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Inventory classification with artificial intelligence: Conceptual framework

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Abstract

In today's world where competition is increasing harshly, it is important to achieve sustainable profits and keep costs competitive. Under these conditions, the importance of supply chain elements is increasing day by day. Management of inventory costs, which constitute a large volume among cost items, affects the performance of companies. The first step to focus on to keep inventory costs under control and improve is inventory classification. Inventory classification, which is at the top of the supply chain elements and closely affects the subsequent phases, it is critical in determining supply chain performance. Thanks to inventory classification, material groups are determined and stock strategies for these groups are clarified. Incorrect inventory classification causes materials to be assigned to incorrect groups, which negatively affects inventory costs and subsequent phases of the supply chain, causing an increase in costs. The most used methods for inventory classification are ABC analysis, multi-criteria inventory classification and optimization. However, the increasing momentum in artificial intelligence studies in recent years has also closely affected inventory classification. The advantages brought by artificial intelligence methods have also created distinctive contributions to inventory classification studies. This study provides a conceptual framework that examines artificial intelligence methods in the field of inventory classification.

Keywords: Supply Chain Management, Inventory Classification, Artificial Intelligence

1. Introduction

The inventory classification has importance according to the volume of items in lots of companies. Given this remarkable diversity, great emphasis is placed on separating the inventory into different classes. This classification requires the application of various management tools and policies tailored to each class (Šimunović and Šarić, 2009). The main role of inventory classification is evident in a segmented supply chain and has a profound impact on cost performance, replenishment strategies, inventory decisions, and the overall design of supply chain processes (Svoboda and Minner, 2022).

With the advancement of technology and the increasing use of artificial intelligence applications in the industry, according to literature research, it has been determined that AI applications are not used actively enough in the field of inventory classification. The motivation of this study is to emphasize the importance of AI applications in the field of inventory classification and to show the usage opportunities.

There are 3 main inventory classification methods manly used past 20 years which are; ABC, multicriteria inventor classification (MCIC), artificial intelligence (AI).

ABC analysis stands out as an extremely popular and widely used analytical approach in inventory classification. This method divides items into three classes: A, B, and C. Class A covers the most critical items, while class C includes the least critical ones, typically determined by a predefined criterion, usually derived from multiplying annual cost usage, annual demand and average unit price.

However, relying on a single criterion such as cost utilization may not always be the most effective decision-making measure. As a result, multi-criteria decision-making methods are used, leading to the concept of multi-criteria inventory classification. Additional criteria include lead time, parts criticality, availability, average unit price, and out-of-stock penalty costs.

Numerous methods have been developed to classify inventory, recognize and integrate multiple criteria, including artificial intelligence approaches such as neural networks, fuzzy logic and genetic algorithms. The application of artificial intelligence involves the creation of intelligent computer systems with capabilities similar to human intelligence. In industrial environments, neural networks find widespread use in solving various challenges such as optimizing cutting conditions, creating tool paths etc. (Šimunović and Šarić, 2009).

Contribution of this work:

(1) A detailed literature analysis is made for the studies using AI in the field of inventory classification and the studies is briefly summarized
(2) The most commonly used AI methods in the field of inventory classification is explained
(3) AI methods that can be used in the industry for inventory classification is explained

2. Literature review

Li et al. (2004) use Artificial Neural Network (ANN) with backpropagation (BP) algorithm for inventory classification problem. The involvement of this model surpasses the deficiencies of input constraints in ANN and develop forecast accuracy. The proposed model is an analytical tool for real world decision-making systems. Lei et al. (2005) also use ANN method. Firstly principal components analysis (PCA) is used for inventory classification problem. Secondly, PCA is integrated to ANN. The findings demonstrate that the suggested hybrid PCA-ANN method has much markedly enhanced prediction accuracy. Tsai and Yeh (2008) use particle swarm optimization (PSO) for inventory classification problem. In this case, inventory items must be classified with exact objectives. This model determines the optimal number of inventory categories and prescribes the classification of items to achieve precise objectives. As a result, PSO based algorithm presents flexibility and effectiveness for solving inventory classification problems. And also the proposed model is compared with ABC method; the new model has comparatively well results. Also Šimunović and Šarić (2009) use ANN for inventory classification problem. ANN is compared with analytical hierarchy process (AHP) model. Results shows that ANN has much more acceptable accuracy.

