Multi-Criteria Inventory Classification using Machine Learning Algorithms

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Abstract

Inventory control is essentially a predominant decision to be undertaken by operations managers of a firm. A proper inventory control system ensures a sufficient amount of goods or materials to meet the firm's demand without facing undersupply or oversupply of materials. Traditionally, decision-makers classify inventory items into various classes or subgroups for easy monitoring and managing stock levels. The classification efficiency can be ameliorated by applying machine learning algorithms. The present paper focuses on developing a hybrid methodology that integrates machine learning algorithms with multi-criteria decision-making (MCDM) to facilitate multi-attribute inventory analysis. This technique enables the operator to leverage the benefits of both ML and MCDM. The data set is initially classified using MCDMs like the Simple Additive weighted (SAW) method and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) model. Performance metrics like overall cost and customer fill rate are utilized to rank the efficiency of the generated MCDM models. Supervised machine learning algorithms like Decision tree, Random Forest, Support Vector Machine (SVM), XG boost and KNN are employed on the MCDM models, and the performance of the system is established in terms of the accuracy of the machine learning algorithm. In order to prevent the inventory model from inclining towards the majority class, upsampling of the dataset is undertaken. Analysing the results, it is concluded that the application of TOPSIS MCDM provides better results for the considered systems in both machine learning and non-machine learning performance indices.

Keywords
Inventory control, ABC classification, Multi criteria decision making, Machine learning, Resampling.

1. Introduction
Inventory-related decision-making and reviewing of any firm should be accomplished judicially since these policies are vital for customer fulfilment (Hatefi et al., 2013). Inventory control methods ensure a sufficient quantity of stock is maintained by a firm, hence enabling customer fulfilment at minimal holding cost (Silver et al., 2017; Sridhar et al., 2021). For ease of inventory management, the inventory items are generally classified into different categories based on the significance to the overall process in the firm. This methodology facilitates the scope for targeted inventory review policies and management. For instance, in the case of the stock that is considered vital to the majority of the process of a firm, it is important that the stock availability is continuously reviewed, whereas the items that are not crucial may not require continuous review. Hence inventory classification enables easier monitoring.

In the classical approach, the yearly monetary consumption value of the inventory items is the only factor in consideration whilst the classification. Later on, several works were conducted highlighting the significance of including other criteria that are relevant to the firm as well in the classification procedure (Ng, 2007). For instance, in the case of spare part dealers, the factors like criticality, risk severity and lead-time are considered primary to the firm than just the consumption value (Bhattacharya et al., 2007). This directed the scope toward the principle of Multi-Criteria Decision Making (MCDM) or Multi-Attribute Decision Making. By definition, multi-criteria decision-making utilizes multiple criteria in determining the preference in evaluating and selecting the best optimal solution from a set of alternatives in the account of the desired output. Throughout the year, researchers developed many MCDMs, even hybrid models of multiple MCDM methods, to ensure proper stock availability within a company and optimal utilization of the available financial resources. MCDM methods like Analytical Hierarchy Process and TOPSIS are widely applied in the real-time industrial application (Ishizaka et al., 2017).

Recently, principles of Machine Learning (ML) models have been incorporated along with the classic decision-making approaches in contemplation of increasing the overall performance of the existing inventory models (Zhang, 2012; Archana et al., 2016). Machine learning enables a better understanding of the significance of the various inventory items, even if the firm deals with a large variety of stock. In ML, the algorithm works on the data associated with the inventory system given as the input, analyses the data points thoroughly and device data-driven interpretation. The advantage of ML algorithms is that even a substantial amount of data can be interpreted effortlessly. Furthermore, the application of ML can significantly reduce the human intervention in the judgement process and reduce the scope of human error. (Archana et al., 2016). Leveraging this research opportunities, the present paper predominantly aims to determine an optimal inventory classification model by incorporating ML and traditional MCDM methodologies. This hybrid methodology reassures the performance of the inventory classification model by adding the generic qualities of machine learning algorithms. The research utilizes Supervised ML, which involves algorithms trained on data with input and expected output. During the training period, the algorithm maps from the input data of the inventory items to the expected output (A, B or C Class) and a comparison of the performance of various inventory items can be effortlessly established. In order to attain the optimal model, performance measures like accuracy along with non-machine learning parameters like overall cost and customer fill rate are taken into account. In this line, the research objectives are framed as follows:

- Develop a hybrid methodology that integrates machine learning (ML) algorithms with multi-criteria decision making (MCDM) techniques to effectively conduct multi-attribute inventory analysis.
- Determine the effectiveness of combining MCDM with ML algorithms in inventory classification.

