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# An integrated decision analytic framework of machine learning with multi-criteria decision making for multi-attribute inventory classification

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ABSTRACT

The purpose of this study is to develop a hybrid methodology that integrates machine learning algorithms with multi-criteria decision making (MCDM) techniques to effectively conduct multi-attribute inventory analysis. In the proposed methodology, first, ABC analyses using three different MCDM methods (i.e. simple-additive weighting, analytical hierarchy process, and VIKOR) are employed to determine the appropriate class for each of the inventory items. Following this, naïve Bayes, Bayesian network, artificial neural network (ANN), and support vector machine (SVM) algorithms are implemented to predict classes of initially determined stock items. Finally, the detailed prediction performance metrics of algorithms for each method are determined. The comprehensive case study executed at a large-scale automotive company revealed that the best classification accuracy is achieved by SVMs. The results also revealed that Bayesian networks, SVMs and ANNs are all capable of successfully dealing with the unbalanced data problems associated with Pareto distribution, and each of these algorithms performed well against all examined measures, thus validating the fact that machine learning algorithms are highly applicable to inventory classification problems. Therefore, this study presents uniqueness in that it is the first and foremost of its kind to effectively combine MCDM methods with machine learning algorithms in multi-attribute inventory classification and is practically applicable in various inventory settings. Furthermore, this study also provides a comprehensive chronological overview of the existing literature of machine learning methods within inventory classification problems.



## 1. Introduction

In the modern world, where we benefit from large data storage units and enhanced computing and processing capabilities, learning algorithms have become increasingly popular as a means of discerning patterns and discovering information from large amounts of data (Alpaydin, 2004). Various algorithms such as artificial neural networks (ANN), Bayesian networks (BN), k-nearest neighbor (k-NN), support vector machines (SVM), and genetic algorithms (GA) offer us to learn from the data, to perform classification, clustering, association, feature selection, and regression for the data provided by any resources. As such, machine learning has become increasingly important and has found practical application in a wide variety of applications like speech recognition, visual processing, and robot control (Wang & Summers, 2012). Just one more sample area in which these algorithms can be of benefit is *inventory analysis*.

In today's competitive global landscape, major organizations need to develop a competitive advantage through differentiating their products or services, be it through price, quality, flexibility or responsiveness (Gunasekaran & Cheng, 2008). Quite often, a firm's ability to deliver a differentiated strategy is inexplicably linked with their supply chain and inventory management capabilities and processes. In the modern business world, an increasing emphasis has been placed on the need for businesses to develop agile supply chains that are fully integrated with information systems in order to evolve best practices that offer innovative solutions (Gunasekaran, Lai, & Edwin Cheng, 2008). To effectively achieve these objectives, it is crucial that organizations are able to seamlessly integrate multiple methodologies and applications

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(Ustun, 2008; Khan, Jaber, & Ahmad, 2014). While doing so will undoubtedly provide immediate practical solutions to many of the problems that are inherent in modern-day industry, further potential lies in a firm's ability to develop information systems of enterprise scale that operate with additional technologies such as radio frequency identification (RFID), expert systems (ES), and artificial intelligence (AI) (Gunasekaran & Ngai, 2014).

In the context of inventory management, machine learning methods can be used to analyze inventory (which often consists of a large number of items with multiple attributes) and classify stock items. In combination, these functionalities can provide powerful methodologies that can inform and support managerial decisions. Although among the vast amount of data mining applications, inventory management focus is relatively rare; in recent years, some studies have started to focus on the potential that multi-attribute inventory classification combined with machine learning algorithms could offer as a means of producing efficient and flexible inventory classification models.

ABC inventory control systems use the well-known Pareto principle (80–20: trivial many versus vital few) to classify items into three distinct classes: A, B, and C, according to their relative significance. Items that belong to Class A are deemed to be few in number, but large in inventory expenses. Class C represents those items that are large in number, but small in inventory expenses and Class B are items that fall somewhere in between the two extremes (Cebi, Kahraman, & Bolat, 2010). ABC analysis is very popular as an inventory control system because it is simple and the outputs of the evaluation are easy to interpret. However, since this approach only considers the total amount of inventory usage to rank and classify inventory items, it is very limited and largely insufficient. As such, a number of additional MCDM methods have emerged as a means of supporting ABC analysis and have become popular as the direct result of their ability to incorporate additional criteria into inventory management including criticality, lead time, commonality, repairability, storage cost, supplier alternative, unit size, order size, etc. Further information together with a summary table that provides an overview of multi-criteria inventory classification studies can be found in the study conducted by Kabir and Sumi (2013).

This study employs various machine learning algorithms to determine the best model in ABC inventory analysis. The organization of the manuscript can be presented as follows: Section 2 provides a literature review of multi-attribute inventory classification with an emphasis on studies using machine learning algorithms. Section 3 briefly outlines research objectives and the proposed methodology. Section 4 reviews methods that are applied in this study and Section 5 illustrates the implementation steps of the proposed method via a real case study. Finally, Section 6 evaluates the findings and Section 7 presents concluding remarks.

## 2. Literature review

This section of the study presents an inclusive literature review of major and state-of-the-art research in multi-attribute inventory classification problem. The purpose of the discussion here is to examine the chronological progression of machine learning algorithms and other data analytic methodologies that are relevant to the current research of this study.

One of the earliest multi-attribute inventory classifications using machine learning was introduced by Guvenir and Erel (1998). The study proposed a new classification model by applying a genetic algorithm (GA). The algorithm determines the weights of criteria as optimizing parameters of an ABC analysis. The genetic algorithm for multi-criteria inventory classification (GAMIC) was implemented with four criteria to stationary items of a university, and results were compared with AHP-based multi-criteria decision making (MCDM) technique. The nineteenth-century Italian Pareto's basic principle known as the 80–20 rule, was implied to inventory management using annual dollar usage value of stock items as a single attribute due to its simplicity and easy applicability (Cebi & Kahraman, 2012). Afterward, since other attributes also appeared to be important factors, the restriction of having a single dimension became a major limitation for the method. To overcome this limitation, Sarai (1980) extended classical ABC analysis into a multiple criteria model as a practical approach for an inventory management application. The model considered some other factors over annual usage value such as conditions of supply, conditions of consumptions, storing conditions and relations among items. Flores and Whybark suggested (1986) and implemented (1987) a multi-attribute inventory classification model. Apart from annual usage amount, their study proposed consideration of additional criteria such as criticality, lead time, commonality or substitutability. A joint-criteria matrix was presented to consider more than one criterion (Flores & Whybark, 1987). Although this matrix approach (a.k.a bi-criteria inventory classification) works well for two criteria, when more than two criteria are required to be considered, the matrix becomes hard to analyze or unpractical to utilize. Cohen and Ernst (1988) used statistical analysis to determine classes of items via cluster analysis. However, this method was required for complex determination processes with many re-evaluations (Cohen & Ernst, 1988).

Flores, Olson, and Doria (1992) proposed the Analytical Hierarchy Process (AHP) (Saaty, 1980) to consider multiple criteria of ABC analysis. Later, Partovi and Burton (1993) and Partovi and Hopton (1994) also implied AHP-based multi-criteria inventory classification methods. Since the AHP provided an easy way to combine various kinds and number of attributes, numerous applications have been utilized using many different attributes. On the other hand, as in most real-cases, constraints are not certain, and some attributes are hard to determine precisely. Therefore, fuzzy logic and its theory were used to have some flexibility in decision parameters or attribute values which had such ambiguity (Zadeh, 2005; Cebi & Kahraman, 2012). In a similar vein, Puente, De Lafuente, Priore, and Pino (2002) suggested a fuzzy model and a probabilistic model for ABC analysis with uncertain data. In the study, demand and cost attributes were considered as fuzzy information. Rezaei (2007) presented a fuzzy model for multi-attribute inventory classification. Cakir and Canbolat (2008) proposed a web-based inventory classification system model using the fuzzy AHP (FAHP) method. The paper integrated fuzzy theory and multi-attribute inventory analysis for a real case study. In a similar vein, Chu, Liang, and Liao (2008) combined ABC analysis and fuzzy classification by proposing an approach called ABC-FC which yielded high accuracy. Using Zeng's FAHP (Zeng, Min, & Smith, 2007), Cebi et al. (2010) classified inventory items by considering multiple attributes in fuzzy numbers. Cebi and Kahraman (2012) proposed a single and two multiple attributes fuzzy models based on both FAHP and fuzzy TOPSIS for information under incomplete and vague conditions. Kabir and Hasin (2012) also proposed an FAHP-based classification. The study used fuzzy logic to determine relative criteria weights. A novel approach by Kabir and Sumi (2013) proposed an integrated methodology by combining Fuzzy Delphi Method (FDM) with Fuzzy Analytic Hierarchy Process (FAHP) along with a real-life data implementation.

