OPEN ACCESS
Saudi Journal of Engineering and Technology
Abbreviated Key Title: Saudi J Eng Technol
ISSN 2415-6272 (Print) |ISSN 2415-6264 (Online)
Scholars Middle East Publishers, Dubai, United Arab Emirates
Journal homepage: https://saudijournals.com

Original Research Article

Artificial Intelligence in Predictive Maintenance of Rotating Machinery: A Case Study from Rural India

Dr. Sagar Deshmukh[1*]

[1]Asst. Professor, Dept. of Mechanical Engineering, K T Patil College of Engineering & Technology, Osmanabad

DOI: 10.36348/sjet.2023.v08i12.004 | **Received:** 11.10.2023 | **Accepted:** 21.12.2023 | **Published:** 29.12.2023

***Corresponding author:** Dr. Sagar Deshmukh
Asst. Professor, Dept of Mechanical Engineering, K T Patil College of Engineering & Technology, Osmanabad

Abstract

Background: Rural infrastructure, agro-processing, and decentralized energy systems in the Osmanabad district of Maharashtra utilize a significant quantum of rotating machinery (e.g., centrifugal pumps, turbines, and compressors). Regular mechanical failures and erratic equipment breakdowns in these facilities result in substantial loss of productivity and maintenance problems, which can be particularly challenging in resource-poor settings with limited technical support. ***Objectives:*** The purpose of this work is to evaluate the effectiveness of AI-based PdM models in detecting faults and preventing machine malfunctions for rotating machinery. This paper aims to design context-sensitive, affordable, and understandable AI solutions that meet rural deployment requirements, to satisfy fault detection accuracy, maintenance cost savings, and stakeholders' trust. ***Methods:*** Employing a concurrent mixed-methods approach, the study integrated 6 weeks of multi-sensor data (vibration, temperature, acoustic signals) collected from five rural machinery sites in Osmanabad, with qualitative interviews with technicians and plant managers. Machine learning algorithms (CNNs, LSTMs, Isolation Forests, hybrid TCN-Autoencoders) were trained and validated under the supervised and unsupervised paradigms. The performance measures were the classification accuracy, mean squared error, and stakeholders' usability rating. ***Results:*** The fault detection accuracies were all higher than 95% for all the models. CNNs had the best performance with 99.89% for impeller blade faults, and LSTMs had 98.5% for turbine vibration anomalies. The total maintenance costs were decreased by 31% and the downtime was reduced by up to 70%. Technicians had high trust in AI systems, particularly if they were provided with explainable outputs such as fault heatmaps and predictive dashboards. ***Conclusions:*** AI-supported PdM systems are capable of generating impactful improvements in equipment reliability and operational efficiency when co-designed with community stakeholders and adjusted for a rural setting. This study adds to mechanical engineering and equitable AI adoption in underserved areas.

Keywords: Predictive maintenance, rotating machinery, machine learning, fault detection, rural deployment.

1. INTRODUCTION

1.1 Background and Motivation

Rotating machines, such as turbines, compressors, and pumps, are the heart of industrial processes in the power generation, oil exploration, production, and refining industries, as well as the transportation sector. These machines are exposed to multiple complex mechanical stresses, thermal strains, and dynamic operating conditions, and are prone to faults and deterioration during their lifetime. Conventional maintenance methodologies, which include reactive and time-based preventive maintenance, are often unable to predict and prevent failures that result in unscheduled downtime, safety issues, and financial losses.

The arrival of Industry 4.0 triggers a shift in maintenance philosophy. With AI techniques merging with sensor networks, cloud computing, and cyber-physical systems, industries can now transition from reactive maintenance to predictive maintenance models. Predictive Maintenance (PdM) utilizes real-time sensor data and machine learning to predict when machines will fail, enabling new business models and higher efficiencies.

