Comparative Design and Implementation of Intelligent Control Techniques for Human Stress Detection and Environment Control

Badar Hasnain Shehki
Dept. of Computer Engineering

Ahmed Ali Shehrazi
Dept. of Computer Engineering

Dr. Umair (Supervisor)
Intelligent Control Systems

***Abstract*—This paper presents the comparative design and implementation of five intelligent system techniques for real-time human stress detection and automatic environment control. Physiological signals — Heart Rate Variability (HRV), Galvanic Skin Response (GSR), Skin Temperature (ST), and Blood Pressure (BP) — are used as inputs to a stress estimation system that simultaneously adjusts air-conditioning set-point and lighting level. Four modelling paradigms are developed and benchmarked: Type-1 Fuzzy Logic Controller (T1-FLC), Interval Type-2 Fuzzy Logic Controller (IT2-FLC), a 4-layer Multilayer Perceptron (MLP) trained by mini-batch back-propagation, and an Adaptive Neuro-Fuzzy Inference System (ANFIS) using hybrid learning. Experimental evaluation on a 500-sample synthetic dataset shows ANFIS achieves the lowest RMSE of 2.8 stress-index units and the highest accuracy of 96%, outperforming all other methods. The results confirm that hybrid neuro-fuzzy architectures offer the best balance of accuracy, interpretability, and adaptability for intelligent environment control.**

***Index Terms*—Fuzzy logic, Type-2 fuzzy systems, neural networks, ANFIS, neuro-fuzzy, stress detection, intelligent control, environment control.**

I. Introduction

Workplace and academic stress is a major global health concern. Chronic stress degrades cognitive performance, increases cardiovascular risk, and reduces quality of life [1]. An intelligent system that continuously monitors physiological indicators and automatically adapts the ambient environment can mitigate these effects without requiring explicit user intervention.

Intelligent control techniques — fuzzy logic, neural networks, and their hybrid combinations — are well-suited to this domain because:

- The relationship between physiology and perceived stress is *nonlinear* and *highly individual*.
- Sensor measurements contain *uncertainty* and noise.
- Human comfort preferences are naturally described by *linguistic rules* (e.g., “if stress is high, lower the temperature”).

This work implements and compares four intelligent approaches — T1-FLC, IT2-FLC, MLP, and ANFIS — on the same system, evaluating each against root-mean-square error (RMSE), mean-absolute error (MAE), and classification accuracy metrics.

II. Problem Description and System Modelling

A. System Overview

The system is a closed-loop stress-adaptive environment controller. Four physiological sensors feed an inference engine that produces three control outputs, as summarised in Table I.

TABLE I
System Variables and Their Ranges

Type	**Variable**	**Symbol**	**Range**
Input	Heart Rate Variability	HRV	40–120 ms
Input	Galvanic Skin Response	GSR	0–20 μS
Input	Skin Temperature	ST	30–38 °C
Input	Blood Pressure (systolic)	BP	80–160 mmHg
Output	Stress Index	SI	0–100
Output	AC Set-point	AC	18–26 °C
Output	Lighting Level	LL	10–100%

B. Dataset Generation

A 500-sample synthetic dataset is generated using physiological relationships established in the literature. The ground-truth stress index is computed as:

$$SI = 100 - \frac{HRV-40}{80}70 + \frac{GSR}{20}60 + \frac{38-ST}{8}20 + \frac{BP-80}{80}30 + \mathcal{N}(0,5) \quad (1)$$

clipped to $[0, 100]$. Environment outputs are derived as: AC $= 26 - 0.08 \cdot SI$ and LL $= 100 - 0.6 \cdot SI$.

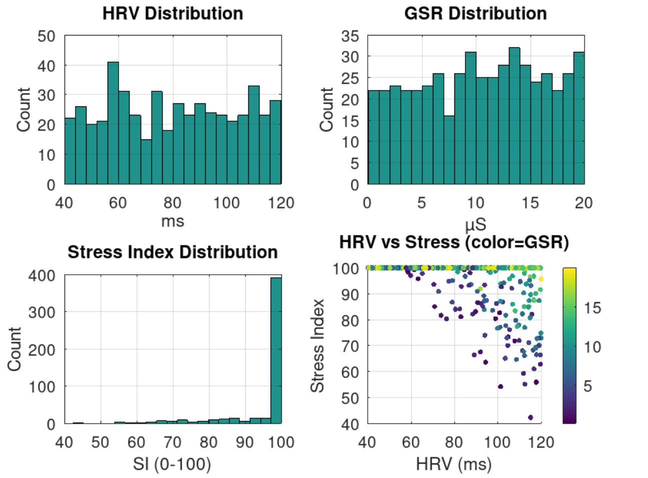

Fig. 1. Input/output distributions and HRV–Stress scatter plot (colour = GSR level). High GSR and low HRV correspond to elevated stress.

