},\{r_2\},\{r_3\},\{r_4\},\{r_5\},\{r_1\ r_3\},\{r_2\ r_3\},\{r_2\ r_5\},\{r_3\ r_5\},\{r_2\ r_3\ r_5\}$$

Table 2: An Inventory Transaction Data Base

TID	ITEMS
1500	$r_1 r_3 r_4$
2500	$r_2 r_3 r_5$
3500	$r_1 r_2 r_3 r_5$
4500	$r_2 r_5$
5500	$r_4 r_6$

In Table 3.3, the inventory policy in frequent item-set r_2, r_3, r_5 is considered. The most frequent items are given as r_2, r_3, r_5 with a support which is greater than the min_sup. It is chosen form various classes of items. According to the apriori algorithm a min_sup of 50% is considered. By taking the min_conf of 60%, the confidence of items and their subsets in r_2, r_3, r_5 remains larger than that. Similarly the confidence of the other frequent item sets are estimated and given in Table 1.4.

Table 3: Inventory Policy in a Frequent Item-Set

Item	Min_Sup (%)	Support	Demand	Unit Cost
r_2	50	75	50,000	30.00
r_3	50	75	40,000	20.50
r_5	50	75	45000	45.52

Table 4: Rules with Confidence

Items	Confidence (%)
$r_2 \to r_3$	66.7
$r_2 \to r_5$	100
$r_2 \to r_3 \cup r_5$	66.7
$r_3 \to r_2$	66.7
$r_3 \to r_5$	66.7
$r_3 \to r_2 \cup r_5$	66.7
$r_5 \to r_2$	100
$r_5 \to r_3$	66.
$r_5 \to r_2 \cup r_3$	66.7

To calculate the opportunity cost of the frequent itemset r_2, r_3, r_5, the following formulae have been used which is given in Equation 3.4.

$$OC_{r2} = C_{r2}.conf(r_2 \to r_2) + C_{r3}.\{conf(r_2 \to r_3) + conf(r_2 \to r_3 \cup r_5)\} + C_{r5}.\{conf(r_2 \to r_5) + conf(r_2 \to r_3 \cup r_5)\}$$
$$= 30 \times 1 + 20.5 \times \{0.667 + 0.667\} + 45.52 \times \{1 + 0.667\}$$
$$= 133.22884$$

Similarly, $OC_{r3} = 121.24368$ and $OC_{r5} = 122.877$

The order policy is modified in a frequent item-set (for items r_2, r_3, r_5) by substituting values of opportunity cost in Equation 5 as

$$I_{nd_{r2}} = \frac{OC_{r2} + H_r}{OC_{r2}} = 1.075058824$$

Similarly, $I_{nd_{r3}} = 1.082478526$ and $I_{nd_{r5}} = 1.081382195$

Now for item r_2, the optimal value of $L_s max$ and the expected total profit per unit time $ETPU(L_s)$ is given by:

$L_s max = 1069.66$ and $ETPU(L_s) = 1454344.943$

Therefore, EOQ of item r_2, can be modified as given as follows:

$EOQ = L_s max \sqrt{I_{nd}} = 1109.077436$

In the similar way, we also calculate the same for items r_3, r_5 and are given in Table 1.5. These values are compared with the existing models and represented in Table 1.6 and Figure 1.1.

Table 5: Modified value with Apriori

Items	$L_s max$	$ETPU(L_s)$	EOQ
r_2	1069.66	1454344.943	1109.077436
r_3	976.211	1546227.476	1015.452148
r_5	980.09	603043.1309	1019.190966

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Table 6: Comparison with existing models

Items	Traditional EOQ	EOQ (Mittal et al.) [76]	EOQ (Present Work)
r_2	1000	1049.88991	1109.077436
r_3	899.427191	943.6349189	1015.452148
r_5	948.6832981	1000.575114	1019.190966

