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RESEARCH ARTICLE

Optimizing air handling unit operations in clean rooms using artificial intelligence

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Abstract

Cleanroom HVAC systems are inherently energy-intensive, as they are required to maintain precise control over both temperature and humidity within stringent limits. Manual controls are no longer adequate, and they cannot adjust to changes in the environment in real time. To provide intelligent, real-time control of cleanroom HVAC, we developed a lightweight AI system using the Classification and Regression Tree (CART) method. Based on real-time inputs, the CART model is used to identify the current system condition and to accordingly predict the optimal operating parameters for the AHU (Air Handling Unit). The entire computation is carried out locally, which enables faster response times and eliminates dependence on cloud-based systems. The model's relatively simple and interpretable structure makes it easy for operators to understand and makes it suitable for edge-level implementation. This leads to the improved overall system performance in terms of robustness and reliability. We tested the proposed system in an ISO Class 8 cleanroom under controlled conditions. During the trials, the temperature remained stable and the humidity stayed within the required range. In addition, the system consumed less energy compared to the earlier setup. The results show that the approach can enhance cleanroom performance while reducing energy consumption.

Keywords: Energy efficiency, energy optimization, edge ai, cleanroom HVAC

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1. Introduction

Artificial intelligence (AI) is increasingly applied to engineering applications such as defect prediction and performance optimization [1],[2] Classification and Regression Tree (CART) models are particularly appropriate effective for developing control strategies in complex and uncertain systems[3],[4],[5]. The growing importance of AI for adaptive HVAC operation under changing occupancy and load conditions has been noted in recent literature [6]; [7]. This work aligns with the smart manufacturing and sustainability objectives of Robert Bosch GmbH, and was carried out at the Bidadi facility in the RBIN/FCM-Bidadi department, which is responsible for digital transformation and utility management. The main challenge within the cleanroom environment is used for assembling lambda (oxygen) sensors, is the requirement for stringent environmental control. However, due to changes in working schedules, workforce and component trials, the internal heat load fluctuates, making it difficult to maintain stable temperature and humidity setpoints.

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2. Industrial context and problem definition

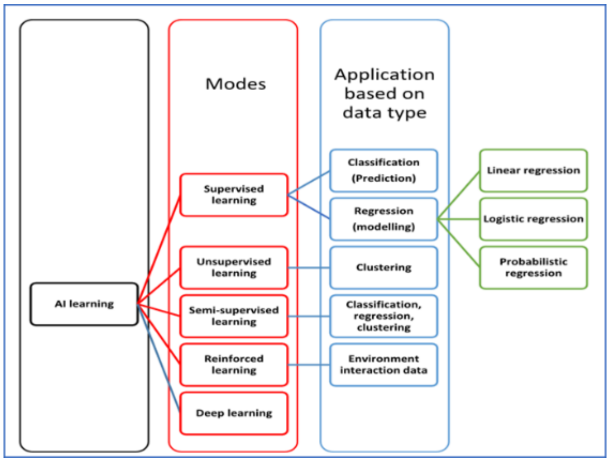


Figure 1. Artificial Intelligence-driven solution before the model implementation

The current manual operation of the HVAC system has caused a number of persistent issues:

a. Frequent deviations in temperature and humidity from the specified limits, along with changing environmental setpoints, resulted in uneven cooling and repeated user complaints.[8]
b. The operators had to enter the cleanroom to set the AHU settings which caused operational delays and increased overhead associated with safety compliance.
c. The AHUs often run at full capacity, irrespective of the actual thermal load, leading to energy waste, equipment stress, and higher operational costs. These problems were verified by sensor data from Bosch's monitoring system.

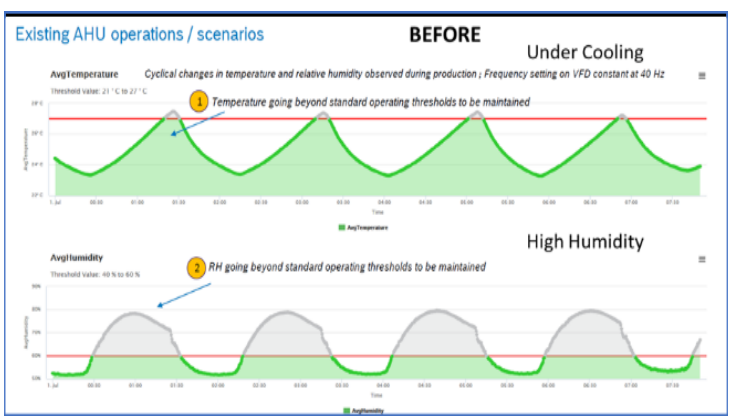


Figure 2. Temp & RH trends taken from online Bosch internal monitoring system before the model implementation

