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Machine Learning-Based Forecasting of LRU Demand and Implementation in Kazakhstan Base Airports

Zhandildinova Karlygash Maratkyzy[1],
Koshanova Sholpan Kenganovna[2], **Seifulla Gulzhan Nurlankyzy**[3]

[1] Master;
Republic of Kazakhstan

[2] Master;
Republic of Kazakhstan

[3] Master;
Republic of Kazakhstan

Abstract. This paper addresses the optimization of aviation spare parts logistics at base airports. Particular attention is given to Line Replaceable Units (LRUs), which play a critical role in ensuring aircraft operational readiness. The limitations of traditional inventory management methods are analyzed, and the need for the implementation of digital technologies is substantiated. An approach to forecasting LRU demand based on machine learning techniques is proposed. An example of economic impact assessment is presented. It is shown that the implementation of intelligent forecasting systems enables a reduction in inventory holding costs and minimizes aircraft-on-ground (AOG) events.
Keywords: *LRU, aviation logistics, machine learning, failure prediction, AOG, inventory management, MRO digitalization.*

Introduction

Modern civil aviation is characterized by a high level of technical complexity and stringent flight safety requirements. The efficiency of aircraft operations directly depends on the timely performance of maintenance and the availability of required spare parts.

Particular importance is attributed to Line Replaceable Units (LRUs) — assemblies and electronic components that can be rapidly replaced without removing the entire system. These include avionics units, navigation modules, onboard computers, and hydraulic controllers. Avionics units represent key elements of the aircraft control system and are designed as modular devices, enabling quick replacement in the event of failure.

The absence of a required component leads to an Aircraft on Ground (AOG) situation, in which the aircraft is unable to perform a flight. This results in direct financial losses, schedule disruptions, and reputational damage for the airline. At the same time, excessive stocking of high-cost components increases inventory holding costs and reduces overall economic efficiency.

Thus, there is a need to achieve a balance between inventory sufficiency and cost minimization. Therefore, this paper examines the theoretical and practical aspects of optimizing aviation spare parts logistics and analyzes the application of machine learning methods for forecasting demand for LRU components and improving inventory management efficiency.

Main part

Features of LRU Logistics

Aviation spare parts logistics has a number of specific characteristics:

- high unit cost;
- irregular failure patterns;
- long lead times;
- dependence on operational intensity;
- strict certification and traceability requirements.

Traditional inventory management methods are based on averaged statistical data. However, demand for LRUs is probabilistic and often nonlinear in nature. Component failures depend not only on operating time but also on environmental conditions, the number of flight cycles, fleet age, and maintenance quality.

Therefore, classical forecasting models do not always provide the required level of accuracy.

Figure 1 illustrates a modern aviation warehouse, the efficient management of which requires strict certification compliance and the implementation of digital technologies to prevent logistics errors and flight delays.

Storage of aviation components requires strict environmental control and certification compliance. Errors in logistics may lead to the unavailability of required components and result in flight delays. [3], [6], [2]

Figure 1
Modern aviation warehouse

Machine Learning Application Capabilities

Machine learning enables the analysis of large volumes of operational data and the identification of hidden patterns.

The following input parameters can be used:

- total aircraft flight hours;
- number of flight cycles;
- component age;
- climatic operating conditions;
- history of previous failures;
- Flight Data Monitoring (FDM) data.

Machine learning algorithms are capable of capturing relationships between these parameters and predicting the probability of failure of a specific component.

Random Forest algorithm:

This method is highly suitable for LRU failure classification, as it effectively processes a large number of variables (temperature, humidity, flight hours) and demonstrates robustness against overfitting on small datasets. In the context of predictive supply, key model hyperparameters include the number of decision trees (*n_estimators*), which improves ensemble accuracy, and the maximum tree depth (*max_depth*), which limits model complexity and prevents overfitting to noise.

Recurrent Neural Networks (LSTM):

These models are well suited for time-series forecasting, as they retain information about previous replacement events and the degradation of avionics unit performance over time. For analyzing long-term dependencies in operational data, the network architecture may include multiple hidden layers with the application of dropout (e.g., with a rate of 0.2–0.3), which enhances model generalization capability and mitigates overfitting.

