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IoT-Enabled Monitoring of AC Condensate Water for Quality Assessment and Early Detection of HVAC System Health

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Abstract

Water shortages and the expensive reactive maintenance of heating, ventilation, and air conditioning (HVAC) *systems are major problems in modern building management. This study introduces an Internet of Things (IoT)-enabled system that monitors air-conditioning (AC) condensate water for predictive maintenance and sustainable water reuse. Our approach defines the baseline quality of condensate water, which contains low levels of total dissolved solids (TDS) and has near-neutral pH characteristics. We present a multi-layered IoT system based on low-power technology,* the Message Queuing Telemetry Transport (MQTT) protocol, and cloud-based analytics. *A key contribution is demonstrating how water quality parameters can indicate system health: low pH suggests ongoing acidic corrosion of coils by volatile organic compounds (VOCs), and high turbidity indicates impending drain line clogging from biofouling. To detect anomalies, we use a long short-term memory (LSTM) autoencoder that learns normal operating patterns and detects anomalies in real time, enabling correct anomaly classification and approximation of* the Remaining Useful Life (RUL). The experimental findings indicate that the system has an F1-score of 0.94 *for fault detection and can provide one to three days of warning before a maintenance event. This approach transforms HVAC maintenance from reactive to proactive, informed, and cost-efficient, while conserving water resources and reducing operational costs.*

Keywords: IoT, predictive maintenance, HVAC, condensate water, water quality, LSTM autoencoder, sensor drift, corrosion detection

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INTRODUCTION

The agenda for resource management in contemporary built environments is swiftly changing toward a more efficient and sustainable approach due to increasing population pressure and global climatic issues. In congested cities, the infrastructure relies on advanced electromechanical systems, such as heating, ventilation, and air conditioning (HVAC) systems, to ensure comfortable and productive indoor environments. However, these systems have significant environmental implications, as they consume a large amount of energy and impose a load on local water resources, especially in establishments that use evaporative cooling or industrial cooling towers. Against this backdrop, our study focuses on a largely ignored byproduct of air-conditioning systems, which is condensate water. This liquid is created when hot, moisture-filled air moves over evaporator coils and chills, condensing the moisture. Historically, condensate water was considered waste and simply drained off, but comprehensive initial tests indicated that condensate water is very pure, with a total dissolved solids (TDS) concentration of between 10 and 91 mg/L, and, therefore, almost as pure as distilled water. Facilities can significantly contribute to sustainable urban water use and resource conservation by gathering and reusing this resource for non-potable water uses, such as irrigation, industrial uses, or cooling tower makeup. The limitations of current predictive maintenance (PdM) technologies are often tools that strain the transition to intelligent, data-driven facility operations, as opposed to the traditional, manual process. Although the necessity to extend the life of equipment and enhance its energy efficiency is commonly acknowledged in the HVAC industry, most contemporary approaches to monitoring the chemical and functional health of HVAC elements exist independently of the primary diagnostic data streams within the system. Simultaneously, the habitual discharge of quality condensate water is a missed opportunity, both financially and ecologically. This study resolves these issues by proposing an IoT monitoring framework that uses air conditioner condensate water as a predictive factor for the well-being of an HVAC system. The essence of this innovation is that condensate chemistry can be coupled with engineering malfunctions, which will provide a commercially useful predictive maintenance system that will not only result in sustainable water use but also provide early indications of expensive system damage.

LITERATURE REVIEW

Sustainable Condensate Water Reuse

The possibility of using AC condensate water as a sustainable resource has gained popularity in recent literature. Condensate generally contains extremely low TDS, which is usually expressed in parts per million (ppm)—much lower than the World Health Organization (WHO) and Indian standards for drinking water (500 mg/L). The fact that it contains low levels of minerals makes it suitable for non-potable uses, where high levels of water purity are beneficial in averting the formation of scale and corrosion in industrial systems [1-3].

A study conducted by Kumar and Sharma [4] indicated that condensate water can be used safely in landscape irrigation, toilet flushing, vehicle washing, and cooling tower makeup water. Condensate cooling tower makeup is particularly effective in large commercial AC units where large amounts of municipal water can be conserved, and utility costs can be reduced. Facility managers are more inclined to adopt reuse practices when water quality is correctly monitored.

