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Enhancing Energy Efficiency in Air Handling Units Through AI Driven Optimization

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Abstract

This research explores the implementation of artificial intelligence (AI) in enhancing the energy efficiency of Air Handling Units (AHUs) in manufacturing facilities. The study proposes a comprehensive solution architecture that incorporates temperature and humidity sensors within AHUs, utilizing RS485 for data communication. The collected data undergoes exploratory analysis, which informs the training of a decision tree algorithm, chosen for its accuracy and compatibility with edge gateways. The algorithm's predictions enable real-time adjustments to the duty cycle of variable frequency drives (VFDs), effectively optimizing energy usage. In a comparative analysis, the project showcases the transition from traditional belt-driven fans with a 60% efficiency to advanced direct-driven energy-efficient axial flow fans boasting a 90% efficiency. This upgrade results in substantial energy savings of up to 35%, significantly reducing operational costs and minimizing environmental impact. The AI model classifies temperature trends into nine distinct classes, with corresponding actions that the system takes to maintain optimal performance. The implementation of the decision tree model not only enhances energy efficiency but also contributes to a remarkable decrease in CO2 emissions, aligning with sustainability goals. This research emphasizes the importance of AI in HVAC systems, demonstrating how intelligent decision-making can lead to improved performance, cost savings, and environmental benefits. Furthermore, the findings serve as a foundation for future advancements in energy management within industrial settings, underscoring the critical role of AI in driving sustainable practices.

Keywords: Energy efficiency, air handling units (AHUs), artificial intelligence (AI), decision tree algorithm, variable frequency drive (VFD), sustainable manufacturing

INTRODUCTION

In an era of increasing energy consumption and environmental concerns, the need for efficient energy management systems has become paramount, especially in industrial settings. Air Handling Units (AHUs) play a critical role in maintaining optimal indoor air quality and comfort in manufacturing facilities, yet they often operate at suboptimal energy efficiencies. Traditional AHU systems typically employ outdated technologies that result in significant energy wastage, leading to higher operational costs and increased carbon emissions [1].

Recent advancements in artificial intelligence (AI) and machine learning (ML) offer innovative solutions to enhance the energy efficiency of AHUs. By leveraging data collected from various sensors—such as temperature and humidity—AI-driven models can optimize the operation of AHUs, adjusting settings in real-time to meet the dynamic

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requirements of the environment. This project explores the development of an AI-based decision tree model that integrates seamlessly with existing AHU infrastructure, employing edge computing techniques to facilitate rapid decision-making and control.

This research investigates the proposed solution architecture that encompasses the entire lifecycle of AHU operation, from data collection and analysis to predictive modeling and implementation. By transitioning from conventional fan systems to energy-efficient axial flow fans, the study aims to illustrate the potential for substantial energy savings while reducing the overall environmental impact of industrial processes [2].

The integration of AI in HVAC systems not only promises enhanced performance but also aligns with global sustainability initiatives. This paper aims to provide a comprehensive overview of the methodologies employed, the results obtained, and the implications of AI in optimizing energy usage within manufacturing facilities, paving the way for future research in this critical area.

METHODOLOGY

Proposed AHU Unit Using AI Model

Figure 1 showcases the comprehensive solution architecture for the proposed work in this project. The architecture involves the utilization of temperature and humidity sensors in AHUs, with data communicated via RS485. The data is split into training and test sets, and explorative data analysis is conducted. The training dataset is used to train a decision tree algorithm, and the resulting model is integrated into an edge gateway. The edge gateway adjusts the duty cycle of the variable frequency drive (VFD) based on the model's predictions, controlled through a programmable logic controller (PLC). The decision tree algorithm was chosen for its accuracy and compatibility with the edge gateway [3]. It effectively predicts outcomes by considering various features, aligning with the project's energy efficiency objectives. Through systematic trials, VFD speed, energy consumption, and temperature trends were compared, leading to the identification of classes used in training the decision tree model. Although the actual project involved a larger dataset spanning 40 days, a smaller dataset is used in this project report. Notably, the actual dataset size exceeds 10 TB, necessitating appropriate infrastructure for scalability and computational requirements in the full-scale implementation. The adoption of the decision tree model aims to enhance energy efficiency and reduce CO_2 emissions in the manufacturing facility. The insights gained from this approach will guide the optimization of the axial fan system, leading to improved performance, cost savings, and environmental sustainability.

