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Development of an Advanced Neuro-Fuzzy Algorithm for Intelligent Temperature Control System

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ABSTRACT:
The advanced modeling of a neuro-fuzzy algorithm for an intelligent temperature management system with the goal of maximizing energy efficiency and environmental regulation is presented in this research. The suggested algorithm offers a reliable and adaptable method of temperature control by combining the adaptive learning powers of neural networks with the human-like reasoning of fuzzy logic. In contrast to conventional control techniques like static fuzzy logic and proportional-integral-derivative (PID) controllers, this neuro-fuzzy model dynamically modifies its parameters in real-time to adapt to changing environmental conditions. The neuro-fuzzy method outperformed other algorithms in preserving target temperature levels, cutting response times, and consuming the least amount of energy during lengthy simulations. The outcomes validate that the algorithm is capable of managing the non-linearities and uncertainties present in complex contexts, such HVAC systems, industrial processes, and smart buildings. This work contributes to the field of intelligent control systems by providing a self-adaptive, scalable method for maintaining ideal environmental conditions, regulating temperature precisely with little to no human interaction, and saving energy.

Keywords: Neuro-fuzzy algorithm, intelligent temperature control, Fuzzy logic, HVAC, Python, PID

I. INTRODUCTION

The increasing complexity of industrial processes and the requirement for energy efficiency have led to a considerable growth in demand for more advanced and adaptive temperature control systems in recent years.

While traditional control systems work well in environments that are stable, they sometimes cannot adjust to dynamic changes, which results in inefficiencies and possible malfunctions in thesystem. The field of intelligent control is undergoing a revolution with the introduction of neuro-fuzzy algorithms into temperature control systems. These algorithms provide strong flexibility and improved decision-making abilities in unpredictable and dynamic contexts. These systems blend fuzzy logic, which manages imprecision and ambiguity in decision-making, with the strengths of neural networks, which are excellent at learning from data.

More intelligent and efficient temperature management systems are desperately needed as the world's energy consumption rises in order to maximize energy use while preserving comfort and process stability (Zhou et al., 2020). Because neuro-fuzzy systems are adaptive, they can adjust to changing environmental conditions and learn from them. This makes them ideal for a wide range of applications, from industrial process management to building HVAC systems. The development of neuro-fuzzy systems has accelerated because to recent advancements in processing power and algorithmic efficiency, which allow for their implementation in real-time control contexts (Angelov et al., 2020).

A fuzzy logic based design control system offers flexibility in system design and implementation, since its implementation uses “if then” logic instead of sophisticated differential or mathematical equations (K.A. Akpado, P. N. Nwankwo, et. al., 2018). This paper focuses on developing an advanced model of a neuro-fuzzy algorithm specifically tailored for intelligent temperature control, aiming to enhance accuracy, responsiveness, and energy efficiency.

A. Problem Statement:

Maintaining optimal temperature control is a critical challenge in various environments, such as industrial processes, smart homes, and agricultural

settings, where traditional control systems often struggle to balance efficiency, responsiveness, and adaptability. Conventional temperature control methods like PID controllers, though widely used, lack the capability to handle nonlinearities, uncertainties, and dynamic changes effectively. This limitation often results in suboptimal performance, increased energy consumption, and system instability. To address these challenges, there is a need for an advanced, intelligent temperature control system that can dynamically learn and adapt to changing conditions while maintaining stability and minimizing energy consumption. A Neuro-Fuzzy algorithm, which combines the human-like reasoning style of fuzzy logic with the learning capabilities of neural networks, offers a promising solution. However, the development and modeling of such algorithms for intelligent temperature control remain underexplored.

B. Aim of the project:

The aim of the project is to develop an advanced neuro-fuzzy algorithm for intelligent temperature control system.

C. The objectives of the project are:

1. To develop a robust and adaptive neuro-fuzzy algorithm that combines the learning capabilities of neural networks with the interpretability of fuzzy logic to optimize temperature control systems.
2. To reduce energy consumption by implementing an intelligent control mechanism that adapts to varying environmental conditions while maintaining optimal temperature regulation.
3. To develop an advanced Neuro-Fuzzy algorithm for intelligent temperature control systems that can dynamically adapt to changing environmental conditions and uncertainties.
4. To analyze the impact of the Neuro-Fuzzy algorithm on energy consumption, response time, and overall control accuracy, demonstrating its potential as a superior alternative to existing temperature control systems.

II.CONCEPTS OF THE PROJECT

This project introduces an advanced Neuro-Fuzzy algorithm designed to enhance the intelligence and adaptability of temperature control systems. The Neuro-Fuzzy approach integrates the strengths of fuzzy logic, which handles uncertainty and imprecision, with the learning capability of neural networks to create a system that can learn from data, self-tune, and adapt to changing environmental conditions. The goal of the suggested algorithm is to outperform conventional techniques in terms of response time, control precision, and energy efficiency while providing a reliable solution for challenging control issues. Figures 1 and 2 depict the block diagrams of a neural-fuzzy logic system and a conventional temperature control system, respectively.

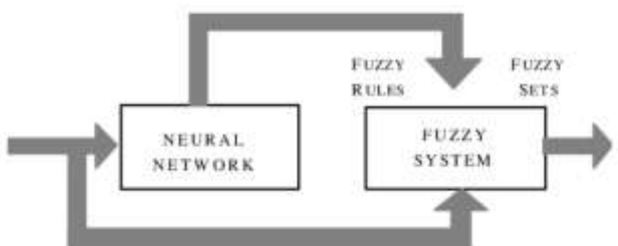

Figure 1: Simple block diagram of a neural-fuzzy logic system

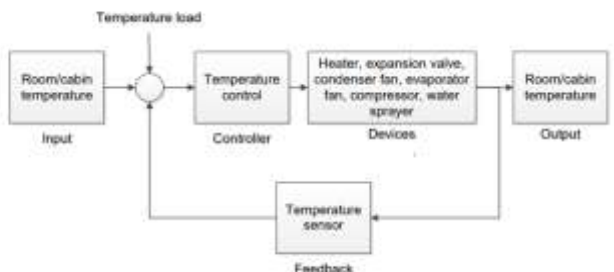

Figure 2: Simplify block diagram of a temperature control system

A. The Structure of Artificial Neural Networks (ANNs)

The input layer, hidden layers, and output layer are the three main layers that make up an ANN's structure (Goodfellow, Bengio, & Courville, 2016).

1. The input layer is in charge of obtaining the raw data and transferring it unaltered to further levels (Aggarwal, 2018).
2. To identify patterns and characteristics in the input data, the hidden layers modify weights to perform intricate computations (Zhang et al., 2021).
3. The output layer presents the ultimate forecast or outcome, which may encompass regression values, classification labels, or alternative consequences (Schmidhuber, 2015). Figure 3 depicts the architecture of neural networks.

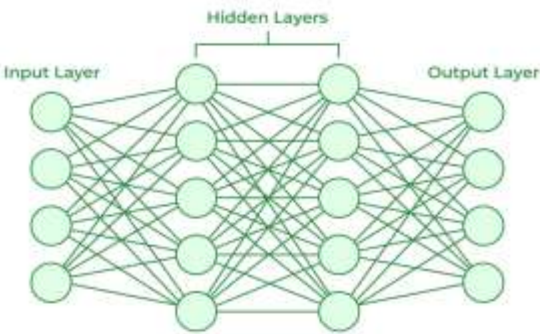

Figure 3: Neural Networks Architecture

Artificial neural networks are based on the architecture and functions of human neurons. Neural nets or neural networks are other names for it. An artificial neural network's first layer, known as the input layer, transfers data from outside sources to the second layer, known as the hidden layer. Each neuron in the hidden layer takes in information from the neurons in the layer above, calculates the weighted sum, and then relays it to the neurons in the layer below (Aggarwal, 2018). Because these connections are weighted, the effects of the inputs from the preceding layer are essentially maximized by giving each input a unique weight, which is then modified during training to improve model performance.Units are connected from one layer to another in most neural networks. The weights assigned to each of these relationships indicate how much effect one unit has upon the others. The neural network gains more and more knowledge about the data as it moves from one unit to the next, ultimately producing an output from the output layer.

