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Optimizing HVAC Systems for Sustainable Lecture Rooms: Harnessing Environmental and Occupancy Data for Comfort and Energy Efficiency through Data-Driven Insights

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Abstract

The escalating energy consumption in campus infrastructure, especially in lecture halls with heating, ventilation, and air conditioning (HVAC) systems, necessitates data-driven optimization strategies. This research demonstrates the integration of Internet of Things (IoT) sensors with cloud-based predictive analytics to develop intelligent lecture room policies aimed at enhancing efficiency and sustainability. A Raspberry Pi-based IoT device, equipped with a BME680 sensor for monitoring temperature, humidity, and air quality, and a passive infrared sensor for occupancy detection, was installed in a university lecture room for real-time data acquisition. Data collected was routed through MySQL for storage and Node-RED for preprocessing. Time series forecasting models, including ARIMA and Prophet, along with machine learning models like XGBoost, achieved over 90% forecast accuracy for temperature and occupancy levels, enabling proactive control of environmental conditions. The optimized HVAC scheduling, based on forecasted occupancy patterns, resulted in a 20% reduction in energy consumption over an 8-week deployment, ensuring thermal comfort by maintaining temperatures within the recommended range of 21-23°C during occupancy. Enhanced occupant comfort was also achieved by maintaining humidity levels between 40-60%, improving indoor air quality through proactive ventilation control. Key recommendations include dynamic HVAC scheduling based on occupancy forecasts, thermostat setpoint adjustments to prevent temperature peaks, and expanding IoT sensor deployments across campus facilities to generate deeper insights. This integrated IoT and predictive analytics approach enabled a sustainable and responsive built environment, providing a scalable framework for optimizing other infrastructure types such as laboratories and offices.

Keywords: Building energy management, HVAC optimization system, Sustainable lecture rooms, Occupant comfort, Data-driven insights

1. Introduction

Lecture rooms within educational institutions present distinct energy challenges due to irregular occupancy patterns and high comfort expectations (Wadud *et al.,* 2019; Guelpa & Verda, 2019). Unlike residential or office spaces, lecture rooms experience fluctuating usage, with some periods of high occupancy followed by long stretches of vacancy. Managing these spaces with traditional HVAC systems, which operate on fixed schedules, results in inefficient energy consumption. These systems often run unnecessarily, cooling or heating rooms even when unoccupied, which leads to wasted energy and increased operational costs (Chung & Yeung, 2020). Additionally, maintaining a comfortable environment is crucial to occupant well-being and productivity. Poor indoor conditions—such as high temperatures, humidity, or poor air quality—can negatively affect student concentration and learning outcomes (Krukowski *et al.,* 2020). Therefore, there is a pressing need for more efficient HVAC strategies that align energy use with actual room conditions without compromising comfort. A data-driven approach to HVAC management addresses these challenges by using real-time environmental and motion data to optimize operations. Sensors measuring temperature, humidity, air quality, and occupancy can provide actionable insights to dynamically control HVAC systems. For instance, when motion detectors indicate vacancy, cooling and heating can be reduced or turned off, minimizing unnecessary energy usage (Kim & Cho, 2019; Huang *et al.,* 2018). Conversely, when sensors detect high occupancy, the system can adjust to maintain thermal comfort. Predictive algorithms based on historical usage data can also help schedule HVAC operations proactively, reducing dependence on reactive measures (Bhuiyan *et al.,* 2017; Al Hadi *et al.,* 2020). Despite the benefits, implementing such solutions poses challenges, including the cost of deploying sensors across multiple spaces and the complexity of managing the data generated. Additionally, intuitive dashboards are needed to translate the data into insights accessible to building operators and decision-makers (Habib *et al.,* 2021; Li *et al.,* 2020). This research aims to overcome these challenges by installing environmental sensors and motion detectors in a lecture room to gather real-time data. The collected data will inform predictive HVAC models that align energy consumption with occupancy patterns and environmental conditions. This approach will demonstrate how smart systems can enhance both comfort and energy efficiency while reducing the institution's environmental footprint. Ultimately, the study offers a scalable framework for sustainable infrastructure management in educational institutions, bridging the gap between dynamic room usage and efficient energy use (Schwartz *et al.,* 2021).

