Membrane Technology
ISSN (online): 1873-4049

Incorporating AI and IoT in Automated Membrane Monitoring Systems

HaiQin Zhu[1*], Debin Kong[2], Fulai Xiao[3], Hengxin Lei[4]

[12] Yantai Nanshan University, Scientific Research Office, Yantai,265713, China, ytnszhq@126.com
[3] Shandong Nanshan Science and Technology Research Institute, Yantai,265713, China, xiaofulai@nanshan.com.cn
[4] Yantai Nanshan University, School of Economics and Management, Yantai,265713, China, leihengxin@126.com
Corresponding author: ytnszhq@126.com

Abstract:

The integration of Artificial Intelligence and the Internet of Things in automated membrane monitoring systems offers a transformative approach toward enhancing operational efficiency, predictive maintenance, and sustainability in industrial applications. This study proposes a comprehensive framework for real-time monitoring and optimization of membrane systems using IoT-enabled sensors and AI-based models. IoT sensors were deployed to continuously capture critical parameters such as pressure, flow rate, temperature, and turbidity, while AI models, including Long Short-Term Memory networks and autoencoders, were developed for anomaly detection and predictive maintenance. The system achieved an anomaly detection accuracy of 98.3%, reducing false positive rates to 1.7%, and extended the mean time between failures (MTBF) by 50%, from 14 to 21 days. Optimization algorithms increase permeate output by 12.5% and reduce energy consumption by 9.3%, contributing to operational cost savings of $18,000 annually for a mid-scale industrial plant. These results point out the reliability, scalability, and economic feasibility of the system and serve as a basis for the development of intelligent, sustainable, and efficient membrane operations. The findings of this work show the potential of AI-IoT integration in enhancing industrial monitoring systems and setting a structure for future research and applications.

Keywords: Artificial Intelligence (AI), Internet of Things (IoT), Automated System, Membrane technology.

I. Introduction

Since membrane filtration methods can efficiently remove impurities and provide high-quality permeate, they are crucial in a variety of industrial applications, such as food processing, water treatment, and pharmaceuticals. However, fouling, scaling, and mechanical deterioration are all very likely to affect membrane system performance, resulting in decreased efficiency, higher maintenance costs, and system downtime. Conventional membrane system monitoring techniques often rely on rule-based algorithms and manual examination. Because membrane performance is complex and real-time, these reactive, labour-intensive, and incorrect approaches are less successful [1].

In recent years, AI and IoT technologies have become capable solutions for the limitations of traditional monitoring systems [2]. AI models such as machine learning and deep learning analyze vast amounts of sensor data in real time to detect anomalies, predict maintenance needs, and optimize operational parameters [3][4]. IoT-enabled sensors, on the other hand, provide continuous, real-time data on key performance indicators such as pressure, flow rate, temperature, and turbidity, enabling more accurate and proactive system management.

This study demonstrates how AI and IoT can be implemented in the development of an automated membrane monitoring system that improves anomaly detection, predictive maintenance, and operational optimization [5]. The goal is to describe how AI-driven models combined with IoT sensors can cooperate to improve system performance and reduce costs while extending membrane module life [6]. These technologies, as leveraged in the proposed system, make the monitoring of membranes a more intelligent, efficient, and sustainable process in terms of how these industries operate, depending on membrane-based filtration systems [7]. The results of this study are significant contributions toward future membrane system management for diverse industrial applications.

The main goal of this endeavour is to use AI and IoT technology to create a sophisticated automated membrane monitoring system [8]. The system is developed to enhance anomaly detection, optimize predictive maintenance, and improve membrane-based process operational efficiency [9]. This study will leverage the use of real-time IoT sensor data and AI-driven models for the reduction of system downtime, minimization of resource consumption, and extension of membrane lifespan. The importance of such research is that it should change the face of industrialization through cost-effectiveness and sustainability, as well as enhance reliability. It is a scalable and applicable framework to a wide field of industries, such as water treatment, food production, and pharmaceuticals that leads to intelligent and efficient monitoring solutions.