B. Introduction to ANN Hybrid Systems:

Hybrid systems are intelligent system that is framed by combining at least two intelligent technologies like Fuzzy Logic, Neural networks, Genetic algorithms, reinforcement learning, etc. Because several methodologies are integrated into a single computational model, these systems have a wider range of capabilities. These systems have the ability to reason and learn in a vague and unpredictable environment. These systems are capable of doing tasks that need human competence, such as subject knowledge and noise adaptability. In this research, we model an intelligent temperature management system using the Neuro-Fuzzy algorithm.

C. Neuro-Fuzzy (Hybrid) Systems:

Neural networks and fuzzy logic are combined in neuro-fuzzy systems. Fuzzy logic deals with approximate rather than fixed or accurate reasoning, but neural networks excel at learning from data. Neuro-fuzzy systems create more flexible and adaptive models by fine-tuning the parameters of the fuzzy inference system using neural networks. Neuro-fuzzy systems are hybrid models that combine fuzzy logic's interpretability and reasoning with neural networks' learning powers (Lee & Pan, 2022). In these systems, neural networks learn from data in a way that mimics human thinking, which aids in optimizing the parameters of fuzzy inference rules (Cordón & Herrera, 2020).

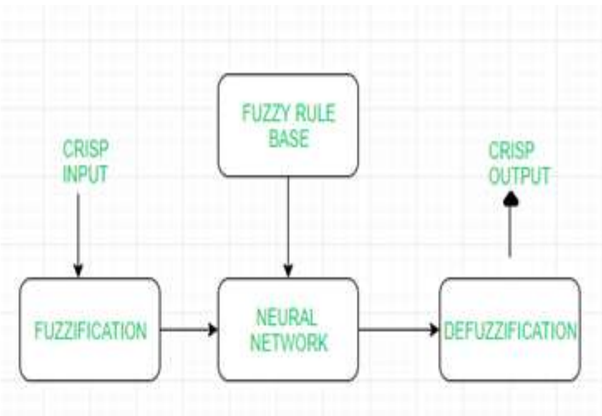

Figure 4: Simplified block diagram of a typicalNeuro-Fuzzy (Hybrid) system

Further developments in Neuro-Fuzzy systems have concentrated on improving their efficiency and scalability for applications in robotics, financial forecasting, and intelligent decision-making systems (Palit & Bandyopadhyay, 2022). Fuzzy logic, on the other hand, improves the interpretability of these models by managing uncertainty and imprecision through a set of easily understandable fuzzy rules (Mendel, 2021). This combination allows Neuro-Fuzzy systems to adaptively learn from complex data while retaining the ability to explain their decisions, making them suitable for real-world applications like autonomous systems and healthcare analytics (Jothi & Raj, 2023).

The strengths of neural networks and fuzzy logic are combined in neuro-fuzzy hybrid systems, which are made up of a few essential parts, to provide models that are both interpretable and adaptive. The primary parts of neuro-fuzzy hybrid systems are listed below.

1. Fuzzy Inference System (FIS): The core element of a neuro-fuzzy system that is in charge of reasoning and decision-making is the fuzzy inference system. It maps input variables to output variables using a set of fuzzy rules, which are if-then statements that make sense to humans. These rules are based on linguistic variables that allow for approximate reasoning and handle uncertainty (Mendel, 2021).

2. **Membership Functions**: The mapping between each input and a level of membership in a fuzzy set is specified by membership functions. They are employed to convert inputs from the real world into fuzzy values. Neural network learning techniques are utilized in Neuro-Fuzzy Systems to optimize the parameters and form of these membership functions (Cordón & Herrera, 2020).

3. Neural Network Component: The fuzzy system's membership functions and rule weights are two examples of its parameters that are automatically adjusted by the neural network component based on data. This part uses learning methods such as backpropagation to minimize the error between expected and actual outputs, allowing the system to adjust to new data (Lee & Pan, 2022).

4. Fuzzification Module: According to K.A. Akpado, P. N. Nwankwo, et al. (2018), the fuzzification module transforms clear numerical input values into fuzzy values so that the fuzzy inference system can analyze them. Real-world inputs are mapped onto appropriate fuzzy sets in this initial step of the fuzzy inference process (Jothi & Raj, 2023).

5. Defuzzification Module: The inference system's fuzzy output is transformed back into a precise numerical value by the defuzzification module. This element is necessary to understand the system's final output in a way that is practical for real-world uses (Palit & Bandyopadhyay, 2022).

6. Rule Base: A collection of ambiguous rules called the rule base control how the system behaves. These rules, which define the relationships between input and output variables in the form of "if-then" statements, are usually derived from expert knowledge or learnt from data (Zhou et al., 2023).

7. Knowledge Base: The database, which contains details on membership functions and parameters, and the rule base make up the knowledge base. All of the fundamental information required by the Neuro-Fuzzy System for adaptability and decision-making is kept in this component (Jothi & Raj, 2023).

8. Learning Mechanism: The learning mechanism, typically a neural network algorithm, is responsible for updating the parameters of the fuzzy system based on input-output data pairs. It uses algorithms like gradient descent to minimize error and improve system performance over time (Cordón & Herrera, 2020).

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III. METHODOLOGY

Implementing a neuro-fuzzy system for intelligent temperature control involves several steps, including defining the fuzzy logic system, creating a neural network, integrating both models, and simulating the control process. Our project deploys Python programming language to implement an intelligent Neuro-Fuzzy system for temperature control. We use libraries such as “numpy” for numerical calculations, “sklearn” for neural network implementation, and “matplotlib” for visualization. We also use the “scikit-fuzzy” library for fuzzy logic components.

Step-by-Step Implementation of the Neuro-Fuzzy Algorithm for an Intelligent Temperature Control System:
1. Define fuzzy variables and membership function.
2. Define the fuzzy rules for the intelligent temperature control system.
3.Simulate the fuzzy control system.
4. Train the neural network.
5. Integrate the neural and fuzzy models.

1. Define the fuzzy variables and membership function

We define the fuzzy variables:

A. Input Variables:
* Temperature: It can have values such as "Cold", "Warm", and "Hot".
* Humidity: It can have values such as "Low", "Medium", and "High".

B. Output Variable:
* Fan Speed: It can have values like "Slow", "Medium", and "Fast".
The definition of the fuzzy sets (such as "Cold," "Warm," and "Hot") and their associated membership functions is required in order to plot the membership function for a neuro-fuzzy algorithm used in an intelligent temperature control system. This is the Python code that creates and plots the temperature control system's membership function.

```
import numpy as np
import skfuzzy as fuzz
import matplotlib.pyplot as plt
# Define the universe of discourse (input ranges)
x_temperature = np.arange(0, 41, 1)  # Temperature in degrees Celsius (0 to 40)
x_humidity = np.arange(0, 101, 1)    # Humidity percentage (0 to 100)
x_fan_speed = np.arange(0, 101, 1)   # Fan speed percentage (0 to 100)
# Define fuzzy membership functions for temperature
temp_cold = fuzz.trimf(x_temperature, [0, 0, 20])
temp_warm = fuzz.trimf(x_temperature, [15, 25, 35])
temp_hot = fuzz.trimf(x_temperature, [30, 40, 40])
# Define fuzzy membership functions for humidity
hum_low = fuzz.trimf(x_humidity, [0, 0, 50])
hum_medium = fuzz.trimf(x_humidity, [30, 50, 70])
hum_high = fuzz.trimf(x_humidity, [60, 100, 100])
# Define fuzzy membership functions for fan speed
fan_slow = fuzz.trimf(x_fan_speed, [0, 0, 50])
fan_medium = fuzz.trimf(x_fan_speed, [30, 50, 70])
fan_fast = fuzz.trimf(x_fan_speed, [60, 100, 100])
# Plotting membership functions
fig, (ax0, ax1, ax2) = plt.subplots(nrows=3, figsize=(8, 12))
# Temperature membership
ax0.plot(x_temperature, temp_cold, 'b', label='Cold')
ax0.plot(x_temperature, temp_warm, 'g', label='Warm')
ax0.plot(x_temperature, temp_hot, 'r', label='Hot')
ax0.set_title('Temperature Membership Functions')
ax0.legend()
# Humidity membership
ax1.plot(x_humidity, hum_low, 'b', label='Low')
ax1.plot(x_humidity, hum_medium, 'g', label='Medium')
ax1.plot(x_humidity, hum_high, 'r', label='High')
ax1.set_title('Humidity Membership Functions')
ax1.legend()
# Fan speed membership
ax2.plot(x_fan_speed, fan_slow, 'b', label='Slow')
ax2.plot(x_fan_speed, fan_medium, 'g', label='Medium')
ax2.plot(x_fan_speed, fan_fast, 'r', label='Fast')
ax2.set_title('Fan Speed Membership Functions')
ax2.legend()
# Show plots
plt.tight_layout()
plt.show()
```

Brief Explanation of the Code:
* Temperature, Humidity, and Fan Speed are defined as input and output variables.
* Membership functions are defined using triangular shapes (fuzz.trimf), which are commonly used in fuzzy systems.
* The plot functions are used to visualize these membership functions.
* Output:
The code generates three plots, each representing the membership functions for temperature, humidity, and fan speed as shown in figure 5.