In parallel with aforementioned fuzzy theory approaches to provide better classification models, using the same data of 47 items provided by Reid (1987) based on the data of a hospital inventory, a series of studies have been conducted employing Data Envelopment Analysis (DEA). First, Ramanathan (2006) developed a simple classification process using weighted linear optimization. An optimal inventory score of an item was determined by a weighted additive function which is used to aggregate the performance of an inventory item regarding different criteria to a single score. This is similar to an output maximizing multiplier DEA model with multiple outputs for a constant input reduces the model (Ramanathan, 2006). Ng (2007) claimed that Ramanathan's DEA-like weighted linear optimization model did not seem very suitable to be applied to these data due to some criteria (such as critical factor) that are categorical and not continuous. Ng (2007) did not consider this criterion and assumed the importance of the criteria is the descending order of other criteria and provided another simple model for multi-attribute inventory classification without a linear optimization. Zhou and Fan (2007) developed the R-model as an enhancement of Ramanathan's model. If an item has a dominating value in terms of relatively less important criterion, even though it has low values in other criteria, still it may be classified as class A as a result of the R-model. This may cause inappropriate classifications. To provide a more reasonable index, the extended model uses two sets of weights that are not only most favorable but also least favorable for each item.

Chen, Li, Kilgour, and Hipel (2008) also proposed a case-based distance model for ABC analysis and compared several previous studies with respect to their outcomes and examined consistencies of these methods. Their model represented an ideal and an anti-ideal-based distance approach and required a training set with representative stock items from each class. The study also compared the outcomes of models of Flores et al. (1992), Ramanathan (2006), Ng (2007), and Zhou and Fan (2007) and confirmed that these different models produce relatively consistent rankings. Hadi-Vencheh (2010) proposed a nonlinear programming model which determines a set of weights for each inventory items by extending Ng (2007)'s classification model. This extended version maintains the effects of weights in the final ranking as an improvement. Hadi-Vencheh and Mohamadghasemi (2011) also developed an integrated fuzzy-AHP model for the multi-criteria ABC inventory classification. In this series of studies using the data of Reid (1987) and Chen (2012) proposed a model using two virtual items as positive and negative ideal items and incorporating the TOPSIS by providing a more comprehensive performance index without any subjectivity. The study also compared its results with other allied methods.

Chen (2011) proposed a peer-estimation based method adopted into multi-criteria ABC inventory classification. The study identifies two sets of criteria weights and provides an aggregated result among the most and the least favorable scores which are claimed to be better performance measurement indicators for inventory classifications while using MCDM.

Apart from many early traditional AHP based multi-attribute classifications, an extensive literature was created introducing studies of various algorithms applied to inventory classification such as fuzzy or probabilistic approaches, a series of DEA-like models, and a few recent method based on TOPSIS. Partovi and Anandarajan (2002) presented two learning algorithms, back propagation (BP) artificial neural nets (ANN) and genetic algorithms (GA) to classify stock keeping units of a pharmaceutical company. The models using the algorithms were also tested with a secondary inventory data provided from an external source. The classification performance of these two methods was compared using statistical techniques. Due to the conformed classification results, GA was superior to BP-ANN. Besides, the study indicated that ANN models outperformed controversial multiple discriminant analysis (MDA) methods. Lei, Chen, and Zhou (2005) presented two methods for ABC analysis. The first method used the principle components analysis (PCA) and the second method combines PCA with ANN deploying the BP algorithm. The study also compared classification abilities using a data set and suggested that a hybrid method could overcome shortcomings of any input limitation of ANNs and help improve the prediction accuracy. There are also other advancements taken place in different machine learning techniques using hybrid approaches such as Bayes-AHP, Fuzzy-VIKOR, VIKOR-GA and AHP-GA. An integrated approach of rough set theory and SVM was adopted into the decision making processes of leak detection scheme through a swarm intelligence technique (Mandal, Chan, & Tiwari, 2012). Also, Tsai and Yeh (2008) proposed a particle swarm optimization (PSO)-based algorithm for multi-attribute inventory classifications. Different numerical studies and a real case study were conducted, and the PSO algorithm was compared against some other classification approaches such as ABC classification. Results suggested that the proposed algorithm performs comparatively better and possesses flexibility in terms of item group number and objectives. Li (2009) suggested a heuristic classification model with two attributes. The study focused on goods classification with the factors of carriers and drivers and developed an algorithm to consider multiple attributes. Two numerical examples proved the superiority of the proposed heuristic algorithm. Yu (2011) compared artificial-intelligence (AI)-based classification techniques with traditional multiple discriminant analysis (MDA) using initially utilized classifications proposed by Reid (1987), Flores et al. (1992), Ramanathan (2006), and Ng (2007). In the study, k-nearest neighbor (k-NN), SVMs, and BP networks were benchmarked. According to the statistical analysis, AI-based techniques provided better accuracy than MDA, whereas SVM enabled even more accurate classification results.

Molenaers, Baets, Pintelon, and Waeyenbergh (2012) proposed a spare part categorization model which presented a classification problem in a decision logic diagram where AHP was deployed to solve sub-level multiple attribute decisions. The proposed model converted criteria affecting the criticality of an item into a single score and assigned items into three different categories. Although the research did not focus on developing a new theoretical classification method but rather provided a suitable classification model for a real case study, it might be generalized to be implemented to other cases in similar industries. Mohammaditabar, Ghodsypour, and O'Brien (2012) developed an integrated model to categorize inventory items as classes A, B, and C using a simulated annealing method. Using all criteria of items, the algorithm defined a dissimilarity index for each pair of items and minimized it in another objective function. A weighted sum of two functions updated according to a current solution. The algorithm was applied to the same data of Reid (1987), and was compared with traditional ABC and with a few other models studied the same data. The model produced better results in terms of dissimilarities and total inventory costs. In a similar vein, Kartal and Cebi (2013) presented an SVM application in the classifying inventory of automobile company using multi-attribute ABC analysis based on the SAW method in a recent study. The study found out that SVMs is successfully applicable to the problem considering the classification accuracies based on examinations of the training set, cross-validation, and percentage splits (Kartal & Cebi, 2013). More recently, as well as presenting a computationally efficient procedure to adjust criteria weights, Hatefi, Torabi, and Bagheri (2014) suggested a modified linear optimization approach to conduct multi-criteria ABC analysis effectively working under the condition of co-existing qualitative and quantitative criteria which eliminating the subjectivity of decision makers.

## 3. Research objectives and methodology

The purpose of this research is to examine the extent to which MCDM methods in combination with data analytic models can be utilized in the ABC analysis. The performance of Bayes networks, naïve Bayes, ANN, and SVM algorithms is evaluated and the accu-

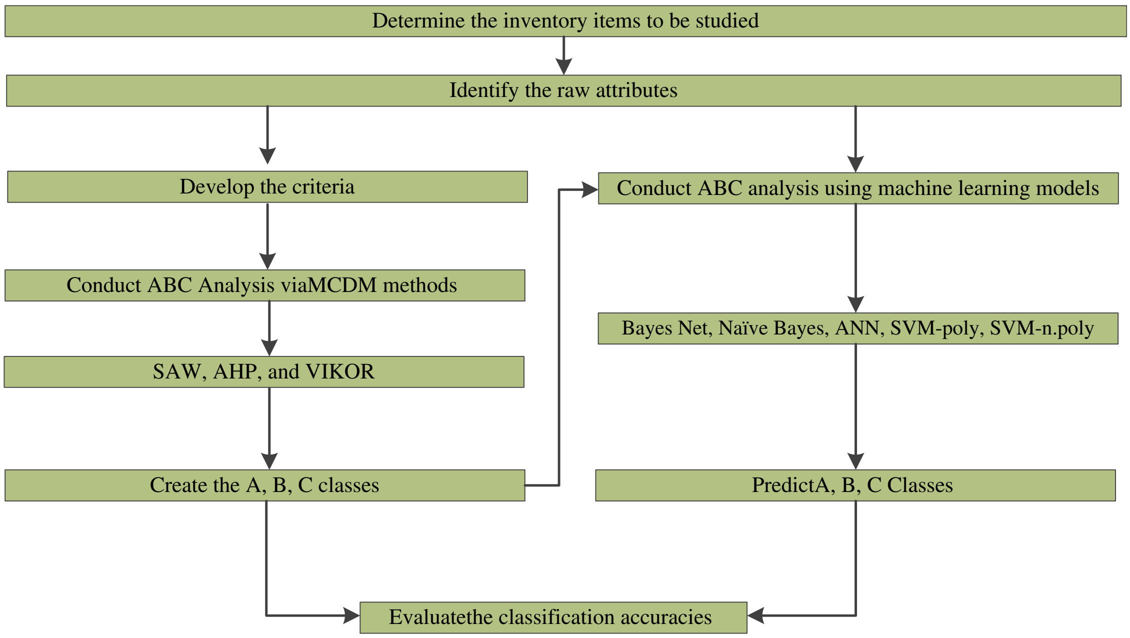


**Fig. 1.** Flowchart of the proposed methodology steps.

racy of the classifications they produce within a real case study that examine an inventory analysis problem is compared. The first step of the study involves identifying the inventory items that are to be analyzed before determining the raw attributes that would derive the decision criteria. These criteria set the foundation for the MCDM methods (i.e., SAW, AHP, and VIKOR) to conduct the ABC analysis. Once the data is organized and the criteria identified, SAW-, AHP- and VIKOR-based MCDM methods are applied to the inventory items to identify the A, B, and C classes of the inventory. Following this, machine learning algorithms are employed using the inventory classes that are initially identified by the MCDM methods. The algorithms are trained and tested using the previously determined classes. Cross-validation and random percentage split tests are utilized to identify the accuracy with which each algorithm is able to classify the items in the inventory. A flowchart of the proposed methodology is depicted in Fig. 1.