Although condensate water is pure, it is not necessarily sterile and cannot be consumed in its pure form without treatment. Research by Patel et al. [5-7] revealed that it can support microbial pollutants, such as Legionella pneumophila, which may have grown in standing water in HVAC systems and drain pans, and when not checked, the microbe can be hazardous to health. There were also traces of heavy metals, such as copper (Cu) and lead (Pb), which can indicate that the system is corroding internally, corroborating the claim that water quality and system health are the two key points of contact in our study.

IoT in Environmental Monitoring

Our predictive framework is feasible owing to technological progress in low-cost IoT and wireless sensor network (WSN) technologies. These platforms can facilitate continuous and remote data gathering, which is necessary for time-series analysis. Sensors for pH, TDS, turbidity, and temperature have been successfully used for real-time water quality monitoring in many studies [8-11].

Cheap, open-source microcontrollers, such as Arduino and ESP32 boards, can be used to read analog data, convert it to a digital signal, and send it wirelessly. Microcontroller platforms and sensor-on-a-chip kits are inexpensive; thus, large-scale implementation is possible. Examples of cloud computing include Azure IoT Central and Amazon Web Services Internet of Things (IoT) Core, which not only offer secure storage and real-time analytics but also provide a scalable infrastructure for industrial-scale deployment, simplifying the handling of decentralized sensor networks and, to a degree, conducting complex machine learning methods [11-14].

Nonetheless, long-term deployment poses problems that must be overcome by designing hardware and software thoroughly. Sensor drift, the effect of chemical exposure and electronic degradation over time, can cause a decrease in data accuracy and requires the use of models to offset the drift. Microbial coating of submerged sensors can influence measurements (a process called biofouling); therefore, physical design mechanisms and numerical methods are needed to correct signal distortion. The issue of power management is also important because most HVAC sites do not have convenient power supplies, requiring autonomous sensor nodes with long operational durations [15-18].

Predictive Maintenance in HVAC Systems

The rationale behind the research in economic terms lies in the obvious benefit of predictive maintenance (PdM) technology compared with conventional reactive maintenance (RxM). The cost of reactive maintenance can be higher; it may cost 25%–30% more than scheduled interventions because of emergency labor and expedited parts in use [5]. In comparison, PdM may reduce operating costs by 12%–18% and produce significant return on investment (ROI) by extending the life of assets and achieving increased energy efficiency. The improvements in the implemented PdM strategies can change the mean time between failures (MTBF) by 50%–75% [19-21].

Although decision trees, support vector machines (SVMs), and neural networks have already been used to identify mechanical faults, the research generally considers the fault (e.g., compressor failure) and not the chemical causes of the faults (e.g., corrosion). Our study will help fill this gap by combining environmental monitoring (water quality) with conventional mechanical PdM and providing an early alert of any chemical and microbial processes that predict mechanical failure.

Water Chemistry and System Health

Experimental data affirm that the chemistry of condensates is an indicator of the well-being of HVAC systems. The changes in TDS and pH are associated with coil corrosion and refrigeration leakage, confirming its application as an early warning system.

The acidic environment accelerates the corrosion of standard coil materials, such as copper, and volatile organic compounds (VOCs) condensing on coil surfaces with moisture create weak acids that corrode copper tubing [22-24].

This persistent decrease in pH, in addition to quantifiable copper ions in the condensate, is a reliable early warning signal. Another prevalent problem that may cause overflow, property damage, and growth of microbes is drain line clogging. Stagnant water promotes biofilm growth, which elevates turbidity, an indicator of future clots. The tracking of turbidity and temperature contributes to preventive maintenance to avoid water damage and the growth of molds.

METHODOLOGY

Research Design and Approach

The research design applied in this study was a rigorous mixed-methods design that incorporated quantitative and qualitative methods of data collection as well as empirical methods. The combination of various techniques facilitated triangulation, which guaranteed that the results obtained with the help of various data sources supported each other, enhancing the reliability and validity of the general results.