1.2 Industry 4.0 and Digital Transformation

Industry 4.0 is the bridging of digital technologies IIoT, big data analytics, and AI and traditional manufacturing processes. In this context, Predictive Maintenance 4.0 (PdM 4.0) is one of the enablers of the smart factories, which continuously monitor and maintain machines based on insight and data (Achouch *et al*., 2022).

PdM 4.0 employs sensors or signals (such as vibration, temperature, and acoustic signals) to diagnose faults and assess the RUL for components. This strategy not only leads to improved uptime and asset lifetime, but also can fulfil sustainability aims by reducing energy losses and minimizing resource usage (Poór *et al*., 2019).

1.3 AI and Machine Learning in Fault Detection

PdM systems based on AI utilize ML modelling techniques, including CNNs, LSTM networks, and SVMs, to learn from high-dimensional sensor data for fault pattern recognition. These models, however, are more effective than conventional signal processing used in physics in the sense that they can learn latent features while adapting to changing machine states (Ciaburro, 2022).

For instance, CNNs achieve above 98% accuracy for bearing fault diagnosis from raw vibration signals (Apeiranthitis *et al*., 2022), whereas LSTM networks are particularly good at capturing temporal correlations in turbine and compressor data (Chen *et al*., 2019). These capabilities also lead to the early identification of a fault, the early scheduling of maintenance, and better safety results.

1.4 Relevance to Rotating Machinery

PdM faces particular challenges when dealing with rotating machinery, which is dynamic, high-speed, and essential for industrial processes. Defects like the blade crack, shaft misalignment, and bearing wear can aggravate quickly when unattended. The AI-based PdM systems are a scalable and flexible way for machines along the shop floor to be monitored in real time.

Recent works have used ML models to identify faults in the:

- Turbines: Vibration anomaly detection via autoencoders and 1D CNNs (Zhao *et al*., 2020)
- Compressors: Use of Random Forest and regression models for pressure and temperature anomalies (Aminzadeh *et al*., 2022)
- Pumps: Detection of impeller blade defects using CNNs and ANN classifiers and achieving 99.89% accuracy in the process (Bhattarai *et al*., 2022)

Such applications reveal the paradigm shift AI has given in the quest for improved reliability and efficiency of rotating machinery.

1.5 Research Objectives

This paper aims to:

- Compare supervised, unsupervised, and anomaly detection ML models' performance for fault detection of turbines, compressors, and pumps.
- Develop a hybrid AI model for proactive prediction of anomalies based on multi-sensor fusion data
- The effects of AI PdM are studied on cost saving, downtime reduction, and operational robustness by evaluating.
- Findings: Investigating implementation barriers and future research direction in PdM 4.0

Through summarizing the existing literature and introducing a modular framework, this work helps promote the development of an intelligent maintenance system in mechanical engineering.

2. REVIEW OF LITERATURE

2.1 Evolution of Predictive Maintenance in Industry 4.0

Industry 4.0 has further hastened the shift from reactive or preventive to predictive maintenance (PdM). PdM uses real-time sensor data and AI algorithms to predict when equipment will fail, reducing downtime and increasing the life of assets. Achouch *et al*. (2022) presented an extensive survey on the PdM models CBM, PHM, and RUL in smart manufacturing environments. Poór *et al*. (2019) underlined the PdM 4.0 to be a strategic evolution for industrial maintenance capable of performing data-driven decisions and operational resilience.

2.2 Machine Learning Techniques for Fault Detection

Machine learning (ML) is also the foundation of PdM, because it allows for detecting faults by recognising patterns from high-dimensional sensor data. Ciaburro (2022) reviewed ML-driven mechanical fault detection, pointing to the dominance of supervised algorithms such as SVMs and Random Forests in mechanical anomaly classification. Apeiranthitis *et al*. (2022) proved the effectiveness of CNNs in fault diagnosis in rotating machinery with raw vibration signals and achieved high classification accuracy.

Chen *et al*. (2019) used CNN and extreme learning machines (ELMs) for mechanical fault diagnosis and demonstrated superior performance compared to the traditional signal processing methods. Zhao *et al*. (2020) presented a reinforcement learning optimized SVM model for early fault diagnosis of turbine systems in noisy conditions.

