Integrated Risk-based Inventory Classification System

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Abstract

Inventory costs constitute a very high percentage of annual expenses of any organization, and thus the effectiveness of the inventory management policies adopted by organizations is critical to their financial success. In today's challenging economic times, efficient inventory classification and planning is more important than ever and can be a key competitive advantage for any organization. In this paper, we develop and test an integrated risk-based inventory classification (IRIC) methodology that addresses the shortcomings of existing methodologies. The developed methodology identifies various attributes of inventory items and groups these attributes in two major categories: risk and cost. A weighted sum approach is used to combine the inventory attributes within each category to form a master attribute for each of the two categories. Finally, an advanced clustering algorithm is used to measure the overall similarity between pairs of inventory items and to classify the items in difference bins based on their closeness to each other. The developed methodology is tested using simulated risk scenarios. A comparison is also made between the IRIC method and the classical ABC analysis using Monte Carlo simulation. The results show that the new methodology is more robust and cost effective as compared to the ABC analysis. The results of this paper will be of interest to industrial engineers and operations managers, who deal with inventory control and planning operations in their respective organizations.

Keywords: clustering, inventory classification, risk-based classification

1. Introduction

Inventory constitutes a very high percentage of annual expenses of any organization, and thus inventory management has always been a critical function for the manufacturing and service organizations across the world. Companies invest significant amount of financial and other resources in managing the inventory of items that they need on a day-to-day basis. These items include raw materials, finished products, tools and equipments, supplies, etc. Failure to manage inventory properly can cause heavy losses to any organization. The effectiveness of the inventory management policies adopted by organizations is critical to their financial success. In today's challenging economic times, efficient inventory classification and planning is more important than ever and can be a key competitive advantage for any organization. According to Stalk et al. (2000) and Barney (1995), one of the key factors that contributed to Walmart's phenomenal growth over the last two decades is their highly effective inventory management policy.

Inventory classification and management is a complex task and a lot of research has been done in this area. One of the oldest and simplest methods of inventory classification is ABC analysis (Fredendall & Hill, 2000). ABC analysis focuses on two attributes associated with every inventory item: demand and cost. The inventory value of each item is calculated by multiplying demand for that item by its cost. Then the inventory items are arranged in descending order of their inventory values. Finally, these items are classified in three groups: group "A" consisting of first 20% items with the highest inventory value, group "B" consisting of next 30% items, and group "C" consisting of remaining 50% items with the lowest inventory value. It is obvious that the group "A" is more important than other groups and should be given more importance by management. Though ABC analysis is easy to understand, its limitation is that it is too simplistic. It is difficult to create highly effective inventory management policies based on only three groups. This limitation of the ABC analysis paved the way for many other sophisticated and complex inventory classification methodologies.

Clustering is another powerful tool that has been extensively used in inventory classification. Clustering techniques classify objects into meaningful sets (Aldenderfer & Blashfield, 1984). The clustering concepts related algorithms and their applications are extensively discussed by Romesburg (2004), Dennis and Meredith (2000), and Everitt et al. (2009).

There are some other notable research efforts in the area of inventory classification. Ramanathan (2006) proposed an ABC inventory classification scheme using weighted linear optimization. Zhou and Fan (2007) provided an extended version of Ramnathan's model that addressed a limitation of Ramnathan's model that could lead to a situation where an inventory item with high value in an unimportant criterion is inappropriately getting classified as a class "A" item. Partovi and Anandarajan (2002) described an ABC inventory classification method using artificial neural networks. Chandra and Kumar (2001) described three generic inventory models that implement inventory decision guidelines to address constant, time varying, and mixed demand patterns and their applications to a textile supply-chain.

One limitation of clustering based classification methodologies is that they consider attributes on individual basis, and thus fail to measure the overall impact of various attributes on two basic cornerstones of a good inventory management policy: risk minimization and cost management. Thus, the literature review of the current state of the art in inventory classification suggests that there is an opportunity to develop a new methodology that will focus on these two cornerstones.

This paper develops an integrated risk-based inventory classification (IRIC) methodology that addresses the shortcomings of existing methodologies. Furthermore, we test and validate the new method using simulated risk scenarios and compare it with classical ABC analysis.

