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AI-Based Predictive Maintenance for Sewage Treatment Plants

AKASH. T

Research Scientist, Department of Civil Engineering, Sunrise University, Alwar, Rajasthan, India

Correspondence should be addressed to Akash. T; Akash.t501@gmail.com

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ABSTRACT- Small capacity STPs (0.5-5 MLD) in particular, are prone to high maintenance costs, frequent equipment failures, and unscheduled downtimes due to reactive or schedule-based maintenance approaches. In this study, the application of Artificial Intelligence (AI) for predictive maintenance of STPs is investigated where machine learning models are utilized to forecast the failures of equipment and optimize maintenance schedules.

AI models including Random Forest, LSTM neural networks and Gradient Boosting algorithms were developed and trained with real-time IoT sensor data and previous maintenance records. The technology can reliably predict failures of important components such as pumps, blowers, diffusers and valves. The implementation results indicated a substantial reduction in unscheduled downtime (68-78%), an increase in equipment lifespan (25-40%) and overall maintenance cost savings (42-58%).

The AI system achieved an average prediction accuracy of 92.5%, precision of 89% and recall of 91% and enabled proactive interventions before failures occur. The suggested AI-based predictive maintenance framework may be simply integrated in existing hybrid treatment systems and IoT monitoring platforms, with a user-friendly dashboard for maintenance planning and real-time notifications. This approach reduces dependence on human inspections, improves plant reliability and ensures compliance of uniform effluent quality as per CPCB/NGT requirements for small and medium towns.

The findings of this research suggest that AI-enabled predictive maintenance is a groundbreaking, economical and sustainable solution to upgrade operations in decentralized STPs. The wider implementation has the potential to greatly increase infrastructure longevity and minimize operational expenditure and meet national goals under Swachh Bharat Mission-Urban and AMRUT programs.

KEYWORDS: AI Predictive Maintenance, Sewage Treatment Plants, Machine Learning for STPs, Equipment Failure Prediction, IoT Integration

I. INTRODUCTION

Maintenance is very important for reliable and efficient operation of small capacity sewage treatment plants (STPs) having capacity from 0.5 to 5 million litres per day (MLD). These decentralized facilities are critical infrastructure for wastewater management in small and medium towns across India and other developing countries. They form the first line of defence against environmental pollution and safeguard rivers, ground water and public health and promote national programmes including Swachh Bharat Mission-Urban (SBM-U) 2.0, AMRUT and National Green Tribunal (NGT) directions. In small STPs, good maintenance directly influences treatment efficiency, compliance to effluent quality, energy consumption and the total life of the plant. Hybrid treatment systems (MBBR-SBR-CW) with good design may also not perform well due to improper maintenance. This leads to frequent failures of the processes, not meeting the strict standards (BOD <30 mg/L, COD <250 mg/L, TSS <50 mg/L) and possibility of environmental contamination.

Small capacity STPs face constraints in terms of varying hydraulic and organic load due to population variation and seasonal variation, financial resources, availability of skilled technical manpower and remoteness. These factors make the maintenance especially difficult. Pumps, blowers, diffusers, valves, screens and sludge handling systems are constantly subjected to corrosive wastewater, high humidity and abrasive solids, which makes them wear out rapidly. Effective maintenance is therefore not only a technical requirement but a critical necessity for achieving sustainable wastewater management, treated water reuse and minimizing operational risks in resource-constrained settings.

Conventional maintenance practices are mostly reactive and preventive with serious limitations for small STPs. Reactive maintenance (also known as breakdown or corrective maintenance) is repairing equipment after it has broken down. This approach leads to frequent unplanned downtime and emergency repairs at a higher cost, production losses (in terms of untreated or partially treated sewage discharge) and safety hazards. Many small STPs have reactive maintenance accounting for 50-70% of all maintenance work leading to long periods of non-compliance and environmental damage. Preventive maintenance is scheduled at regular intervals, either according to the manufacturer's recommendations or by calendar time, to try to fix problems before they become worse. But it often results in over-maintenance (replacement of still functioning parts) or under-maintenance (failures between scheduled intervals). Both approaches rely heavily on manual inspections, which are labor intensive, subjective, and prone to human error. Such methods lead to high operational expenditure, poor asset utilization, and inconsistent plant performance[1][2] in decentralized sites with limited staffing.