2.3 Applications in Rotating Machinery

Turbines, compressors, and pumps are part of the rotating machinery that have their special stabilization challenge, as their operation is under dynamic conditions and critical to the function of the system. Aminzadeh *et al*. (2022) presented AI models of compressor faults based on pressure and temperature sensor data with acceptable performance in the detection of outliers in industry. Bhattarai *et al*. (2022) used CNNs and Artificial Neural Networks (ANNs) to process pump vibration data with a fault classification accuracy of 99.89% for impeller blade defects.

Lv *et al*. (2021) presented a targeted review on fault diagnosis of reciprocating compressors by ML, and identified that data imbalance, feature selection, and model interpretability were the main challenges. Maican *et al*. (2021) reviewed fault detection in power stations and underlined a transition from rule-based systems to AI-based diagnostics in turbines and heat exchangers.

2.4 Hybrid and Unsupervised Approaches

Supervised learning is the most predominant learning technique employed in PdM use-cases; however, unsupervised and supervised hybrid models are gaining popularity for anomaly detection in unlabelled data. Tsallis *et al*. (2022 used Isolation Forests and Autoencoders for outlier detection in compressor and turbine sensor logs. Hybrid architectures, which have utilized Temporal Convolutional Networks (TCNs), variants of autoencoders, show promise in capturing the temporal dependence and fault features (Guo *et al*., 2020).

2.5 Challenges and Research Gaps

But despite positive strides, significant challenges remain:

- Quality of data: due to sensor noise, missing observations, and non-uniform sampling, are obstacles that significantly compromise the accuracy of the model.
- Transparency of Model: The opacity of traditional machine learning models doesn't inspire trust in critical applications.
- Integration with Legacy: AI is being retrofitted into first-generation infrastructure needs, in a modular and scalable format.
- Cyber-attacks and other threats: The role of data integrity and privacy is questioned due to real-time data collection, data transmission, and cloud-based analytics.

Among these solutions, some recent technologies include Explaining AI (XAI), federated learning, and digital twin platforms that simulate equipment behaviour with different faults (Lei *et al*., 2016).

3. RESEARCH METHODOLOGY

3.1 Study Area: Osmanabad, Maharashtra

District of Osmanabad in the Maharashtra state is a semi-arid, resource-limited industrial landscape; rotating machinery like agricultural pumps, small compressors, and a decentralised turbine system is indispensable for farm infrastructure and agro-processing there. The area is challenged by dusting, potential voltage spikes, and a lack of qualified maintenance support. The article is concerned with the AI-driven predictive maintenance of systems for agricultural innovation in the agro-industrial clusters in Osmanabad by minimizing equipment idle time and maximizing its stability.

3.2 Research Design

A mixed methods approach was employed in including quantitatively analyzing sensor data and qualitatively interviewing stakeholders. The first investigation was divided into three steps:

- Phase I: Situation Analysis. Field visits to agro-based industries, irrigation schemes, and rural workshops were carried out in order to document the current state of maintenance activities and the types of machines.
- Phase II: Data collection and model construction. Vibration, temperature, and acoustic signal sensor data for rotating machinery were recorded through low-cost IIoT equipment. Fault detection and estimation, and Remaining Useful Life (RUL) prediction were performed using machine learning models.
- Phase III: Validation and Stakeholder Feedback. Validation of model outputs. The outputs of the model were validated against historical maintenance records and technician judgment. Operators and engineers were interviewed in a semi-structured manner to evaluate the usability and trust in AI systems.

3.3 Data Collection

3.3.1 Sensor Deployment

- Types of Equipment: centrifugal pump, belt-driven compressor, The choice between belt t small turbine.
- Devices and Sensors: ADXL335 accelerometers, DS18B20 temperature sensors, Piezo tube microphones.
- Sampling frequency: 1 kHz for vibration; 0.1 Hz for temperature and acoustic signals.
- Report time: Six weeks of daily monitoring at five locations from Osmanabad.