Decision-making process for ai implementation

Objective of the decision	The primary objective was to maintain the required temperature and humidity in the cleanroom despite fluctuating internal heat loads. A secondary goal was to enhance consistency, eliminate manual intervention, and improve energy efficiency.
Create context for success	Discussions were held with the assembly team to understand their concerns and gather data on environmental variations. Their actual operational requirements were documented. After internal review and approval from the department head, the team decided to transform these challenges into opportunities by adopting a digital transformation approach rather than continuing with manual correction activities.
Frame the issue properly	A detailed analysis was carried out to assess the impact of environmental deviations on assembly quality, production loss, and component condensation caused by high humidity. All AHU-related issues—including design limitations, current working load, and fluctuating production patterns—were listed and examined.
Generate alternatives	Several potential alternatives from an AHU perspective were evaluated, including: ➢ Manually adjusting blower speed according to heat-load variations ➢ Automating airflow adjustment using a differential pressure sensor ➢ Developing an AI-based control logic to modulate AHU blower speed based on real-time heat-load prediction
Evaluate alternatives	Each alternative was assessed with respect to feasibility and effectiveness: ➢ Manual blower-speed adjustments were deemed unsuitable due to unpredictable heat-load patterns. ➢ A pressure-switch–based solution offered partial improvement but could not accurately analyze or predict heat-load variations. ➢ The AI-based approach offered the most robust and advanced solution, supporting digitalization and predictive control.
Choose the best alternatives	Following a detailed review and team discussions, the AI-based heat-load prediction and blower-speed modulation system was selected as the most effective option to address existing environmental variations and enhance operational reliability.

Table 1. Decision Making Process

2.1. Cleanroom requirements for lambda sensor assembly

Our sensors need to be manufactured in a controlled environment.[9] The temperature should be between 23 and 25 degrees Celsius, and the humidity should be approximately 50%. It was difficult to keep it that way. When we changed the way, we worked or the number of people working the temperature and humidity changed too.

2.2. Sensor installation and data collection

To monitor and regulate the cleanroom environment, temperature and RH sensors were strategically installed and integrated into Bosch's Deep sight monitoring system. As shown in Figure 2.

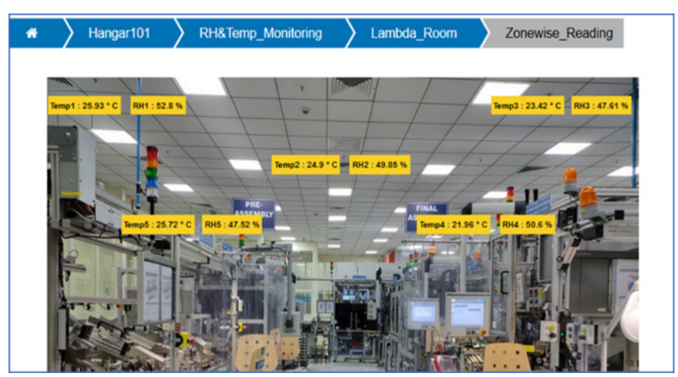


Figure 3. Internal Bosch Online monitoring system showing the RH and Temperature values

Over two months we collected 40,000 environmental data points across a range of operational scenarios. That provided us with useful training and pattern-recognition materials.

2.3. Observations on environmental variations

The data revealed cyclic variations in temperature even though the blower was run at a constant speed, indicating that the system was not adjusting.The high humidity levels were uncomfortable for the workers and raised concerns about corrosion.[10] Overcooling during calm nights increased the likelihood of condensation. Real-time monitoring clearly indicated that the AHU configuration was not responsive enough. implementation