2. Literature Review

ABC classification is one of the most commonly used inventory classification method but many scientists has opposed it because it only considers annual rupee usage as the only criteria and it does not consider other criteria. To fill this gap, multi criteria decision making methods has been introduced. Opricovic and Tzeng (2002) proposed few methods such as VIKOR and TOPSIS. They basically compare the steps and the solution obtained by employing TOPSIS and VIKOR and Weighted linear optimization method which considers multiple criteria for ABC classification. Accordingly, Ng (2005) has proposed a simple classifier method which depicts as the count of criteria decreases ranking the criteria may affect the classification and as the number of criteria considered increases ranking becomes difficult for decision makers.

Bhattacharya et al. (2007) has developed a distance based method for ABC analysis, it is generally application of TOPSIS in inventory items by using a technique called ANOVA.As the extensions to Ramanathan's method, Hadi-Vencheh (2009) has proved that classification model not only combines many criteria but also keeps the impacts of weights in the final solution which improves the previous Ng model. Many other criteria such as Lead time, Unit cost, Annual rupee usage, Critical factor, etc. have been considered in classification of inventory items. In addition, customer fill rates for the inventory control has been proposed by Babiloni (2012). The paper identifies the simplest method to find the lowest base stock that guarantee the achievement of the target fill rate under any discrete demand context. Hatefi et al. (2013) has proposed a method where MCIC of ABC analysis with both quantitative and qualitative criteria which helped the managers to evaluate inventory items and increase the perception of inventory items. AHP method is also used in automobile rubber components by Balaji and Kumar (2014) examined and assessed the judgement of stock framework and loads acquired for various containers and grouping these containers, detectability to store in warehouse.

Artificial Intelligence, especially Machine Learning is the one of the domain that is finding substantial application in considerably majority of the departments of a firm. Machine Learning facilitates a data-driven learning method of analysing and deducing significant insights from big data effortlessly. Supervised classification type machine learning algorithms are found to have wide range of application in the field of inventory control and management. In this direction, Zhang (2012) introduced the basic idea, theory and application of Support Vector Machine algorithm, hence validating the usability of the ML approach in real-time industrial scenario. Song and Lu (2015) worked on application and prediction of a medical case of risk analysis associated with major depressive disorder using the decision tree approach. In an attempt to enhance the performance measures, a combination of various ML algorithms and improvised version of algorithms were introduced in the last decade. For instance, Archana et al. (2016) proposed an improved random forest classifier by incorporating an instance filter method to improve the performance. Ankita et al. (2021) proposed a multi class random forest classifier anent the small plant peptides and hence comparing the efficiency obtained with the classical approaches. The methodology framed for conducting the present research was primarily motivated from these insights derived from the literature. The same is discussed in detail in the subsequent section.

3. Research Methodology

The present research primarily focuses on establishing a hybrid methodology in facilitating superior multi attribute inventory analysis by incorporating MCDM along with Machine learning algorithms (Zhang, 2012). In the first instance all inventory items under consideration of the study is analysed and raw attributes for individual items are identified. Following this, criteria significant towards inventory control of the system are to be established. The inventory items are hence classified to A, B and C classes respectively on application of the MCDM models like Simple Additive Weightage (SAW) and TOPSIS. Furthermore, for comparison of the performance of various MCDM models Customer fill rate and overall cost is calculated for each model. In order to attain better predictability, supervised machine learning algorithms like Decision tree, Random forest, SVM, XG boost and KNN are applied to the dataset followed by calculation of overall accuracy. The performance of the various MCDM models considered are compared based on machine learning as well as non-machine learning parameters facilitating more efficient and easy inventory associated decision making. The entire research methodology is depicted in Figure 1.