The paper is organized as follows. Section 2 describes the developed IRIC method. Section 3 presents the testing and validation of the IRIC method. Section 4 provides comparison of the IRIC method with the classical ABC analysis. Section 5 provides conclusions.

2. IRIC Methodology

The IRIC methodology exclusively focuses on two major goals of inventory management: risk minimization and cost effectiveness. Unlike existing methodologies, the new method classifies the attributes of inventory items in two classes: risk-related attributes and cost attributes as shown in Figure 1 below. It is obvious that there are trade-offs involved among these two types of attributes. For example, if one decides to implement a policy that only focuses on cost minimization, then such a policy may not be robust enough to sustain the changes in market demand and supply, and may result in excessive backorders. Thus, there needs to be a right balance between risk and cost effectiveness. The developed methodology tries to achieve that right balance.

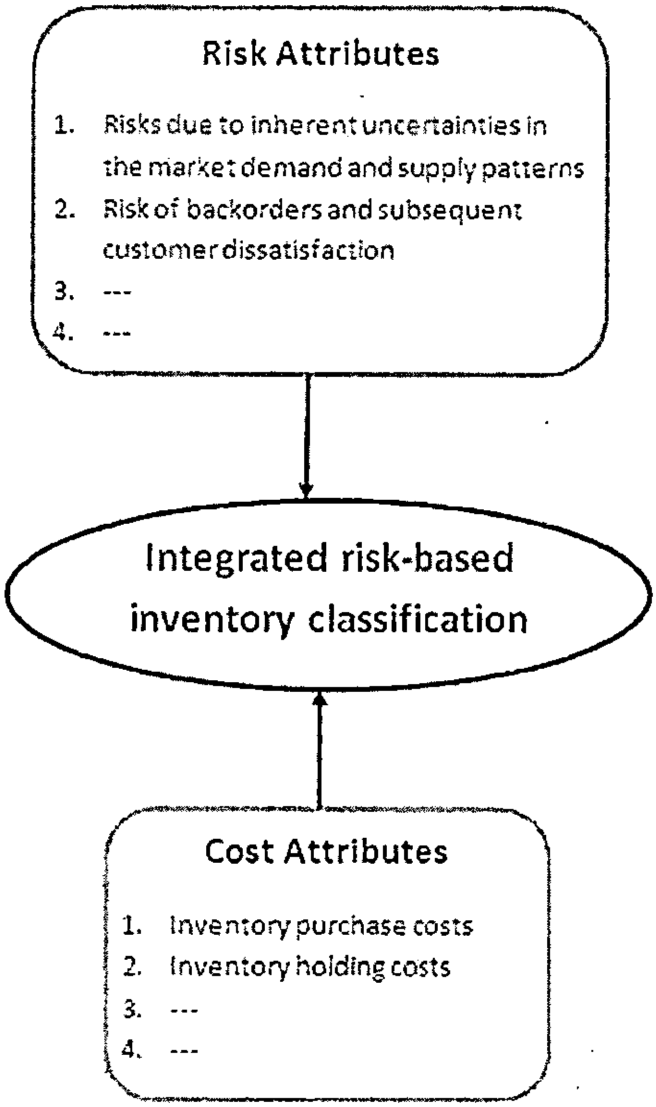


Figure 1. Elements of integrated risk-based inventory classification method

The first step in the new methodology is to identify and list all the inventory attributes associated with the inventory items and classify them in above-mentioned two categories. Next, a data matrix is created in which inventory items form the columns of the matrix and attributes form the rows of the matrix as shown in Figure 2:

	1	2	3	4
A	V_{1A}	V_{2A}	V_{3A}	V_{3A}
B	V_{1B}	V_{2B}	V_{3B}	V_{4B}
C	V_{1C}	V_{2C}	V_{3C}	V_{4C}
D	V_{1D}	V_{2D}	V_{3D}	V_{4D}

Inventory Items

Attributes

Attribute values for individual inventory items

Figure 2. Data matrix showing inventory items and associated attributes

Next, attributes within individual categories are combined together to form one master attribute for each category. Different attributes are measured in different units. Thus, we normalize them to make them unit-less and then use weighted sum approach to merge them together. For example, assume that there are *n* attributes, $r_1, r_2, \ldots, r_n$ in the risk category. Then the value of the master risk-attribute which is weighted sum of the normalized values of individual attributes can be defined as:

$$r_i = \sum_{k=1}^{n} w_k * \frac{r_{k.i}}{r_{k.max} - r_{k.min}} \qquad \text{Eq. 1}$$

where, r_i is the value of the master risk-attribute associated with i^{th} inventory item.