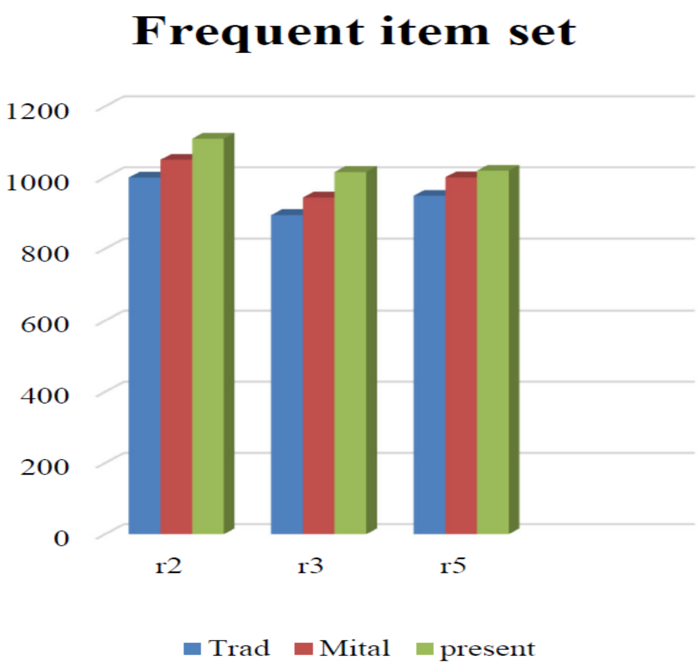

Figure 1: Comparison of EOQ values obtained in proposed method (Apriori) with the state-of-art methods

4.2. Case-II: Association rule mining with clustering

Here, we apply the idea of transaction clustering based on large goods to a database of inventory transactions in order to create consistent groups. After the data has been clustered, an apriori method is applied to it to provide association rules. To get to the EOQ for subpar products, we also have to figure out the opportunity cost. To evaluate the inventory policy proposed here, we use the following parameters, which are based on those proposed by Mittal et al. [1] and Patro et al. [2]: min_sup=60%, min_conf=75%, O_c=100/cycle, H_c=\$5/unit/year, r=1unit/min, S_c=0.5/unit, P_c=25/unit, B_c=\$20/unit, S= \$50/unit, W=175 200 units/year.

Let us consider the database set D and the inventory item-set,
$I = \{x_1, x_2, x_3, x_4, x_5, x_6, x_7\}$. Each row indicates an inventory transaction in the set, ITD = {ITD 1, ITD 2, ITD 3, ITD 4, ITD 5, ITD 6}, that is given in Table 3.7.

Table 7: An Inventory Transaction Database

ITD	Items
ITD 1	x_1 x_2 x_3
ITD 2	x_1 x_2 x_3 x_4
ITD 3	x_1 x_2 x_3 x_5
ITD 4	x_1 x_2 x_6
ITD 5	x_4 x_7 x_8
ITD 6	x_4 x_7 x_9

Association rules between these exchanges are generated using an apriori method. Table 1.8 displays the parameter values for inventory policy that are used to calculate the opportunity cost of various items.

Retrieval Number:100.1/ijeat.D40810412423
DOI: 10.35940/ijeat.D4081.0412423
Journal Website: www.ijeat.org

Published By:
Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP)

Table 8: Parameter values for inventory policy

Item	D	P_c	H_c	S	S_{imp}
x_1	50,000	30.00	3	60.00	25.00
x_2	40,000	20.50	2	40.00	17.00
x_3	40,000	45.52	4	60.00	40.00
x_4	50,000	50.00	5	90.00	45.00
x_5	50,000	45.52	4	70.00	40.00
x_6	40,000	40.00	4	65.00	35.00

Assuming a minimum of 60% support and a total of 6 transactions in the inventory transaction database. In this case, the formula yields a sizable item that involves at least four exchanges. Table 3.9 displays the results of our calculations for each cluster.

Table 9: Clustering details

Clustering	Large	Small
C_1 = {ITD 1, ITD 2, ITD 3, ITD 4, ITD 5, ITD 6}	$L_1 = \{x_1, x_2\}$	$S_1 = \left\{\begin{matrix} x_3, x_4, x_5, x_6, \\ x_7, x_8, x_9 \end{matrix}\right\}$
C_2= {C_1= {ITD 1, ITD 2, ITD 3, ITD 4}, C_2= {ITD 5, ITD 6}}	$L_1 = \{x_1, x_2, x_3\}$ $L_2 = \{x_4, x_7\}$	$S_1 = \{x_4, x_5, x_6\}$ $S_2 = \{x_8, x_9\}$
C_3= {C_1 = {ITD 1, ITD 2}, C_2 = {ITD 3, ITD 4}, C_3 = {ITD 5, ITD 6}}	$L_1 = \{x_1, x_2, x_3\}$ $L_2 = \{x_1, x_2\}$ $L_3 = \{x_4, x_7\}$	$S_1 = \{x_4\}$ $S_2 = \{x_3, x_5, x_6\}$ $S_3 = \{x_8, x_9\}$

