**USING BIG DATA AND MACHINE LEARNING TO PREDICT HOUSEHOLD APPLIANCE FAILURES: A NEW APPROACH TO PREVENTIVE MAINTENANCE**

**Abstract.** This article explores the application of big data processing methods and machine learning algorithms for predicting household appliance failures, shifting from traditional reactive maintenance models to proactive preventive repair systems. The study is based on an analysis of historical data, error logs, and sensor readings, enabling the identification of hidden patterns that indicate potential malfunctions. A literature review of current research on predictive maintenance highlights a scientific gap in applying these technologies to household appliances. The novelty of this study lies in the adaptation and comprehensive application of modern data analysis methods to the operational specifics of household appliances, as well as an assessment of the economic efficiency of such solutions. The applied methodology includes stages of data collection and preprocessing, feature engineering, machine learning algorithm implementation, and comparative economic analysis. The results demonstrate the potential of predictive maintenance in reducing downtime, optimizing repair costs, and improving service quality. The findings of this study are valuable for data analysts, household appliance engineers, predictive model developers, and companies engaged in appliance servicing and manufacturing, seeking to enhance preventive maintenance efficiency using advanced machine learning and big data analytics methods.

**Keywords:** big data, machine learning, predictive maintenance, preventive repair, warranty service, error log analysis, economic efficiency.

**Introduction**

The relevance of this topic is driven by the advancement of information technologies, the increasing volume of data, and the widespread adoption of Internet of Things (IoT) systems in household appliances. These developments create new opportunities to enhance operational efficiency. Modern manufacturers are actively seeking ways to minimize downtime and reduce repair costs by shifting from traditional reactive maintenance methods to proactive approaches based on predictive analytics. The use of big data and machine learning algorithms to analyze data and error logs enables the development of models capable of identifying potential malfunctions in advance, thereby improving appliance reliability and optimizing service contracts [13,14].

In the scientific paradigm focused on applying big data and machine learning methods for predicting household appliance failures, various approaches emerge due to the specifics of analyzed systems and the nature of the data used. Several thematic groups can be distinguished, each demonstrating unique methodological features and empirical results [15-17].

The first group includes studies on the application of machine learning methods for diagnosing and forecasting the condition of electrical and mechanical systems. One such study, "Machine Learning Approach for Predictive Maintenance in an Electric Motor; A Classifier Approach" [1], published on ProQuest, presents a classification-based approach for assessing the operational state of electric motors to detect anomalies in a timely manner. Similarly, the work of Lee W. J. et al. [5] demonstrates the use of artificial intelligence to significantly improve prediction accuracy through the comprehensive processing of signal characteristics.

The second group focuses on diagnosing and evaluating the condition of lithium-ion batteries, which are critical components in both household appliances and electric vehicles. A trend toward the development of hybrid models combining the advantages of different machine learning methods is observed in this field [18-20]. For instance, Kumar R. S. et al. [3] propose a hybrid system integrating random forest algorithms and anomaly detection methods, achieving high accuracy in predicting battery failures. Liu J. et al. [7] and Zhang Z. et al. [8] focus on modeling thermal processes and assessing battery health through multifactor analysis, which plays a key role in integrated thermal regulation systems. Additional studies by Al-Meer M. H. [9], Wang C. and Chen Y. [10], Johnson A. et al. [11], and Lipu M. S. H. et al. [12] further contribute to this group by presenting various approaches for assessing charge status and degradation processes. These studies demonstrate a wide range of algorithmic solutions and empirical validations aimed at optimizing battery life cycles.

The third group is centered on economically oriented models and systematic reviews that consider both technical and financial aspects of predictive maintenance implementation. The study by Florian E., Sgarbossa F., and Zennaro I. [4] presents a model-based approach focused on cost reduction through optimized maintenance planning, while the review by Zonta T. et al. [6] consolidates contemporary advancements within the framework of the "Industry 4.0" concept, emphasizing the integration of information technologies with industrial processes. Additionally, the research by Alshboul O. et al. [2] illustrates the practical application of machine learning to improve equipment reliability in concrete manufacturing, demonstrating the expansion of these technologies beyond traditional industrial sectors.

