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Adoption of Artificial Intelligence Techniques for Inventory Management: A Case Study in the Aviation Sector

Vikram Cathiyavadi Grahamspet Narendran[1], Arumugam Seetharaman[2], Koilakuntla Maddulety[3]

[1]S.P. Jain School of Global Management, Dubai, UAE
[2]S.P. Jain School of Global Management, Singapore
[3]S.P. Jain School of Global Management, Mumbai, India
Email: vikram.dm19dba003@spjain.org

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Abstract

Spares management is of great significance as it not only regulates the flow of the inventory but also impacts the financial status of the company's balance sheet. All organizations continuously try to maintain optimum inventory levels in order to not only meet their supplies and demands but also ensure there is no "excess or less inventory" that can directly influence the financial data. To perform the balancing act of these conflicting requirements is an ongoing process, especially in volatile industries like aviation with fluctuations in demand, lead time, and criticality. The aim is to categorize spares based on multiple criteria using AI techniques in the aviation sector by expanding the traditional VED classification method to achieve better inventory control.

Keywords

Inventory Management, Artificial Intelligence, Machine Learning, Deep Learning, Spares Management, Multi-Criteria Inventory Classification

1. Introduction

Flight simulation is essentially recreating a ground-based, synthetic environment to train the pilots and evaluate their skills and technical development. The important goal of a real-time Full Flight Simulator (FFS) is to recreate the conditions of a real aircraft in order to impart training to the pilots at an affordable price when compared to teaching in the sky (Oberhauser et al., 2015).

Full-flight simulators have various systems associated with them, like the avionics, motion and control loading systems, visual image generation and projection systems, power cabinets, computer systems, complex interface systems, etc. With such multifarious systems in place, the reliability of these simulators is deeply impacted by the availability of spares. The non-availability of spare parts to perform maintenance and address failures can result in tasks in an Aircraft-On-Ground (AOG) situation. An AOG situation has a negative impact on the customer and acts as a deterrent to the company's profit and reputation. The aim of inventory management, especially in an in-service sector like aviation, is to reduce inventory costs without compromising customer satisfaction (Shenoy & Rosas, 2018).

The classification of spare parts using various techniques helps achieve this goal and paves the way for efficient inventory management. Accurate inventory item classification assists organizations in maintaining an advantage over their competitors and helps inventory managers optimize warehouse space by reducing waste. Inventory classification techniques can be broadly classified into three categories:

- Single-criteria inventory classification
- Bi-criteria inventory classification
- Multi-criteria inventory classification

Single-criteria inventory classification is usually not preferred by researchers, as it takes only one parameter into consideration and can neglect some important factors crucial for inventory handling. Although bi-criteria inventory classification circumvents problems posed by single-criteria inventory classification by using a matrix approach to provide an efficient way to group items, it can still miss some important features, such as lead time, inventory cost, commonality and obsolescence. On the other hand, MCIC methods consider many different factors such as lead times and demand fluctuations, which makes inventory classification both efficient and accurate (Nareshchandra & Desai, 2019). VED analysis was used to group aircraft simulator spares. Vital parts are those that are highly important, and a lack of parts categorized under this section will severely hamper the functioning of FFS and can result in an AOG. Important spares are categorized as essential parts; the non-availability of parts under this section can cause downtime in simulators. Moderately important spares are categorized under this section; the unavailability of spares can cause minor stoppages. By extending the VED classification and adding other dimensions such as lead times, demand fluctuations and safety stock, AI techniques such as supervised, unsupervised and deep learning algorithms were used to classify spares based on multiple criteria for full flight aircraft simulators.

1.1. Research Questions and Problems

This study focused on the factors that influence the successful classification of spares based on multiple criteria using AI techniques. Consequently, the following research questions were formulated based on the research gaps identified in the existing literature.

- How can multi-criteria inventory classification using supervised learning influence the management of spares in the aviation sector?
- How can multi-criteria inventory classification by using unsupervised learning aid in the effective management of spares in the aviation sector?
- How can multi-criteria inventory classification by using deep learning techniques influence spares management in the aviation sector?
- What was the outcome of the research when the model was used in a case study to classify spares using multiple criteria?