Therefore, cluster C_2 is considered because cost obtained is minimum in comparison to cluster C_1 and C_3. So, the given transaction database is clustered into two clusters as, C_1 = {ITD 1, ITD 2, ITD 3, ITD 4} and C_2 = {ITD 5, ITD 6}. Then apriori algorithm is applied on both clusters to obtain frequent sets. $\{x_1, x_2, x_3\}$ and $\{x_4, x_7\}$ are the most frequent itemset in cluster C_1 and C_2 respectively. Confidence of items in both frequent itemset are calculated using Equation 2, and given in Table 10.

Table 10: Confidence of frequent item-set in cluster C_1 and cluster C_2

For Cluster C_1		For Cluster C_2	
Items	**Confidence**	**Items**	**Confidence**
$x_1 \rightarrow x_2$	100	$x_4 \rightarrow x_7$	100
$x_1 \rightarrow x_3$	75	$x_7 \rightarrow x_4$	100
$x_1 \rightarrow x_2 \cup x_3$	75		
$x_2 \rightarrow x_1$	100		
$x_2 \rightarrow x_3$	75		
$x_2 \rightarrow x_3 \cup x_4$	75		
$x_3 \rightarrow x_1$	100		
$x_3 \rightarrow x_2$	100		
$x_3 \rightarrow x_1 \cup x_2$	100		

Then the opportunity cost in the frequent item-set $I = \{x_1, x_2, x_3, x_4, x_7\}$ can be calculated by formulae given in Equation 4.

Opportunity cost of item:

$$X_1 = OC_{(x_1)} = C_{x_1}.conf(x_1 \rightarrow x_1) + C_{x_2}.\{conf(x_1 \rightarrow x_2) + conf(x_1 \rightarrow x_2 \cup x_3)\}$$
$$+ C_{x_3}.\{conf(x_1 \rightarrow x_3) + conf(x_1 \rightarrow x_2 \cup x_3)\}$$

$$= 30 \times 1 + 20.50 \times \{1 + 0.75\} + 45.52 \times \{0.75 + 0.75\}$$
$$= 30 + 35.875 + 68.28$$
$$= 134.155$$

Now, I_{nd} (index) of item x_1 formulated using this opportunity cost as,

$$I_{nd(x_1)} = \frac{H_r + OC_{(x_1)}}{OC_{(x_1)}} = 1.07534221$$

Similarly, for the frequent items of both clusters C_1 and C_2 opportunity cost and index value are calculated. Then after the optimal value of $L_s max$, the expected total profit per unit time $ETPU(L_s)$, and EOQ of items of frequent item sets for both clusters can be modified as given in Table 1.11. Comparison of these values with the existing models are represented in Table 1.12 and Figure 1.2.

Table 11: Modified values with association rule mining clustering

Items	OC_k	I_{nd}	$L_s max$	$ETPU(L_s)$	EOQ
x_1	134.155	1.07534221	1952.93	1459235.363	2025.163184
x_2	141.28	1.070781427	2090.14	743508.6028	2162.846964
x_3	146.52	1.06825007	1461.03	538932.4641	1510.064851
x_4	84	1.11904762	1545.13	1962567.359	1634.516498
x_7	84	1.11904762	1935.95	1257192.183	2047.945619

Table 12: Comparison of the proposed model (with clustering) and the existing models

Items	Traditional EOQ	EOQ (Mittal et al.) [5]	EOQ (Present Work)
x_1	1825.741858	1915	2025.163184
x_2	2000	2099	2162.846964
x_3	1414.213562	1483	1510.064851
x_4	1414.213562	1474	1634.516498
x_7	1825.741858	1881	2047.945619

