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ИНТЕГРАЦИЯ МЕТОДОВ МАШИННОГО ОБУЧЕНИЯ И СТАТИСТИЧЕСКОГО АНАЛИЗА ДЛЯ ПРОГНОЗИРОВАНИЯ СРОКА СЛУЖБЫ И ОПТИМИЗАЦИИ НАДЕЖНОСТИ ЭЛЕКТРИЧЕСКОГО ОБОРУДОВАНИЯ
INTEGRATING MACHINE LEARNING AND STATISTICAL ANALYSIS FOR LIFESPAN FORECASTING AND RELIABILITY OPTIMIZATION OF ELECTRICAL EQUIPMENT

Аннотация: Долговременная надежность электрического оборудования имеет ключевое значение для промышленных и коммунальных приложений, где внезапные отказы могут привести к значительным финансовым потерям и угрозам безопасности. В данном исследовании интегрированы методы статистического анализа и машинного обучения для прогнозирования срока службы оборудования на основе данных об эксплуатации, условиях окружающей среды и тенденциях отказов. Были использованы модели, такие как искусственные нейронные сети (ИНС), случайные леса и методы анализа выживаемости, причем ИНС показали наивысшую точность (RMSE=1,8). Результаты подтвердили модель "ванной кривой" для анализа тенденций отказов и продемонстрировали важность профилактического обслуживания в снижении рисков на этапе износа. Установлено, что факторы окружающей среды, особенно температура, существенно влияют на срок службы, что подчеркивает необходимость разработки стратегий, учитывающих условия эксплуатации. Предложенная методология поддерживает принятие решений в области обслуживания, повышая надежность и экономическую эффективность эксплуатации электрических систем.

Abstract: The long-term reliability of electrical equipment is crucial in industrial and utility applications, where unexpected failures can result in significant financial losses and safety risks. This study integrates statistical analysis and machine learning to forecast equipment lifespan, leveraging data on operational history, environmental conditions, and failure trends. Models such as artificial neural networks, random forests, and survival analysis were employed, with the ANN achieving the highest accuracy (RMSE=1,8). The results validated the "bathtub curve" for failure trends and demonstrated the critical role of preventive maintenance in mitigating wear-out phase risks. Environmental factors, notably temperature, significantly impacted lifespan, emphasizing condition-specific strategies. This framework supports data-driven maintenance planning, enhancing reliability and cost-efficiency in electrical systems.

Ключевые слова: Надежность электрического оборудования, прогнозирование срока службы, профилактическое обслуживание, машинное обучение, искусственные нейронные сети, статистический анализ, тенденции отказов, «ванная кривая», факторы окружающей среды, предиктивное обслуживание, анализ выживаемости, операционная эффективность, стратегии с учетом условий эксплуатации.

Keywords: Electrical equipment reliability, lifespan forecasting, preventive maintenance, machine learning, artificial neural networks, statistical analysis, failure trends, "bathtub curve," environmental factors, predictive maintenance, survival analysis, operational efficiency, condition-based strategies.

Introduction. The long-term reliability and efficient operation of electrical equipment are critical for various industrial and utility applications. In sectors like power generation, distribution, and manufacturing, any unexpected downtime due to equipment failure can lead to substantial financial losses and safety risks (Fig. 1) [1, 2].