1.2. Research Objectives

Based on the above research questions, the following research objectives were formulated.

- To analyze how multi-criteria inventory classification using supervised learning techniques assist in the management of spares in the aviation sector.
- To assess the influence of multi-criteria inventory classification using unsupervised learning techniques while managing spares in the aviation sector.
- To analyze how multi-criteria inventory classification using various deep learning techniques assisted in the management of spares in the aviation sector.
- To analyze the outcome of research by testing the model with a case study in the aviation sector by classifying spares for full flight aircraft simulators.

1.3. Scope of the Study

Very few studies have focused on classifying spares based on multiple criteria, especially in the aviation sector. Given that full flight simulator spares management is affected due to incorrect classification, resulting in poor customer satisfaction and equipment downtime, there is a need to develop a framework to address the issue of spares management.

1.4. The Rationale behind Choosing ML Algorithms for Inventory Management

According to Mondol (2021) and Paul et al. (2019) companies irrespective of sectors can find it extremely difficult to manage their inventory, especially when there are fluctuations in spares demand, fluctuations in prices, and uncertain lead times associated with inventory. They further go on to add that the dependence only on traditional methods for managing inventory without using modern technologies such as AI can only address basic issues related to inventory but cannot give effective solutions as modern-day supply chains are intrinsically complex with multiple layers and many stakeholders, sometimes even geographically apart. Moreover, traditional methods can be error-prone and time-consuming, do not offer real-time monitoring capability, and create mistrust amongst various stakeholders in a supply chain. Kumar (2018) suggests that traditional inventory classification methods, when combined with modern technologies such as artificial intelligence and its subsets, machine learning and deep learning can streamline the entire processes within the supply chain, like inventory management, warehouse management, warehouse and logistics management, as these sophisticated algorithms allow real-time monitoring capabilities and, thereby, if implemented, can increase inventory turnover, reduce operational bottlenecks, handle demand fluctuations, improve overall efficiency, and increase customer satisfaction.

1.5. Research Framework

The research framework is only a starting point and is in no way used to determine the presence, nature, strength, or mediation effect of any variable. The likelihood of a relationship between variables determined through a comprehensive literature review is depicted graphically in **Figure 1** below.

2. Literature Review

Inventory classification plays a pivotal role in sustaining a competitive edge in many sectors, from capital-intensive industries such as the petroleum, mining and automotive sectors to service-oriented sectors such as telecommunication, rail and airlines. Proper inventory classification techniques not only consistently segregate parts based on their various attributes but also prevent them from being unavailable for maintenance and repair, as the unavailability of critical parts can lead to serious repercussions (Sarmah & Mohanrana, 2015).

ML algorithms are very capable of analyzing and streamlining inventory, especially when classifying spares and supporting effective operations management. Recent studies show that using ML techniques to manage inventory with multiple attributes plays a significant role in reducing ordering, holding and shortage costs (Kartal et al., 2016).

While classifying items, especially for asset-intensive industries where the quantity is very large, it becomes practically impossible to pay attention to each item. In traditional ABC single-criteria classification based on the 80 - 20 Pareto principle, some key parameters, such as lead time, demand fluctuation and expected failure, are not considered, which leads to the incorrect classification of items. Even two-dimensional classification is not effective enough as there is a likelihood of some important attribute being missed. However, multi-criteria classification, which considers three or more attributes, circumvents this problem and is very effective in separating the most critical items from the less important ones, thereby preventing stock-outs of important items (Kumawat & Samad, 2018).