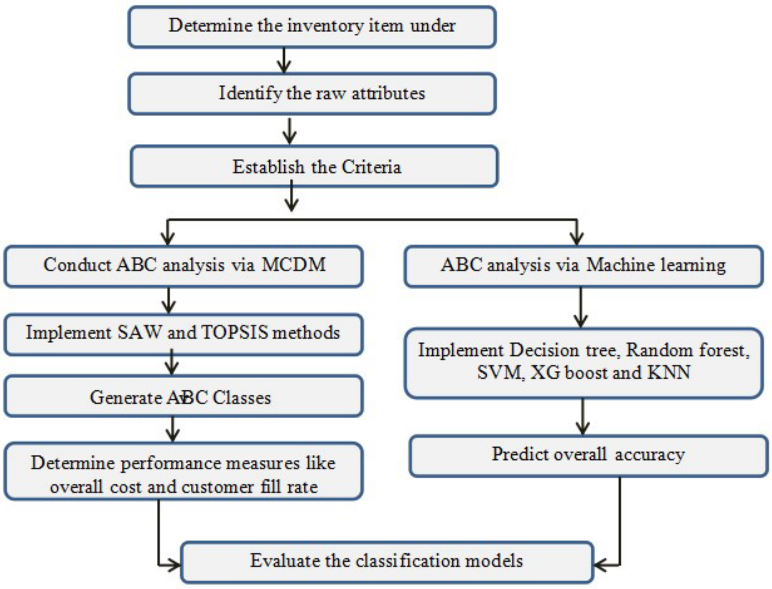

Figure 1. Flowchart of the methodology

3.1 Performance Measures

In order to facilitate comparison of various inventory control models generated (here SAW and TOPSIS), several performance measures are utilized. The performance measure considered here are customer fill rate and overall cost.

3.1.1 Customer Fill Rate

The customer fill rate is the factor that signifies percentage of demand from the customer end that is fulfilled in the specified amount of time. The ideal condition has a strong fill rate or percentage value near 100 % and implies demands are met with smoothly without facing the consequence of backorders or lost sales. The customer fill rate assures the extent to which they can rely on the supplier on the account of demand satisfaction, hence can remarkably affect supplier's relationship with its customers. As a result, this parameter could be considered as beneficial criteria for the decision maker. The procedure for determining fill rate is as follows:

1. Calculate the annual demand, Di

2. Di = Annual rupee usage / Average unit cost …… (1)
3. Calculate the order quantity *Qi*

$$Q_i = \sqrt{\frac{2A\,D_i}{H}} \qquad \text{…… (2)}$$

4. Calculate the standard deviation lead time demand $\sigma_L = \sigma\sqrt{L}$
5. Calculate the safety factor, k

$$k = \Phi^{-1}(CSL) \qquad \text{…… (3)}$$

6. Calculate Loss function of the standard normal distribution G(k) (Silver et al. 2017)

$$G(K) = \frac{1}{\sqrt{2\Pi}} e^{-\frac{k^2}{2}} - k(1 - \Phi(k)) \text{……. (4)}$$

7. Calculate the fill rate for each item

$$FR = 1 - \frac{\sigma\sqrt{L}}{Q} G(k) \text{…….. (5)}$$

8. Calculation of overall fill rate

$$FR_T = \frac{\sum_{i=1}^{n} FR_i D_i}{\sum_{i=1}^{n} D_i} \qquad \text{……. (6)}$$

9. Calculation of satisfied demand for each item = $FR_i D_i$

3.2.2 Overall Cost

The overall cost is the maximal cost incurred involved in handling inventory items including fixed as well as variable cost associated from the procurement of the item to its storage. Conventionally cost incurred is a non-beneficial criterion; hence the alternative with least overall cost will be desired. The proposed study the components of cost under consideration are-

Annual stock out costs: This comprises of the lost profits or loss associated with shortage of inventory on a yearly basis. Annual ordering cost: It is the cost incurred whilst generation and processing of order of materials to the supplier end. Annual holding cost: is the cost incurred on account of warehousing and storage of unsold inventory. This is the cost associated with labour, storage and indemnity. Here cost associated with holding of both cycle stock as well as safety stock is considered.

