



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 to calculate EOQ. Furthermore, the cross-selling impacts are more pronounced when the issues are defective. Initially, several data mining approaches are investigated to determine the best strategy for establishing the necessary link among the item sets. By factoring in the cross-selling implications, we can gain a better understanding of the EOQ and advance the project further. As it is anticipated that every lot contains some level of flaw, the work involves thorough inspection of each lot. 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.

INTRODUCTION I.

 \mathbf{T} he acquisition, availability, and processing of data to

retrieve the needed information have 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 facilitates development, growth, and informed strategic decision-making. The primary purpose of data mining is to extract useful information from massive amounts of raw data. With this newfound understanding of the data's interconnectedness,

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 ORCID Raipur (Chhattisgarh), University. India. 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 Authors. Published by Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP). This is an open access article under the CC-BY-NC-ND license http://creativecommons.org/licenses/by-nc-nd/4.0/

Companies can develop innovative promotional plans that more accurately predict the market success of their products. 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 helps gain an edge over other businesses. Data mining can benefit from the fresh perspectives provided by such easily accessible materials. Further exploration leads to the effective management of data mining tools by augmenting 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 practice 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. Determining the Economic Order Quantity (EOQ) for each item can be challenging when managing large а inventory. Classification, the process by which inventory is organised into categories, will make this process much more straightforward. Inventory EOQ modelling, aided by association rule mining, clustering, and classification approaches, facilitates efficient stock control. In the real world, the sale of one item may affect the sale of another due to underlying interdependencies between them. The cross-selling effect refers to the potential for a decline in sales when two businesses are poorly integrated. 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 lessthan-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 to deal with this kind of stock-out scenario.

Published By: Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP) 57 © Copyright: All rights reserved.



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% screening is complete, 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 more comprehensive model for imperfect stock items that considers the effects 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, as noted by Patro et al.[2].

A literature review demonstrates how cross-selling effects can be utilised to create EOQ models that incorporate a fixed discount for the percentage of defectives, even when screening all products. The EOQ inventory model aims to determine the optimal percentage of screening present in each lot, enabling the calculation of the profit made by paying attention to the ideal order or lot size. Yet, new avenues for study are opened up by the fact that the crossselling 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 conducting a thorough inspection of the lot in question and deducting an appropriate rate for any flaws identified. Its goal is to provide workable solutions to actual business issues by contrasting new and old inventory practises in light of crossselling 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-used 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, which contains a set of items $r_1, r_2, r_3, \dots, r_n$. In this, the "Support" of an item means its frequency of occurrence in the whole transactions. For the item r_1 , it can be expressed as:

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

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

 $conf(r_1 \rightarrow r_2)$ Refers to the frequency at which it is purchased.

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

A common item set can be determined using a supportconfidence 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.

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

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

Step 2 consists of two subcomponents: apriori creation and candidate counting assistance. This process involves generating a candidate item-set, searching the database, and comparing the count of items for which each candidate has support to the minimum 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 perform a join to create candidates, while in the prune step, we utilise the Apriori property to eliminate items with rare subsets. In the present work, we also considered a different example involving the clustering of transactions (Wang et al. In this context, "big items" refer to goods that appear in only a small number of transactions within a given cluster due to their similarities. The sum of its sales in that cluster defines a product's popularity.

Published By: Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP) 58 © Copyright: All rights reserved.



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



So, large items present in a cluster are homogeneous, and support is at least equal to the 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 small items, and the inter-cluster cost, which is the sum of large items across 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:

- 1. Allocation phase: Each transaction is sequentially read and assigned to a cluster, either an existing one or a new one.
- 2. Refinement phase: Costs are minimised.

In the third scenario, an ABC categorisation 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 account for a higher rate of total dollar consumption (the product of unit price and annual demand of an 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 crossselling effect is achieved.

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

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

where denotes the items present in a frequent item-set and represents the subset of items not including the number of items. For that gives $conf(i \rightarrow i) = 1$.

The opportunity cost of an item k can be described as the lost cost of that item due to the effect of cross-selling. It can be represented by the relation

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

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 = cost of holding item k per unit. Will be used later to modify the order policy along with opportunity cost. The present work analyses mathematically the modelling of EOQ with imperfect items, considering some assumptions that are closer to realistic situations. Now, let us think that the items in the frequent item set are delivered instantaneously with the order size L_s .