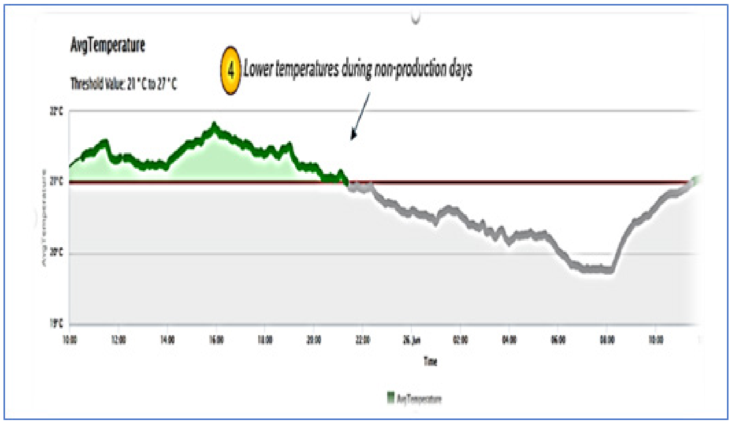


Figure 4. Temperature trends taken from online Bosch internal monitoring system before the model implementation

2.4. Root cause analysis

Our analysis was additionally extended by 5-Why analysis and cause and effect diagrams [11]. The root cause analysis identified three issues, irregular use of the Air Handling Unit (AHU), sometimes excessive and sometimes insufficient, variation in internal heat load due to dynamic occupancy, [12] and absence of automated feedback to control blower speed. Together,these factors resulted in unstable environmental conditions in the cleanroom. To idetify the root causes, a 5-Why analysis and a cause-and-effect diagram were created.

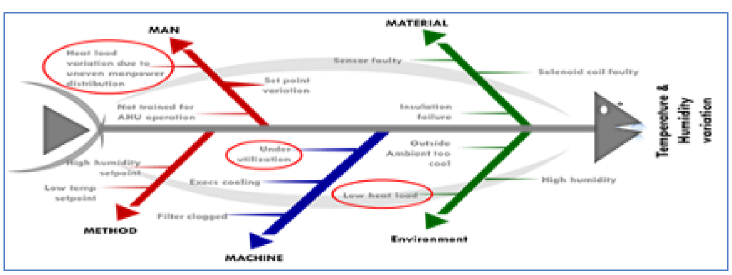


Figure 5. Ishikawa diagram done by the primary author as part of internal root cause identification

2.4. Root Cause Analysis using 5Why for AHU/Assembly Issues

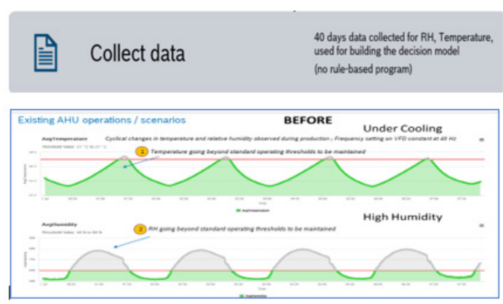
Table 2. Root Cause Analysis of AHU/Assembly Issues

SL No	Root cause 1: Under utilization	Root cause 2: Fluctuating heat load	Root cause 3: No/Less heat load
1. Why?	No optimum load for AHU	Uneven Manpower distribution in assembly enclosure	No/ Less heat load during night shift for AHU
2. Why?	Workforce & equipment heat load not sufficient/varying	No fixed assembly target & fluctuating target	No assembly but AHU must run
3. Why?	Component trail & customer approval is going on	Customer order not yet finalized	24 X 7 Humidity level to be maintained in assembly cleanroom
4. Why?	New product & system utilization is less	New component	
5. Why?	Intermediate issue		

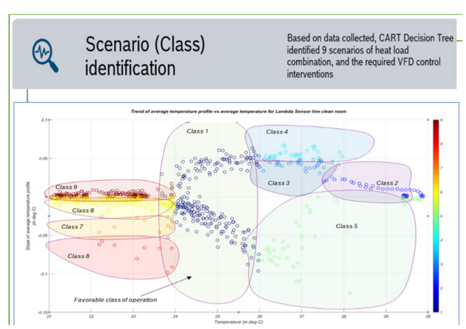
2.5. Methodology

We began by collecting the data, identifying operational scenarios (classes), building and evaluating the CART model and deploying the model.