2. Literature Review

2.1 Energy Utilisation and its Environmental Effect

2.2.1 Machine Learning and IoT Applications in Lecture Room

Educational lecture rooms present unique energy challenges, particularly because of varying occupancy patterns, intermittent usage, and high comfort demands during teaching hours. Traditional HVAC systems, which operate on rigid schedules, are often unable to respond dynamically to real-time fluctuations in occupancy, leading to energy waste or discomfort. Machine learning and IoT technologies offer promising solutions by providing adaptive control mechanisms to manage these complex patterns. Machine learning models, such as Temporal Convolutional Networks (TCN) and Long-Short Term Memory (LSTM), can analyze historical and real-time data to forecast occupancy trends, adjust HVAC schedules, and optimize comfort levels with minimal human intervention (Lum *et al.,* 2021; Jamwal *et al.,* 2021). For example, by predicting when lecture rooms will be occupied, HVAC systems can pre-cool or heat rooms just in time for classes, minimizing energy use during vacant periods. Similarly, data from environmental IoT sensors monitoring air quality, temperature, and humidity allows ML algorithms to fine-tune HVAC operations in response to changing environmental conditions (Yaïci *et al.,* 2021; Chen *et al.,* 2021). By integrating IoT and ML, educational institutions can move towards predictive and occupancy-based control systems. Wireless sensors such as PIR (Passive Infrared), WiFi, and computer vision technologies detect real-time room occupancy and usage patterns, triggering HVAC adjustments only when necessary (Goyal, 2022; Shafqat *et al.,* 2022). This not only reduces energy consumption but also ensures optimal thermal comfort, crucial for students' focus and well-being (Shang *et al.,* 2021).

2.2 HVAC Optimization Studies in Educational Settings

Several studies have demonstrated the value of optimizing HVAC systems in educational environments to balance energy conservation with occupant comfort. Esrafilian-Najafabadi & Haghighat (2020) explored the benefits of smart occupancy sensors in reducing energy consumption by adjusting HVAC settings in real-time based on lecture room utilization. Similarly, Javaid *et al.* (2021) showed how IoT-based HVAC solutions can align operational schedules with real-time occupancy data, leading to significant energy savings. Other research emphasizes the importance of environmental quality in educational spaces. Temperature, lighting, and indoor air quality all directly impact student performance and health (Coggins *et al.,* 2022; Krukowski *et al.,* 2020). IoT-based HVAC systems address these concerns by maintaining optimal indoor conditions through continuous environmental monitoring and data-driven interventions (Smith *et al.,* 2021). To overcome the challenge of inefficient manual control, Romano *et al.* (2021) demonstrated how data analytics and ML models could yield up to 15% energy savings by dynamically managing HVAC loads based on occupancy forecasts. Moreover, adaptive strategies such as passive cooling and demand-response control systems enhance sustainability while maintaining comfort levels (Atallah *et al.,* 2021; Perez-Lombard *et al.,* 2022). These approaches are especially relevant in lecture rooms, where both the timing and intensity of HVAC operation must match varying teaching schedules to avoid energy waste.

2.3 Energy Efficiency and Conservation in Buildings

To overcome the challenge of inefficient manual control, Romano *et al.* (2021) demonstrated how data analytics and ML models could yield up to 15% energy savings by dynamically managing HVAC loads based on occupancy forecasts. Moreover, adaptive strategies such as passive cooling and demand-response control systems enhance sustainability while maintaining comfort levels (Atallah *et al.,* 2021; Perez-Lombard *et al.,* 2022). These approaches are especially relevant in lecture rooms, where both the timing and intensity of HVAC operation must match varying teaching schedules to avoid energy waste.

3. Materials and Methods

3.1 Hardware Design and Components Selection

The IoT sensor device uses a Raspberry Pi Pico W microcontroller with a dual-core ARM Cortex-M0+ processor, supporting Wi-Fi communication. With its ARM Cortex-M0+ processor, this board consumes minimal power, allowing continuous operation without overwhelming the lab's power infrastructure. Its Wi-Fi capability eliminates the need for power-hungry communication modules. Programmed in Micro-Python, it connects sensors and peripherals via