## 4. The review of the integrated methods

In this section, methods which are used in the proposed hybrid methodology are briefly reviewed. First, three different MCDM methods (SAW, AHP, and VIKOR) that are widely applied multi-attribute decision-making methods and employed in this study are summarized. Then, the machine learning algorithms that are employed and compared in the study (i.e. Bayes classifiers, ANNs, and SVMs) are reviewed. While algorithms like ANN and SVM are commonly used techniques for classification purposes, Bayes classifiers like the naïve Bayes and Bayesian networks are also popular techniques within machine learning applications (Soria, Garibaldi, Ambrogi, Binganzoli, & Ellis, 2011).

### *4.1. Multi-criteria decision making methods for classification*

Each MCDM method has its own strengths and weaknesses; some have no adaptability to certain kinds of criteria or various levels of measurement, some are incapable of incorporating human judgment into the model, and some are computationally intensive. SAW, AHP, VIKOR, (Kaya & Kahraman, 2010; Chithambaranathan, Subramanian, Gunasekaran, & Palaniappan, 2015), ELECTRE and PROMETHEE (Corrente, Greco, & Słowiński, 2013) are among widely used MCDM methods. Among those MCDMS, with the purpose of application in this study, AHP is the most useful and the fundamental method under this current scenario since it easily allows conducting a "group decision making". This study also included SAW and VIKOR as two comparative methods.

#### *4.1.1. Simple Additive Weighting (SAW)*

The SAW method (a.k.a weighted linear combination or scoring method) is a commonly used method for multi-criteria decision making (Chen, 2012). The SAW is one of the most straightforward techniques to model MCDM problems. The method uses the weighted criterion values to evaluate an alternative. An evaluation score is calculated for each alternative. The weights of the criteria are multiplied with the scaled values of a given alternative, and then each alternative is ranked in order to compute an overall evaluation score. The weights of the relative importance may directly be assigned by decision makers (Afshari, Mojahed, & Yusuff, 2010).

The utility of the $i$th alternative, $u_i$ is calculated by Eq. (1) where $w_j$ refers to the weight of the $j$th criterion, $r_{ij}$ denotes the normalized preferred score of the $i$th alternative for the$j$th criterion;

$$u_i(x) = \sum_{j}^{n} w_j r_{ij}(x) \tag{1}$$

For an given alternative, a bigger preference value is more likely to score higher. The best alternative $A^*$ is provided by Eq. (2) (Churchman & Ackoff, 1954) where $x_j^*$ is the desired level or the maximum of $x_{ij}$, in which the normalized preferred rating with respect to $j$th criterion for the $i$th alternative equals to $x_{ij}/x_j^*$. Hence, $r_{ij}$ gets a value between 0 and 1 whereas the rank of alternative is determined with respect to overall evaluation values, i.e. utilities.

$$A^* = \{u_i(x_j^*) | \max_i u_i(x_{ij}) | i = 1, 2, \ldots, n\} \tag{2}$$

#### *4.1.2. Analytical Hierarchy Process (AHP)*

Analytical Hierarchy Process is one of the most popular MCDM methods invented by Saaty (1980) and it has been applied to numerous areas in decision making problems with respect to selecting among alternatives including planning, allocating resources, and resolving conflicts. The main powerful feature of AHP is its ability to combine multiple criteria while effectively evaluating subjective opinions of decision-makers. This ability makes it applicable to combine it with other methodologies (Datta, Sambasivarao, Kodali, & Deshmukh, 1992; Subramanian & Ramanathan, 2012). Hence, there is a wide range of literature about the applications of AHP (Flores & Whybark, 1987). A comprehensive review on applications of AHP in operations management was released by Subramanian and Ramanathan (2012), which systematically categorizes the published literature between 1990 and 2009.

The process is simply based on expert judgments, pair-wise comparisons, and assigning relative weights to the criteria (Molenaers et al., 2012). A decision maker or makers determine both the importance of criteria and alternatives. A ratio scale from 1 to 9 is used to evaluate relative importance via pair-wise comparison matrices (Saaty, 1980). The overall score of each alternative is computed via the normalized eigenvector of the priority matrix (Molenaers et al., 2012). A detail description of AHP can be found in Saaty (1980).

#### 4.1.3. VIKOR

VIKOR method is a compromise multi-attribute ranking method first applied to a multi-objective optimization problem (Duckstein & Opricovic, 1980), then appeared with the name VIKOR as an abbreviation of Vise Kriterijumska Optimizacija Kompromisno Resenje (Opricovic, 1998). Later, a comparative analysis (2004) and an extended version of the method were released by Opricovic and Tzeng (2007). VIKOR evaluates every alternative with respect to each criterion assuming that an order of consensus may be established (Opricovic & Tzeng, 2004). After determining and evaluating the alternatives, the VIKOR is applied to rank the alternatives and to provide a solution to decision makers (Opricovic & Tzeng, 2007). VIKOR uses an aggregating function ($L_p - metric$) in a compromise programing, where $1 \leqslant p \leqslant \infty; i = 1, 2, \ldots, n;\ j = 1, 2, \ldots, J$ (Yu, 1973; Zeleny, 1982; Opricovic & Tzeng, 2004):

$$L_{pj} = \left\{ \sum_{i=1}^{n} \left[ w_i (f_i^* - f_{ij}) / (f_i^* - f_i^-) \right]^p \right\}^{1/p} \quad (3)$$

where $i$ and $j$ denote the $i$th criterion and the$j$th alternative, and $w_i$ is the weight of $i$th criterion, the main steps of the method may be summarized as follows (Opricovic & Tzeng, 2004; Wei & Lin, 2008):

i. Determine the best function values ($f_i^*$, maximum of $f_{ij}$) and worst function values ($f_i^-$, minimum of $f_{ij}$) for each attribute.
ii. Compute the $S_j$ and $R_j$ values using Eqs. (4) and (5).

$$Sj = \sum_{j=1}^{n} w_i (f_i^* - f_{ij}) / (f_i^* - f_i^-) \quad (4)$$

iii. $R_j = \max_i \left( w_i (f_i^* - f_{ij}) / (f_i^* - f_i^-) \right),$ (5)

Compute the $Q_j$ value for each alternative using Eq. (6) where $S^*$ is the minimum of $S_j$; $S^-$ is the maximum of $S_j$; and $R^-$ is the maximum of $R_j$

$$Q_j = v(S_j - S^*)/(S^- - S^*) + (1 - v)((R_j - R^*)/(R^- - R^*)) \quad (6)$$

Here, $v$ is a compromise attitude value of expert evaluations as a weighting strategy for the criteria or considered as the maximum group utility; and usually $v = 0.5$ is preferable.
iv. Rank the $S$, $R$, and $Q$ values in descending order.
v. Test the results for acceptance with respect to two conditions:

First, the difference between the $Q_j$ values of the best two alternatives should be bigger than $D(Q) = 1/(J - 1)$ as shown by Eq. (7). Second, the alternative which has the minimum $Q_j$ value must have the highest value for at least one of its $S_j$ and $R_j$ values.

$$Q(p_2) - Q(p_1) \geqslant D(Q) \quad (7)$$

vi. If one of the conditions in step (v) is not satisfied, the condition in Eq. (8) must be satisfied to confirm the acceptance of the results.

$$Q(p_M) - Q(p_1) < D(Q) \quad (8)$$

where $p_M$ is the alternative in the $M$th position of the ranked $Q_j$ list. This condition must be satisfied for the maximum $M$.

### 4.2. Machine learning algorithms for classification

#### 4.2.1. Bayes classifiers

Bayes classifiers are probabilistic classifier algorithms based on Thomas Bayes' basic law of probability which is known as Bayes theorem that is shown in Eq. (9).

$$P(A/B) = \frac{P(B/A) \times P(A)}{P(B)} \quad (9)$$

Eq. (9) presents the relationship between the probabilities and the conditional probabilities of $A$ and $B$. A naïve Bayes classifier is a simple algorithm with the assumption of independent attributes, which means the algorithm assumes that attributes do not affect each other by means of probability. For a given series of $n$ attributes, a naïve Bayes classifier makes calculations with $2n!$ independent assumptions. Despite its simplicity and limitations, conventional naïve Bayes is still a widely used learning algorithm for classification (Soria et al., 2011). Indeed, it is a particular case of Bayesian networks (Friedman, Geiger, & Goldszmidt, 1997).

Bayesian networks are rather sophisticated algorithms to analyze probabilities under uncertainty and therefore, they allow capturing more complex information from the data analyzed. Thus, in particular, cases where Naïve Bayes classifiers perform poorly, a Bayesian Network might be expected to achieve better learning outcomes (Friedman et al., 1997). Bayesian Network encodes probabilistic relationships for a set of interest nodes in uncertain conditions using graphical models. A graphical model represents knowledge about uncertain nodes and provides a qualitative structure showing relationships between corresponding variables, a user, and a system incorporating the probabilistic model (Lockamy & McCormack, 2010).

#### 4.2.2. Artificial neural network

Artificial neural network is a learning algorithm which is capable of solving classification problems. An ANN model is composed of a number of parallel, dynamic, and interconnected neuron network systems. A neuron operates a defined mathematical processor using inputs to produce outputs (Ko, Twari, & Mehmen, 2010). By parallel processing of multiple inputs, the network may determine the relationships between variables (Hamzacebi, Akay, & Kutay, 2009).