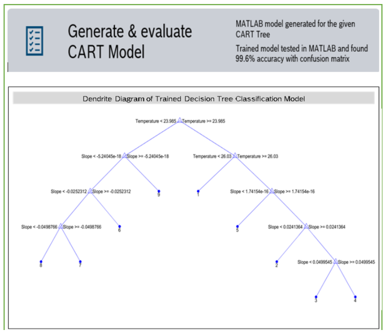
A. Collection of data



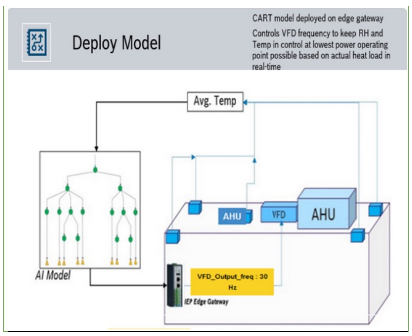
B. Scenario (Class)identification



C. Generate & evaluate CART Model



D. Deploy Model



3. Model building and implementation

3.1. Data cleaning and feature extraction

Our dataset was cleaned and relevant features were extracted. The slope represented the rate at which heat loads varied. Using a scatter diagram of temperature versus slope, We created groups corresponding to nine distinct patterns.

The CART model had the following characteristics :

- Temperature (°C)
- percentage of relative humidity
- Temperature Slope (°C/min): calculated over a period of five minutes
- Former Class State (used to maintain stability across changes)
- Rate of Sensor Sampling:

One sample per minute from the temperature sensor

One sample per minute from the relative humidity sensor

Slope Calculation Formula:

$$\text{Slope} = \frac{T(t) - T(t - 5\text{ min})}{5}$$

This curve represents the rate of temperature change and shows the real-time dynamics of heat-load. A scatter plot of temperature vs slope, revealed nine distinct patterns corresponded to various environmental circumstances.

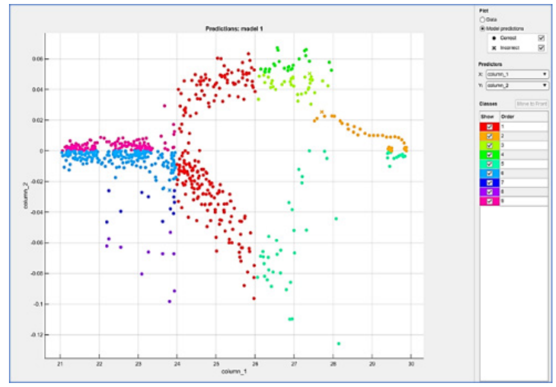


Figure 6. Scatter diagram showing predicted class values(generated using MATLAB)

3.2. Slope-based classification for control logic

Nine classifications have been created from the data: slope ranges: (negative, neutral, and positive) and temperature zones (low, medium, and high).

Each class was associated with a particular action for using the VFD to adjust the blower speed.

Validation of Class Definitions:

The identified patterns were grouped into nine distinct classes, each class corresponds to a specific VFD blower-speed control action. [13] These classes were analysed and validated using MATLAB plots, and input from domain experts, particularly for boundary cases in which classification was ambiguous. Proper care was taken to ensure correct labelling under such conditions. These validated classes were used to develop a rule-based AI system to generate control actions based on real-time operating conditions [14]. This helps the system respond to actual environmental variations observed inside the cleanroom....

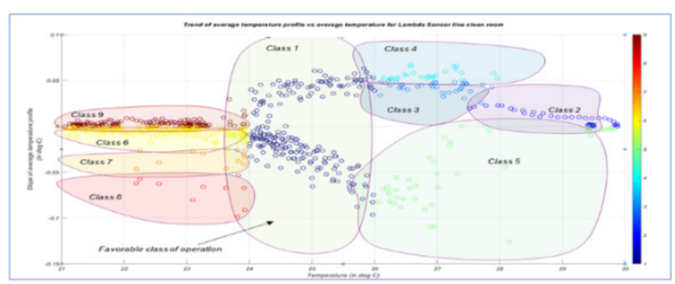


Figure 7. Classification diagram classifying the heat load class of the heat load conditions over the observation period from primary author

3.3. Model workflow and architecture

Process: The sensors collect date every minute,

The slope is calculated over the last 5 minutes.

The current environmental condition is determined using nine-class logic. The frequency of VFD was changed from 30 to 50 Hz.

All of this was done via an Edge Gateway connected to the Bosch network [15], and decisions were made locally without the need for a central server.