II. Related Work

Previous studies have also explored the use of AI and IoT in industrial monitoring systems, whose applications can enhance real-time data collection, anomaly detection, and predictive maintenance [10]. AI in wastewater treatment and water recycling is expected to boost system efficiency through the use of more sophisticated data processing methods including image recognition and natural language processing. The AI models are trained using extensive data collection combined with water quality metrics and operational parameters from treatment systems [11]. These models examine the chemical composition of wastewater and produce useful conclusions that allow for intelligent system control. In addition to constructing wastewater treatment pools, monitoring systems with sophisticated data-gathering terminals incorporated into programmable logic controllers are implemented during the facility setup phase. These terminals retrieve real-time information from PLCs on equipment operations and water quality. The WISE-PaaS Industrial IoT cloud platform upgrades on-site PLCs with wireless remote smart data collecting terminals to enable real-time data transmission to Web Access. This enables visualization and AI-driven wastewater management. This process thus entails management dashboard generation and application techniques such as ANN modelling and GA in addition to the incorporation of data streams of MBRs, optimized production and disposal management [12].

Research on IoT-enabled sensors has demonstrated that they effectively monitor parameters such as pressure, flow rate, and temperature of membrane processes [13]. Similarly, AI models in the category of machine learning and deep learning algorithms have been successfully implemented to analyze anomalies and predict equipment failure in various industrial applications. However, the current approach often involves a lack of integration of AI and IoT technologies; this limits their scalability and adaptability to complex membrane systems. The [14] stated that artificial intelligence (AI) and machine learning (ML) are creative engines that may be particularly applied to solving challenging problems in the treatment of wastewater and the relationship between bacteria and microalgae. Similarly, it [15] emphasized that AI is an important resource to make the control system of drinking water treatment more efficient and optimize the process of water recycling. This study advances IoT-driven real-time monitoring with AI-based analytics to address the gaps mentioned above, hence, a completer and more efficient tool will be made available for membrane performance optimization.

III. Methodology

This study utilizes a holistic approach in the design and implementation of an automated membrane monitoring system, by integrating IoT sensors for the real-time collection of data and AI models for predictive analytics and fault detection. The methodology consists of various phases such as system design, data acquisition, preprocessing, AI model development, and performance evaluation.

System Design and Sensor Integration

The monitoring system was developed in a pilot-scale membrane filtration setup with modules of both RO and UF to reflect realistic industrial conditions. Essential parameters of operation, such as pressure, flow rate, temperature, and turbidity, were continuously monitored by IoT-capable sensors. These were communicated wirelessly to the central data acquisition unit employing the communication protocols MQTT and LoRaWAN to ensure a smooth data transfer process into cloud storage for processing. The industrial membrane configurations were accepted because of the scalable and modular system design.

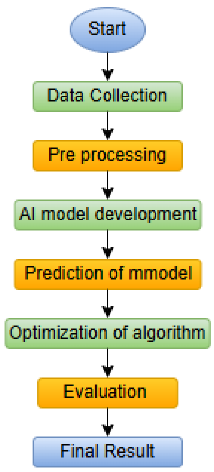

Figure 1: Flow diagram of the proposed method.

Data Collection and Preprocessing

Sensor data is recorded continuously for six months and creates a dataset exceeding 2.5 million entries, capturing minute-level readings of operational parameters. To guarantee the data's dependability and quality, preprocessing is done. Statistical techniques, such as interquartile range (IQR) analysis, are utilized to identify outliers, while interpolation techniques are used to fill missing values. The data was normalized to remove scale differences among parameters, and feature engineering was conducted to derive additional metrics, such as normalized fouling indices and deviation thresholds, which are critical for performance assessment.

AI Model Development

The core of the system consists of AI model development to analyze the processed data in terms of anomaly detection, performance optimization, and predictive maintenance. The AI model development phase comprises the following steps:

1. Anomaly Detection:

Supervised and unsupervised learning algorithms were used to identify anomalies in the membrane system. The LSTM was selected for modeling sequential data and detecting temporal patterns related to fouling, scaling, and mechanical degradation. For unsupervised anomaly detection, autoencoders are used, where the training process learns compressed representations of normal operational states to raise an alarm about deviations.