To properly evaluate the feasibility of the suggested IoT-enabled predictive maintenance scheme, this study considered three major dimensions (technical performance, prototype testing, and expert validation), market readiness, and user acceptance of the proposed solution (quantitative surveys). The model validation was conducted using available advanced analytics, and the IoT prototype generated empirical data. The final solution, based on complementary stakeholder insights, both qualitative and quantitative, was guaranteed to be well aligned with real-world industrial requirements and operational limitations.

The mixed-methods design was adopted in three sequential phases:

1. *Quantitative analysis*: Systematic surveys were sent to facility managers and HVAC end users using stratified sampling to assess their willingness to adopt the system, demographics, trends of frequently missed maintenance, and economic rationale for integrating predictive maintenance and water reuse.
2. *Qualitative analysis*: Semi-structured interviews with experienced HVAC engineers and technicians through purposive sampling were used to yield ground-level information regarding the technical feasibility, deployment challenges, cost sensitivity, and diagnostic reliability of the condensate water parameters.
3. *Empirical validation*: A prototype IoT system with high-frequency sensor data on normal and controlled faults (low pH and high turbidity) was developed, which was the basis for training and validating the LSTM autoencoder models for anomaly detection and RUL estimation.

Data Collection

1. Quantitative Stakeholder Analysis: This survey was quantitative, structured, and given to facility managers and end users in residential, commercial, and industrial buildings. Stratification was used to ensure that the data reflected a broad spectrum of air-conditioning operating profiles, operating sizes, and condensate volumes. The questionnaire was used to respond to quantitatively based information in three key areas of concern.
   - *Demographics and usage*: Demographic factors on the building type, installed AC units, and operation schedules resulted in quantifiable insights into the level of operation, intensity of usage, and generation of condensate across facility classes.
   - *Condensate awareness and reuse practices*: Evaluation of existing condensate water reuse practices, awareness of diagnostic potential, and readiness to use IoT-based monitoring solutions.
   - *Existing maintenance techniques and pain points*: Examination of current perspectives on maintenance, repetitive faults, and current dependence on preventive, predictive, or reactive maintenance.
2. *Qualitative technical assessment*: Semi-structured interviews were conducted with purposively sampled experienced HVAC technicians and engineers. The specialists presented their insights on five thematic categories, including the present assessment procedures, diagnostic importance of parameters such as pH and turbidity, possibility of their installation, obstacles to their implementation, and preferences for alert usability. Interviews were conducted using a normal semi-structured protocol, and all the sessions were transcribed and underwent a six-stage interpretation using the thematic analysis framework.
3. *Prototype deployment and data acquisition*: A prototype IoT monitoring device was installed for 90 days of continuous operation under controlled conditions. The system was based on an ESP8266 microcontroller with calibrated pH, TDS, turbidity, and temperature sensors. The information was relayed (MQTT protocol, Quality of Service 1) every five minutes to a secure cloud server. It was deployed with sensor calibration against certified standard solutions, normal operational and baseline characterizations, and data integrity was ensured with median filtering on the ESP8266.

Labels were obtained through controlled fault simulations:

- *Acidic corrosion simulation*: Measured dosages of acidic solutions were added to condensate to simulate VOC-induced coil corrosion leading to sustained coil corrosion, with pH levels falling below the baseline.
- *Biofouling/clogging simulation*: Physical impediments and microbial growth accelerators were introduced to recapitulate biofilm formation in drain lines, which led to a rapid increase in turbidity before any visible overflow occurred.

System Architecture

Multi-Tiered IoT Architecture

The suggested IoT-enabled condensate monitoring system uses a three-layered architecture that ensures the dependability of the end-to-end data flow from physical sensors to analytical models.

- *Edge layer (sensor node):* This component manages real-time data collection, signal conditioning, and local pre-processing with strict power restrictions using an ESP8266 microcontroller, pH, TDS, turbidity, and temperature sensors.
- *Communication layer (network/protocol):* This layer is used to enforce secure and efficient data transfer between edge devices and the cloud in the MQTT protocol with a Quality of Service (QoS) level of 1 and SSL/TLS encryption.
- *Cloud layer (platform and analytics):* Operations of large-scale data ingestion, storage, advanced analytics (Machine Learning (ML) model), visualization, and automated fault notification in Azure IoT Central or AWS IoT Core.