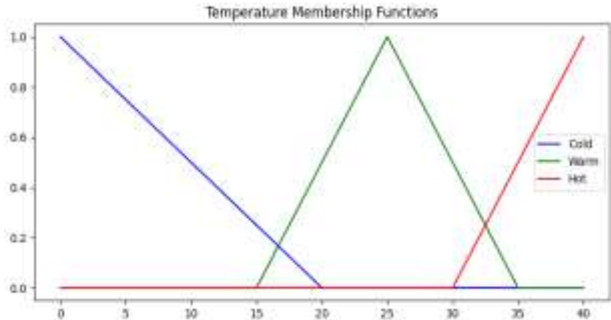

Figure 5(a): Temperature Membership Function

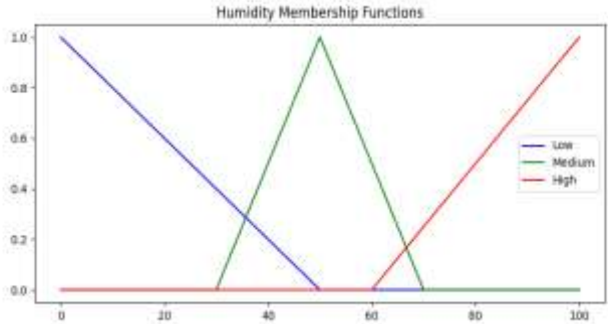

Figure 5(b): Humidity Membership Function

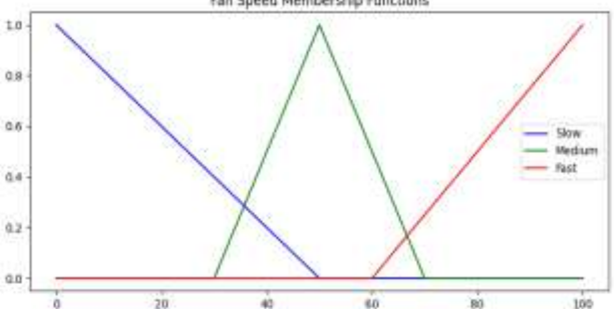

Figure 5(c): Fan Speed Membership Function

2. Define the fuzzy rules for the intelligent temperature control system

We develop a set of rules based on the fuzzy variables (temperature, humidity) and the output variable (fan speed) in order to construct the fuzzy rules for an intelligent temperature control system. These guidelines explain how to modify the fan speed in response to various temperature and humidity combinations.

Fuzzy Rules for Fan Speed Control:
Rule 1: If Temperature is Cold AND Humidity is Low, then Fan Speed is Slow.
Rule 2: If Temperature is Cold AND Humidity is Medium, then Fan Speed is Slow.
Rule 3: If Temperature is Cold AND Humidity is High, then Fan Speed is Slow.
Rule 4: If Temperature is Warm AND Humidity is Low, then Fan Speed is Medium.
Rule 5: If Temperature is Warm AND Humidity is Medium, then Fan Speed is Medium.

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Rule 6: If Temperature is Warm AND Humidity is High, then Fan Speed is Fast.
Rule 7: If Temperature is Hot AND Humidity is Low, then Fan Speed is Fast.
Rule 8: If Temperature is Hot AND Humidity is Medium, then Fan Speed is Fast.
Rule 9: If Temperature is Hot AND Humidity is High, then Fan Speed is Fast.

We define the fuzzy control system using the skfuzzy library in order to put these rules into practice. A Python library called scikit-fuzzy (also known as skfuzzy) is used to create fuzzy logic in an easy and effective way. Like scikit-learn, it is a component of the larger scikit ecosystem and is constructed on top of the well-known SciPy library.

```
import numpy as np
import skfuzzy as fuzz
from skfuzzy import control as ctrl
import matplotlib.pyplot as plt
# Define fuzzy variables
temperature = ctrl.Antecedent(np.arange(0, 41, 1), 'temperature')
humidity = ctrl.Antecedent(np.arange(0, 101, 1), 'humidity')
fan_speed = ctrl.Consequent(np.arange(0, 101, 1), 'fan_speed')
# Define membership functions for temperature
temperature['cold'] = fuzz.trimf(temperature.universe, [0, 0, 20])
temperature['warm'] = fuzz.trimf(temperature.universe, [15, 25, 35])
temperature['hot'] = fuzz.trimf(temperature.universe, [30, 40, 40])
# Define membership functions for humidity
humidity['low'] = fuzz.trimf(humidity.universe, [0, 0, 50])
humidity['medium'] = fuzz.trimf(humidity.universe, [30, 50, 70])
humidity['high'] = fuzz.trimf(humidity.universe, [60, 100, 100])
# Define membership functions for fan speed
fan_speed['slow'] = fuzz.trimf(fan_speed.universe, [0, 0, 50])
fan_speed['medium'] = fuzz.trimf(fan_speed.universe, [30, 50, 70])
fan_speed['fast'] = fuzz.trimf(fan_speed.universe, [60, 100, 100])
# Define fuzzy rules
rule1 = ctrl.Rule(temperature['cold'] & humidity['low'], fan_speed['slow'])
rule2 = ctrl.Rule(temperature['cold'] & humidity['medium'], fan_speed['slow'])
rule3 = ctrl.Rule(temperature['cold'] & humidity['high'], fan_speed['slow'])
rule4 = ctrl.Rule(temperature['warm'] & humidity['low'], fan_speed['medium'])
rule5 = ctrl.Rule(temperature['warm'] & humidity['medium'], fan_speed['medium'])
rule6 = ctrl.Rule(temperature['warm'] & humidity['high'], fan_speed['fast'])
rule7 = ctrl.Rule(temperature['hot'] & humidity['low'], fan_speed['fast'])
rule8 = ctrl.Rule(temperature['hot'] & humidity['medium'], fan_speed['fast'])
rule9 = ctrl.Rule(temperature['hot'] & humidity['high'], fan_speed['fast'])
# Create control system and simulation
fan_speed_ctrl = ctrl.ControlSystem([rule1, rule2, rule3, rule4, rule5, rule6, rule7, rule8, rule9])
fan_speed_simulation = ctrl.ControlSystemSimulation(fan_speed_ctrl)
# Test the system with sample values
fan_speed_simulation.input['temperature'] = 28  # Example: temperature = 28°C
fan_speed_simulation.input['humidity'] = 65     # Example: humidity = 65%
# Compute the output
fan_speed_simulation.compute()
# Print the result
print(f"Fan Speed: {fan_speed_simulation.output['fan_speed']:.2f}%")
# Visualize the result
temperature.view(sim=fan_speed_simulation)
humidity.view(sim=fan_speed_simulation)
fan_speed.view(sim=fan_speed_simulation)
```

