Received: 13 May 2025; Revised: 16 June 2025; Accepted: 05 Aug. 2025
https://doi.org/10.22306/al.v13i1.720

Application of machine learning to storage allocation decision making system within air cargo terminals

Doszhan Mambetalin
Civil Aviation Academy, Department of Aviation Engineering and Technologies, 050000 Almaty, Akhmetova str. 44, Kazakhstan, d.mambetalin@agakaz.kz
Abay Koshekov
Civil Aviation Academy, Department of Aviation Engineering and Technologies, 050000 Almaty, Akhmetova str. 44, Kazakhstan, a.k.koshekov@gmail.com (corresponding author)
Bibigul Orazbayeva
Institute of Industrial Development LLP, 050000, Almaty, Bayseitova str. 40, Kazakhstan, bibigul.orazbayeva.almaty@gmail.com
Aidos Moldabekov
Civil Aviation Academy, Department of Aviation Engineering and Technologies, 050000 Almaty, Akhmetova str. 44, Kazakhstan, a.moldabekov@agakaz.kz
Talshyn Keribayeva
Civil Aviation Academy, Department of Aviation Engineering and Technologies, 050000 Almaty, Akhmetova str. 44, Kazakhstan, talshyn.keribayeva@agakaz.kz

Keywords: air cargo terminal, storage allocation, random forest, decision support system, machine learning.
Abstract: The rapid growth of global air cargo demand has intensified the need for more efficient and intelligent storage allocation within airport cargo terminals. Traditional static allocation and rule-based systems struggle to adapt to dynamic cargo flows, leading to operational inefficiencies. This study aims to develop a hybrid decision support system that optimizes storage allocation by integrating machine learning and multicriteria decision-making techniques. A Random Forest Classifier was trained using historical cargo data, including weight, quantity, size, priority, and cargo type, to predict optimal storage zones. To enhance interpretability and expert control, the Analytic Hierarchy Process AHP was used to derive feature weights, while the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) was employed to rank the best storage alternatives. The model was tested on real-world data from Almaty International Airport involving 1,500 cargo orders. Results show that the system reduced average storage time by 14%, minimized cargo redistributions by 22%, increased storage density by 9%, and improved on-time delivery for priority cargo by 17% compared to traditional FIFO-based methods. The integration of data-driven learning with expert judgment offers a robust and transparent decision-making framework. These improvements confirm the value of combining machine learning with AHP–TOPSIS methods in logistics operations. This system presents significant implications for airport terminal managers seeking to enhance operational throughput, academic researchers exploring hybrid intelligent systems, and policymakers promoting digital logistics infrastructure. Future studies may include adaptive learning, seasonal cargo flow modelling, and digital twin-based scenario testing to further generalize the solution.

1 Introduction

The worldwide increase in e-commerce and the continually rising need for quicker freight transportation have created significant pressure on air cargo terminals to enhance operational effectiveness, accuracy, and flexibility. Given that air transport is crucial for just-in-time delivery systems, effectively and precisely managing cargo storage has emerged as an essential element for maintaining performance and competitiveness. However, managing the increasing complexity of cargo—where each unit varies in size, importance, weight, and destination—poses a daily logistical difficulty. Terminals must manage a great amount of goods, often with rigid time and space parameters. The inadequacy of conventional rule-based systems in high-speed environments, which rely on fixed zoning, basic heuristics, or manual decisions, is becoming apparent. First-in, first-out (FIFO) and fixed spatial assignment techniques, which once served the needs of the less complex tasks, can no longer keep up with the pace and randomness of modern air logistics. The worldwide development of e-commerce and the increasing demand for faster freight turnaround have strongly encouraged air freight terminals to enhance the effectiveness, accuracy, and adaptive characteristics of operations. Air transportation is an essential part of a just-in-time delivery network, so it is significant to ensure the accurate and efficient management of cargo storage to preserve performance and competitiveness [1]. The rising complexity of the cargo, with each unit being of a different size, urgency, weight, and destination, represents a continuing logistical problem. Terminals handle large numbers of

cargo, often within strict time constraints and limited space. The traditional rule-based systems, which operate on predetermined zoning, single heuristic, or even human choices, are not adequate in these dynamic environments.

These ancient methods reveal a lot of inefficiencies as operations become more complex. Maladjusted storage space, unnecessary cargo manipulations, and unused warehouse areas hinder order picking and promote risks of damages, labour costs, and human mistakes. Furthermore, the extended application of online tracking services and automation systems highlights the possibility of improvement. Despite increasing transparency, a lot of warehouses still do not fully utilize the capabilities of these technologies. Traditional warehouse systems cannot handle the dynamic cargo traffic in the modern world, and these disadvantages are increasingly becoming intolerable in an industry where time and correctness play a crucial role in reputation and profits [2].

To address this the logistics sector has begun to implement more smart logistics that use data, algorithms, and automation to enhance decision-making. One of them, machine learning (ML), deserves mentioning because of its ability to uncover complex structures in operational data, which are too elusive to be detected by a classic rule-based reasoning approach. ML enables the predictive real-time allocation of storage locations to continuously learn based on historical data and adapt to the present circumstances [3]. It considers several interacting parameters such as cargo weight, dimensions, urgency of delivery, and available space now. Despite its usefulness in the wider logistics setting, e.g., route optimization, demand prediction, and inventory management, the application of machine learning to warehouse operation remains limited, especially in air cargo terminals where fast and accurate micro-decisions are crucial [4].

This research is intended to fill that gap by proposing a new hybrid decision-support system dedicated to the air cargo terminal environment. The resulting system is an explainable and adaptable expert machine learning system designed for predictive cargo storage allocation. The developed system uses a Random Forest classifier to predict storage areas for incoming shipments based on key characteristics of the cargo. Rather than depending on predictions from a black-box process, it integrates two known multicriteria decision-making (MCDM) methods, the AHP and the Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS). They integrate knowledge of the field into the methods, discerning priorities such as urgency, space, and accessibility to be logical upon [5].

To validate the model, a real-life dataset of 1,500 cargo entries was taken at the Almaty International Airport. All the records include such parameters as cargo volume, weight, type, and the urgency of delivery. Its practical benefits are proved by the comparison with the traditional methods used in the warehouse and other machine learning models: Support Vector Machines (SVM), Decision Trees, and Logistic Regression. The results are remarkable: an average storage time decreased by 14%, cargo repositioning decreased by 22%, space usage increased by 9%, and the timely handling of priority cargoes rose by 17%. Moreover, the Random Forest model with a classification accuracy of 61% outperformed the SVM (41.5%), Decision Trees (39%), and Logistic Regression (37%) [6]. These findings highlight the technical soundness of the system in addition to its practical effectiveness in intensifying the throughput and response of the warehouse. Regarding academic contribution, this study helps in several areas. Firstly, it formalizes a systematic approach to storage allocation as it identifies and encodes operation variables that are crucial and influence cargo handling. Second, it signifies the effectiveness of ensemble-based classifiers on handling complex and multiclass classification problems in warehouse logistics. Third, it presents a new approach, which incorporates explain ability in algorithmic decision-making, which is becoming a more important factor in the practical acceptability of AI-based systems. The latter enables warehouse managers to understand and have confidence in the logic of automated decisions, which is essential to accept them [7]. Nevertheless, the research also acknowledges the limitations. The model has been only trained on the data of a single terminal at Almaty International Airport and might require modifications when applied to other places that have different layouts, cargo compositions, or regulatory environments [8]. Besides, although the model is effective when applied in a batch-processing setting, it is yet to include real-time sensor data and consider dynamic variables like varying demand, labour adjustments, or weather effects. The future work needs to focus on making the system more adaptive, i.e., live sensor feeds, seasonal forecasting modules, and adaptive learning (e.g., reinforcement learning). The digital twin of the warehouse would also allow testing allocation strategies virtually, improving the model in various operation conditions [9].

