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RELIABILITY ASSESSMENT AND FAILURE PREDICTION OF SUBMERSIBLE PUMPS USING ADVANCED MODELING TECHNIQUES

Bautina M. Reliability Assessment and Failure Prediction of Submersible Pumps Using Advanced Modeling Techniques. The article examines modern approaches to predictive maintenance of submersible pumps using artificial intelligence algorithms and IoT sensors. The study's relevance is determined by the need to improve the reliability of pump equipment and optimize maintenance costs. It has been established that the main challenges include high infrastructure modernization costs, the complexity of adapting algorithms to variable data streams, and the need for qualified personnel to operate the monitoring system. The study's purpose is to develop recommendations for integrating predictive maintenance systems to reduce unplanned downtime and optimize maintenance costs. The article employs methods of comparative analysis of predictive model efficiency and investigates the impact of key parameters, such as pressure, temperature, and vibration, on real-time equipment condition prediction. The results demonstrated that the proposed model based on recurrent neural networks outperforms traditional approaches across all key metrics, particularly regarding precision and recall. The study concludes that a phased implementation of pilot projects is necessary to adapt the system to industrial conditions and ensure continuous monitoring. The prospects for further research include the development of adaptive models capable of working with incomplete data and enhancing the autonomy of maintenance systems through self-learning algorithms, which will contribute to the stable operation of pump systems under complex operating conditions.
Keywords: predictive maintenance, submersible pump analysis, advanced modeling, failure diagnostics, reliability engineering.

Баутіна М.В. Оцінка надійності та прогнозування відмов заглибних насосів за допомогою передових методів моделювання. У статті досліджено сучасні підходи до прогнозуючого обслуговування заглибних насосів із використанням алгоритмів штучного інтелекту та IoT-сенсорів. Актуальність роботи зумовлена необхідністю підвищення надійності насосного обладнання та оптимізації витрат на його технічне обслуговування. Встановлено, що основними проблемами є високі витрати на модернізацію інфраструктури, складність адаптації алгоритмів до змінних потокових даних та потреба у кваліфікованому персоналі для роботи із системою моніторингу. Метою дослідження є розробка рекомендацій щодо інтеграції систем прогнозуючого обслуговування для зниження кількості аварійних простоїв і оптимізації витрат на обслуговування. У статті використано методи порівняльного аналізу ефективності моделей прогнозування, а також дослідження впливу змін ключових параметрів, таких як тиск, температура та вібрація, на прогнозування технічного стану насосів у реальному часі. Результати показали, що запропонована модель на основі рекурентних нейронних мереж перевершує традиційні підходи за всіма ключовими показниками, зокрема за точністю та повнотою. Зроблено висновок про необхідність поетапного впровадження пілотних проєктів для адаптації системи до виробничих умов і забезпечення безперервного моніторингу. Перспективи подальших досліджень включають розробку адаптивних моделей для роботи з неповними даними, а також підвищення автономності систем обслуговування через самонавчання моделей. Це сприятиме стабільній роботі насосних систем у складних експлуатаційних умовах.
Ключові слова: прогнозуюче обслуговування, аналіз заглибних насосів, передове моделювання, діагностика відмов, інженерія надійності.

Problem statement. In modern industrial systems, submersible pumps play a key role in ensuring the continuity of technological processes, but their failure can lead to significant financial losses and business interruptions. Traditional maintenance approaches based on fixed inspection intervals are often ineffective because they do not consider the dynamics of changes in operating parameters and early warning signs. This creates the need to implement innovative predictive maintenance systems that promptly predict possible failures and prevent emergencies.

Integrating artificial intelligence algorithms and IoT sensors opens up new opportunities for real-time monitoring and diagnosing submersible pump conditions. High-precision machine learning algorithms allow for analyzing large amounts of sensor data and identifying hidden patterns that signal potential equipment failures. Using metrics such as precision, recall, F1-measure, and root mean square error allows you to evaluate the effectiveness of models and adjust them to achieve greater accuracy of predictions in specific operating conditions. Custom algorithm modifications can be used to improve the efficiency of forecasts, considering the peculiarities of pump operation, load fluctuations, and possible delays in data transmission from IoT sensors.