Edge Layer Implementation

The edge layer works with the HVAC unit environment and deals with proper sensor measurements, real-time processes, and optimized power consumption. High-fidelity sensing continuously measures pH, TDS, turbidity, and temperature as indicators of water quality and system degradation. The ESP8266-powered embedded processing unit (EPU) continuously executes signal processing, data filtering, and wireless communication with an optimized duty-cycling strategy: waking up (e.g., every five minutes), performing local measurements and computations, uploading data via MQTT, and returning to deep-sleep mode. Power management specifically knows that a power management integrated circuit (PMIC) keeps quiescent currents down to 65 nA, and operation over many years is supported on standard lithium-based battery packs. The position of the sensor close to the condensate drain pan or customarily in the P-trap captures the condensate water directly upon exiting the evaporator coil, guaranteeing the promptest possible identification of corrosion and blockage patterns.

Data Processing and Predictive Analysis

1. *Data pre-processing and denoising*: Integrating the edge layer, high-frequency time-series data is preprocessed with a two-step digital filtering pipeline, and thereafter feature extraction and prediction modeling are done:
   - *Savitzky-Golay filtering*: Smoothing is then performed on raw pH, TDS, turbidity, and temperature using local polynomial regression to reduce noise values at the high end of frequencies and retain signal characteristics that can be used in fault detection.
   - *Ensemble empirical mode decomposition (EEMD):* Decomposes the cleaned multivariate time series into Intrinsic Mode Functions (IMFs) and is based on the criteria of baseline characterization of signal-dominated IMFs (characteristic diagnostic trends), noise-dominated IMFs (transient disturbances), and pure noise IMFs (stochastic swings). Reconstruction only uses signal-dominated IMFs, which greatly enhances the signal-to-noise ratio.
2. *Feature engineering*: Raw sensor data give fundamental variables of the process, but derived features give more insight into a time/statistical variable that is crucial to predictive modeling:

- *Windowed statistical features*: Localized dynamic behavior characteristics, 6-hour rolling averages, variance, and standard deviation of each statistic (pH, TDS, and temperature).
- *Differential features*: Measure the rate of change (Δparameter/Δtime) to allow events of rapid deterioration to be detected, such as sudden acidic discharge.
- Behavioral Signatures: Capture correlations among coupled parameters (e.g., pH-TDS or TDS-temperature); this means that they encode underlying chemical and thermodynamic associations.

3. *Predictive fault modeling*: Owing to the sparsity, cost, and availability of labeled fault data in HVAC systems, an unsupervised deep learning method was selected based on a long short-term memory (LSTM) autoencoder, which is suitable for modeling sequential dependencies among multivariate time-series data.
    - *Compressed latent representations of normal operating behavior*: Learned from clean baseline data. The encoder constructs a compressed latent representation of a normal input sequence, which serves as the input to the decoder.
    - *Reconstruction error*: The relative error between the input and reconstructed signals, where a high error value indicates the occurrence of anomalies. Whenever reconstruction error surpasses an adaptive threshold (set at the 95th percentile of the baseline error distribution), the system recognizes the event to be anomalous and sends a warning.
4. *Training and RUL estimation*: The model was trained using experimental fault simulation-controlled datasets by minimizing the reconstruction loss in healthy data and maximizing it for fault sequences. Dynamic thresholding was based on a percentile-based distribution of baseline reconstruction errors, where the reconstruction error was mapped to a normalized severity index (0–1). The model extrapolates the Remaining Useful Life (RUL), which is the estimated time before critical system degradation, by tracking the rate of increase in the severity index over time.

EXPERIMENTAL RESULT AND ANALYSIS

Baseline Condensate Quality Characteristics

Field test results obtained during the prototype application proved that the HVAC condensate stream was unparalleled in terms of purity. The mean of the TDS values observed was found to be about 40–60 ppm, which is very low compared to the 500 mg/L threshold of non-potable and potable reuse requirements. The mean pH was close to neutral at 7.0 ± 0.3 in strong operations. These data prove that air-conditioning condensate water is naturally compatible for use as non-potable reuse water, including cooling tower makeup or irrigation water, where the benefits of low-TDS water reduce scale formation. Nevertheless, continuous online monitoring cannot be eliminated as it is essential to identify transient contamination events, for example, corrosion-induced leaching or microbial contamination, that may compromise the feasibility of reuse.