According to Wu (2016) and Yung et al. (2021), multi-criteria classification can be achieved using either:

- Mathematical models
- AI-based techniques

Mathematical models: The analytic hierarchy process, data envelopment analysis (DEA) and fuzzy rule-based approach are the most commonly used mathematical models for MCIC. Analytic hierarchy processing is an organized

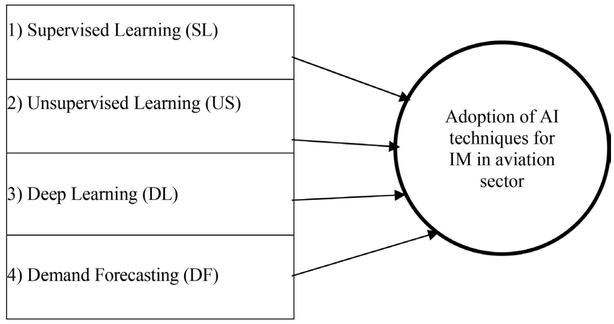

Figure 1. Research framework.

way of modelling the problem at hand. It comprises a general goal, a number of choices or alternative choices to achieve the target and a set of criteria that correlate the alternatives to the intended goal. DEA, on the other hand, is a method to measure or evaluate the performance and efficiency of decision-making units with numerous inputs and outputs specific to the organization. The extension of DEA models has successfully been used in real-world situations, especially in the inventory management setup, to classify inventory based on multiple criteria (Ladhari et al., 2016).

AI-based techniques: Computer science, IoT, AI and ML techniques are widely used in many fields, and one of their common applications is in the areas of inventory and supply chain management, especially for classifying inventory using multiple features. According to Toorajipour et al. (2021), some of the most commonly used AI-based techniques for MCIC of items are:

- Deep Learning (ANNs)
- Supervised ML techniques
- Unsupervised ML techniques

These algorithms form the core of this section and will be discussed in detail.

2.1. Deep Learning

DL can be considered a subset of ML, which is, in turn, a subset of AI. The basis of DL is akin to the function of neurons in the human brain and mimics its patterns for decision-making. It is a NN that consists of several layers, each of which consists of many nodes called as neurons. They are mainly used in parallel processing and have widely distributed data control and processing power. ANNs, on the other hand, are very adept at solving real-world problems because of their ability to process like a human brain. In his study, Wu (2016) compared mathematical models such as analytic hierarchy processing and DEA with ANN-based models for MCIC of spare parts, and the final results confirmed that the ANN model significantly outperformed the mathematical models. NNs have proven to be effective in solving and modelling complex and poorly understood problems. Because of their robustness, they are able to solve some real-world problems through capabilities that include predicting a company's bankruptcy, predicting a company's stock credit level, establishing a product warranty, speech and pattern recognition, face alignment, character recognition, spare parts classification, stock market forecasting, medical diagnosis, character recognition, spare parts demand prediction and prediction of foreign exchange rates (Abiodun et al., 2018; Amirkolaii et al., 2017; Mirjankar & Patil, 2018). According to Fu et al. (2018), AI techniques recently received much attention for classifying spare parts with extreme demand fluctuations. Yang et al. (2021) developed a model to classify spare parts with multiple attributes, such as lead time, lumpy demand, reorder point and cost, using a deep convolutional NN, with good results. In his study, Wu (2016) compared mathematical models such as analytic hierarchy processing and DEA with ANN-based models for MCIC of spare parts, and the final results confirmed that the ANN model significantly outperformed the mathematical models. Kumawat and Samad (2018) used ANNs to classify the inventory of large items in retail stores based on multiple criteria such as cost, unit shelf life, profit per unit, lead time and demand for an item. The model successfully classified inventory in retail stores with great precision and accuracy. In another study, Kartal and Cebi (2013) concluded that ANNs are very accurate classifiers and could be used to address a myriad of inventory management problems.

2.2. Supervised Machine Learning

ML is a subset of AI used for knowledge extraction. It is an amalgamation of statistics, AI and computer science used for statistical inference, predictive analysis and real-time data.ML applications can be used in every walk of life. Companies such as Netflix, Amazon and Facebook make use of numerous ML models to keep track of their customer database and offer recommendations and solutions. Supervised learning, a type of ML, is the most commonly used, as it enables the computer to learn from past data, which it then applies to the present to predict future data (Geron, 2017). According to Wu (2016), some of the commonly used algorithms for classifying inventory are:

- Support vector machine (SVM)
- K-nearest neighbors
- Naïve Bayes
- Random Forest