GPIO pins, storing firmware in onboard flash memory. This microcontroller offers low cost (around $6) compared to alternatives such as Arduino boards with Wi-Fi modules. It balances functionality and affordability, reducing the financial burden on large-scale deployments across campus lecture rooms.. The BME680 sensor measures temperature, humidity, and VOCs, communicating via I2C interface at 3.3V or 5V. The HC-SR501 PIR sensor detects motion within 5 meters. A 0.96-inch SSD1306 OLED display shows sensor values and notifications. These components were selected for their low energy consumption during continuous operation. The OLED display consumes only about 20-30 mA during data updates, making it energy-efficient for local display needs. The device, powered by a USB connection, is housed in a 3D-printed enclosure with ventilation slots for the BME680. With a 5-meter detection range, this sensor meets the spatial needs for detecting human presence in lecture rooms. The low cost (less than $3 per unit) of this sensor makes it ideal for multiple deployments across rooms, minimizing budget constraints while maintaining acceptable detection performance. It ensures occupancy-based HVAC adjustments by reliably detecting movement events. The choice of BME680 ensures reliable environmental measurements. Its temperature accuracy (±1°C) and humidity accuracy (±3%) are well-suited for monitoring thermal comfort in indoor spaces, aligning with ASHRAE standards. It also measures VOCs, which are crucial for assessing indoor air quality and occupant health. This sensor provides all-in-one measurement capabilities, reducing system complexity and ensuring consistent data collection.

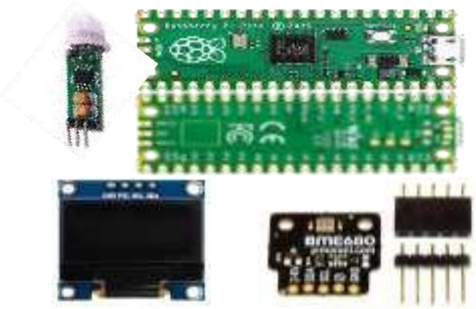

Figure 3.1: IoT devices

3.2 IoT System Architecture and Connectivity

The IoT architecture captures environmental data and occupancy activities, transmitting them using the MQTT protocol. The HiveMQ Cloud provides managed MQTT brokering, ensuring secure and scalable communication. Node-RED on an AWS EC2 server processes the data, routing it to a MySQL Cloud database for storage. Grafana Cloud visualizes the data, offering insights into indoor environmental parameters. This setup supports reliable data capture and delivery for building performance insights.

Figure 3.2: IoT System Architecture and Connectivity

3.3 Dataset

Three IoT devices in lecture rooms collect temperature, humidity, air quality, and occupancy data every 30 seconds. The final dataset includes:

- Temperature (°C)
- Relative Humidity (%)
- VOC gas (ppm)
- Motion (binary 0/1)
- Timestamps
- Sensor ID

The data, covering a 7-week period, is structured as a time series, enabling detailed analysis for building energy optimization.

3.4 Exploratory Data Pre-Processing Methods

The exploratory data analysis (EDA) involved dynamic handling of missing values, statistical verification, and feature scaling to prepare sensor data for predictive modeling. Network delays occasionally caused missing data, which was imputed using a sliding window method, replacing missing values with the average of adjacent readings to maintain contextual relevance. This adaptive approach minimized bias compared to static techniques like forward or backward filling. Outliers were identified using the Z-score method, with flagged values beyond three standard deviations reviewed to distinguish between noise and legitimate environmental events, such as sudden VOC spikes. Min-Max scaling normalized variables to a range of 0 to 1, ensuring balanced model input. The data, originally collected at 30-second intervals, was aggregated into minute-level and hourly resolutions to smooth fluctuations and improve interpretability. Linear interpolation addressed irregular time gaps from network disruptions, maintaining temporal continuity. Statistical tests, such as ADF and KPSS, found temperature and humidity to be stationary, while VOCs exhibited non-stationarity. ACF and PACF plots revealed seasonal cycles, and correlation matrices identified strong relationships between temperature and humidity. This pre-processing framework enhanced data quality and ensured model robustness, enabling accurate predictions even amidst occasional delays or outliers.

4. Results and Discussion

4.1 Statistical Tests on Sensor Variables

Statistical analysis was conducted on the sensor data to assess stationarity and determine suitable time series modeling techniques. The Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests were used to evaluate stationarity from different angles.