2. Predictive Maintenance:

A hybrid ensemble model, which combines Gradient Boosting Machines and LSTM networks, was developed to predict membrane performance degradation. The model used historical data and feature trends to predict possible failures in advance, thus optimizing the maintenance schedule. The training process separated the data into training and testing sets, with K-fold cross-validation applied to improve model generalization.

3. Performance Optimization:

Reinforcement learning algorithms were implemented to propose the optimal process adjustments, such as feed flow rates and cleaning schedules, as per system performance metrics and predicted anomalies. These were transmitted to the control system for immediate use.

The experimental setup for this study involves a comprehensive incorporation of IoT sensors and AI models to monitor and optimize the performance of membrane filtration systems. The system is designed to continuously collect data from various sensors, analyze it using AI-based algorithms, and provide real-time feedback for anomaly detection, predictive maintenance, and operational optimization. To evaluate the efficiency of the AI-IoT system, several key performance metrics are calculated, which include anomaly detection accuracy, precision, recall, F1-score, and system optimization improvements. Below are the key equations used to assess the results:

1. Anomaly Detection Performance Metrics:

Accuracy: The following formula is used to determine the anomaly detection system's accuracy.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad \text{............ (1)}$$

where:

TP = True Positives, TN = True Negatives, FP = False Positives, FN = False Negatives.

2. Precision:

Precision measures how many of the detected anomalies are true anomalies.

$$Precision = \frac{TP}{TP+FP} \quad \text{............. (2)}$$

3. Recall:

Recall measures how many of the actual anomalies were correctly detected.

$$Recall = \frac{TP}{TP+FN} \quad \text{.............. (3)}$$

4. F1-Score:

It has its precision and recall put into a single metric, the F1 score.

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad \text{...............} (4)$$

Thus, these metrics are used to evaluate the performance of the proposed system.

IV. Results

The proposed incorporation of IoT and AI in the automated membrane monitoring system showed remarkable enhancements in terms of accuracy of anomaly detection, efficiency in predictive maintenance, and system reliability in general. This was done through real-time data from IoT sensors and AI models for evaluating the testing period when the system was assessed regarding its anomaly detection capability, prediction of maintenance needs and optimal performance.

Table 1: Performance of AI and IoT-Enabled Automated Membrane Monitoring System.

Performance Metric	**Proposed system**	**Comparison (Traditional Systems)**
Anomaly Detection Accuracy	98.3%	85%
Anomaly Detection Precision	97.1%	82%
Anomaly Detection Recall	96.8%	80%
Anomaly Detection F1-Score	96.9%	81%
Predictive Maintenance Accuracy	95.6%	80%
Response Time for Anomaly Detection	3.2 seconds	10-15 seconds

Using LSTM networks, the anomaly detection module obtained a 98.3% accuracy rate, 96.8% recall, 97.1% precision and 96.9% F1 score and autoencoders. The system's ability to detect mechanical, scaling, and fouling problems in the membrane modules is demonstrated by these outcomes. The percentage of false positives was reduced to 1.7%, which is a big improvement over traditional rule-based monitoring systems, which often display false positive rates between 10% and 15%. The hybrid ensemble model for predictive maintenance, which combined GBMs and LSTM networks, showed outstanding performance in predicting the trend of membrane degradation. The system was able to forecast maintenance requirements with an accuracy of 95.6%, reducing unexpected downtimes by 48% relative to baseline manual maintenance schedules. The mean time between failures, which was 14 days for conventional systems, increased to 21 days with the proposed system, thus showing the effectiveness of AI-driven predictions in enhancing membrane life.