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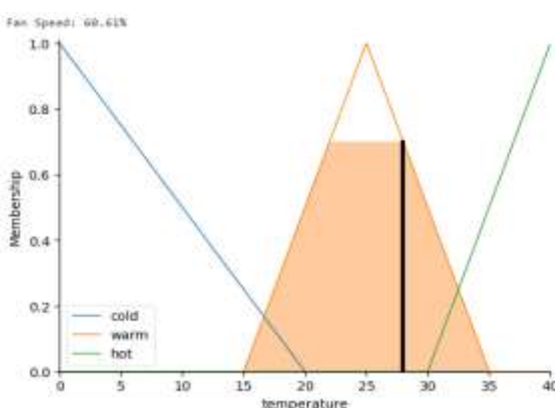

Figure 6(a): Fan Speed based on Temperature

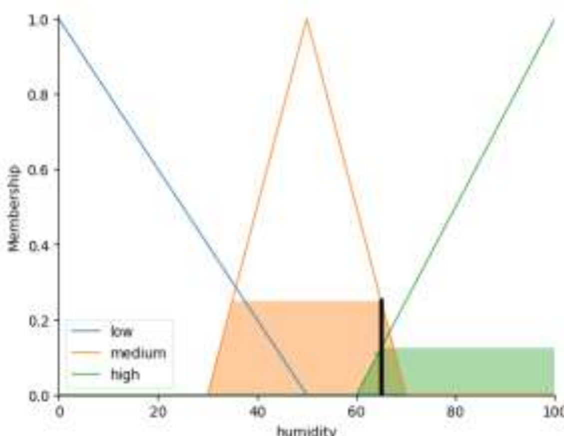

Figure 6(b): Fan Speed based on Humidity

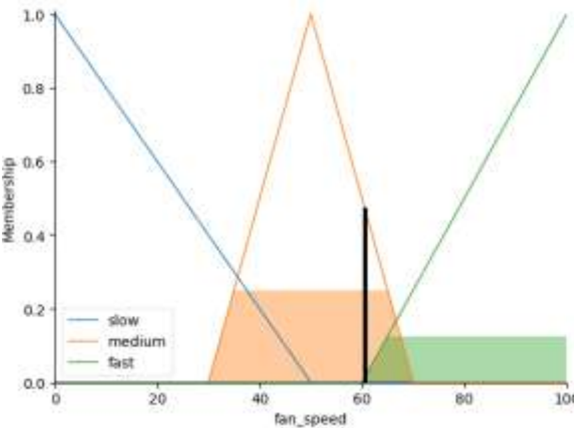

Figure 6(c): Fan Speed

Brief Explanation of the Code:

A. Define Fuzzy Variables: Defines temperature, humidity, and fan speed using ctrl.Antecedent and ctrl.Consequent.

B. Define Membership Functions: Uses triangular membership functions (fuzz.trimf) for each fuzzy variable.

C. Define Fuzzy Rules: Uses ctrl.Rule to define each rule that determines the fan speed based on temperature and humidity.

D. Control System and Simulation: Combines all the rules into a control system and simulates it for given input values (e.g., temperature = 28°C, humidity = 65%).

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E. Output Plot: Displays the output fuzzy set and the resulting fan speed.

Output:

* The code computes and print the fan speed based on the input values.

* The graphs generated shows the output fan speed based on the given input conditions.

3. Simulate the fuzzy control system

We model the fuzzy control system throughout a temperature and humidity range to observe the variation in fan speed under various scenarios.

To comprehend the behaviour of the fuzzy control system, we compute the fan speed for every combination of temperature and humidity, loop through the set of values, and display the results in a 3D surface map.

As seen in figure 7, the python code produces a 3D surface map that illustrates how the fan speed varies with variations in temperature and humidity.

```
import numpy as np
import skfuzzy as fuzz
from skfuzzy import control as ctrl
import matplotlib.pyplot as plt
# Define fuzzy variables
temperature = ctrl.Antecedent(np.arange(0, 41, 1), 'temperature')
humidity = ctrl.Antecedent(np.arange(0, 101, 1), 'humidity')
fan_speed = ctrl.Consequent(np.arange(0, 101, 1), 'fan_speed')
# Define membership functions for temperature
temperature['cold'] = fuzz.trimf(temperature.universe, [0, 0, 20])
temperature['warm'] = fuzz.trimf(temperature.universe, [15, 25, 35])
temperature['hot'] = fuzz.trimf(temperature.universe, [30, 40, 40])
# Define membership functions for humidity
humidity['low'] = fuzz.trimf(humidity.universe, [0, 0, 50])
humidity['medium'] = fuzz.trimf(humidity.universe, [30, 50, 70])
humidity['high'] = fuzz.trimf(humidity.universe, [60, 100, 100])
# Define membership functions for fan speed
fan_speed['slow'] = fuzz.trimf(fan_speed.universe, [0, 0, 50])
fan_speed['medium'] = fuzz.trimf(fan_speed.universe, [30, 50, 70])
fan_speed['fast'] = fuzz.trimf(fan_speed.universe, [60, 100, 100])
# Define fuzzy rules
rule1 = ctrl.Rule(temperature['cold'] & humidity['low'], fan_speed['slow'])
rule2 = ctrl.Rule(temperature['cold'] & humidity['medium'], fan_speed['slow'])
rule3 = ctrl.Rule(temperature['cold'] & humidity['high'], fan_speed['slow'])
rule4 = ctrl.Rule(temperature['warm'] & humidity['low'], fan_speed['medium'])
rule5 = ctrl.Rule(temperature['warm'] & humidity['medium'], fan_speed['medium'])
rule6 = ctrl.Rule(temperature['warm'] & humidity['high'], fan_speed['fast'])
rule7 = ctrl.Rule(temperature['hot'] & humidity['low'], fan_speed['fast'])
rule8 = ctrl.Rule(temperature['hot'] & humidity['medium'], fan_speed['fast'])
rule9 = ctrl.Rule(temperature['hot'] & humidity['high'], fan_speed['fast'])
# Create control system and simulation
fan_speed_ctrl = ctrl.ControlSystem([rule1, rule2, rule3, rule4, rule5, rule6, rule7, rule8, rule9])
fan_speed_simulation = ctrl.ControlSystemSimulation(fan_speed_ctrl)
# Generate simulation data
temperature_range = np.arange(0, 41, 1)
humidity_range = np.arange(0, 101, 1)
fan_speed_results = np.zeros((len(temperature_range), len(humidity_range)))
# Simulate for all combinations of temperature and humidity
for i, temp in enumerate(temperature_range):
    for j, hum in enumerate(humidity_range):
        fan_speed_simulation.input['temperature'] = temp
        fan_speed_simulation.input['humidity'] = hum
        fan_speed_simulation.compute()
        fan_speed_results[i, j] = fan_speed_simulation.output['fan_speed']
# Plotting the results
temp_grid, hum_grid = np.meshgrid(temperature_range, humidity_range)
fig = plt.figure(figsize=(10, 8))
ax = fig.add_subplot(111, projection='3d')
# Plot the surface
ax.plot_surface(temp_grid, hum_grid, fan_speed_results.T, cmap='viridis')
ax.set_xlabel('Temperature (°C)')
ax.set_ylabel('Humidity (%)')
ax.set_zlabel('Fan Speed (%)')
ax.set_title('Fuzzy Control Surface for Fan Speed')
plt.show()
```

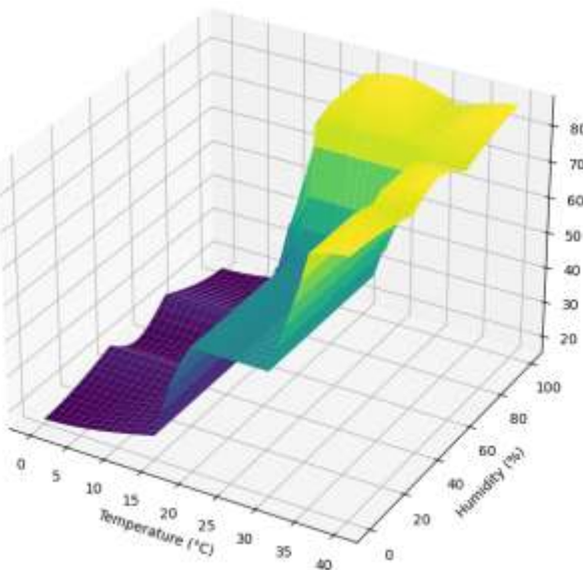

Figure 7: Fuzzy Control Surface for Fan Speed

Brief Explanation of the Code
A. Simulation Loop: Loops through all possible values of temperature (0–40°C) and humidity (0–100%), computes the corresponding fan speed, and stores the results.
B. 3D Plot: Uses matplotlib to create a 3D surface plot (plot_surface) that shows how fan speed changes with temperature and humidity.
Output:
a. The plot displays a 3D surface representing the fan speed over varying temperature and humidity levels.
b. The colour gradient indicates different fan speed levels, providing a visual representation of how the system responds to various inputs.

