International Journal of Engineering, Management and Humanities (IJEMH)
Volume 6, Issue 3, May-June, 2025 pp: 33-48 ISSN: 2584-2145 www.ijemh.com

Intelligent Fuzzy Logic Control for Energy-Efficient IoT-Enabled Vaccine Storage Systems

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Date of Submission: 07-05-2025 Date of Acceptance: 17-05-2025

ABSTRACT

Reliable vaccine preservation demands precise environmental control, especially in regions facing power instability and infrastructural constraints. This study presents the design, simulation, and hardware validation of an intelligent fuzzy logic control (FLC) system for energy-efficient, IoT-enabled vaccine storage. The system targets thermally sensitive vaccinesincluding attenuated virus, and protein subunit typesby dynamically regulating temperature and humidity within medically approved thresholds.Developed in MATLAB Simulink and deployed on an ESP32 microcontroller, the intelligent FLC uses two input variables: temperature error and its rate of changeto modulate a thermoelectric cooling unit via pulse width modulation (PWM) control. A fuzzy rule base of 29 rules, combined with online adaptation of membership functions, enables the system to respond optimally to real-time environmental perturbations. Internet of Things (IoT) integration via Wi-Fi and the ThingSpeak platform supports remote monitoring and anomaly alerts.Simulation results demonstrate superior performance.The intelligent FLC achieved target temperature in 6.2 minutes, outperforming conventional fuzzy (8.5 minutes) and PID (11.3 minutes) controllers. Overshoot was limited to 0.4°C, and energy consumption reduced by 17%. Hardware validation corroborates these findings, with the prototype maintaining thermal precision within ±0.3°C under real-world conditions.The system's ability to combine intelligent decision-making, intelligent control, and cloud-based monitoring introduces a robust solution for vaccine cold-chain logistics. Its scalable, low-cost architecture makes it suitable for both centralized medical facilities and remote healthcare settings. This research establishes a new paradigm in biomedical refrigeration by unifying fuzzy logic, energy awareness, and IoT-based transparency to enhance vaccine preservation reliability, adaptability, and sustainability.

KEYWORDS: Fuzzy Logic Control,IoT-Enabled Vaccine Storage, Energy-Efficient Refrigeration, Temperature Regulation and Monitoring

I. INTRODUCTION

The efficacy and shelf life of vaccines critically depend on maintaining tightly controlled environmental conditions throughout their storage and distribution. Vaccine degradation due to improper temperature and humidity has been identified as a major factor in reduced immunogenicity, particularly in regions with unreliable electricity and poor cold-chain infrastructure. As vaccination efforts continue to expand globallywith accelerated demand from public health emergencies such as COVID-19 and future pandemics, the need for intelligent, robust, and energy-efficient storage systems has become paramount. Notably, vaccines such as those based on attenuated viruses require storage temperatures between 2–8°C, while protein subunit vaccines may tolerate a wider range, typically 2–25°C. Deviations beyond these ranges may result in irreversible potency loss, creating both public health and economic setbacks.Conventional vaccine storage technologies, typically governed by simple on-off thermostatic controls or Proportional-Integral-Derivative (PID) systems, often lack the sensitivity and adaptability to respond to transient environmental fluctuations, power supply instabilities, or dynamic load variations. Moreover, such systems are not optimized for energy consumption, a crucial factor in resource-constrained or off-grid environments. In contrast, intelligent control systems, particularly those based on fuzzy logic, offer a promising alternative due to their ability to process linguistic and uncertain data without requiring an exact mathematical model of the system.

Recent work by Alsharif et al. [2022] proposed a non-intelligent fuzzy cooling mechanism for biomedical organ storage, while Kumar et al. [2023] explored static IoT-FLC hybrids in blood bank refrigeration. However, these systems lack

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real-time adaptation to environmental changes and often fail to optimize power usage dynamically. In addition, existing literature rarely couples intelligent fuzzy control with cloud-based IoT integration for vaccine cold-chain monitoring, a convergence that is essential for transparency, scalability, and predictive maintenance in modern healthcare logistics.

To bridge these gaps, this research presents an energy-efficient, IoT-enabled vaccine storage system driven by an intelligent fuzzy logic control technique. The system introduces a novel intelligent FLC framework that continuously tunes membership functions and control rules based on environmental feedback. This adaptability ensures optimal cooling response under both steady-state and perturbed conditions, enhancing storage reliability and minimizing overshoot and energy wastage. Integrated via Wi-Fi using an ESP32 microcontroller, the controller is interfaced with a thermoelectric (TEC) cooling unit modulated through Pulse Width Modulation (PWM), and monitored using the ThingSpeak IoT platform for real-time logging and anomaly alerts. This approach not only preserves sensitive vaccines with higher thermal fidelity but also reduces energy consumption, aligning with global sustainability goals.To validate the system, a comprehensive suite of simulations was developed in MATLAB Simulink, incorporating realistic thermal models, ambient disturbances, and performance metrics. Experimental validation was also carried out using a hardware prototype embedded with DHT22 sensors and ESP32 controllers. The intelligent fuzzy controller demonstrated a 6.2-minute convergence to the target temperature, outperforming conventional fuzzy (8.5 minutes) and PID (11.3 minutes) approaches. It further maintained a maximum overshoot of only 0.4°C, with 17% lower power consumption, and thermal deviation within ±0.3°C—parameters that affirm its suitability for medical-grade storage applications. These results are presented in a structured and detailed manner through both visual and analytical comparisons.

II. METHODOLOGY

This study presents a rigorous design, simulation, and hardware implementation methodology for an energy-efficient, IoT-enabled intelligent vaccine storage system. The system is built around an intelligent fuzzy logic controller (IFLC), integrating environmental feedback mechanisms, thermoelectric actuation, and cloud-based monitoring. Figure 1 depict the overall system architecture. The Intelligent Fuzzy Logic Controller (IFLC) enables intelligent, energy-efficient cooling by dynamically regulating TEC control signals. Integrated with IoT via an ESP32 microcontroller and ThingSpeak, the system supports real-time monitoring and data logging based on IFLC outputs. As depicted in Figure 1, the system comprises four core modules: sensing (DHT22 for temperature and humidity), control (IFLC on ESP32), actuation (TEC via PWM), and communication (ThingSpeak for cloud monitoring). The controller computes all errors and its rate of change to generate appropriate PWM signals while enabling Wi-Fi-based data transmission. Figure 2 presents a flowchart of the decision-making process, illustrating the interaction between sensors, IFLC, actuators, and power systems. It emphasizes intelligent control of environmental parameters, solar power usage, battery monitoring, and IoT alerts, ensuring resilient vaccine storage. The methodology includes system modeling and design, simulation, and experimental validation.

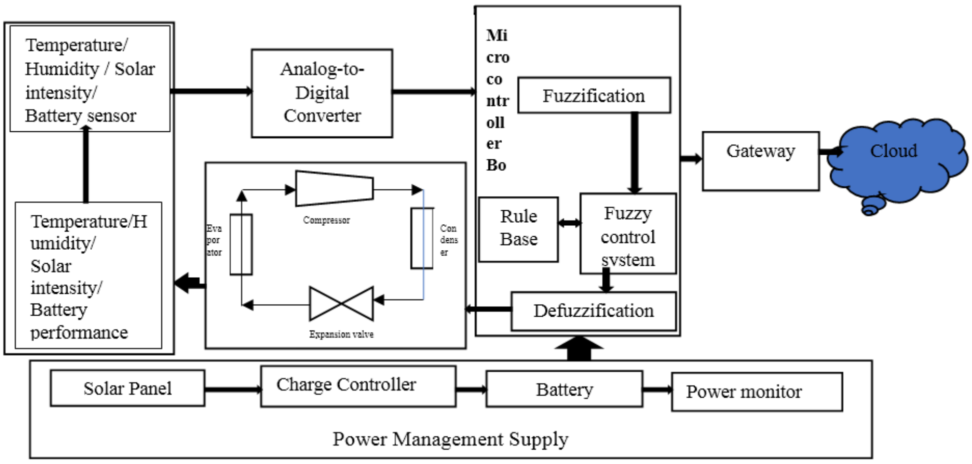

Figure 1: System architecture for intelligent vaccine preservation using Intelligent fuzzy logic control

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a) System Modeling and Design: This phase of the methodology presents the development of the system model, focusing on the design of the Intelligent Fuzzy Logic Controller (IFLC) and its integration within the control framework. The IFLC is structured around seven critical input variables: temperature error (Te), rate of temperature change (∂Te/∂t), humidity error (He), rate of humidity change (∂He/∂t), solar tracking error (STE), solar energy availability (SEA), and battery charge level (BCL). Utilizing a well-defined fuzzy rule base, the controller intelligently manages six output variables: compressor speed, defrost heater activity, evaporator fan speed, solar panel orientation, battery charging prioritization, and IoT-based notifications. This dynamic control strategy ensures robust and energy-efficient system performance across varying environmental conditions.