Advantages of the ML-based approach:

- higher forecasting accuracy;
- adaptability to changing operating conditions;
- capability for continuous model self-learning;
- reduction of uncertainty in inventory planning.

Thus, an intelligent system can proactively determine the potential demand for specific LRUs and adjust inventory policies accordingly. [4], [7], [8], [10]

Predictive Supply System Architecture

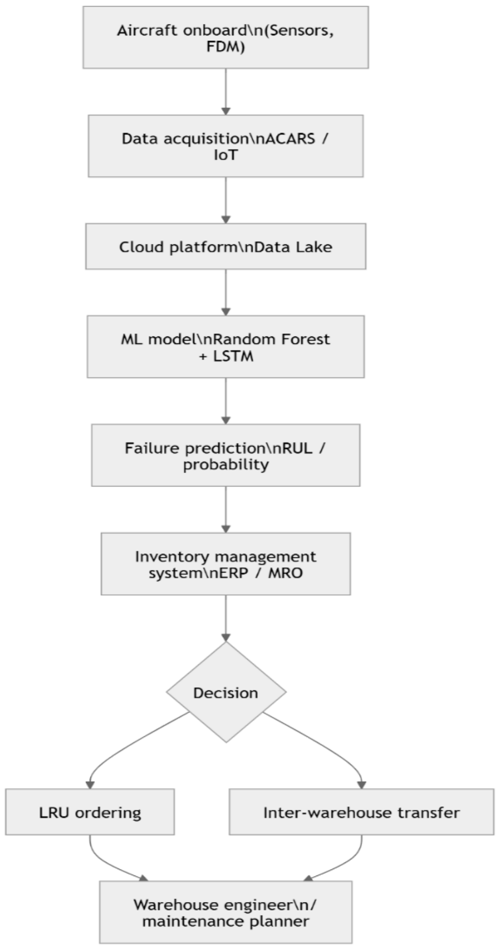


Figure 2
Predictive Supply System Architecture

This Figure 2 shows a predictive supply chain architecture for aircraft maintenance.

It starts with onboard aircraft sensors and Flight Data Monitoring (FDM), which continuously collect operational data. The data is transmitted through ACARS and IoT systems to a cloud-based Data Lake, where it is stored and processed.

A machine learning model (Random Forest combined with LSTM) analyzes the data to predict component failures by estimating Remaining Useful Life (RUL) and failure probability.

The predictions are then integrated into an ERP/MRO inventory management system, which supports maintenance decision-making. Based on the results, the system either triggers LRU (Line Replaceable Unit) orders or initiates inter-warehouse part transfers.

Finally, warehouse engineers and maintenance planners use these decisions to ensure timely supply and maintenance of aircraft components.

Economic efficiency assessment

To clearly demonstrate the effectiveness of the proposed method, a hypothetical example of operating a fleet of 10 aircraft is considered.

Initial data:

- Average annual demand for an avionics LRU: 24 units
- Cost per unit: 5,000,000 KZT
- Safety stock (traditional method): 4 units
- Safety stock (ML method): 2 units (due to improved forecasting accuracy)

Direct financial effect (capital release)

A reduction of the safety stock by 2 units allows the airline to release a significant amount of working capital:

2×5,000,000=10,000,000 KZT2 \times 5{,}000{,}000 = 10{,}000{,}000 \text{ KZT}2×5,000,000=10,000,000 KZT

Result: 10,000,000 KZT of working capital is released.

E=ΔS×C

where:

E — released capital (economic effect)

ΔS — reduction of safety stock (units)

— cost of one LRU unit

Substitution:

E=2×5,000,000=10,000,000 KZTE = 2 \times 5{,}000{,}000 = 10{,}000{,}000 \text{ KZT}E=2×5,000,000=10,000,000 KZT

Optimization of Logistics Costs

In traditional inventory management methods, shortages often lead to AOG (Aircraft on Ground) situations, requiring emergency delivery of spare parts. The cost of "critical" logistics (AOG shipping) is 5-10 times higher than the cost of planned delivery.

