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# AI-Driven Predictive Maintenance for Aeration Systems in Wastewater Treatment: A Hybrid and Explainable AI Framework

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**Abstract:** This paper proposes a predictive maintenance framework for aeration systems in wastewater treatment plants (WWTPs), specifically addressing their substantial energy consumption (40-75%) and operational challenges associated with diffuser deterioration. The proposed framework integrates a hybrid AI model comprising Random Forest (RF) for initial prediction and variable analysis, and Long Short-Term Memory (LSTM) networks for time series forecasting. Simulation data from the Benchmark Simulation Model No. 2 (BSM2) forms the basis for training the model with a focus on specific conditions such as partial and total diffuser blockages. Initial results show that the model can achieve more than 90% accuracy in identifying failures, which in turn can result in a 10-15% reduction in energy consumption and a 20% increase in diffuser life. Although this study focuses on prediction and validation, further research will aim to enhance interpretability through the integration of Explainable AI (XAI) methods, such as LIME and SHAP, to provide detailed insights into the model's decision-making process. Additionally, the framework will be extended to address other degradation scenarios and incorporate optimization techniques for adaptive aeration control based on AI predictions. This approach provides a scalable and interpretable solution for improving WWTP operational performance while maintaining energy efficiency.

**Keywords**: predictive maintenance; aeration systems; wastewater treatment plants; explainable AI

## 1. INTRODUCTION

In wastewater treatment plants (WWTPs), aeration systems account for a substantial part of the energy consumption, ranging from 40 to 75% [Mamais et al. (2015)]. This is because of the deterioration of air diffusers, which results in low oxygen transfer efficiency (OTE) [Metcalf et al., 2014], increasing the operation costs and compromising the effluent treatment quality in the plant. The current research seeks to develop a predictive maintenance framework that employs the use of artificial intelligence (AI) and simulation data from a wastewater treatment benchmark system to avoid unexpected failures, which are a consequence of the traditional preventive maintenance. The goal is to predict the potential failure of the aeration system and enhance the maintenance strategies. The primary contribution of this study is the development of a WWT prediction model based on neural networks (NNs), using data from Benchmark Simulation Model No. 2 (BSM2). BSM2 provides realistic operational conditions and allows to create diverse scenarios of degradation in aeration systems [Jeppsson et al., 2007]. Another important integration is the use of Explainable AI, a new technology that enables the identification of the reasons behind the decisions made by the prediction system and the justification of why a certain fault was identified.

## 2. METHODOLOGY

### 2.1. Data Collection and Simulation

The dataset in this study is collected from the BSM2 framework which dynamically simulates the behaviour of WWTPs in normal conditions. The input and output data selected for training and testing the prediction model are depicted in Figure 2.1 (a), which gives a general idea about how data was organized. To ensure that only high-quality data was used for training the NNs, some pre-processing steps like smoothing and normalization were applied, to remove noise and inconsistencies.

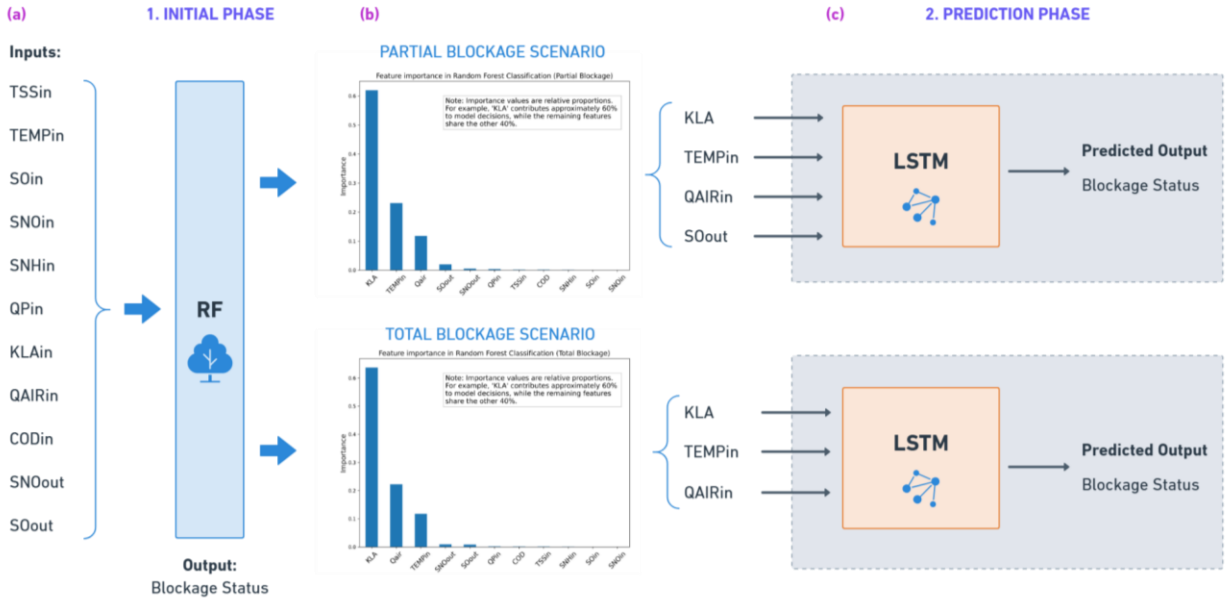


**Figure 2.1** Architecture of the hybrid AI model for predictive maintenance in aeration systems: input selection and scenario-based prediction phases.