A typical multilayer ANN can be described as follows (Partovi & Anandarajan, 2002). Output layer neurons get a summation function (or transfer function) and determines degrees to which sum is important to producing outputs. For a certain neuron, when an input vector is defined as $x = [x_1, x_2, \ldots, x_n]$ and a weight vector as $w = [w_1, w_2, \ldots, w_n]$, the summed transfer function is described with $f$ given by Eq. (10).

$$f\left(\sum_{i=1}^{n} w_i x_i\right) \tag{10}$$

A typical neuron has more than one output, and the sum of the outputs goes into this transfer function that serves as an activation switch with regard to the inputs (Partovi & Anandarajan, 2002). Although various types of transfer functions such as unit step (threshold), piecewise linear, sigmoid, and Gaussian are commonly used, the selection of the function depends on the input characteristics into the neural network as in Eq. (11).

$$f(w'x) = 1/(1 + e^{(-w'x)}) \tag{11}$$

Among these transfer functions, the sigmoid which is a very basic non-linear function as a composition of logistic and tangential functions is one of the most common because its output is continuous and ranges from 0 to 1 (Zahedi, 1993). Due to the increasing complexity of problems, it is expected that multilayer ANNs are to be used for multi-attribute inventory classification (Partovi & Anandarajan, 2002).

### 4.2.3. Support vector machines

SVMs are one of the most popular machine learning methods developed by Vladimir Vapnik based on statistical learning theory (Cortes & Vapnik, 1995). SVM is a supervised learning algorithm, which may perform classification using priory defined categories or regression (hence sometimes called support vector regression) (Vapnik, 1998; Lu & Wang, 2010). Due to its useful features and promising empirical performance, SVM algorithm is gaining more popularity (Cho, Asfoura, Onar, & Kaundinya, 2005). It tends to perform better for the under complex problems of production and supply chain due its strong features and the use of variety of kernels. Its structural risk minimization (SRM) feature shows superiority to other traditional empirical risk minimization (ERM)-based methods by allowing a reduction in both classification error and model's structural complexity. SRM minimizes the expected risk of an upper bound while ERM minimizes the error of the training data. Hence, SVMs provide a good generalization performance with a higher computational efficiency in terms of speed and complexity, then easily deals with multi-dimensional data (Cho et al., 2005). In addition, SVM works relatively well under many circumstances even when there is a small sample dataset (Cristianini & Shawe-Taylor, 2000).

SVM classifier takes the inputs of different classes, and then builds input vectors into a feature space to find the best separating hyperplane. The hyperplane which places at the maximum distance from the nearest points of the dataset is defined as optimal. (Kecman, 2005; Shiue, 2009). The points which identify optimal hyperplane to separate different classes in a data set are named *support vectors*. These are critical elements to train the classifying algorithm (Kecman, 2005). In a feature space, to find the optimal hyperplane, Lagrange multipliers are introduced to solve a quadratic problem. SVM's classification process is briefly reviewed as follows:

For a basic two-class classification problem, in a given data set, where $\boldsymbol{x}_i$ is a feature vector of the $i$th example in training set; $y_i$ is an indicator output in a form of binary value corresponding to the $i$th example, $y_i$ would be described as in Eq. (12).

$$y_i = \begin{cases} +1 & \text{if } \mathbf{x_i} \text{ in class 1} \\ -1 & \text{if } \mathbf{x_i} \text{ in class 2} \end{cases} \tag{12}$$

When condition (12) is considered for all pairs of ($\boldsymbol{x}_i$, $y_i$) for $i = 1, 2, \ldots, m$, where $m$ is the number of training items, the set expression would be followed by Eq. (13).

$$\left\{(\mathbf{x_i}, y_i) | x_i \in R^N, y_i \in \{-1, 1\}\right\}_{i=1}^{m} \tag{13}$$

where $\boldsymbol{w}$ is an $N$ dimensional weight vector and $b$ is a bias, for the given set separating hyperplane of parameters $\boldsymbol{w}$ and $b$ would be written as in Eq. (14).

$$\mathbf{w}^T\mathbf{x_i} + b = 0 \tag{14}$$

Then following inequalities in Eq. (12) classify vectors in two sides of the hyperplane.

$$\mathbf{w}^T\mathbf{x_i} + b > 0 \quad \text{for } y_i = +1 \tag{15a}$$

$$\mathbf{w}^T\mathbf{x_i} + b < 0 \quad \text{for } y_i = -1 \tag{15b}$$

However, to separate the given set, there are many possible choices of $\mathbf{w}$ and b referring to a different hyperplane. SVMs maximize the distance between the hyperplane and the closest points in the set. These closest points are called support vectors, and parallel lines on these points on both sides of the hyperplane are called boundaries. In other words, to find the optimal hyperplane, SVMs classify data points by maximizing the region between the boundaries, which is called "margin". Since no data points are desired between the boundaries, possible outputs are constrained to Eqs. (16a) and (16b) with a normalized maximum margin.

$$y_i(\mathbf{w}^T\mathbf{x_i} + b) \geqslant +1 \quad \text{for } i = 1, 2, \ldots, m \tag{16a}$$

$$y_i(\mathbf{w}^T\mathbf{x_i} + b) \geqslant -1 \quad \text{for } i = 1, 2, \ldots, m \tag{16b}$$

These two equations can be combined into a single equation simply by multiplying Eq. (16b) with $(-1)$ as in Eq. (17).

$$y_i(\mathbf{w}^T\mathbf{x_i} + b) \geqslant +1 \tag{17}$$

The distance of the margin can be described by $2/\|w\|$ which is equal to $2/\sqrt{\mathbf{w}^T\mathbf{w}}$. Since minimization is usually preferred for optimization problems, its reciprocal is to be minimized, $(1/2)\sqrt{\mathbf{w}^T\mathbf{w}}$. Also, since the square root function is an increasing function, to simplify the optimization, the square root can be removed. Then, the optimal hyperplane can be achieved by a quadratic optimization problem which minimizes $\frac{1}{2}\mathbf{w}^T\mathbf{w}$. Therefore, for the optimal hyperplane, the quadratic problem model can be formed as in Eq. (18).

$$\min_{w,b} \frac{1}{2}\mathbf{w}^T\mathbf{w}$$

$$\text{s.t. } y_i(\mathbf{w}^T\mathbf{x_i} + b) \geqslant 1 \quad \text{for } i = 1, 2, \ldots, m \tag{18}$$

where $\alpha_i$ are non-negative Langrage multipliers for $i = 1, 2, \ldots, m$, this model can be solved by determining the solution of the dual problem based on Karush–Kuhn–Tucker conditions shown in Eq. (19):

$$\max \sum_{i=1}^{m} \alpha_i - \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{m} \alpha_i \alpha_j y_i y_j \mathbf{w}^T\mathbf{x}_j$$

$$\text{s.t. } \sum_{i=1}^{m} \alpha_i y_i = 0, \quad \text{and} \quad i = 1, 2, \ldots, m \tag{19}$$

This is the simplest problem of SVM assuming a linearly separable dataset. However, in real-life situations, most data sets cannot simply be linearly separable. Hence, a penalty parameter ($C$) allowing some training errors can make the separation feasible (Cristianini & Shawe-Taylor, 2000). In addition, a *kernel trick* makes separation easier by mapping the original feature space onto a higher dimensional feature space (Vapnik, 1998). The trick reduces the complexity of the problem, which is formed as in function $K$ of Eq. (20).

$$K(x_i, x_j) = \varphi(x_i)^T \varphi(x_j) \tag{20}$$

Polynomial kernel, Gaussian radial basis function as in Eq. (21), and sigmoid function as in Eq. (22) are amongst the most commonly used kernel functions.

$$K(x_i, y_j) = ((x_i, y_j) + 1)^p \tag{21}$$

$$K(x_i, y_j) = \exp\left(-\|(x_i - y_j)\|^2 / 2\sigma^2\right) \tag{22}$$

When the $C$ parameter and a kernel function is imposed, the problem transforms into a new quadratic model as shown in Eqs. (23) and (24).

$$\max \sum_{i=1}^{m} \alpha_i - \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{m} \alpha_i \alpha_j y_i y_j \varphi(\mathbf{x}_i)^T \varphi(\mathbf{x}_j) \tag{23}$$

$$\text{s.t.} \sum_{i=1}^{m} \alpha_i y_i = 0, \quad 0 \leqslant \alpha_i \leqslant C \text{ and } i = 1, 2, \ldots, m \tag{24}$$

When the dual problem is solved, the optimal hyperplane is determined. More detailed information about SVM algorithms and applications can be found in Vapnik (1998), Cristianini and Shawe-Taylor (2000), and Kecman (2005).