Support vector machine: This robust and widely used supervised ML algorithm is capable of both classification and regression. It performs exceptionally well on complex datasets and is suited for the classification of medium-to-large datasets. First introduced by Vapnik in 1995, it has since taken rapid strides, and its applications have been used in fault diagnostics, handwriting recognition, text classification, bioinformatics, image detection and predictive maintenance. SVMs have been used in the inventory setup to classify inventory with multiple attributes. Lolli et al. (2019) used a combination of SVM and ANN to classify inventory based on multiple criteria having intermittent demand on very large datasets and achieved very high accuracy. Kartal et al. (2016) proposed a hybrid model with SVMs and compared the performance of the model with traditional mathematical models such as multiple discriminant analysis and analytic hierarchy processing. The supervised SVM classification ML model performed better, establishing its superiority over other models. They concluded that SVMs are precise and accurate classifiers capable of solving real-world problems in supply chain and inventory management.

K-nearest neighbors: Another popular, and perhaps the simplest, supervised ML technique is mostly used for classification and pattern recognition. This simple but effective non-parametric algorithm works on the principle of considering exactly one nearest neighbor closest to the training data point with respect to the point where the prediction needs to be made. It is a distance-based lazy algorithm that does not make data assumptions, does its learning in the testing phase and only stores data points during the training phase (Jiao et al., 2019; Wu, 2016). As the selection of a proper k-value is key to its performance, an improved version of the K-nearest neighbors' algorithm, which was capable of dynamically assigning the value for k, was proposed by Gong and Liu (2011). This novel K-nearest neighbors' model, where the k-values could be easily optimized, has been found to be very useful in the inventory classification of items with many features (Yang et al., 2021). The K-nearest neighbors model works very well on small-to-medium datasets but struggles when the number of inputs is large, as computation becomes expensive if more features are added. Despite its computational challenges when applied to big datasets, k-nearest neighbors outperformed mathematical models such as analytic hierarchy processing and DEA when classifying inventory with multiple criteria (Wu, 2016).

Naïve Bayes: This probabilistic classifier ML technique based on the Bayes theorem is one of the most popular algorithms used for classification issues. The algorithm works on the principle that features or predictors are independent of each other, that is, changing the value of one feature has no effect on another feature (Agarwal et al., 2015). Naïve Bayes assesses the probability of each and every classification by merging the prior and conditional probabilities into a single formula. Unlike K-nearest neighbors, the computation complexity does not increase with an increase in inputs, so it performs really well on large datasets. Naïve Bayes, with its ability to handle both continuous and discrete data, has found its usefulness in inventory management and, similar to most supervised ML techniques, outperformed mathematical models, such as analytic hierarchy processing, multiple discriminant analysis and DEA, when classifying inventory with multiple criteria (Wu, 2016).