Retrieval Number:100.1/ijeat.D40810412423 DOI: <u>10.35940/ijeat.D4081.0412423</u> Journal Website: <u>www.ijeat.org</u> The number of items of good quality, the size of the lot, and the items of defective quality.

$$L_{s} - pL_{s} = (1 - p)L_{s}$$
(1.6)

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

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

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

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

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

The cycle-wise total revenue is defined as:

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

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

The cycle-wise total profit =

$$TP(L_s) = TR(L_s) - TC(L_s)$$
(1.11)

$$TP(L_{s}) = \left[\frac{2SL_{s}^{2} + \left\{O_{c} + P_{c}L_{s} + S_{c}L_{s} + H_{c}\left(\frac{L_{s}(1-p)T}{2} + \frac{pL_{s}}{r}\right)\right\}(L_{s}p+1)}{2L_{s} + L_{s}p+1}\right] - \left[O_{c} + P_{c}L_{s} + S_{c}L_{s} + H_{r}\left(\frac{L_{s}(1-p)T}{2} + \frac{pL_{s}^{2}}{r}\right)\right]$$
(1.12)

Total profit unit-wise formulated by:

$$TPU(L_s) = TP(L_s)/T$$
(1.13)
where, $T = \frac{L_s(1-p)}{D}$

$$TPU(L_s) = \frac{2D(SL_s - O_c - P_cL_s - S_cL_s)}{2L_s + L_sp + 1} \left(\frac{1}{1 - p}\right) - \frac{H_cL_s^2}{2L_s + L_sp + 1} (1 + p)$$
(1.14)

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



Published By: Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP) © Copyright: All rights reserved.

59

$$ETPU(L_{s}) = \frac{2D(SL_{s} - O_{c} - P_{c}L_{s} - S_{c}L_{s})}{2L_{s} + L_{s}E[p] + 1}E\left(\frac{1}{1 - p}\right) - \frac{H_{c}L_{s}^{2}}{2L_{s} + L_{s}E[p] + 1}(1 + E[p])$$
(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

$$ETPU'(L_{s}) = \left(\frac{1}{(2L_{s} + L_{s}E[p] + 1)^{2}}\right) \left(\begin{array}{c} 2DS - 2DP_{c} - 2DC_{s} + 4DO_{c} \\ + 2DO_{c}E[p]E\left(\frac{1}{1-p}\right) - 2H_{c}L_{s}^{2} \\ - H_{c}L_{s}^{2}(E[p])^{2} - 3H_{c}L_{s}^{2}E[p] \\ - 2H_{c}L_{s} - 2H_{c}L_{s}E[p] \\ - 2H_{c}L_{s} - 2H_{c}L_{s}E[p] \end{array} \right)$$
(1.16)

The second derivative of Equation 3.15 $ETPU''(L_s) = -\left(\frac{2}{(2L_s + L_s E[p] + 1)^3}\right)(2 + E[p])$ $\begin{pmatrix} 2DS - 2DP_c - 2DC_s + 4DO_c \\ + 2DO_c E[p]E\left(\frac{1}{1-p}\right) + H_c + H_c E[p] \end{pmatrix}$ (1.17)

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

$$L_{s}max = \sqrt{\frac{(2DS - 2DP_{c} - 2DC_{s} + 4DO_{c} + 2DO_{c}E[p])E(\frac{1}{1-p})}{2H_{c} + 3H_{c}E[p] + H_{c}(E[p])^{2} + \frac{2H_{c}}{L_{s}} + \frac{2H_{c}}{L_{s}}(E[p])}}$$
(1.18)

For a significant value of $L_{s'}$, $\frac{1}{L_s} \rightarrow 0$

$$L_{s}max = \sqrt{\frac{(2DS - 2DP_{c} - 2DC_{s} + 4DO_{c} + 2DO_{c}E[p])E(\frac{1}{1-p})}{2H_{c} + 3H_{c}E[p] + H_{c}(E[p])^{2}}}$$
(1.19)

The amount to order of a particular set of goods is equal to their worth in. This work optimises the order quantity by considering 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:

$$EOQ = L_s max \sqrt{I_{nd}}$$
(1.20)

IV. NUMERICAL EXAMPLE

Cost, selling price, annual demand, and other factors are just a few of the elements that must be considered to complete the task at hand. To verify the present work, we examined three numerical cases. Apriori is an association rule mining method that combines clustering and classification, utilising data 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, it is assumed that the defective proportion is uniformly distributed with a probability density function. The expected values are given as follows: E[1/(1-p)] = 1.02055.

4.1. Case I: Apriori

To illustrate the developed model, we adopt the parameter values shown in Table 3.1, as per Mittal et al., and analyse the inventory situation.