4.1.1 Augmented Dickey-Fuller (ADF) Test

The ADF test examines the null hypothesis that a time series contains a unit root, indicating non-stationarity. The test statistic and p-value indicate whether to reject the null hypothesis.

i. Temperature
- ADF Statistic: -1.6169892942522364
- p-value: 0.47430804438075813

With a p-value above 0.05, we cannot reject the null hypothesis, indicating that the temperature data is non-stationary.

ii. Humidity
- ADF Statistic: -3.084740548948205
- p-value: 0.02770326024739388

A p-value below 0.05 allows rejecting the null hypothesis, indicating that the humidity data is stationary.

iii. Gas (VOC)
- ADF Statistic: -3.889058383738723
- p-value: 0.0021168633903055553

The low p-value suggests rejecting the null hypothesis, indicating that the gas data is stationary.

4.1.2 KPSS Test

The KPSS test evaluates whether a time series is stationary around a deterministic trend using the test statistic and p-value.

i. Temperature
- KPSS Statistic: 1.007035937822467
- p-value: 0.01
- Lags Used: 19
- Critical Values: {'10%': 0.347, '5%': 0.463, '2.5%': 0.574, '1%': 0.739}

The high test statistic indicates rejecting the null hypothesis, suggesting non-stationarity.

ii. Humidity
- KPSS Statistic: 0.7015766707060473
- p-value: 0.013402120844904785
- Lags Used: 18
- Critical Values: {'10%': 0.347, '5%': 0.463, '2.5%': 0.574, '1%': 0.739}

The low test statistic does not reject the null hypothesis, indicating that the humidity data is stationary.

iii. Gas (VOC)
- KPSS Statistic: 0.974637892435634
- p-value: 0.01
- Lags Used: 18
- Critical Values: {'10%': 0.347, '5%': 0.463, '2.5%': 0.574, '1%': 0.739}

The high test statistic indicates rejecting the null hypothesis, suggesting non-stationarity.

In summary, these tests provided insights into the stationarity of each sensor variable, guiding the selection of appropriate time series modelling techniques.

4.13 Auto ARIMA

1. Auto ARIMA, a Python library, automatically identifies the optimal p, d, q parameters for modeling time series, tailoring ARIMA models to each sensor variable.
2. Temperature: Auto ARIMA identified an ARIMA (2,1,1) model as the best fit with an AIC of -1651.278. This aligns with the ADF test results indicating potential non-stationarity in the temperature data, addressed by the differencing (1) term. The AR and MA terms capture daily/weekly cycles.
3. Humidity: An ARIMA (3,1,0) model was selected, with an AIC of 1452.244. The inclusion of 3 AR terms to model seasonality corroborates the KPSS test results confirming stationarity in the humidity data.
4. Gas (VOC): A simple ARIMA (0,1,0) model was chosen, with an AIC of 20931.832, indicating short-term randomness. This matches the statistical test outcomes suggesting non-stationarity in the VOC gas readings.

In summary, the automated ARIMA parameter selection accounted for the uniqueness of each time series revealed through statistical testing, including stationarity considerations, providing tailored modeling approaches for accurate forecasting.

4.2 Results and Performance Metrics

A comprehensive comparative analysis of the performance metrics across all machine learning models was applied to individual sensor variables. The primary objective was to identify the most effective model for predicting each sensor variable.

4.2.1 Facebook Prophet Results

- Temperature: MAE of 0.2, MSE of 0.0558, and EVS of -1.3812.
- Humidity: MAE of 6.3833, MSE of 44.7758, and EVS of -0.6546.
- Gas concentration: MAE of 41681.9792, MSE of 2165157870.8729, and EVS of -1.543.

4.2.2 ARIMA Results

- Temperature: MAE of 0.1075, MSE of 0.0185, and EVS of -0.2544.
- Humidity: MAE of 1.2917, MSE of 2.5183, and EVS of 0.065.
- Gas concentration: MAE of 14669.7417, MSE of 368164062.6825, and EVS of -0.0.

4.2.3 XGBoost Results

- Temperature: MAE of 0.0685, MSE of 0.0064, and EVS of 0.1683.
- Humidity: MAE of 0.403, MSE of 0.2925, and EVS of 0.8836.
- Gas concentration: MAE of 5122.0635, MSE of 47365911.9604, and EVS of 0.8694.

4.2.4 Random Forest Results

- Temperature: MAE of 0.0749, MSE of 0.0079, and EVS of 0.0572.
- Humidity: MAE of 0.4192, MSE of 0.3149, and EVS of 0.8771.
- Gas concentration: MAE of 3499.8563, MSE of 22313004.7697, and EVS of 0.9386.