2.3. Unsupervised Machine Learning

Unlike supervised ML models, which are trained on labelled data by identifying raw data such as images, text files and videos and adding some useful information to enable the model to learn from them, unsupervised learning is used when data labelling is not possible, and the need to hide patterns from the given dataset arises. In other words, unsupervised learning encapsulates all aspects of ML that have a known output but do not have a teacher or supervisor to assist in learning (James et al., 2013; Mahesh, 2020). K-means clustering is the most commonly used unsupervised learning partitioning algorithm. It is an iterative algorithm that segregates an unlabeled dataset into k different clusters in a manner in which each dataset belongs to only similar groups. If the value of k = 2, there will be two clusters, and when k = 3, there will be a total of three clusters, and so on. Each cluster is associated with a centroid, and the goal is to minimize the distance between data points and the cluster in which they are placed. The k-means clustering algorithm is used in many aspects of inventory management, particularly in homogenizing spare parts with intermittent and non-intermittent demand patterns. Because of their ability to work on labelled input data without supervision, the computation complexity is reduced (Baluga-ni et al., 2019). Aktepe et al. (2018) used a partition clustering algorithm to classify items based on multiple criteria. Using the k-means algorithm, a new grouping method called FNS, an abbreviation of functional, normal and small, was created, and the application of this method allowed for improved inventory management by eliminating stock-out problems, reducing costs, decreasing the time required for IC and increasing efficiency. According to Zowid et al. (2019), the application of unsupervised Gaussian mixture models for the managing, controlling and classifying of inventory is gaining in importance. This powerful unsupervised partition-based ML technique, based on probability distribution, groups data into clusters and works better than k-means clustering because k-means uses a distance-based model to group data in a circular way, while Gaussian mixture models use a distribution-based model. Gaussian mixture models were successful in classifying inventory with multiple attributes and performed very well in terms of accuracy of classification, computational time and efficiency. Another popular unsupervised learning technique that is very effective on outliers is the density-based clustering technique. It has advantages over k-means clustering in that the number of clusters need not be decided upfront, and it creates clusters based on varying densities. Density-based spatial clustering of applications with noise is the most popular density-based clustering algorithm that segregates clusters of high density from those of low density, and it is very adept at detecting noise or outliers in a given dataset. Density-based spatial clustering of applications with noise algorithms was found to be very effective in managing inventory, especially in solving stock-keeping unit aggregation problems (Jackson et al., 2018).

2.4. Demand Forecasting

Smart and accurate demand forecasting reduces inventory costs, improves target stock levels and reorder points, reduces customer lead time and storage space, decreases holding costs and increases the inventory turnover ratio. Accurate spares demand forecasting in asset-intensive and high-reliability operations industries, such as aviation, nuclear power plants and hospitals, is of utmost importance, as the non-availability of a part can seriously impact operations, leading to financial losses and customer dissatisfaction. In addition, inaccurate forecasting can seriously hamper spare parts management and lead to excesses or shortages of inventory. AI-powered demand forecasting techniques deliver better performance and give higher prediction accuracy than traditional forecasting methods, thereby aiding in better inventory management (Amirkolaii et al., 2017). The main situation in which traditional forecasting methods fail is when the nature of the demand is sporadic. Based on the two statistical coefficients, namely, average demand interval (ADI) and square of the coefficient of variation (CV^2), the demand data are classified as smooth, intermittent, erratic or lumpy.

Smooth: Demand forecasting is easy, as the demand is even and regular in nature with respect to time and quantity (ADI < 1.32 and $CV^2 < 0.49$).

Intermittent: There is little to no variation in the demand quantity, but there is much variation in time (ADI ≥ 1.32 and $CV^2 < 0.49$).

Erratic: There is little to no variation in time, but there is much variation in demand quantity (ADI < 1.32 and $CV^2 \geq 0.49$).

Lumpy: There is much variation in both time and quantity. This type of demand data is extremely unpredictable and difficult to forecast. Traditional forecasting methods work well for smooth data, but for data types that are intermittent, erratic and lumpy, DL algorithms, such as artificial NNs, give significantly better results than conventional methods (Adur Kannan et al., 2020).

3. Research Methodology

Quantitative research methods employ statistical, mathematical or numerical analyses of the collected data. In this research, the acceptance and employment of AI technologies for multi-criteria inventory classification were analyzed and supported by a survey with open-ended and closed questions. This phase was used to analyze and identify the relationships between all variables. The hypotheses that were formulated in the qualitative phase of the research were tested during this phase. An underlying aspect of the survey was to identify the respondents' knowledge about the research topic. Leaders and management professionals from various industries, such as aviation and aerospace and technology provided responses. Respondents included management personnel and technology providers from multinational companies, such as Boeing, Airbus, Emirates Airlines, Quest Aerospace, Infosys, Apple and Microsoft, all of which have their footprint in multiple geographical locations. Thus, the survey was successful in collecting around 400 responses from various geographical locations and people from different industries without compromising on either quality or quantity. This research uses an approach that is hypothetico-deductive in nature. To establish a cause-and-effect relationship between variables, the research questions were analyzed and examined with a reductionist method. The generalized conceptual model was developed for the aviation sector using a structural equation model in ADANCO PLS-SEM and was also used to postulate the hypotheses. The model was then tested in a real-world scenario to classify full-flight aircraft spare parts based on multiple criteria with irregular lead times and fluctuating demands. Python Libraries such as Keras, Tensor Flow, Scipy and Sckitlearn were used to classify inventory based on multiple-criteria.