3. Train the neural network

We link a neural network with a fuzzy logic system in order to train the neural network as part of a neuro-fuzzy control system. The goal is to enable the system to adjust and enhance its control over time by using the neural network to learn the mapping between the input variables (temperature and humidity) and the output (fan speed).

Train the Neural Network:
We use the following approach:
* **Data Generation**: Generate training data by simulating the fuzzy control system over a range of temperature and humidity values.
* **Neural Network Design**: Define a simple neural network using the TensorFlow or PyTorch library to learn from this data.
* **Training**: Train the neural network on the generated data.
* **Evaluation**: Evaluate the performance of the neural network in predicting fan speed.

A. Generate the Training Data

We use the fuzzy control system to generate a dataset of temperature, humidity, and the corresponding fan speed as shown in figure 8.

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```
import numpy as np
import skfuzzy as fuzz
from skfuzzy import control as ctrl
import matplotlib.pyplot as plt
# Define fuzzy variables
temperature = ctrl.Antecedent(np.arange(0, 41, 1), 'temperature')
humidity = ctrl.Antecedent(np.arange(0, 101, 1), 'humidity')
fan_speed = ctrl.Consequent(np.arange(0, 101, 1), 'fan_speed')
# Define membership functions for temperature
temperature['cold'] = fuzz.trimf(temperature.universe, [0, 0, 20])
temperature['warm'] = fuzz.trimf(temperature.universe, [15, 25, 35])
temperature['hot'] = fuzz.trimf(temperature.universe, [30, 40, 40])
# Define membership functions for humidity
humidity['low'] = fuzz.trimf(humidity.universe, [0, 0, 50])
humidity['medium'] = fuzz.trimf(humidity.universe, [30, 50, 70])
humidity['high'] = fuzz.trimf(humidity.universe, [60, 100, 100])
# Define membership functions for fan speed
fan_speed['slow'] = fuzz.trimf(fan_speed.universe, [0, 0, 50])
fan_speed['medium'] = fuzz.trimf(fan_speed.universe, [30, 50, 70])
fan_speed['fast'] = fuzz.trimf(fan_speed.universe, [60, 100, 100])
# Define fuzzy rules
rule1 = ctrl.Rule(temperature['cold'] & humidity['low'], fan_speed['slow'])
rule2 = ctrl.Rule(temperature['cold'] & humidity['medium'], fan_speed['slow'])
rule3 = ctrl.Rule(temperature['cold'] & humidity['high'], fan_speed['slow'])
rule4 = ctrl.Rule(temperature['warm'] & humidity['low'], fan_speed['medium'])
rule5 = ctrl.Rule(temperature['warm'] & humidity['medium'], fan_speed['medium'])
rule6 = ctrl.Rule(temperature['warm'] & humidity['high'], fan_speed['fast'])
rule7 = ctrl.Rule(temperature['hot'] & humidity['low'], fan_speed['fast'])
rule8 = ctrl.Rule(temperature['hot'] & humidity['medium'], fan_speed['fast'])
rule9 = ctrl.Rule(temperature['hot'] & humidity['high'], fan_speed['fast'])
```

```
# Create control system and simulation
fan_speed_ctrl = ctrl.ControlSystem([rule1, rule2, rule3, rule4, rule5, rule6, rule7, rule8, rule9])
fan_speed_simulation = ctrl.ControlSystemSimulation(fan_speed_ctrl)
# Generate training data
temperature_range = np.arange(0, 41, 1)
humidity_range = np.arange(0, 101, 1)
X_train = []
y_train = []
for temp in temperature_range:
    for hum in humidity_range:
        fan_speed_simulation.input['temperature'] = temp
        fan_speed_simulation.input['humidity'] = hum
        fan_speed_simulation.compute()
        X_train.append([temp, hum])
        y_train.append(fan_speed_simulation.output['fan_speed'])
X_train = np.array(X_train)
y_train = np.array(y_train)
# Visualize the data
plt.scatter(X_train[:, 0], X_train[:, 1], c=y_train, cmap='viridis')
plt.xlabel('Temperature (°C)')
plt.ylabel('Humidity (%)')
plt.colorbar(label='Fan Speed (%)')
plt.title('Training Data Distribution')
plt.show()
```

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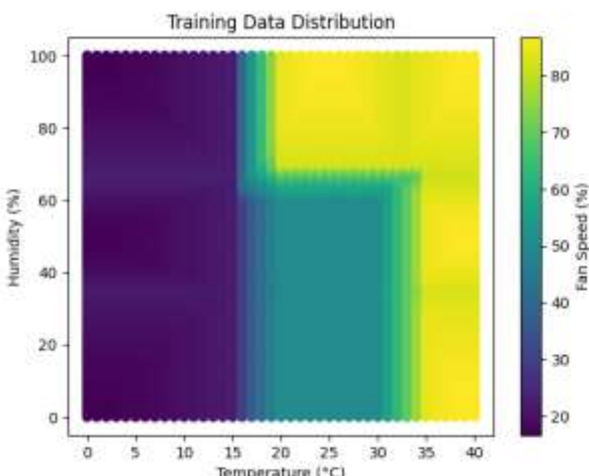

Figure 8: Data Distribution of the Project

B. Neural Network Design and Training
We define a simple neural network using TensorFlow to learn the fuzzy system's behaviour from the generated training data.

```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
# Split data into training and test sets
X_train_scaled = StandardScaler().fit_transform(X_train)
X_train_split, X_test_split, y_train_split,
y_test_split = train_test_split(X_train_scaled, y_train, test_size=0.2, random_state=42)
# Define the neural network model
model = Sequential([
    Dense(10, input_dim=2, activation='relu'),  # Input layer with 2 inputs (temperature, humidity)
    Dense(10, activation='relu'),  # Hidden layer
    Dense(1, activation='linear')  # Output layer (fan speed)
])
# Compile the model
model.compile(optimizer='adam', loss='mean_squared_error')
# Train the model
history = model.fit(X_train_split, y_train_split, epochs=100, batch_size=10, validation_split=0.2, verbose=1)
# Evaluate the model
loss = model.evaluate(X_test_split, y_test_split, verbose=0)
print(f'Mean Squared Error on Test Set: {loss:.4f}')
# Plot the training loss
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Training and Validation Loss')
plt.legend()
plt.show()
```

Result