The use of an ML model allows to:

• Shift up to 80% of emergency orders into the planned category.

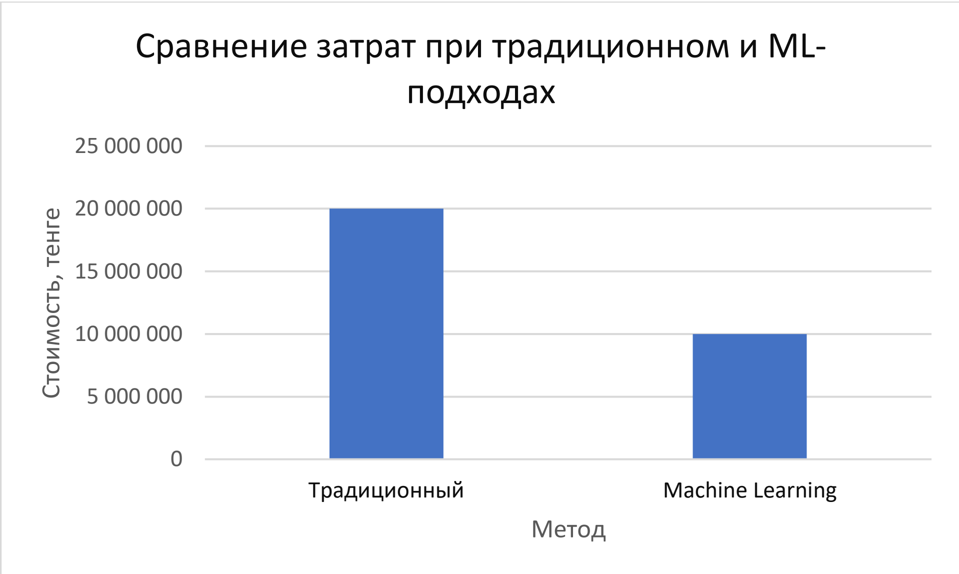
• Reduce annual storage costs by decreasing the volume of occupied warehouse space.

Improvement of Operational Readiness (Time Factor)

Predictive models enable the implementation of the "failure notification" concept. The engineering department receives data on the need to replace a component 50-100 flight hours before its actual failure. This makes it possible to:

• Reduce unplanned aircraft downtime by 15-20%.

• Prepare technical personnel and tools in advance by the time the aircraft arrives at the home base airport.



Discussion of Results

In the context of the digital transformation of the aviation industry, the implementation of intelligent management systems is becoming a necessity.

Global practice shows that major airlines and aircraft manufacturers are actively implementing predictive analytics and Big Data technologies in maintenance systems.

Forecasting LRU demand based on machine learning enables a transition from a reactive maintenance model to a proactive one.

This means that technical decisions are made not after a failure occurs, but before it happens.

Examples of LRU Forecasting Applications in Global Practice

In recent years, major airlines and aircraft manufacturers have been actively implementing predictive analytics and machine learning systems for spare parts management.

Example 1: Lufthansa Technik

Lufthansa Technik has implemented the digital platform AVIATAR, which uses data analytics and machine learning methods to predict the technical condition of aircraft components.

The system analyzes:

• equipment operating parameters
• maintenance data
• failure history
• operational conditions

Thanks to the implementation of this system, the airline has been able to:

• reduce the number of unscheduled failures
• decrease AOG (Aircraft on Ground) events
• optimize LRU inventory levels
• improve fleet technical dispatch reliability

According to the company, the use of digital forecasting systems enables a reduction in unplanned flight delays by 15–20%.

Example 2: Delta Air Lines

Delta Air Lines actively uses Predictive Maintenance technologies to analyze the condition of aircraft components.

At its hub airport, Hartsfield-Jackson Atlanta International Airport, failure prediction systems for aircraft components have been implemented.