4. Data Analysis and Hypothesis Testing

The measurement and the structural model, which incorporates statistical testing of hypotheses, were put to the test using the variance-based structural equation modeling software package ADANCO 2.3.2 in order to get useful and insightful result (author). Construct reliability and convergent validity are used to check the reliability of the three constructs. Author J.F. Hairin his book "An introduction to structural equation modelling" define the lower and upper bounds of rho (ρ_A), rho (ρ_c) and Cronbach's alpha as shown in **Table 1** below.

From **Table 1** and **Table 2** with AVE > 0.5 and reflector indicator loading > 0.708 it is evident that all the four independent variables display good reliability t-tests are crucial in identifying whether there are meaningful connections between the various elements in the model, according to research by Hair et al. (2011). **Figure 2** shows the structural model for the research undertaken using ADANCO.2.3.1.

The structural equation model has an R-squared value of 0.611 for the dependent variable, indicating that the contributory variables of this model account for ≈ 61% of the variance in this latent variable. For partial-least squares, a value above 0.5 is generally considered the acceptable norm (Henseler & Fassott, 2010). A total of four direct and three indirect effects were postulated and tested in this research. The decision to accept or reject the hypothesis was based on the t-values of both dependent and independent variables. Bootstrapping with 5000 iterations was used for modeling. The following Hypotheses were put forward and tested:

H1: Deep learning techniques used for multi-criteria inventory classification significantly influence the management of spares in the aviation sector through artificial neural networks (ANN), recurrent neural networks (RNN), deep neural networks (DNN), and convolutional neural networks (CNN) algorithms.

H2: Supervised machine learning techniques used for multi-criteria inventory classification significantly influence the management of spares in the aviation sector through support vector machines (SVMs), K-nearest neighbors (KNN), Naïve Bayes (NB) and Random Forest algorithms.

H3: Unsupervised machine learning used for multi-criteria inventory classification significantly influences the management of spares in the aviation sector through Apriori, Eclat, k-means clustering (k-NN), and density-based clustering (DBSCAN) algorithms.

H4: Demand forecasting significantly influences the management of spares in the aviation sector through smooth, intermittent, erratic and lumpy demand data.

H5: DL applications used for multi-criteria inventory classification through the mediation of DF significantly influence the management of spares in the aviation sector.

H6: SL applications used for multi-criteria inventory classification through the mediation of DF significantly influence the management of spares in the aviation sector.

Table 1. Construct reliability.

Construct	Dijstra-Hensler's rho A	Joresskog's rho C	Cronbach's alpha
SL	0.8024	0.8605	0.7964
US	0.7503	0.8247	0.7340
DL	0.7797	0.8533	0.7803
DF	0.7902	0.8504	0.7763
OM	0.7902	0.8504	0.7763

Table 2. Convergent validity.