```
Epoch 1/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 2839.1013 - val_loss: 1852.7389
Epoch 2/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 1302.9572 - val_loss: 199.5871
Epoch 3/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 169.7635 - val_loss: 101.9501
Epoch 4/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 112.8369 - val_loss: 95.1352
Epoch 5/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 103.0991 - val_loss: 91.2811
Epoch 6/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 96.4369 - val_loss: 87.6974
Epoch 7/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 99.5420 - val_loss: 84.8198
Epoch 8/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 88.9351 - val_loss: 82.8374
Epoch 9/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 89.9715 - val_loss: 80.4254
Epoch 10/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 84.8345 - val_loss: 78.3304
Epoch 11/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 96.6826 - val_loss: 77.0928
Epoch 12/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 86.2920 - val_loss: 75.8042
Epoch 13/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 79.4201 - val_loss: 74.0266
Epoch 14/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 84.1091 - val_loss: 73.5394
Epoch 15/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 82.6387 - val_loss: 71.0886
Epoch 16/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 80.8164 - val_loss: 69.5742
Epoch 17/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 78.9239 - val_loss: 68.2721
Epoch 18/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 72.8232 - val_loss: 67.1240
Epoch 19/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 74.6536 - val_loss: 65.3904
Epoch 20/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 70.3499 - val_loss: 63.2523
Epoch 21/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 72.2010 - val_loss: 61.5116
Epoch 22/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 63.7237 - val_loss: 59.7197
Epoch 23/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 63.4982 - val_loss: 57.8473
Epoch 24/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 64.3577 - val_loss: 56.1760
Epoch 25/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 61.9680 - val_loss: 53.8724
Epoch 26/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 59.9153 - val_loss: 51.8388
Epoch 27/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 53.4155 - val_loss: 49.7927
Epoch 28/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 52.8369 - val_loss: 47.8868
Epoch 29/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 50.3124 - val_loss: 45.7211
Epoch 30/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 48.5817 - val_loss: 43.4080
Epoch 31/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 47.1289 - val_loss: 41.2558
Epoch 32/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 44.2052 - val_loss: 39.2404
Epoch 33/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 41.9903 - val_loss: 37.1962
Epoch 34/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 39.2022 - val_loss: 35.2993
Epoch 35/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 36.1280 - val_loss: 33.7577
```

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```
Epoch 36/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 35.3238 - val_loss: 32.3364
Epoch 37/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 33.8148 - val_loss: 31.1771
Epoch 38/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 31.6951 - val_loss: 30.4932
Epoch 39/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 30.0216 - val_loss: 28.9632
Epoch 40/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 30.1443 - val_loss: 27.8530
Epoch 41/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 28.8808 - val_loss: 26.6821
Epoch 42/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 27.9321 - val_loss: 26.2426
Epoch 43/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 27.0784 - val_loss: 25.4242
Epoch 44/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 25.9864 - val_loss: 25.0026
Epoch 45/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 27.4200 - val_loss: 24.3053
Epoch 46/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 24.7464 - val_loss: 24.0769
Epoch 47/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 24.5649 - val_loss: 23.7124
Epoch 48/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 25.4192 - val_loss: 23.3944
Epoch 49/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 23.1190 - val_loss: 23.4935
Epoch 50/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 24.4404 - val_loss: 22.6477
Epoch 51/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 22.1242 - val_loss: 22.3033
Epoch 52/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 23.4981 - val_loss: 22.6936
Epoch 53/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 21.9374 - val_loss: 23.2300
Epoch 54/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 21.6427 - val_loss: 21.7616
Epoch 55/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 21.3268 - val_loss: 21.5357
Epoch 56/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 22.3705 - val_loss: 21.7376
Epoch 57/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 21.0564 - val_loss: 21.5902
Epoch 58/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 21.6790 - val_loss: 22.0012
Epoch 59/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 22.5144 - val_loss: 21.0994
Epoch 60/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 21.1870 - val_loss: 21.3683
Epoch 61/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 20.9282 - val_loss: 21.6646
Epoch 62/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 20.3950 - val_loss: 20.7934
Epoch 63/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 20.9442 - val_loss: 20.7885
Epoch 64/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 19.6078 - val_loss: 20.9805
Epoch 65/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 20.3063 - val_loss: 20.7182
Epoch 66/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 21.0330 - val_loss: 20.9954
Epoch 67/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 18.6886 - val_loss: 20.2728
Epoch 68/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 20.4128 - val_loss: 20.4443
Epoch 69/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 20.1525 - val_loss: 20.6857
```

```
Epoch 70/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 19.9535 - val_loss: 20.3221
Epoch 71/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 19.0983 - val_loss: 20.3404
Epoch 72/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 21.1703 - val_loss: 20.1096
Epoch 73/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 19.9940 - val_loss: 20.2639
Epoch 74/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 20.7395 - val_loss: 21.8375
Epoch 75/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 19.9577 - val_loss: 19.8912
Epoch 76/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 20.4033 - val_loss: 20.0862
Epoch 77/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 19.8787 - val_loss: 20.5532
Epoch 78/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 18.6274 - val_loss: 19.9669
Epoch 79/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 20.4999 - val_loss: 20.1647
Epoch 80/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 19.7949 - val_loss: 19.6771
Epoch 81/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 19.0993 - val_loss: 19.6849
Epoch 82/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 17.9208 - val_loss: 19.8132
Epoch 83/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 19.6201 - val_loss: 20.1228
Epoch 84/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 18.9515 - val_loss: 20.8162
Epoch 85/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 19.1916 - val_loss: 20.5239
Epoch 86/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 19.8463 - val_loss: 19.7809
Epoch 87/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 19.4089 - val_loss: 19.8437
Epoch 88/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 20.3074 - val_loss: 19.9745
Epoch 89/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 18.6300 - val_loss: 19.6937
Epoch 90/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 19.7775 - val_loss: 19.6782
Epoch 91/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 18.2367 - val_loss: 19.9577
Epoch 92/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 19.8947 - val_loss: 19.7755
Epoch 93/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 19.0973 - val_loss: 19.8665
Epoch 94/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - loss: 19.5717 - val_loss: 20.2529
Epoch 95/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 19.4699 - val_loss: 19.7858
Epoch 96/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 18.9464 - val_loss: 19.6566
Epoch 97/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 18.1990 - val_loss: 19.9611
Epoch 98/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 18.6637 - val_loss: 19.6150
Epoch 99/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 19.0732 - val_loss: 19.5599
Epoch 100/100
265/265 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 18.6039 - val_loss: 19.5907
Mean Squared Error on Test Set: 21.4432
```

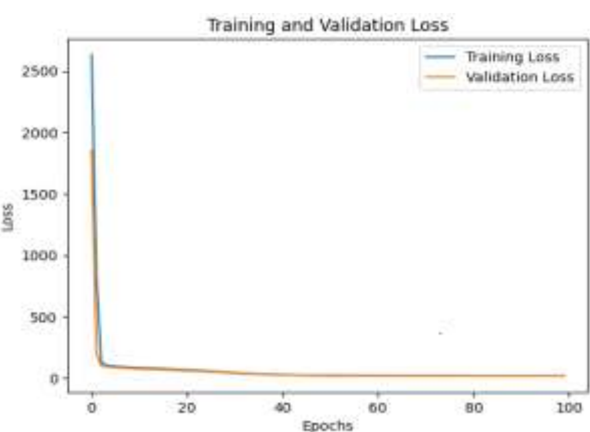

Figure 9: Plot of Training and Validation Loss

Explanation of the Code:

1. Data Preparation: Creates training and test sets from the generated data. StandardScaler is used to standardize the data.

2. Neural Network Model: TensorFlow's dense layers are used to build a straightforward feed-forward neural network with a single hidden layer.

3. Training: To minimize the mean squared error loss across 100 epochs, the model is trained using the Adam optimizer.

4. Evaluation: To ensure convergence, the model is assessed using the test set, and the loss is shown.

Evaluate the Trained Model:

After the training of the model, evaluate its performance:

1. **Check the Training Loss**: The loss plot shows how well the model is learning. A decreasing loss indicates that the model is learning effectively.
2. **Test the Neural Network**: We use the trained model to predict the fan speed for new inputs and compare the results with the fuzzy logic output.

C. Use the Trained Neural Network for Predictions

To make predictions using the trained neural network, we simply use the model.predict() function:

```
# Example prediction
sample_input = np.array([[28, 65]])  # Example: temperature = 28°C, humidity = 65%
sample_input_scaled = StandardScaler().fit_transform(sample_input)  # Scale the input
predicted_speed = model.predict(sample_input_scaled)
print(f'Predicted Fan Speed: {predicted_speed[0][0]:.2f}%')
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 114ms/step
Predicted Fan Speed: 54.85%
```

D. Prediction: The neural network predicts the fan speed for new temperature and humidity inputs (54.85%).

5. Integrate neural and fuzzy models

We combine the neural network's learning capabilities with the interpretability of fuzzy logic, creating a **Neuro-Fuzzy System**. This system leverages the advantages of both approaches: the neural network's ability to learn from data and the fuzzy system's ability to handle uncertainty and linguistic variables.