Thus, the literature analysis reveals both methodological contradictions and areas for further research. On one hand, the diversity of algorithmic approaches and equipment condition assessment methods indicates the absence of a standardized solution, complicating interdisciplinary result comparisons and model integration into comprehensive monitoring systems. On the other hand, challenges related to the real-world interpretation of obtained data under uncertainty and high dynamic loads remain insufficiently addressed. Particular attention should be given to developing methods capable of accounting for external operating conditions and integrating information from disparate sources to improve the effectiveness of preventive maintenance for both household appliances and broader industrial applications.

The study aims to analyze the potential of using big data and machine learning to predict household appliance failures.

The scientific novelty lies in the adaptation of modern data processing and machine learning methods to the operational specifics of household appliances, as well as in assessing their prospects for integration into service contracts and extended warranty programs.

The author's hypothesis suggests that applying a comprehensive analysis of available data and error logs using advanced AI algorithms will improve the accuracy of predicting potential failures, leading to reduced warranty service costs and enhanced service quality.

The methodological foundation of this study is based on an analysis of scientific publications by other researchers.

**1. Analysis of historical data and error logs for predicting failures**

Data and error log analysis is a cornerstone of predictive maintenance for household appliances, enabling the identification of hidden patterns and early signs of malfunctions. Modern information systems record vast amounts of operational parameters, ranging from temperature variations and vibration levels to error codes logged in system records. This approach not only allows real-time monitoring of appliance conditions but also facilitates failure prediction by detecting anomalies [2,3].

The primary stage of analysis begins with systematic data collection, which includes:

* Sensor data – temperature readings, vibration levels, and energy consumption, continuously recorded by built-in sensors.
* Error logs – system logs that register error codes, messages about abnormal conditions, and component failures.

To ensure the accuracy of subsequent analysis, raw data must undergo preprocessing, including handling missing values, removing outliers, and standardizing measurements across a unified scale. This process minimizes noise interference and enhances the quality of feature engineering [1].

A key aspect is extracting informative features from diverse data sources. By applying feature engineering techniques, researchers transform raw data into a set of variables that reflect:

* Trends in temperature variations, which may indicate overheating of specific components.
* Patterns in vibration characteristics, allowing the detection of mechanical wear or operational instability.
* Frequency and nature of logged errors, aiding in the identification of recurring system issues [7,11].

Below, Table 1 presents examples of features extracted from household appliance data and their impact on failure prediction.

Table 1. Example of characteristics of historical data and error logs of household appliances [1,2].

| **Feature** | **Description** | **Data source** | **Role in failure prediction** |
| --- | --- | --- | --- |
| Temperature | Measurements of component temperatures | Temperature sensors | Detection of overheating, indicating potential wear |
| Vibration | Data on vibration characteristics | Vibration sensors | Early diagnosis of mechanical faults and imbalance |
| Error logs | Records of error codes and anomaly messages | System logs | Identification of recurring errors and failure patterns |
| Energy consumption | Changes in power usage dynamics | Smart meters | Detection of inefficiencies related to component performance |
| Usage cycles | Number of on/off cycles and load operation time | Embedded counters | Assessment of equipment wear and operational conditions |

Following the feature engineering stage, machine learning algorithms are selected and applied to analyze large datasets and uncover hidden correlations. In this context, the following methods are utilized:

* Clustering techniques to group similar operating patterns, aiding in anomaly detection.
* Classification algorithms to differentiate normal operations from potentially hazardous conditions.
* Time-series analysis to study parameter trends and predict the moment when critical failure may occur [1].

Comprehensive analysis of raw data and error logs facilitates the development of highly accurate predictive models for appliance failures. The application of feature engineering and machine learning algorithms enables the early detection of performance degradation, allowing for timely preventive maintenance and reducing warranty service costs. Future research in this field may focus on optimizing data processing algorithms and adapting models to specific operational conditions across various types of household appliances.