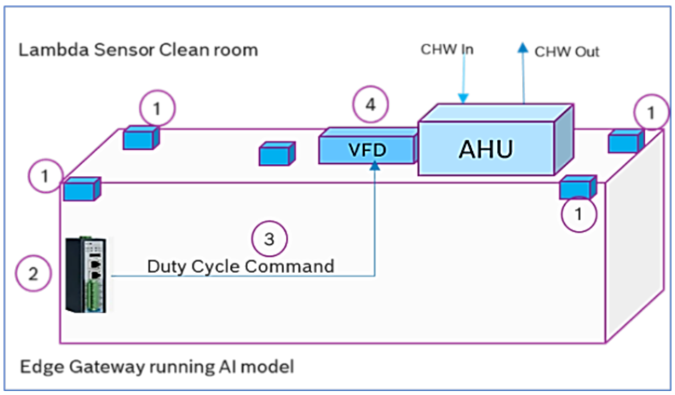


Figure 8. Installation diagram for Edge AI based optimisation control of Air handling units

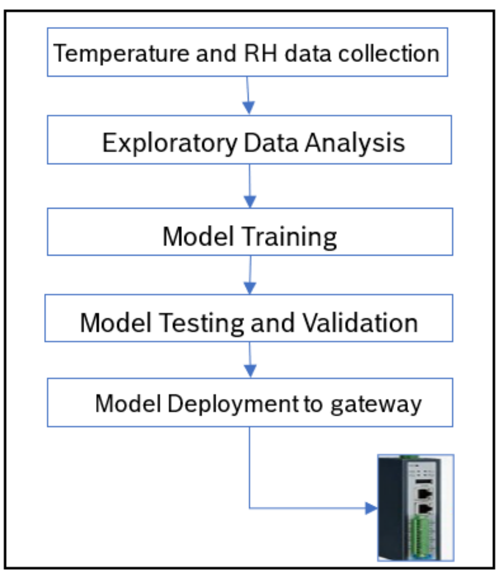


Figure 9. Sequence of Process Flow of the Air Handling Unit

3.4. CART-based testing and validation

Data were split 70% for training and 30% for testing. Performance summary:

- Accuracy: 99.6
- Precision: 0.98
- Recall: 0.97
- F1-Score: 0.97

Confusion Matrix Interpretation:

Only three misclassifications (mainly during suddenheat-load changes). The confusion matshowed

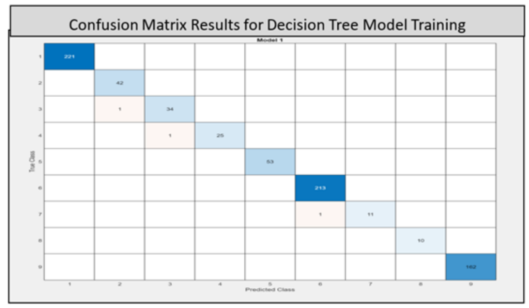


Figure 10. Identifying of leaves in a decision tree for the given training data set generated in MATLAB

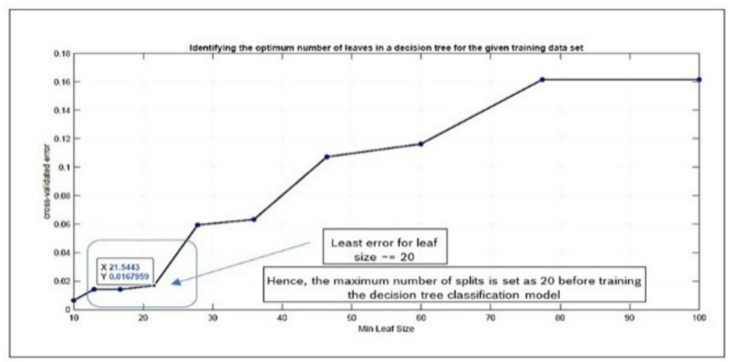


Figure 11. Confusion Matrix Results for Decision Tree Model Training generated model performance

3.5. Edge integration and system parameters

AI was implemented on an edge device(ECU-1251-2LAN 4COM Gateway)to manage real-time control independently of the cloud

System specifications:

VFD frequency range: 30–50 Hz.

Airflow: 1200–1500 CFM.

Communication Modbus/BACnet.

These specifications ensured environmentally friendly and energy efficient AHU operation that [16].