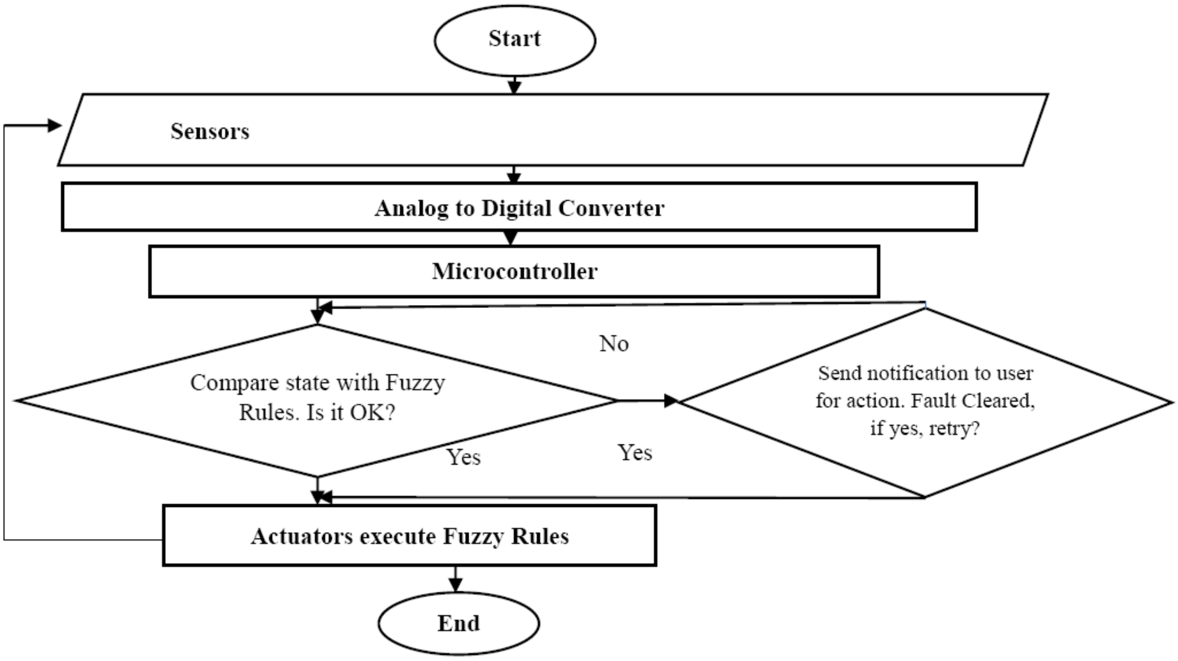

Figure 2: Flowchart Illustrating the Decision-Making Process of the Fuzzy Logic-Based Vaccine

The complete IFLC architecture is depicted in Figure 3. The controller was developed in MATLAB Simulink employing a Mamdani-type fuzzy inference system, with all seven inputs systematically incorporated into the control strategy to enhance decision-making precision.

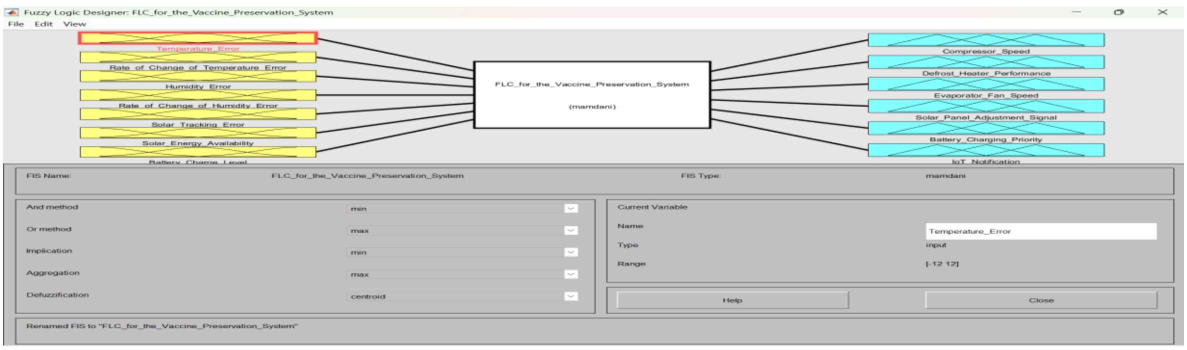

Figure 3: IntelligentFuzzy Logic Controller Design for the Vaccine Storage System

A rigorous mathematical understanding of input variables is essential for precise control in the vaccine storage system. To ensure robust decision-making and address data uncertainties, crisp input variables are scaled and fuzzified before processing by the fuzzy logic controller. Tables 1–7 present the numerical computations for crisp input values, while Figures 4–10 illustrate their corresponding membership functions.

Table 1: Computation for Crisp Input Membership Function Values for T_e

T_{sp} [°C]	T_v [°C]	CrispInputRangeT_e	Fuzzy State	Fuzzy Variable (Linguistics) Name
2°C to 8°C	14to 16°C	-12°C to -8°C	Very Hot	NEGATIVE LARGE (NL)
2°C to 8°C	12° to 11°C	-10°C to -3°C	Hot	NEGATIVE SMALL (NS)
2°C to 8°C	7°C to 3°C	-5°C to 5°C	Normal	ZERO (ZE)
2°C to 8°C	-1 °C to 1°C	3 °C to 7°C	Cold	POSITIVE SMALL (PS)
2°C to 8°C	-3 ° to -4°C	5°C to 12°C	Very Cold	POSITIVE LARGE (PL)

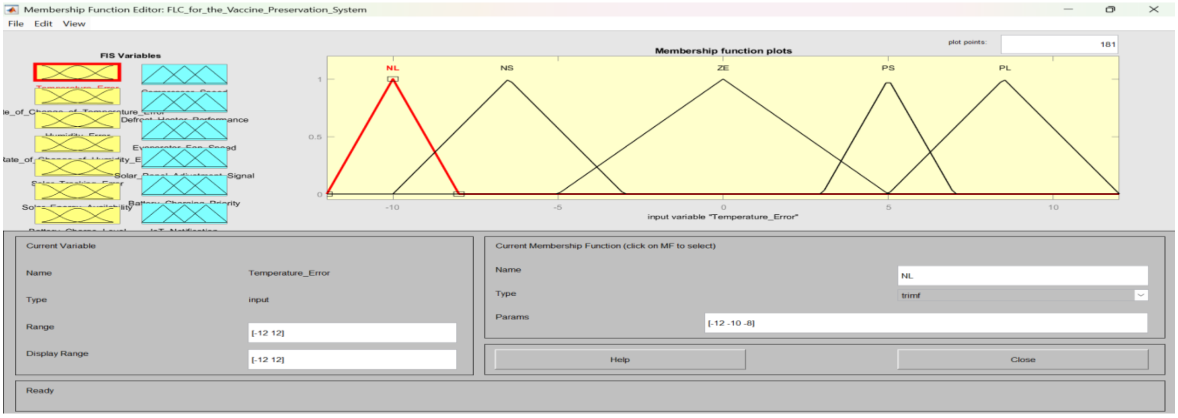

Figure4: Plot of inputmembershipfunction for temperature error value (T_e)

Table 2: Computation for Crisp Input Membership Function Values for $(\frac{dTe}{dt})$