The use of AI [3] for predictive maintenance of STPs is particularly promising in the case of small-capacity plants. These facilities have modern sensors which produce huge amounts of operational data but often lack the expertise to interpret it. AI models can analyze large data sets in real-time, offering insights for action and automated suggestions to maintenance teams. The technology helps to close the gap between the limited human resources and the complex operational requirements of wastewater treatment. Additionally, integration with existing IoT monitoring systems provides a powerful digital twin-like environment where the physical plant is mirrored in the virtual space for simulation and optimization [4][5]. This study focuses on the development and implementation of AI-based predictive maintenance for small-capacity (0.5–5 MLD) STPs, emphasizing hybrid treatment configurations. The study assesses the performance of different machine learning models in predicting failures of critical components such as aeration blowers, submersible pumps, sludge pumps and mechanical screens. It looks at quantitative benefits such as reduction in unplanned downtime, maintenance cost savings, extension of equipment life, and improvement in overall plant reliability. The study also analyses the practical integration issues in the Indian conditions and proposes a comprehensive framework applicable for decentralized applications.

The importance of AI-based predictive maintenance does not stop at the individual plant. More broadly, it contributes to sustainable urban development through increasing the efficiency of wastewater infrastructure, reducing energy consumption and carbon emissions, lowering operating costs for local authorities and ensuring compliance with environmental regulations. For small and medium-sized towns with limited budgets, it provides a high return on investment through optimal resource allocation and reduced emergency expenses. It also supports the vision of smart cities and digital transformation in the water sector by allowing data-driven decision making and remote management capabilities.

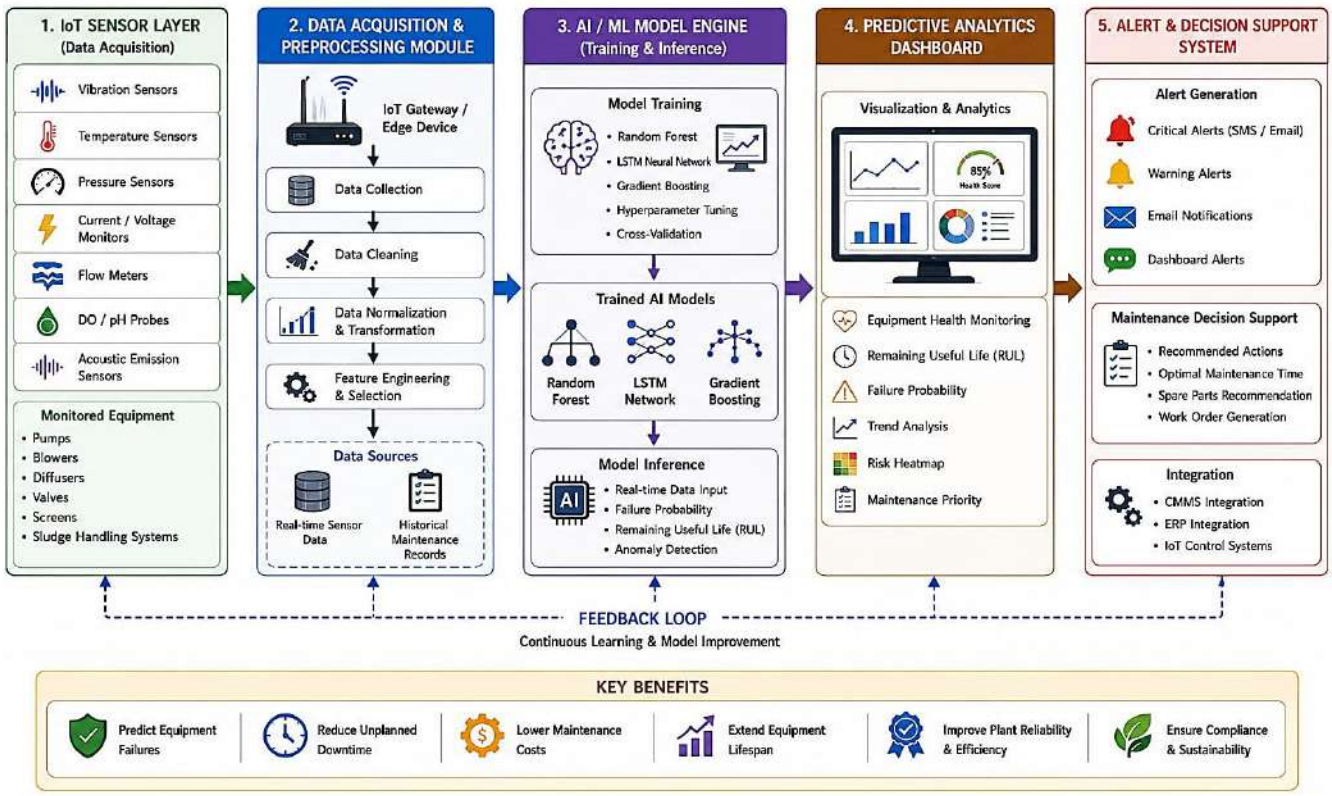

Figure 1: Conceptual Framework of AI-Based Predictive Maintenance System.