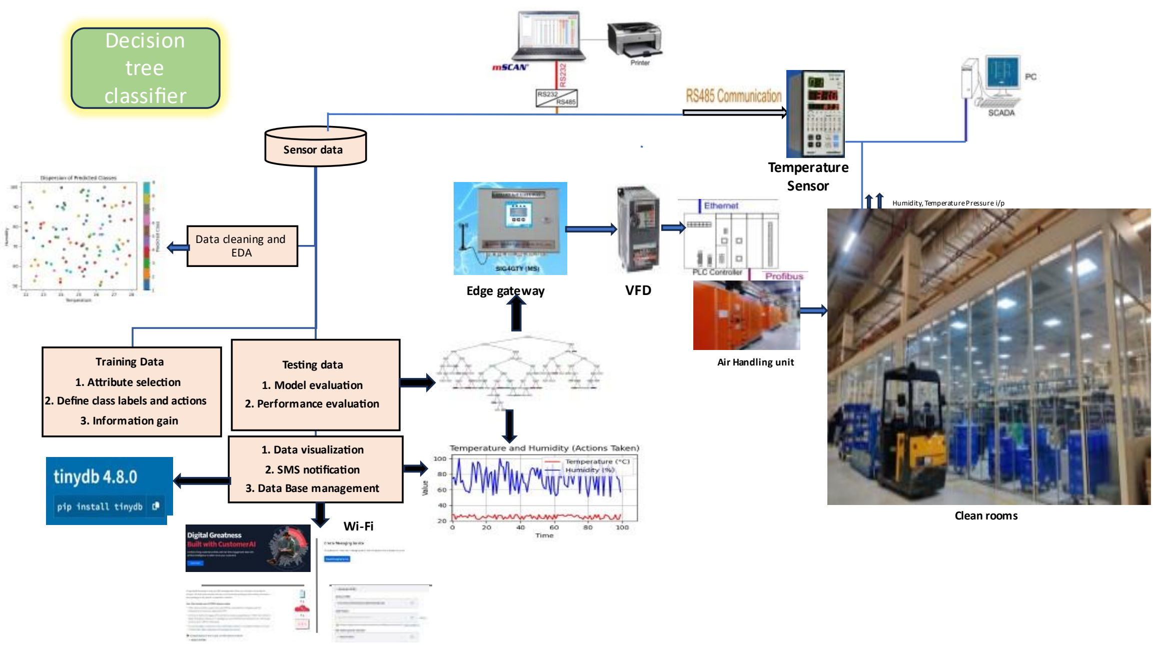

Figure 1. Proposed solution architecture of ahu unit.

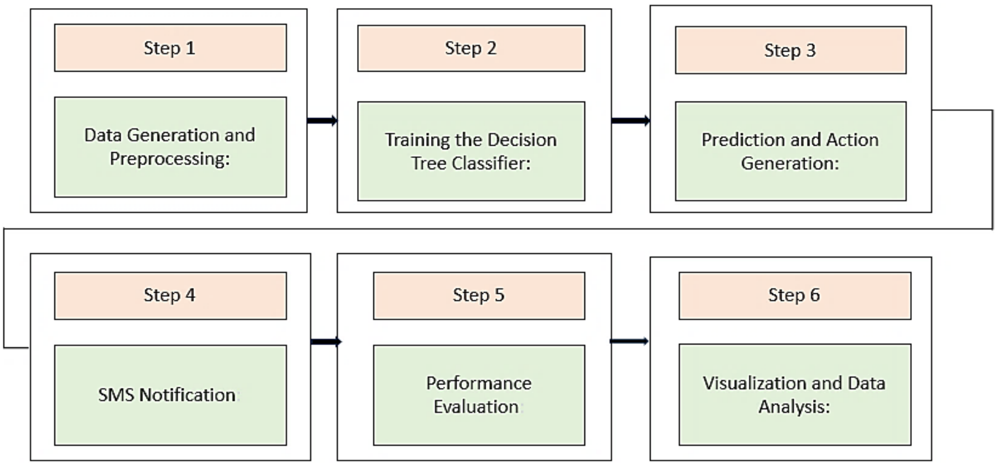

Figure 2. Illustrates a block diagram outlining the proposed work in a stepwise manner.