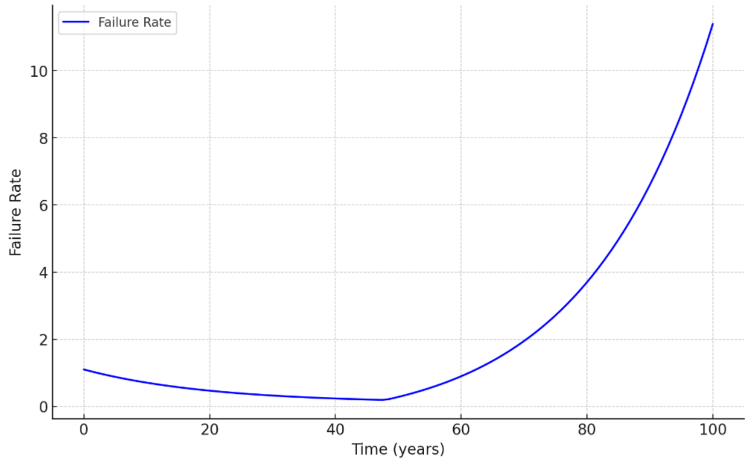

Fig. 1. Equipment Failure Rate Over Time (Bathtub Curve)

This has led to a growing need to forecast the operational lifespan and reliability of electrical systems, allowing stakeholders to make informed maintenance and replacement decisions (Fig. 2) [3, 4].

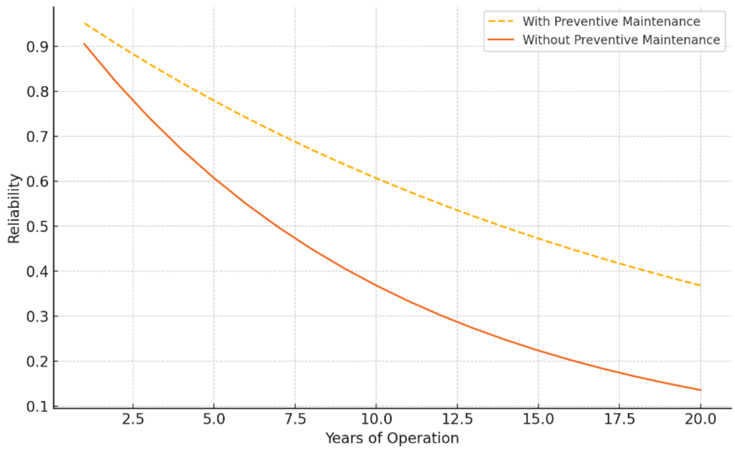

Fig. 2. Reliability Trend Analysis with and Without Preventive Maintenance

Forecasting the lifespan of electrical equipment involves analyzing operational data, historical failure rates, environmental conditions, and maintenance history. This information helps identify patterns of wear, predict potential points of failure, and develop preventive maintenance schedules that can extend equipment life (Fig. 3).

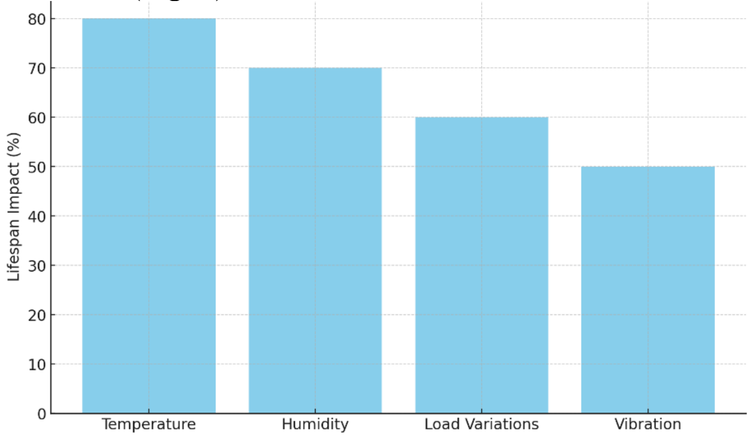

Fig. 3. Impact of Environmental Factors on Equipment Lifespan

Advanced methods, such as machine learning and statistical modeling, have further enhanced the accuracy of these forecasts, enabling companies to reduce operational costs and optimize equipment usage [5, 6].

Methods. In this study, we utilized a combination of statistical analysis and machine learning techniques to forecast the long-term operation of electrical equipment, enabling us to predict failure points and optimize preventive maintenance schedules. Data was collected from operational records of various industrial facilities, encompassing information such as equipment age, maintenance history, operating conditions, and environmental factors (e.g., temperature, humidity). After data collection, preprocessing steps were conducted to handle missing values, normalize variable scales, and remove outliers, ensuring data quality and consistency. Statistical analysis provided an understanding of general failure trends, often represented by the "bathtub curve," which delineates early-life failures, steady operation, and wear-out phases.