Yu (2011) uses 2 different methods as AI and traditional multiple discriminant analysis (MDA), and compare them for inventory classification problems. The Support Vector Machine (SVM), BPN and K-Nearest Neighbors (KNN) algorithms are used as AI techniques. The findings indicate that AI techniques has markedly enhanced results than MDA. The comparison of internal AI techniques' results show that SVM has much more better results than others. Mohammaditabar et al. (2012) try to find the best policy simultaneously, simulated annealing (SA) method is employed to obtain suitable solutions, and the obtained results are compared with those of other models including annual dollar usage, AHP weighted score, and the proposed method with differences and total inventory values, and show that SA has better results than other models according to minimizing both dissimilarity and total inventory values. Kabir and Hasin (2013) use the incorporation of fuzzy analytic hierarchy process (FAHP) and ANN for MCIC problem. To verify this, a novel model is tried at a large power engineering company in Bangladesh. Lolli et al. (2014) propose a new hybrid AHP and K-means clustering model for MCIC problems. This method aims to avoid the hidden bad score which is AHP-K-Veto. To prevent obscure detrimental ratings, a different approach is introduced which is AHP-K-Veto. In the sorting process, each criterion is considered separately, and the use of a veto system prevents an item from being ranked as top/bottom in the overall aggregation if it is evaluated as high/bad on at least one criterion . As a result of this study, veto system is a guarantee for hidden problems but clustering validity index can be getting worse. Xue (2014) use fuzzy ANN for inventory classification problem. As a result, this method is used at manufacturing enterprise resource plan system. Šarić et al. (2014) use multi-criteria methods (AHP method and cluster analysis) and ANN for inventory classification problems. As a result, ANN has a more acceptable accuracy than AHP.

Kartal et al. (2016) introduce a new hybrid system with multicriteria decision making and machine learning for inventory classification. To define appropriate class of items, simple-additive weighting, AHP, VIKOR techniques are used and naïve Bayes, Bayesian network, ANN and SVM algorithms are added to forecast the initial set of classes inventory items. As a result of this study, machine learning methods can be effectively used in multicriteria inventory classification problems. And also SVM classified inventory has much more better results than Bayesian classifiers. Combining machine learning and MCIC methods can support managerial decision making. López-Sotoa et al. (2017)'s aim is to identify a new class for if there would be created a new product for multicriteria ABC ecosystem. To clear up this problem, for training discrete ANN by using passing greedy strategy to add on neurons to hidden layer, a multi-start constructive algorithm is developed. This model is used on a 3 different large datasets. As a result, the proposed model has a great level of generalization for these large datasets. Lolli et al. (2017)'s purpose is classifying inventories automatically parallel with industry 4.0 technologies. To accomplish this objective, a MCIC method is suggested, utilizing supervised classifiers such as decision trees and random forests. Decision trees and random forests are used for optimizing MCIC. The new method is used at a real-world case and seeked for most accurate tree and random forest. The comparison between uncontrolled MCIC method and the proposed model show that the proposed model has much more better results.

Isen and Boran (2018) work on a new hybrid sytem which includes AI methods. 3 AI models are used which are; fuzzy c-means (FCM), genetic algorithm, adaptive neuro-fuzzy inference system. For optimization of FCM, genetic algorithm is used and then clustering FCM algorithm and producing the adaptive neuro-fuzzy inference system classification model. Through the new system; there is no need for a new classification process if there is new product. This new hybrid system is implemented to a real life case and compared with an ANN model. The results show that the new hybrid model is more successfull than the ANN model. Zhang et al. (2018) have 2 main purposes which are both inventory classification and replenishment model identification. For classification; FCM algorithm is combined with genetic algorithm and SA algorithms. The proposed model used for a MCIC problem. The criterias are annual dollar usage, lead time and criticality. These 3 techniques can be combined by the named of GSAA-FCM. As a result of this model, the lowest inventory cost can be reached. Agarwal and Mittal (2019) use multi-level association rule mining for inventory classification problem. This study helps to define the most profitable product for experts.

Zhang et al. (2019) propose a new inventory classification method based on grey rough set and probabilistic neural network. With the help of this study, applicability and feasibility of the model is provided a scientific basis for enterprises to make decisions on inventory management and control. Lolli et al. (2019) use machine learning methods which are SVM with a Gaussian kernel and deep neural networks for inventory classification problems. The results show that the proposed model can be used for intermittent demands and the new model has excellent accuracy that can be used for inventory classification problems. Mohamadghasemi et al. (2019), in order to tackle the MCIC problem, the TOPSIS approach is employed, leveraging Gaussian Interval Type-2 Fuzzy Sets (GIT2FSs) as a methodology. The results show that the new model has much more logical results than TOPSIS, Ng-model and R model.