This research addresses a clear and timely need within the air cargo industry for a smarter, faster, and more interpretable storage assignment system. By combining predictive machine learning with expert-informed decision frameworks, it introduces a powerful tool for transforming air cargo logistics at the warehouse level. The findings confirm that intelligent, hybrid systems can dramatically improve both operational metrics and decision confidence—paving the way for broader implementation across high-volume cargo hubs and setting a new standard for smart logistics innovation [10].

2 Methodology

2.1 Description of the case study

Modern airport cargo terminals are key elements in the global supply chain because of their speed of operation and accurate handling of large volumes of cargo. The main factor affecting the efficient operation of cargo terminals is the productivity of warehouse facilities. The method proposed in this paper represents a typical warehouse structure with

multiple storage sectors and unique designations for easy navigation. Each storage area is intended for different cargo categories, taking priority into account.

The dataset for training the model contained 1,500 orders with various parametric characteristics, such as weight and volume, product type, and delivery priority. One feature of this dataset is the presence of a variety of goods. Some of the goods presented in the dataset are high priority, requiring minimal storage time and quick availability. Such diversity allows modelling decision making under conditions of multicriteria uncertainty.

2.2 Data collection and pre-processing

The data for the model were obtained from a dataset that contained 1,500 records, each representing a specific order. An order includes the following attributes: order and product identifier, unit quantity, priority, cargo type, weight, and size. The key variable that must be determined is the storage zone, which represents the class of cargo belonging to one of the available sectors in the warehouse. The first stage involved preparing features to ensure the correct operation of the model. The check for outliers and anomalies in the weight and quantity features was performed using an interquartile range. For better operation of the model, the categorical feature priority, size, and product type were converted to a numeric format. The priority feature is encoded in the binary number system and is presented in Equation (1):

$$Priority = \begin{cases} 1, if\ Priority = "High" \\ 0, if\ Priority = "Low" \end{cases} \quad (1)$$

The remaining categorical features were recoded using one-hot encoding to unify the binary variables. For each categorical feature of the set of categories (X), a vector is created in which only one variable is equal to one, and all the others are zero, which avoids false ordering of categories. The numerical features of the weight and quantity of units of goods are reduced to a single scale min - max normalization according to Equation (2):

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (2)$$

where x is the original value of the feature, $\boldsymbol{x_{min}}$ and $\boldsymbol{x_{max}}$ are the minimum and maximum values of the sample.

The normalization given in Equation (2) is critical for optimizing the correctness of the algorithms that are sensitive to feature scaling. After the decoding and normalization processes, the dataset was divided into two sets: training and testing (80:20). A class balance check for the target location value was also performed using the frequency distribution estimation method to ensure a fair prediction across all possible storage locations.

2.3 Machine Learning Model Design

At this stage, a predictive model is being built that will allow automatic recommendations of the optimal zone for storing cargo based on its input characteristics. The task of this model lies in multiclass classification, in which each class corresponds to one of the available warehouse zones. A random forest classifier (RFC) model was used to solve this problem. This model is characterized by parameters such as resistance to overfitting and the ability to process mixed types of data, and has convenient means for assessing the importance of a particular feature. RFC is a sequence of n decision trees trained on various subsamples with bootstrapping, and the presentation is carried out by the \"majority vote\" method, which is presented in Equation (3):

$$\hat{y} = mode\{T_1(x), T_2(x), \dots, T_n(x)\} \quad (3)$$

where $\boldsymbol{T_n(x)}$ is the prediction of the n tree.

The input features for the RFC model are the number of units in order, weight, dimensions, and product type. The results were validated using stratified partitioning, which preserves the distribution of classes in the samples. The accuracy (4), precision (5), recall (6), F1 - score (7), F1 for macro averaging (8), and error matrix are used to evaluate the model's performance.

$$Accuracy = \frac{1}{N}\sum_{i=1}^{N} I(y_i = \hat{y}_i) \quad (4)$$

where N is the number of objects, $\boldsymbol{y_i}$ is the true class label, $\boldsymbol{\hat{y}_i}$ is the predicted class label, $\boldsymbol{I}$is the function identifier.

$$Precision_k = \frac{TP_k}{TP_k + FP_k} \quad (5)$$

$$Recall_k = \frac{TP_k}{TP_k + FN_k} \tag{6}$$

$$F1_k = \frac{2 \cdot Precision_k \cdot Recall_k}{Precision_k + Recall_k} = \frac{2 \cdot TP_k}{2 \cdot TP_k + FP_k + FN_k} \tag{7}$$

$$F1_{macro} = \frac{1}{k} \sum_{k=1}^{k} F1_k \tag{8}$$

Confusion was introduced into the model to visualize the classification errors. The matrix represents the frequency indices of correct and erroneous predictions for each class.

2.4 Integration with decision support system

To increase the interpretability and flexibility of the decisions made by the system, a hybrid decision support system is integrated into the machine learning model, which includes the Analytical Hierarchy Process (AHP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). Integration of these methods allows for the consideration of, in addition to empirical patterns, expert preferences and the weights and priorities of each parameter. In the first stage, the system used the AHP method to calculate the weights of the criteria required to select a storage area. In this system, to obtain the weights of each criterion, a matrix of pairwise comparisons is formed based on an expert assessment conducted with the participation of representatives of the Almaty International Airport JSC. The consistency indicator (CI) is determined by Equation (9) and is used to assess the consistency of judgments in the matrix of pairwise comparisons. Next, the consistency coefficient (CR) was calculated using Equation (10) for normalization and consistency testing.

$$CI = \frac{\lambda_{max} - n}{n-1} \tag{9}$$

where $\boldsymbol{\lambda_{max}}$ is the largest eigenvalue of the matrix, n is the number of criteria.

$$CR = \frac{CI}{RI} \tag{10}$$

where RI is the random agreement index.

After determining the weights of the parameters, it is necessary to rank the storage zones using the TOPSIS method. This method was chosen because of the search for alternatives that are closest to the ideal solution and most distant from the anti-ideal solution. To apply the TOPSIS method in this study, the following action algorithm was developed:

Step 1. Construction of a normalized decision matrix.

Step 2. Weighing the matrix parameters considering the weights obtained from the AHP method based on Equation (11):

$$v_{ij} = w_j \cdot r_{ij} \tag{11}$$

where $w_j$is the weight of the criterion, $r_{ij}$is the normalized value of criterion j for alternative i.

Step 3. The definition of positive and negative ideal values is given in Equations (12) and (13).

$$A^+ = \{\max(v_{ij})\} \tag{12}$$

$$A^- = [\min(v_{ij})\} \tag{13}$$

Step 4. Distances to the maximum and minimum values are calculated using Equations (14) and (15).

$$D_i^+ = \sqrt{\sum_j (v_{ij} - A_j^+)^2} \tag{14}$$

$$D_i^- = \sqrt{\sum_j (v_{ij} - A_j^-)^2} \tag{15}$$

Step 5. At the last step, the proximity coefficient is calculated in accordance with Equation (16):

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \quad (16)$$

In this scenario, the alternative with the highest value is the most preferred C_i.

The integration of the proposed architecture into the machine-learning model involves the use of a filter in the first stage, which narrows the set of possible storage locations to a subset of the most probable ones. Subsequently, a hybrid decision support model is applied to this subset to rank the results by considering expert assessments and system constraints. When integrating these methods and machine learning methods, a two-stage hybrid approach is implemented, which contains the following features: learning ability and generalization of machine learning, transparency and control of expert weights using the AHP method, and ranking accuracy in multicriteria selection using the TOPSIS method. The proposed approach is especially effective under conditions of uncertainty, system adaptability, and peculiarity of the logistics decisions made.