Table	1: Set Parameters	of Inventory	Situation
-------	-------------------	--------------	-----------

Minimum support or min_sup	50%
Minimum confidence or min_conf	60%
0 _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 $\{1500, 2500, 3500, 4500, 5500\}$. 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 database as follows:

$$\begin{array}{c} \{r_1\}, \{r_2\}, \{r_3\}, \{r_4\}, \{r_5\}, \{r_1 \ r_3\}, \{r_2 \ r_3\}, \\ \{r_2 \ r_5\}, \{r_3 \ r_5\}, \{r_2 \ r_3 \ r_5\} \end{array}$$

Table 2: An Inventory Transaction Database

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 for frequent item sets is considered. The most frequent items are listed, along with support that exceeds the minimum support (min_sup). It is chosen from various classes of items. According to the Apriori algorithm, a minimum support (min_sup) of 50% is considered. By setting the minimum confidence to 60%, the confidence of items and their subsets remains larger than that. Similarly, the confidence of the other frequent item sets is estimated and given in Table 1.4.



Published By:
Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP)
60 © Copyright: All rights reserved.

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



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 3: Inventory Policy in a Frequent Item-Set

Fable	4:	Rules	with	Confidence

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

To calculate the opportunity cost of the frequent itemset, the following formulae have been used, as given in Equation 3.4.

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

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 the item r_2 , the optimal value of $L_s max$ and the expected total profit per unit time $ETPU(L_s)$ is given by: $L_s max = 1069.66 \text{ and } ETPU(L_s) = 1454344.943$

Therefore, the EOQ of an item can be modified as follows: $EOQ = L_s max \sqrt{I_{nd}} = 1109.077436$

Similarly, we also calculate the same for items, which are given in Table 1.5. These values are compared with those of existing models and are represented in Table 1.6 and Figure 1.1.

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

Table 5: Modified value with Apriori



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

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

Table	6:	Com	parison	with	existing	models





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

4.2. Case-II: Association rule mining with clustering

Here, we apply the concept of transaction clustering based on large goods to a database of inventory transactions 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%, $O_{c=100/cycle}$, $H_{c=\$5/unit/year}$, $r_{=1unit/min}$, $S_{c=0.5/unit}$, $P_{c=25/unit}$, $B_{c=\$20/unit}$, $S_{=\$50/unit}$, $W_{=175,200,unit}$, $W_{=175,200,unit}$, $W_{=175,200,unit}$, $S_{=100/cycle}$, $S_{=100$

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 represents an inventory transaction in the set ITD = {ITD 1, ITD 2, ITD 3, ITD 4, ITD 5, ITD 6}, as listed in Table 3.7.

	-		
ITD	Items		
ITD 1	$x_1 x_2 x_3$		
ITD 2	$x_1 x_2 x_3 x_4$		
ITD 3	$x_1 x_2 x_3$	<i>x</i> ₅	
ITD 4	$x_1 x_2$	<i>x</i> ₆	
ITD 5	<i>x</i> ₄	$x_7 x_8$	
ITD 6	<i>x</i> ₄	$x_7 \qquad x_9$	

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



Retrieval Number:100.1/ijeat.D40810412423 DOI: <u>10.35940/ijeat.D4081.0412423</u> Journal Website: <u>www.ijeat.org</u> Published By:
Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP)
62 © Copyright: All rights reserved.

Item	D	P _c	H _c	S	S _{imp}
<i>x</i> ₁	50,000	30.00	3	60.00	25.00
<i>x</i> ₂	40,000	20.50	2	40.00	17.00
<i>x</i> ₃	40,000	45.52	4	60.00	40.00
<i>x</i> ₄	50,000	50.00	5	90.00	45.00
<i>x</i> ₅	50,000	45.52	4	70.00	40.00
<i>x</i> ₆	40,000	40.00	4	65.00	35.00

Table 8: Parameter values for inventory	policy
--	--------

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				
$C_{1} = \{\text{ITD 1, ITD 2, ITD 3, ITD} \\ 4, \text{ITD 5, ITD 6}\}$	$L_1 = \{x_1, x_2\}$	$S_{1} = \begin{cases} x_{3}, x_{4}, x_{5}, x_{6}, \\ x_{7}, x_{8}, x_{9} \end{cases}$				
$C_{2=} \{ C_{1=} \{ \text{ITD 1, ITD 2, ITD 3,} \\ \text{ITD 4} \}, C_{2=} \{ \text{ITD 5, ITD 6} \} \}$	$L_1 = \{x_1, x_2, x_3\}$ $L_2 = \{x_4, x_7\}$	$S_{1} = \{x_{4}, x_{5}, x_{6}\}$ $S_{2} = \{x_{8}, x_{9}\}$				
$ \begin{bmatrix} C_{3} \\ $	$L_{1} = \{x_{1}, x_{2}, x_{3}\}$ $L_{2} = \{x_{1}, x_{2}\}$ $L_{3} = \{x_{4}, x_{7}\}$	$S_{1} = \{x_{4}\}$ $S_{2} = \{x_{3}, x_{5}, x_{6}\}$ $S_{3} = \{x_{8}, x_{9}\}$				