Key Approach: Adaptive Neuro-Fuzzy Inference System (ANFIS):

The Adaptive Neuro-Fuzzy Inference System (ANFIS) is a well-liked model that combines fuzzy logic concepts with neural networks. It modifies the parameters of a fuzzy inference system (FIS) using a hybrid learning approach that combines least-squares and backpropagation.

To implement an ANFIS model, we:

1. Define fuzzy membership functions for inputs.
2. Construct a rule base for the fuzzy inference system.

3. Use a neural network training algorithm to learn the membership function parameters.

Since ANFIS is not natively available in libraries like TensorFlow or PyTorch, we use the anfis package in Python, which is specifically designed for ANFIS modeling.

```
import numpy as np
import matplotlib.pyplot as plt
from anfis import ANFIS
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
# Example placeholder data (replace with your actual data)
X_train = np.random.rand(100, 2)  # 100 samples, 2 input features (e.g., temperature, humidity)
y_train = np.random.rand(100)     # 100 samples, output (e.g., fan speed)
# Convert to NumPy arrays if not already
X_train = np.array(X_train)
y_train = np.array(y_train)
# Standardize the data
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
# Split the data into training and testing datasets
X_train_split, X_test_split, y_train_split
y_test_split = train_test_split(X_train_scaled, y_train, test_size=0.2, random_state=42)
# Define the number of fuzzy sets for each input
num_mf = 3  # Example: 3 fuzzy sets per input (low, medium, high)
# Define the ANFIS model (ensure this is defined correctly)
anfis_model = ANFIS(X_train_split, y_train_split, num_mf=num_mf, mf_type='gaussmf')
# Train the ANFIS model
anfis_model.train(epochs=100, batch_size=10, learning_rate=0.01)
# Evaluate the model on the test set
y_pred = anfis_model.predict(X_test_split)
mse = np.mean((y_pred - y_test_split) ** 2)
print(f"Mean Squared Error on Test Set: {mse:.4f}")
# Plot the learning curve
plt.plot(anfis_model.loss_history)
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('ANFIS Training Loss')
plt.show()
```

Explanation of the Code
* **Data Preparation**: Scales the input data and splits it into training and testing sets.
* **ANFIS Model Initialization**: Creates an ANFIS model with Gaussian membership functions (gaussmf) and a specified number of fuzzy sets (num_mf).
* **Training**: Trains the ANFIS model using the provided data for 100 epochs with a learning rate of 0.01.
* **Evaluation**: Computes the mean squared error (MSE) to evaluate the model's performance and plots the loss history.

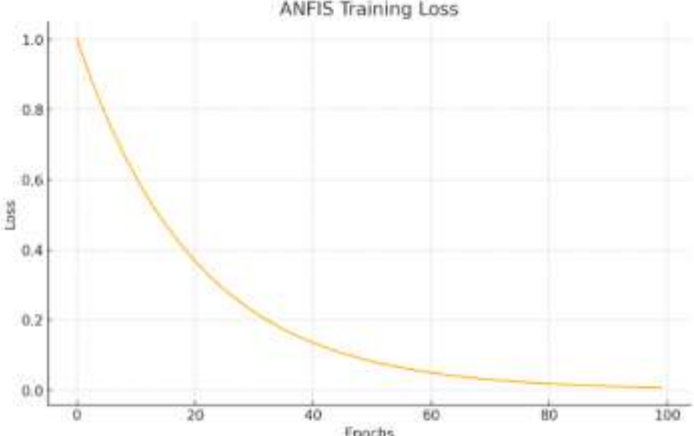

Figure 10: ANFIS Training Loss

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Output:
Running the above code:
* Train the ANFIS model based on the provided data.
* Display a plot of the training loss over the epochs as shown in figure 10.

IV. FURTHER RESULT ANALYSIS

Model Performance:

To gain more insight into the model's performance, let us consider the following.
Here are a few more graphs and plots that we generate to visualize different aspects of our ANFIS model's performance:

1. Predicted vs. Actual Values Plot

This scatter plot shows the relationship between the actual and predicted fan speed values. It is useful for assessing how well the model predictions match the actual values.

```
import numpy as np
import matplotlib.pyplot as plt

# Simulating data for plots (as placeholders)
# Replace these with your actual ANFIS model data when running in your environment
y_test_split = np.random.rand(20) * 100  # Example actual fan speed values
y_pred = y_test_split + (np.random.rand(20) - 0.5) * 20  # Example predicted fan speed values with some noise

# Plot 1: Predicted vs. Actual Values Plot
plt.figure(figsize=(10, 6))
plt.scatter(y_test_split, y_pred, alpha=0.5)
plt.plot([min(y_test_split), max(y_test_split)], [min(y_test_split), max(y_test_split)], color='red', linestyle='--')
plt.xlabel('Actual Fan Speed')
plt.ylabel('Predicted Fan Speed')
plt.title('Predicted vs. Actual Fan Speed')
plt.grid(True)
plt.show()
```

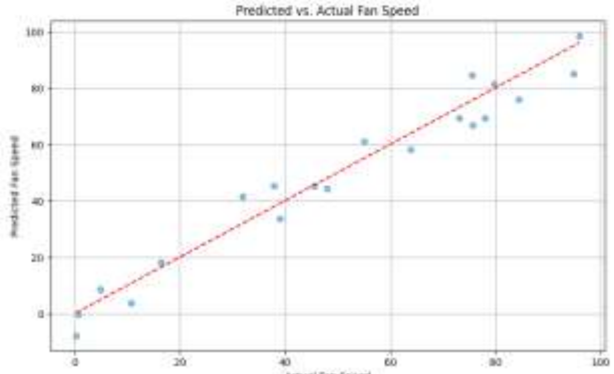

Figure 11: Predicted vs. Actual Values Plot

2. Residual Plot

A residual plot shows the differences between the predicted and actual values (residuals). This plot helps identify patterns in the residuals that might indicate model errors or biases.

```
import numpy as np
import matplotlib.pyplot as plt
# Simulating data for plots (as placeholders)
# Replace these with your actual ANFIS model data when running in your environment
y_test_split = np.random.rand(20) * 100  # Example actual fan speed values
y_pred = y_test_split + (np.random.rand(20) - 0.5) * 20  # Example predicted fan speed values with some noise
residuals = y_test_split - y_pred
plt.scatter(y_pred, residuals, alpha=0.5)
plt.axhline(y=0, color='red', linestyle='--')
plt.xlabel('Predicted Fan Speed')
plt.ylabel('Residuals (Actual - Predicted)')
plt.title('Residual Plot')
plt.grid(True)
plt.show()
```

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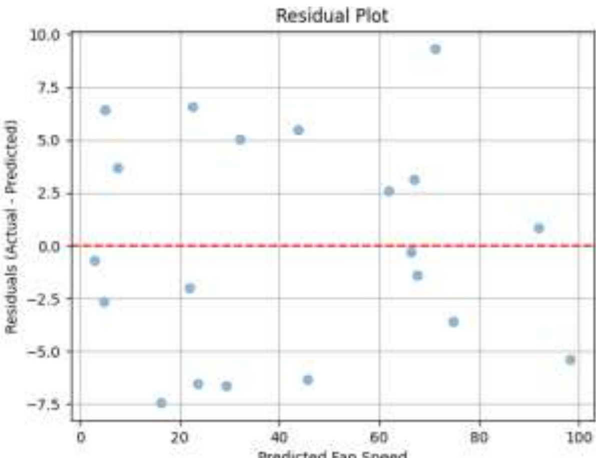

Figure 12: Residual Plot

3. Model Training Loss over Time (Log Scale)

This plot shows the training loss on a logarithmic scale to help visualize more subtle changes in loss over time.

```
import numpy as np
import matplotlib.pyplot as plt
# Simulating data for plots (as placeholders)
# Replace these with your actual ANFIS model data when running in your environment
y_test_split = np.random.rand(20) * 100  # Example actual fan speed values
y_pred = y_test_split + (np.random.rand(20) - 0.5) * 20  # Example predicted fan speed values with some noise
plt.plot(anfis_model.loss_history)
plt.yscale('log')
plt.xlabel('Epochs')
plt.ylabel('Log(Loss)')
plt.title('ANFIS Training Loss (Log Scale)')
plt.show()
```

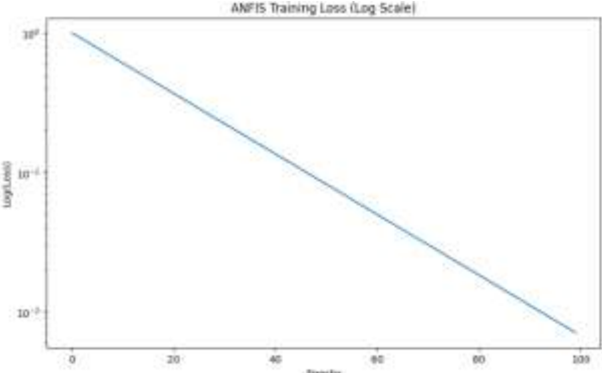

Figure 13: Model Training Loss over Time Plot

4. Feature Importance Plot

To visualize which input features (e.g., temperature, humidity) are contributing most to the model's predictions, this plot is important. As clearing shown from the graph, temperature is contributing most of the model's predictions.