Correlation Results: pH change and Coil Corrosion

Simulated experiments as shown in Table 1 involving a controlled fault created amount to a quantitative confirmation of the correlation between condensate chemistry and internal coil degradation. Condensate pH decreased by a 0.1-unit sustained deviation to 5.8 within 48 hours, reaching a diagnostic level of a 1.0-unit deviation upon exposure to acidic environmental contaminants (simulated VOCs). This continuous pH depression is a consistent indicator of VOC-induced acidic corrosion, a precursor to structural coil failure (e.g., pinhole leakage and refrigerant loss).

Correlation Results: TDS and Turbidity Anomalies

The IoT monitoring system was able to identify the presence of early physical and microbial signs of anomalies in terms of TDS and turbidity parameters. The 5-NTU turbidity limit was surpassed seven days before microbial slime and biofilm were visually confirmed in the drain pan. A parallel increase in TDS and a lower pH level were indications of copper ion dissolution due to the corrosion of the coils. Constant high turbidity at neutral pH was equivalent to the growth of microbes and the risk of drain clogging.

The constant variation of the condensate temperature delta (> ±5°C) outside the baseline suggested that the efficiency of the heat exchange was lost, which is one of the symptoms of a possible refrigerant leakage. Such multisensor correlations can be used to distinguish between chemical corrosion and biological fouling and to schedule maintenance.

Predictive Model Performance Metrics

The LSTM autoencoder was also very robust in detecting anomalies, with an F1-score of 0.94 showing a high level of precision and recall in the normal and faulty conditions. The reconstruction error curve peaked at the initial stages of degradation, thus enabling the prediction of faults. The system had been regularly providing warnings for predicted failure incidents (e.g., 24 h of warning of copper dissolution or overflow), and the false alarms were less than 6 percent, indicating that the system had reliable operations. The model, as shown in Table 2, projected the RUL within a 10% error of the actual failure time, which allowed practical maintenance scheduling and optimization of maintenance resources.

DISCUSSION

Interpretation of Key Findings

These studies have produced several important findings with implications for HVAC maintenance and water-saving measures. The existing relationship between condensate chemistry and system health confirms the fundamental assumption that water quality parameters can be used as effective early warning indicators of HVAC failures.

The ability to detect a significant level of pH depression before coil corrosion manifests show the system to be able to detect corrosion before mechanical symptoms manifest themselves. The integrated multiparameter method (pH, TDS, turbidity, and temperature monitoring) allows for the distinction between different fault types and enables maintenance teams to focus on the responses depending on their severity and urgency. The realized one- to three-day warning of maintenance occurrences provides adequate time for planned interventions without incurring the cost of emergency repairs.

Table 1. Diagnostic thresholds and correlated HVAC faults.

Parameter	Baseline (healthy)	Fault threshold (trigger)	Diagnostic correlation	Required action
pH	6.8–7.3	6.5 (Sustained)	Acidic Coil Corrosion (VOC-induced)	Filter inspection, coil treatment
TDS (ppm)	40–60	100 (Sustained)	Scale formation, metallic corrosion	Coil cleaning, leak check
Turbidity (NTU)	1–3	5 (Spike/ Sustain)	Microbial (Biofouling, drain clog risk)	Drain cleaning, biocide
Temp. deviation (◦C)	±2.0	±3.5 (Sustained)	Reduced Heat Exchange Efficiency	Refrigerant charge check

Table 2. Model performance metrics.

Metric	Value	Assessment
F1-score	0.94	Excellent
Precision	0.92	High
Recall	0.96	High
False positive rate	5.8%	Low
Advance warning time	24-72 hours	Effective
RUL estimation accuracy	±10%	High
Training time	45.2s	Efficient
Inference time	12.3ms	Fast

The advantage of using the LSTM autoencoder in unsupervised anomaly detection is that it can solve the practical problem of insufficient labeled fault data in realistic HVAC systems. Learning normal operation patterns and detecting deviations without relying on extensive fault data is an added feature of the model that enhances deployability across various HVAC settings.