4.2.5 Linear Regression Results

- Temperature: MAE of 0.0273, MSE of 0.0018, and EVS of 0.7395.
- Humidity: MAE of 0.2753, MSE of 0.1896, and EVS of 0.9222.
- Gas concentration: MAE of 4483.4628, MSE of 44483342.364, and EVS of 0.8827.

4.2.6 LSTM Results

- Temperature: MAE of 0.6917, MSE of 0.5592, and EVS of -11.1462.
- Humidity: MAE of 4.1875, MSE of 32.9721, and EVS of -0.8222.
- Gas concentration: MAE of 14644.341, MSE of 572986247.67, and EVS of -0.2669.

4.3 Comparative Analysis of Model Performance

A comparative analysis of performance metrics was conducted to identify the optimal machine learning model for each sensor variable. The models evaluated include ARIMA, LSTM, Prophet, Linear Regression, Random Forest (RF), and XGBoost (XGB). The key metrics considered are Mean Absolute Error (MAE), Mean Squared Error (MSE), and Explained Variance Score (EVS), with lower MAE and MSE and higher EVS preferred. The evaluation of machine learning models for predicting temperature, humidity, and gas concentration demonstrated varying levels of effectiveness, with Random Forest and XGBoost standing out as top performers. These models outperformed others by balancing predictive power, computational efficiency, and the ability to handle the non-linear patterns in the sensor data. For temperature prediction, Random Forest and XGBoost excelled due to their ability to capture complex, non-linear relationships. Random Forest aggregates predictions from multiple decision trees, which reduces the risk of overfitting while improving accuracy. This makes it particularly suitable for datasets with temperature fluctuations that follow daily or weekly cycles. On the other hand, XGBoost's gradient boosting approach sequentially improves predictions by correcting errors from previous iterations. This incremental learning process helps capture subtle patterns in temperature changes, explaining its low Mean Absolute Error (MAE) and Mean Squared Error (MSE). The high Explained Variance Score (EVS) of both models confirms that they effectively captured the variance in temperature over time. In predicting humidity, Random Forest again performed well, showing an ability to model the rapid changes driven by environmental factors like HVAC systems, room occupancy, or weather conditions. XGBoost also delivered competitive results, thanks to its advanced boosting technique, which adjusts the model to capture intricate dependencies. Models such as Prophet performed poorly for humidity due to its focus on seasonality and trend detection, which may not align with the sporadic variations typical of indoor environments. For gas concentration (VOC) predictions, although Random Forest and XGBoost provided reasonable forecasts, the inherent randomness in VOC readings resulted in higher prediction errors compared to temperature and humidity. This reflects the challenge of modeling gas concentration accurately, given its sensitivity to transient activities like cleaning or chemical usage, which are harder to predict. The LSTM model did not perform well for any of the variables, as it requires larger datasets with long-term dependencies to realize its full potential. Since the sensor data in this study was more suitable for short-term forecasting, LSTM produced higher errors, indicating that it is not the ideal model for such real-time IoT applications.