SL	0.5537
US	0.5872
DL	0.5393
DF	0.7046
OM	0.7046

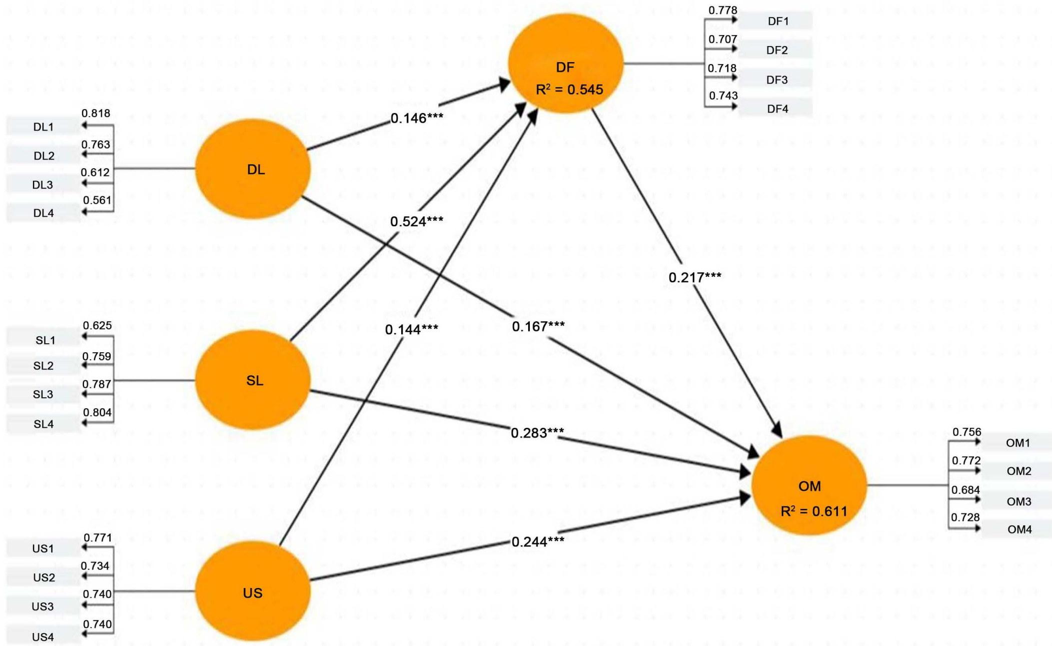

Figure 2. Structural equation model.

H7: US applications used for multi-criteria inventory classification through the mediation of DF significantly influence the management of spares in the aviation sector.

All seven hypotheses i.e., four direct and three indirect were accepted at 1% confidence level (t > 2.59) (Table 3).

4.1. Results Obtained from Case Study Undertaken

A case study was undertaken to classify spares based on multiple criteria for full

Table 3. Direct and indirect effects inference table.

Direct Effects Inference							
S no.	Hypothesis	Effect	Original Coefficient	Std Error	T-Value	P-Value (2-sided)	Hypothesis Supported/Not Supported
1	**H1**	DL-->OM	0.1675	0.0427	3.9245	0.0001	Supported
2	**H2**	DF-->OM	0.2174	0.0436	4.9892	0.0000	Supported
3	**H3**	SL-->OM	0.2832	0.0500	5.6669	0.0000	Supported
4	**H4**	US-->OM	0.2442	0.0407	6.0053	0.0000	Supported

DL: Deep Learning Technology; DF: Demand Forecasting; SL: Supervised Learning; US: Unsupervised Learning; OM: Output Measures.

flight simulators. The data used in this study was collected from a leading manufacturer of commercial aircraft simulators. A total of 10,000 spare parts were analyzed and categorized as either vital, essential, or desirable, taking into consideration the lead time and fluctuations in demand as shown in Table 4 below. High lead times for parts were assumed to be more than 45 days, moderate lead times were between 15 and 30 days, and low lead times were given a range of 15 days or less. This assumption was made by analyzing the historical records.

4.2. Preprocessing of Data

The preprocessing phase focused on assimilating, segregating, cleaning, and transforming data so as to eliminate outliers, handle missing data, and eliminate inconsistencies. As neural networks are prone to overfitting, it was ensured that the training dataset was not small, and all outliers were removed in the preprocessing phase so that the model does not make predictions on noisy data. Techniques such as regularization were used to overcome overfitting by reducing the model complexity and keeping only relevant features such as lead time, criticality, fluctuations in demand, failure rate etc. in order to ensure it performs well on both training and testing data. Python libraries such as Scipy, TensorFlow, Scikit-learn, Keras, Theano, Matplotlib, and Pandas were used for preprocessing, analyzing, and interpreting historical data.

Various artificial intelligence algorithms were used to perform the analysis, and the results obtained are summarized in Table 5. The sample size is n = 10,000 spares. From Table 5, it can be clearly identified that the SVM supervised classification machine algorithm performed the best, followed by the artificial neural network. Unsupervised learning algorithms performed poorly when compared to supervised and deep learning algorithms.