ECU-1251-2LAN 4COM Modbus/BACnet/101/104/DNP3/PLC/Azure/AWS IoT Gateway

Figure 12. Edge Device used in the AI model used for Heat & humidity Calculation

Validation

We compared live AHU responses with model predictions across all nine classes and found that the VFD's behaviour matched the model outputs exactly

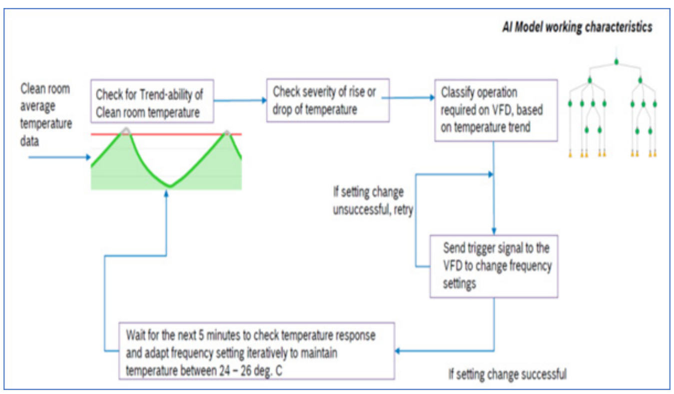


Figure 13. Model workflow for Validation of the model implementation

3.6. Experimental setup / cleanroom specifications

Cleanroom Environment

Testing was performed in a Class 1000 Bosch cleanroom, maintaining strict temp and RH to ensure product quality. Specs:

1. Room Volume-120m3
2. temp-23± 2degree C
3. RH-50± 10%
4. Changes-25 to 30 per Hour

VFD control logic transformed class outputs into blower-speed adjustments, maintaining settings where they needed to be.

Sensors and Instrumentation

High-accuracy sensors were used for continuous real-time monitoring of environmental parameters [17].

Parameter	Sensor Manufacturer & Model	Accuracy / Range
Temperature (°C)	Siemens QFA21	±0.5°C (0–50°C)
Relative Humidity (%)	Honeywell HIH-4000	±2% RH (0–100%)
Airflow (CFM)	TSI 8362	±3% of reading
Chilled Water Flow / BTU	Endress+Hauser	±1%

Table 3. Data of Parameters post-deployment of High accuracy sensors

- Sensors were calibrated before deployment to ensure accurate measurements.
- Data were collected at 1-minute intervals and logged into the Bosch internal monitoring system.

VFD Control Logic

The Variable Frequency Drive(VFD)controlling the AHU blower was linked to the AI model outputs through a class-to-frequency mapping as summarized below:

Control Class	Predicted Heat Load	VFD Frequency (Hz)
Low	< 500 W	35–45
Medium	500–1000 W	45–55
High	1000–1500 W	55–65
Very High	> 1500 W	65–70

Table 4. Data of the VFD controling the Blower

- The AI model categorized real-time temperature slopes and environmental measurements into these control classes.
- The VFD was used to dynamically control blower speed based on the mapped frequency to minimize energy consumption while maintaining prescribed temperature and relative humidity limits.

Airflow and Ventilation Balance

CFD models were used to analyze airflow patterns, ensuring laminar flow in critical areas, maintaining balance between supply and exhaust, and minimizing the formation of hot and cold spots.

Heat Load Estimation

The internal heat load in the clean room was estimated from environmental sensor data and internal equipment. The contribution of individual pieces of equipment was calculated by converting their power ratings into equivalent thermal loads (in watts). In addition, the rate of change of temperature (temperature slope) was used as an indicator of environmental heat variations.

To evaluate the impact of the proposed system, energy consumption was monitored using chilled water BTU meters before and after AI implementation, providing a direct measurement of energy usage.

3.7. Classification and regression tree (cart)

The Classification and Regression Tree (CART) model was chosen for the AI-based cleanroom control system for a number of technical and practical reasons. The main reason is that it has a transparent and rule-based structure, which makes it easier for operators to understand the model's decision-making process. Moreover, compared with models such as neural networks and support vector machines. it has shorter training times and requires relatively low computational resources. It also performs well on structured datasets commonly encountered in cleanroom settings.

Hyperparameter tuning was performed using a grid search, considering parameters such as maximum depth, minimum samples and splitting criteria. Pruning was used to reduce overfitting, and k-fold cross-validation was used to evaluate model performance. These decisions are supported by previous studies indicating decision-tree based methods are reliable for fast and interpretable HVAC control applications.