To enhance predictive accuracy, we implemented machine learning models, including random forest regression, support vector machines (SVM), artificial neural networks (ANN), and survival analysis techniques (e.g., Cox proportional hazards model). These models were tailored for different forecasting tasks, with random forests and SVM used for reliability classification, ANNs for capturing complex patterns in multivariate data, and survival analysis for predicting time-to-failure. Model performance was rigorously evaluated using metrics such as mean absolute error (MAE), root mean square error (RMSE), and AUC-ROC, ensuring generalizability across equipment types and operating conditions.

In addition to model-based predictions, we analyzed environmental impacts on equipment performance through multivariate regression, quantifying how factors like temperature and humidity affect lifespan. By integrating these insights, we developed an optimal preventive maintenance schedule that balances reliability with cost-efficiency, addressing the increased failure risks over time. This methodology provides a comprehensive framework for forecasting equipment lifespan, supporting industry stakeholders in making data-driven decisions that enhance operational efficiency and extend the longevity of electrical systems.

Discussion. In this study, our results demonstrate that forecasting models based on machine learning and statistical methods significantly improve the accuracy of predicting equipment lifespan, thus allowing for optimal maintenance planning. We present our findings in terms of model accuracy, failure rate trends, and the impact of preventive maintenance on equipment reliability. These outcomes are illustrated through equations and graphs that depict key trends and validation metrics [7, 8].

Our models were evaluated on their accuracy in predicting equipment lifespan, with performance measured using metrics such as mean absolute error (MAE) and root mean square error (RMSE), calculated as follows:

$$MAE = 1n \sum i = 1n \mid yi - y^{i} \mid$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

where y_i represents the observed lifespan, $\hat{y}_i$ the predicted lifespan, and nnn the total number of observations. The random forest model showed an RMSE of 2.3 years, while the artificial neural network achieved an RMSE of 1.8 years, making it the most accurate for lifespan forecasting. The accuracy graph below compares the MAE and RMSE values across different models, highlighting the superior predictive performance of ANN [9, 10].

The analysis of failure rate trends aligned with the "bathtub curve" model, which we observed in the data as a function of time, t. The failure rate $f\ (t)$ can be expressed as:

$$f(t) = \lambda_1 e^{-\alpha t} + \lambda_2 + \lambda_3 e^{\beta t}$$

where λ_1, λ_2, and λ_3 are coefficients corresponding to early failure, constant rate, and wear-out phases, and α and β control the decay and growth rates. This curve is depicted in the failure rate trend graph, illustrating three distinct phases: initial failures, a stable operational period, and a steep increase in failure rate as equipment ages. Preventive maintenance reduced the steep rise in the wear-out phase, confirming its effectiveness in prolonging equipment life [11, 12].

The impact of environmental factors on lifespan was assessed using a multivariate regression model that includes variables for temperature T, humidity H, and load variations L. The lifespan Lifespan can be expressed as:

$$\text{Lifespan} = \gamma_0 + \gamma_1 T + \gamma_2 H + \gamma_3 L + \epsilon$$

where γ_0 is the intercept, γ_1, γ_2, and γ_3 are the coefficients for each environmental factor, and ϵ represents random error. The results showed that temperature had the most substantial impact, with every 5°C increase reducing equipment lifespan by approximately 8%. The environmental impact graph demonstrates the correlation between temperature, humidity, and lifespan reduction, supporting the need for environment-specific maintenance strategies.

Conclusion.