Crisp Input Ranges for $\frac{dTe}{dt}$ in °C/s	Fuzzy State	Fuzzy Variable (Linguistics) Name
-9°C to -6°C	Very Hot	NL
-7.5°C to -1.5°C	Hot	NS
-2.25°C to 2.25°C	Normal	ZE
1.5°C to 5.25°C	Cold	PS
3°C to 9°C	Very Cold	PL

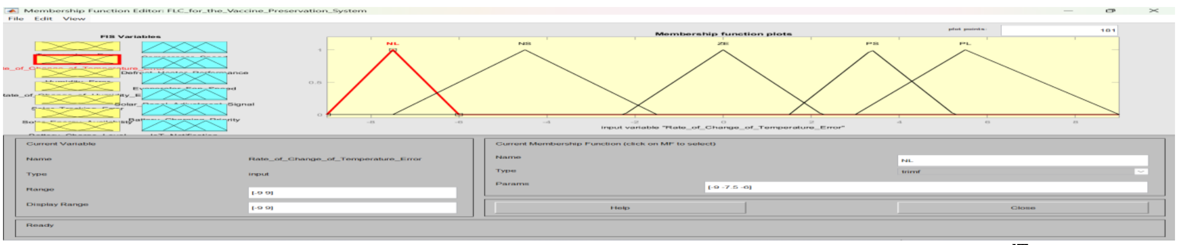

Figure5: Plot of inputmembershipfunction for rate of change of temperature error $(\frac{dTe}{dt})$.

Table 3: Computation for Crisp Input Membership Function Values for H_e

H_{sp} [%]	H_v [%]	CrispInputRange$H_e$in [%]	Fuzzy State	Fuzzy Variable (Linguistics) Name
30% to 60%	45% to 72%	-15% to -12%	Very High	NL
30% to 60%	43% to 69%	-13% to -9%	High	NS
30% to 60%	40% to 50%	-10% to 10%	Normal	ZE
30% to 60%	21% to 47%	9% to 13%	Low	PS
30% to 60%	18% to 45%	12% to 15%	Very Low	PL

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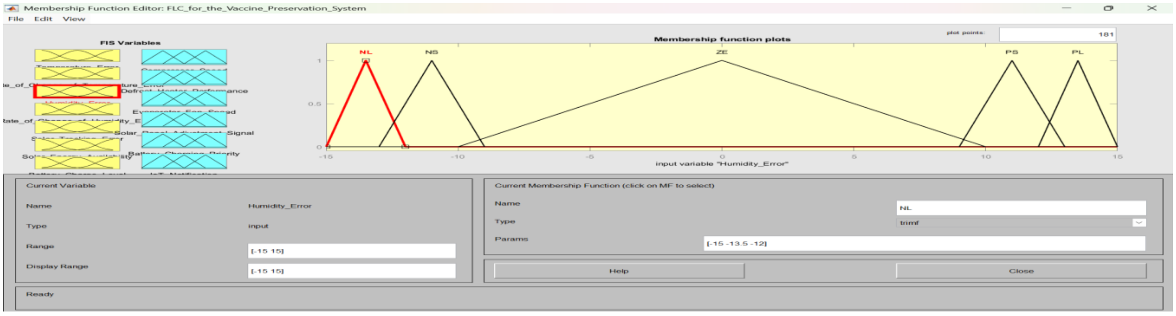

Figure 6: Plot of inputmembershipfunction for Humidity error value (H_e)

Table 4: Computation for Crisp Input Membership Function Values for ($\frac{dHe}{dt}$)

Crisp Input Ranges for $\frac{dHe}{dt}$ in %/s	Fuzzy State	Fuzzy Variable (Linguistics) Name
-10% to -7%	Very High	NEGATIVE FAST (NL)
-7.5% to -4%	High	NEGATIVE SLOW (NS)
-5% to 5%	Normal	ZERO (ZE)
4.5% to 7.5%	Low	POSITIVE SLOW (PS)
6.5% to 10%	Very Low	POSITIVE FAST (PL)

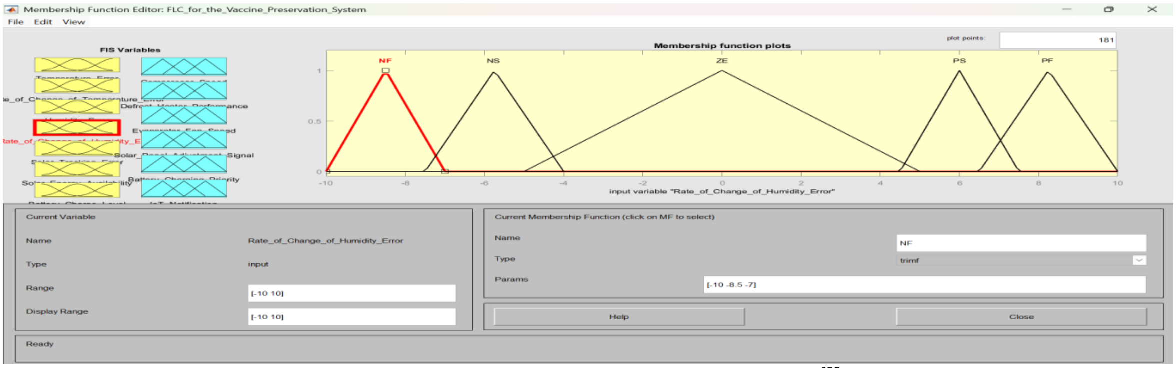

Figure7: Plot of inputmembershipfunction for ($\frac{dHe}{dt}$)

Table 5: Computation for Crisp Input Membership Function Values for (STE)

Solar Panel Optimal Position Range in degree	Solar Panel Actual Position Range in degree	Crisp Input for Solar Tracking Error in degree	Fuzzy Variable (Linguistics) Name
45 to 50	55 to 50	-10 to 0	NEGATIVE (NEG)
70 to 90	75 to 85	-5 to 5	ZERO (ZE)
90 to 120	90 to 110	0 to 10	POSITIVE (POS)

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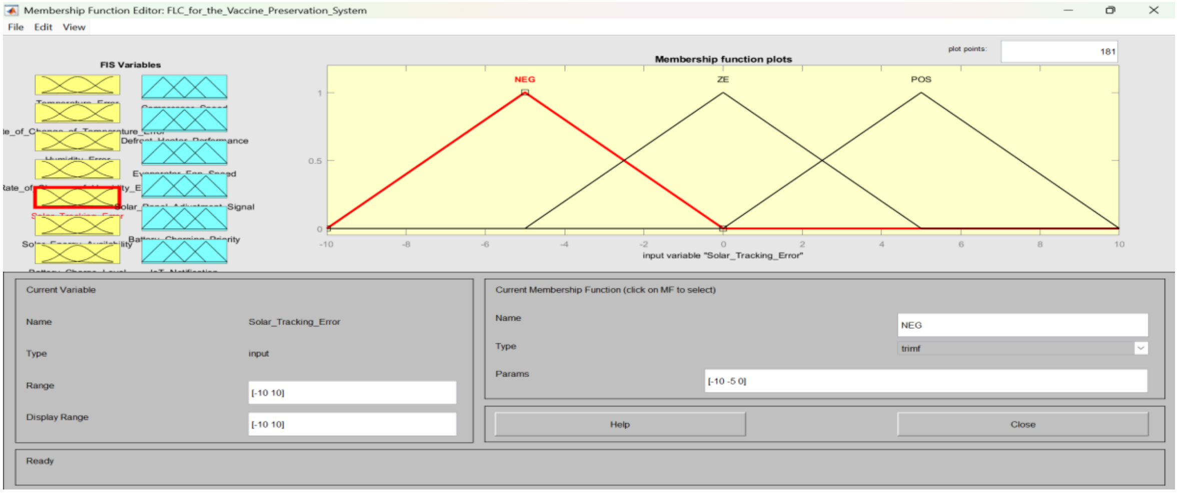

Figure8: Plot of inputmembershipfunction for Solar Tracking Error (STE)