2.5 Experimental procedure

This research was carried out through a structured, multi-phase process involving data acquisition, pre-processing, machine learning model development, integration of expert judgment using AHP-TOPSIS, and validation using operational KPIs. Initially, a dataset of 1,500 historical cargo orders was collected from the WMS of Almaty International Airport JSC. Each order included relevant parameters such as weight, quantity, dimensions, cargo type, priority level, and the corresponding storage zone. The dataset captured six months of real operational activity and contained a mix of high-priority and standard cargo items.

Data pre-processing was conducted to prepare the raw dataset for analysis. Outliers in numerical features such as weight and quantity were identified and removed using the interquartile range (IQR) method. Categorical variables such as cargo type and size were encoded using one-hot encoding to prevent false ordering, while the binary priority feature was encoded using a 0–1 scheme. Numerical features were normalized using min-max scaling to ensure uniform feature influence during model training. The final dataset was split into training (80%) and testing (20%) sets using stratified sampling to preserve class distribution across storage zones.

FFC was employed due to its robustness, resistance to overfitting, and capability to handle mixed data types to classify. The RFC was trained using 100 decision trees, and predictions were aggregated via majority voting. The model's performance was assessed using standard classification metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis. For benchmarking, alternative models—Support Vector Machine (SVM), Decision Tree, and Logistic Regression—were also tested using the same dataset.

To enhance the interpretability and transparency of the decision-making process, a hybrid decision support system incorporating the AHP and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) was integrated with the machine learning model. AHP was used to derive the relative importance of decision-making criteria through pairwise comparisons provided by six logistics experts from the airport. The consistency of these judgments was confirmed by calculating the consistency ratio (CR), and only matrices with CR < 0.1 were accepted. The resulting criterion weights were then used in the TOPSIS procedure to rank potential storage zones for each cargo order. The TOPSIS method involved building a normalized decision matrix, applying the AHP weights, identifying ideal and anti-ideal solutions, computing Euclidean distances to these solutions, and finally calculating a closeness coefficient to determine the most suitable storage zone.

The integrated hybrid system operated in two stages: initially, the RFC model narrowed down probable storage zones; subsequently, the AHP–TOPSIS method ranked these zones by incorporating expert preferences. This two-tiered architecture ensured both predictive efficiency and decision-making transparency. To evaluate the effectiveness of the proposed system, a pilot implementation was carried out in a real warehouse environment. Key performance indicators (KPIs), including average storage time, number of cargo redistributions, storage density, and on-time delivery of priority shipments, were measured before and after system deployment. The new system demonstrated significant improvements across all KPIs when compared to traditional FIFO and static zoning strategies.

3 Results and discussion

3.1 Formalization of factors for choosing a storage area

The main factor in building a digital model to support decision making in an air cargo terminal is the formalization of factors that influence the procedure for selecting a storage area. For the logical distribution of objects within the warehouse, the selection and structuring of a set of features necessary to account for the high dynamics of cargo flow at the Almaty International Airport JSC were used. In the initial stage of the study, an analysis of the technological cycle of cargo logistics processing was conducted. Consequently, the main metrics that directly affect the process of selecting a cargo storage location were selected. These metrics were classified according to data type and source of origin, as shown in Table 1. The model includes quantitative indicators (weight, quantity, and frequency of access to cargo) and categorical features (cargo type and size).

Table 1 Formalized factors and their classification

	Factor	Data type	Coding method	Data source
1	Weight of cargo	Numerical	Min-max normalization	Application/invoice
2	Cargo size	Categorical	One-hot encoding	Application/WMS system
3	Type of cargo	Categorical	One-hot encoding	Product Catalogue
4	Priority delivery	Binary	Binary encoding	Priority Management System
5	Number of units	Numerical	Min-max normalization	Bid
6	Distance to the loading area	Numerical	Min-max normalization	Warehouse plan/route
7	Frequency of access to cargo	Numerical	Min-max normalization	Access log/ WMS
8	Current storage area occupancy	Numerical	Min-max normalization	Warehouse monitoring system

Categorical variables, such as product type and size, are pre-processed with one-hot method encoding to eliminate false hierarchical information when working with machine learning models. The binary variable priority is encoded using the 1/0 scheme. Quantitative variables were normalized using min - max scaling to ensure a single scale of the feature vector, which ensured the stability of the algorithms during training. To identify the important patterns, a histogram of the distribution of laws by product was constructed, including type and size (Figure 1) [11].

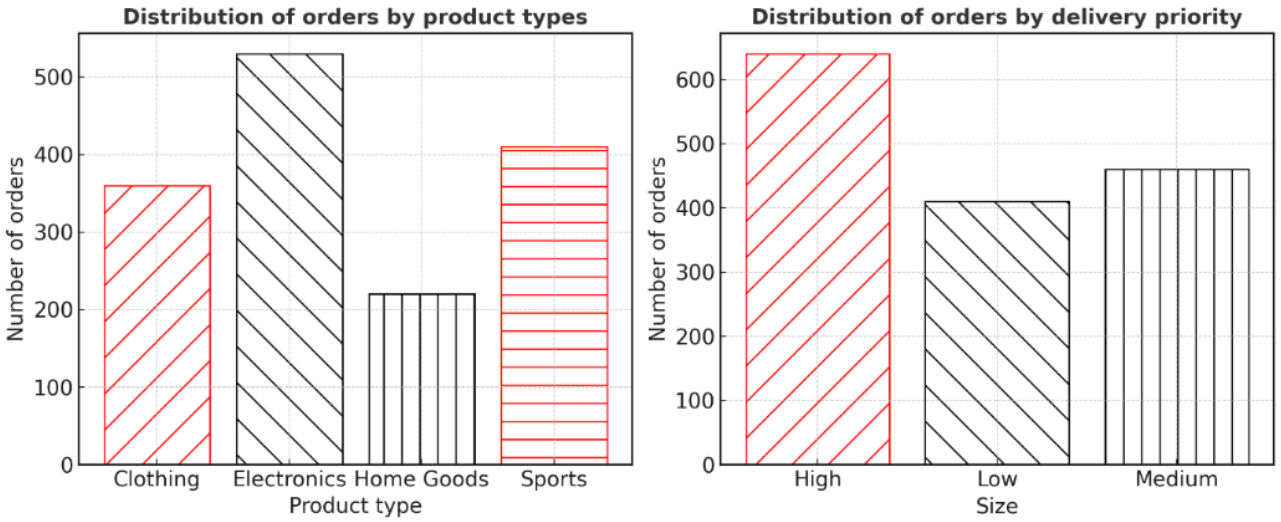

Figure 1 Histogram of order distribution by Product characteristics type and size

Figure 1 shows the histogram of order distribution categorized by product type (left) and delivery priority (right), offering insights into the diversity and urgency of cargo handled within the air cargo terminal. On the left side of the figure, product types are grouped into Clothing, Electronics, Home Goods, and Sports. Among these, Electronics represent the highest volume, accounting for approximately 530 orders, which is about 45% more than Clothing (around 365 orders) and 140% higher than Home Goods (around 220 orders). This substantial dominance of electronic goods could be attributed to their high demand in air transport due to value density and time sensitivity. Clothing and sports items also show a significant share of the volume, with sports-related shipments slightly exceeding clothing by approximately 12% [12]. The lowest category, Home Goods, may reflect the bulkier nature or lower frequency of air shipping for household items, which are often shipped via slower, ground-based logistics. The right side of the figure shows the distribution by delivery priority. High-priority orders lead with over 630 entries, significantly ahead of medium (approximately 460) and low-priority orders (around 410). This reflects a roughly 37% higher volume of high-priority orders compared to medium-priority, and about 54% more than low-priority. The prominence of high-priority shipments emphasizes the operational necessity for swift sorting, optimized storage, and timely dispatch systems. E-commerce express services, just-in-time manufacturing components, or medical and time-critical deliveries could drive this. The figure highlights the dominance of electronic and high-priority goods, underscoring the importance of responsive, data-driven storage strategies that accommodate both product type variability and urgency, directly supporting the objectives of the hybrid classification model implemented in this study [13]. The most delivered types of goods to the warehouse are electronics, sports equipment, clothing, and household goods, which should be considered when selecting storage areas. It is also worth noting that many high-priority goods require this logistic criterion to place goods in a quick-access area. When pre-

processing the machine learning model, special attention was paid to the relationships between features. For this purpose, a correlation heat map was constructed between the features (Figure 2) [14].