10. Overall cost = Annual stock out costs + Annual ordering cost + Annual holding cost of (cycle stock + safety stock)

$$= \left(\frac{D}{Q}\right) p_{u\geq}(k) B_1 + \frac{AD}{Q} Cr + \left(\frac{Q}{2} + k\sigma_L\right) H \text{……. (7)}$$

where,

D = annual demand
Q = order quantity
k = safety factor
H = holding cost
$p_{u\geq}(k)$ = probability that a unit normal (mean 0, standard deviation 1) variable takes on a value of *k* or larger.
$p_{u\geq}(k)$ Is often expressed as $1 - \phi$ (k), where ϕ (k) is the cumulative distribution function (or the left tail) of the unit normal evaluated at *k* (Silver et al. 2017)
σ_L = standard deviation of demand over a replenishment lead time, in units
B_1 = specified fixed cost per stock out occasion
Cr = Ordering cost per order.

4. Data Collection and Implementation

The data utilised for the study is the data of 47 Items are to be classified based on 4 criteria: Annual rupee usage, Average unit cost, criticality factor and Lead time for inventory classification (Farrukh et. al., 2015). Classification methods such as SAW and TOPSIS were implemented to sort 47 different items in the warehouse (Table 1). Then Machine Learning models such as Decision Tree, Random Forest, SVM, XG Boost, KNN were used to predict the accuracies of the classification. Before the application of MCDM methods criteria must be decided. Main characteristics were obtained from raw attributes and criteria are Annual Rupee Usage, Average Unit Cost, Lead Time, Criticality Factor were applied to SAW and TOPSIS.

Table 1. Items and Attributes

Item no	**Annual Rupee Usage**	**Average Unit Cost**	**Lead Time**	**Critical Factor**

1	5840.64	49.92	2	1
2	5670	210	5	1
3	5037.12	23.76	4	1
-	-	-	-	-
-	-	-	-	-
-	-	-	-	-
46	28.8	28.8	3	0
47	25.38	8.46	5	0

4.1 Implementation of SAW

First it is assumed that all four attributes are having equal simple weights and all the criteria are positive related to the score of the inventory items. Normalized preferred score is calculated following that utility formula is used to calculate the score. After obtaining the scores items were ranked in descending order as item with highest score is given rank 1 and least score is given as 47. By taking Pareto 80-20 distribution into consideration, top 20% of the items were classified as class A, the next 30% were given as class B and the remaining 50% were given as class C.

Table 2. Classification based on SAW

Item no	**SAW Score**	**Rank**	**Class**
1	1.38533	7	A
2	2.63732	1	A
3	1.45281	6	A
-	-	-	-
-	-	-	-
-	-	-	-
46	0.4495	40	C
47	0.68297	30	C

Column 1 in Table 2 shows item number and column 2 shows the SAW score that is obtained after using the utility formula and column 3 shows the ranking of the order based on the decreasing order of the score and last column shows the classification of the respective item.

4.2 Implementation of TOPSIS

It is assumed that all four attributes are having equal simple weights and Annual Rupee Usage and Critical Factor are considered to be a beneficial criterion, whereas unit cost and lead time are assumed to be non-beneficial. Initially, the decision matrix was prepared and the normalized and weighted normalized decision matrix was calculated. The ideal best and ideal worst for each criterion were calculated following the standard TOPSIS procedure. Euclidian distance from the ideal best and the ideal worst were calculated and performance score for each item was determined. The alternatives are ranked based on the decreasing order of the obtained performance score. Finally, the items are classified (20% as class A, the next 30% as class B and the remaining 50% as class C) based on Pareto's 80-20 distribution (Table 3). Column 1 in Table 3 shows the item number and column 2 shows the Euclidean distance from the ideal best and the column 3 shows the Euclidean distance from ideal worst, column 4 shows Performance Score and Column 5 shows the Ranking of the item based on the decreasing order of the performance score and last column shows the classification.

Table 3. Classification based on TOPSIS

Item no	**Euclidean distance (Si+) from ideal best**	**Euclidean distance (Si-) from ideal worst**	**Performance score**	**Rank**	**Class**
1	0.0347	0.1976	0.850616	2	A
2	0.15672	0.146	0.482298	19	B

3	0.04223	0.19006	0.818185	3	A
-	-	-	-	-	-
-	-	-	-	-	-
-	-	-	-	-	-
46	0.15122	0.14019	0.481073	21	B
47	0.15546	0.14916	0.489655	17	B

4.3 Calculation of Customer Fill Rate and Overall Cost

Customer fill rate and overall cost (Table 4 and 5) were calculated using the formula presented in sub-sections 3.1.1 and 3.1.2 respectively, based on the following assumptions

- That Ordering Cost(Cr) for any item is equal to 1(unit ordering cost).
- The standard deviation of the demand per year for an item i is assumed to be X% of Demand $\sigma i = X \times Di$ (where X=1,2.5),
- Holding cost H = 20% of Average unit cost,
- Continuous review policy.