Therefore, clustering is considered because the cost obtained is minimum compared to the other options C_3 . Thus, the given transaction database is clustered into two clusters, namely {ITD 1, ITD 2, ITD 3, ITD 4} and {ITD 5, ITD 6}. Then, the Apriori algorithm is applied to both clusters to obtain frequent sets. And are the most frequent itemsets in clusters, respectively. The confidence of items in both frequent itemsets is calculated using Equation 2 and is given in Table 10.

	-			
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			

Table 10: Confidence of frequent item-set in cluster ${\cal C}_1$ and cluster ${\cal C}_2$

Then, the opportunity cost in the frequent item set can be calculated using the formula given in Equation 4.

Opportunity cost of the item:

$$\begin{split} X_{1} &= OC_{(x_{1})} = C_{x_{1}}.conf(x_{1} \rightarrow x_{1}) + C_{x_{2}}.\{conf(x_{1} \rightarrow x_{2}) + conf(x_{1} \rightarrow x_{2} \cup x_{3})\} \\ &+ C_{x_{3}}.\{conf(x_{1} \rightarrow x_{3}) + conf(x_{1} \rightarrow x_{2} \cup x_{3})\} \end{split}$$

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

Now, the index of the item formulated using this opportunity cost is,

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





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

Similarly, for the frequent items of both clusters, the opportunity cost and index value are calculated. Then, after determining the optimal value of the expected total profit per unit time and the EOQ of items in frequent item sets for both clusters, the values can be modified as given in <u>Table 1.11</u>. A comparison of these values with existing models is presented in Table 1.12 and Figure 1.2.

Items	OC_k	I _{nd}	L _s max	$ETPU(L_s)$	EOQ
x_1	134.155	1.07534221	1952.93	1459235.363	2025.163184
<i>x</i> ₂	141.28	1.070781427	2090.14	743508.6028	2162.846964
<i>x</i> 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 11: Modified values with association rule mining clustering

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

Items	Traditional EOQ	EOQ (Mittal et al.) [5]	EOQ (Present Work)
<i>x</i> ₁	1825.741858	1915	2025.163184
x_2	2000	2099	2162.846964
<i>x</i> ₃	1414.213562	1483	1510.064851
x_4	1414.213562	1474	1634.516498
<i>x</i> ₇	1825.741858	1881	2047.945619





4.3 Case-III: Classification

To evaluate 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:

$$O_{c = 100/\text{cycle}}, H_{c = 25\% \text{ of unit cost}}, r_{=1\text{unit/min}}, S_{c = 5\% \text{ of unit cost}}, w = 120000 \text{ units/year}$$

Let us consider the inventory database set that contains an 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 <u>Table 1.13</u>.

64

Retrieval Number:100.1/ijeat.D40810412423 DOI: <u>10.35940/ijeat.D4081.0412423</u> Journal Website: <u>www.ijeat.org</u> Published By: Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP) © Copyright: All rights reserved.





TID	Transactions
T1	$t_1 t_2 t_4$
T2	$t_1 t_3 t_5 t_6$
Т3	$t_2 t_4 t_6 t_8 t_9$
T4	$t_{3} t_{5} t_{7}$
T5	$t_2 t_4 t_8 t_9$
T6	$t_1 t_2 t_3 t_4$
Τ7	$t_2 t_5 t_7 t_8 t_9$
T8	$t_2 t_3 t_6 t_7$
T9	$t_4 t_9$

Table 13: An Inventory Transaction Database

The parameter values for inventory policy used to compute the opportunity cost of various items are represented in <u>Table 1.14</u>. <u>Table 1.15</u> presents ABC classifications for the items listed in Table 1.13, categorised by conditions.

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 14: Parameter values for inventory policy with dollar usage

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 the EOQ of each class, we need to consider the transactions containing items of the same class, which are given in <u>Table 16</u>. The Apriori algorithm is applied to calculate the support and confidence of items in each group, which are then used to determine the opportunity cost and are specified in <u>Table 17</u>. 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: $\sup({}^{t_2})=6$, $\sup({}^{t_9})=4$.



Retrieval Number:100.1/ijeat.D40810412423 DOI: <u>10.35940/ijeat.D4081.0412423</u> Journal Website: <u>www.ijeat.org</u> Published By:
Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP)
65 © Copyright: All rights reserved.