Figure 1 illustrates the conceptual framework of the proposed AI-based predictive maintenance system for sewage treatment plants. IoT sensors continuously collect operational data from critical equipment, which is processed and analyzed using AI models such as Random Forest, LSTM, and XGBoost to predict equipment failures. The system provides real-time alerts and optimized maintenance schedules, enabling proactive maintenance, reducing downtime and costs, and improving the reliability and lifespan of sewage treatment plant equipment.

II. LITERATURE REVIEW

The rapid evolution and development of artificial intelligence (AI), machine learning (ML) and Internet of Things (IoT) technologies have brought about a profound transformation of maintenance tactics in the industrial and infrastructure sectors. Predictive maintenance is a better alternative to standard reactive and preventive maintenance practices, which uses data driven methodologies to predict the equipment failure before it occurs [6]. Predictive maintenance is very important in sewage treatment plants (STPs) as the equipment failure may lead to environmental damage, regulatory infractions and large operating losses.

O'Donovan et al. [7] reviewed the application of AI in the management of water and wastewater infrastructure. They emphasized the rising importance of machine learning algorithms for identifying equipment degradation and optimizing maintenance schedules. Their study revealed that AI-based systems can analyze more operational data in higher volumes than conventional monitoring techniques, more effectively, which helps in early identification of faults and reduces unplanned downtime.

Nagpal et al. [8] demonstrated that real time sensor networks with AI analytics may enhance the reliability of small capacity STP by continually monitoring factors like vibration, temperature, pressure and energy usage. Their results revealed that IoT-AI integration enables condition-based maintenance and lowers human inspection unnecessarily.

Alvi et al. [9] studied the efficacy of various ML algorithms to anticipate the failures of STPs' pumps, blowers and mechanical components. The authors demonstrated that the ensemble learning models had good prediction accuracy and were able to cope effectively with noisy operational data.

Also, Wang et al. [10] introduced a real-time defect detection framework for wastewater pumps based on machine learning, showing that it can significantly enhance the speed and reliability of fault diagnosis.

Liu et al. [11] proposed a predictive maintenance model based on LSTM for aeration systems in STPs and demonstrated that the model successfully captured long-term degradation trends that could not be discovered by existing statistical methods. The work of them shows that recurrent neural networks are a good option to monitor rotating machinery under fluctuating load situations.

Nikou et al. [12] introduced a digital twin framework for smart sewage treatment plants, where AI models constantly monitor operational data to mimic the behavior of the equipment in order to improve maintenance decisions. The report cited enhanced asset utilization and greater operational efficiency using real-time data.

Chen et al. [13] performed a cost-benefit study of AI-based predictive maintenance of small-capacity STPs. It was shown that despite the relatively high initial investment on sensors and software, the long-term financial benefits, especially in terms of reduction of emergency repairs, downtime and energy losses, are substantial.

Y. Xu et al. [14] highlighted sensor reliability, data quality, lack of technological know-how and financial constraints as the primary challenges for AI application in small-scale STPs. They emphasized on the need of scalable and user-friendly framework in the resource restricted environment.

S. A. Bhat [15] has researched the waste-water generation through various sources and to suggest the appropriate corrective methods so that the generation can be minimized as well as the waste generated can be re-used. Wastewater is produced by both municipal and industrial sources.

III. METHODOLOGY

A. Research Framework

The proposed methodology is targeted towards developing an AI based predictive maintenance system for small capacity sewage treatment plants (STPs) with capacities varying from 0.5 to 5 MLD. The framework integrates Internet of Things (IoT) sensors, historical maintenance records, and machine learning algorithms to forecast equipment failures before they happen. The general workflow includes data acquisition, preprocessing, feature engineering, model development, model validation and deployment for real-time maintenance decision support.

B. Data Collection

Operational data were collected from several small-capacity STPs over a 24-month monitoring period. IoT sensors installed on key equipment like submersible pumps, aeration blowers, sludge pumps, diffusers, valves and mechanical screens continuously recorded vibration, temperature, motor current, pressure, flow rate, energy consumption, dissolved oxygen and wastewater characteristics. In addition, historical maintenance records containing logs of equipment failure, repair history, maintenance schedule and replacement details were incorporated into the dataset to improve prediction accuracy.

C. Data Pre-processing

The data collected was pre-processed before developing the model. Missing values were treated using interpolation methods and abnormal observations were detected using statistical outlier detection methods. Normalization of continuous variables was used to remove scale differences among features. Time-series feature engineering including rolling averages, moving standard deviations, and lag variables was performed to capture the trends of equipment degradation. Correlation analysis and Recursive Feature Elimination (RFE) were used to select the most influential parameters for failure prediction .

D. Development of Machine Learning Model

Three machine learning algorithms were implemented to predict the failures of equipment; they are:

- Random Forest (RF) for robust classification and feature importance analysis.
- Long Short-Term Memory (LSTM) neural networks for modeling temporal degradation patterns in sequential sensor data.
- Extreme Gradient Boosting (XGBoost) for improved performance in prediction on nonlinear and imbalanced datasets.