Table 4. Fill rate and overall cost for TOPSIS

Annual demand (Di)	**Order quantity (Qi)**	**Cycle service level (CSL)**	**Safety factor (k)**	**G (k)**	**Fill rate for an item (Fri)**	**Satisfied demand**	**Overall Cost**
117	4.84122	0.99	2.3263	0.003	0.99743	116.70	146.826
27	1.1333	0.95	1.6448	0.021	0.9720	26.245	163.797
-	-	-	-	-	-	-	-
-	-	-	-	-	-	-	-
1	0.5892	0.95	1.6448	0.021	0.99845	0.99845	4.6528
3	1.8831	0.95	1.6448	0.021	0.99812	2.994	4.4494

Table 5. Fill rate and overall cost for SAW

Annual demand (Di)	**Order quantity (Qi)**	**Cycle service level (CSL)**	**Safety factor (k)**	**G (k)**	**Fill rate for an item (Fri)**	**Satisfied demand**	**Overall Cost**
117	4.84122	0.99	2.3263	0.003	0.99743	116.70089	146.826
27	1.1333	0.99	2.3263	0.003	0.99600	26.892	197.4747
-	-	-	-	-	-	-	-
-	-	-	-	-	-	-	-
1	0.5892	0.90	1.2815	0.047	0.9965	0.9965	5.4107
3	1.8831	0.90	1.2815	0.047	0.9958	2.987	5.1429
*G(k): Loss function value							

4.4 Implementation of Machine Learning algorithms

Machine learning algorithms are implemented to conduct the ABC inventory analysis. The present research employs supervised machine learning algorithms like Decision tree, Random forest, SVM, XG boost and KNN. Four attributes (Annual Rupee Usage, Average Unit Cost, Lead Time, Criticality Factor) were taken as inputs, and classes of the items determined by the MCDM methods were selected as outputs. Before applying any machine learning algorithm outlier detection is implemented. It is the process of detecting and subsequently excluding outliers from given dataset. Visualization technique such as Histogram, Box Plot, Scatter Plot are commonly used for the detection of Outliers. The range and distribution of attribute values are important to machine learning algorithms. Outliers in the data can sabotage and mislead the training process, resulting in longer training periods, less accurate models, and worse outcomes. Once the outliers are detected and removed, the following standard procedures are followed for the implementation of ML.

Step 1: Data Processing

In this step, first importing of required libraries for making respective algorithm is loaded, then data set is inserted in a data frame and splitting of the data into training and testing set is also being done in this part.
Step 2: Fitting respective algorithm to the Training set
Here an object is created and respective algorithm is fitted into that object.
Step 3: Confusion matrix and classification report
In this step confusion matrix shows the number of correct and incorrect predictions. Classification report gives the idea of accuracy precision and f1 score.

4.5 Implementation of Upsampling

As the data is very small, upsampling is done to increase the number of items to 3000 items (Table 6).

Table 6. Amended dataset of 3000 items

Item no	Annual Rupee Usage	Average Unit Cost	Lead Time	Critical Factor
1	4769.56	27.73	1	1
2	4769.56	27.73	1	1
-	-	-	-	-
-	-	-	-	-
-	-	-	-	-
1500	75.4	37.7	2	1
1501	224	56	1	1
-	-	-	-	-
-	-	-	-	-
2999	181.8	60.6	3	0.5
3000	883.2	110.4	5	1

The MCDM and ML algorithms are repeated on this amended dataset and fill rates, overall cost are calculated again. Finally, the evaluation parameters such as precision, accuracy, recall and f1 score are also calculated.

5. Results and Discussion

The section provides and the results and insights derived by analysing the obtained results in detail.