А		В		С	
T1	t_1	T2	t_5	T1	$t_2 t_4$
T2	$t_1 t_3 t_6$	T3	t ₈	Т3	$t_{2} t_{4} t_{9}$
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	$t_{1} t_{3}$	Τ7	$t_{5} t_{7} t_{8}$	Τ7	$t_{2} t_{9}$
T8	$t_{3} t_{6}$	Т8	t_7	Т8	t_2
				Т9	$t_4 t_9$

Table 16: Transactions containing items of the A, B, and C groups

Α		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

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

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

Category	Items	Opportunity cost	Index
А	t_1	20.05	1.059053979
	t_3	18.75	1.039230485
	t ₆	18.26	1.046822763
В	t_5	24.53	1.054565135
	t ₇	24.49	1.035112428
	t ₈	21.88	1.055584955
С	t_2	33.2	1.054965311
	t_4	38	1.032370803
	t_9	41.25	1.029857301

Table 18: Index values for groups of ABC classification

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

> Published By: Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP) 66 © Copyright: All rights reserved.





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 19: Modified ordering policy

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





V. **SUMMARY**

The proposed model examines the EOQ inventory model for goods with faulty quality for a standard 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, faulty products are often 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 aim to understand how cross-selling effects influence 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 items. 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 examining ABC categorisation, we have reviewed every item in each category and compared the results to the ordering policies derived from the analysis. To assess the credibility and reliability of each numerical example, an a priori 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 funds 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 or consent to participate, as it presents evidence that is not subject to interpretation.	
Availability of Data and Material/ Data Access Statement	Not relevant.	
Authors Contributions	All authors have equal participation in this article.	

Published By: Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP) 67 © Copyright: All rights reserved.



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

REFERENCES

- 1. Mandeep Mittal, Juhi Singh and Sarla Pareek[1]. A new approach for EOQ calculation using modified opportunity cost. Recent Advances in Computer Science and Communications (Formerly: Recent Patents on Computer Science), 15(1):106_110, 2022. [CrossRef]
- Xiaobin Wang and Wansheng Tang[3]. Fuzzy EPQ inventory models 2. with backorder. Journal of Systems Science and Complexity, 22(2):313_323, 2009. [CrossRef]
- 3. Chung-Yuan Dye and Tsu-Pang Hsieh[2]. A particle swarm optimization for solving joint pricing and lot-sizing problem with uctuating demand and unit purchasing cost. Computers & Mathematics with Applications, 60(7):1895_1907, 2010. [CrossRef]
- Rashmi Rani Patro, Rojalini Patro, Mitali Madhusmita Nayak, and 4. Srikanta Patnaik[2]. A particle swarm optimization based eoq model in a imperfection production system with variable discount and shortages. - International Journal of Computational Intelligence in Control, 13(2):63 69, 2021
- 5. Chandra K Jaggi, Satish K Goel, and Mandeep Mittal[2]. Credit nancing in economic ordering policies for defective items with allowable shortages. Applied Mathematics and Computation, 219(10):5268 5282, 2013. [CrossRef]

AUTHOR PROFILE



Mr. Bhawani Sankar Panigrahi, presently working as Assistant Professor in the Department of CSE (AI & ML) at Vardhaman College of Engineering (Autonomous), Hyderabad, Telangana State. Qualified M.Tech. in Computer Science Engineering from KIIT University, Bhubaneswar in 2006. Member of professional societies such as IEEE, ISTE, IE, CSTA, INAE, and many more. He

has more than 16 Years of undergraduate and postgraduate engineering teaching experience and has published 2 Patents (Granted), 12 research articles in international 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 an Associate Professor at Kalinga University, Naya Raipur, Chhattisgarh. He has 22 years of academic experience and 5 years of industrial experience. He has published more than 120 international journals. He has also attended 76 conferences. His areas of interest include Machine Learning, Hadoop, Python, Artificial Intelligence, Compiler Design, IoT, and

Algorithms.



Dr. Pabitra Kumar Tripathy is an Associate Professor in the Department of Computer Science and Engineering at Kalam Institute of Technology, Berhampur, Ganjam. He has over 18 years of teaching experience and 5 Years of Academic activities. He received his Ph.D. award from Kalinga University, Chhattisgarh, in 2022. His areas of

interest include Machine Learning, Artificial Intelligence, Computer Graphics, Compiler Design, and Algorithms, among others. He also authored two textbooks in international publications, including those by Wiley and CRC Press. He has published two patents, four articles in international journals, and presented at two conferences.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of the Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP)/ journal and/or the editor(s). The Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP) and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.



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) 68 © Copyright: All rights reserved.