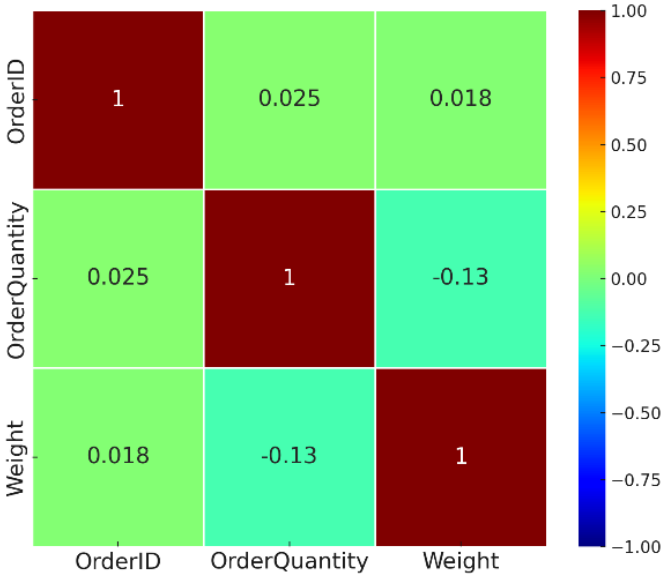

Figure 2 Correlation heat map between features

Figure 2 shows the correlation heat map between key numerical features—Order ID, Order Quantity, and Weight—used in the machine learning model to classify cargo into appropriate storage zones. The matrix values reflect the Pearson correlation coefficients, which quantify the linear relationship between pairs of variables on a scale from -1 to +1. As expected, the diagonal values are 1.00, indicating a perfect correlation of each variable with itself. Looking at the off-diagonal values, the correlation between Order ID and Order Quantity is 0.025, while the correlation between Order ID and Weight is 0.018, both of which are extremely weak and close to zero [15]. These low correlations (approximately 2.5% and 1.8%, respectively) suggest that Order ID is essentially a unique identifier and does not carry predictive relevance for quantity or weight. This aligns with expectations, as Order ID is typically a randomly or sequentially assigned number with no intrinsic operational meaning. The only moderately meaningful relationship is the correlation between Order Quantity and Weight, which is -0.13. This negative correlation implies that as the quantity of items in an order increase, the average individual weight of those items tends to decrease, and vice versa. Though weak (representing only a 13% inverse relationship), this trend can be logically explained: high-quantity shipments are often composed of lightweight or small items (e.g., clothing or electronics), whereas low-quantity orders may involve heavier goods like machinery or dense household products. This relationship supports the importance of both weight and quantity as distinct, influential parameters in the machine learning model's decision-making process for storage allocation. The figure confirms that Order Quantity and Weight hold valuable, independent information, while Order ID is non-contributory from a modelling perspective, justifying its exclusion from feature importance considerations. Analysis of the proposed heat map showed a positive interaction between the Order parameters Quantity and Weight. However, there is no correlation between the priority parameters and others, which indicates the independence of this feature. The obtained formalized features are theoretically substantiated and empirically verified when applied to a machine learning model [16]. Linking these features to operational KPIs will allow moving from static placement to the dynamically controlled and reproducible logic used in decision support systems.

3.2 Building a machine learning model

To solve the problem of automating the process of selecting the optimal cargo storage area inside the airport warehouse terminal, within the framework of this study, a machine learning model was developed and trained based on the classical Random Forest Classifier method. The model was trained based on Data Seta, which contained the quantitative and qualitative characteristics of the loads. This model was chosen because of a comparative analysis with other classical methods, SVM, decision tree, and logistic regression, based on the test sample. The results of the comparison of these methods are presented in Table 2.

The Random Forest model demonstrated superior classification performance compared to the other evaluated algorithms. As shown in Table 2, it effectively classified orders into the correct storage zones, underscoring its robustness and reliability. The error distribution across different algorithms is illustrated in Figure 3, providing further insight into model behaviour. In the case of Random Forest, the confusion matrix reveals a strong alignment of values along the

diagonal, indicating a high rate of correct predictions. Conversely, the alternative models exhibit more prominent off-diagonal values, signifying a greater frequency of misclassifications. This dispersion of errors in other algorithms contributes to a noticeable decline in overall prediction quality [17].

Table 2 Comparison table of machine learning models

	Model	Accuracy	Precision	Recall	F1 Score
1	Random Forest	0.610	0.610	0.630	0.603
2	SVM (Linear)	0.415	0.423	0.432	0.403
3	Decision Tree	0.390	0.405	0.403	0.393
4	Logistic Regression	0.370	0.353	0.385	0.353