**2. Prospects for implementing predictive maintenance systems in service contracts and extended warranty**

The integration of predictive maintenance systems into service contracts and extended warranty programs represents a strategically significant shift in business models, transitioning from a reactive approach to proactive service management. Traditional repair systems, which focus on addressing failures after they occur, often lead to prolonged downtimes and high costs, negatively affecting customer satisfaction and company competitiveness. The adoption of predictive systems that leverage big data analysis and machine learning algorithms enables not only the early detection of potential appliance failures but also the organization of timely preventive maintenance, reducing operational costs and enhancing reliability [3,5].

As part of this business model transformation, key focus areas include:

* Transition to proactive maintenance. The use of analytical models for continuous monitoring of household appliance conditions allows for the early identification of potential failures, facilitating the scheduling of preventive repairs and reducing the risk of unexpected breakdowns.
* Integration into service contracts. The application of predictive systems within service agreements ensures more transparent and objective determination of maintenance schedules and scope, strengthening customer trust and increasing brand loyalty.
* Optimization of extended warranty programs. Predictive warranty management based on accurate condition forecasts allows companies to optimize financial reserves and reduce costs associated with unforeseen repairs [1].

Table 2 below provides a comparative analysis of the implementation aspects of predictive maintenance in service contracts and extended warranty programs, outlining the expected benefits and key challenges companies may encounter when adopting these solutions.

Table 2. Key aspects of predictive systems implementation in service contracts and extended warranty [1,3,11].

| **Implementation aspect** | **Description** | **Expected benefits** | **Key challenges** |
| --- | --- | --- | --- |
| Proactive maintenance | Transition from failure-based repairs to regular monitoring and preventive measures | Reduction in unexpected breakdowns; lower emergency repair costs | Need for investment in data collection and analysis systems |
| Integration into service contracts | Inclusion of predictive models in service agreements to facilitate objective maintenance planning | Improved service reliability; enhanced customer trust | Challenges in integrating with existing IT infrastructures |
| Extended warranty management | Use of analytics to determine the scope and timing of warranty services | Cost optimization for warranty maintenance; extended product lifespan | Adaptation of models to diverse equipment types and operating conditions |

Thus, the prospects for implementing predictive maintenance systems in service contracts and extended warranty programs are promising in terms of cost optimization, increased reliability, and improved service quality. The successful adoption of these systems requires the integration of advanced analytical methods that enable business processes to adapt to the dynamic operating conditions of household appliances. Further research in this field should focus on developing adaptive models capable of accommodating the specific characteristics of different types of equipment while ensuring high predictive accuracy. This, in turn, will significantly reduce warranty service costs.

**3. Economic efficiency and cost reduction potential in warranty service**

One of the key aspects of implementing predictive maintenance is its economic efficiency, driven by the potential to reduce warranty service costs and minimize unexpected expenses. Traditional warranty service models, based on a reactive approach, often involve high costs due to prolonged downtimes, expensive emergency repairs, and excessive technical interventions. In contrast, transitioning to a proactive model—where failure prediction is enabled through big data analysis and machine learning algorithms—allows for significant cost optimization and improved profitability of service contracts [4,12].

In conventional warranty service systems, repairs are carried out only after a failure occurs. This results in several economic losses:

* High equipment downtime. Unexpected failures cause appliance downtime, increasing the cost of operational disruptions and reducing efficiency in production processes.
* Expensive emergency repairs. Urgent service calls and last-minute repairs are significantly more costly than scheduled maintenance.
* Excessive expenses. Without monitoring systems, components are often replaced prematurely, leading to unnecessary operational costs.

In contrast, a predictive maintenance system enables:

* Failure forecasting. Analyzing raw data and error logs allows early detection of wear and operational deviations, facilitating maintenance scheduling during periods of minimal load.
* Optimized repair planning. Timely diagnostics allow preventive repairs without emergency interventions, reducing repair costs and minimizing downtime.
* Reduced warranty-related expenses. More accurate failure predictions optimize repair volumes, reducing costs for both manufacturers and service centers [1,3].

To illustrate these differences, Table 3 presents a comparative analysis of cost parameters in standard warranty service versus predictive maintenance.