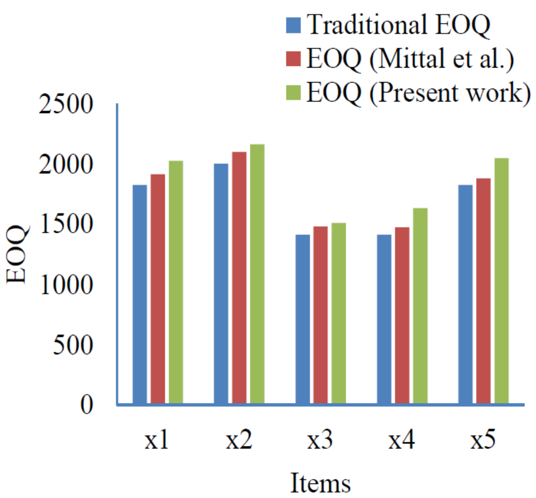

Figure 2: Comparison of EOQ values obtained in proposed method (association rule mining with clustering) with the state-of-art methods

4.3 Case-III: Classification

For the purpose of evaluating this paper, we consider a second case study. The inventory is separated into three groups—A, B, and C—using the ABC classification system, which divides items by their dollar value. To get to the EOQ for subpar products, we also have to figure out the opportunity cost. According to Mittal et al.[1], and Patro et al.[2], we utilise the following values for the parameters required to analyse the aforementioned inventory condition:

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O_c = 100/cycle, H_c = 25% of unit cost, r=1unit/min, S_c =5% of unit cost, w = 120000 units/year

Let us Consider the inventory database set ID that contains inventory item-set, $ID = \{t_1,t_2,t_3,t_4,t_5,t_6,t_7,t_8,t_9\}$. Each row indicates an inventory transaction in the set, TID = {T1, T2, T3, T4, T5, T6, T7, T8, T9}, that is given in Table 1.13.

Table 13: An Inventory Transaction Database

TID	Transactions
T1	$t_1\ t_2\ t_4$
T2	$t_1\ t_3\ t_5\ t_6$
T3	$t_2\ t_4\ t_6\ t_8\ t_9$
T4	$t_3\ t_5\ t_7$
T5	$t_2\ t_4\ t_8\ t_9$
T6	$t_1\ t_2\ t_3\ t_4$
T7	$t_2\ t_5\ t_7\ t_8\ t_9$
T8	$t_2\ t_3\ t_6\ t_7$
T9	$t_4\ t_9$

The parameter values for inventory policy used to compute the opportunity cost of various items are represented in Table 1.14. Table 1.15 represents ABC classifications for the items given in Table 1.13 with respect to conditions.

Table 14: Parameter values for inventory policy with dollar usage

Item	P_c	D	Dollar	S	Sip	H_c	C_s
t_1	10	7000	70000	20	12	2.5	0.5
t_2	15	1500	22500	30	25	3.75	0.75
t_3	6	10000	60000	10	8	1.5	0.3
t_4	10	1000	10000	30	20	2.5	0.5
t_5	11	3500	38500	25	15	2.75	0.55
t_6	7	10000	70000	20	10	1.75	0.35
t_7	7	5000	35000	15	10	1.75	0.35
t_8	10	3000	30000	10	15	2.5	0.5
t_9	10	1000	10000	25	20	2.5	0.5

Table 15: ABC classification of inventory items

Classification groups	Items
A (dollar usage $>=$ 60000)	$t_1\ t_3\ t_6$
B (dollar usage 30000 - 60000)	$t_5\ t_7\ t_8$
C (dollar usage $<$ 30000)	$t_2\ t_4\ t_9$

Now to find EOQ of each class, we need to consider the transactions containing items of same class, is given in Table 16. Applying apriori algorithm support and confidence of items of each group are calculated in order to obtain the opportunity cost and specified in Table 17. For items of group A: sup(t_1)=3, sup(t_3)=4, sup(t_6)=3, for group B: sup(t_5)=3, sup(t_7)=3, sup(t_8)=3, and for group C: sup(t_2)=6, sup(t_4)=5, sup(t_9)=4.