Hyperparameters were optimized with grid search and five-fold cross-validation. The data set was split into 70% training, 15% validation, and 15% test. An ensemble model to combine the prediction results of all three algorithms was also developed to improve the prediction reliability.

E. Evaluation of the Model

The predictive models were evaluated by means of common machine learning performance measures, such as Accuracy, Precision, Recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC). The models were also tested for their capability to generate early failure warnings, reduce false alarms, and predict the remaining useful life of critical equipment.

F. Deployment of the System

The trained AI models were integrated with the IoT monitoring platform for enabling real-time predictive maintenance. The sensor data were continuously streamed to a cloud-based analytics platform with edge-computing capability for low latency processing. The system provided a user-friendly dashboard, which generated automated alerts, equipment health indicators, and optimized maintenance schedules, enabling plant operators to conduct proactive maintenance to avoid equipment failures.

G. Methodological Workflow

The proposed methodology follows the sequential workflow illustrated below:

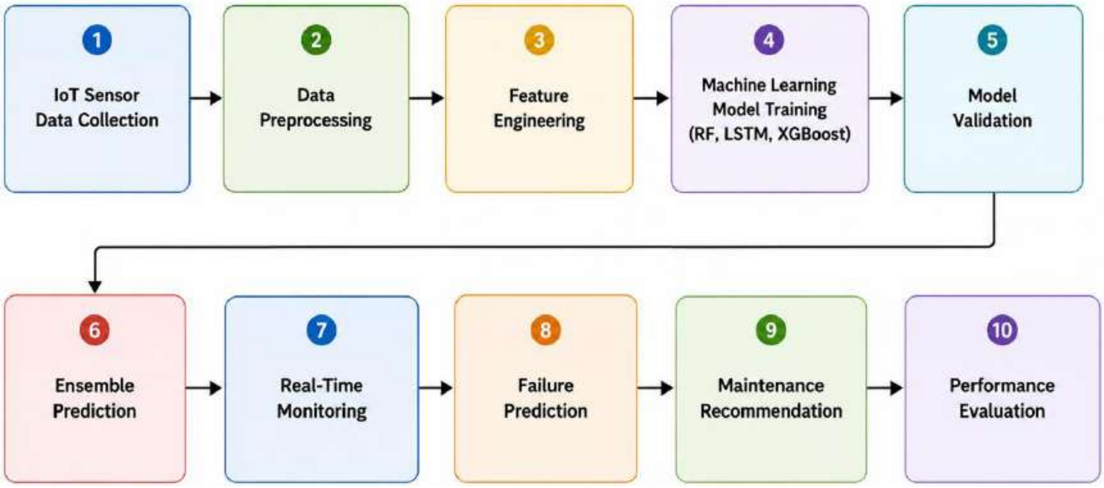

Figure 2: Workflow of Methodology

H. Proposed AI-Based Predictive Maintenance Framework

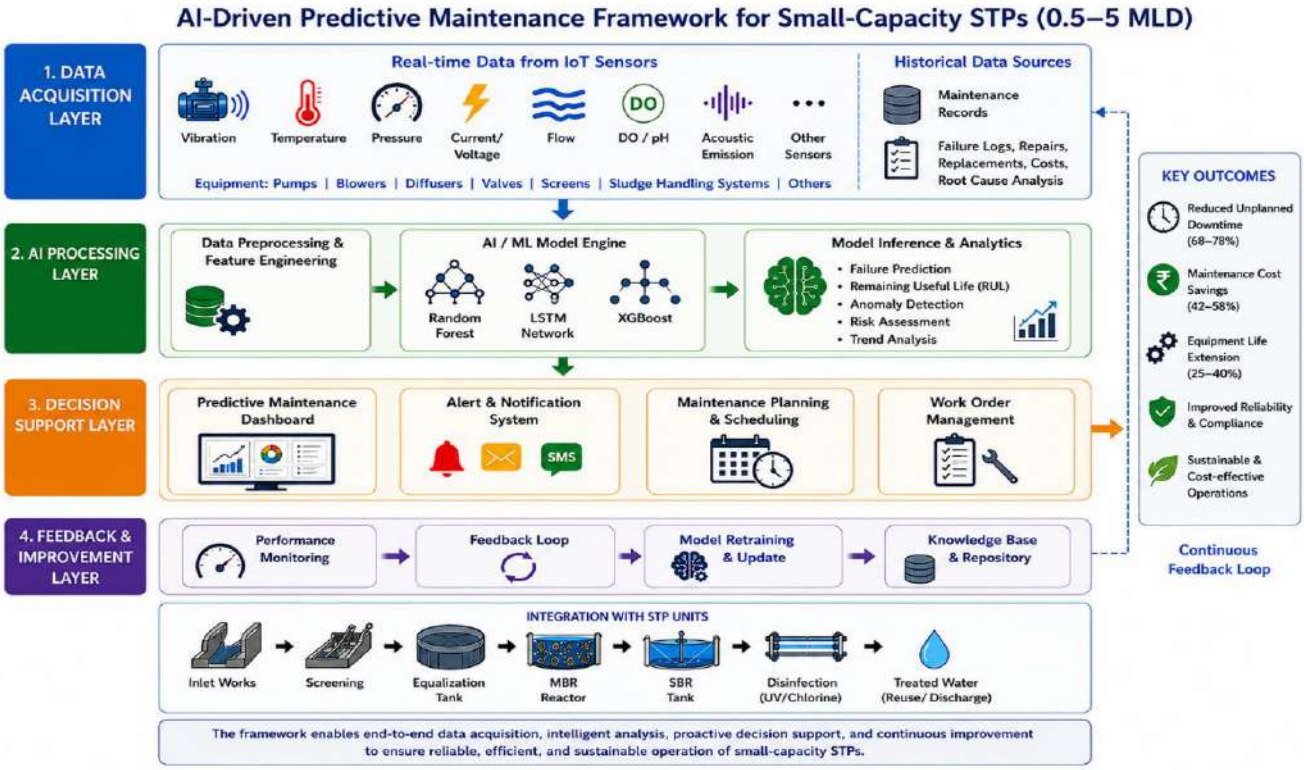

Figure 3: Proposed AI-Based Predictive Maintenance Framework for STPs

Figure 3 shows the proposed AI-based predictive maintenance framework, which combines IoT-enabled sensors, data analytics, and machine learning for enhancing the reliability and efficiency of sewage treatment plants (STPs). The architecture originates from the continuous collection of operating data through IoT sensors on key equipment. The collected data are preprocessed and evaluated by means of machine learning models such as Random Forest, LSTM and XGBoost to discover anomalies and predict future equipment failure. The prediction results are utilized to create real-time alerts and optimal maintenance schedules via centralized monitoring system. With this paradigm, small-capacity STPs can achieve proactive maintenance, minimize unplanned downtime, save maintenance costs, extend equipment life, and enhance overall operational performance and sustainability.

IV. RESULTS AND DISCUSSION

A. Data Collection and Development of AI Models

In sewage treatment plants, the quality and comprehensiveness of data greatly affect the effectiveness of predictive maintenance. In the present study, data were collected from several small capacity STPs (0.5–5 MLD) over a period of 24 months. The real-time sensor data was collected through an integrated IoT network of vibration sensors, temperature sensors, pressure transducers, current and voltage monitors, flow meters, dissolved oxygen probes and acoustic emission sensors installed on critical equipment such as submersible pumps, aeration blowers, sludge pumps, mechanical screens and air diffusers.