Cui et al. (2021) propose 2 different hybrid methods for MCIC problems. One of them is BBO-BPN (biogeography-based optimization (BBO) and BPN). Second of them is AMPSO-BPN (adaptive mutation particle swarm optimizer (AMPSO) and BPN). The main purpose is optimizing training parameters. As a result of this study BBO-BPN and AMPSO-BPN have more successful classification results than other hybrid models which are BPN, PSO-BPN, DE-BPN, GA-BPN. Svoboda and Minner (2022) use genetic algorithm to train decision trees based on machine learning classifier which it allows much more sensitive classification decisions for inventory classification problem. As a result of this study; the decision trees produce visual rules and explain paths from data to reasonable cost classification. Kaabi (2022) uses AI techniques to define the weights for TOPSIS to solve inventory classification problems. As a result, this novel model has better results than some existing models in the literature. And also this model is competitive and has satisfactory results. Khanorkar and Kane (2023) use 3 different classification methods and compare their results. These methods are classical ABC method, AHV method (Hadi-Venchech) and K-means algorithm. The results show that K-means outperforms.

3. Materials and methods

Challenges in inventory classification include classifying inventory items into groups for effective management. AI based techniques leverage symbolic logic and advanced computing technology to create various learning algorithms for the classification process (Yu, 2011).

As shown in Figure 1, 23 articles using AI in the field of inventory classification were published between 2000 and 2023. In this study, the studies in these articles is examined in detail.

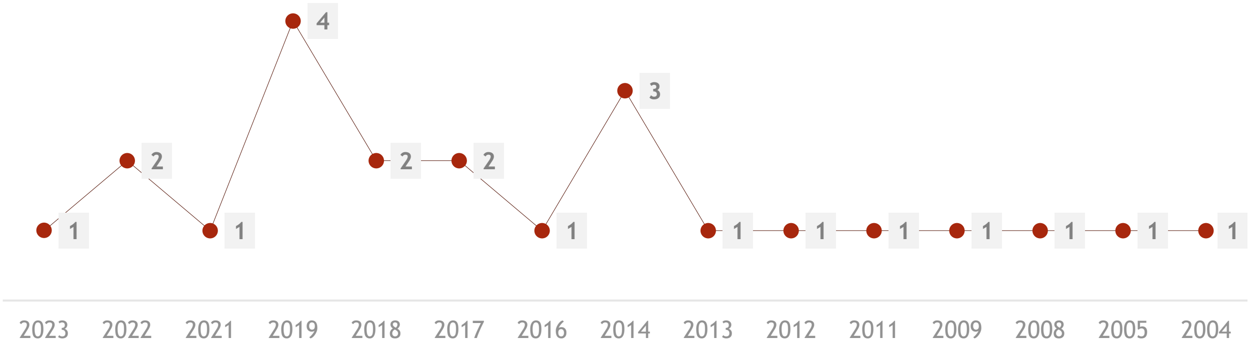

Figure 1. Litreature Review in AI methods for Inventory Classification

The most commonly used AI methods in the field of inventory classification are ANN, SVM and K-NN.

3.1 Artificial Neural Network

ANNs are computational systems inspired by the brain's simplified model, comprising interconnected nodes known as neurons. ANNs consist of three key components: the processing elements (neurons), the network topology defining their connections, and the learning algorithms governing their behavior. ANNs offer dual benefits: Firstly, they excel at uncovering and interpreting complex, nonlinear relationships and interactions among input variables. Secondly, the patterns identified and the accuracy estimates derived from ANNs remain independent of assumptions regarding variable distributions, providing robustness in diverse data scenarios (Lei et. al, 2005). BPNs emerge as the prevailing method for categorizing data when training ANN. They employ supervised learning techniques and a feedforward design to execute intricate tasks like recognizing patterns, sorting into categories, and predicting future trends. A typical BPN setup comprises three layers of neurons: the input layer, the hidden layer, and the output layer. The input layer captures the input signals or data points, while the output layer reflects the outcomes or predictions corresponding to those inputs. Meanwhile, the hidden layer acts as a crucial intermediary, fostering connections between the input and output layers through a network of interlinked weights (Yu, 2011).