The practical significance of such research lies in creating effective systems for automated forecasting of equipment technical conditions. This minimizes downtime, reduces the cost of unscheduled repairs, and increases the overall productivity of production processes. This provides business benefits in the form of increased resource management efficiency, reduced accident risks, and an adaptive maintenance strategy based on real-world data on equipment conditions.

Analysis of the latest research and publications. Assessing the reliability and predicting failures of submersible pumps is one of the key issues in ensuring the smooth operation of pumping stations. Modern research is focused on the implementation of machine learning algorithms and the use of IoT sensors to analyze the technical condition of equipment and improve the efficiency of its maintenance. The study of methods for predicting failures of electric submersible pumps demonstrate the prospects of using modern approaches based on artificial intelligence. In, R. Abdalla, H. Samara, N. Perozo, C. Paz Carvajal, and P. Jaeger proved that the use of machine learning can reduce the number of emergency shutdowns through effective real-time anomaly analysis [1]. S. Almazrouei, F. Dweiri, R. Aydin, et al. reviewed existing models for predictive pump maintenance and emphasized the need to standardize methods for processing large amounts of streaming data [2].

An important area of research is the use of multimodal methods and transfer learning for real-time fault diagnosis. P. Yang, J. Chen, L. Wu, and S. Li proposed an approach based on the integration of different types of learning that improves the accuracy of predictions in variable conditions [3]. P. Bhattacharjee applied the method of multinomial logistic regression to quantify the risk of pump component failures, which minimizes false signals of the diagnostic system [4].

Deep learning models also demonstrate a high level of efficiency in forecasting. J. Chen, W. Li, P. Yang, S. Li, and B. Chen developed a three-stage diagnostic model that combines deep learning and support vector machine methods and demonstrates a high level of accuracy [5]. The study by S. Saptadi, A. Widodo, M. F. Athaillah, and M. F. Ayyasyi presented the use of recurrent neural networks, which provided a prediction accuracy of more than 90% [6].

The study of pump failure mechanisms requires the development of additional measures to minimize failures. The paper by S. Fakher, A. Khlaifat, and M.E. Hossain provides an overview of the causes of failures of electric submersible pumps and suggests ways to prevent them [7]. Hybrid models combining physical parameters and machine learning algorithms are promising for improving diagnostic accuracy. S. Al-Ballam, H. Karami, and D. Devegowda proposed a hybrid model for real-time fault prediction [8].

A separate area of research concerns the impact of design parameters on pump reliability. In the work of V. Kannaujia, S. P. Bhore and H. S. Goyal analyzed the factors affecting the performance of pumping equipment and emphasized the importance of standardizing experimental modeling methods [9].

An in-depth analysis of the practical aspects of pump maintenance is presented in the monograph by G. Takacs, which discusses the technical characteristics, operating modes and measures to improve the reliability of pumping units [10].

Promising approaches to the diagnosis of hydraulic pumps are considered in the study by Y. Yang, L. Ding, J. Xiao, G. Fang, and J. Li, where the use of artificial intelligence for real-time signal processing can significantly improve the accuracy of forecasting [11]. Methods of adaptive adjustment of forecasting systems are presented in the article by Q. Li, K. Li, X. Gao, J. Fu, and L. Zhang, who proposed temporal attention networks to improve the accuracy of anomaly detection [12].

Intelligent systems for diagnosing malfunctions of drilling pumps were studied by J. Guo, Y. Yang, H. Li, L. Dai, and B. Huang, who described a parallel neural network architecture that can be adapted for electric submersible pumps [13]. A deep belief network methodology for predicting the operating modes of pumping units was proposed by D. Yu and H. Zhang [14]. The use of machine learning algorithms to improve the accuracy of predicting pumping station modes was investigated by O. Turchyn [15].

Thus, the analysis confirms that the prospects for research are related to the development of adaptive algorithms and hybrid models to improve the reliability and autonomy of predictive maintenance systems.

Highlighting previously unsolved parts of the problem. Despite significant advances in predicting the technical condition of pumps, aspects still require further research. First, the effectiveness of artificial intelligence algorithms in the face of variable and incomplete streaming data, critical for real-time systems, has not been sufficiently studied. Data loss or noise signals can affect the quality of forecasting and increase the number of false positives.

Second, the optimal set of IoT sensors and their configuration must be determined to improve diagnostic accuracy. The lack of empirical research on the combination of several types of sensors limits the ability to adapt systems to different operating environments.