## 2.2. Scenarios Modelled

To create challenges and conditions similar to those found in real life, specific issues were modelled as occurring in the aeration system. These induced problems could be categorised into three main simulation scenarios. The first one is related to the partial or total blockage of the diffusers through which air flow is inhibited and oxygen transfer is reduced. The second one refers to pressure losses which may be caused by leakage or wear of components, and which leads to reduction in the effectiveness of the system. In the third scenario, the reduced oxygen transfer is a result of fouling by particles or other residues that affect the efficiency of the aeration process. For this abstract, the first scenario was designed to depict the general deterioration of an aeration system, the data generated being used to train the AI models that could help in determining the operational issues and the effective predictive maintenance strategies, when operated under real world conditions.

## 2.3. Hybrid AI Model

The proposed AI model combines RF and LSTM networks, presenting a novel approach that enhances the ability to extract meaningful insights from data while offering robust predictions for time-series dynamics. RF excels in understanding relationships between variables, making initial decisions, and identifying deviations from normal operational patterns. However, RF alone cannot capture the temporal dependencies inherent in the data collected from BSM2. To address this limitation, the hybrid model integrates LSTM, which is well-suited for forecasting degradation trends and predicting the timing of potential equipment failures. Although LSTM requires longer training-time and is less interpretable compared to RF, it effectively models sequential dependencies in the data. By combining these two approaches, the hybrid model leverages the strengths of both techniques, with RF providing interpretability and initial insights, and LSTM delivering accurate time-series predictions [Kumar et al., 2020]. The training process for the hybrid model consisted of two distinct phases (Figure 2.1): the independent training of RF and the prediction training of LSTM components, that can be followed by the integration of the NN in BSM2 for further testing and validation in a simulated practical environment.

## 3. VALIDATION AND RESULTS

The validation of an AI model is essential to ensure the reliability of the information generated by the system. Each model, RF and LSTM, was validated individually before being integrated into the hybrid system to ensure that both components perform effectively. To validate the RF model, k-fold cross-validation was applied to ensure robust performance across different data subsets and to prevent overfitting. Performance metrics, including accuracy, precision, recall, and F1-score, were calculated. For the partial blockage scenario, RF achieved an accuracy of 100% and an F1-score of 1, demonstrating its capability to identify relationships between variables [Ribeiro et al., 2016]. It also extracted the variables needed for the next step of training, visible in Figure 2.1 (b). The LSTM models in Figure 2.1 (c) were trained and then evaluated using Mean Squared Error (MSE) and Mean Absolute Error (MAE) to assess its ability to handle temporal dependencies in the data during both training and validation phases. Figure 3.1 illustrates the training progress and validation curves for partial and total blockage, showing a consistent reduction in errors over time.