5.1 Numerical and Graphical results

After implementation of MCDM method for 47 items, performance measures such as overall cost and fill rate were obtained. The classification method which has the least overall cost and highest fill rate is considered as the optimal classification when Non ML parameters are used for finding out the optimal. Standard deviation is considered for two cases where X=2.5% of Demand and X=1% of Demand (Table 7).

Table 7. Results obtained when the standard deviation is 2.5% of demand

Sl. No.	MCDM method	Std. Dev = 2.5% of demand		Std. Dev = 1% of demand	
		Total Fill rate	Overall Cost	Total Fill rate	Overall Cost
1	SAW	0.98958	1930.102	0.995831	1367.519
2	TOPSIS	0.99457	1898.899	0.997829	1357.618

From Table 7, it can be inferred that the TOPSIS method has the high total fill rate and low overall cost compared to SAW in both the cases. The results are further supplemented by an item-wise analysis of fill rates as exhibited in Figure 2.

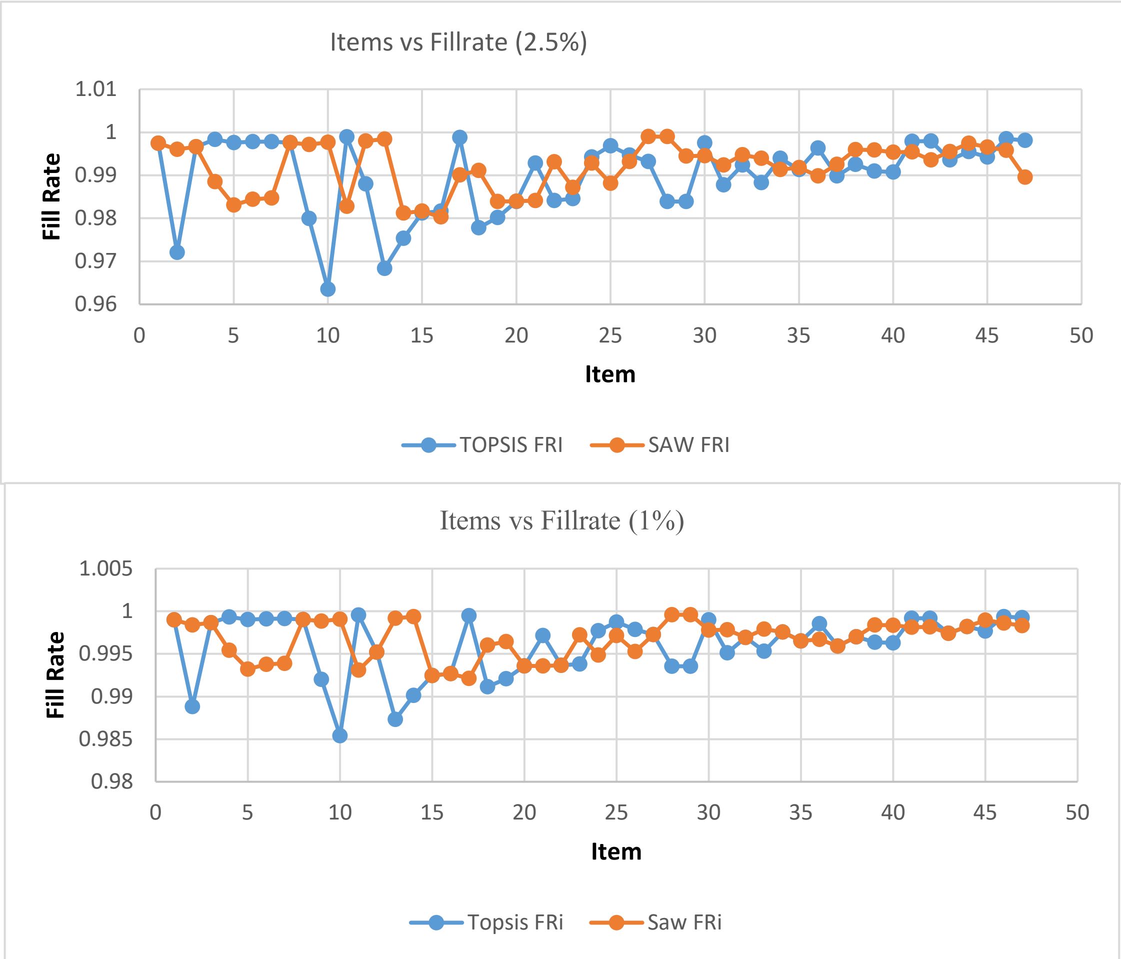

Figure 2. Items vs Fill rate when standard deviation is 2.5% and 1% of demand**.**