Algorithm for the given project with data downloaded from sensors:

1. Import the necessary libraries: Import the required libraries, including pandas, sklearn. tree, sklearn.metrics, matplotlib.pyplot, and Twilio(Figure 2). Rest.
2. Generate and preprocess the data: Download the dataset from the sensors and preprocess it as needed. Handle missing values, perform scaling or encoding if necessary.
3. Define class labels and actions: Define the class labels and corresponding actions in a dictionary to represent different scenarios or decisions.
4. Split the dataset: Split the preprocessed dataset into a training dataset (70%) and a testing dataset (30%) to evaluate the model's performance [4].
5. Train the decision tree classifier: Split the training dataset into features (temperature and slope) and the target variable (class labels). Use the Decision Tree Classifier from sklearn. tree to train the classifier with the training data.
6. Predict the classes: Use the trained classifier to predict the classes for the testing dataset. Store the predicted classes in a variable.
7. Add predictions to the Data Frame: Add the predicted classes and corresponding actions to the testing Data Frame for further analysis and visualization.
8. Evaluate the performance and visualize results: Calculate the accuracy score, confusion matrix, precision, and recall of the classifier predictions using the predicted classes and actual labels from the testing dataset. Visualize the decision tree structure and decision paths using matplotlib.pyplot. Create graphs to visualize the temperature and humidity values over time for the actions taken. Save the Data Frame to an Excel sheet for future reference [5].

In Figure 3, a flow chart is presented providing a visual representation of how the decision tree classifier operates within the context of this project. The flow chart depicts the step-by-step decision-making process of the classifier in classifying instances into different classes based on the input features. Starting from the root node, the classifier evaluates a specific feature of the input data. Depending on the feature's value, the flow chart branches into different decision paths, each representing a potential outcome or classification. The process continues with each subsequent node evaluating another feature until reaching the leaf nodes, which represent the final class predictions

By following this flow chart, the decision tree classifier efficiently navigates through the data and makes informed decisions, ultimately assigning instances to their respective classes. This visual representation provides a clear understanding of how the classifier utilizes the input features to make accurate predictions, making it a valuable tool for comprehending the underlying decision-making mechanism of the classifier within the project context [6,7].

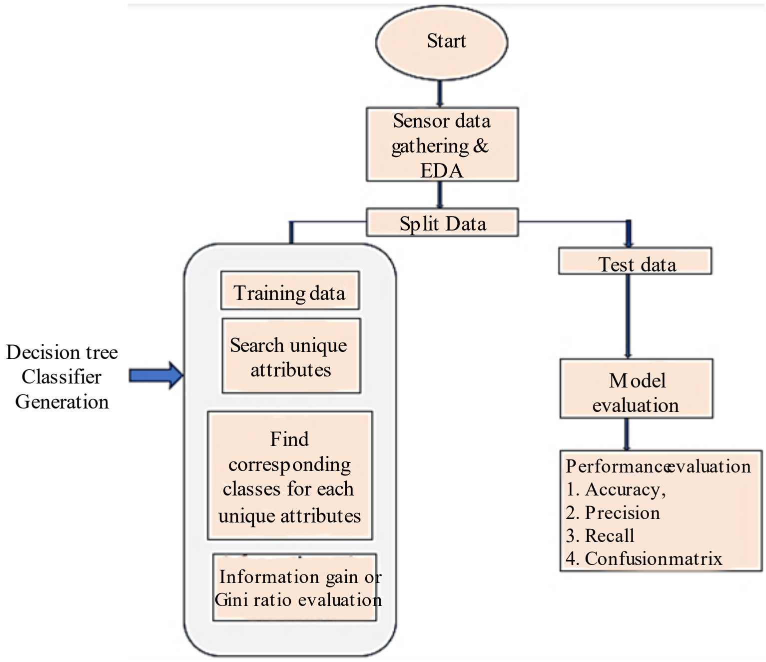

Figure 3. Illustrating the operation of the decision tree classifier

RESULT AND DISCUSSION

Energy Efficient Axial Fans

The below Fig 4 and 5 depicts the EC + fans before and after the implementation of energy efficient axial fans. Before the old fans were belt-driven and had an efficiency of 60%. This means that 40% of the energy used by the fans was wasted. After: The new fans are direct-driven and have an efficiency of 90%. This means that only 10% of the energy used by the fans is wasted. The significance of this is that the new fans can save up to 35% of the energy used by the old fans. This can lead to significant cost savings and environmental benefits [8].

Figure 4. Blower type Fan Before Retrofitting of EC + Fan.