Table 16: Transaction containing items of A, B, C group

A		B		C	
T1	t_1	T2	t_5	T1	$t_2\ t_4$
T2	$t_1\ t_3\ t_6$	T3	t_8	T3	$t_2\ t_4\ t_9$
T3	t_6	T4	$t_5\ t_7$	T5	$t_2\ t_4\ t_9$
T4	t_3	T5	t_8	T6	$t_2\ t_4$
T6	$t_1\ t_3$	T7	$t_5\ t_7\ t_8$	T7	$t_2\ t_9$
T8	$t_3\ t_6$	T8	t_7	T8	t_2
				T9	$t_4\ t_9$

Table 17: Confidence of items group A, B, C

A		**B**		**C**	
Confidence	**Value**	**Confidence**	**Value**	**Confidence**	**Value**
$t_1 \rightarrow t_3$	0.66	$t_5 \rightarrow t_7$	0.66	$t_2 \rightarrow t_4$	0.66
$t_1 \rightarrow t_6$	0.66	$t_5 \rightarrow t_8$	0.33	$t_2 \rightarrow t_9$	0.5
$t_1 \rightarrow t_3 \cup t_6$	0.33	$t_5 \rightarrow t_7 \cup t_8$	0.33	$t_2 \rightarrow t_4 \cup t_9$	0.33
$t_3 \rightarrow t_1$	0.5	$t_7 \rightarrow t_5$	0.66	$t_4 \rightarrow t_2$	0.8
$t_3 \rightarrow t_6$	0.5	$t_7 \rightarrow t_8$	0.33	$t_4 \rightarrow t_9$	0.6
$t_3 \rightarrow t_1 \cup t_6$	0.25	$t_7 \rightarrow t_5 \cup t_8$	0.33	$t_4 \rightarrow t_2 \cup t_9$	0.4
$t_6 \rightarrow t_1$	0.33	$t_8 \rightarrow t_5$	0.33	$t_9 \rightarrow t_2$	0.75
$t_6 \rightarrow t_3$	0.66	$t_8 \rightarrow t_7$	0.33	$t_9 \rightarrow t_4$	0.75
$t_6 \rightarrow t_1 \cup t_3$	0.25	$t_8 \rightarrow t_5 \cup t_7$	0.33	$t_9 \rightarrow t_2 \cup t_4$	0.5

We use these confidence values and, calculated the opportunity cost for items of each category. Then index values are calculated in order to modify ordering policy for items by substituting values of opportunity cost in Equation 5 and are given in Table 1.18.

Table 18: Index values for groups of ABC classification

Category	**Items**	**Opportunity cost**	**Index**
A	t_1	20.05	1.059053979
	t_3	18.75	1.039230485
	t_6	18.26	1.046822763
B	t_5	24.53	1.054565135
	t_7	24.49	1.035112428
	t_8	21.88	1.055584955
C	t_2	33.2	1.054965311
	t_4	38	1.032370803
	t_9	41.25	1.029857301

The optimal value of $L_s max$, $ETPU(L_s)$, and EOQ of items of each of three classification groups are calculated and given in Table 19. A comparison of the proposed method with the state-of-art methods is given in Table 20 and graphically shown in Figure 1.3.

Retrieval Number:100.1/ijeat.D40810412423
DOI: 10.35940/ijeat.D4081.0412423
Journal Website: www.ijeat.org

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and Sciences Publication (BEIESP)

Table 19: Modified ordering policy

Items	$L_s max$	$ETPU(L_s)$	EOQ
t_1	765.933	65262.11714	811.1643912
t_3	1165.54	35621.61795	1211.264699
t_6	1102.31	125874.6077	1153.9232
t_5	521.191	46120.60722	549.6298573
t_7	770.318	37288.99159	797.3657353
t_8	501.421	27532.98501	529.2924637
t_2	292.728	20491.50061	308.8178856
t_4	296.26	18956.97161	305.8501741
t_9	292.897	13913.16909	301.6421139

Table 20: Comparison of the proposed model (with Classification) and existing models

Items	Traditional EOQ	EOQ (Mittal et al.) [?]	EOQ (Present Work)
t_1	748	808	811.1643912
t_5	505	543	549.6298573
t_2	283	304	308.8178856