3.8. Data preprocessing

The dataset, consisting of around 40,000 data points, was prepared as follows:

- Data were collected directly from the cleanroom using sensors measuring temperature and relative humidity to ensure quality and reliability, as this work is data driven process [18].
- Missing values (less than 2%) were filled using linear interpolation.
- Class imbalance was addressed using random over-sampling.
- Feature values were normalizing to the interval [0,1].
- Outliers were removed using the Interquartile Range (IQR) method.
- Noise reduction was performed using a moving average filter with a window size of five.

4. Results and discussion

After deploying the AI system, we monitored the cleanroom for over 15 days. Environmental conditions remained within the target ranges:

- Temperature stuck to 23 ± 2°C
- RH held at 50 ± 10%

Statistical validation showed that temperature deviation decreased from 2.8°C to 1.9°C and that RH variance decreased; both changes were confirmed by paired t-tests.

4.1. Environmental stability

Table 5 presents the mean, variance, and range of temperature and RH before and after AI implementation shows the temperature and relative humidity statistics before and after the implementation of the intelligence model showcasing the stability and performance during operation [19].

Parameter	Baseline (Before AI)	After AI Deployment	% Reduction in Variance
Temperature (°C)	Avg: 25.1 ± 2.8	Avg: 23.2 ± 1.9	32%
Relative Humidity (%)	Avg: 56 ± 12	Avg: 51 ± 8	33%

Table 5. The Temp and RH Statistics (Baseline vs AI Model)

4.2. Energy consumption

The proposed AI-based approach dynamically modulates blower speed, [20] yielding approximately a 60% reduction in blower energy consumption. This enhancement is clearly underlined by an analysis comparison between the baseline system and the AI-based model [21].

Component	Baseline Energy (kWh/day)	AI Model Energy (kWh/day)	% Reduction
AHU Blower	500	200	60%
Chiller	850	750	11.83%
Total	1350	950	29.6%

Table 6. Energy Consumption Comparison (Baseline vs AI Model)

Sample calculation for % reduction**:**

$$\%\text{Reduction} = \frac{500 - 200}{500} \times 100 = 60\%$$

4.3. Operational autonomy and blower speed distribution

The AI model processed real-time environmental data, calculated slopes, mapped readings to the appropriate control class, and operated continuously without human intervention. It provides evidence that an interpretable, edge-ready AI can achieve precise climate control in advanced manufacturing cleanrooms, [22] thereby improving quality and efficiency. (Gao et al.2024).

Blower Speed (Hz)	% Time (Baseline)	% Time (AI)
30–40	15%	5%
40–50	40%	25%
50–60	35%	55%
60–70	10%	15%

Table 7. AHU Blower Speed Distribution (Baseline vs AI Control)

The AI model concentrated the blower's operation in the 50-60 hz range, energy consumption

4.4 Limitations and future work

Despite the observed improvements, certain limitations remain. The current model not capture the seasonal variations and external disturbances such as door openings and maintenance works [23]. The models robustness and adaptability could be increasing the training periods . In addition, system scalability can be enhanced through integration with a centralized building management system.

In the future, this model might be improved to investigate heat produced by spinning shafts at bearings [24]; and heat produced by smart beams in use [25]providing an air heating system. In buildings equipped with air heating systems, indoor climate is commonly controlled based on a reference zone, which leads to unsatisfactory thermal condition in the other zones. In addition, this strategy is not energy-efficient for buildings due to overheating that can occur in some zones. This study presents control logic for a novel-designed demand-controlled ventilation and air heating system and develops a variable air volume (VAV.