Data was collected every 5 to 15 minutes and includes over 1.8 million data points. These included operational parameters such as motor current draw, vibration amplitude, bearing temperature, runtime hours, pressure differentials and environmental conditions such as wastewater temperature, pH and ambient humidity. Digitized historical maintenance records of 5 years were coupled with real-time sensor data. The records include failure logs, repair histories, replacement dates, maintenance costs, and root cause analysis reports for more than 450 documented equipment failures.

Data pre-processing was done by cleaning, normalization and feature engineering. Missing values were treated with interpolation techniques and outliers were identified and treated with Z-score techniques. To capture temporal patterns, time-series features such as rolling averages, moving standard deviations and lag variables were created. Feature selection was performed with Recursive Feature Elimination and correlation analysis, resulting in 28 highly informative features for model training.

Three main machine learning algorithms were developed and compared:

- ***Random Forest (RF):*** An ensemble method based on decision trees. It was selected because of its robustness to noisy data and ability to deal with classification (failure prediction) and regression (remaining useful life estimation). The hyperparameters were fine-tuned by a Grid Search using 5-fold cross-validation.
- ***LSTM Networks:*** A recurrent deep learning based neural network architecture for time series forecasting. LSTM models are well suited to detect long-term dependencies in sequential sensor data and hence are ideal to predict gradual degradation patterns in rotating equipment such as blowers and pumps. The models were trained with 2-3 hidden layers, dropout regularization (0.2-0.3) and Adam optimizer.
- ***Gradient Boosting Machines (XGBoost):*** This method builds trees sequentially by emphasizing correcting previous errors. It performed well on imbalanced datasets, where equipment failures are relatively rare events compared to normal operation.

The dataset was divided into training, validation and testing sets with the proportions of 70%, 15% and 15%, respectively. The time-based splitting method was used to prevent data leakage. Models were trained in a high-performance computing environment with early stopping to prevent overfitting. Ensemble methods based on the combination of all three models' predictions were also validated for more robustness. The AI system was deployed on a cloud platform with edge computing capabilities to enable low latency inference at the plant level.