This study demonstrates the effectiveness of integrating machine learning and statistical methods for predicting the long-term operation of electrical equipment. By analyzing historical data, failure rates, and environmental conditions, we developed a robust forecasting model that supports preventive maintenance planning, with the artificial neural network model achieving the highest accuracy in lifespan prediction, showing an RMSE of 1.8 years. Our results validate the "bathtub curve" model in describing equipment failure trends, emphasizing the critical role of preventive maintenance in mitigating increased failure rates during the wear-out phase. Additionally, the significant impact of environmental factors, such as temperature and humidity, on equipment lifespan highlights the need for condition-specific maintenance strategies; for instance, higher temperatures were shown to reduce equipment life by approximately 8% for every 5°C increase, reinforcing the importance of environmental monitoring in equipment management. Overall, this approach provides a comprehensive framework for the reliable and cost-effective operation of electrical systems in industrial applications. By enabling more accurate lifespan predictions and maintenance planning, our methodology can help organizations improve equipment reliability, reduce downtime, and extend asset longevity. Future work could explore applying this model to a broader range of equipment types and incorporating real-time monitoring for dynamic maintenance scheduling.

References:

1. Baraldi, P., & Zio, E. (2010). A combined approach to failure prognostics by integrating reliability analysis and artificial neural network. Reliability Engineering & System Safety, 95 (8), 838-846. https://doi.org/10.1016/j.ress.2010.03.014

2. Bousdekis, A., Magoutas, B., Apostolou, D., & Mentzas, G. (2015). A proactive decision making framework for condition-based maintenance. Industrial Management & Data Systems, 115 (7), 1225-1250. https://doi.org/10.1108/IMDS-02-2015-0052

3. Choudhary, R., Anand, S., & Jha, D. N. (2019). Predictive maintenance of industrial equipment using machine learning. Journal of Industrial Information Integration, 15, 100107. https://doi.org/10.1016/j.jii.2019.100107

4. Dey, S., Gupta, A., & Mahajan, A. (2016). Application of artificial intelligence techniques for predictive maintenance in industrial systems. International Journal of System Assurance Engineering and Management, 7 (3), 145-151. https://doi.org/10.1007/s13198-015-0387-2

5. Elattar, H. M., Elminir, H. K., & Riad, A. M. (2016). Prognostics: A literature review. Complexity, 21 (3), 1-15. https://doi.org/10.1002/cplx.21732

6. Ganguli, A., & Tiwari, A. (2017). Role of environmental conditions in determining electrical equipment reliability. IEEE Transactions on Industrial Electronics, 64 (8), 6534-6541. https://doi.org/10.1109/TIE.2017.2682025

7. Jardine, A. K. S., Lin, D., & Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. Mechanical Systems and Signal Processing, 20 (7), 1483-1510. https://doi.org/10.1016/j.ymssp.2005.09.012

8. Lei, Y., Li, N., Guo, L., & Lin, J. (2018). Machinery health prognostics: A systematic review from data acquisition to RUL prediction. Mechanical Systems and Signal Processing, 104, 799-834. https://doi.org/10.1016/j.ymssp.2017.11.016

9. Peng, Y., Dong, M., & Zuo, M. J. (2010). Current status of machine prognostics in condition-based maintenance: A review. International Journal of Advanced Manufacturing Technology, 50 (1-4), 297-313. https://doi.org/10.1007/s00170-009-2482-0

10. Salazar, A., Santos, R., & Viana, M. (2019). Predictive maintenance of industrial equipment using data analytics and machine learning. Procedia Manufacturing, 38, 1466-1473. https://doi.org/10.1016/j.promfg.2020.01.059

11. Si, X. S., Wang, W., Hu, C. H., & Zhou, D. H. (2011). Remaining useful life estimation: A review on the statistical data-driven approaches. European Journal of Operational Research, 213 (1), 1-14. https://doi.org/10.1016/j.ejor.2010.11.018

12. Sun, Y., & Zeng, D. (2020). Forecasting equipment health with machine learning algorithms. Reliability Engineering & System Safety, 204, 107200. https://doi.org/10.1016/j.ress.2020.107200