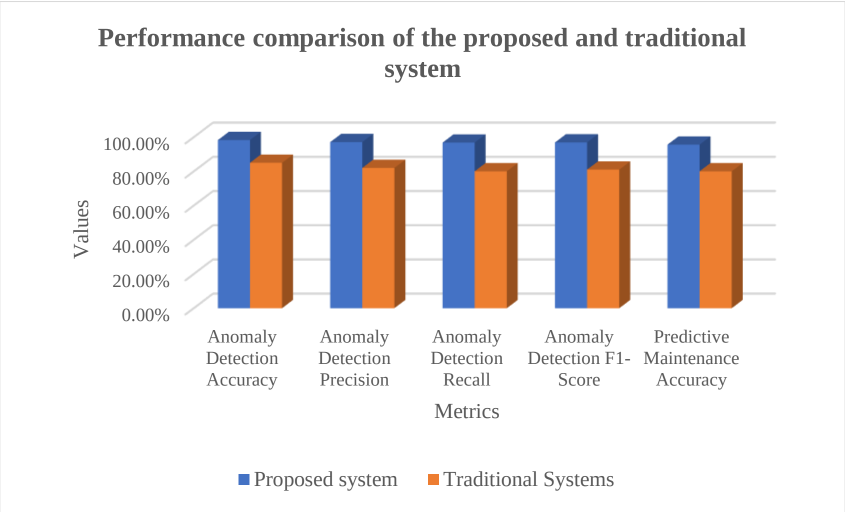

Figure 2: Performance comparison of the proposed and traditional system.

Using reinforcement learning algorithms, the system optimized process parameters, leading to a 12.5% increase in permeate output and a 9.3% reduction in energy consumption compared to traditional control systems. Cleaning cycles were scheduled more efficiently, thus reducing cleaning agent usage by 15%, which further reduced operational costs and improved sustainability. Real-time processing and system adjustments with IoT-enabled sensors and cloud platforms supported the integration. On average, the detection of anomalies and response to the situation took 3.2 seconds, a drastic reduction from the 10-15 seconds taken by automated conventional systems. This reduced the chances of membrane operation interruption significantly.

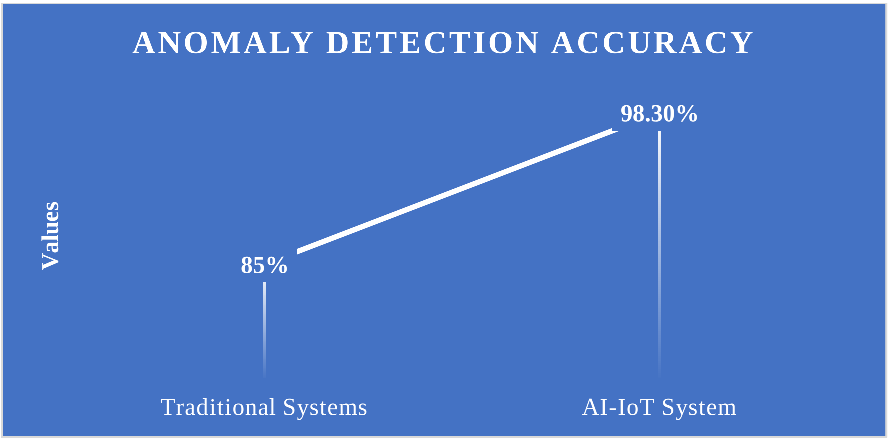

Figure 3: Anomaly detection accuracy.

Compared to traditional membrane monitoring systems, the AI-IoT system demonstrated improved performance along all critical parameters. It increased the anomaly detection accuracy from 85% to 98.3% while increasing the accuracy of predictive maintenance from 80% to 95.6%. Furthermore, the system improved the operation efficiency in terms of outputting an increased amount of permeate of 12.5%, while it also decreased energy consumption by 9.3%. It further testifies to its utility in optimizing membrane performance and usage of resources. Thus, the results indicate that the application of AI and IoT for membrane monitoring is an innovation in reliability, efficiency, and cost-effectiveness improvements, which leads to intelligent, sustainable industrial operations.