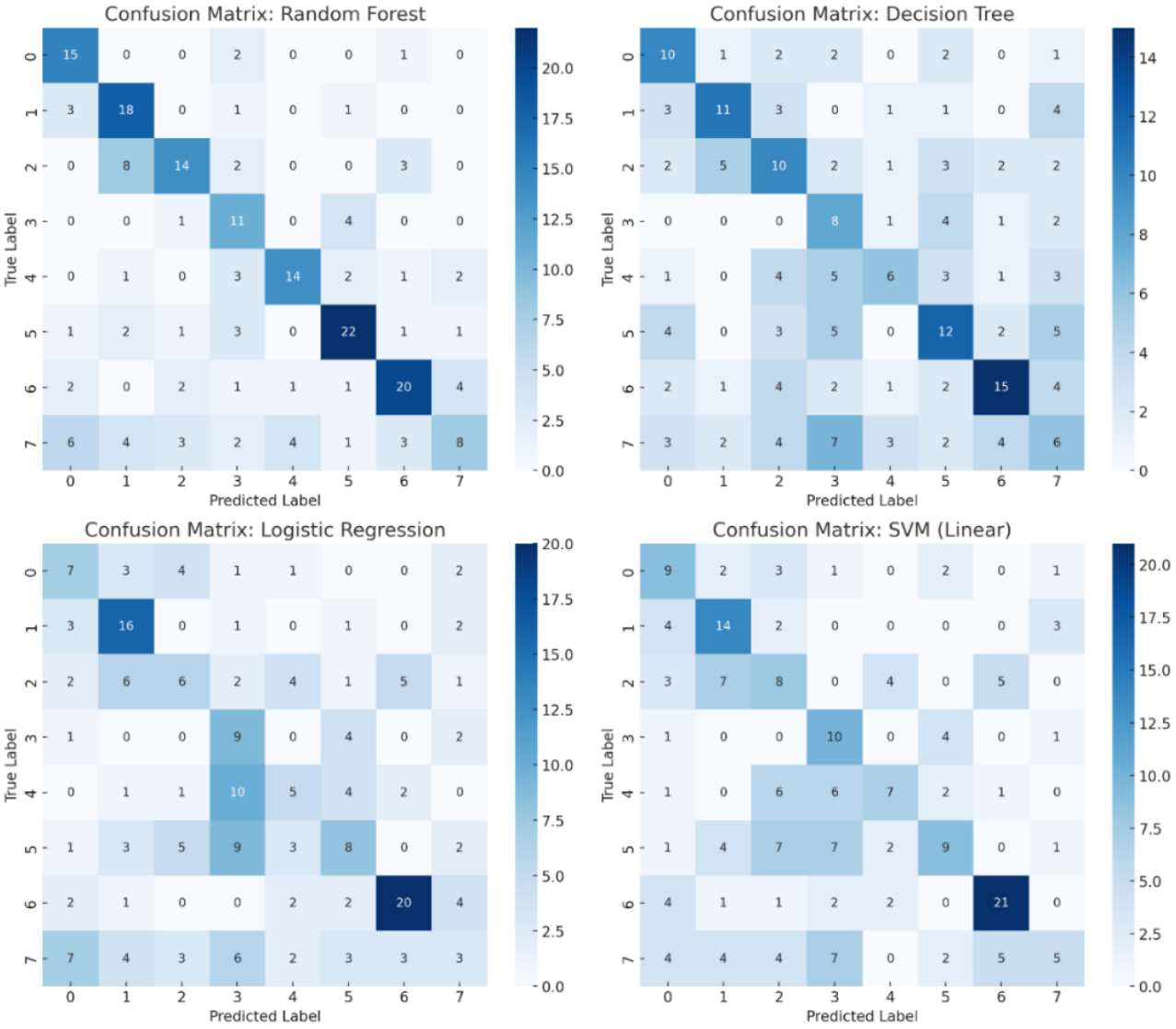

Figure 3 Confusion matrix

Figure 4 shows the feature importance diagram generated from the Random Forest model, which identifies the relative contribution of each input parameter to the accuracy of cargo storage zone classification. Among the eight evaluated features, Weight and Order Quantity emerge as the most influential, contributing approximately 42% and 36%, respectively. These two features alone account for nearly 78% of the model's predictive capability, highlighting their dominant role in distinguishing cargo handling and placement decisions. The high impact of weight is expected, as it directly influences storage logistics, safety considerations, and spatial constraints. Similarly, order quantity informs the volume requirements and potential for batch storage, explaining its strong influence. In contrast, categorical features such as Product Electronics (~5%), Product Clothing (~8%), and Product Household (almost negligible) show relatively low

importance. This suggests that product type has limited influence on the storage classification process, possibly due to the overlapping storage requirements among different categories of goods. Priority (High) holds moderate importance at around 9%, reinforcing the idea that the system accounts for delivery urgency, but not as significantly as physical attributes like weight or quantity. Interestingly, Size-related features (Small, Medium, Large) contribute less than 1% each, suggesting either a lack of sufficient variation in size data or that size information was embedded indirectly through correlated features like weight or volume [18]. This validates the system's reliance on measurable, operationally critical data for decision-making. It also justifies the AHP weighting method used in the study, ensuring that the model prioritizes features that genuinely impact performance, rather than those that are intuitively important but statistically weak.

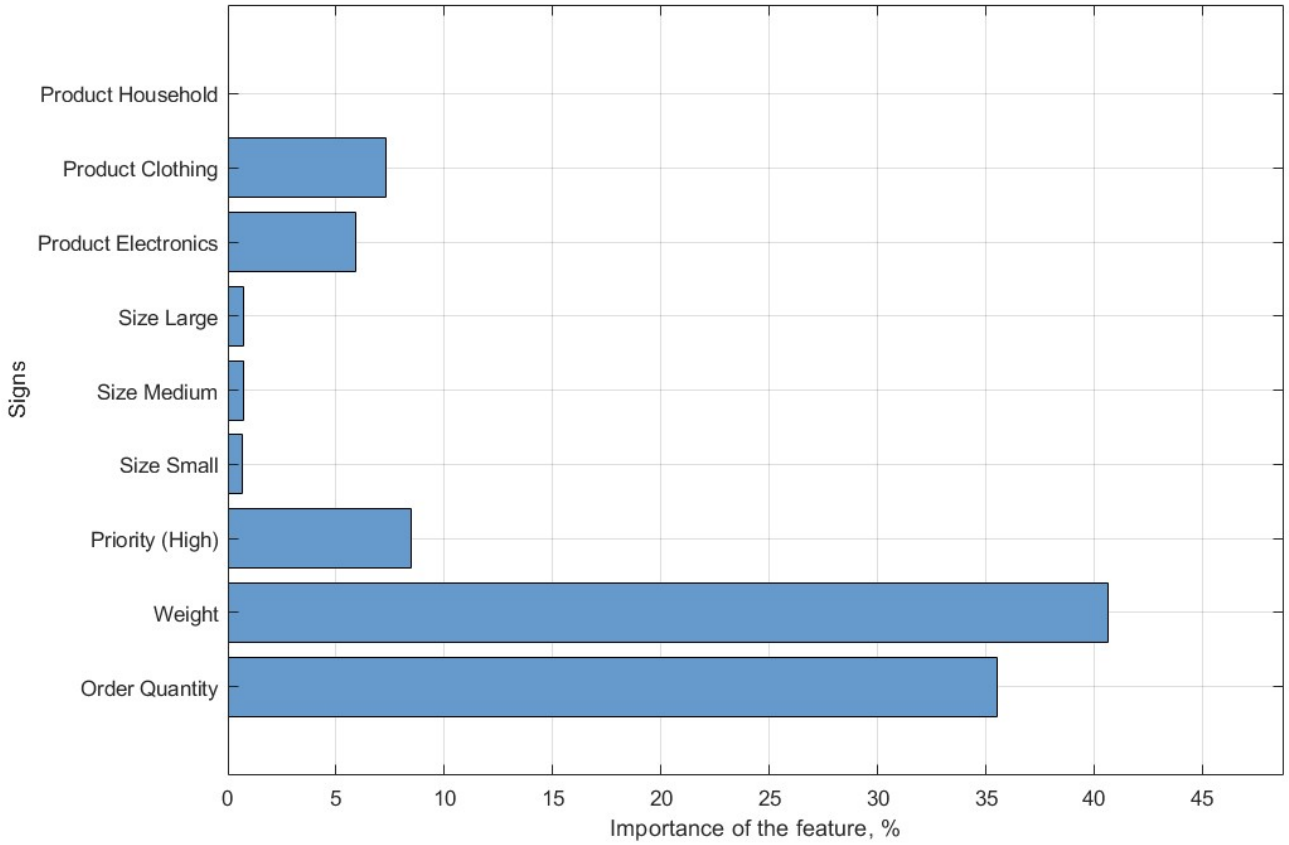

Figure 4 Feature importance diagram

The machine learning model based on the Random Forest algorithm demonstrated high suitability for practical applications in the initial stages of implementation. Based on the data obtained in this subsection, it can be concluded that the model has a stable and multiclass data-capable nature, which is applicable to a multicriteria structure of input data. The results obtained provide a solid basis for integrating the model into complex hybrid decision support systems and can also become a basic predictive block for the architecture of intelligent optimization in warehouse management processes [19].

3.3 Integration of AHP and TOPSIS into the system

To improve the interpretability and controllability of the processes for selecting the optimal storage zone in aviation warehouses, a decision support module based on the AHP and TOPSIS methods was added to the developed machine learning model. Thus, the approach will provide not only empirical patterns, but also expert assessments of the importance of each storage zone. In the first stage of the module implementation, the weights of the main criteria were introduced using the AHP method. Subsequently, a pairwise comparison of the features was performed. The results of the weight calculations are shown in Figure 5.