Table 6: Computation for Crisp Input Membership Function Values for SEA

Crisp Input Ranges for SEA in W/m^2	**Fuzzy State**
0 to 200	Very Low (VL)
195 to 400	Low (L)
395 to 600	Medium (M)
595 to 800	High (H)
795 to 1000	Very High (VH)

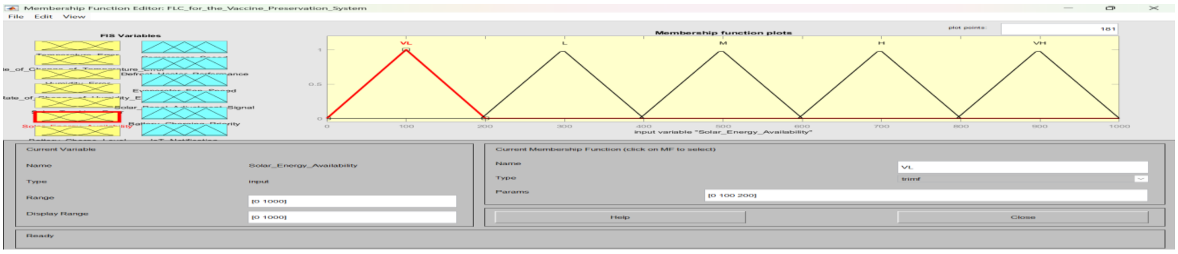

Figure9: Plot of inputmembershipfunction for Solar Energy Availability (SEA)

Table 7: Computation for Crisp Input Membership Function Values for BCL

Crisp Input Ranges for BCL in %	**Fuzzy State**
0 to 20	Very Low (VL)
19 to 40	Low (L)
39 to 60	Medium (M)
59 to 80	High (H)
79 to 100	Very High (VH)

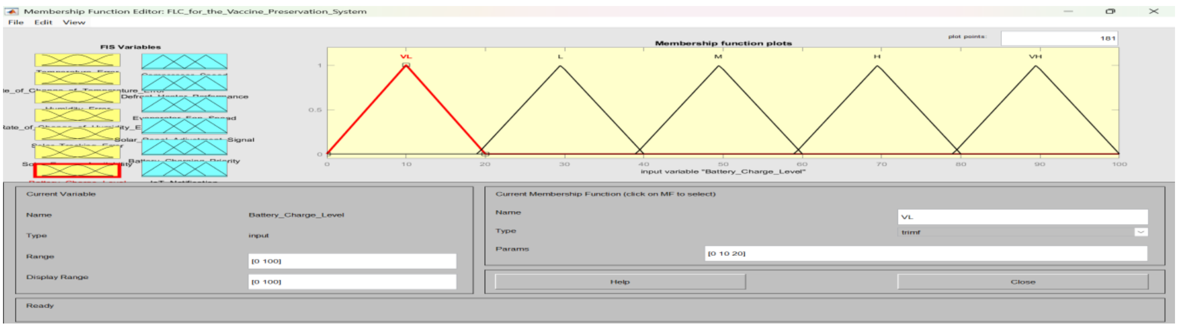

Figure 10: Plot of inputmembershipfunction for Battery Charge Level (BCL)

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The IFLC functions as the decision-making core of the vaccine storage system, facilitating intelligent regulation of critical operational parameters. By continuously analyzing input variables, the FLC ensures thermal stability, energy conservation, and optimized airflow while maximizing solar energy utilization and maintaining battery longevity. The IoT notification system categorizes alerts into three levels: NO ALERT, WARNING, and ALERTto provide vaccine handlers with real-time status updates and proactive maintenance guidance. Tables 8–13 present the influence of input variables on output regulation, while Figures 11–16 illustrate the IFLC's membership functions, demonstrating the system's capability for precise and efficient control.

Table 8:Compressor Speed (Output variables) Control based on T_e and $\frac{dTe}{dt}$

S/N	Input Variables		Output Variables		
	T_e	$\frac{dTe}{dt}$	Compressor Speed in (RPM)	Compressor Speed Range in %	Linguistic Variables
1	-12 to -8ºC	-9 to -6ºC	2399.9 to 3000	79 to 100	VERY HIGH SPEED (VHS)
2	-10 to -3ºC	-7.5to -1.5ºC	1799.9 to 2400	59 to 80	HIGH SPEED (HS)
3	-5 to 5ºC	-2.25 to 2.25ºC	1199.9 to 1800	39 to 60	MEDIUM SPEED (MS)
4	3 to 7ºC	1.5 to 5.25ºC	599.9 to 1200	19 to 40	LOW SPEED (LS)
5	5 to 12ºC	3 to 9ºC	0 to 600	0 to 20	VERY LOW SPEED (VLS)

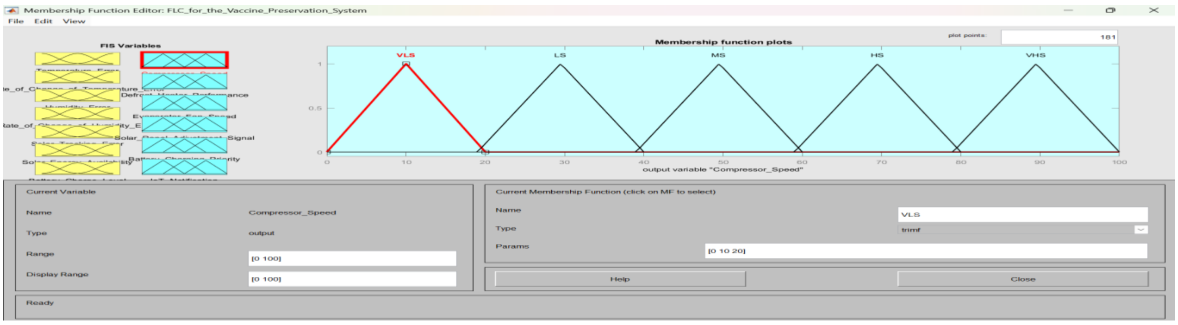

Figure 11: Membershipfunction plot for Compressor Speed Control based on T_e and $\frac{dTe}{dt}$

Table 9:Defrost Heater (Output variables) Control based onT_e and $\frac{dTe}{dt}$

S/N	Input Variables		Output Variables		
	T_e	$\frac{dTe}{dt}$	Defrost Heater (Duty Cycle in minutes) Range	Defrost Heater Range in %	Linguistic Variables
1	-12 to -8ºC	-9 to -6ºC	1 to 3	0 to 20	VERY LOW HEATING (VLH)
2	-10to -3ºC	-7.5 to -1.5ºC	2.99 to 5	19 to 40	LOW HEATING (LH)
3	-5 to 5ºC	-2.25to 2.25ºC	4.99 to 7	39 to 60	MEDIUM HEATING (MH)
4	3 to 7ºC	1.5 to 5.25ºC	6.99 to 9	59 to 80	HIGH HEATING (HH)
5	5 to 12ºC	3 to 9ºC	8.99 to 11	79 to 100	VERY HIGH HEATING (VHH)

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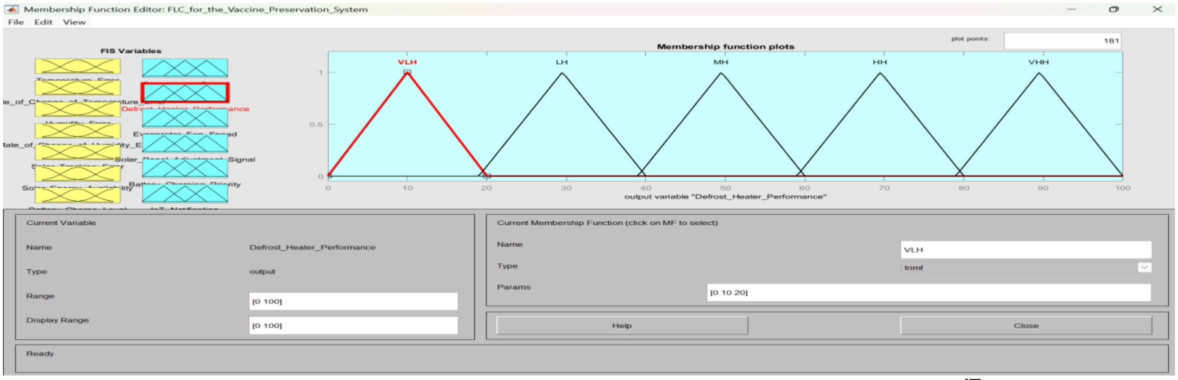