## 5. Case study

This study was conducted at one of the largest international automotive production companies located in Turkey. The production facility includes various warehouses which handle numerous inventories. Of these, the industrial inventory warehouse holds inventory items that have historically unpredictable demand, such as cutting tools, hand tools, safety equipment, chemical materials, building materials, packaging materials, cleaning and any other supplies, and consumables. The inherent in unpredictable nature of these items entails that it is hard to manage demand and determine inventory requirements. In this real case study, various multi-attribute inventory analysis techniques were applied to the problem. First, MCDM classification methods were implemented to sort the 715 different items in the warehouse. Following this, machine learning methods were deployed to perform the prediction for the multi-attribute inventory analysis. Each item had various characteristics in terms of inventory management processes. Seven items were omitted from the analysis due to missing values. The characteristics of a sample inventory are illustrated in Table 1 as raw attributes while Table 2 provides a description of each attribute.

In order to make models simpler and pairwise comparisons easier, before applying SAW, AHP, and VIKOR based multi-attribute inventory classification methods to the problem, some of the related raw attributes were combined as criteria. To make calculations possible, any verbal expressions were quantified via numerical values based on discussions with engineers of the related department in the company. While these criteria and combined attributes are shown in Table 3 with their directly assigned additive weights, the transformation of verbal expressions to numeric are illustrated in Table 4.

Main characteristics which were derived from raw attributes, criteria (i.e. criticality, demand, and supply), unit cost, and unit size were applied to the MCDM classification models.

*Criticality* was determined as a combination of *risk* and *demand fluctuation* attributes. It indicates the importance of stock items in terms of pending and projected manufacturing steps (Flores et al., 1992). There are many types of risks that might result from the supply chain or similar production processes. Although the term "risk" is vague and often poorly defined, it is a frequently used term both in daily language and among supply chain terminologies. This is mainly because mostly the origin or results of the risk are not easily determined (Heckmann, Comes, & Nickel, 2015). Here in this current study's context, the *risk* attribute describes the level of operational criticality for an item with verbal expressions (i.e. high, medium, or low). The attribute *demand fluctuation* refers to a verbal expression to define the type of recent fluctuations in demand for an item (Bacchetti, Plebani, Saccani, & Syntetos, 2013; Molenaers et al., 2012).

*Demand* criterion was described as the combination of daily usage and average stock attributes. It consists of both the usage amount of an item and amount of its stock (Cebi et al., 2010). The higher the daily usage and the higher the average stock, the higher the demand.

*Supply* characteristic, a value based on the relative importance of supplying an inventory item, was derived from the combination of attributes "lead time" and "consignment" (Bylka, 2013; de Matta, Lowe, & Zhang, 2014)). The attribute *lead time* was considered as the average time interval between ordering and receiving an order of an item in the last year inventory record of the company (Cebi & Kahraman, 2012). The inventory in the industrial material warehouse is a group of inventory that consists of items of which supplication time is significant (Lockamy & McCormack, 2010).

To achieve a reduced inventory cost and supplying problems, some companies work with the third party logistic firms (Basligil, Kara, Alcan, Ozkan, & Caglar, 2011) or use vendor-managed inventory (VMI) (Lee & Ren, 2011; Zanoni, Jaber, & Zavanella, 2012). Similar to these practices, the current company in this study places some of its inventory in the warehouse without owning them. This inventory, which is in the warehouse but is still owned by the supplier, is called consignment stock (CS) (Bylka, 2013). The attribute "*consignment stock*" determines whether or not an item is a consignment inventory (de Matta et al., 2014). Consignment stocks are contracted with vendors and are subject to treatments similar to vendor managed inventory (VMI) (Stålhane, Andersson, Christiansen, & Fagerholt, 2014). Because this case study company does not own consignment items, they are in secondary impor-

**Table 1**
Raw attributes and a sample list of the inventory data.

| ID | Risk | Demand fluctuation | Average stock | Daily usage | Unit cost | Lead time | Consignment stock | Unit size |
|---|---|---|---|---|---|---|---|---|
| 1 | Low | Stable | 62 | 1.06 | 0.49758 | 19 | Yes | Small |
| 2 | Low | Stable | 6 | 0.05 | 0.41922 | 21 | No | Small |
| 3 | Low | Decreasing | 48 | 1.73 | 1.75395 | 22 | Yes | Small |
| 4 | Low | Stable | 9 | 0.36 | 0.10877 | 17 | No | Small |
| 5 | Low | Decreasing | 91 | 1.2 | 0.4933 | 17 | Yes | Small |
| 6 | Low | Decreasing | 123 | 1.01 | 0.4933 | 17 | Yes | Small |
| . | . | . | . | . | . | . | . | . |
| 712 | Low | Stable | 12 | 0.004 | 7 | 0 | No | Large |
| 713 | Low | Stable | 18 | 0.004 | 7 | 0 | No | Large |
| 714 | Low | Stable | 4 | 0.004 | 7 | 0 | No | Large |
| 715 | Normal | Stable | 91 | 0.53 | 0.95418 | 17 | No | Medium |

**Table 2**
Descriptions of raw attributes.

| Raw attributes | Description | Measurement scale |
|---|---|---|
| Risk | Operational criticality level for an item | High, medium, low |
| Demand fluctuation | Type of recent fluctuations in demand for an item | Increasing, stable, unknown decreasing, ending |
| Average stock | Average amount of current holding units | Numeric value > 0 |
| Daily usage | Daily average unit usage amount of an item | Numeric value > 0 |
| Lead time | Average time interval between ordering and receiving an order for an item | Numeric value >= 0 |
| Consignment stock | Whether an inventory which is in warehouse but is still owned by the supplier | Yes, no |
| Unit cost | Purchasing cost of an item to the company as an amount of money | Numeric value > 0 |
| Unit size | Size of an item 's volume occupied in storage | Large, medium, small |

**Table 3**
Combined attributes and additive weights.

| Criteria | Combined attributes | Additive weights |
|---|---|---|
| Criticality | Risk | 0.78 |
| | Demand fluctuation | 0.22 |
| Demand | Daily usage | 0.71 |
| | Average stock | 0.29 |
| Supply | Lead time | 0.75 |
| | Consignment | 0.25 |

**Table 4**
Transformation (verbal to normalized numeric).

| Attribute | Verbal expression | Assigned value | Normalized value |
|---|---|---|---|
| Risk | High | 8 | 0.47 |
| | Normal | 6 | 0.35 |
| | Low | 3 | 0.18 |
| Demand fluctuation | Increasing | 90 | 0.36 |
| | Stable | 70 | 0.28 |
| | Unknown | 50 | 0.20 |
| | Decreasing | 40 | 0.16 |
| | Ending | 0 | 0.00 |
| Consignment stock | No | 4 | 0.80 |
| | Yes | 1 | 0.20 |
| Unit size | Large | 8 | 0.53 |
| | Medium | 5 | 0.31 |
| | Small | 2 | 0.13 |

tance and only make a small contribution to the supply importance of an item. A bigger value for the attribute "supply" requires a higher level of importance in inventory management and more care due to the safety of supply and providing desired service level from storage to the production process (Aissaoui, Haouari, & Hassini, 2007).

*Unit cost* is one of the most important characteristics of inventory management (Mohammaditabar et al., 2012). Here, it is considered as the purchasing price of an item to the company (Flores et al., 1992; Cebi et al., 2010).

*Unit size*, which was derived from the attribute for "unit volume", is the last creation. It refers to the volume occupied by an item in the warehouse (Schmid, Doerner, & Laporte, 2013). An item which requires a larger space gets a higher value for the storage creation.

### 5.1. Implementing SAW-based MCDM method

First, to implement the SAW method, simple weights for each attribute were directly determined by personal judgments of industrial engineers who are in charge of warehouse management. Then the utility formula as in Eq. (1) of Section 4 and the data was integrated. After the integration, alternatives were ranked in descending order with respect to their overall utility scores. Simply, for each item, criteria values were multiplied with associated weights and summed to be ranked.

Once SAW scores and ranks were obtained, items were assigned into classes according to Pareto's 80–20 rule (Cebi & Kahraman, 2012). The items in the top 20% were determined as class A, the bottom 50% determined as class C and the middle 30% determined as class B (Kartal & Cebi, 2013). For some sample data, scores and assigned classes are illustrated on Table 5.

### 5.2. Implementing AHP-based MCDM method

A decision matrix to compare the importance of attributes was filled by decision makers, and the group decision was calculated by using geometric mean. Consistency ratio of the matrices was calculated to test the validity. Due to the consistency ratio of 3.16% as being below the rule of thumb threshold of 10%, the decisions were considered to be valid. Group decision matrix and the determined weights for each attribute are shown in Table 6.

After the validation, normalized data, and the weights were used to provide total weighted-points for each inventory item. Then the items were sorted in descending order. Hence, A, B or C inventory classes were assigned to items by the Pareto's principle. Some examples of ranking and classes of items using AHP method are shown in Table 7.