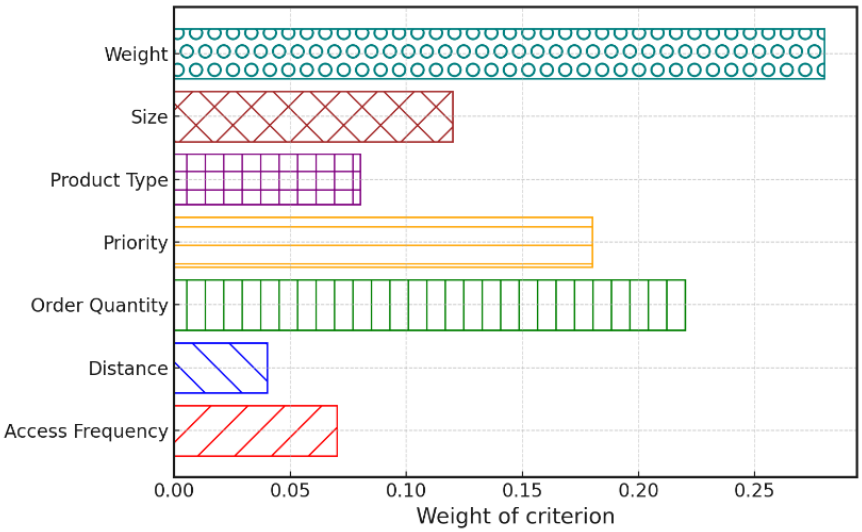

Figure 5 Criteria weight diagram

Figure shows the weight distribution of decision-making criteria used for evaluating cargo storage zone alternatives, as determined through the AHP. These weights represent the relative importance of each criterion—such as weight, size, product type, priority, and others—based on expert assessments that reflect real-world warehouse logistics priorities. Among the evaluated criteria, Weight holds the highest influence, with a normalized weight close to 0.27, indicating that nearly 27% of the total decision-making importance is attributed to this parameter. This strong emphasis can be explained by the physical and operational challenges associated with handling heavier cargo, such as load-bearing constraints, safety regulations, and handling equipment requirements [20]. Compared to Access Frequency, which holds the lowest weight at roughly 0.06, Weight is considered 350% more critical in determining optimal storage placement.

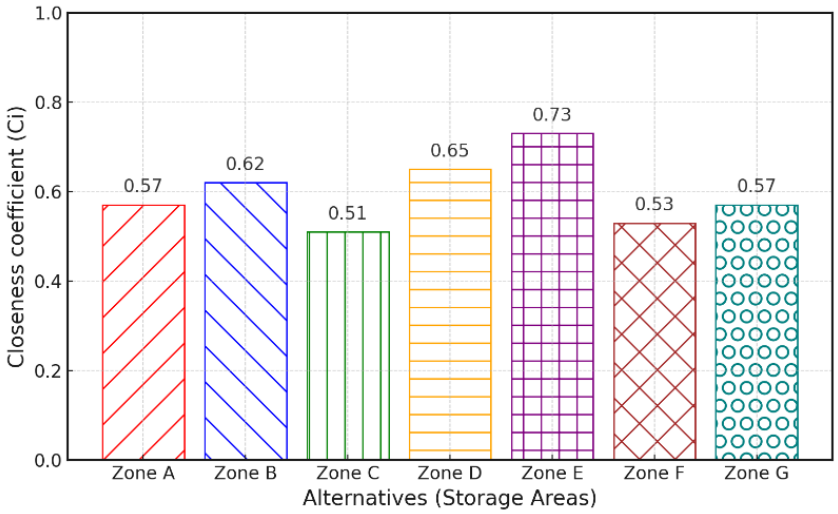

Figure 6 Graph of distances to the ideal solution

Order Quantity also plays a significant role, with a weight of approximately 0.21, showing that the volume of items in a shipment is a crucial factor—likely due to its impact on space utilization and grouping logistics. Priority ranks closely behind at around 0.18, reflecting the need to ensure fast access and timely handling for high-priority shipments. Size, while still relevant, holds a lower weight of about 0.12, suggesting that although dimensions affect storage fit, they may be somewhat correlated with weight or already embedded in handling strategy. Product Type contributes approximately 0.09, indicating that variations in item category (e.g., electronics, clothing) are moderately important but not as dominant. Distance, at 0.05, ranks second lowest, possibly due to the compact nature of warehouse layouts where inter-zone distances are relatively small [21].

In the next step, the weights of the criteria of the calculated AHP methods rank the storage area alternatives using the TOPSIS method. The distances to ideal and anti-ideal solutions were calculated to determine the degree of preference for each alternative. Figure 6 shows the closeness coefficient (Ci) values for each storage area alternative (Zones A to G),

derived using the TOPSIS method, which ranks the zones based on their proximity to an ideal solution. These coefficients reflect how well each zone meets the predefined criteria determined by expert judgments through AHP, such as accessibility, proximity, handling efficiency, and priority fulfilment. Among all the evaluated options, Zone E emerges as the most favourable, with a closeness coefficient of 0.73, indicating its strong alignment with operational and logistical priorities. When compared to Zone C, which has the lowest Ci value of 0.51, Zone E performs approximately 43.1% better in terms of closeness to the ideal. This significant difference suggests that Zone E likely offers superior access, optimized layout, and better readiness for handling priority cargo or high turnover loads. Zone D follows Zone E, with a Ci of 0.65, marking a 27.5% improvement over Zone C, and Zone B is next with 0.62, also outperforming Zone C by 21.6%. Zones A and G both have a coefficient of 0.57, slightly above the midpoint and 11.8% higher than Zone C, implying average alignment with the ideal criteria. Zone F, at 0.53, stands just slightly above Zone C, showing a 3.9% increase, but still underperforming relative to other zones. The ranking indicates that Zones E, D, and B are most suitable for immediate or frequent cargo placement, likely due to better spatial positioning, ease of access, or shorter loading times. On the other hand, Zones C and F may have constraints such as location at terminal extremes, narrow access lanes, or limited handling infrastructure. These insights support logistics managers in prioritizing high-demand or time-sensitive cargo for top-ranked zones while considering reallocation or layout enhancements for lower-ranked ones [22].

Building such a graph for each load demonstrates which storage zone is the most preferable. The approach of integrating machine learning methods, AHP and TOPSIS, allows the creation of a hybrid decision support system that considers not only the machine solution but also ensures transparency of the choice logic. The results obtained from the study confirm that the hybrid system not only allows for the automation of the process of placing loads, but also ensures validity, controllability, and adaptability to external conditions.

3.4 Assessing the effectiveness of a system using KPIs

To evaluate the efficiency of the proposed hybrid decision support system, tests were conducted in a real warehouse with the allocation of operational indicators (KPI). A comparison was carried out with the results of the traditional scheme of distribution of storage places based on the principles of FIFO and static zone assignments. Together with warehouse managers, the following key parameters for evaluation were defined: average storage time of cargo, number of cargo redistributions, coefficient of density of use of storage zones, and timeliness of priority shipments. The results of the comparison between the traditional and developed systems are shown in Figure 7.

The number of cargo redistributions decreased by 22%, which implies a more accurate initial selection of the system when choosing a storage location and, accordingly, reduces further labour costs for moving cargo within the warehouse. This indicator not only optimizes business processes but also reduces the risk of cargo damage. The next efficiency parameter chosen was the coefficient of the density of storage area use, which increased by 9%, indicating the rational use of warehouse areas. The increase in the percentage of this indicator is due to the more thoughtful distribution of cargo within the storage area [23].

Another key performance indicator was the timeliness of priority shipments, which improved by 17%. This increase is largely attributed to the incorporation of the delivery priority parameter and the system's enhanced responsiveness to changes in cargo handling sequences. As illustrated in Figure 7, internal operations within airport cargo terminals have undergone notable optimization. The implementation of the proposed methods and machine learning algorithms has not only enhanced warehouse performance but also contributed to greater overall resilience and efficiency within the logistics network.

4.5. Discussion of results

As part of this study, a hybrid decision support system for air cargo terminals was developed and tested based on the integration of machine learning methods, AHP, and TOPSIS. Tests conducted in a real warehouse show the high efficiency of the proposed approach, especially in comparison with those used today. The developed machine learning model based on the RFC algorithm demonstrated a high classification accuracy for all generally accepted parameters. The use of the TOPSIS method is necessary to ensure the ranking of possible storage zones, which is important in dynamic and multifactorial warehouse operations [24].