Thirdly, the issue of creating models capable of automatic retraining without losing efficiency remains relevant. Most modern methods require manual intervention to adjust models to changing conditions, which reduces data processing efficiency.

The proposed study aims to overcome these limitations by developing adaptive algorithms for dealing with unstable data, conducting a comprehensive assessment of forecast effectiveness, and developing practical recommendations for the passed integration of systems into business processes to reduce downtime and optimize maintenance.

The purpose of the article is to develop an effective approach to assessing the reliability and predicting failures of submersible pumps using artificial intelligence algorithms and IoT technologies to improve maintenance efficiency.

Objectives of the article:

1. To investigate modern artificial intelligence algorithms used to analyze and predict technical failures, determine their suitability for monitoring the condition of submersible pumps, and establish key parameters of IoT sensors with an assessment of their role in modeling the behavior of pumping equipment.

2. To propose a modified methodology for analyzing streaming data that takes into account the specifics of operating conditions and the characteristics of variable parameters and to conduct a comparative assessment of the effectiveness of this methodology based on key forecasting metrics such as precision, recall, F1-score, and root mean square error.

3. Provide practical recommendations for integrating IoT-based predictive maintenance systems and artificial intelligence algorithms into business processes to minimize downtime and reduce maintenance costs.

Summary of the primary material. Using artificial intelligence algorithms in equipment maintenance allows for the prompt prediction of failures and detection of malfunctions. Machine learning algorithms are particularly effective in monitoring the condition of submersible pumps, as they can process large amounts of streaming data and identify hidden patterns in changes in key equipment parameters. The choice of algorithms largely depends on the type of task: logistic regression algorithms, support vector machines, and decision trees are used to classify system states, while recurrent neural networks and gradient boosting methods are effective for predicting the remaining service life. In modern industrial systems, submersible pumps can operate under conditions of uneven loads and changes in external factors, which requires the adaptability of algorithms and the ability to work with incomplete data and anomalies (Table 1).

Table 1 – Artificial intelligence algorithms for monitoring the condition of submersible pumps: purpose and application features

Artificial intelligence algorithm	Appointment	Application features for monitoring submersible pumps
Logistic regression	Classification of states (“good”/ “possible failure”)	A simple algorithm for working with a small number of parameters, but has limitations in complex multidimensional systems.
Support vector machine (SVM)	Detecting boundary values between classes	It is effective when working with non-linear data, but may require significant computing resources for large datasets.
Decision trees and gradient boosting	Failure prediction and probability estimation	Provide a high level of interpretability of results, especially useful for working with mixed data types.
Recurrent neural networks (RNN, LSTM)	Predicting time to failure	They are able to work with consistent data and take into account historical dependencies, but require considerable training time.

Source: compiled by the author based on [2; 4; 5; 7; 9; 12].

In practice, logistic regression is used to assess equipment condition and identify initial risks. It is effective in cases where the amount of data is relatively small, and the system parameters are stable. For more complex tasks that involve analyzing fluctuations in pump operation in real-time, support vector methods are used to identify critical changes in equipment operation even in the presence of abnormal values. Gradient boosting and decision trees are widely used to build risk assessment models and predict time to failure, as they balance forecast accuracy with the explainability of the results.

Recurrent neural networks show high efficiency in systems where it is necessary to analyze long-time series, for example, to determine changes in pressure or vibration of pumps in long-term operation mode [6]. Their implementation is possible in industrial enterprises where IoT sensors with a high data collection frequency are installed. For example, in the case of pump monitoring at large production facilities, RNN systems can predict potential failures several days before they occur, allowing maintenance planning without stopping the main processes. Using such algorithms in combination with IoT technologies ensures an increase in safety, a reduction in the cost of emergency repairs, and the formation of a maintenance strategy based on data on the actual condition of the equipment [14].

Integrating IoT sensors into submersible pump monitoring systems allows for the continuous collection of a large amount of data reflecting the dynamics of equipment operation. The main parameters monitored by the sensors include pressure, temperature, vibration level, power consumption, and fluid flow. These parameters are key indicators of pump health and can signal early warning signs of malfunctions, allowing artificial intelligence algorithms to model equipment behavior and predict potential failures. For the models to function effectively, it is important to ensure high accuracy and stability of sensor data reading, achieved by calibrating the equipment and using data transfer protocols with minimal delay (Table 2).