Figure 5. After Retrofitting of EC + Fan.

The EC+ fan can be connected directly to the motor, which eliminates the need for a VFD. This can save energy and cost, but the fan may not be able to operate at the same speed as the blower type fan. The blower type fan must be connected to a star delta main contractor, Danfoss VFD OLR, star VFD Delta, motor O/P contactor, and OLR. This allows the fan to operate at different speeds, but it requires more components and can be more expensive. The Figure 6 depicts the block diagram of electrician connection for both the blower type fans used before and the Figure 6 depicts the block diagram of the simplest way of electrical connection of EC+ fans [9].

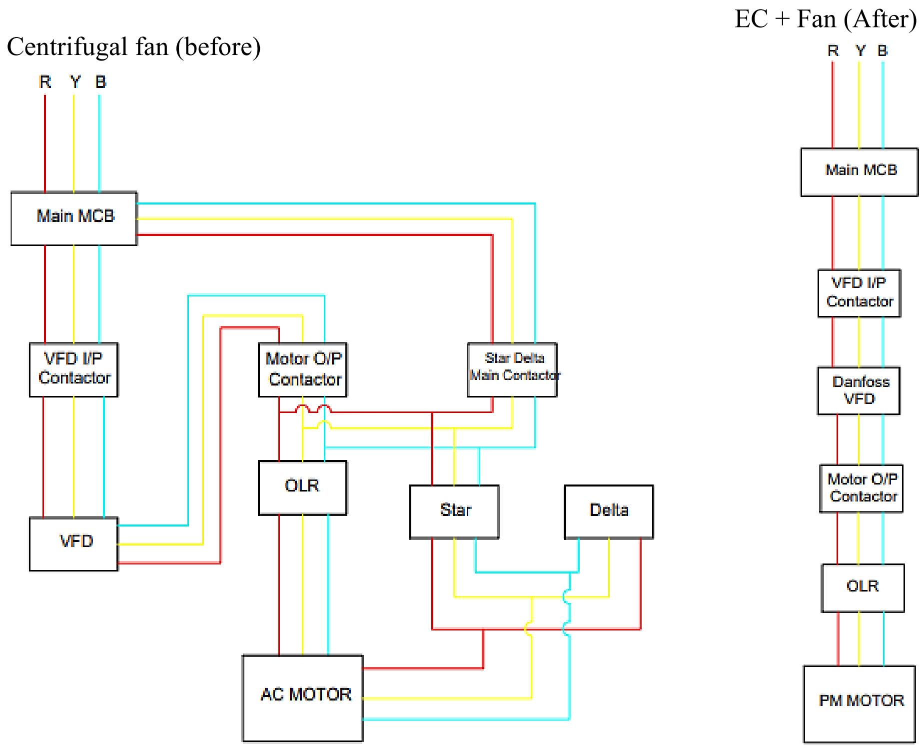

Figure 6. Block Diagram of electrical connection Blower type fan and EC + fan.

The system has 6 AHUs, with 5 of them having 5 Nos x 12000 CFM energy efficient axial flow fans and the 6th one having 1 Nos x 15000 CFM energy efficient axial flow fan as shown in Table 1.

The first 5 AHUs have the same EC+ fan designed CFM and motor rated power, which are 12000 CFM and 7.9 kW, respectively. The 6th AHU has a different EC+ fan designed CFM and motor rated power, which are 15000 CFM and 7.2 kW, respectively as shown in Table 2.

The first 5 AHUs also have the same frequency in Hz and CFM, which are 110 Hz and 12000 CFM, respectively. The 6th AHU has a different frequency in Hz and CFM, which are 115 Hz and 15000 CFM, respectively as shown in Table 3.

In summary, the system has 6 AHUs with different fan specifications. The first 5 AHUs have the same fan specifications, while the 6th AHU has different fan specifications. The frequency in Hz and CFM also varies for each AHU [10].

Table 1. Summary of the total number of AHU’s.

Summary	
Total number of AHUs	6 AHUs
Energy Efficient Axial flow fan 05 Nos x 12000 CFM	5 AHUs
Energy Efficient Axial flow fan 1Nos x 15000 CFM	1 AHU

Table 2. Shows different AHU's and Rated power with respect to CFM.