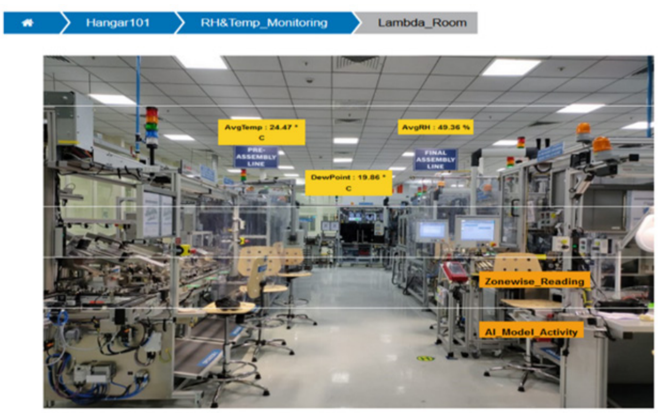


Figure 14. Controlled Temperature & Humidity & within the Cleanroom Range

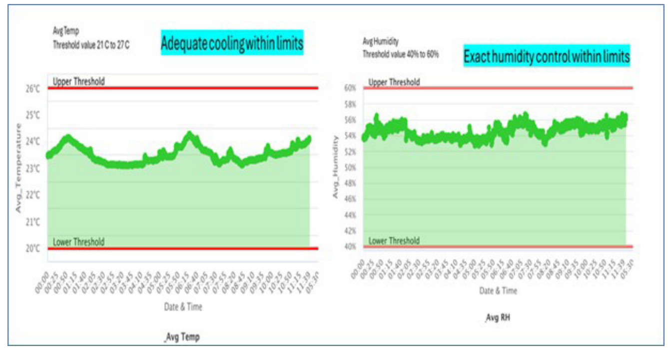


Figure 15. Temp & RH trends taken from online Bosch internal monitoring system After the model implemented

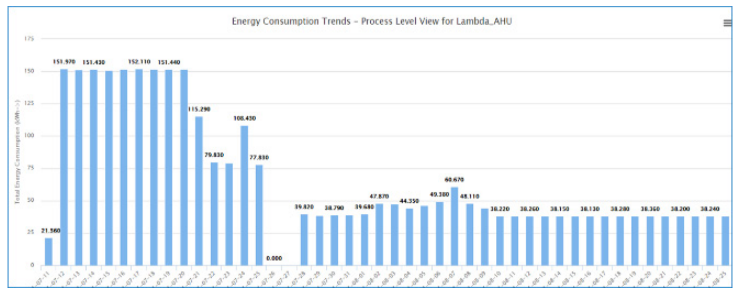


Figure 16. Energy Reduction taken from online Bosch internal monitoring system after the model implementation

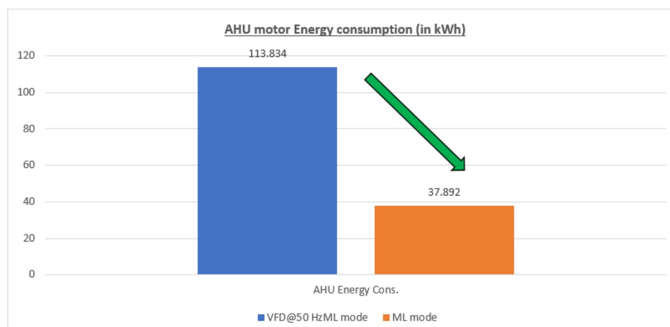


Figure 17. Energy savings comparison for AHU motor with & without AI model, energy data taken from Bosch internal EMS

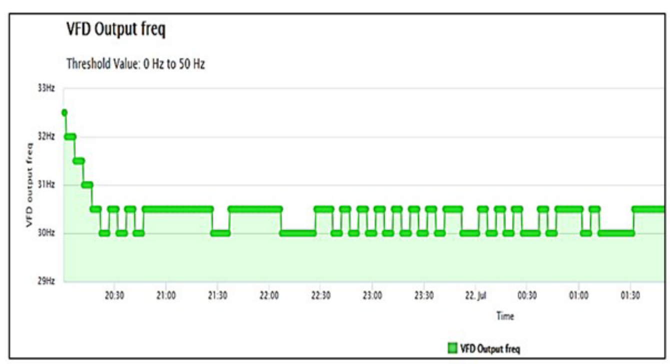


Figure 19. VFD modulation trends as per the commands from AI model to preadjust according to the predicted heat load taken from Bosch internal monitoring system

5. Conclusion

It is concluded that. The air handling unit in the cleanroom can be controlled by the artificial intelligence system, [26].

The mechanism keeps the humidity and temperature within the desired levels.[27]ventilation and air conditioning (HVAC.

The system provides a scalable method for controlling the cleanroom's air handling equipment. This reduces energy consumption. Certain restrictions apply to the system.

In future work, longer training-data periods and occupancy sensors may be included. To distribute the benefits across multiple zones or facilities, the technology can be integrated into a building management system.

The artificial intelligence system creates groundwork for artificial intelligence integration into air conditioning, heating, and ventilation systems,

The use of Al in HVAC systems, in general, can pave the way for its wider application in smart manufacturing and facility management

Appendices

1. Artificial intelligence-driven solution
2. Decısıon -makıng process for aı ımplementatıon
3. Root cause analysis using 5 why
4. Ishikawa diagram-fish bone diagram
5. Scatter diagram showing predicted class values (generated using MATLAB)

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