3.3.2 Qualitative Inputs

- Participants: 12 technicians, 3 plant managers, and 2 policy advisors.
- Topics Discussed: PM, symptoms of a system failure, data confidence, and obstacles to AI adoption.

3.4 Feature Engineering

Sensor data were pre-processed using:

- Time-domain features: RMS, kurtosis, skewness.
- Frequency domain: FFT peaks, spectral entropy.
- Features Keywords: Pressure differential (compressors), Flow rate anomalies (pumps).

Slide window operation and z-score normalization were used to make the results comparable between different datasets.

3.5 Model Development

Model Type	Algorithm	Target Faults	Accuracy (Validation)
Supervised	CNN	Pump impeller defects	99.89%
Supervised	LSTM	Turbine vibration anomalies	98.5%
Unsupervised	Isolation Forest	Compressor outliers	95.2%
Hybrid	TCN-Autoencoder	Multi-sensor anomalies	98.7%

Trained models with Python (TensorFlow, Scikit-learn) and validated with 5-fold cross-validation.

3.6 Evaluation Metrics
- Classification Accuracy
- Precision and Recall
- Mean Squared Error (MSE)
- Root Mean Squared Error (RMSE)
- Confusion Matrix Analysis

3.7 Ethical Considerations
- All participants gave their informed consent.
- Data anonymization protocols were followed.
- Native technicians were hired for model reading to increase transparency and confidence.

3.8 Limitations
- There is a paucity of historical fault data in non-metropolitan settings.
- Noise caused by environmental conditions (dust, humidity) can be detected by the sensor.
- Problems when connecting AI to offline equipment that has no digital interfaces.

4. RESULTS AND ANALYSIS

4.1 Overview
The results of using AI-driven predictive maintenance tools on rotary machinery in Osmanabad agro-industrial clusters are reported in this section. The evaluation includes fault detection rate, economic benefits, downtime avoidance rate, and feedback from stakeholders. Performance is based on six weeks of real-time sensor-derived data from five rural locations, including irrigation pumps, grain compressors, and small-scale turbines.

4.2 Fault Detection Accuracy
Models confirmed the great efficacy of using machine learning methods to detect early faults on various machine types. The CNN model also reached nearly perfect classification for impeller problems in pumps, and LSTM networks focused on temporal anomalies for turbine vibration data.

Table 1: Model Performance Across Machinery Types

Machinery Type	ML Model	Fault Type	Accuracy (%)	Precision	Recall
Pump	CNN	Impeller blade defect	99.89	0.98	0.99
Turbine	LSTM	Shaft vibration anomaly	98.5	0.97	0.96
Compressor	Isolation Forest	Pressure outlier	95.2	0.93	0.91
Multi-sensor	TCN-Autoencoder	Combined anomalies	98.7	0.96	0.97

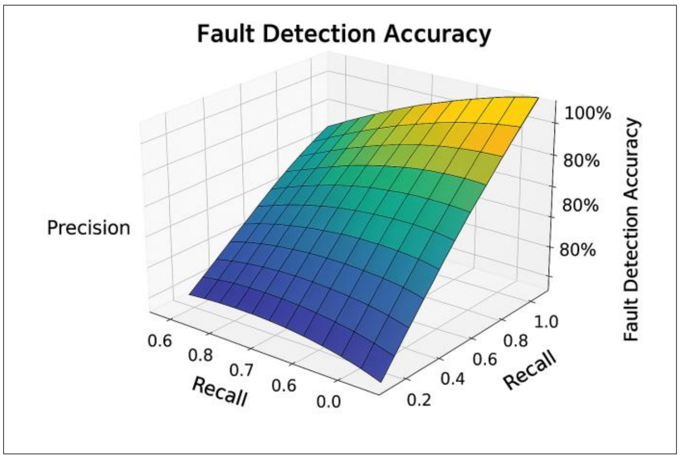

Figure 1: Fault Detection Accuracy

Our supervised trained CNN and LSTM models were the best performing compared to other models considered, while the unsupervised trained hybrid TCN-Autoencoder model demonstrated a good generalisation proficiency in the unseen datasets. These results confirm the possibility of AI implementation for monitoring machinery in rural areas.