Analysing the first plot, focusing on SAW, item 27 has highest fill rate and item 16 has lowest fill rate, In TOPSIS, item 11 has highest fill rate and item 10 has the lowest fill rate when the standard deviation is 2.5% of annual demand. From the second plot, in SAW, item 28 has highest fill rate and item 17 has lowest fill rate. In TOPSIS, item 11 has highest fill rate and item 10 has the lowest fill rate when the standard deviation is 1% of annual demand. Following the MCDM, the Machine Learning Algorithms (MLAs) are also implemented. Evaluation metrics such as confusion matrix, precision, recall, f1 score were obtained. As the volume of data is small, stratified cross validation is used to obtain overall accuracy (Table 8).

Table 8. Overall accuracies for SAW and TOPSIS

Sl. No.	Type of MLA	Overall accuracy for SAW	Overall accuracy for TOPSIS
1	Decision Tree	60.5	66
2	Random Forest	71.5	71
3	SVM	79	78.5
4	KNN	55	64.5
5	XGboost	74	81

Table 8 offers interesting but inconsistent results. For instance, when Decision Tree algorithm is applied, TOPSIS is found to have high accuracy compared to SAW. When Random Forest algorithm is applied, SAW method exhibits high accuracy compared to TOPSIS. When SVM is applied, SAW is having high accuracy compared to TOPSIS. When KNN algorithm is applied, TOPSIS is having high accuracy compared to SAW. When XGboost algorithm is applied, TOPSIS is having high accuracy compared to SAW.

5.2 Proposed Improvements

As the volume of data was small and evaluation metrics are not ideal, hence upsampling is done. Here the volume of data is increased from 47 items to 3000 items. Again the whole process is repeated and new evaluation metrics were obtained (Table 9).

Table 9. Results obtained after Upsampling

Sl. No.	MCDM method	Std. Dev = 2.5% of demand		Std. Dev = 1% of demand	
		Total Fill rate	Overall Cost	Total Fill rate	Overall Cost
1	SAW	0.99103	151422.16	0.99641	102308.72
2	TOPSIS	0.99619	147470.00	0.99847	100725.45

Similar to the previous results, it is found that TOPSIS has the high total fill rate and low Overall Cost compared to SAW in both the cases. Furthermore, Table 10 exhibits the evaluation metrics such as recall, precision, F1 score and accuracy for each machine learning algorithm with respect to the MCDM method. The accuracy levels of the MCDM-ML pairs are also portrayed in Figure 3.

Table 10. Evaluation metrics for MCDM based Machine Learning methods

Sl. No.	MLA	MCDM	Class	Precision	Recall	F1 score	Accuracy (%)
1	Decision Tree	SAW	A	0.67	1.00	0.80	
			B	1.00	0.25	0.40	81.5
			C	0.08	1.00	0.89	
		TOPSIS	A	1.00	0.50	0.67	
			B	0.67	1.00	0.80	83
			C	1.00	0.83	0.91	
2	Random Forest	SAW	A	1.00	1.00	1.00	
			B	1.00	0.80	0.89	90
			C	0.80	1.00	0.89	
		TOPSIS	A	1.00	0.33	0.50	
			B	0.40	1.00	0.57	89
3	SVM		A	0.81	0.94	0.87	
		SAW	B	0.50	0.30	0.37	
			C	0.75	0.79	0.77	85
			A	0.43	1.00	0.61	
		TOPSIS	B	1.00	0.41	0.25	
			C	0.95	0.91	0.93	84.5
4	XGBoost		A	0.67	1.00	0.80	
		SAW	B	1.00	0.50	0.67	88
			C	1.00	1.00	1.00	
		TOPSIS	A	1.00	1.00	1.00	
			B	0.67	1.00	0.80	89.5
			C	1.00	0.75	0.86	
5	KNN	SAW	A	0.45	0.45	0.45	
			B	0.25	0.80	0.33	80
			C	0.83	0.83	0.83	
		TOPSIS	A	1.00	1.00	1.00	
			B	0.50	1.00	0.67	81
			C	1.00	0.71	0.83	