The system analyzes data from:

• aircraft sensors
• operational parameters
• maintenance history

Results of implementation:

• reduced flight delays
• decreased aircraft downtime
• optimized distribution of spare parts between warehouses

Example 3: Airbus Skywise

Airbus has developed the digital platform Skywise, which is widely used by many airlines to analyze operational data.

The platform integrates information on:

• aircraft system health status
• maintenance activities

- spare parts data

The use of Skywise allows prediction of failure probability for specific LRUs and enables early dispatch of required components to base airports.

This leads to:

- reduced repair time
- improved logistics efficiency
- lower inventory holding costs.

Table 1

Comparison of Traditional Approach and Machine Learning-Based Approach

Criterion	**Traditional Approach**	**Machine Learning-Based Approach**	**Data Source (for ML)**
Forecasting accuracy	Moderate, depends on statistical data	High, considers multiple factors	Machine learning models based on aggregated data
Use of operational data	Limited	Comprehensive (FH, FC, climate, failure history)	Onboard sensors (FDM), weather data, maintenance logs
Risk of AOG occurrence	High	Reduced	Predictive analytics of system degradation
Inventory volume	Excessive	Optimized	Integration with ERP warehouse system
System flexibility	Low	High (adaptive to changes)	Continuous model retraining
Decision-making speed	Low	High	Automated dashboards
Economic efficiency	Limited	Improved	Financial logistics metrics
Forecasting capability	Limited	Predictive (before failure occurs)	Time series algorithms (LSTM, ARIMA)

The conducted comparison shows that the application of machine learning methods significantly improves the efficiency of aviation spare parts inventory management. In contrast to traditional approaches, ML models provide more accurate forecasting and help reduce the risk of AOG (Aircraft on Ground) events. [9], [7], [8], [3], [10]

Application Opportunities in Kazakhstan

The implementation of predictive analytics systems in the aviation industry of the Republic of Kazakhstan is of strategic importance. The use of such technologies at major hub airports such as Almaty International Airport and Astana International Airport will enable the creation of a unique intelligent monitoring network.

To improve forecasting accuracy under Kazakhstan's conditions, the ML model should include the following specific factors:

• Consideration of the sharply continental climate: For airports in Astana and Almaty, accounting for extreme temperature fluctuations (from -30°C in winter to +40°C in summer) is critical. Rapid changes in temperature and humidity accelerate the degradation of electronic components and capacitors in avionics units. Incorporating meteorological data into machine learning algorithms will enable more accurate failure prediction specific to the region.

• Creation of a unified digital ecosystem: Implementing the system across the country's major aviation hubs will allow the formation of a shared failure database. This will create a "collective intelligence" effect, where failure data from one carrier can improve spare parts demand forecasting for the entire industry, increasing the competitiveness of national airlines.

Expected results for the domestic market:

1. Reduction in AOG events: Early prediction and positioning of required LRUs in Almaty and Astana.

2. Optimization of inventory levels: Transition from excessive stockholding to a Just-in-Time model.

3. Reduction in operational costs: Minimization of urgent air shipment expenses from Europe or Asia.

4. Improvement of flight safety: Timely replacement of components in a pre-failure state increases aircraft reliability. [1], [2], [6], [5], [3]

Conclusion

This work investigated the problem of optimizing logistics for aviation spare parts of LRU type. It was established that traditional inventory management methods based on static statistics do not provide sufficient flexibility in modern aviation, leading to unnecessary financial losses and aircraft downtime (AOG).

The scientific novelty of the proposed approach lies in the use of machine learning (ML) methods for analyzing multi-factor data: flight hours, cycles, failure history, and—most importantly for Kazakhstan—climatic conditions. The conducted analysis and calculations showed that:

• Implementation of an ML system can reduce safety stock levels of expensive components (for avionics, for example, by 2 times), releasing significant working capital.

• Shifting up to 80% of unscheduled replacements into planned maintenance significantly reduces logistics costs.

In the long term, the creation of an intelligent forecasting system will become the foundation for the digital transformation of Kazakhstan's aviation industry, enabling a transition to condition-based maintenance and improving Maintenance, Repair and Overhaul (MRO) efficiency at an international level.

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