$r_{k.i}$ is the value of the k^{th} attribute in the risk category for i^{th} inventory item.

$r_{k.max}$ is the maximum possible value of k^{th} attribute in the risk category.

$r_{k.min}$ is the minimum possible value of k^{th} attribute in the risk category.

$1 \geq w_k \geq 0$ $(j = 1, \ldots, k)$ denotes the weight (importance) assigned to the k^{th} attribute in the risk category such that, $\sum_{k=1}^{n} w_{jk} = 1$.

Similarly, the value of the master cost-attribute, c_i associated with the i^{th} inventory item can be obtained as follows:

$$c_i = \sum_{k=1}^{n} w_k * \frac{c_{k.i}}{c_{k.max} - c_{k.min}} \qquad \text{Eq. 2}$$

where, $c_{k.i}$ is the value of the k^{th} attribute in the cost category for i^{th} inventory item.

$c_{k.max}$ is the maximum possible value of k^{th} attribute in the cost category.

$c_{k.min}$ is the minimum possible value of k^{th} attribute in the cost category.

After obtaining the values for two master attributes for all the inventory items, we create a table similar to table 1. Following Romesburg (2004), our next step is to apply a distance measure to obtain the overall closeness of each pair of inventory items and form a clustering tree that classifies the inventory items in appropriate groups based on the overall similarities/ dissimilarities among them. A variety of distance measures are available for the measurement of overall similarity between pairs of inventory items. Some examples are Euclidean distance, City block distance, Minkowski distance, etc. See Everitt et al. (2009), Gower (1985) or Gower and Legendre (1986) for more extensive lists of distance measures. In this paper, we use Euclidean distance as our distance measure. The Euclidean distance between i^{th} and j^{th} inventory item can be given by following equation:

$$d_{ij} = \left[(r_i - r_j)^2 + (c_i - c_j)^2\right]^{1/2} \qquad \text{Eq. 3}$$

where,

r_i and r_j represent the values of master risk attribute for i^{th} and j^{th} inventory items respectively.

$r_i$and r_j represent the values of master risk attribute for i^{th} and j^{th} inventory items respectively.

After determining the values of Euclidean distance measures for all pairs of inventory items, we use clustering algorithm as suggested by Everitt et al. (2009) to classify the inventory items in appropriate group. A common inventory management policy can be devised for each group instead of individual inventory management policies for each item within a group.

3. Testing and validation

To test the methodology, we created a small hypothetical scenario in which we considered 20 inventory items and only three inventory attributes: monthly demand, purchasing cost, and monthly inventory holding cost. Out of these three attributes, monthly demand can be classified as a risk attribute and the purchasing cost and the holding cost can be classified as cost attributes. The Monte Carlo simulation was used to generate values of average monthly demand and purchasing cost for each inventory item. The monthly holding cost was considered one hundredth of the purchasing cost.

We used the economic order quantity (EOQ) inventory management policy for validation purpose. EOQ allows inventory management officials to decide how much inventory to order at one time. EOQ can be applied to inventory management when the demand for the item is relatively constant over time (Sweeny, Anderson, Williams, & Martin, 2008). The point of EOQ provides a compromise between small amounts of on hand inventory (ordering new inventory frequently) and large amounts of on hand inventory (Sweeny, Anderson, Williams, & Martin, 2008). We calculated EOQ values for each of the 20 inventory items using following formula:

$$EOQ = \sqrt{\frac{2CD}{H}} \qquad \text{Eq. 4}$$

Where,

C is the ordering cost per order. In this example, we used uniform ordering cost of $300 per order for all the orders.

D is monthly demand.