There are mainly 3 focused articles that uses ANN for inventory classification:

a) Li et al. (2004) presents the estimation approach of hybrid model for multi-criteria classification of inventory items. They uses rough sets for multi-criteria inventory classification. If there is a inventory items that cannot be correctly classified with rough sets is classfied with ANN. The presented method not only overcomes the weaknesses of input limitation in ANN, but also can moreover develop the estimation accuracy. As a result, three comparable simulation experiments are conducted for the real inventory classification problem with ANN using BP algorithm and and rough sets method. Proposed model is proven to be a promising analytical tool in real world systems.

b) Lei et al. (2005) used 2 different method for inventory classificaiton. First one is principal components analysis (PCA). The second one is hybrized PCA with artificial neural networks (ANNs) with BP algorithm. Result shows that proposed hybrid method with ANN has more prediction accuracy.

c) Xue (2014) focuses on multi-attribute classification model and fuzzy artificial neural network. Firstly, the inventories are classified. After that, a decision tree model is described according to the inventory classification outcomes. If multi-attribute decision is needed, the value of the node is determined by the fuzzy neural network, and the material inventory strategy could be decided by the classification tree. Finally, the application of the model in a manufacturing enterprise resource planning system is presented.

3.2 Support Vector Machine

SVMs deviate from conventional neural networks by embracing structural risk minimization over empirical risk minimization. They employ a linear model to create nonlinear boundaries between classes by transforming input vectors into a high-dimensional feature space using nonlinear mapping. Support vectors, representing the training samples nearest to the maximum margin hyperplane, hold significant importance in determining the discriminative capability of SVMs (Yu, 2011).

There are mainly 3 focused articles that uses SVM for inventory classification:

a) Yu (2011)'s purpose is comparing traditional methods with AI methods. SVM, backpropagation networks, k-nearest neighbor (k-NN) is used as AI methods. As a traditional method multiple discriminant analysis (MDA) is used. As a result, AI methods has more accuracy than MDA. And also results indicate that SVM is most accurate method comparing to other AI methods.

b) Kartal et al. (2016) aims to develop machine learning algorithms for multi-criteria inventory classification. As a multi-criteria algorithm simple-additive weighting, analytical hierarchy process, and VIKOR are used. After that Bayesian network, ANN, and SVM algorithms are implemented. The results indicates that machine learning methods can be used effectively at inventory classification problems. SVMs has more accuracy than the Bayesian classifiers.

c) Lolli et al. (2019) used SVM with a Gaussian kernel and deep neural networks. The inventory system adopted here is suitable for intermittent demands but can also meet non-intermittent demands. Two large datasets are used and it shows that AI methods has great accuracy. Proposed method can be applied to inventory classification systems.

3.3 K-Nearest Neighbors

K-NN represents a non-parametric approach for classifying data points. It begins by measuring the distance or similarity between observations. Then, when classifying a new data point, it assigns it to the group shared by the majority of its k-closest neighbors. The success of K-NN hinges on selecting the right value for k, which dictates how many neighbors influence the classification decision. (Yu, 2011).

Yu (2011)'s used SVMs, BPNs, and k-NN algorithm for inventory classification problems. The results indicates that AI methods has more accuracy comparing to traditional methods.

4. Managerial implication and conclusions

This paper outlines the outcomes of an analysis of how inventories are classfied with AI in academic research, aimed at enhancing decision-making within supply chain management. Inventory classification is a very critical step for inventory control and management. In order to carry out efficient inventory management, inventory classification must be done correctly. Although the most classic inventory classification method is ABC, this method no longer meets all needs. For this reason, decision makers and researchers have turned to different methods. Studies in recent years have focused on AI methods and have been shown to provide better results than traditional methods. It is expected that the use of AI hybrid methods will increase in future studies to increase the efficiency of inventory classification studies.

The findings from this literature review within the realm of inventory classification encompass several key aspects: (1) This research explains mostly uses AI methodologies utilized in inventory classification, (2) The endeavors of academic researchers in inventory classification are synthesized, encompassing problem identification, solution approaches, and outcomes, (3) This investigation elucidates the academic community's endeavors in developing solutions for identified issues, (4) It tracks the evolving trends in methodological approaches over time, (5) Particular emphasis is placed on studies employing AI hybrid methodologies, (6) this paper helps to find alternative AI methods that can be used for businesses that manage inventory .

This research specifically targets inventory classification methodologies implemented from the year 2000 onwards. This paper provides an in-depth elucidation of research conducted on inventory classification, serving as a valuable reference for individuals entering the field and informing the direction of future investigations.

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