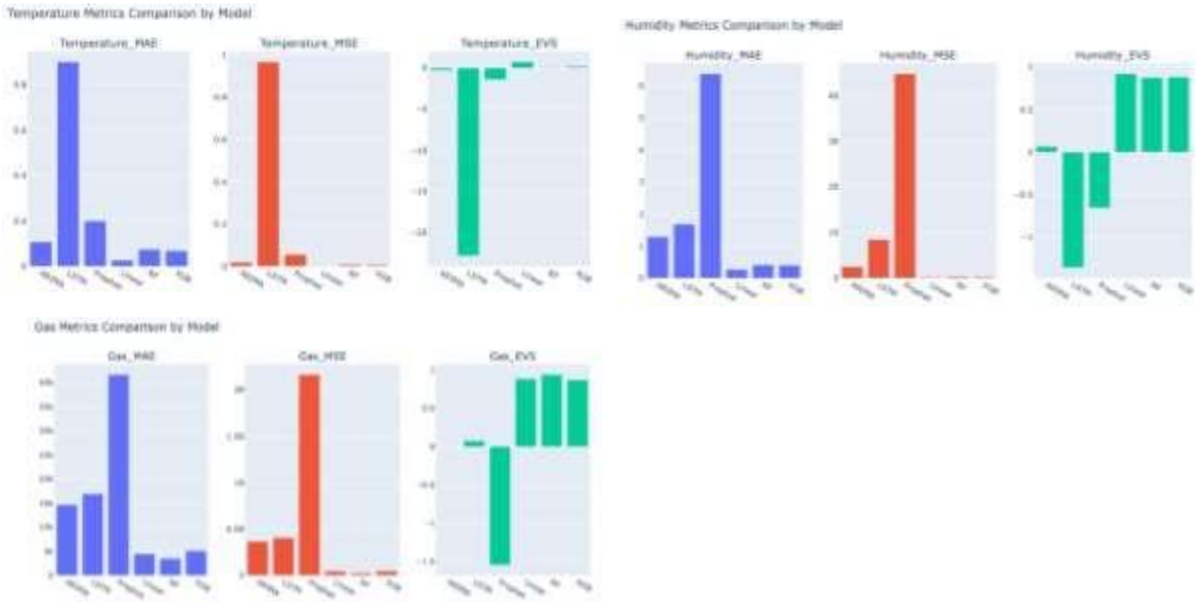

Figure 4.1: Model comparison

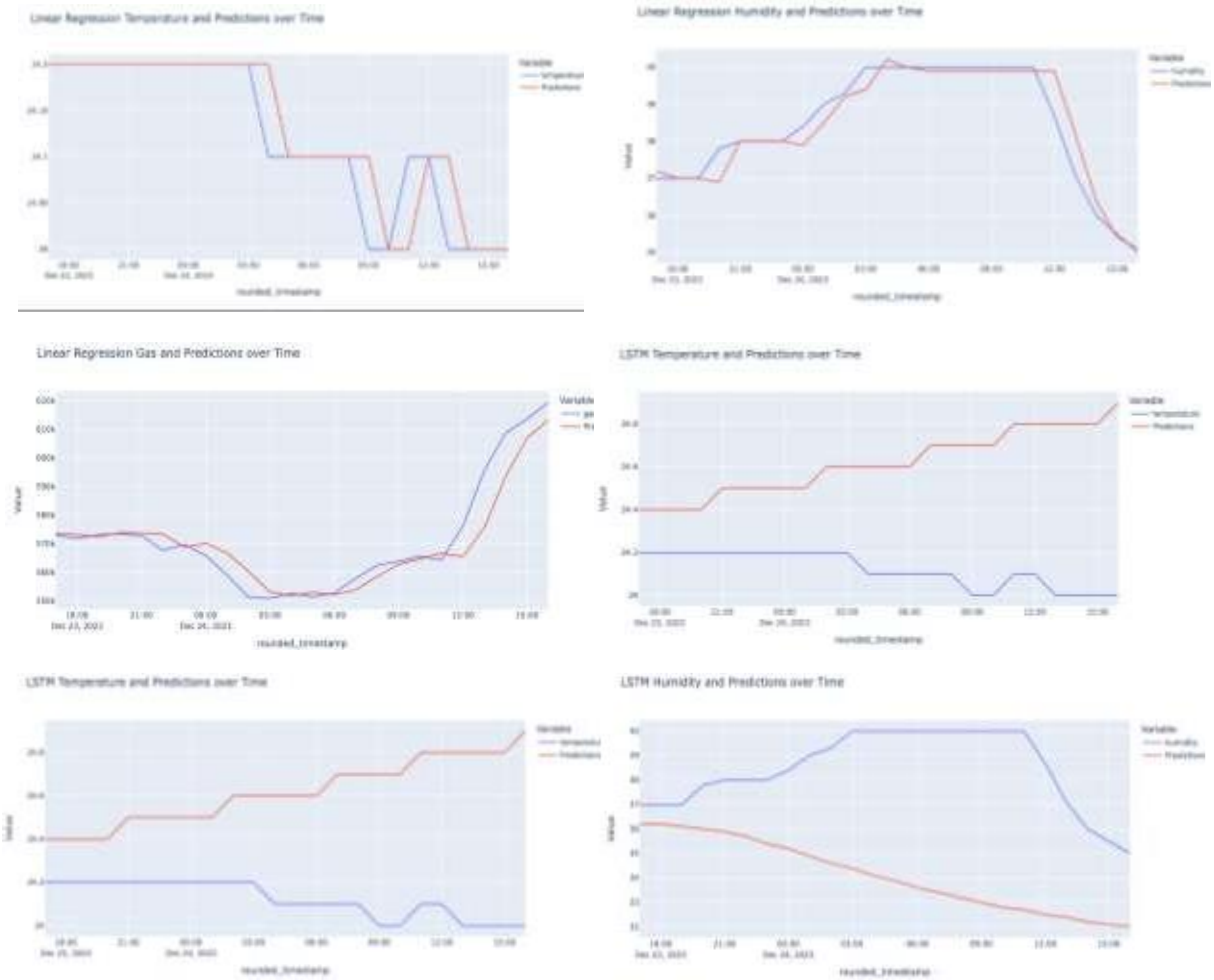

Figure 4.2: Timeseries plot for the actual parameter verses prediction of the models