H is monthly inventory holding cost.

Table 1 shows the simulated monthly demand and purchasing cost, and the calculated values of EOQ for each of the 20 hypothetical inventory items.

Table 1. Monthly demand, purchasing cost and EOQ values

Inventory item	Monthly demand	Purchasing cost ($)	EOQ
1	669	6.00	2587
2	627	33.00	1068
3	870	17.00	1752
4	1,710	20.00	2265
5	1,974	18.00	2565
6	798	20.00	1547
7	492	35.00	918
8	549	43.00	875
9	2,100	8.00	3969
10	957	29.00	1407
11	1,644	8.00	3511
12	594	19.00	1370
13	381	33.00	832
14	207	16.00	881
15	114	53.00	359
16	2,787	5.00	5783
17	795	13.00	1916
18	99	112.00	230
19	417	23.00	1043
20	1,182	9.00	2807

Next, we calculate the values of master risk attribute and master cost attribute for each inventory item using Eq.1 and Eq. 2 respectively as shown in Table 2. Since monthly demand is the only attribute in the risk category, the value of master risk attribute will be the normalized value of the monthly demand. There are two attributes in the cost category. Hence, we need to assign weights of importance to these two attributes. We assigned arbitrary weights of 0.8 for the purchasing cost and 0.2 for the holding cost.

Table 2. Values of master risk attribute and master cost attribute for individual inventory items.

Inventory Item	Master Risk Attribute	Master Cost Attribute
1	0.249	0.056
2	0.233	0.308
3	0.324	0.159
4	0.636	0.187
5	0.734	0.168
6	0.297	0.187
7	0.183	0.327
8	0.204	0.402
9	0.781	0.075
10	0.356	0.271
11	0.612	0.075
12	0.221	0.178
13	0.142	0.308
14	0.077	0.150
15	0.042	0.495
16	1.037	0.047
17	0.296	0.121
18	0.037	1.047
19	0.155	0.215
20	0.440	0.084

Next, we calculate the Euclidean distances for all pairs of inventory items using Eq. 3, and use clustering algorithm to classify the inventory items in appropriate bins. In this example, we created 6 bins as shown in the dendrogram of inventory items in Figure 3. The inventory items are listed on X-axis and the similarity scores among them are displayed on Y-axis. The items belonging to different bins are shown in different colors. For example, item numbers 1, 3, 6, 17 and 20 belong to the same group and these items are shown in a distinct red color. Similarly, item number 18 is in its own group and is shown in a distinct purple color.