Figure 12: Membershipfunction plot for Defrost Heater based on T_e and $\frac{dTe}{dt}$

Table 10:Evaporator Fan Speed (Output variables) Control based on (H_e) and ($\frac{dHe}{dt}$)

S/N	Input Variables		Output Variables		
	H_e (%)	$\frac{dHe}{dt}$ (%)	Evaporator Fan Speed in (RPM)	Evaporator Fan Speed Range in %	Linguistic Variables
1	12 to 15	6.5 to 10	0 to 500	0 to 20	VERY LOW SPEED (VLS)
2	9 to 13	4.5 to 7.5	499.9 to 1000	19 to 40	LOW SPEED (LS)
3	-10 to 10	-5 to 5	999.9 to 1500	39 to 60	MEDIUM SPEED (MS)
4	-13to -9	-7.5 to -4	1499.9 to 2000	59 to 80	HIGH SPEED (HS)
5	-15 to -12	-10 to -7	1999.9 to 2500	79 to 100	VERY HIGH SPEED (VHS)

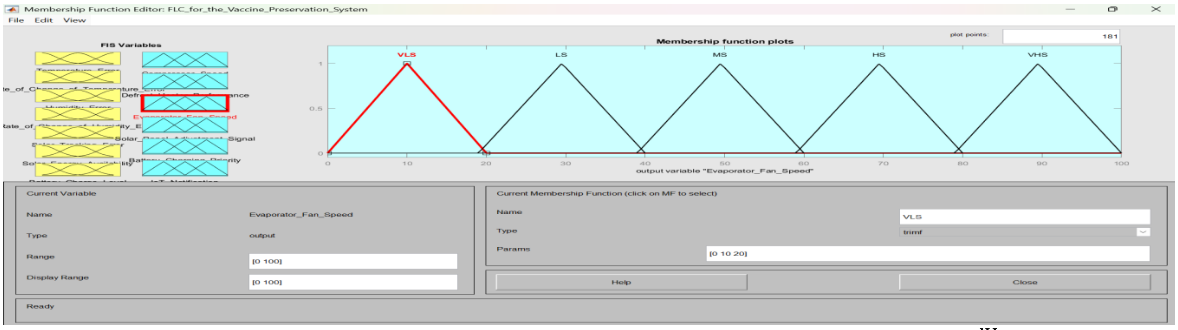

Figure 13: Membershipfunction plot for Evaporator Fan Speed Control based on (H_e) and ($\frac{dHe}{dt}$)

Table 11:Solar Panel Adjustment Signal (Output variables) based on STE and SEA in degree

S/N	Input Variables		Output Variables	
	STE	SEA (W/m^2)	Solar Panel Adjustment in degree	(Linguistic Variables) Adjustment Directions
1	-10 to 0 (NL)	0 to 200 (VL)	-7 to -4	STRONG LEFT (STL)
2	-10 to 0 (NL)	195 to 400 (L)	-5 to -2	SMALL LEFT (SML)
3	-5 to 5 (ZE)	395 to 600 (M)	-3 to 3	NO ADJUSTMENT (NA)
4	0 to 10 (PL)	595 to 800 (H)	2 to 5	SMALL RIGHT (SMR)
5	0 to 10 (PL)	795 to 1000 (VH)	4 to 7	STRONG RIGHT (STR)

Higher solar energy availability (SEA) leads to increased system adjustments to maximize energy capture, whereas larger solar tracking errors (STE) prompt more significant corrections to minimize misalignment. Conversely, when SEA is low and tracking errors are minimal, adjustments are reduced or omitted to conserve energy, as the potential benefits are negligible.

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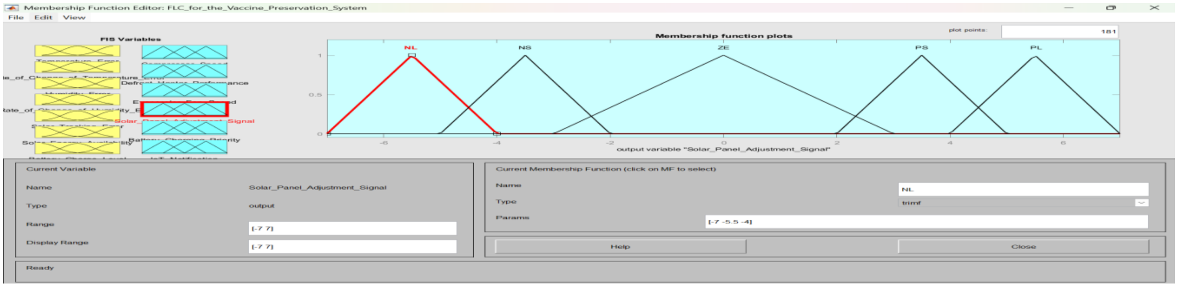

Figure 14: Membershipfunction plot for Solar Panel Adjustment Signal based on STE and SEA

Table 12:Battery Charging Priority (Output variables) Control based on BCL and SEA in %

S/N	Input Variables		Output Variables	
	Crisp input BCL in %	Fuzzy State	Battery Charging Priority Range in %	Linguistic Variables
1	0 to 20	Very Low	0 to 20	VERY HIGH PRIORITY(VHP)
2	19 to 40	Low	19 to 40	HIGH PRIORITY (HP)
3	39 to 60	Medium	39 to 60	MEDIUM PRIORITY (MP)
4	59 to 80	High	59 to 80	LOW PRIORITY(LP)
5	79 to 100	Very High	79 to 100	VERY LOW PRIORITY (VLP)

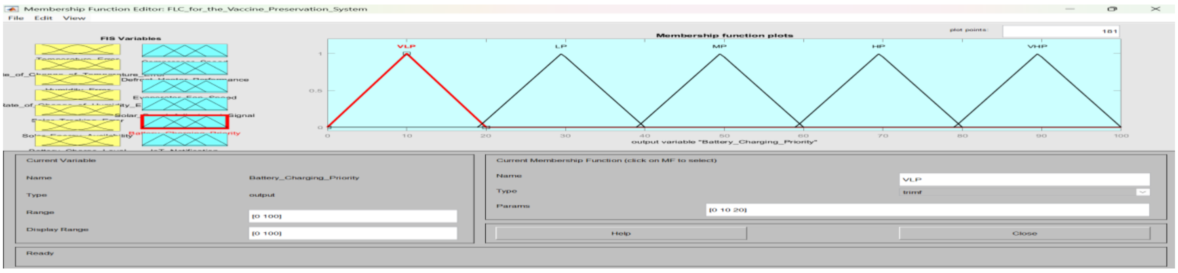

Figure 15: Membershipfunction plot for Battery Charging Priority based on BCL and SEA

Table 13:IoT Notification Membership Function and Linguistics Variables for the Vaccine Storage System

S/N	IoT Notification Membership Function Range	Notification State
1	-30 to 30	NO ALERT
2	30 to 70	WARNING
3	70 t0 130	ALERT

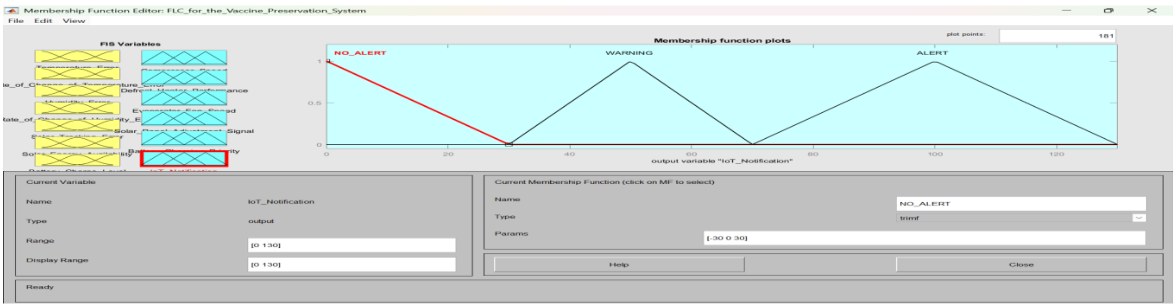

Figure 16: Membershipfunction plot for IoT Notification

Figure 16 illustrates the IoT notification system, which classifies operational states into NO ALERT, WARNING, and ALERT based on urgency levels. NO ALERT denotes optimal conditions, WARNING signals an approach toward critical thresholds, and ALERT necessitates immediate intervention to prevent system failure.To facilitate smooth state transitions, overlapping membership functions are employed:NO ALERT (decreases linearly from 1 at 0 to 0 at 30), WARNING (attains a peak membership value of 1 between 30 and 70) andALERT (increases linearly from 70 to 1 at 100).This intelligent framework enhances real-time decision-making by providing timely, actionable notifications, thereby improving vaccine storage efficiency and ensuring system reliability.