**Table 5**
Sample ranking and classes of items using the SAW method.

| ID | SAW score | Cumulative SAW score | Cumulative % of items | Class |
|---|---|---|---|---|
| 701 | 0.3014 | 2.7464 | 1.89 | A |
| 252 | 0.2434 | 34.8081 | 23.98 | A |
| ... | ... | ... | ... | ... |
| 81 | 0.2388 | 40.3441 | 27.79 | B |
| 616 | 0.2146 | 60.1244 | 41.42 | B |
| 559 | 0.2032 | 82.0373 | 56.52 | B |
| ... | ... | ... | ... | ... |
| 135 | 0.2025 | 85.2853 | 58.75 | C |
| 109 | 0.1860 | 105.3443 | 72.57 | C |
| 356 | 0.1729 | 121.0256 | 83.37 | C |
| 292 | 0.1522 | 138.8954 | 95.68 | C |
| 494 | 0.1080 | 145.1605 | 100.00% | C |

**Table 6**
AHP group decision matrix and determined weights.

| Attribute | Criticality | Cost | Supply | Demand | Unit size | Weights |
|---|---|---|---|---|---|---|
| Criticality | 1.00 | 2.47 | 2.76 | 2.90 | 0.89 | 0.33 |
| Unit cost | 0.41 | 1.00 | 0.69 | 0.69 | 0.58 | 0.12 |
| Supply | 0.36 | 1.44 | 1.00 | 1.44 | 1.00 | 0.18 |
| Demand | 0.34 | 1.44 | 0.69 | 1.00 | 1.00 | 0.15 |
| Unit size | 1.13 | 1.71 | 1.00 | 1.00 | 1.00 | 0.22 |

**Table 7**
Sample ranking and classes of items using the AHP method.

| ID | Descending weighted sums | Cumulative weighted sums | Percentage of cumulative weighted sums | Cumulative number of items | Cumulative percentage of items | Inventory classes |
|---|---|---|---|---|---|---|
| 485 | 0.4094 | 0.4094 | 0.28% | 1 | 0.14% | A |
| 442 | 0.4085 | 0.8179 | 0.55% | 2 | 0.28% | A |
| . | . | . | . | . | . | . |
| 288 | 0.2468 | 37.8842 | 25.63% | 142 | 20.06% | B |
| 214 | 0.2466 | 38.1308 | 25.80% | 143 | 20.20% | B |
| 240 | 0.2464 | 38.3772 | 25.96% | 144 | 20.34% | B |
| . | . | . | . | . | . | . |
| 699 | 0.2089 | 85.4284 | 57.79% | 355 | 50.14% | C |
| 97 | 0.2089 | 85.6373 | 57.93% | 356 | 50.28% | C |
| 377 | 0.1137 | 147.6061 | 99.85% | 706 | 99.72% | C |
| 122 | 0.1117 | 147.7177 | 99.93% | 707 | 99.86% | C |
| 494 | 0.1114 | 147.8291 | 100.00% | 708 | 100.00% | C |

### 5.3. Implementing VIKOR-based MCDM method

In this study, the final multi-attribute method applied for the ABC analysis is VIKOR. The relative importance of each attribute had already been determined via the AHP method earlier. The same attribute weights were taken as the weights for the VIKOR method and ranking were obtained by sorting $S$, $R$, and $Q$ values of the items. In the final stage, to categorize stock items into classes A, B, and C; Pareto's rule is deployed in a similar way to SAW and AHP methods. In this method, attribute weights refer to the parameters. After the normalization for each attribute the best value $fi^*$ and the worst value $fi-$ were determined due to the explanations in Section 4. All the five attributes considered as positive values with respect to their decreasing effect on the importance of inventory in terms of managerial issues. Applied weights and the calculated best and worst values are seen in Table 8.

In this step, the distances from each value to the best value were computed according to Eq. (6). Then the values were summed to determine the final values. As in general, v was taken as equal to 0.5. $S^*$ and $S^-$ were determined to be 0.355 and 0.755, $R^*$ and $R^-$ were calculated as 0.1271 and 0.33 by using Eqs. (4) and (5) in Section 4. As the last step, $Q$ values of VIKOR were calculated by Eq. (6) and the items were ranked in ascending order. Since the results meet conditions (7) and (8) in Section 4, the ranking was considered to be acceptable. Finally, Pareto's principle was applied to the items to determine inventory classes. Sample ranking and inventory classes of the classified items are in Table 9.

**Table 9**
Sample ranking and classes of items using the VIKOR method.

| $j$ | $Qj$ | Cumulative number of items | Cumulative percentage of items | Inventory classes |
|---|---|---|---|---|
| 442 | 0.0000 | 1 | 0.14% | A |
| 485 | 0.0930 | 2 | 0.28% | A |
| ... | ... | ... | ... | ... |
| 49 | 0.3104 | 142 | 20.06% | B |
| 331 | 0.3114 | 143 | 20.20% | B |
| 484 | 0.3122 | 144 | 20.34% | B |
| ... | ... | ... | ... | ... |
| 95 | 0.4177 | 355 | 50.14% | C |
| 356 | 0.4183 | 356 | 50.28% | C |
| 3 | 0.9940 | 706 | 99.72% | C |
| 6 | 1.0000 | 707 | 99.86% | C |
| 5 | 1.0000 | 708 | 100.00% | C |

### 5.4. Implementation of machine learning algorithms

This application implemented the machine learning algorithms to conduct the ABC inventory analysis. Eight different attributes (risk, demand fluctuation, average stock, daily usage, unit cost, lead time, consignment stock, and unit size) were taken as inputs, and classes of the items determined by the initial MCDM methods were selected as outputs.

A Bayesian network is a network structure which is a directed acyclic graph (DAG) over a set of variables represented by a group of probability distributions. There are various software technologies which are nicely designed with the ability to conduct systematic experiments to compare the performance of Bayes nets over other general purpose classifiers like support vector machines, and artificial neural networks (Bouckaert, 2008). In this study, BayesNet classifier algorithm was implemented for the Bayesian Network. Bayes Network learning uses various search algorithms and quality metrics. Here, K2 search algorithm was used with the simple estimator which produces direct estimates of the conditional probabilities. With $\alpha$ parameter set to 0.5, it uses *maximum likelihood* estimates. Without a visualization of the network graph itself, but detailed accuracy outcomes were evaluated in this case study. Then in order to measure the performance of Bayes Net, Naive Bayes, ANN, SVM-poly kernel, and SVM-normalized poly kernel algorithms, classification accuracy measures were considered for each method.

**Table 8**
The weights and the calculated best and worst values.

| $i$ | $Wi$ | $fi^*$ | $fi-$ |
|---|---|---|---|
| 1 | 0.33 | 0.1500 | 0.05794800 |
| 2 | 0.12 | 0.1200 | 0.00000034 |
| 3 | 0.18 | 0.1800 | 0.00000030 |
| 4 | 0.15 | 0.1340 | 0.00750000 |
| 5 | 0.22 | 0.1232 | 0.02860000 |

## 6. Results and discussion

At first, 10-fold cross-validated accuracies of each of the algorithm deployed were calculated. Those accuracies are compared and contrasted to the random splitting of the data (i.e. 66.66% of training set vs. 33.33% of the testing set) which is also known as percentage split. Classification accuracies of the algorithms via each performance mode for all MCDM methods are tabulated in Table 10.

In terms of performance across the whole test-bed, Naïve Bayes classifier was the least accurate with an average of 62.09% accuracy. The Bayes Net algorithm was the second lowest performer, with an average of 75.36% overall accuracy. Although in terms of a number of performance metrics ANN demonstrated slightly superior accuracy than the SVM-normalized poly kernel, as a result of its overall performance it was positioned in the middle of the accuracy range, with an accuracy of 85.30%. SVMs outperformed

**Table 10**
Accuracies of algorithms by classification method.

| Classification method | Accuracy performance type | Accuracy for each algorithm (%) | | | | |
|---|---|---|---|---|---|---|
| | | Naive Bayes | Bayes Net | ANN | SVM poly | SVM n.poly |
| SAW based | Cross validation | 59.46 | 76.41 | 84.88 | 88.41 | 84.89 |
| | Percentage split | 58.09 | 65.14 | 78.44 | 90.45 | 86.31 |
| AHP based | Cross validation | 63.27 | 73.58 | 86.44 | 91.94 | 86.72 |
| | Percentage split | 62.65 | 65.97 | 70.95 | 92.53 | 85.48 |
| VIKOR based | Cross validation | 74.71 | 86.15 | 95.62 | 94.49 | 95.06 |
| | Percentage split | 54.35 | 84.89 | 95.43 | 93.77 | 95.44 |

all models in terms of their ability to accurately classify the inventory items in this case study. The SVM-poly kernel demonstrated the highest rate of accuracy with an average of 91.93% and the SVM-normalized poly kernel is positioned the second best with an average accuracy of 88.99% as illustrated in Table 11.

As Table 11 indicates, the classification algorithms deployed within the proposed methodology demonstrated an ability to predict the ABC classification of inventory items with high accuracy. However, the inherent nature of the inventory classification problem (A, B, C classes) results in a number of imbalanced classes. Existing research indicates that machine learning methods do not perform very well with such imbalanced data sets (Visa & Ralescu, 2005; Weiss & Provost, 2003). Table 12 tabulates the number of the items in each class of the original inventory data.

When the algorithms were trained with unbalanced class distribution, machine learning algorithms tend to predict in favor of majority class by assuming equal misclassification cost and/or balanced class distribution. There are different strategies for sampling in literature such as under-sampling, over-sampling, and synthetic minority over-sampling technique or stratified sampling for classification problems with machine learning algorithms (Hens & Tiwari, 2012) Yet, ABC inventory classification problem in its nature has the Pareto assumption for class distribution and this does not allow analysts directly to make all the data balanced. Therefore, it is needed to distinguish training set and testing set. From a given data set, it is possible to create an evenly distributed training set using random under sampling methods and then provide a separated data set to test which has a distribution of Pareto assumption. In other words, a balanced data set can be created to train algorithms then a test data of Pareto distribution can be supplied.