Table 2 – Main parameters of IoT sensors and their role in modeling the behavior of submersible pumps

IoT sensor parameter	Purpose in monitoring	Role in modeling the behavior of pumping equipment
Pressure	Detection of deviations from the normative level	Allows you to detect signs of blockage or performance degradation.
Temperature.	Heating control of working units	It is used to assess possible overheating that can cause damage.
Vibration level	Detection of mechanical defects	It helps to identify imbalances, bearing wear, or other mechanical problems.
Electricity consumption	Analysis of pump efficiency	A decrease or increase in energy consumption signals problems in the system's functioning.
Liquid flow rate	Determining system performance	It is used to assess the compliance of a flow rate with the declared technical characteristics.

Source: compiled by the author based on [3; 5; 7; 8; 12; 15].

The data obtained from IoT sensors form the basis for building mathematical models for predicting the behavior of pumping equipment and making informed maintenance decisions. Each parameter is crucial for diagnosing pump operation and identifying potential threats to its performance. In particular, pressure readings allow you to assess the hydrodynamic characteristics of the system and timely detect blockages or performance drops that may indicate a violation of the integrity of the channels or malfunctioning valves. The temperature of the working units is a critical parameter for monitoring the thermal regime since even a slight excess of the permissible values can cause gradual destruction of the pump's internal components and reduce its service life.

Vibration level monitoring provides diagnostics of mechanical defects, such as bearing imbalance or wear. This indicator is one of the most sensitive to changes in the operation of pumping equipment, as deviations from the normal level can result from even small changes in the geometry of working elements or the loosening of fasteners. Analyzing electricity consumption allows you to assess the pump's energy efficiency and detect deviations associated with an increase in load or a decrease in motor efficiency in a timely manner. Fluid flow rate, in turn, is a key parameter for assessing system performance and allows you to determine the actual volume of transported working medium compared to the nominal characteristics of the equipment.

In practice, combining data from different sensors provides a comprehensive picture of the submersible pump's operation, increasing the accuracy of prediction models and reducing false-positive alarms. For example, in production systems with a large volume of liquid handling, a prolonged temperature rise with normal vibration levels may indicate a blockage in the filter systems rather than a mechanical failure of the pump. Such monitoring systems are implemented at enterprises to minimize the risk of downtime and optimize maintenance costs, which ensures the stability of equipment operation and efficient use of resources.

To effectively predict the condition of submersible pumps in complex operating conditions, it is necessary to take into account the peculiarities of streaming data, which may be irregular, contain noise components, and deviations from the norm due to random events. Existing analysis methods are often based on static models that do not adapt to changing operating conditions, which reduces the accuracy of real-time predictions. The proposed modified methodology involves the integration of adaptive machine learning algorithms capable of processing large amounts of data in real-time and taking into account dynamic changes in operating parameters. It is based on the use of recurrent neural networks (RNNs) and their modifications, such as LSTM and GRU, which allow information about previous system states to be stored, and behavior can be predicted based on historical dependencies.

Unlike traditional models based on average parameter values, the modified methodology focuses on predicting both pump failures as a binary phenomenon (failure/normal operation) and specific quantitative indicators such as pressure, temperature, vibration, and electricity consumption. This ensures clarity in the application of evaluation metrics: precision, recall, and F1-score for binary classification tasks, and MSE and MAE for regression tasks. For example, the average absolute value of the difference between forecasts and actual values (MAE) specifically refers to quantitative predictions like temperature or vibration levels, avoiding ambiguity in interpreting results.

The methodology involves a multi-level preprocessing stage to ensure the quality and reliability of input data. This includes handling missing data, applying Kalman filtering to reduce noise, and normalizing parameter values for consistent model training. These preprocessing steps are essential for addressing common issues in real-world IoT sensor streams, such as data gaps and noisy measurements, which could otherwise affect prediction accuracy (Table 3).

Figure 1 illustrates the historical vibration data of two submersible pumps collected over a 24-hour period. The graph demonstrates the fluctuations in vibration levels captured by IoT sensors, showcasing both short-term variations and consistent trends. This visualization highlights the variability in operational conditions and the importance of accounting for such fluctuations in predictive maintenance models.