4.4 Dashboard Visualizations

The developed Grafana monitoring dashboard proved to be an effective tool for real-time visualization of IoT sensor data and predictive model outputs. Key features of the dashboard include interactive line graphs that track temperature, humidity, and VOC gas concentration over time. These charts provide a comprehensive view of environmental conditions, allowing users to monitor changes and trends efficiently.

5. Conclusions and Recommendations

This research demonstrates the feasibility of integrating IoT-based analytics with predictive models to optimize academic infrastructure. Although primarily adopting established methodologies, such as ARIMA and Random Forests, the study validates the potential of end-to-end IoT implementation on a smaller scale. With an accuracy of 95% for 24-hour forecasts of temperature, humidity, and pressure, the models have shown promise. However, expanding sensor coverage and refining predictive techniques will further enhance performance and enable broader application across various academic spaces. The study found low occupancy during weekends, overnight hours, and holidays, revealing opportunities to conserve energy through demand-based HVAC scheduling. Automated systems should be programmed to switch off HVAC systems during non-use periods. Leveraging machine learning models like Random Forests, the system can predict peak usage times and pre-cool or pre-heat the lecture room in anticipation of high occupancy, improving both comfort and energy efficiency. Temperature data showed afternoon peaks beyond recommended levels, suggesting the need for cooling setpoints to be adjusted to 21°C–23°C during periods of heavy use. This fine-tuning can enhance thermal comfort without overburdening the system. Institutions might also consider installing smart thermostats that automatically adapt setpoints based on real-time sensor inputs. The sensor data revealed humidity levels exceeding 60%, posing risks of mold and bacterial growth. Installing dedicated dehumidifiers configured to maintain humidity within the 40%–60% range will prevent such problems while promoting better air quality. The use of XGBoost models can enhance humidity control by predicting spikes and triggering dehumidification systems preemptively. Further, the research identified VOC concentrations surpassing 4 million ppm during crowded periods, signaling inadequate ventilation. To address this, upgrading ventilation systems with HEPA filters and increasing air exchange rates will help maintain healthy indoor air. Strategically placing air quality sensors near HVAC vents and seating areas will provide more accurate environmental monitoring and allow real-time adjustments to ventilation. The study acknowledges the limitations of the current setup, such as the limited number of sensors and network disruptions that caused data gaps. Expanding the sensor network to cover multiple areas within lecture rooms, such as front, middle, and back sections, will offer better spatial coverage. Addressing network delays through redundant data storage solutions or backup data transmission protocols will enhance data continuity. Future research could explore cross-validation techniques to ensure model robustness under varying conditions. Additionally, the generalization of the models to other spaces—like administrative offices or larger lecture halls—remains a challenge. Transfer learning methods can be explored to adapt models built for one environment to other spaces with minimal re-training.

References

Al Hadi, A., Silva, C. A. S., Hossain, E., & Challoo, R. (2020). Algorithm for demand response to maximize the penetration of renewable energy. *IEEE Access*, *8*, 55279-55288.

Bhuiyan, S. M., Khan, J. F., & Murphy, G. V. (2017). Big data analysis of the electric power PMU data from smart grid. In *SoutheastCon 2017* (pp. 1-5). IEEE.

Chen, H.B., Zhao, H., Hua, Q., Ye, Y., Wang, H., Tan, S.X.D. & Tlelo-Cuautle, E. (2021). Thermal-sensor-based occupancy detection for smart buildings using machine-learning methods. *ACM Transactions on Design Automation of Electronic Systems (TODAES)*, *23*(4), pp.1-21.

Chung, W., & Yeung, I. M. H. (2020). A study of energy consumption of secondary school buildings in Hong Kong. *Energy and Buildings, 226*, 110388. https://doi.org/10. 1016/j.enbuild.2020.110388.