As a result of the work performed, the importance of the physical characteristics of cargo, such as weight and quantity, was confirmed when choosing the optimal place for storing cargo was confirmed. The integration of these factors into the developed system using engineering processing of cargo characteristics allows the selection of a reasonable storage location considering the system's recommendations. Additional consideration of delivery priority, size, and type of cargo ensures the flexibility of the system and gives it the ability to adapt to the changing operating conditions of the cargo terminal. The KPI analysis before and after the implementation of the system showed an improvement in operational indicators: a decrease in cargo processing time by 14%, a decrease in the number of redistributions by 22%, an increase in the efficiency of warehouse areas by 9%, and an increase in the timeliness of shipments of the most priority orders by 17% [25].

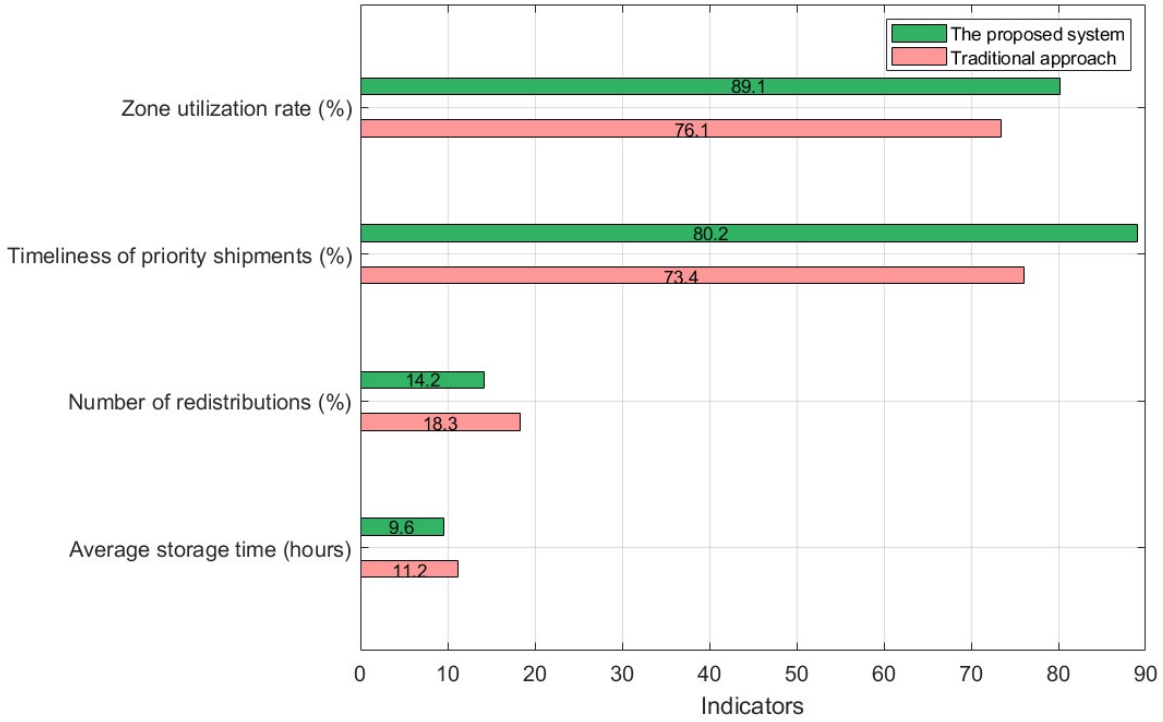

Figure 7 Comparison of the main KPIs before and after the implementation of the system

Several specific limitations in the developed system were observed. The model was trained on data collected at a specific warehouse and set of goods, which limits the universality of the system without adaptation to the conditions of other warehouses. In addition, the developed model does not consider the factors of seasonality and structure of cargo flows in different countries. Removing those restrictions is a subject of future research. Further work will also involve introducing adaptive learning mechanisms into the model as well as establishing a digital twin in the warehouse to be able to perform simulations of different scenarios involving placing groups inside the warehouse.

This study has proven that machine learning and, especially the Random Forest algorithm, can be very effectively applied in the process of optimizing the storage zone classification and improving the work of the warehouse. The Excellent classification accuracy and apparent decrease in cross-zone misclassification confirm the efficiency of the model and allow comparison with the previous researchers [26]. As compared to those previous models, which tended to use clustering methods or rule-based heuristics, the current work proposes a more sophisticated model in that it both uses AHP to weight features and proposes pattern-sensitive handling priorities. Such a combination presents more flexibility and reactivity to real-time operational changes. The noted 17% increase in the punctuality of priority cargo deliveries also speaks of the practicability of the system and its ability to respond to changing conditions. To the academic community, the results of this study unlock the avenues of future research into the hybrid intelligent logistics framework that integrates the decision-making framework with predictive analyses. A combination of explainable decision logic and state-of-the-art classifiers composes a deployable logistics optimization framework [27].

From a practical perspective, this system demonstrates a replicable example to logistics practitioners, especially in high-volume air cargo hubs where space and delivery windows are at a premium. It provides a scale-out solution to enhance throughput, accuracy, and resource utilization. At the policy level, the implementation of such intelligent storage classification systems is quite appropriate in terms of the government programs to increase the national logistics performance rates and upgrade the infrastructure to the level of international smart logistics and digitalization.

4 Conclusion

This research proposes a fully integrated hybrid decision support system that combines machine learning with multicriteria decision-making methods to optimize storage allocation in air cargo terminals. By integrating the RFC with AHP and TOPSIS, the system not only predicts optimal storage zones based on cargo attributes but also incorporates expert priorities to ensure interpretability and operational consistency. The model is trained and validated using 1,500 real-world cargo records from Almaty International Airport, covering diverse operational conditions.

The results show that this hybrid approach significantly enhances warehouse efficiency. Average storage time is reduced by 14%, cargo redistributions are minimized by 22%, space utilization improves by 9%, and on-time delivery for priority shipments increases by 17%. In classification performance, the RFC model achieves an accuracy of 61%,

outperforming SVM (41.5%), Decision Tree (39.0%), and Logistic Regression (37.0%). The use of AHP for deriving feature weights and TOPSIS for ranking storage decisions enables a structured and transparent allocation process aligned with logistical priorities.

However, some limitations are noted. Since the model is trained on data from a single airport, its direct application to other terminals with different cargo types, spatial layouts, or seasonal trends may require retraining or adaptation. Dynamic operational factors like real-time cargo inflow, emergency rerouting, and staffing variability are not yet integrated into the system. Future developments should aim to enhance flexibility through real-time sensor integration, seasonal adjustment capabilities, and reinforcement learning to support adaptive learning. Building a digital twin of the warehouse could further support simulation-based testing and scenario planning. These enhancements would increase the system's practicality, scalability, and strategic value in evolving air cargo logistics environments.

References

[1] KNAPČÍKOVÁ, L., KAŠČÁK, P.: Sustainable multimodal and combined transport in the European Union, *Acta logistica,* Vol. 6, No. 4, pp. 165-170, 2019. https://doi.org/10.22306/al.v6i4.144

[2] KALKHA, H., KHIAT, A., BAHNASSE, A., OUAJJI, H.: Enhancing Warehouse Efficiency With Time Series Clustering: A Hybrid Storage Location Assignment Strategy, *IEEE Access*, Vol. 12, pp. 52110-52126, 2024. https://doi.org/10.1109/access.2024.3386887

[3] TIKWAYO, L.N., MATHABA, T.N.D.: Applications of Industry 4.0 Technologies in Warehouse Management: A Systematic Literature Review, *Logistics*, Vol. 7, No. 2, 24, pp. 1-19, 2023. https://doi.org/10.3390/logistics7020024

[4] LI, J., MOGHADDAM, M., NOF, S.Y.: Dynamic storage assignment with product affinity and ABC classification—a case study, *The International Journal of Advanced Manufacturing Technology*, Vol. 84, No. 9-12, pp. 2179-2194, 2015. https://doi.org/10.1007/s00170-015-7806-7