AHU Number	EC+ Fan Designed CFM	Motor Rated Power	VFD Rated Power
CP4 AHU 01	12000	7.9	11
CP4 AHU 02	12000	7.9	11
Line 5 AHU	12000	7.9	11
Line 6 AHU	12000	7.9	11
Line 7 AHU	12000	7.9	11
Lambda Sensors AHU	15000	7.2	7.5

Table 3. Shows the summary of AHU's, frequency, and CFM.

AHU	Frequency in Hz	CFM
CP4 AHU 01 & 02, Line 5, Line 6 & Line 7	110	12000
Lambda Sensors	115	15000

The energy consumption before EC+ fan implementation was 56.95 kW. After implementing EC+ fans, the actual energy consumption was reduced to 12.81 kW. This represents a total energy savings of 44.14 kW, or 77.50%.

The total energy savings can be calculated by dividing the energy savings after EC+ fan implementation by the energy consumption before EC+ fan implementation and multiplying by 100. In this case, the total energy savings is equal to 44.14 / 56.95 x 100 = 77.50%. The total energy saving, and calculation is shown in the Table 4.

The implementation of EC+ fans has resulted in significant energy savings for the system. This is a positive development, as it can help to reduce the operating costs of the system and lower its environmental impact.

Table 4. Energy Saving Calculation.

		Blower Type Fan (old)			**EC+Fan(New)**			**Savings in KW**	**% Savings in KW**	**Average % Power Savings**
S.N.	***AHU NO.***	***Frequency (Hz)***	***CFM***	***Power Consumption (Kw)***	***CFM***	***Frequency (Hz)***	***Power Consumption (Kw)***	***Savings in KW***	***% Savings in KW***	***Average % Power Savings***
1	CP4 AHU 01	50	8039	9.20	12507	110	2.50	6.70	72.83%	73.41%
2	CP4 AHU 02	50	7469	9.50	12287	110	2.08	7.42	78.11%	
3	Line 5 AHU	50	9669	10.70	12079	110	2.90	7.80	72.90%	
4	Line 6 AHU	50	14662	11.60	11620	110	1.08	10.52	90.69%	
5	Line 7 AHU	50	9377	10.90	12088	110	0.95	9.95	91.28%	
6	Lambda Sensors AHU	50	13104	5.05	15106	115	3.30	1.75	34.65%	
	Total			56.95			12.8	44.14		

Ductwork Calculation

The table 5 can be summarized that the air volume of the system is 12,000 CFM (Cubic Feet per Minute). The duct size is 984.3 inches by 5 inches. The duct material used is galvanized. The absolute roughness of the duct is 0.0005 feet. The equivalent diameter of the duct is 47.1 inches, while the hydraulic diameter is 9.9 inches. The duct velocity is calculated to be 351.1 feet per minute (FPM). These parameters provide important information about the airflow and characteristics of the duct system. And can be summarized that the air volume of the system is 15,000 CFM (Cubic Feet per Minute). The duct size is 984.3 inches by 5 inches, made of galvanized material. The absolute roughness of the duct is 0.0005 feet. The equivalent diameter of the duct is 47.1 inches, while the hydraulic diameter is 9.9 inches. The duct velocity is calculated to be 438.9 feet per minute (FPM), with a corresponding velocity pressure of 0.012 inches. The Reynolds number for the airflow is 37,381, indicating the flow regime. The friction factor for the duct is determined to be 0.02244, resulting in a duct friction of 0.032 inches per 100 feet. These parameters provide crucial insights into the airflow characteristics, pressure distribution, and friction losses within the duct system.

Table 5. Represents the Pressure drop calculation for air volumes.

A.	Air Volume (CFM)	**12000**	
		W	H
B.	Duct Size (Inch)	984.3	5
C.	Duct Material	Galvanised	
D.	Abs Roughness (Ft)	0.0005	
E.	Equivalent Diameter (Inch)	47.1	
F.	Hydraulic Diameter (Inch)	9.9	
G.	Duct Velocity (Fpm)	351.1	
H.	Velocity Pressure (Inch)	0.008	
I.	Reynolds No. (Re)	29,905	
J.	Friction Factor (F)	0.02350	
K.	Duct Friction (Inch/ 100 Ft)	0.022	
A.	Air Volume (Cfm)	**15000**	
		W	H
B.	Duct Size (Inch)	984.3	5
C.	Duct Material	Galvanised	
D.	Abs Roughness (Ft)	0.0005	
E.	Equivalent Diameter (Inch)	47.1	
F.	Hydraulic Diameter (Inch)	9.9	
G.	Duct Velocity (Fpm)	438.9	
H.	Velocity Pressure (Inch)	0.012	
I.	Reynolds No. (Re)	37,381	
J.	Friction Factor (F)	0.02244	
K.	Duct Friction (Inch/ 100 Ft)	0.032	