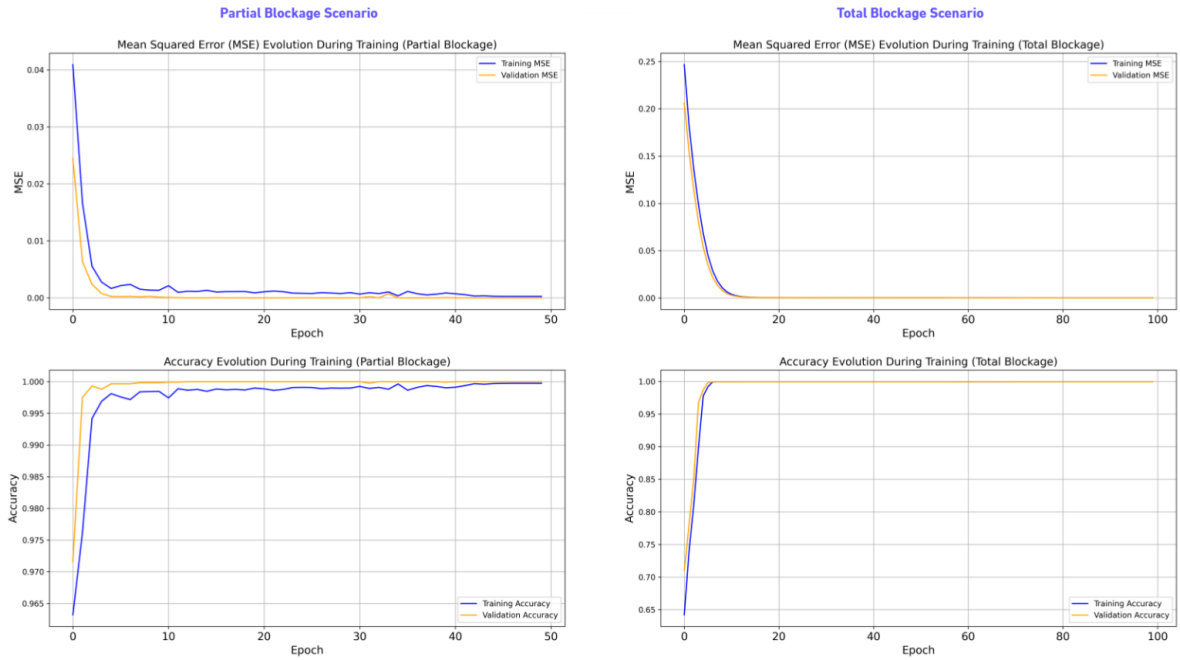


**Figure 3.1** MSE and Accuracy evolution during training and validation for partial and total blockage scenarios.

Table 3.1 offers an overview of the network performance metrics. The hybrid AI model (RF-LSTM) would be implemented into the Simulink environment to enable real-time simulation and experimental evaluation. This integration is planned as an important step for dynamically assessing the model within the BSM2 environment under various operational conditions, particularly for predicting potential failures or degradation patterns in aeration systems.

**Table 3.1** Key performance metrics for RF and LSTM models under partial and total blockage scenarios.

| Random Forest | | | LSTM Neural Network | | |
|---|---|---|---|---|---|
| **Metric** | **Partial Blockage** | **Total Blockage** | **Metric** | **Partial Blockage** | **Total Blockage** |
| *Accuracy* | 1.00 | 1.00 | *Final Training Loss* | 0.0019 | 0.0018 |
| *F1-Score* | 1.00 | 1.00 | *Final Validation Loss* | 0.0021 | 0.0002 |
| *Top Feature Importance* | KLA (61.98%) | KLA (63.73%) | *Final Validation Accuracy* | 0.9897 | 1.0 |

## 4. DISCUSSION AND FUTURE WORK

In this extended abstract, we outlined the methods and initial findings of the proposed research, specifically focusing on the development of the hybrid AI framework for predictive maintenance of aeration systems in wastewater treatment plants. The framework integrates RF for initial decision-making and variable importance analysis with LSTM networks for temporal forecasting. The findings highlight the feasibility of the proposed framework, demonstrating high precision and reliability in predicting system degradation. Initial experiments using partial diffuser blockage scenarios validated the model's predictive capabilities.

Future research will extend this work by including additional degradation conditions, such as total diffuser blockage and pressure loss due to leakage or wear, to evaluate the system's robustness under more realistic conditions. Additionally, Explainable AI (XAI) techniques, including LIME and SHAP, will be integrated into the predictive framework. These techniques will offer local and global insights into the model's decision-making process, enhancing operator trust and providing actionable feedback [Ribeiro et al., 2016]. The integration of the hybrid AI model within MATLAB and Simulink environments will also be explored further to enable real-time predictions and facilitate practical implementation in wastewater treatment operations. These steps will include implementing adaptive optimization techniques based on AI predictions to reduce energy consumption and operational costs while maintaining the quality of effluent treatment.

This extended abstract provides an initial step toward developing a comprehensive predictive maintenance framework. Detailed methods, extended results, and practical insights will be addressed in the full study, building on the foundation established here.

## REFERENCES

**[Jeppsson et al., 2007]** Jeppsson, U., Pons, M.N., Nopens, I., Alex, J., Copp, J.B., Gernaey, K.V., Rosen, C., & Steyer, J.-P. 2007. Benchmark Simulation Model No. 2: General protocol and exploratory case studies. Water Science and Technology, 56(8), 67–78.

**[Kumar et al., 2020]** Kumar, N., Sharma, V., & Arora, A. 2020. Artificial Intelligence in Predictive Maintenance for Industrial Applications: Trends, Challenges, and Future Directions. Journal of Industrial Information Integration, 18, 100132.

**[Mamais et al., 2015]** Mamais, D., Noutsopoulos, C., Dimopoulou, A., Stasinakis, A., & Lekkas, T.D. 2015. Wastewater treatment process impact on energy savings and greenhouse gas emissions. Water Science and Technology, 71(2), 303–308.

**[Metcalf et al., 2014]** Metcalf & Eddy, Inc. 2014. Wastewater Engineering: Treatment and Resource Recovery. McGraw-Hill Education, New York.

**[Ribeiro et al., 2016]** Ribeiro, M.T., Singh, S., & Guestrin, C. 2016. "Why should I trust you?": Explaining the predictions of any classifier. In: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD '16). ACM, New York, pp. 1135–1144.