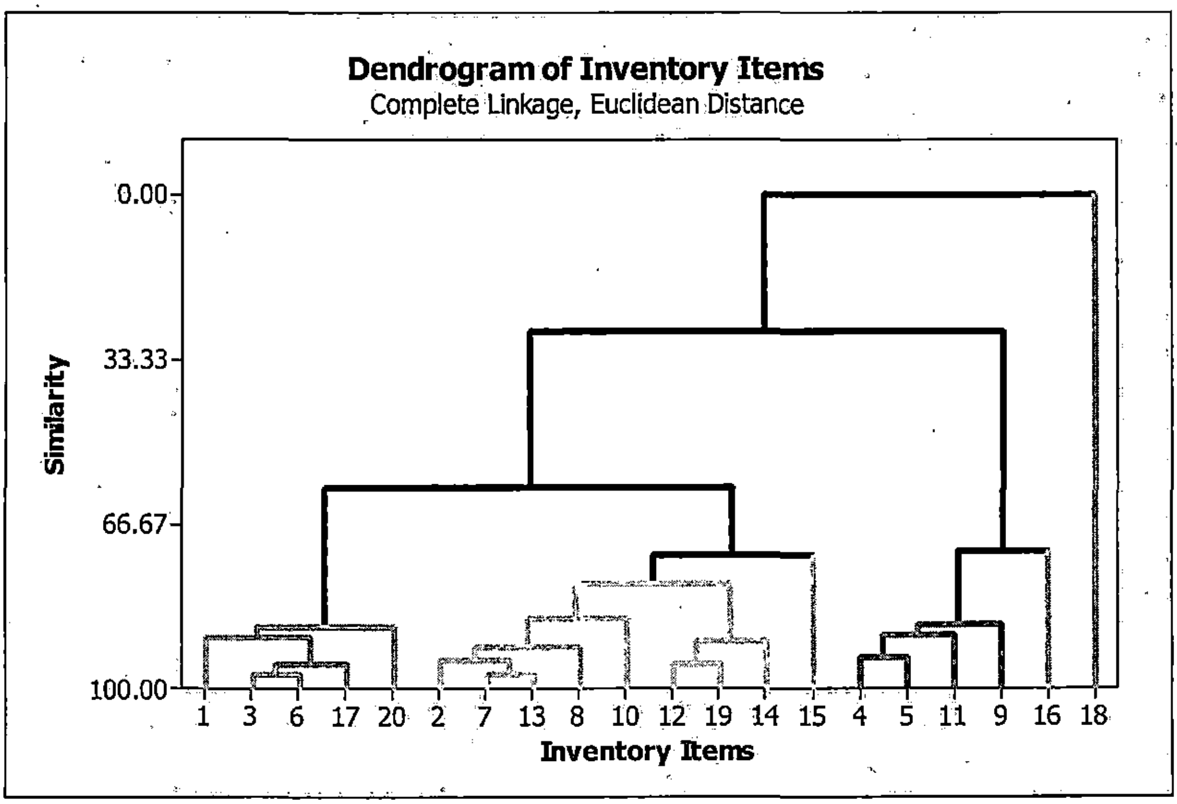


Figure 3. Dendrogram of inventory items

4. Comparison with the ABC analysis

This section describes the comparison of the IRIC method with the classical ABC analysis. First, we performed the ABC inventory analysis on the 20 hypothetical inventory items discussed in section 2, and classified them into three groups as shown in Table 3. Item numbers 5 and 6 belong to group A. Item numbers 10, 8, 2, and 7 belong to group B and the remaining items belong to group C.

Table 3. ABC analysis on inventory items.

Inventory Item	Usage	Usage	Cumulative Usage	Group
5	35532	11.37%	11.37%	A
4	34200	10.94%	22.31%	A
10	27753	8.88%	31.19%	B
8	23607	7.55%	38.75%	B
2	20691	6.62%	45.37%	B
7	17220	5.51%	50.88%	B
9	16800	5.38%	56.25%	C
6	15960	5.11%	61.36%	C
3	14790	4.73%	66.09%	C
16	13935	4.46%	70.55%	C
11	13152	4.21%	74.76%	C
13	12573	4.02%	78.78%	C
12	11286	3.61%	82.39%	C
18	11088	3.55%	85.94%	C
20	10638	3.40%	89.35%	C
17	10335	3.31%	92.65%	C
19	9591	3.07%	95.72%	C
15	6042	1.93%	97.66%	C
1	4014	1.28%	98.94%	C
14	3312	1.06%	100.00%	C

As we know, we obtained three inventory groups using ABC analysis and six inventory groups using the IRIC methodology. Next, we calculated average EOQ values for each group based on the EOQ values for the individual items in that group. Next, we generated monthly demand for each of the 20 inventory items for 12 months using the triangular distributions. A small sample of triangular distributions is shown in Figure 4:

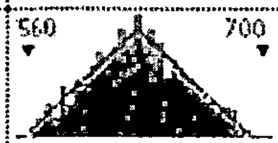
Graph	Min	Mean	Max
	606	668	733
	568	627	687
	785	869	955
	1545	1707	1875
	1783	1974	2160
	721	798	875
	444	491	540

Figure 4. A sample of triangular distributions used to generate the monthly demand

Finally, we ran 1000 iterations of Monte Carlo simulation for the whole year (12 months) for the ABC analysis as well as for the IRIC method to compare the total annual cost and the total annual revenue under each method. The selling price of each inventory item was considered three times its purchase cost for calculating the total annual revenue. Figures 5, 6, 7, and 8 show the results of our simulation. Figures 5 and 6 show the distribution of total annual cost and the distribution of total annual revenue respectively under the IRIC method. Similarly, Figures 7 and

8 show the distribution of total annual cost and the total annual revenue under the ABC analysis. The simulated results for the total annual revenue also take into consideration the losses due to inability to satisfy full demand because of inventory shortages. Each figure below shows a graph of the spread of the data on the left and values of important statistical parameters such as minimum, maximum, mean, and standard deviation on the right.