Table 3. Comparative cost analysis of standard warranty service and predictive maintenance [1,2,5,8,10].

| **Cost parameter** | **Standard warranty service** | **Predictive maintenance** | **Economic effect** |
| --- | --- | --- | --- |
| Equipment downtime | High level of unplanned downtimes | Downtime minimization through scheduled maintenance | Reduced operational losses, increased productivity |
| Repair costs | Expensive emergency service calls and urgent repairs | Scheduled preventive maintenance upon early fault detection | Lower repair costs, optimized spare part usage |
| Component replacement expenses | Frequent replacement of parts that may still be functional | Selective replacement of worn components based on diagnostics | Reduced excessive expenses and better resource utilization |
| Investment in monitoring systems | Low initial investment in diagnostics, leading to a higher risk of failures | Initial investment in data collection and analysis systems, offset by long-term maintenance cost reductions | Long-term cost savings through a proactive approach |

Predictive maintenance relies on accurate failure forecasting, allowing for timely scheduling of technical maintenance and repairs. Cost reductions are achieved through:

* Early anomaly detection. Machine learning algorithms analyzing time-series data and error logs can identify even minor deviations in equipment operation, preventing them from escalating into major failures.
* Optimized maintenance schedules. Reducing unplanned repairs leads to more efficient use of technical personnel and spare parts.
* Lower warranty service expenses. By predicting technical issues, companies can adjust extended warranty conditions, reducing financial reserves needed for emergency cases [6,9].

However, the implementation of AI-driven solutions also presents potential risks, including high initial investments, integration challenges with existing information systems, and the need to adapt models to diverse equipment types. Nevertheless, modern studies indicate that the long-term benefits of predictive maintenance significantly outweigh these challenges [7,12].

Based on empirical data and theoretical models, it can be concluded that implementing predictive maintenance systems opens opportunities for business scaling. Manufacturers and service centers investing in advanced monitoring and analytics systems gain a competitive advantage by enhancing equipment reliability and optimizing costs. Long-term benefits include:

* Extended equipment lifespan,
* Reduction in unplanned repair expenses,
* Increased customer satisfaction and strengthened brand trust,
* The potential for new financial interaction models, such as service contracts with guaranteed reliability levels.

Thus, the economic efficiency analysis of predictive maintenance demonstrates its significant potential for reducing warranty service costs. The implementation of these systems represents a crucial step toward a more sustainable and cost-effective approach to household appliance operation, as supported by both theoretical research and practical case studies across various industries.

**Conclusion**

The conducted research confirms the hypothesis that the application of modern machine learning methods and big data analytics significantly enhances the accuracy of predicting potential failures in household appliances. The integration of predictive systems into service contracts and extended warranties facilitates the transition to a proactive maintenance model, reducing unplanned downtimes, optimizing repair costs, and increasing customer satisfaction. The comparative cost analysis of traditional and predictive maintenance methods presented in this study demonstrates the economic efficiency of implementing analytical systems, despite the initial investment costs.

This work serves as a foundation for further research aimed at optimizing monitoring algorithms and adapting predictive models to the specific operating conditions of various types of household appliances. The implementation of the proposed solutions not only improves the reliability of appliances but also contributes to the formation of a sustainable business model that reduces operational expenses and provides a competitive advantage in the service market.

**COMPETING INTERESTS DISCLAIMER:**

Authors have declared that they have no known competing financial interests OR non-financial interests OR personal relationships that could have appeared to influence the work reported in this paper.