*b) Rule Design for the Fuzzy Logic-based Controller in the Vaccine Storage System:*The core of the intelligent control strategy developed in this work lies in its fuzzy logic-based reasoning system.To enhance system responsiveness, robustness, and energy efficiency, theIFLC was developed based on a rule-weighted Mamdani inference architecture. This enables the controller adapts in real-time by dynamically adjusting the influence of individual fuzzy rules in response to system performance feedback.A total of 29 expert-derived fuzzy control rules were implemented across five subsystems: compressor speed, defrost heater, evaporator fan, solar panel tracking, and IoT-based notification logic. Each rule R_i is associated with a time-varying weight $W_i(t)\in[0,1]$, representing the relevance or applicability of the rule under current operating conditions.The intelligent mechanism continuously monitors key performance indicators, such as temperature error (T_e), humidity error (H_e), battery charge level (BCL), and solar energy availability (SEA). These indices are used to update the rule weights using an error-driven learning law:

$$W_i(t+1)=W_i(t) + \eta\cdot e(t)\cdot\phi_i(x)$$

where η is the learning rate (e.g., 0.01–0.1), $e(t)$ is the deviation from the target state (e.gtemperature or humidity error), and $\phi_i(x)$ is the normalized firing strength of rule R_i.

The adopted method follows a heuristic error-based rule weighting approach, where each fuzzy rule's weight is updated during runtime according to its effectiveness in minimizing the control error. Specifically, the difference between the current and previous error (denoted as ΔE) is used to evaluate the effectiveness of each rule. Rules that contribute to error reduction are reinforced by increasing their weights, while ineffective or detrimental rules are weakened.

Mathematically, the weight W_i of rule i is updated according to:

$$W_i(t+1)=W_i(t)+ \eta\cdot\text{sign}(E(t-1)-E(t))\cdot[E(t-1)-E(t)]$$

This strategy enables interpretable, computationally efficient adaptation while avoiding the complexity and convergence issues of gradient-based methods. It offers self-tuning behavior by dynamically enhancing or suppressing control actions in real time, emulating cognitive decision-making under uncertainty. Implementation is achieved in MATLAB/Simulink using the Fuzzy Logic Toolbox, complemented by custom MATLAB Function blocks for weight updates and intelligent feedback. Table 14 presents the complete rule base, supporting precise, context-aware control under varying environmental conditions and with Figure 18 is the rule editor of the fuzzy logic controller for the Vaccine Storage SystemThe following code initializes the fuzzy inference system (FIS) with equal rule weights and dynamically updates them based on the improvement or deterioration in control performance in real times. This heuristic approach ensures rule weights adapt to reduce control error without compromising interpretability.

```
% Load and initialize FIS
fis = readfis('base29expertrules.fis');
for i = 1:length(fis.Rules)
fis.Rules(i).Weight = 1; % Set default rule weight
end
% Intelligent rule weighting function
function updatedFIS = updateRuleWeights(fis, error,
previousError)
alpha = 0.01;  % learning rate
deltaError = error - previousError;
ruleOutput = evalfis(fis, [error, deltaError]);
improvement = abs(previousError) - abs(error);
for i = 1:length(fis.Rules)
rule = fis.Rules(i);
if improvement > 0
rule.Weight = min(rule.Weight + alpha *
improvement, 1);
else
rule.Weight = max(rule.Weight - alpha *
abs(improvement), 0.1);
end
fis.Rules(i) = rule;
end
updatedFIS = fis;
end
```

TheIFLC decision-making framework is governed by these logical conditions;

i) Temperature Regulation

IF $T_{Actual} > T_{Desired}$, **THEN**output = **Negative**, indicating overheating beyond the target range.

IF $T_{Actual} \leq T_{Desired}$,**THEN** output = **Positive**, indicating that the system is within or below the optimal thermal range.

ii) Humidity Regulation

IF $H_{Actual} > H_{Desired}$, **THEN** output = **Negative**, indicating that the system maintains humidity within the acceptable range.

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IF $H_{Actual} < H_{Desired}$, **THEN** output = **Positive**, suggesting that the system is operating **below**the desired humidity range, potentially affecting vaccine stability.

Table 14: Intelligent Rule Base for the Operational Configuration of the IFLC.

Rule No	T_e	$(\frac{dTe}{dt})$	H_e	$(\frac{dHe}{dt})$	STE	SEA	BCL	Output Actions	Intelligent Weight (W_i)
Compressor Speed Control (Based on T_e and $\frac{dTe}{dt}$)									
1	NL	NL	-	-	-	-	-	**VHS** to rapidly cool the system	W_i1
2	NL	NS	-	-	-	-	-	**HS** for moderate cooling because system is stabilizing	W_i2
3	NS	ZE	-	-	-	-	-	**MS** to gradually stabilize temperature	W_i3
4	ZE	PS	-	-	-	-	-	**LS** to maintain stability with minimal cooling	W_i4
5	PS	PL	-	-	-	-	-	**VLS** to avoid overcooling to maintain system balance.	W_i5
6	PL	ZE	-	-	-	-	-	**VLS** to slowly reduce cooling to stabilize temperature.	W_i6
Defrost Heater Control (Based on T_e and $\frac{dTe}{dt}$)									
7	NL	NL	-	-	-	-	-	**VLH** to minimize heating to avoid further overheating.	W_i7
8	NL	NS	-	-	-	-	-	**VLH** to suppress heater operation to balance the temperature.	W_i8
9	NS	ZE	-	-	-	-	-	**LH** to gradually activate heater to balance conditions.	W_i9
10	ZE	PS	-	-	-	-	-	**MH** to moderate heating to stabilize temperature.	W_i10
11	PS	PL	-	-	-	-	-	**HH** to ncrease heating to prevent freezing.	W_i11
12	PL	PL	-	-	-	-	-	**VHH** to maximize heating to restore normal system conditions.	W_i12
13	ZE	NL	-	-	-	-	-	**VLH** to suppress heating to maintain normal operation.	W_i13
Defrost Heater Control (Based on T_e and H_e)									
14	PL	-	NL	-	-	-	-	**HH.** The system will prioritize heating to counteract extreme cold conditions.	W_i14
15	NS	-	PS	-	-	-	-	**MH** to balance heating to manage conditions.	W_i15
16	ZE	-	ZE	-	-	-	-	**LH** to maintain minimal heating to	W_i16