Coggins, A.M., Wemken, N., Mishra, A.K., Sharkey, M., Horgan, L., Cowie, H., Bourdin, E. & McIntyre, B. (2022). Indoor air quality, thermal comfort and ventilation in deep energy retrofitted Irish dwellings. Building and Environment, 219, p.109236.

Esrafilian-Najafabadi, M. & Haghighat, F. (2021). Occupancy-based HVAC control systems in buildings: A state-of-the-art review. Building and Environment, 197, p.107810.

Goyal, M. (2022). An Extended Approach Pertaining to the Energy Prediction of HVAC Plant using Machine Learning Techniques.

Guelpa, E. & Verda, V., (2019). Thermal energy storage in district heating and cooling systems: A review. Applied Energy, 252, p.113474.

Habib, R., Ahmed, S., & Patel, H. (2021). Technological integration challenges in optimizing HVAC systems for energy conservation. Journal of Building Technology and Environmental Engineering, 14(3), 189-203.

Huang, L., Chen, Y., & Wang, Q. (2018). Real-time data analytics for energy conservation in educational facilities. International Journal of Sustainable Engineering, 5(4), 210-225.

Jamwal, A., Agrawal, R., Sharma, M., Kumar, A., Kumar, V., & Garza-Reyes, J. A. A. (2021). Machine learning applications for sustainable manufacturing: a bibliometric-based review for future research. Journal of Enterprise Information Management, 35(2), 566-596.

Javaid, M., Haleem, A., Singh, R.P., Rab, S. & Suman, R. (2021). Significance of sensors for industry 4.0: Roles, capabilities, and applications. Sensors International, 2, p.100110.

Kim, T.-Y. & Cho, S. B. (2019) 'Particle swarm optimization-based CNN-LSTM networks for forecasting energy consumption', 2019 IEEE Congress on Evolutionary Computation (CEC) [Preprint]. doi:10.1109/cec.2019.8789968.

Krukowski, A., Smith, B., & Johnson, C. (2020). Comfort and productivity in educational settings: An empirical study. Sustainable Learning Environments Journal, 12(2), 45-61.

Li, J., Wang, H., & Zhao, X. (2020). User-friendly interfaces for conveying environmental insights: A case study of educational institutions. Journal of Sustainable Technology, 7(2), 78-94.

Lum, K. L., Mun, H. K., Phang, S. K., & Tan, W. Q. (2021). Industrial electrical energy consumption forecasting by using temporal convolutional neural networks. In MATEC Web of Conferences (Vol. 335, p. 02003). EDP Sciences.

Romano, P., Prataviera, E., Carnieletto, L., Vivian, J., Zinzi, M. & Zarrella, A. (2021). Assessment of the urban heat island impact on building energy performance at district level with the eureca platform. *Climate*, *9*(3), p.48.

Schwartz, Y., Godoy-Shimizu, D., Korolija, I., Dong, J., Hong, S. M., Mavrogianni, A., & Mumovic, D. (2021). Developing a data-driven school building stock energy and indoor environmental quality modelling method. *Energy and Buildings, 249*(2), 111249. https://doi.org/ 10.1016/j.enbuild.2021.111249.

Shafqat, W., Lee, K.T. & Kim, D.H. (2022). A Comprehensive Predictive-Learning Framework for Optimal Scheduling and Control of Smart Home Appliances Based on User and Appliance Classification. *Sensors*, *23*(1), p.127.

Shang, J., Liu, Y. & Lei, Y. (2021). OneNet-based smart classroom design for effective teaching management. In 2021 4th International Conference on Information Systems and Computer Aided Education (pp. 2746-2751).

Smith, M., Bevacqua, A., Tembe, S. & Lal, P. (2021). Life cycle analysis (LCA) of residential ground source heat pump systems: A comparative analysis of energy efficiency in New Jersey. *Sustainable Energy Technologies and Assessments*, *47*, p.101364.

Wadud, Z., Royston, S. & Selby, J., (2019). Modelling energy demand from higher education institutions: A case study of the UK. Applied Energy, 233, pp.816-826.

Yaïci, W., Krishnamurthy, K., Entchev, E. & Longo, M. (2021). Recent advances in Internet of Things (IoT) infrastructures for building energy systems: A review. *Sensors*, *21*(6), p.2152.