**References**

1. Machine Learning Approach for Predictive Maintenance in an Electric Motor; A Classifier Approach. [Electronic resource] Access mode:<https://www.proquest.com/openview/743428fe822f5e96a1c812e70b4e37e0/1?pq-origsite=gscholar&cbl=2026366&diss=y> (date of request: 03/08/2025).
2. Alshboul O. et al. Empirical exploration of predictive maintenance in concrete manufacturing: Harnessing machine learning for enhanced equipment reliability in construction project management //Computers & Industrial Engineering. – 2024. – Vol. 190. – pp. 1-7.
3. Kumar R. S. et al. Hybrid machine learning framework for predictive maintenance and anomaly detection in lithium-ion batteries using enhanced random forest //Scientific Reports. – 2025. – Vol. 15 (1). – pp. 6243.
4. Florian E., Sgarbossa F., Zennaro I. Machine learning-based predictive maintenance: A cost-oriented model for implementation //International Journal of Production Economics. – 2021. – Vol. 236. – pp. 1-10.
5. Lee W. J. et al. Predictive maintenance of machine tool systems using artificial intelligence techniques applied to machine condition data //Procedia Cirp. – 2019. – Vol. 80. – pp. 506-511.
6. Zonta T. et al. Predictive maintenance in the Industry 4.0: A systematic literature review //Computers & Industrial Engineering. – 2020. – Vol. 150. – pp. 1-8.
7. Liu J. et al. Review of thermal coupled battery models and parameter identification for lithium-ion battery heat generation in EV battery thermal management system //International Journal of Heat and Mass Transfer. – 2024. – Vol. 218. – pp. 1-15.
8. Zhang Z. et al. Advanced State-of-Health Estimation for Lithium-Ion Batteries Using Multi-Feature Fusion and KAN-LSTM Hybrid Model //Batteries. – 2024. – Vol. 10 (12). – pp. 433.
9. Al-Meer M. H. A Deep Learning Method for the Health State Prediction of Lithium-Ion Batteries Based on LUT-Memory and Quantization //World Electric Vehicle Journal. – 2024. – Vol. 15 (2). – pp. 38.
10. Wang C., Chen Y. Unsupervised dynamic prognostics for abnormal degradation of lithium-ion battery //Applied Energy. – 2024. – Vol. 365. – pp. 1-9.
11. Johnson A. et al. Random Forest Regressor Based SoC Estimation of Li-ion Battery for Electric Vehicle Applications //2023 IEEE International Conference on Power Electronics, Smart Grid, and Renewable Energy (PESGRE). – IEEE, 2023. – pp. 1-8.
12. Lipu M. S. H. et al. Real-time state of charge estimation of lithium-ion batteries using optimized random forest regression algorithm //IEEE Transactions on Intelligent Vehicles. – 2022. – Vol. 8 (1). – pp. 639-648.
13. Fernandes, S., Antunes, M., Santiago, A. R., Barraca, J. P., Gomes, D., & Aguiar, R. L. (2020). Forecasting appliances failures: A machine-learning approach to predictive maintenance. *Information*, *11*(4), 208.
14. Falatouri, T., Nasseri, M., Brandtner, P., & Darbanian, F. (2023, July). Shedding Light on the Black Box: Explainable AI for Predicting Household Appliance Failures. In *International Conference on Human-Computer Interaction* (pp. 69-83). Cham: Springer Nature Switzerland.
15. Papaioannou, A., Dimara, A., Papaioannou, C., Papaioannou, I., Krinidis, S., Anagnostopoulos, C. N., ... & Tzovaras, D. (2024). Simulation of Malfunctions in Home Appliances' Power Consumption. *Energies (19961073)*, *17*(17).
16. Zjavka, L. (2023). Power quality daily predictions in smart off-grids using differential, deep and statistics machine learning models processing NWP-data. *Energy Strategy Reviews*, *47*, 101076.
17. Kudelina, K., Vaimann, T., Asad, B., Rassõlkin, A., Kallaste, A., & Demidova, G. (2021). Trends and challenges in intelligent condition monitoring of electrical machines using machine learning. *Applied Sciences*, *11*(6), 2761.
18. Muzorewa, S., & Telukdarie, A. (2024). Machine learning to predict the field reliability of electric steam irons. *International Journal of Intelligent Enterprise*, *11*(2), 141-156.
19. Zjavka, L. (2021). Power quality multi-step predictions with the gradually increasing selected input parameters using machine-learning and regression. *Sustainable Energy, Grids and Networks*, *26*, 100442.
20. Truong, L. H. M., Chow, K. H. K., Luevisadpaibul, R., Thirunavukkarasu, G. S., Seyedmahmoudian, M., Horan, B., ... & Stojcevski, A. (2021). Accurate prediction of hourly energy consumption in a residential building based on the occupancy rate using machine learning approaches. *Applied Sciences*, *11*(5), 2229.