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								stabilize operation.	
17	PS	-	PL	-	-	-	-	**HH**. Controlled heating to maintain operational balance.	W_i17
Evaporator Fan Speed Control (Based on H_e and $\frac{dHe}{dt}$)									
18	-	-	NL	NF	-	-	-	**VHS** to maximize dehumidification	W_i18
19	-	-	NS	NS	-	-	-	**HS** to moderate dehumidification	W_i19
20	-	-	ZE	ZE	-	-	-	**MS** to maintain desired humidity level	W_i20
21	-	-	PS	PS	-	-	-	**LS** to reduce fan speed to stabilize humidity.	W_i21
22	-	-	PL	PF	-	-	-	**VLS** to minimize fan operation for current conditions.	W_i22
Solar Tracking Control(Based on STE and SEA)									
23	-	-	-	-	NEG	VH	-	**STL** to adjust solar panel significantly for optimal capture.	W_i23
24	-	-	-	-	ZE	M	-	**NA** There is no adjustment to panel position.	W_i24
25	-	-	-	-	POS	VL	-	**STR** to optimize panel angle positively.	W_i25
Battery Charging Priority (Based on BCL and SEA)									
26	-	-	-	-	-	VH	VL	**VHP** to Prioritize battery charging to prevent depletion.	W_i26
27	-	-	-	-	-	M	M	**MP** to balance charging and system demands.	W_i27
28	-	-	-	-	-	VL	VH	**VLP** to limit charging to avoid overcharging.	W_i28
IoT Notification Logic (Based on System State)									
Rule	*Input*				*Description*			*Notification*	*Intelligent Weight (W_i)*
29	Various				Contextual alerts			No Alert/Warning/Alert	W_i29

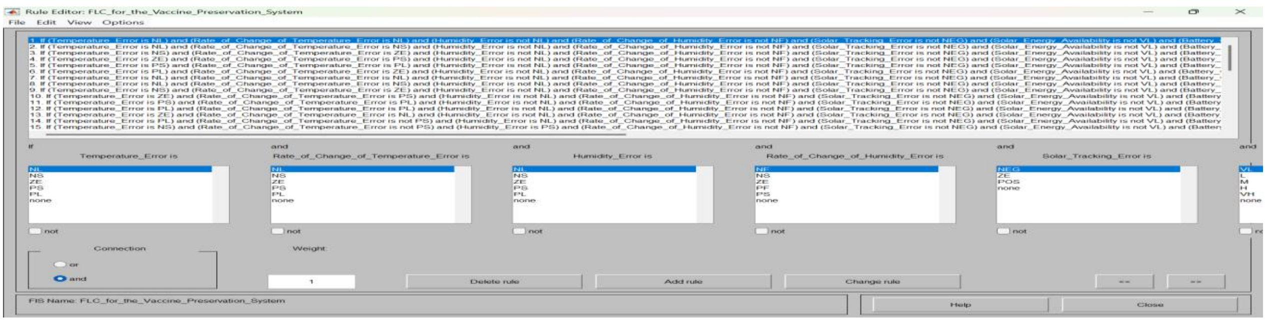

Figure 18: Rule Editor for the Fuzzy Logic Controller for the Vaccine Storage System

*c) Simulation and Performance Evaluation:*The Simulink model depicted in Figure 17**,** was developed using MATLAB/Simulink to simulate and validate the intelligent fuzzy logic controller designed for intelligent vaccine storage. The model adopts a modular architecture that facilitates systematic input-output mapping, in accordance with the fuzzy rules defined in Table

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14.The key features of the Simulink model include: Compressor control(via fuzzy rules tuned to internal temperature and rate of temperature change), Defrost heater and fan control (to regulate humidity and prevent ice buildup), Battery and solar energy logic (to prioritize energy efficiency) and IoT alerting system (to notify users of critical events based on intelligent rule evaluation).

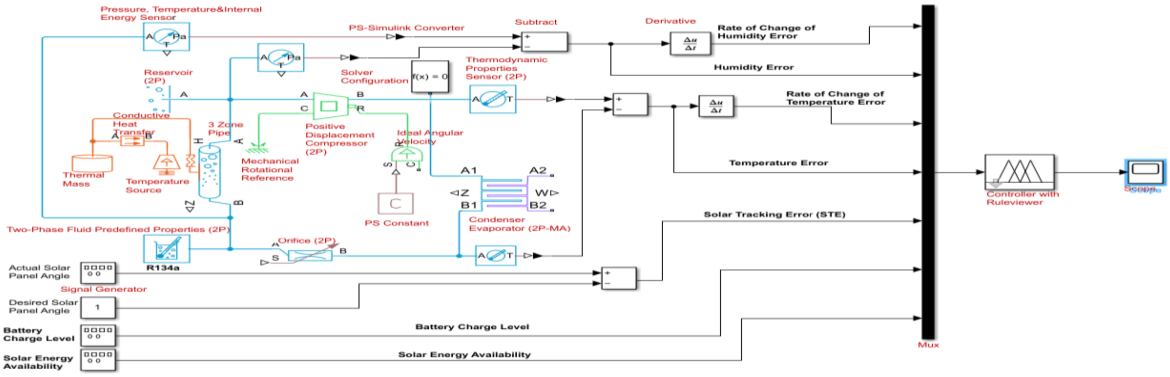

Figure 17: Simulink model of the Intelligent Fuzzy Logic Control System

The system is tested under fluctuating ambient conditions and performance assessed based on temperature stability (to maintain the target setpoint of 2°C–8°C despite load or ambient variations), energy efficiency(toreduce compressor/heater duty cycle through intelligent control), alert responsiveness (for timely and contextual warnings for human intervention) and robustness (for a reliable adaptation across different scenarios without retraining).

d) Experimental Validation: To assess the real-world performance of the intelligent fuzzy logic controller, an experimental prototype of a 200-liter vaccine refrigeration unit was developed. The setup included DS18B20 temperature sensors, an ESP32 IoT microcontroller, PWM-controlled variable-speed compressor, thermal load resistors, and INA219 energy monitoring, with MATLAB Simulink used for real-time control and data acquisition.Three operational scenarios were tested over 72 hours:Steady Load Testunder ambient fluctuations (25–35°C),Dynamic Load Test simulating vaccine handling and Fault Injection Test to evaluate controller adaptability.Each scenario was performed using a conventional ON-OFF controller, a fixed-rule fuzzy controller, and the intelligent fuzzy logic system. The performance metrics included:Temperature Stability (TS) for RMS deviation from the 5°C target,Energy Consumption (EC) indicating total kWh used,System Responsiveness (SR) representing recovery time after disturbance and Fault Recovery Index (FRI) for defining the percentage of successful fault recoveries.

III. RESULT AND ANALYSIS

The performance of the Intelligent Fuzzy Logic Controller (IFLC) for energy-efficient, IoT-enabled vaccine storage was evaluated through MATLAB/Simulinksimulationsshown in Figure 18, the Rule viewer of the IFLC for the Vaccine Storage System in Figure 19, the Surface viewer of the IFLC for the Vaccine Storage Systemand experimentally validated using a 200-liter prototype unit. The analysis focuses on thermal regulation, energy consumption, fault recovery, actuator responsiveness, and IoT-based anomaly detection, benchmarked against conventional PID and non-intelligent fuzzy logic controllers.

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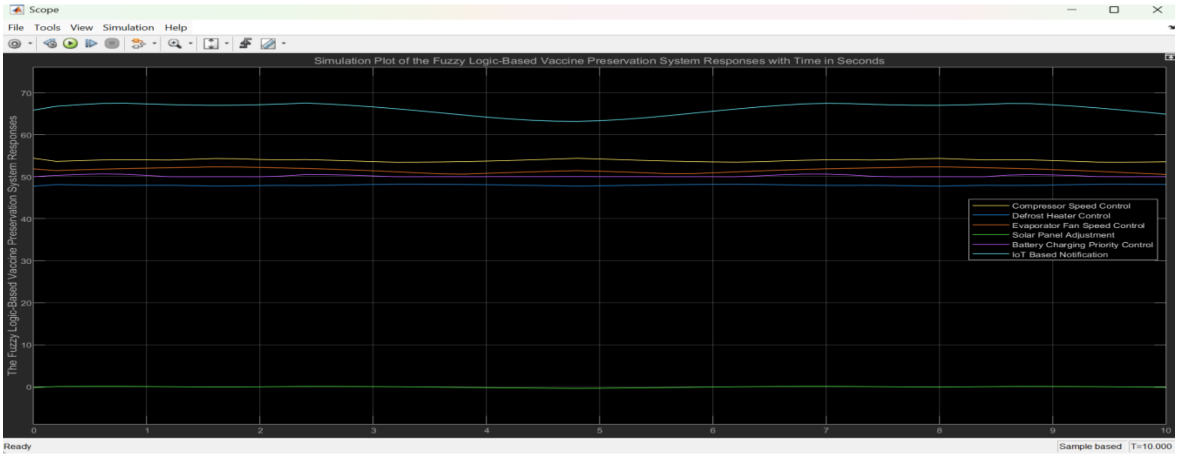

Figure 18: Simulation plot of system Response versus time in seconds.