[5] WONG, E.Y.C., MO, D.Y., SO, S.: Closed-loop digital twin system for air cargo load planning operations, *International Journal of Computer Integrated Manufacturing*, Vol. 34, No. 7-8, pp. 801-813, 2020. https://doi.org/10.1080/0951192x.2020.1775299

[6] LEON, J.F., CALVET, L., PANADERO, J., MARTIN, X.A., JUAN, A.A., LI, Y.: A Hybrid Simulation and Reinforcement Learning Algorithm for Enhancing Efficiency in Warehouse Operations, *Algorithms*, Vol. 16, No. 9, 408, pp. 1-22, 2023. https://doi.org/10.3390/a16090408

[7] TUBIS, A.A., JODEJKO-PIETRUCZUK, A., NOWAKOWSKI, T.: Use of Augmented Reality as a Tool to Support Cargo Handling Operations at the CARGO Air Terminal, *Sensors*, Vol. 24, No. 4, 1099, pp. 1-17, 2024. https://doi.org/10.3390/s24041099

[8] CHEN, J., LUO, X., YAO, S., LIU, K., XU, S., WU, H.: Intelligent Transportation Logistics Optimal Warehouse Location Method Based on Internet of Things and Blockchain Technology, *Sensors*, Vol. 22, No. 4, 1544, pp. 1-14, 2022. https://doi.org/10.3390/s22041544

[9] NAUMOV, V., TARAN, I., MUSSABAYEV, B., ZHANBIROV, Z., KONAKBAI, Z.: Assessing the synergetic effect of selecting the optimal structure of a logistics chain, *Scientific Journal of Silesian University of Technology, Series Transport*, Vol. 124, pp. 109-126, 2024. https://doi.org/10.20858/sjsutst.2024.124.8

[10] MOHAMED, M.: Toward Smart Logistics: Hybrization of Intelligence Techniques of Machine Learning and Multi-Criteria Decision-Making in Logistics 5.0, *Multicriteria Algorithms with Applications*, Vol. 1, pp. 42-57, 2023. https://doi.org/10.61356/j.mawa.2023.16261

[11] SERVOS, N., TEUCKE, M., FREITAG, M., LIU, X.: Travel Time Prediction in a Multimodal Freight Transport Relation Using Machine Learning Algorithms, *Logistics*, Vol. 4, No. 1, 1, pp. 1-22, 2019. https://doi.org/10.3390/logistics4010001

[12] SODIYA, E., AMOO, O., UMOGA, U., ATADOGA, A.: AI-driven warehouse automation: A comprehensive review of systems, *GSC Advanced Research and Reviews*, Vol. 18, No. 2, pp. 272-282, 2024. https://doi.org/10.30574/gscarr.2024.18.2.0063

[13] SPILIOTIS, E., MAKRIDAKIS, S., ASSIMAKOPOULOS, V., SEMENOGLOU, A.A.: Comparison of statistical and machine learning methods for daily SKU demand forecasting, *Operational Research*, Vol. 22, No. 3, pp. 3037-3061, 2020. https://doi.org/10.1007/s12351-020-00605-2

[14] AMOSU, O., KUMAR, P., OGUNSUJI, Y., ONI, S., FAWORAJA, O.: AI-driven demand forecasting: Enhancing inventory management and customer satisfaction, *World Journal of Advanced Research and Reviews*, Vol. 23, No. 2, pp. 708-719, 2024. https://doi.org/10.30574/wjarr.2024.23.2.2394

[15] TANG, Y.-M., TSUI, S.-Y., LAU, Y.-Y., HO, G.T.S.: Integrated Smart Warehouse and Manufacturing Management with Demand Forecasting in Small-Scale Cyclical Industries, *Machines*, Vol. 10, No. 6, 472, pp. 1-15, 2022. https://doi.org/10.3390/machines10060472

[16] XU, Y., YANG, Z., ZHAO, X., CHEN, Y.: Research on a Mixed Gas Classification Algorithm Based on Extreme Random Tree, *Applied Sciences*, Vol. 9, No. 9, 1728, pp. 1-17, 2019. https://doi.org/10.3390/app9091728

[17] KOSHEKOV, K., ANAYATOVA, R., SAVOSTIN, A., SEIDAKHMETOV, B., FEDOROV, I.: Aviation Profiling Method Based on Deep Learning Technology for Emotion Recognition by Speech Signal, *Transport and Telecommunication Journal*, Vol. 22, No. 4, pp. 471-481, 2021. https://doi.org/10.2478/ttj-2021-0037
[18] KONIUKHOV, V.: Improving the segmentation of the vertebrae using a multi-stage machine learning algorithm, *Radioelectronic and Computer Systems*, Vol. 2024, No. 4, pp. 83-90, 2024. https://doi.org/10.32620/reks.2024.4.07
[19] ZAVADSKAS, E., PAMUČAR, D., MARDANI, A., STEVIĆ, Z.: Multi-Criteria Decision-Making Techniques for Improvement Sustainability Engineering Processes, *Symmetry*, Vol. 12, No. 6, 986, pp. 1-6, 2020. https://doi.org/10.3390/sym12060986
[20] DERETARLA, Ö., ERDEBILLI, B., GÜNDOĞAN, M.: An integrated Analytic Hierarchy Process and Complex Proportional Assessment for vendor selection in supply chain management, *Decision Analytics Journal*, Vol. 6, 100155, pp. 1-11, 2022. https://doi.org/10.1016/j.dajour.2022.100155
[21] RAUT, R., RAUT, V., NARKHEDE, B., GARDAS, B.: Multi-criteria decision-making approach: a sustainable warehouse location selection problem, *International Journal of Management Concepts and Philosophy*, Vol. 10, No. 3, pp. 260-281, 2017. https://doi.org/10.1504/ijmcp.2017.085834
[22] KOSHEKOV, K., TOIGANBAYEV, B., KOSHEKOV, A., KENBEILOVA, S., PIRMANOV, I., TOGAMBAYEV, R.: Development of a neural network approach for risk management in helicopter technical condition diagnostics, *Eastern-European Journal of Enterprise Technologies*, Vol. 6, No. 3 (132), pp. 25-36, 2024. https://doi.org/10.15587/1729-4061.2024.312345
[23] UMER, R., FERRARA, M., AHMADIAN, A., SALAHSHOUR, S., TOUQEER, M., OMAR, A.: Selection of solar tracking system using extended TOPSIS technique with interval type-2 pythagorean fuzzy numbers, *Optimization and Engineering*, Vol. 22, No. 4, pp. 2205-2231, 2021. https://doi.org/10.1007/s11081-021-09623-1
[24] SHEZAN S., KAMWA I., ISHRAQUE F., MUYEEN S., HASAN, K., SAIDUR, R., RIZVI, S., SHAFIULLAH, M., AL-SULAIMAN, F.: Evaluation of Different Optimization Techniques and Control Strategies of Hybrid Microgrid: A Review, *Energies*, Vol. 16, No. 4, 1792, pp. 1-30, 2023. https://doi.org/10.3390/en16041792
[25] SAHOO, R., PASAYAT, A., BHOWMICK, B., FERNANDES, K., TIWARI, M.: A hybrid ensemble learning-based prediction model to minimise delay in air cargo transport using bagging and stacking, *International Journal of Production Research*, Vol. 60, No. 2, pp. 644-660, 2021. https://doi.org/10.1080/00207543.2021.2013563
[26] MIZRAK, F., AKKARTAL, G.: Determining and Evaluating The Strategies of Air Cargo Freight Forwarders to Increase Business Volume with AHP Method, *Journal of Aviation*, Vol. 7, No. 2, pp. 226-232, 2023. https://doi.org/10.30518/jav.1262860
[27] NATH, P., UPADHYAY, R.: Reformation and optimization of cargo handling operation at Indian air cargo terminals, *Journal of the Air Transport Research Society*, Vol. 2, 100022, pp. 1-10, 2024. https://doi.org/10.1016/j.jatrs.2024.100022

Review process
Single-blind peer review process.