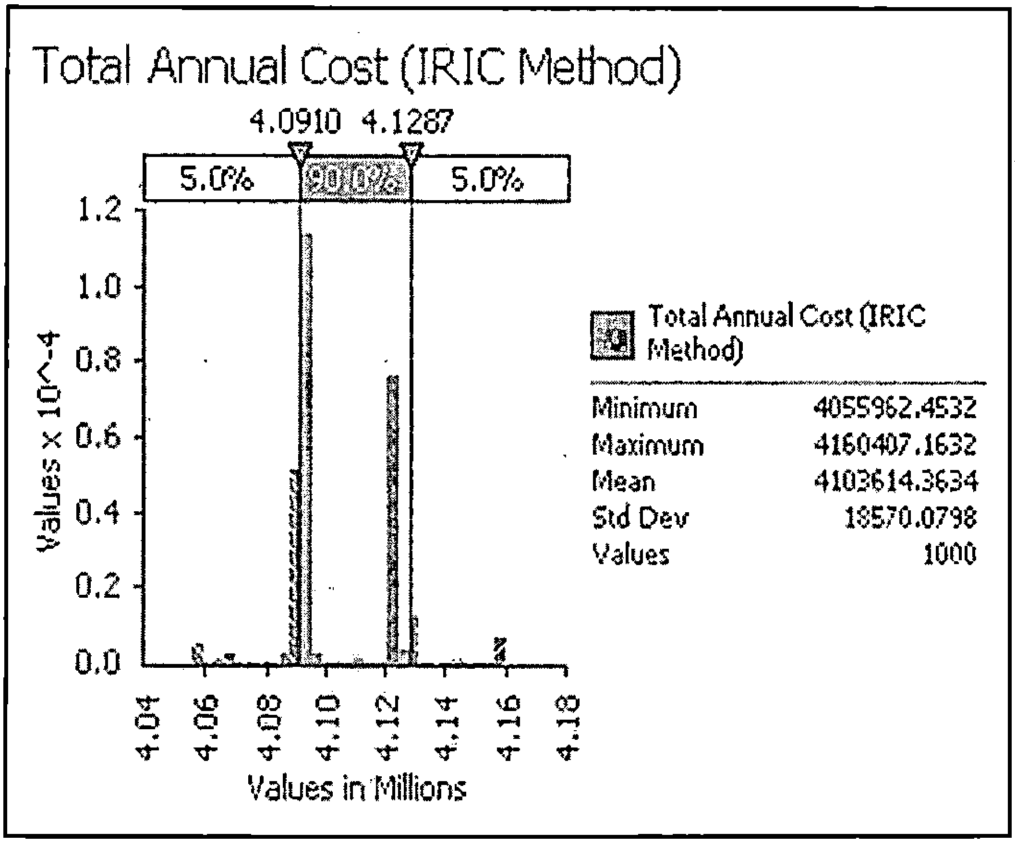


Figure 5. Distribution of total annual cost under the IRIC method

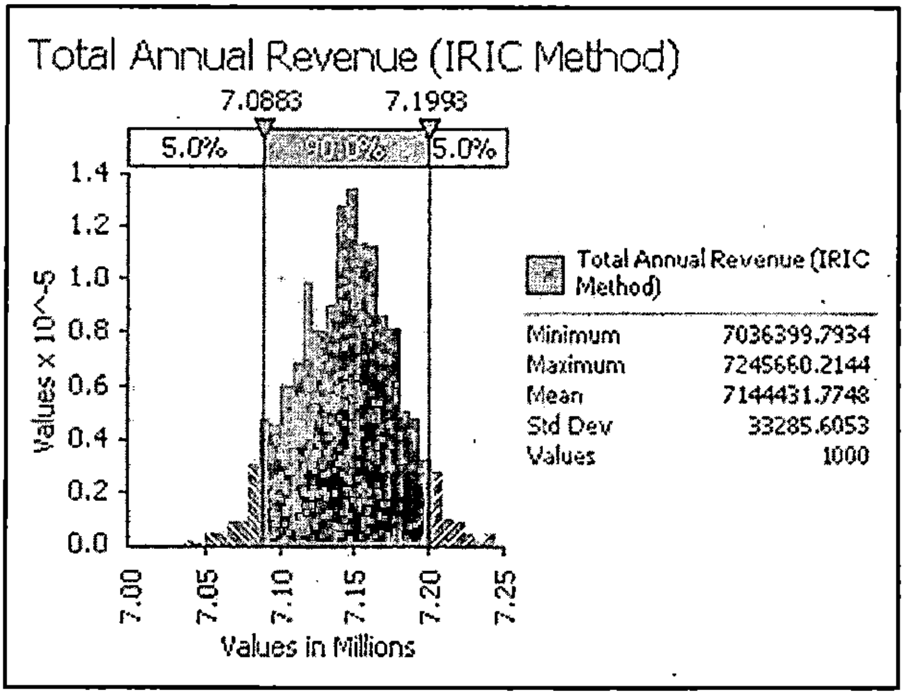


Figure 6. Distribution of total annual revenue under the IRIC method

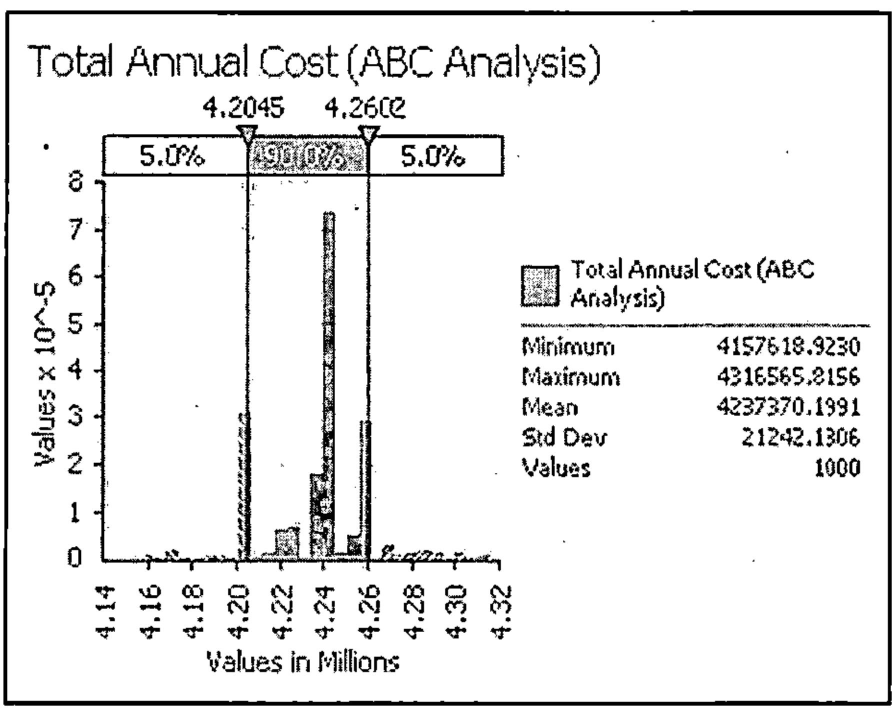


Figure 7. Distribution of total annual cost under ABC analysis

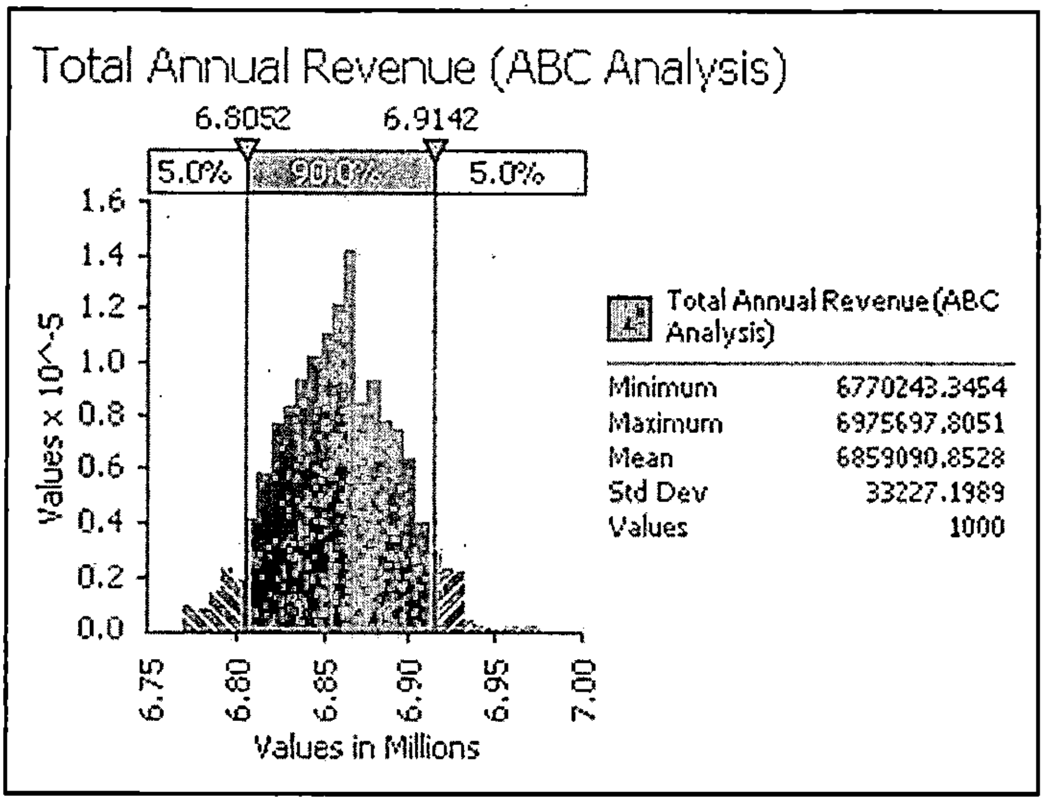


Figure 8. Distribution of total annual revenue under ABC analysis

Comparing the simulated results in Figure 5 and Figure 7, we can see that the IRIC method is more cost effective as compared to ABC analysis. Additionally, the standard deviation of the distribution shown in Figure 5 is less than the standard deviation of the distribution shown in Figure 7 indicating that the IRIC method is more robust as compared to the ABC analysis.

Similarly, comparing the simulated results in Figures 6 and 8, we note that the total annual revenue generated using the IRIC method is higher than the total annual revenue generated using ABC analysis. This observation further strengthens the argument that the