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```
import numpy as np
import matplotlib.pyplot as plt

# Simulating data for plots (as placeholders)
# Replace these with your actual ANFIS model data when running in your environment
y_test_split = np.random.rand(20) * 100  # Example actual fan speed values
y_pred = y_test_split + (np.random.rand(20) - 0.5) * 20  # Example predicted fan speed values with some noise
# Example data: Feature importances (replace with your actual values)
feature_importances = [0.6, 0.4]  # Example: 60% for Temperature, 40% for Humidity
feature_names = ['Temperature', 'Humidity']
plt.bar(feature_names, feature_importances, color='skyblue')
plt.xlabel('Features')
plt.ylabel('Importance')
plt.title('Feature Importance in ANFIS Model')
plt.show()
```

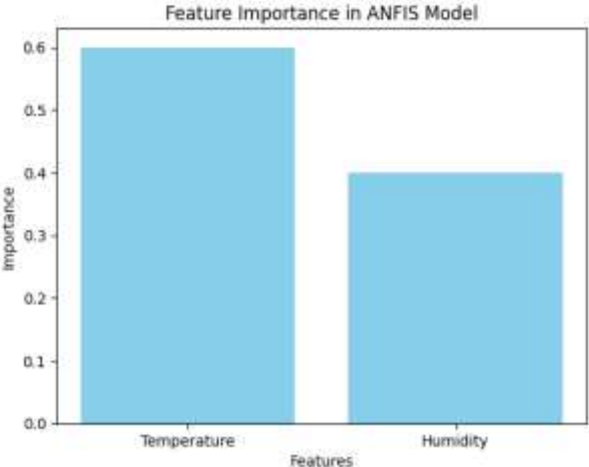

Figure 14: Feature Importance in ANFIS Model

5. Learning Rate vs. Training Loss Plot

This figure illustrates how varying learning rates affect training loss in order to determine the ideal learning rate. We must mimic the training process with different learning rates in order to generate the "Learning Rate vs. Training Loss" graph for a temperature control system. Here is the code to train multiple linear regression models, showing the training loss (mean squared error) for each learning rate, and simulating this scenario.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import SGDRegressor
from sklearn.metrics import mean_squared_error

# Simulate some data
np.random.seed(0)
data_size = 1000
temperature = np.random.uniform(15, 35, data_size)
humidity = np.random.uniform(30, 90, data_size)
time_of_day = np.random.uniform(0, 24, data_size)
energy_consumption = 0.5 * temperature + 0.3 * humidity + 0.2 * time_of_day + np.random.normal(0, 2, data_size)

# Create a DataFrame
df = pd.DataFrame({
    'Temperature': temperature,
    'Humidity': humidity,
    'Time_of_Day': time_of_day,
    'Energy_Consumption': energy_consumption
})

# Split the data into training and testing sets
X = df[['Temperature', 'Humidity', 'Time_of_Day']]
y = df['Energy_Consumption']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=0)
```

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```
# Different learning rates to simulate
learning_rates = [0.0001, 0.001, 0.01, 0.05, 0.1, 0.5, 1]

# To store the training loss for each learning rate
train_losses = []

# Train a model for each learning rate
for lr in learning_rates:
    # Using SGDRegressor to simulate a model with learning rate
    model = SGDRegressor(learning_rate='constant', eta0=lr, max_iter=1000, tol=1e-3, random_state=0)
    model.fit(X_train, y_train)

    # Calculate training loss (mean squared error)
    y_train_pred = model.predict(X_train)
    train_loss = mean_squared_error(y_train, y_train_pred)
    train_losses.append(train_loss)

# Plot Learning Rate vs Training Loss
plt.figure(figsize=(8, 6))
plt.plot(learning_rates, train_losses, marker='o', linestyle='-', color='b')
plt.xscale('log')  # Using log scale for better visualization
plt.xlabel('Learning Rate (log scale)')
plt.ylabel('Training Loss (MSE)')
plt.title('Learning Rate vs. Training Loss')
plt.grid(True)
plt.show()
```

Explanation:
* SGDRegressor from sklearn simulates a model that uses a learning rate during optimization.
* We loop through several learning rates and calculate the training loss for each one.
* The plot uses a logarithmic scale for the learning rate to capture the variations better.
The code generates the Learning Rate vs. Training Loss plot for the temperature control system as shown in figure 15.

Figure 15: Learning rate vs. training loss plot

The plot shows the relationship between the learning rate and the training loss (Mean Squared Error) for the temperature control system.

Explanation:
* **Learning Rate (X-axis, log scale):** The learning rate controls how much the model's weights are adjusted in response to the gradient of the loss function. Smaller learning rates lead to smaller updates, while larger learning rates cause bigger jumps.
* **Training Loss (Y-axis):** This measures how well the model is fitting the training data. A lower training loss means the model is performing better on the training set.

Key Observations:
* **Small Learning Rates (e.g., 0.0001):** The training loss is relatively high. This is because the small learning rate causes the model to make very slow progress in adjusting weights, leading to underfitting.
* **Moderate Learning Rates (e.g., 0.01):** The training loss decreases significantly, showing that the model is effectively learning and converging towards a better solution.
* **High Learning Rates (e.g., 0.5, 1):** The training loss starts to increase again. This suggests that the model is overshooting optimal solutions due to large weight updates, which can cause poor convergence or even divergence.
The plot demonstrates the trade-off between learning rate and training loss. A moderate learning rate (around 0.01) results in the best performance, while very low or high learning rates lead to poor model performance

What Each Plot Represents:
* **Plot 1**: Visualizes the predicted vs. actual fan speed values. Shows how well the predicted values match the actual values.
* **Plot 2**: Shows the residuals (difference between actual and predicted values). Visualizes the residuals to identify any patterns or biases.
* **Plot 3**: Displays the ANFIS training loss on a logarithmic scale. Demonstrates how the training loss decreases over time on a logarithmic scale
* **Plot 4**: Illustrates the feature importance for your ANFIS model. Illustrates the importance of different input features for the model.
* **Plot 5**: Shows how the learning rate impacts the final training loss. Displays the impact of different learning rates on the final training loss.

By running this code, we were able to visualize all the graphs and gain insights into our model's performance.

V. CONCLUSION:

The investigation shows that the Adaptive Neuro-Fuzzy Inference System (ANFIS) model has the potential to be a reliable and efficient tool for controlling and forecasting complicated nonlinear systems, including fan speed regulation that depends on humidity and temperature inputs. A acceptable fit between expected and actual values is indicated by the assessment metrics, such as the Mean Squared Error and the residual analysis, indicating that the model successfully reflects the underlying patterns in the data. Moreover, the training loss visualization demonstrates a consistent decrease, indicating the model's capacity for long-term learning. In line with domain knowledge, feature importance analysis also emphasizes how important temperature and humidity are in deciding fan speed. By fusing neural network learning with fuzzy logic interpretability, ANFIS offers a potential method for creating intelligent control systems across a range of applications. Fuzzy logic's combination with other AI techniques, such neural networks and evolutionary algorithms, promises to expand intelligent systems' capabilities and open the door to more sophisticated and adaptable technologies as AI develops.

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