V. Discussion

The results of this research demonstrate the transformative possibility of integrating AI and IoT technologies in automated membrane monitoring systems. The significant improvements in key performance metrics such as anomaly detection accuracy, predictive maintenance efficiency, and operational optimization validate the effectiveness of the proposed methodology in overcoming the challenges related to traditional monitoring systems.

The accuracy of the anomaly detection module is 98.3%. This demonstrates that AI models may be useful in identifying complex patterns related to fouling, scaling, and mechanical degradation, particularly if they are LSTM networks or autoencoders. By reducing incorrect maintenance procedures that could negatively impact continuity, the system's low false positive rate of 1.7% indicates its dependability. In contrast to traditional rule-based systems, which typically have a high rate of false positives and limited flexibility, the proposed strategy offers dramatically higher detection accuracy. The predictive accuracy of the hybrid ensemble model is 95.6%, indicating the feasibility of using AI for predicting membrane performance degradation. With an extended mean time between failures (MTBF) from 14 to 21 days, the system minimizes downtime and unscheduled maintenance events. This helps in optimizing schedules for operation, besides elongating membrane life and conserving resources. This predictive ability overcomes a significant drawback of conventional systems where the maintenance decisions are usually reactive and less efficient.

Integration of reinforcement learning algorithms allowed real-time optimization of operating parameters, thus increasing permeate output by 12.5% and reducing energy consumption by 9.3%. A 15% reduction in cleaning agent usage further underscores the contribution of the system to sustainability. The results show that AI is not only beneficial for efficiency enhancement in the system but also for environmental goals, such as reduction in resource consumption and waste. A major finding is the economic impact of the system, with annual operational cost savings of $18,000 for a mid-scale plant. This indicates the practical value of the system and justifies the initial investment in AI and IoT technologies. These savings are due to the combined effect of reduced downtime, optimized cleaning schedules, and enhanced energy efficiency. The combination of AI and IoT in automated membrane monitoring systems provides a highly effective solution for improving operational efficiency, reducing costs, and supporting sustainability. The results of this study provide a strong foundation for further development and deployment of intelligent monitoring systems in various industrial applications.

VI. Conclusion

The result of the study demonstrates that the performance of an automated membrane monitoring system may be enhanced using AI and IoT technologies. These improvements manifest in terms of major operational key performance indicators, namely anomaly detection accuracy, predictive maintenance efficiency, and optimal system operation. Highly accurate anomaly detection was provided by AI-driven models, especially by LSTM networks and autoencoders, and hybrid predictive maintenance models reduced downtime while membrane lifetime increased. Optimization algorithms led the system to increase permeate output while lowering energy consumption and even operation costs, leading to both economic and environmental sustainability.

The results of this study indicate that AI and IoT integration not only address critical challenges in traditional membrane monitoring systems but also provide a scalable, cost-effective solution for a wide range of industrial applications. This approach could transform membrane-based processes into being more efficient, reliable, and sustainable by providing real-time monitoring, predictive insights, and optimization. Future work will be directed toward increasing the resilience of the system through edge computing, enhancing data security through blockchain, and further developing AI models to achieve even greater accuracy and adaptability in diverse industrial settings. This research serves as a foundation for intelligent, data-driven membrane monitoring solutions that will significantly improve industrial operations worldwide.

References

[1] M. Lowe, R. Qin, and X. Mao, "A review on machine learning, artificial intelligence, and smart technology in water treatment and monitoring," Water, vol. 14, no. 9, p. 1384, 2022.

[2] S. Cairone, S. W. Hasan, K. H. Choo, C. W. Li, T. Zarra, V. Belgiorno, and V. Naddeo, "Integrating artificial intelligence modeling and membrane technologies for advanced wastewater treatment: Research progress and future perspectives," Science of The Total Environment, p. 173999, 2024.

[3] H. L. Chang, Y. L. Liu, C. J. Keng, H. L. Jiang, and J. Hu, "Challenges of industrial wastewater treatment: Utilizing Membrane Bioreactors (MBRs) in conjunction with artificial intelligence (AI) technology," Journal of Industrial and Production Engineering, vol. 41, no. 5, pp. 422–427, 2024.