IRIC method is more cost effective. The standard deviation values of 33285 and 33227 for the distribution shown in Figures 6 and 8 respectively are almost same indicating that there is not much difference between the spread of the annual revenue values simulated under the two methods.

5. Conclusions

In this paper, we proposed a new integrated risk-based inventory classification methodology that addresses the shortcoming of existing methodologies such as ABC analysis. We also tested the methodology using simulated risk scenarios and compared it with the ABC analysis using the Monte Carlo simulation. The results showed that the new methodology is robust and more cost effective as compared to the ABC analysis. A software prototype is developed that can be used and tested by organizations.

Our future work will focus on trade-off analysis between the two important aspects: risk minimization and cost effectiveness. For example, the inventory groups formed based on only risk minimization will be different that the groups that are formed based on only the cost effectiveness. Currently, we give equal importance to these two aspects, but it would be interesting to study how the groups will vary as the decision makers change their preference level for these two aspects of inventory management.

6. Acknowledgements

This project was supported by Morehead State University's Faculty Research Grants. The author is grateful to the members of the Research and Creative Productions Committee for making this effort possible. The author is grateful to Jared May, a student of the Applied Engineering & Technology (AET) department, who actively work on this project as the undergraduate research fellow. He helped with the development of the prototype and running the simulated scenarios. The author is also grateful to Prof. Y. You of the Applied Engineering & Technology (AET) Department for her invaluable guidance during the progress of this project. Finally, we would like to thank Prof. A. Zargari, Chair of the AET department for reviewing the paper and providing valuable inputs.

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