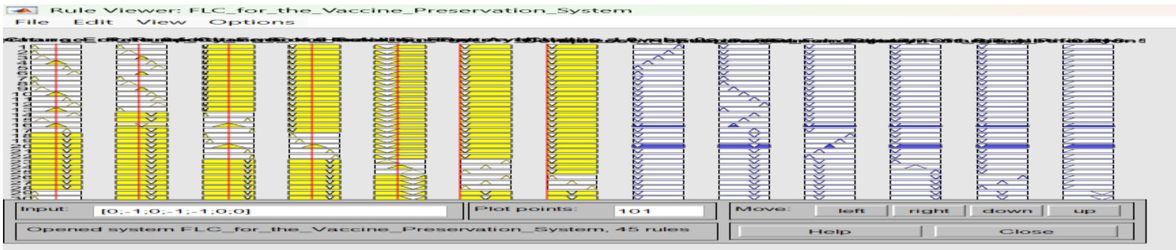

Figure 19: Rule viewer of the IFLC for the Vaccine Storage System

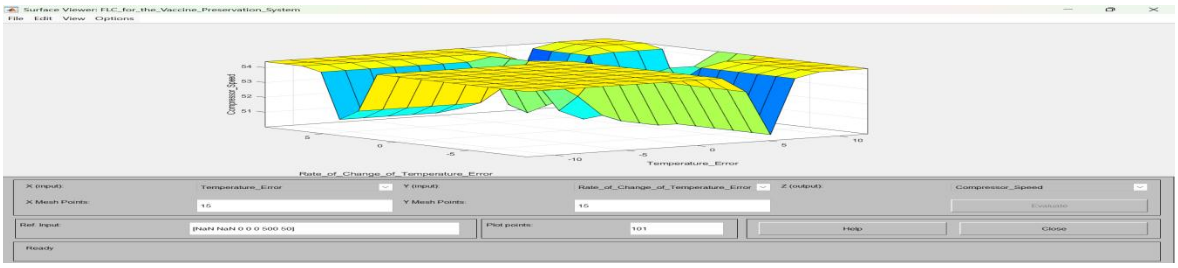

Figure 20: The Surface Viewer of the IFLC for the Vaccine Storage System

Table 15 presents a consolidated summary of the key performance metrics, highlighting the dynamic response characteristics, control precision, and energy efficiency achieved by the vaccine storage system. The IFLC consistently outperformed the baseline controllers across all scenarios.

Table 15: Comparative Performance Summary of Control Techniques

Performance Metric	**PID Controller**	**Static FLC**	**Intelligent FLC**
Temperature Regulation			
Time to Reach 5°C (min)	11.3	8.5	6.2
Max Temp Overshoot (°C)	±1.2	±0.8	±0.4
RMS Temp Deviation (°C)	0.90	0.62	0.32
Energy and Actuation			
Compressor Duty Cycle (%)	72	60	52
Energy Consumption (Normalized)	1.00	0.89	0.83 (17% reduction)
Avg Fan Speed (RPM)	Constant(1800)	Variable	Optimized (1000-2000)
Defrost Heater Activity (%)	High(Static)	Periodic	Contextual(10-40%)
System Responsiveness and Fault Recovery			
Fault Recovery Time (sec)	>240	180	118
IoT Alert Trigger Latency (sec)	-	65	<40
Thermal Stability Under Door Opening	±2.8°C	±1.5°C	±0.7°C

Recovery Time After Load Disturbance	160 sec	100 sec	<85 sec

The results demonstrate that the IFLC rapidly adjusts compressor speed and heater duty cycles based on real-time feedback from temperature error, humidity variation, solar energy availability, and battery status. The controller's intelligent rule-weighting mechanism ensures responsive yet energy-conscious operation by selectively prioritizing cooling, dehumidification, and charging processes.Post-simulation analysis using MATLAB's Rule Viewer and Surface Viewer confirmed nonlinear response surfaces aligned with dynamic environmental conditions. Additionally, IoT integration via ThingSpeak enabled real-time alerts categorized into NO ALERT, WARNING, and ALERT states, ensuring timely human intervention during anomalies. Experimental validation under ambient fluctuations and simulated faults revealed strong agreement with simulation data, further substantiating the robustness and deployability of the system.

IV. DISCUSSION

The Intelligent Fuzzy Logic Controller (IFLC) demonstrated superior performance over conventional PID and static fuzzy controllers in regulating the thermal and energy dynamics of the IoT-enabled vaccine storage system. Achieving a target temperature in 6.2 minutes with a minimal overshoot of ±0.4°C and RMS deviation of 0.32°C, the IFLC exhibited rapid convergence and high thermal stability which are key requirements for preserving vaccine efficacy. Compared to PID (11.3 minutes, ±1.2°C) and static FLC (8.5 minutes, ±0.8°C), this performance underscores the effectiveness of dynamic rule weighting and intelligent inference.Energy efficiency was also significantly improved. The IFLC reduced compressor duty to 52% and achieved a 17% decrease in energy consumption, highlighting its ability to intelligently allocate resources. Actuator outputs, including fan speed and defrost heater duty cycles, were contextually optimized, ensuring minimal energy wastage while maintaining environmental precision. Fault recovery time was reduced to 118 seconds, and IoT-based alert latency was under 40 seconds, enabling real-time diagnostics and intervention.Unlike prior non-intelligent fuzzy or statically integrated IoT systems, the IFLC introduced in this work continuously adjusted control actions based on environmental feedback and performance indices. This adaptivity, combined with a scalable, low-cost hardware design and cloud-based monitoring, positions the system as a viable solution for cold-chain resilience, particularly in off-grid settings.Experimental validation confirmed simulation results, affirming the controller's robustness, responsiveness, and energy-aware operation. The integration of solar energy and battery feedback further enhances its sustainability. Overall, the IFLC sets a new benchmark for intelligent vaccine preservation, combining fuzzy reasoning, intelligent control, and IoT transparency into a unified, deployable framework.

V. CONCLUSION

This study presented a novel integratedintelligent fuzzy logic control (IFLC) framework for energy-efficient, IoT-enabled vaccine storage, capable of maintaining critical thermal conditions with enhanced precision and reduced energy consumption. Through dynamic rule weighting and real-time environmental feedback, the system achieved faster convergence, minimal overshoot, and improved fault recovery compared to PID and static fuzzy approaches. IoT integration further enabled proactive monitoring and anomaly alerts, ensuring robust and transparent operation.The system's low-cost, scalable design makes it well-suited for deployment in both centralized facilities and remote, off-grid healthcare environments. Future enhancements may include integrating machine learning techniques for automated rule optimization and predictive maintenance, as well as expanded field validation under diverse climatic and logistical scenarios. These developments will further solidify the IFLC's role in advancing intelligent, resilient cold-chain systems for global vaccine distribution.

Acknowledgement: The author is grateful for the expert's contributions of the corresponding Author which resulted in the success of this research study.
Funding: There was no external financial support for this research study.
Conflict of Interest: There are no conflicts of interest for the Author.
Contributions by Author:
Ebiye B. Afekoro: Conceived the research idea and developed the framework for the study. Designed the fuzzy logic control system and methodology, performed system modeling and simulations, analyzed the results, and authored the initial draft of the manuscript. Contributed to structuring the

manuscript and interpreting findings for practical applications in vaccine storage.
Dr. Donatus U. Onyishi: Provided expert guidance on control system design and implementation. Critically reviewed and refined the fuzzy logic model, ensuring the accuracy and robustness of the control strategy. Conducted in-depth revisions, improving the clarity, coherence, and technical rigor of the manuscript. Assisted in finalizing the manuscript and aligning it with relevant research standards.
Both authors reviewed and approved the final version of the manuscript for submission.
Ethics Consideration: Not applicable.
Data Availability Statement: Not applicable.

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