Considering the distribution of each classification method, new training, and testing sets are created from the analyzed data set. All the algorithms are re-trained using balanced data sets and tested by the supplied tests. Table 13 demonstrates the number of items in equally balanced training data set and Pareto distributed supplied test data set. Fig. 2 pictorially illustrates their distributions with percentages of A, B, and C classes.

**Table 11**
Average classification accuracies of algorithms.

| Accuracy performance type | Accuracy of algorithms (%) | | | | |
|---|---|---|---|---|---|
| | Naive Bayes | Bayes net | ANN | SVM poly | SVM n.poly |
| Cross validation | 65.81 | 78.71 | 88.98 | 91.61 | 88.89 |
| Percentage split | 58.36 | 72.00 | 81.61 | 92.25 | 89.08 |
| Overall average | 62.09 | 75.36 | 85.30 | 91.93 | 88.99 |

**Table 12**
Original (unbalanced) data distribution.

| Class | Training | Test | Sum |
|---|---|---|---|
| A | 94 | 47 | 141 |
| B | 143 | 72 | 215 |
| C | 235 | 117 | 352 |
| Total | 472 | 236 | 708 |

**Table 13**
Balanced (under sampling) data distribution.

| Class | Training | Supplied test | Sum |
|---|---|---|---|
| A | 64 | 77 | 141 |
| B | 64 | 115 | 179 |
| C | 64 | 192 | 256 |
| Total | 192 | 384 | 576 |

Table 10 reports the prediction accuracy of each method deployed, which is one of the most commonly reported performance measurements to evaluate classification performance of machine learning algorithms. However, imbalanced data sets are also considered to negatively affect the performance assessment (Weiss, 2004; Joshi, Kumar, & Agarwal, 2001); as such, accuracy alone may not provide a sufficient measure to assess the outcomes of this current research. Therefore, the current data sets employed to train the algorithms were now balanced in this study. Nonetheless, the testing data would still not be balanced as a result of the requirement for its Pareto distribution. As such, due to the interpretation convenience in multi-class classification tasks and based on confusion matrixes, additional detailed accuracy measurements (i.e. precision, recall, *F*-measure, and ROC area Sokolova & Lapalme, 2009) were also employed as shown in Table 14.

Those measurements are defined by each class in the data set. Therefore, by simply weighting measurements with class distributions, WEKA provides unique a weighted average for each measurement to evaluate the measurements globally. However, this does not comprise the effects of the importance of class type. This is a more important concern in the evaluation of inventory classification problems (Sun, Kamel, Wong, & Wang, 2007). In ABC analysis, the less represented class in inventory data, A, indeed is the most important class. As a solution to this, an additional global measurement is devised by adjusting the weighted averages with Pareto's class importance. These adjustment calculations are provided as follows.

In a testing data set of $n$ classes, where $c_i$ is the frequency of $i$th class, relative frequency of the class ($r_i$) is given by Eq. (25)

$$r_i = c_i \Big/ \sum_{i=1}^{n} c_i \tag{25}$$

For a given outcome of a classification algorithm, where $p_i$ is the Pareto importance weight for the $i$th class, $AW_i$ is the adjusted weight of the for the $i$th class is expressed in Eq. (26)

$$AW_i = r_i p_i \tag{26}$$

Building upon this, the adjusted weighted average of the measurement (AWAM) can be defined by Eq. (27)

$$\mathrm{AWAM} = \sum_{i=1}^{n} M_i AW_i \tag{27}$$

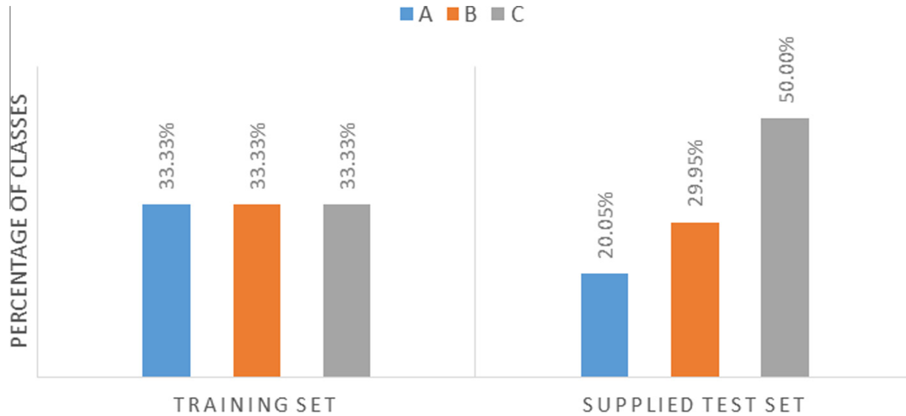


**Fig. 2.** Distributions of training set (balanced) and supplied test set (pareto).

**Table 14**
Performance metrics for MCDM-based machine learning methods.

| ML algorithm | MCDM | Class | Precision | Recall | *F*-Measure | ROC Area | Accuracy (%) |
|---|---|---|---|---|---|---|---|
| Naïve Bayes | SAW | A | 0.526 | 0.130 | 0.208 | 0.863 | 60.156 |
| | | B | 0.494 | 0.339 | 0.402 | 0.718 | |
| | | C | 0.636 | 0.948 | 0.762 | 0.893 | |
| | AHP | A | 0.615 | 0.208 | 0.311 | 0.905 | 60.417 |
| | | B | 0.463 | 0.330 | 0.386 | 0.689 | |
| | | C | 0.645 | 0.927 | 0.761 | 0.817 | |
| | VIKOR | A | 0.600 | 0.195 | 0.294 | 0.896 | 54.427 |
| | | B | 0.460 | 0.643 | 0.536 | 0.717 | |
| | | C | 0.606 | 0.625 | 0.615 | 0.671 | |
| Bayes net | SAW | A | 0.714 | 0.844 | 0.774 | 0.941 | 66.146 |
| | | B | 0.482 | 0.235 | 0.316 | 0.669 | |
| | | C | 0.684 | 0.844 | 0.755 | 0.880 | |
| | AHP | A | 0.627 | 0.610 | 0.618 | 0.928 | 70.052 |
| | | B | 0.523 | 0.487 | 0.505 | 0.743 | |
| | | C | 0.822 | 0.865 | 0.843 | 0.905 | |
| | VIKOR | A | 0.768 | 0.948 | 0.849 | 0.945 | 88.802 |
| | | B | 0.823 | 0.809 | 0.816 | 0.934 | |
| | | C | 0.944 | 0.911 | 0.951 | 0.960 | |
| ANN | SAW | A | 0.973 | 0.948 | 0.961 | 0.998 | 96.354 |
| | | B | 0.932 | 0.948 | 0.940 | 0.990 | |
| | | C | 0.979 | 0.979 | 0.979 | 0.997 | |
| | AHP | A | 0.961 | 0.948 | 0.954 | 0.997 | 94.271 |
| | | B | 0.927 | 0.878 | 0.902 | 0.983 | |
| | | C | 0.945 | 0.979 | 0.962 | 0.993 | |
| | VIKOR | A | 0.924 | 0.948 | 0.936 | 0.994 | 93.49 |
| | | B | 0.933 | 0.852 | 0.891 | 0.978 | |
| | | C | 0.940 | 0.979 | 0.959 | 0.990 | |
| SVM_poly | SAW | A | 0.961 | 0.961 | 0.961 | 0.992 | 95.573 |
| | | B | 0.915 | 0.939 | 0.927 | 0.951 | |
| | | C | 0.979 | 0.964 | 0.971 | 0.983 | |
| | AHP | A | 1.000 | 0.961 | 0.980 | 0.991 | 96.354 |
| | | B | 0.932 | 0.948 | 0.940 | 0.959 | |
| | | C | 0.969 | 0.974 | 0.971 | 0.979 | |
| | VIKOR | A | 0.914 | 0.961 | 0.937 | 0.966 | 90.365 |
| | | B | 0.790 | 0.948 | 0.862 | 0.920 | |
| | | C | 0.994 | 0.854 | 0.919 | 0.954 | |
| SVM_Npoly | SAW | A | 0.747 | 0.922 | 0.826 | 0.948 | 84.635 |
| | | B | 0.802 | 0.704 | 0.750 | 0.786 | |
| | | C | 0.920 | 0.901 | 0.911 | 0.918 | |
| | AHP | A | 0.696 | 0.922 | 0.793 | 0.942 | 83.073 |
| | | B | 0.824 | 0.730 | 0.774 | 0.815 | |
| | | C | 0.911 | 0.854 | 0.882 | 0.918 | |
| | VIKOR | A | 0.758 | 0.935 | 0.837 | 0.961 | 90.365 |
| | | B | 0.894 | 0.878 | 0.886 | 0.926 | |
| | | C | 0.989 | 0.906 | 0.946 | 0.964 | |

where an accuracy measurement (precision, recall, *F*-Measure, or ROC area) of *i*th class can be denoted by $M_i$. AWAM is the global average of the measurement across all classes adjusted by the weights based on Pareto's assumption.