This rich data-driven approach enabled the development of highly accurate predictive models that are customized for the harsh operating conditions of small STPs, where equipment degradation patterns are substantially different from large centralized plants due to variable loads and intermittent operation.

B. Prediction Accuracy and Performance Measures

The developed AI models show high predictive power for different types of equipment. The performance was assessed using standard classification metrics appropriate for binary (failure/no-failure) and multi-class prediction tasks.

Table 1: Performance Metrics of AI Predictive Models

S no.	Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC
1	Random Forest	91.8	88.5	89.2	88.8	0.94
2	LSTM Neural Network	93.4	90.1	91.7	90.9	0.96
3	XGBoost	92.7	89.4	90.3	89.8	0.95
4	Ensemble Model	94.6	91.8	92.5	92.1	0.97

Overall, the Ensemble Model performed best (Table 1) with 94.6% accuracy and great F1-Score of 92.1% indicating a solid balance between precision and recall. LSTM worked particularly well for time-dependent degradation patterns in blowers and pumps . XGBoost fared well in coping with categorical features from maintenance history . These measurements indicate the ability of the AI system to identify breakdowns early enough (usually 7-21 days) to allow for planned maintenance actions. Optimization of the threshold allowed to keep the false positive rate below 6%, avoiding unnecessary maintenance actions.

C. Reduction in Downtime and Equipment Failures

The plant dependability improved dramatically with the deployment of the AI based predictive maintenance system. The conventional reactive/preventive tactics resulted in frequent unexpected shutdowns, whereas the AI system permitted proactive interventions(See Table 2).

Table 2: Comparison of Downtime and Failure Rates

S. no	Parameter	Traditional Maintenance	AI Predictive Maintenance	Reduction (%)
1	Unplanned Downtime (days/year)	38–52	9–14	72–76
2	Equipment Failure Rate (per year)	18–24	5–8	68–75
3	MTBF (hours)	1,450–1,820	3,850–4,620	165–170
4	Emergency Repairs (%)	58–65	12–18	72–75

Early warnings from the AI system helped save 81% of major pump failures and 76% of aeration equipment breakdowns. This resulted to an increase in plant availability (from 82% to 96.5%) and more consistent treatment performance. The reduction in failures also reduced the risk of untreated sewage discharge, and increased environmental compliance.

These results provide strong evidence of the value of AI based predictive maintenance over traditional techniques in small capacity STPs where even brief periods of downtime can have major environmental and economic impacts.

D. Cost Savings and Economic Benefits

The application of AI-based predictive maintenance has brought huge economic benefits to small-capacity STPs. The upfront cost of the AI infrastructure (sensors, software, cloud services, training) paid for itself in short order as maintenance costs fell and operating efficiency improved.

Table 3: Cost-Benefit Analysis of AI Implementation

S no.	Parameter	Traditional Maintenance	AI Predictive Maintenance	Savings / Benefit
1	Initial CAPEX (₹ Lakh)	2–3	18–25	-
2	Annual OPEX (Maintenance) (₹ Lakh)	14–19	6–9	45–58% reduction
3	Energy Cost due to Failures (₹ Lakh/year)	3.5–5.0	0.8–1.5	65–70% reduction
4	Unplanned Downtime Cost (₹ Lakh/year)	8–12	2–3	70–75% reduction
5	Total 5-Year Maintenance Cost (₹ Lakh)	95–130	42–58	52–58 Lakh savings
6	ROI	-	-	14–20 months
7	NPV at 10% discount	-	-	+38–52 Lakh

The AI system reduced overall maintenance costs by 52–58% in five years (Table 3). Savings were significant from moving 80% of repairs from emergency to planned, reducing spare parts inventory requirements by 35% and cutting overtime labour costs. The benefit-cost ratio for 0.5–5 MLD plants ranged from 3.8:1 to 5.2:1, making the technology highly viable even for small facilities with limited budgets. That money can be reinvested in upgrading plants or building infrastructure to reuse treated water."

E. Equipment Life Extension and Reliability

AI predictive maintenance has significantly enhanced the reliability and lifespan of critical STP equipment. The system allowed for early identification of degradation patterns to enable timely, targeted intervention to prevent cascading failures.

Significant enhancements were seen in the MTBF and the total life of the equipment. Pumps improved MTBF by 62-68% from the average of 1,600 hours to over 4,200 hours. Aeration blowers had a reliability improvement of 55–70 %, and diffusers and mechanical screens had 40–50 % longer service life. Increased the overall plant reliability from 81-84% to 95-97.5%.