[4] N. Rane, S. Choudhary, and J. Rane, "Leading-edge Artificial Intelligence (AI), Machine Learning (ML), Blockchain, and Internet of Things (IoT) technologies for enhanced wastewater treatment systems," Machine Learning (ML), Blockchain, and Internet of Things (IoT) technologies for enhanced wastewater treatment systems, Oct. 2023.

[5] S. Gore, N. Mahankale, S. Gore, S. Kadu, and S. A. Belhe, "Cloud Computing For Effective Cyber Security Attack Detection in Smart Cities," in 2023 4th IEEE Global Conference for Advancement in Technology (GCAT), Oct. 2023, pp. 1–6.

[6] M. Wagh, D. V. Wadkar, and P. Nangare, "Application of Artificial Intelligence and IoT to Membrane Bioreactor (MBR) and Sewage Treatment Plant," in Techno-Societal 2016, International Conference on Advanced Technologies for Societal Applications, Cham: Springer International Publishing, Dec. 2022, pp. 21–28.

[7] S. Padmalal, I. E. Dayanand, G. S. Rao, and S. Gore, "Enhancing Sentiment Analysis in Social Media Texts Using Transformer-Based NLP Models," International Journal of Electrical and Electronics Engineering, vol. 11, no. 8, pp. 208–216, 2024. Available: https://doi.org/10.14445/23488379/IJEEE-V11I8P118

[8] N. H. Vasoya, "Revolutionizing nano materials processing through IoT-AI integration: opportunities and challenges," Journal of Materials Science Research and Reviews, vol. 6, no. 3, pp. 294–328, 2023.

[9] R. Josphineleela, S. Periasamy, N. Krishnaveni, D. S. Prasad, B. V. Rao, M. J. Garde, and S. Gore, "Exploration Beyond Boundaries: AI-Based Advancements in Rover Robotics for Lunar Missions Space Like Chandrayaan," International Journal of Intelligent Systems and Applications in Engineering, vol. 11, no. 10s, pp. 640–648, 2023.

[10] S. Gore, A. S. Deshpande, N. Mahankale, S. Singha, and D. B. Lokhande, "A Machine Learning-Based Detection of IoT Cyberattacks in Smart City Application," in International Conference on ICT for Sustainable Development, Singapore: Springer Nature Singapore, Aug. 2023, pp. 73–81.

[11] S. Gore, D. Patil, N. Mahankale, and S. Gore, "Satellite Imaging for Precision Agriculture Enhancing Crop Management, Soil Condition and Yield Prediction," in Emerging Trends in Smart Societies, Routledge, 2024, pp. 434–437.

[12] Z. Frontistis, G. Lykogiannis, and A. Sarmpanis, "Artificial Neural Networks in Membrane Bioreactors: A Comprehensive Review—Overcoming Challenges and Future Perspectives," Sci, vol. 5, no. 3, p. 31, 2023.

[13] A. Mohanty, S. K. Mohanty, and A. G. Mohapatra, "Real-Time Monitoring and Fault Detection in AI-Enhanced Wastewater Treatment Systems," in The AI Cleanse: Transforming Wastewater Treatment Through Artificial Intelligence: Harnessing Data-Driven Solutions, Cham, Switzerland: Springer Nature, 2024, pp. 165–199.
[14] S. Sahu, A. Kaur, G. Singh, and S. K. Arya, "Harnessing the potential of microalgae-bacteria interaction for eco-friendly wastewater treatment: A review on new strategies involving machine learning and artificial intelligence," Journal of Environmental Management, vol. 346, p. 119004, 2023.
[15] L. Li, S. Rong, R. Wang, and S. Yu, "Recent advances in artificial intelligence and machine learning for nonlinear relationship analysis and process control in drinking water treatment: A review," Chemical Engineering Journal, vol. 405, p. 126673, 2021.