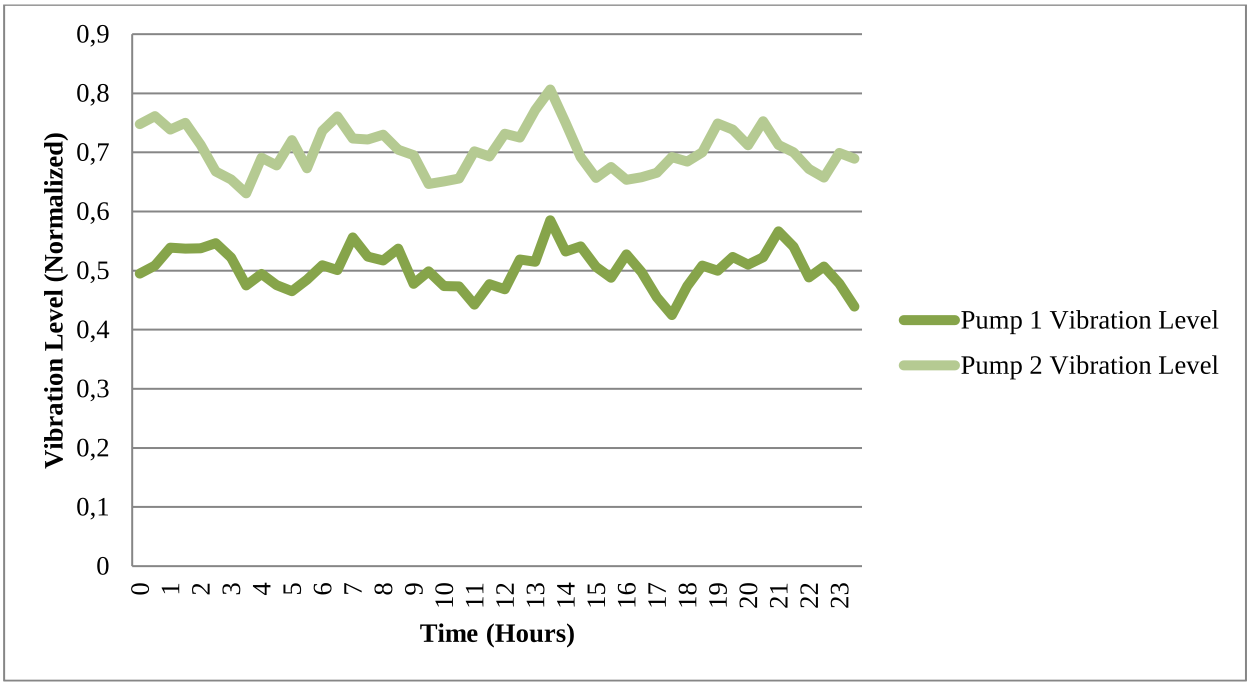

Fig. 1. Historical vibration data of submersible pumps
Source: author's own development

As shown in Figure 1, the vibration levels of both pumps exhibit periodic fluctuations due to normal operational dynamics, with Pump 2 displaying slightly higher baseline vibrations. The ability to analyze and predict such patterns allows the proposed model to distinguish between minor operational variations and critical deviations that could signal impending failures. By incorporating these historical trends into model training, the methodology ensures higher accuracy in predicting both pump failures and quantitative performance metrics.

Table 3 – Elements of a modified methodology for analyzing streaming data for monitoring submersible pumps

Element of the methodology	Description of functionality	Expected results of the application
Preliminary data filtering	Reducing noise and eliminating anomalous values	Increase the accuracy of system parameter analysis
Using modified RNNs (LSTM/GRU)	Forecasting based on time series	Improving forecasts by taking into account historical changes
Adaptive model training	Retraining based on new data	Increasing the relevance of the model in the face of change
Evaluation Using Targeted Metrics	Separate evaluation for predicting pump failures (F1-score, Recall) and pump parameters (MSE, MAE)	Objective assessment of forecast quality in real time

Source: author's own development

The proposed modified methodology for analyzing streaming data is designed to enhance the accuracy of failure predictions and improve the monitoring system by addressing the unique characteristics of submersible pump operation. The use of recurrent neural networks (RNNs), including LSTM and GRU modifications, allows the system to effectively process sequential time series and identify relationships between variable parameters. Unlike traditional statistical methods that rely on fixed analysis intervals and averages, this methodology accounts for both short-term fluctuations and long-term changes, providing more precise detection of potential malfunctions.