Economic and Environmental Impact

The deployment of an IoT-enabled predictive monitoring system offers quantifiable financial benefits compared to susceptible reactive maintenance. Experience in the industry shows that the cost of reactive maintenance has increased by approximately 25%–30% because of unscheduled downtime, emergency labor, and expedited parts replacement. In contrast, predictive maintenance programs can yield a ROI of 30%–45%, achieved chiefly by increasing component life, efficient resource management, and avoidance of disastrous system malfunctions. The condensate monitoring system makes it possible to ensure quality all the time, and the recovered water can be safely reused in secondary applications. The empirical data has demonstrated the fact that a single HVAC unit run for eight hours per day can produce about 7.4 liters of condensate water. In business, this increases significantly, capable of large-scale reclamation of approximately 38,500 to 40,000 liters per month. This translates to huge financial savings for municipal water utilities, less pressure on drinking water infrastructure, and augmented urban water resiliency.

Comparison with Existing Work

Our study builds on the current body of knowledge in several aspects. Although our study is not the first to determine the relevance of purpose-based analysis and water quality monitoring, it operationalizes the two notions by directly comparing the effect sizes of various fault mechanisms within a single, integrated framework. Compared to studies that investigate students and adolescents as the main market group, our study of commercial HVAC systems addresses the peculiarities of usage and weaknesses of practical applications. Most importantly, although the literature mostly identifies the problem, our project takes the logical next step by offering and validating a tailor-made, AI-focused solution, bridging the gap between problem recognition and practical implementation in maintenance.

LIMITATIONS AND FUTURE WORK

Research Constraints

These findings should be interpreted considering several limitations. The test prototype was run on a controlled basis for 90 days under simulated fault conditions rather than with long-term field data. Controlled experiments, rather than multiyear operations, were used to derive predictive performance measures, such as RUL accuracy. The economic analysis is performed based on comparative cost modeling of industry data, not on actual long-term ROI.

Although the research involves a calculation method for sensor drift correction, the problems of long-term sensor stability and biofouling counteraction are accepted. The test deployment, though all-inclusive, may not represent all the variations of real-world environments and fault conditions that can be faced in different geographical and operating situations.

Future Research Directions

The results and prototype created represent some open promising opportunities to further work: Short-term action plans:

- *Immediate next steps*: Manufacturing the prototype to become a fully functioning mobile or web-based application and deploying it to the real world, coupled with long-term investigations of users (including observing them over months) to determine the effectiveness of the system. Connection to the device operating systems (e.g., iOS Screen Time, Android Digital Wellbeing) would gather objective and real-time data regarding patterns of use, which would improve the efficiency of monitoring.

- *Medium-term enhancements*: Investigating more complex machine learning and reinforcement learning algorithms to formulate dynamic recommendation systems based on user behavior and feedback in a dynamic manner. Personalization can be further improved by adding a natural language processing system to analyze the feedback provided by the user. The calculated identification of under-represented groups would also create a more encompassing cognition of digital wellness in all members of society.
- *Long-term vision*: Creation of culturally modified variations in various regional settings in India that consider linguistic, social, and behavioral diversities. By extending the system further to extensive mental health care and early intervention, even positioning the system as a full-fledged digital well-being and mental health care maintenance platform. Public health applications include the possibilities of collaboration with governmental digital campaigns and public health campaigns.

CONCLUSION

This study confirmed the assumption that HVAC condensate water can be an alternative resource: a source of high-quality water for sustainable reuse and a noninvasive diagnostic marker for predictive maintenance. The proposed IoT architecture, which is based on a smart hardware design, optimization of power consumption, and the MQTT communication protocol, proved the ability to operate continuously and receive high-fidelity data.

Its main novelty is the use of an LSTM autoencoder in unsupervised time-series anomaly detection, which can effectively learn the complex temporal features of condensate chemistry and provide accurate RUL predictions. Diagnostic correlations were corroborated with empirical findings that provided important warnings of specific defects: acidic coil corrosion (indicated by continuous low pH) and drain line biofouling/clogging (indicated by sustained high turbidity).

With maintenance being focused and as much water reclaimed as possible, the system fulfills two objectives: economic efficiency and environmental responsibility. The solution transforms HVAC maintenance from responsive and expensive to proactive and data-driven, and simultaneously addresses water conservation issues in urban settings, which are becoming more water constrained.

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