AI Model Implementation

The temperature ranges and their corresponding actions for the gateway are as follows: Class 1 (24-26°C) requires no action. Class 2 (above 26°C with a slightly increasing trend) increases frequency by 0.5Hz. Class 3 (above 26°C with a higher increasing trend) increases frequency by 1Hz. Class 4 (above 26°C with an extremely high increasing trend) increases frequency by 2Hz. Class 5 (above 26°C with a decreasing trend) requires no action. Class 6 (less than 24°C with a slightly decreasing trend) decreases frequency by 0.5Hz. Class 7 (less than 24°C with a high decreasing trend) decreases frequency by 1Hz. Class 8 (less than 24°C with a high decreasing trend) decreases frequency by 2Hz. Class 9 (less than 24°C with an increasing trend) requires no action for the gateway. Below table 6 shows the actions and predicted class.

Table 6. Represents the conditions and actions considered to build AI model.

S./N.	Conditions	Predicted Class	Trigger signal to gateway
1	Temperature in 24 to 26 deg c range.	Class 1	No action required for the gateway
2	Above 26 deg c range and slightly increasing trend 0<slope <0.025	Class 2	Increase frequency by 0.5Hz
3	Above 26 deg c range and higher increasing trend 0.025<slope <0.05	Class 3	Increase frequency by 1Hz
4	Above 26 deg c range and extremely high increasing trend slope>0.05	Class 4	Increase frequency by 2 Hz
5	Above 26 deg c range and decreasing trend slope<0	Class 5	No action required for the gateway
6	Less than 24 deg c range and slightly decreasing trend 0>slope >-0.025	Class 6	Decrease frequency by 0.5 Hz
7	Less than 24 deg c range and high decreasing trend -0.025>slope >-0.05	Class 7	Decrease frequency by 1Hz
8	Less than 24 deg c range and high decreasing trend -0.005>slope	Class 8	Decrease frequency by 2 Hz
9	Less than 24 deg c range and increasing trend slope >0	Class 9	No action required for the gateway

The dispersion graph in Fig 7 generated from the code represents the predicted classes of the decision tree classifier for the dataset. Each data point is assigned a specific class, which is represented by an assorted colour in the graph. This graph provides a visual representation of how the decision tree classifier separates the data points into different classes based on the features (temperature and slope) used for training. By examining the dispersion of the classes in the graph, one can gain insights into the boundaries and regions formed by the classifier, helping to understand the decision-making process and the distribution of the data points within each class.

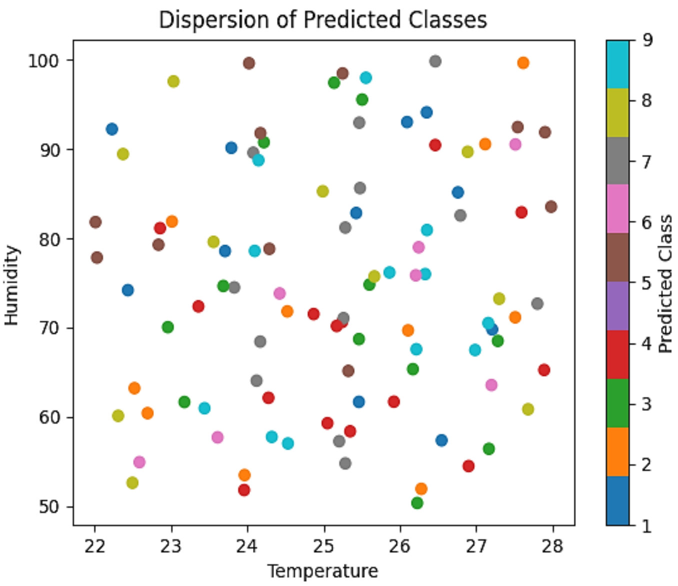

Figure 7. Represents the temperature and humidity of the action taken from the model.