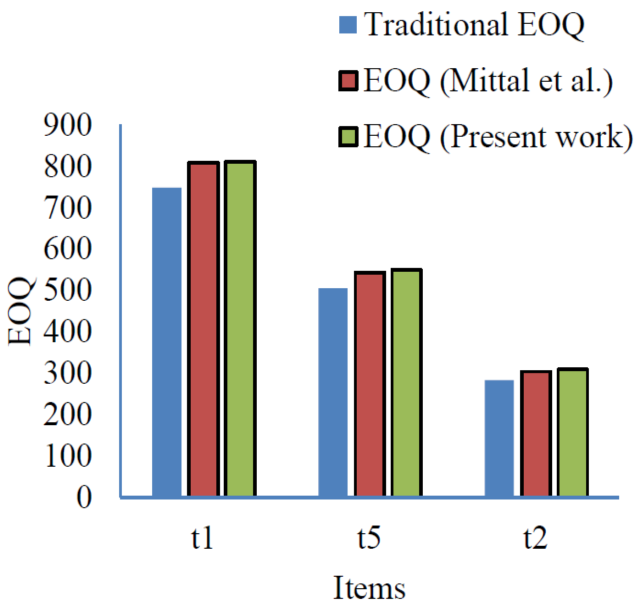

Figure 3: Comparison of EOQ values obtained in proposed method (ABC classification) with the state-of-art methods

V. SUMMARY

The proposed model investigates the EOQ inventory model for goods with faulty quality for a common item-set using the EOQ equations. It also includes the introduction of discounts that are allowed in proportion to the number of defective items in a received lot. The lot is screened 100% to separate the good from the bad. Later on, faulty products are offered at a discount. To better understand the concept, we will use three examples: apriori classification, clustering, and the ABC classification. In addition, by incorporating proportionate discount and data mining methods, we hope to learn how the cross-selling effects change the lot size, EOQ, and ETPU for defective products. We use three datasets, each of which includes sales and purchases of a distinct variety of inventory item. A set of parameters, including varied costs, selling prices, annual demand, etc., must be met before the task can be completed. If an inventory transaction database is clustered using the Apriori algorithm, more association rules are generated and selected, leading to a higher net profit. When looking at ABC categorization, we have examined every single item in every single category and compared the results to the ordering policies that were derived from the analysis. To assess credibility and reliability in each numerical example, an apriori approach is employed. The resulting opportunity costs are then used to adjust the economic order quantity (EOQ).

DECLARATION

Funding/ Grants/ Financial Support	We did not receive any fund for this work.
Conflicts of Interest/ Competing Interests	We declare that No conflicts of interest to the best of our knowledge.
Ethical Approval and Consent to Participate	No, the article does not require ethical approval and consent to participate with evidence.
Availability of Data and Material/ Data Access Statement	Not relevant.
Authors Contributions	All authors have equal participation in this article.

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AUTHOR PROFILE

Mr. Bhawani Sankar Panigrahi presently Research Scholar, Kalinga University, Naya Raipur (Chhattisgarh), India. Qualified M.Tech. in Computer Science Engineering from KIIT University Bhubaneswar in 2006. Member of professional society like IEEE, ISTE, IE, CSTA, INAE and many more. He is having more than 16 Years of UG and PG Engineering teaching experience and has published 2 Patents (Granted), 12 research articles in international and journals and conferences. His research areas include Machine learning, Biometrics, IoT, Digital Image processing and pattern clustering. He is an Infosys certified trainer.

Dr. Sanjay Kumar is working as Associate Professor in Kalinga University, Chhattisgarh Naya Raipur. He has having a 22 years academic experience and 5 years of industrial experience. He has published more than 120 international journals. He has also attended 76 conferences. His area of Interest is Machine Learning, Hadoop, Python, Artificial Intelligence, Compiler Design, IoT, Algorithms.

Dr. Pabitra Kumar Tripathy is working as Associate Professor in the department of Computer Science and Engineering in Kalam Institute of Technology, Berhampur Ganjam. He has a teaching experience of 18+ years and 5 Years of Academic activities. He got his Ph.D award from Kalinga University, Chhattisgarh in 2022. His area of Interest is Machine Learning, Artificial Intelligence, Computer Graphics, Compiler Design, Algorithms etc…. He also authored two text books in international publication like Wiley and CRC press. He has published 2 Patents,4 articles in international journals and two conferences.