**Table 15**
Adjusted weights.

| Class | $i$ | Relative class frequency (class distribution) ($r_i$) | Class importance weight (pareto assumption) ($p_i$) | Adjusted weight ($AW_i$) |
|---|---|---|---|---|
| A | 1 | 77/384 | 80/100 | **0.69** |
| B | 2 | 115/384 | 15/100 | **0.20** |
| C | 3 | 192/384 | 5/100 | **0.11** |

**Table 16**
Adjusted weighted accuracy measurements (AWAMs) by each model.

| Machine learning algorithm | MCDM method | Class | Precision AWAM | Recall AWAM | *F*-measure AWAM | ROC AWAM |
|---|---|---|---|---|---|---|
| Naïve Bayes | SAW | 0.53 | 0.26 | 0.31 | 0.84 | 60.16 |
| | AHP | 0.59 | 0.31 | 0.37 | 0.85 | 60.42 |
| | VIKOR | 0.57 | 0.33 | 0.38 | 0.84 | 54.43 |
| Bayes net | SAW | 0.67 | 0.73 | 0.68 | 0.88 | 66.15 |
| | AHP | 0.63 | 0.61 | 0.62 | 0.89 | 70.05 |
| | VIKOR | 0.80 | 0.92 | 0.85 | 0.94 | 88.80 |
| ANN | SAW | 0.97 | 0.95 | 0.96 | 1.00 | 96.35 |
| | AHP | 0.95 | 0.94 | 0.94 | 0.99 | 94.27 |
| | VIKOR | 0.93 | 0.93 | 0.93 | 0.99 | 93.49 |
| SVM_poly | SAW | 0.95 | 0.96 | 0.96 | 0.98 | 95.57 |
| | AHP | 0.98 | 0.96 | 0.97 | 0.98 | 96.35 |
| | VIKOR | 0.90 | 0.95 | 0.92 | 0.96 | 90.36 |
| SVM_Npoly | SAW | 0.78 | 0.88 | 0.82 | 0.91 | 84.64 |
| | AHP | 0.74 | 0.88 | 0.80 | 0.91 | 83.07 |
| | VIKOR | 0.81 | 0.92 | 0.86 | 0.95 | 90.36 |

**Table 17**
Overall AWAMs of each algorithm.

| Algorithm | Precision | Recall | *F*-Measure | ROC area | Accuracy |
|---|---|---|---|---|---|
| Naïve Bayes | 0.56 | 0.30 | 0.35 | 0.84 | 58.33 |
| Bayes net | 0.70 | 0.75 | 0.72 | 0.91 | 75.00 |
| ANN | 0.95 | 0.94 | 0.94 | 0.99 | 94.70 |
| SVM_poly | 0.95 | 0.95 | 0.95 | 0.97 | 94.10 |
| SVM_Npoly | 0.78 | 0.89 | 0.83 | 0.93 | 86.02 |

**Table 18**
Comparative average classification accuracies by algorithm.

| Training data | Naïve Bayes | Bayes net | ANN | SVM poly | SVM Npoly |
|---|---|---|---|---|---|
| Unbalanced | 58.36 | 72.00 | 81.61 | 92.25 | 89.08 |
| Balanced | 58.33 | 75.00 | 94.70 | 94.10 | 86.02 |
| Average | 58.35 | 73.50 | 88.16 | 93.18 | 87.55 |

Table 15 shows the adjusted weights for each class calculated from Eqs. (25) and (26) by multiplying relative class frequencies from the distribution of test data and class importance from Pareto assumption.

In Table 16, by classification method, global performance metrics of the algorithms are compared through both average accuracy and Adjusted weighted accuracy measurements (AWAMs).

Finally, in Table 17 overall performance averages of the algorithms across classification methods are compared through both accuracy and adjusted weighted average measurements, whereas Table 18 provides a comparison between the overall accuracy measures before and after balancing data sets.

The machine learning algorithms deployed in this study are strong in predictive capability and flexibly applicable in terms of their adaptive features. However, there is no such approach that would fit to all situations. Therefore, we have used several algorithms comparatively that are suggested in literature. Also, a brief comparison of SVM, Bayesian Classifiers, and ANN in terms of relative performance and characteristics are presented in Table 19.

**Table 19**
A comparison of SVM, Bayesian classifiers, and ANN.

| SVM | | Bayesian classifiers | | ANN | |
|---|---|---|---|---|---|
| Advantages | Disadvantages | Advantages | Disadvantages | Advantages | Disadvantages |
| Does not suffer from multiple local minima. Solution to an SVM is global and unique | Decision is based on support vectors, and often does not represent all the input | Represent the probabilistic relationships between inputs and output | Independence assumptions between the features seldom satisfied in practice | Capable of modeling highly nonlinear systems | Do not have an interpretable decision model (black box) |
| Computational complexity does not depend on dimensionality of the input space | Substantial memory and time requirements for quadratic programming on large data sets | Low complexity, high scalability, linear computational time | Can be outperformed by other approaches | ANN computations may be carried out in parallel to save computational time | Requires high computational resource, may converge on local minim |
| Less prone to over fitting when parameters are used effectively | Determination of parameters and kernel are sensitive to over-fitting | Requires a small amount of training data | Dependencies among variables cannot be evaluated | Often works well for large and imprecise datasets | Prone to over-fitting and, substantial fine-tuning required for parameters |

## 7. Conclusions and future research directions

This paper describes a "generic" hybrid methodology of the multi-criteria decision-making models integrated with machine learning methods for the analysis of multi-attribute inventory classification problem. Once inventory classes are determined through the use of three different MCDM methods, machine learning algorithms are employed to predict the pre-identified classes of each classification method. The compared effectiveness of each of the algorithms is then assessed.

Since SVM and the other machine learning algorithms described in this study were used as supervised learning techniques, it was necessary to determine the A, B, and C classes that would be employed within the training and the testing data. As such, prior to the implementation of the machine learning algorithms, MCDM methods (i.e. SAW, AHP, and VIKOR) were to be applied. Although in some cases, depending on the various data sets, the prediction of algorithms may not be very accurate due to the issues with data distribution and measurement (Soria et al., 2011), the case study demonstrated that all algorithms were able to classify inventory items very accurately. It is widely accepted in the machine learning field that the unbalanced distribution of ABC classes may impact the accuracy of classification; as such, an evenly distributed training set was created using random under sampling methods before a separate data set, which incorporated a distribution of Pareto assumption, was developed for the testing purposes. This novel hybrid approach with balanced data also achieved a very similar, but on average even slightly higher rate of accuracy. This comparison also demonstrated that the balanced data distribution did not improve the accuracy of the poorest performing Naïve Bayes' classification at all, whereas it did significantly increase the accuracy of ANN's performance from an average of 81.61% to 94.70%. For both approaches of the data treatment, the SVMs were able to predict the classes of inventory items the most accurately. However, unlike ANN, SVMs did not demonstrate any significant change across the unbalanced and balanced data sets. Having held the tests through a 10-fold cross-validated experimental setup, it is confident to state that the results are robust and are not actually affected by a random data splitting strategy. The superior performance of the SVM in both scenarios can be attributed to the fact that SVMs use the marginal, but not average, values in the data set to construct the classification prediction model.

However, as noted previously in this paper, accuracy alone is not sufficient to thoroughly evaluate and compare classification mechanisms. Therefore, based on the confusion matrixes, a number of detailed accuracy measurements, including precision, recall, *F*-measure and ROC area, were also employed. These measurements indicated that the performance of Naïve Bayes' changed dramatically according to the class type while Bayes Net approach performed better than Naïve Bayes, but still not as well as SVMs and ANNs. An additional global measurement was also devised by adjusting the weighted averages according to the Pareto's class importance. This made it possible to compare the overall performance of each of the algorithms by both considering simultaneously relative class frequencies from the distribution of the test data and the class importance from the Pareto assumption. ANN and SVM revealed extremely impressive performance outputs in all measurements. As a result, this new global measurement also supported the findings that ANNs and SVMs are accurate classifiers both of which can be effectively applied to inventory management problems with the multi-criteria decision-making models.

The results of this study indicate that machine learning methods can be very effectively applied to the multi-attribute inventory classification problem via the proposed methodology. This was validated with a large amount of inventory data. Of the machine learning methods employed, SVMs classified inventory items with more accuracy than the Bayesian classifiers. The research findings suggest that this integrated novel methodology that combines the machine learning algorithms with MCDM models would provide useful insights to support managerial decision making and improve inventory management strategies.

Although the predictive abilities of machine learning techniques entail that do have the potential to work with missing data, in the current study it was only possible to analyze 708 of the 715 items because of some missing values. It would, therefore, be useful for future research to examine the effects that various missing values and alterations to sample sizes have on the accuracy of classifications. Alternatively, the performance of machine learning algorithms could be compared with less, uncertain, and missing data. In the case of SVMs in particular, there would hypothetically be some advantages of working with such data, and such an approach might be suitable for cases that incorporate fewer samples and more attributes. In this study, eight different attributes (risk, demand fluctuation, average stock, daily usage, unit cost, lead time, consignment stock, and unit size) were employed to predict inventory classes, since the methods used in this study work effectively with multiple attributes. In addition, these algorithms provided us with an opportunity to use raw attributes, including categorical values and verbal expressions. However, more studies should be conducted that employ additional data sets and/or different machine learning algorithms along with various MCDM methods to compare the extent to which the generic hybrid methodology proposed in this study can efficiently classify inventory items.

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