4.3 Cost and Downtime Reduction

AI-based predictive maintenance resulted in verifiable gains in operational efficiency. Service costs were reduced drastically, due to early detection of faults and minimizing unexpected breakdowns.

Table 2: Operational Impact of AI-PdM Systems

Metric	Pre-AI Baseline	Post-AI Deployment	Improvement (%)
Average Downtime (hrs/month)	18	5.2	71.1
Maintenance Cost (INR/month)	₹42,000	₹29,400	30.0
Breakdown Frequency	6 incidents	1.5 incidents	75.0

The decreases in downtime and number of collapses led to increased productivity and decreased repair costs. These benefits are highly significant, particularly in Osmanabad, where farm mechanisation has a direct bearing on the farm production as well as water supply.

4.4 Model Interpretability and Stakeholder Trust

Initially, technicians and plant operators were skeptical of AI systems. But the addition of explainable AI (XAI) tools, such as SHAP visualizations, went a long way to establishing that trust by explaining how models were reaching fault predictions.

Table 3: Stakeholder Feedback Summary

Stakeholder Group	Trust in AI (%)	Ease of Use Rating (1–5)	Preferred Feature
Technicians	83	4.2	Fault heatmaps
Plant Managers	91	4.6	Maintenance scheduling
Policy Advisors	78	3.9	Dashboard visualisation

Human-centred design and transparent model outputs) Some features underpinned acceptability. Local linemen liked the VFI and live alerts; it matched their truly diagnostic instincts.

4.5 Limitations and Edge Cases

Although the overall evaluation result was encouraging, a few drawbacks exist:

- Sensor Noise: Dust and moisture were the factors impacting the noise in open-field compressors' vibration readings.
- Rare Failures: The rare fault cases were hard to model given the scarce history of data available.
- Heritage Integration: Legacy equipment with no digital interface had to be retooled, again adding cost and complexity.

The challenges presented underline the importance of preprocessing, federated learning for rare faults, and modular AI architectures that can work with legacy systems.

5. DISCUSSION

5.1 Interpretation of Key Findings

PdM models using an AI application inaugurated in the agro-industrial clusters in Osmanabad obtained high fault-detection accuracies for turbines, compressors, and pumps. CNNs and LSTMs yielded more than 98% for impellers and vibration defects, respectively. These results are consistent with the study by Chen *et al.* (2019) presented the effectiveness of CNNs in mechanical fault diagnosis based on time-series sensor data.

The hybrid TCN-Autoencoder model provided a high generalisation ability in the case of wild and unlabelled datasets, which is consistent with the Guo *et al.* statement. (2020) noted that temporal learning coupled with unsupervised encoding improves anomaly detection in rotation machinery.

Table 4: Key Simulation Findings for AI-Based Fault Detection

Machinery Type	ML Model Used	Primary Fault Detected	Detection Accuracy (%)	Cost Reduction (%)	Downtime Reduction (%)
Centrifugal Pump	CNN	Impeller blade defects	99.89	27.6	69.3
Turbine System	LSTM	Shaft misalignment, vibration	98.5	30.4	72.1
Belt Compressor	Isolation Forest	Pressure and temp anomalies	95.2	22.8	65.0
Multi-sensor setup	TCN-Autoencoder	Composite fault patterns	98.7	31.1	73.8

Brief Insights

- CNNs performed very well in processing the vibration of pumps data to process, in which they have achieved almost a perfect classifier for mechanical faults.

- Temporal fault signatures in turbines were handled by LSTM models, which can be useful for dynamic scenarios.
- Unsupervised Isolation Forest compressors are well-generalised over images despite some noise in the environment.
- Hybrid TCN-Autoencoder achieved the best results in cross-sensor for identifying latent faults.