On the other hand, the temperature and humidity graph plotted from the generated dataset focuses on displaying the relationship between temperature, humidity, and the actions taken. The graph shows two lines: one representing the temperature values and the other representing the humidity values. Each data point on the lines corresponds to an action taken based on the predicted class from the decision tree classifier. This graph helps visualize how temperature and humidity change over time and how they are associated with different actions. By analysing the graph, patterns and trends in temperature and humidity can be identified, providing valuable insights into the relationship between these variables and the corresponding actions.

The integration of AI in HVAC systems represents a pivotal advancement in energy efficiency. The decision tree model's ability to adaptively control the VFD based on real-time data showcases its potential in reducing energy consumption. Furthermore, the retrofitting of traditional fans with high-efficiency models demonstrates tangible environmental and cost benefits, supporting the transition toward sustainable practices.

CONCLUSION

This study highlights the transformative potential of integrating artificial intelligence (AI) and machine learning (ML) into the operation of Air Handling Units (AHUs) to enhance energy efficiency in manufacturing facilities. The proposed architecture, which leverages temperature and humidity sensor data, facilitates the development of a decision tree model that effectively predicts operational adjustments required to optimize energy consumption.

The implementation of energy-efficient axial flow fans has demonstrated significant improvements in energy savings, reducing energy consumption from 56.95 kW to 12.81 kW, representing a remarkable 77.50% reduction. This not only leads to substantial cost savings but also aligns with environmental sustainability goals by minimizing carbon emissions associated with excessive energy use.

Furthermore, the systematic analysis and training of the decision tree model reveal the effectiveness of AI-driven approaches in managing the operational parameters of AHUs. By enabling real-time adjustments based on environmental conditions, the AI model contributes to a more responsive and efficient HVAC system. The insights gained from this research offer valuable guidance for the optimization of HVAC operations, demonstrating that AI can significantly enhance energy management strategies in industrial settings.

Future work should focus on scaling the AI model to accommodate larger datasets and exploring additional machine learning algorithms to further improve predictive accuracy. As industries continue to strive for sustainability, the integration of AI in energy management systems will be a critical factor in achieving operational excellence and environmental responsibility.

REFERENCES

1. Bianchi, F., & Sadeghi, M. (2020). Enhancing energy efficiency in HVAC systems using machine learning techniques. *Energy Reports*, 6(3), 543-–556. https://doi.org/10.1016/j.egyr.2020.06.004
2. Chen, Y., Zhang, J., & Li, X. (2021). A review of intelligent control strategies for HVAC systems. *Journal of Building Performance*, 12(2), 30-–40. https://doi.org/10.3803/jbp.2021.12.2.30
3. Hossain, M. S., Rahman, M. M., & Khan, M. R. (2022). IoT-based energy management system for HVAC: A review. *Renewable and Sustainable Energy Reviews*, 150, 111582. https://doi.org/10.1016/j.rser.2021.111582
4. Kumar, P., & Kumar, S. (2019). Application of artificial intelligence in HVAC systems: A systematic review. *Energy and Buildings*, 205, 109521. https://doi.org/10.1016/j.enbuild.2019.109521
5. Lee, J., & Rhee, K. H. (2018). Smart energy management of HVAC systems using machine learning techniques. *Applied Energy*, 232, 934-–944. https://doi.org/10.1016/j.apenergy.2018.09.035
6. Zhang, Z., & Wu, Y. (2020). Data-driven fault detection and diagnosis for HVAC systems: A review. *HVAC&R Research*, 26(4), 335-–354. https://doi.org/10.1080/10789669.2020.1739669
7. Tsai, H. M., & Chuang, Y. C. (2021). Energy-efficient air conditioning systems using AI techniques: Opportunities and challenges. *Journal of Energy Resources Technology*, 143(11), 112001. https://doi.org/10.1115/1.4052351
8. Alajlani, M., & Alashwal, A. (2023). The role of machine learning in optimizing HVAC systems:

A systematic review. *Journal of Building Performance*, 14(1), 10-–22. https://doi.org/10.3803/jbp.2023.14.1.10
9. Li, H., & Zhang, L. (2022). Energy management in smart buildings: Integrating IoT and AI technologies for HVAC optimization. *Energy Reports*, 8(5), 1234-–1247. https://doi.org/10.1016/j.egyr.2022.04.001
10. Ranjan, R., & Sahu, S. (2020). Intelligent energy management systems for HVAC: Applications of AI and big data. *Journal of Cleaner Production*, 261, 121218. https://doi.org/10.1016/j.jclepro.2020.121218