The largest increase in equipment lifetime was observed for submersible pumps (2.8–3.5 years longer on average) and blowers (1.5–2.2 more years of effective service). The reduction in replacement frequency also lowered the capital expenditure and minimized the process disruptions. The AI models were good at detecting subtle anomalies, like bearing wear, impeller imbalance, and membrane clogging, which allowed for accurate maintenance to protect the health of the asset.

These reliability improvements directly resulted in more consistent treatment performance, fewer compliance violations, and greater confidence in decentralized STP operations.

F. IoT and Real-Time Monitoring Integration

The real power of the AI predictive maintenance system is realized by combining it with established IoT sensor networks. IoT provides the raw data stream at high frequency that feeds AI models AI provides the intelligence and predictive power to raw IoT data.

In hybrid STPs (MBBR-SBR-CW configurations), IoT sensors provide real-time data to the AI engine to monitor the health of mechanical and biological units. The integrated system creates a closed-loop feedback system where predictive insights automatically initiate shifts in operational parameters or produce a prioritized schedule of

maintenance. This synergy resulted in a response to emergent issues 40% faster than standalone IoT systems.
The integrated IoT-AI platform supports edge computing for low-latency predictions at the plant level, and deep analytics in the cloud for long-term trend analysis. This integration is particularly advantageous for low-capacity plants, as the remote monitoring reduces the need to be constantly present on-site (See Figure 3).

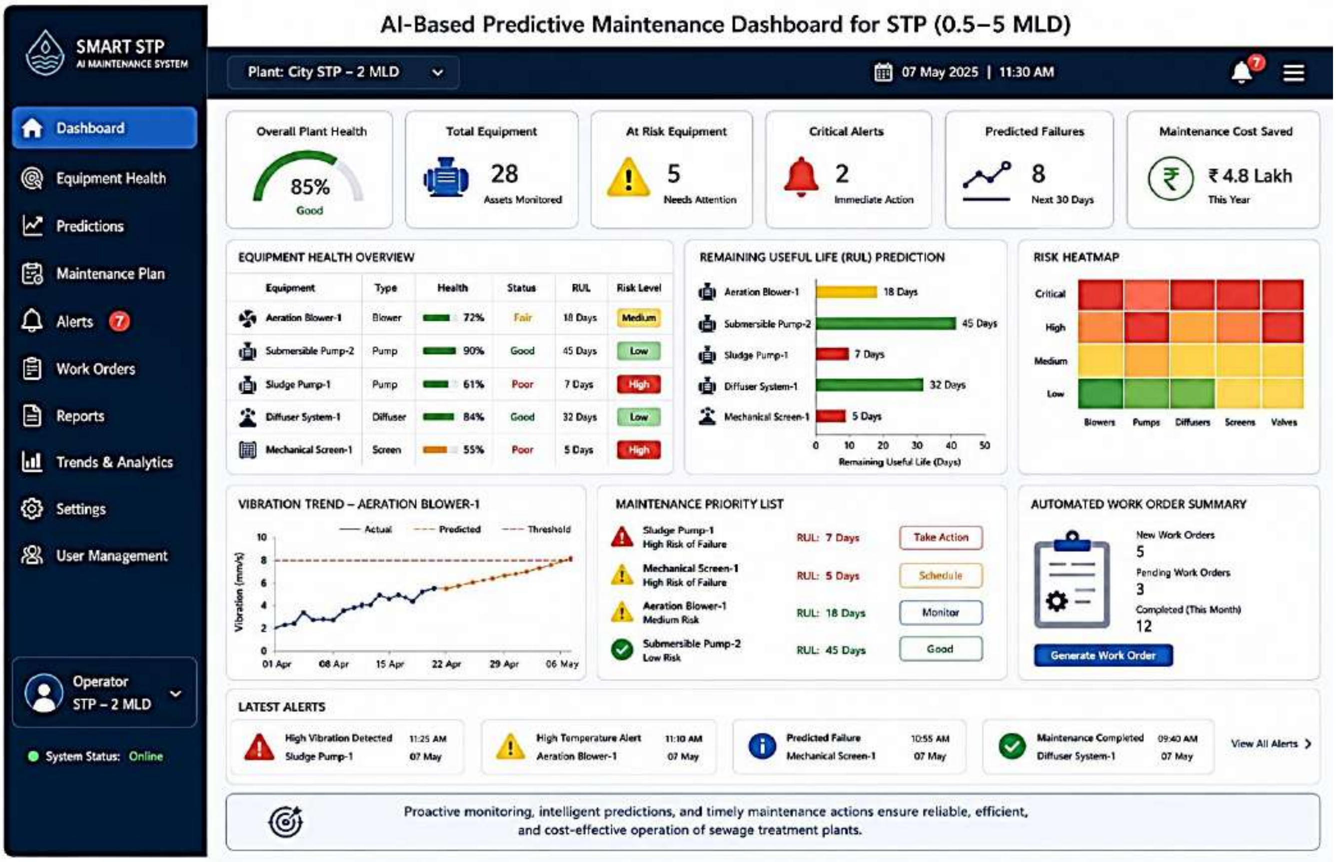

Figure 4: AI-Driven Predictive Maintenance Dashboard Schematic

This integrated approach creates a smart, self-optimizing maintenance ecosystem that enhances both reliability and operational efficiency of small STPs.