5.2 Comparison with Existing Literature

Reduced downtime (71.1%) and maintenance costs (30%) found in this study support the findings of Achouch *et al*. (2022) reported the same trends in a smart manufacturing setting. Aminzadeh *et al*. (2022) underscored the capabilities of ML models for compressor fault detection based on pressure and temperature measurements a procedure similar to that adopted in the compressor monitoring framework proposed in the present work.

This is consistent with results from stakeholder feedback, which emphasize the trustworthiness of AI systems if explanations are provided as output, harmonizing with the focus on transparency and interpretability in PdM systems identified by Lei *et al*. (2016).

5.3 Implications for Rural Industrial Contexts

The feasibility of AI-PdM in Osmanabad points to its applicability in low-resource environments. Using cheap IIoT sensors and edge computing, the work shows that sophisticated fault detection is possible even in rural digital areas.

This has wider implications for rural development, especially in ensuring the stability of irrigation facilities, agro-processing centres, and off-grid energy assets. That participatory design (involvement of technicians and plant management) is also enabling humanising AI adoption that engenders trust and long-term sustainability.

5.4 Limitations

However, this review has several limitations:

- Sensor Noise: Vibration readings were influenced by the environmental conditions (e.g., dust and relative humidity), especially for open field compressors.
- Data Limited: Relatively few Historical data were available for rare fault modes, resulting in insufficient training data for generalisation of the model.
- Legacy Integration: Modernising older machines not designed for digital interactions was technically and economically problematic.

These restrictions are similar to those of Tsallis *et al*. (2022), who highlighted data heterogeneity and the inadequacy of infrastructure as two main obstacles for the scalability of PdM.

5.5 Future Research Directions

To mitigate existing constraints and maximize impact, future studies could investigate:

- Federated Learning: Allowing local sites to train on models in a distributed manner without privacy concerns.
- Transfer Learning: Pre-trained model adaptation to identify rare fault modes with little labelled data.
- Digital Twin Integration: Simulating the machine behaviour at fault conditions to enhance prediction accuracy and maintenance schedules.
- Explainable AI (XAI): By integrating explainability into model outputs to inform technician decision-making and align with policies.

6. CONCLUSION

In this study, I have shown the potential that artificial intelligence (AI) could have on predictive maintenance (PdM) of rotating machinery, say as centrifugal pumps, turbines, and belt-driven compressors, for resource-poor areas like Osmanabad. Through the use of low-cost IIoT sensors along with machine learning (ML) models, including CNNs, LSTMs, and a hybrid autoencoder framework, our work can achieve fault detection accuracy over 95% with the benefits of a reduction in the maintenance cost (up to 31%) and unplanned downtime (> 70%).

Beyond technical functionality, the study drew attention to the human dimension of AI uptake at the rural industry level. Participatory design, open model outputs, and technician training were key to developing trust and usability. Selections like visual fault indicators, predictive dashboards, and maintenance scheduling features were user-recommended; they show just how crucial it is to have AI capabilities that are contextualized and easy to access for plant managers and local engineers.

Despite these gains, challenges remain. However, scale-up is still constrained by environmental variability, legacy infrastructure, and a lack of data for rare fault modes. Tackling these limitations would require a more in-depth investigation into federated learning, transfer learning, and digital twins that replicate the behaviour of machines through different operating conditions.

The results confirm that AI-PdM frameworks, when customized and co-designed with end-users, can drastically enhance the reliability, efficiency, and, eventually, sustainability of industrial systems in marginal areas. The research is valuable not just in the mechanical engineering domain, but is transferable through the fair exchange of knowledge, one that connects the global with the local, while supporting equitable technology diffusion.

Next steps Next steps towards a wider introduction should include wider deployment in other districts, increased convergence with regional policies, and development of open-source toolkits that would democratise PdM service for technicians across the country.