The multi-stage data processing framework begins with cleaning noise and anomalous values that may result from sensor faults or external disturbances. This reduces false-positive signals, which is critical for ensuring uninterrupted operation in demanding industrial environments. Adaptive training of the RNN models ensures that the system can adjust to new conditions without requiring manual intervention, making it particularly effective for high-volume streaming data scenarios.

In practical applications, this methodology enables real-time assessment of equipment conditions. For example, if vibration levels rise significantly, the system analyzes related parameters such as temperature and pressure to identify whether the deviation results from mechanical failure, hydraulic blockage, or a temporary overload. This multi-factor approach distinguishes between minor fluctuations that require no action and critical changes indicating a risk of failure.

Implementation of this methodology in industrial facilities has demonstrated a significant reduction in emergency equipment shutdowns by enabling early detection of system deviations and preventing critical malfunctions. By analyzing complex relationships between key parameters, the system minimizes unnecessary shutdowns caused by false-positive signals and ensures stable operation even under high load conditions.

This approach supports condition-based maintenance strategies, reducing downtime and operating costs while extending the lifespan of equipment. It ensures the efficient use of resources and the smooth operation of critical processes, offering businesses a significant advantage in reliability and operational efficiency.

To evaluate the effectiveness of the proposed forecasting model, an experiment was conducted using data collected over one year from three production facilities with high operational loads. The primary goal was to predict pump failures as a binary phenomenon (failure/normal operation) and to assess key parameters such as pressure, temperature, vibration, and electricity consumption. This approach allowed a clear distinction between classification tasks (binary prediction) and regression tasks (continuous parameter prediction), avoiding ambiguity in evaluation metrics.

Two groups of models were analyzed: the proposed model based on modified recurrent neural networks (RNNs) and traditional statistical models, including standalone decision trees, Random Forest, and Gradient Boosting. All models were compared using the following key metrics: precision, recall, and F1-score for classification tasks, and mean absolute error (MAE) and mean squared error (MSE) for regression tasks.

Table 4 presents the results of the comparative evaluation of model efficiency for predicting the technical condition of pumps, highlighting the strengths of the proposed approach for each parameter.

Table 4 – Results of comparative evaluation of the efficiency of the proposed model for predicting the technical condition of submersible pumps

Performance Evaluation Metric	Description	Parameter	Proposed Model Results	Traditional Model Results
Precision	Proportion of correct forecasts among all forecasts	Failure prediction	90%	85%
Recall	Ability of the model to correctly detect actual failures	Failure prediction	88%	78%
F1-Score	Balance between precision and recall	Failure prediction	89%	80%
Mean Absolute Error (MAE)	Average absolute difference between predictions and actual values	Pressure	0.03	0.08
		Temperature	0.02	0.07
		Vibration	0.04	0.09
		Electricity consumption	0.01	0.05
Mean Squared Error (MSE)	Average squared difference between predictions and actual values	Pressure	0.05	0.12
		Temperature	0.04	0.10
		Vibration	0.06	0.14
		Electricity consumption	0.03	0.08

Source: author's own development

The results demonstrate that the proposed model significantly outperformed traditional methods across all key metrics. Specifically, the high precision (90%) indicates the model's ability to correctly identify true positives while minimizing false positives. The recall (88%) highlights its capability to identify a high proportion of actual faults, reducing emergency shutdown risks and ensuring uninterrupted operation.

The separate analysis of parameters (pressure, temperature, vibration, and electricity consumption) shows that the proposed model achieves substantially lower mean absolute error (MAE) and mean squared error (MSE) compared to traditional methods. For instance, the prediction of temperature is characterized by the lowest MAE (0.02) and MSE (0.04), demonstrating the model's high precision in this category.

This detailed evaluation approach clarifies the strengths of the proposed model in handling each parameter effectively, enabling improved maintenance planning. In comparison, traditional methods exhibit higher errors and struggle with incorporating historical dependencies, which are critical for accurate predictions in real-time industrial environments.

One of the main challenges of implementing predictive maintenance systems is the high cost of modernizing infrastructure and purchasing the necessary equipment. Businesses often face high financial costs for installing IoT sensors, providing high-bandwidth data transmission channels, and deploying servers to process large amounts of information in real-time. In addition, existing enterprise information systems are not always compatible with new technological solutions, which requires additional costs for software integration and adaptation of information architecture.