5. Conclusion

The research questions posed in chapter one was addressed by testing and evaluating seven hypotheses representing direct and indirect associations between variables. Chapter 4 dedicated to statistical analysis, details the testing and

Table 4. VED classification matrix.

Class	Parameters
VITAL (V)	• Very high criticality when unavailable will render the simulator AOG. • High customer lead time. (>45 days) • Moderately high customer lead time. (>15 days and <45 days) • Intermittent, Sporadic and lumpy demands were variation in either demand or quantity is taken into consideration.
ESSENTIAL (E)	• High criticality when unavailable causing downtime on the simulator. • Moderately high customer lead time (>15 days and <45 days) • Low customer lead time (<15 days) • Intermittent and Sporadic demands were variation in either demand or quantity is taken into consideration
DESIRABLE (D)	• Moderate to low criticality causing minor interruptions when unavailable. • Low customer lead time < 15 days • Intermittent to smooth demand where no variation in time or quantity is considered.

Table 5. Classification accuracy of AI algorithms.

Variables	Algorithms	True Positive (TP)	True Negative (TN)	False Positive (FP)	False Negative (FN)	Accuracy $\frac{(TP+TN)}{(TP+FP+TN+FN)}$
Deep Learning	ANN	6003	2867	680	450	88.7%
	CNN	6003	2869	681	451	88.5%
	RNN	6003	2867	680	450	88.7%
	DNN	6002	2867	681	450	88.6%
Supervised Learning	SVM	6042	2969	617	371	90.01%
	K-NN	5999	2823	710	468	88.2%
	NB	5999	2823	710	468	88.2%
	RF	5898	2825	750	527	87.2%
Unsupervised Learning	APRIORI	4981	2499	1607	913	74.8%
	ECLAT	4907	2556	1621	916	74.6%
	K-MEANS CLUSTERING	4981	2499	1607	913	74.8%
	DBSCAN	4981	2499	1607	913	74.8%

explanation of these hypotheses to provide solutions and give statistical evidence to the research questions posed. The right conclusions were drawn about each of the stated study objectives based on the inferences made from all of the information gathered so far in this thesis.

5.1. Contribution to Theory and Practice

The researcher sought assistance from the literature by referring to papers published during the preceding six years. Although a number of articles have been published on inventory control and management, the combination of variables DL, SL, US and DF for multi-criteria inventory classification of full flight aircraft simulator spare parts has not been explored. The validity of the proposed research model was also evaluated in the research.

5.2. Contributions towards Academic Literature

The researcher sought assistance from the literature by referring to papers published during the last six years. Though a number of articles have been published on classifying inventory, the usage of various AI algorithms for multi-criteria inventory classification of full flight simulators with irregular lead times have not been explored.

5.3. Limitations and Scope for Future Research

The research thesis is concluded in this section. The research was successful in identifying four independent variables: deep learning (DL), supervised learning (SL), unsupervised learning (US), and demand forecasting (DF), and one dependent variable, which is Multicriteria Inventory classification using AI techniques for spares management in the aviation sector (OM) Out of the seven hypotheses postulated, four were direct effects and three were indirect effects. Four independent variables, deep learning (DL), supervised learning (SL), unsupervised learning (US), and demand forecasting (DF), and one dependent variable, Multicriteria Inventory classification using AI techniques for spares management in the aviation sector (OM), were identified. All variables were statistically significant, with supervised learning having the maximum weightage. Also, the supervised learning algorithm Support Vector Machines (SVMs) performed the best when it came to classifying spare parts with varying lead times and demand fluctuations.

No empirical study is devoid of limitations, and this research is no exception. The research considered only lead times and demand fluctuations for inventory classification; other important parameters such as inventory costs and ordering costs were not considered and could be explored in the future. Also, the research was too narrow focusing mainly on aviation sector. The future work could explore the possibility of incorporating the model for classifying spares across high reliability operation sectors and see how it performs. Also, the possibility of classifying spares based on multiple criteria using AI techniques by utilizing ABC, FSN, or XYZ can also be explored.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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