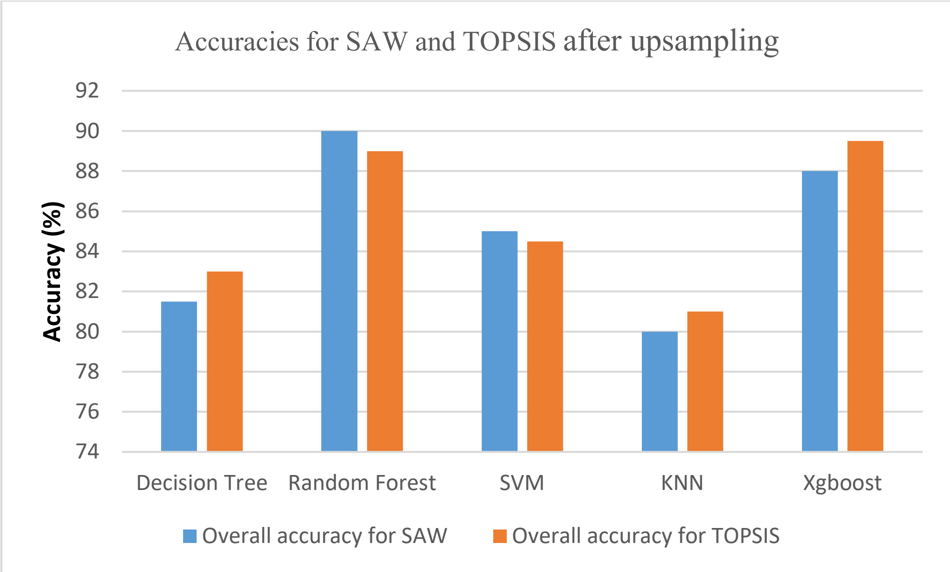

Figure 3. Graphical representation of Accuracies after upsampling for SAW and TOPSIS

When Decision tree is applied for SAW and TOPSIS, it is found that SAW has accuracy 81.5% while TOPSIS has 83% and when Random forest is applied for SAW and TOPSIS, it is found that SAW has accuracy 90% while TOPSIS has 89% and when Support Vector Machine is applied for SAW and TOPSIS, it is found that SAW has accuracy 85% while TOPSIS has 84.5% and when XGBoost is applied for SAW and TOPSIS, it is found that SAW has accuracy 88% while TOPSIS has 89.5% and when KNN is applied for SAW and TOPSIS it is found that SAW has accuracy 80% while TOPSIS has 81% are obtained.

6. Conclusion

A generic hybrid technique of multi-criteria decision-making models combined with machine learning methods for analysing multi-attribute inventory classification problems is presented in this research. Inventory classes were determined by employing two different MCDM approaches, TOPSIS and SAW. Following the classification, five machine learning algorithms, i.e., Decision Tree, Random Forest, Support vector machine, XGboost, and KNN, were employed to anticipate the pre-identified classes of each classification method. After checking and eliminating outliers, the dataset has been divided into a training dataset and a testing dataset. Once the division is done, then evaluation metrics like confusion matrix, precision, recall, f1 score, and accuracy were obtained. After analysing the results, it is evident that TOPSIS is best MCDM technique for multi-criteria inventory classification situations in all aspects like the fill rate and overall cost when compared to SAW. Although the prediction of algorithms may not be exact in some circumstances, depending on the various data sets, owing to concerns with data distribution and measurement, the case study proved that all algorithms were able to categorize inventory items exceptionally effectively. It is commonly acknowledged in the field of machine learning that an imbalance distribution of ABC classes can affect classification accuracy; thus, an evenly distributed training set was created using random under-sampling methods before a different data set, which included a distribution with Pareto assumption.

As previously stated in this study, accuracy alone is insufficient for comprehensively evaluating and comparing categorization systems. Further research using additional data sets and/or alternative machine learning algorithms, as well as multiple MCDM methodologies, can be employed to examine the extent to which the general hybrid methodology suggested in this work can efficiently categorize inventory items. Most importantly, the hybrid ML-MCDM methodology can be applied for inventory classification in a real-world situation involving thousands of inventory items.

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