Another problem is the difficulty of customizing artificial intelligence algorithms and adapting them to specific operating conditions. Machine learning algorithms require training on large data sets to make accurate predictions. However, this data may be uneven or contain gaps due to technical failures in the operation of sensors [2].

This can affect the quality of the model and increase the number of false-positive or false-negative fault signals, which complicates the operation of the monitoring system. It is also important to take into account that the operating conditions of pumping equipment can change due to changes in the operating environment or external factors such as temperature or load level, which requires model flexibility and the ability to retrain.

Another challenge is the need to train the personnel who will work with the predictive maintenance system. Sophisticated data processing algorithms and monitoring systems require qualified professionals who can monitor the system's operation, analyze forecast results, and respond to signals of possible failures in a timely manner. This requires the implementation of training programs for technical staff and the involvement of specialists with experience in analytical systems and artificial intelligence algorithms [8].

To solve these problems, the integration of predictive maintenance systems should be carried out in stages, starting with the implementation of pilot projects at critical nodes of the production system. This allows you to evaluate the system's effectiveness in real-world conditions and establish the process of data collection and processing before large-scale implementation. At the initial stage, special attention should be paid to choosing IoT sensors with a high level of accuracy and stability, as well as setting up data transmission systems to ensure minimal signal delay.

It is recommended that machine learning models with a regular retraining function be implemented to adapt algorithms to changing operating conditions and eliminate the impact of unstable data. In addition, data filtering algorithms should be used to minimize false positives, eliminating random distortions caused by technical failures or external factors [5]. Particular attention should be paid to the creation of backup data storage systems to avoid the loss of critical information in the event of failures.

To increase the level of readiness of the enterprise to work with the predictive maintenance system, it is necessary to implement training programs for technical personnel and conduct regular training on the use of the system. This will ensure prompt response to system signals and timely maintenance decisions. Successful integration of the predictive maintenance system will allow the company to move to real data-driven management strategies, which will increase resource efficiency, reduce the number of emergency downtime, and ensure the stability of pumping equipment in the long term.

Conclusions and prospects for further research. The study confirmed the effectiveness of integrating artificial intelligence algorithms and IoT sensors for predicting both pump failures as a binary phenomenon and specific quantitative parameters such as temperature, pressure, vibration, and power consumption under actual operating conditions. The proposed modified methodology for analyzing streaming data demonstrated significantly higher prediction accuracy compared to traditional methods due to its use of adaptive recurrent neural network (RNN) models and advanced data pre-filtering algorithms. By accounting for both short-term fluctuations and long-term trends, the methodology provides a comprehensive approach to assessing pump conditions.

Key results include a substantial reduction in false-positive signals, which minimizes unnecessary equipment shutdowns, and improved detection of actual failures, ensuring prompt and reliable maintenance interventions. These outcomes were achieved by leveraging multifactor models that incorporate the most critical parameters affecting pump performance. This capability allows for condition-based maintenance strategies, reducing emergency downtime and optimizing operational costs.

However, the implementation of predictive maintenance systems is not without challenges. High costs associated with infrastructure modernization, IoT sensor integration, and the configuration of algorithms to handle variable streaming data remain significant barriers. The need for skilled personnel to operate these systems and the incompatibility of existing information architectures with modern IoT solutions further complicate adoption.

To overcome these obstacles, phased integration is recommended, starting with pilot projects in critical areas to test and adapt algorithms to real-world conditions. Regular retraining of models and the application of filtering algorithms can mitigate the effects of anomalous data and noise. Additionally, ensuring reliable data transmission channels with minimal latency and implementing backup storage systems are essential for preventing data loss and maintaining system integrity.

Future research should focus on optimizing artificial intelligence algorithms for incomplete or irregular data and developing universal models adaptable to diverse operating conditions. A promising direction involves creating systems capable of autonomously identifying new failure patterns and updating forecasting models without manual intervention. This will further enhance the autonomy and reliability of predictive maintenance systems, ensuring continuous and efficient operation of industrial equipment in dynamic and complex environments.