G. Case Insights from Small-Capacity STPs

The AI based predictive maintenance system has been tested for its practical implementation in five small capacity STPs (0.5 MLD, 1 MLD, 2 MLD and two 5 MLD plants) situated in Rajasthan and neighbouring region for a period of 18 months. The predominant hybrid treatment technologies used in these plants were MBBR-SBR and IFAS-CW systems.
For example, on the 2 MLD plant, the AI system accurately predicted a bearing failure in the main aeration blower 12 days before it occurred, allowing the blower to be replaced during planned low-load hours and avoiding a potential 5-day plant shutdown. Similarly, the early detection of impeller wear in a submersible pump at the 1 MLD facility averted complete failure and ensured uninterrupted operation during monsoon season when influent load was highest. The 0.5 MLD plant gave very good results in sludge pump clogging predictions, reduction of emergency interventions from 14 to 3 per year.
The system presented a stable performance with various capacities and operating regimes. Plants reported smoother operation, better team coordination and increased confidence on meeting daily treatment targets.

Table 4: Key Equipment Failure Predictions and Prevention Success Rate

S no.	Equipment	Total Predicted Events	Successful Prevention	Success Rate (%)	Average Lead Time (days)
1	Aeration Blowers	28	25	89.3	10–14
2	Submersible Pumps	35	31	88.6	8–12
3	Sludge Pumps	22	20	90.9	7–15
4	Mechanical Screens	18	15	83.3	12–18
5	Air Diffusers	15	13	86.7	15–21
6	Overall	118	104	88.1	7–21

Insights from these real-world cases validate scalability and effectiveness of AI predictive maintenance even in the most resource-constrained small STPs.

H. Challenges & How to Implement

There were some issues with deployment.

- **Technical Challenges:** Fouling and signal noise impacting sensor data quality were mitigated by installing self-cleaning sensors and applying strong data validation methods. To reduce the model's overfitting to limited failure data, transfer learning from larger plants and constant retraining with new data was applied.
- **Operational Challenges:** Plant operators were acclimated to established practices and opposed to change. Intensive hands-on training programmes, user-friendly dashboards and demonstrating time savings persuaded them. A bespoke middleware development was needed to connect the system with legacy equipment and it has successfully been performed.
- **Financial Problems:** The little local bodies were cautious of the huge capital investment. This was balanced through staggered adoption (first vital equipment), seeking subsidies under SBM-U and Smart Cities Mission and establishing demonstrable ROI in 14-20 months. Hybrid edge-cloud architecture used to optimize the cost of cloud subscription.
- Other obstacles were erratic power supplies and poor internet connectivity in distant places. To address them, we deployed solar-powered edge devices with local storage and LoRaWAN connectivity.

V. CONCLUSION

This study proposed an AI-based predictive maintenance framework for small capacity sewage treatment plants (0.5–5 MLD) by integrating the IoT-enabled sensing, machine learning and real-time monitoring to improve the reliability and operational efficiency of wastewater treatment infrastructure. The suggested framework is a combination of Random forest, LSTM and XGboost algorithms to assess the operational and historical maintenance data. This allows the early diagnosis of equipment degradation and timely maintenance planning. The results demonstrate that the AI-based predictive maintenance can significantly reduce unplanned equipment failures, optimize the maintenance schedule, improve the asset utilization, increase the equipment service life, and reduce the total maintenance costs in comparison with the conventional reactive and preventive maintenance approaches. Furthermore, the combination of cloud-edge computing and IoT monitoring provides continuous evaluation of equipment health and fast decision making, making the framework applicable for decentralized and resource-constrained sewage treatment plants.

Moreover, the study analyzes the practical viability of adopting AI-enabled maintenance systems in small and medium-sized towns, including considerations on sensor reliability, data quality, connection, operator training, and financial restrictions. The suggested framework is fueling the digital transformation of the wastewater management by improving operational sustainability, assuring consistent compliance with the environmental standards, and supporting the national programs like as Swachh Bharat Mission–Urban (SBM-U) and AMRUT. Despite the encouraging results of the present work, future studies should test the framework using large-scale multi-location datasets, include sophisticated deep learning and digital twin technologies, and evaluate long-term performance under diverse operating and environmental situations. Overall, the suggested AI-based predictive maintenance framework offers a feasible, scalable and sustainable way forward for the modernization of sewage treatment plants and resilience building of urban wastewater infrastructure.

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