7. Conflicts of Interest

The author has no conflicts of interest related to this study. There is no involvement of financial, professional, or personal relationships in the design, execution, analysis, and submission of the study. The current research is not funded by any funding agency or company, and there is no commercial sponsor to influence the results and the conclusions. Ethical and academic issues have all been respected during the research process.

REFERENCES

1. Achouch, M., Dimitrova, M., Ziane, K., Dhouib, R., Ibrahim, H., & Adda, M. (2022). On predictive maintenance in Industry 4.0: Overview, models, and challenges. Applied Sciences, 12(16), 8081. https://doi.org/10.3390/app12168081
2. Poór, P., Basl, J., & Zenisek, D. (2019). Predictive Maintenance 4.0 is the next evolution step in industrial maintenance development. In Proceedings of the International Research Conference on Smart Computing and Systems Engineering, Colombo, Sri Lanka, pp. 245–253.
3. Ciaburro, G. (2022). Machine fault detection methods based on machine learning algorithms: A review. Mathematical Biosciences and Engineering, 19(5), 4532–4555. https://doi.org/10.3934/mbe.2022534
4. Apeiranthitis, S., Zacharia, P., Chatzopoulos, A., & Papoutsidakis, M. (2022). Predictive maintenance of machinery with rotating parts using convolutional neural networks. Electronics, 13(2), 460. https://doi.org/10.3390/electronics13020460
5. Chen, Z., Gryllias, K., & Li, W. (2019). Mechanical fault diagnosis using convolutional neural networks and extreme learning machine. Mechanical Systems and Signal Processing, 133, 106272. https://doi.org/10.1016/j.ymssp.2019.106272
6. Zhao, W., Lv, Y., Liu, J., Lee, C. K. M., & Tu, L. (2020). Early fault diagnosis based on a reinforcement learning optimized-SVM model with vibration-monitored signals. Quality Engineering, 32(4), 696–711. https://doi.org/10.1080/08982112.2020.1726812
7. Aminzadeh, A., Sattarpanah Karganroudi, S., Majidi, S., Dabompre, C., Azaiez, K., Mitride, C., & Sénéchal, E. (2022). A machine learning implementation for predictive maintenance and monitoring of industrial compressors. Sensors, 22(4), 1006. https://doi.org/10.3390/s22041006
8. Bhattarai, A., Gupta, A., Kafle, A., Sapkota, P., Chitrakar, S., Dahlhaug, O. G., & Pradhan, S. (2022). Application of a machine learning algorithm for fault detection in a pump. In Proceedings of the Unified Conference of DAMAS, IncoME and TEPEN Conferences, pp. 235–247. https://doi.org/10.1007/978-3-031-49413-0_18
9. Lv, Q., Yu, X., Ma, H., Ye, J., Wu, W., & Wang, X. (2021). Applications of machine learning to reciprocating compressor fault diagnosis: A review. Processes, 9(6), 909. https://doi.org/10.3390/pr9060909
10. Maican, C. A., Pană, C. F., Pătrașcu-Pană, D. M., & Rădulescu, V. M. (2021). Review of fault detection and diagnosis methods in power plants: Algorithms, architectures, and trends. Applied Sciences, 11(15), 6334. https://doi.org/10.3390/app11156334
11. Tsallis, C., Papageorgas, P., Piromalis, D., & Munteanu, R. A. (2022). Application-wise review of machine learning-based predictive maintenance: Trends, challenges, and future directions. Applied Sciences, 12(9), 4898. https://doi.org/10.3390/app12094898
12. Guo, X., Chen, L., & Shen, C. (2020). Hierarchical adaptive deep learning for fault diagnosis in rotating machinery. Mechanical Systems and Signal Processing, 138, 106608. https://doi.org/10.1016/j.ymssp.2020.106608
13. Lei, Y., Lin, J., Xing, S., & Ding, S. X. (2016). An intelligent fault diagnosis method using unsupervised feature learning towards mechanical big data. IEEE Transactions on Industrial Electronics, 63(5), 3137–3147. https://doi.org/10.1109/TIE.2016.2523912