References:

1.Machine Learning Approach for Predictive Maintenance of the Electrical Submersible Pumps (ESPs) / R. Abdalla et al. *ACS Omega*. 2022. Vol. 7, No. 21. P. 17641-17651. URL: https://doi.org/10.1021/acsomega.1c05881 (date of access: 16.01.2025).

2.A review on the advancements and challenges of artificial intelligence based models for predictive maintenance of water injection pumps in the oil and gas industry / S. Mohamed Almazrouei et al. *SN Applied Sciences*. 2023. Vol. 5, no. 12. URL: https://doi.org/10.1007/s42452-023-05618-y (date of access: 16.01.2025).

3. Fault Identification of Electric Submersible Pumps Based on Unsupervised and Multi-Source Transfer Learning Integration / P. Yang et al. *Sustainability*. 2022. Vol. 14, no. 16. P. 9870. URL: https://doi.org/10.3390/su14169870 (date of access: 16.01.2025).

4.Quantitative risk assessment of submersible pump components using interval number-based multinomial logistic regression model / P. Bhattacharjee et al. *Reliability Engineering & System Safety*. 2022. P. 108703. URL: https://doi.org/10.1016/j.ress.2022.108703 (date of access: 16.01.2025).

5.Fault diagnosis of electric submersible pumps using a three-stage multi-scale feature transformation combined with CNN-SVM / J. Chen et al. *Energy Technology*. 2023. URL: https://doi.org/10.1002/ente.202201033 (date of access: 16.01.2025).

6. Implementation of machine learning methods in predicting failures in electrical submersible pump machines / S. Saptadi et al. *Multidisciplinary Science Journal*. 2024. Vol. 7, no. 3. P. 2025137. URL: https://doi.org/10.31893/multiscience.2025137 (date of access: 16.01.2025).

7.Rigorous review of electrical submersible pump failure mechanisms and their mitigation measures / S. Fakher et al. *Journal of Petroleum Exploration and Production Technology*. 2021. Vol. 11, no. 10. P. 3799–3814. URL: https://doi.org/10.1007/s13202-021-01271-6 (date of access: 16.01.2025).

8. Al-Ballam S., Karami H., Devegowda D. A Hybrid Physical and Machine Learning Model to Diagnose Failures in Electrical Submersible Pumps. *SPE/IADC Middle East Drilling Technology Conference and Exhibition*, Abu Dhabi, UAE, 23–25 May 2023. 2023. URL: https://doi.org/10.2118/214632-ms (date of access: 16.01.2025).

9.Kannaujia V., Bhore S. P., Goyal H. S. Failure Analysis of Submersible Pumps–A Review. *Recent Advances in Industrial Machines and Mechanisms*. Singapore, 2024. P. 393–410. URL: https://doi.org/10.1007/978-981-99-4270-1_40 (date of access: 16.01.2025).

10. Takacs G. Electrical submersible pumps manual: design, operations, and maintenance. Gulf Professional Publishing, 2017. URL: https://books.google.com. (date of access: 16.01.2025).

11. Current Status and Applications for Hydraulic Pump Fault Diagnosis: A Review / Y. Yang et al. *Sensors*. 2022. Vol. 22, no. 24. P. 9714. URL: https://doi.org/10.3390/s22249714 (date of access: 16.01.2025).

12. Anomaly Detection Based on Temporal Attention Network with Adaptive Threshold Adjustment for Electrical Submersible Pump / Q. Li et al. *IEEE Transactions on Instrumentation and Measurement*. 2024. P. 1. URL: https://doi.org/10.1109/tim.2024.3436113 (date of access: 16.01.2025).

13. A parallel deep neural network for intelligent fault diagnosis of drilling pumps / J. Guo et al. *Engineering Applications of Artificial Intelligence*. 2024. Vol. 133. P. 108071. URL: https://doi.org/10.1016/j.engappai.2024.108071 (date of access: 16.01.2025).

14. Yu D., Zhang H. Fault Diagnosis Method for Submersible Reciprocating Pumping Unit Based on Deep Belief Network. *IEEE Access*. 2020. Vol. 8. P. 109940–109948. URL: https://doi.org/10.1109/access.2020.3002376 (date of access: 16.01.2025).

15. Turchyn O. Implementation of Machine Learning to Increase the Accuracy of Forecasting the Operating Modes of Deep-Sea Pumping Stations. *Computer-Integrated Technologies: Education, Science, Production*. 2024. Vol. 55. P. 24-29