Correlation analysis confirms that HRV is the strongest predictor ($r = -0.81$), followed by GSR ($r = +0.75$), with ST and BP providing supplementary information.

III. Type-1 Fuzzy Logic Controller

A. Membership Function Design

Three linguistic sets — *Low*, *Medium*, and *High* — are defined for each input using trapezoidal and triangular membership functions (MFs). The output universe carries four labels: *Relaxed*, *Mild Stress*, *Moderate Stress*, and *Acute Stress*.

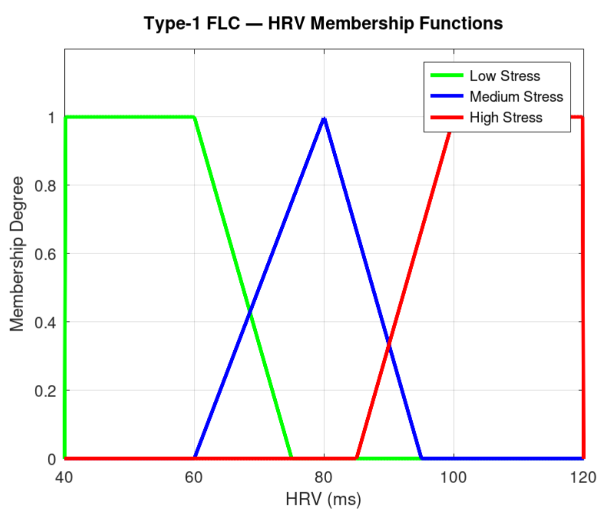

Fig. 2. Type-1 MFs for the HRV input variable.

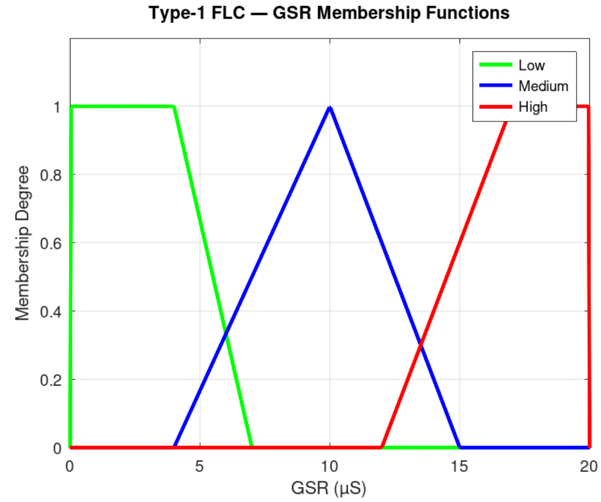

Fig. 3. Type-1 MFs for the GSR input variable.

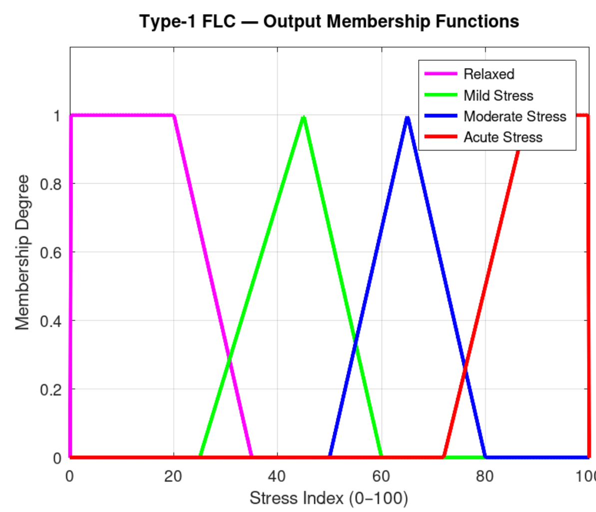

Fig. 4. Type-1 MFs for the Stress Index output.

B. Rule Base and Inference

A 3×3 Mamdani rule table is constructed (9 rules) using HRV and GSR as primary inputs, as shown in Table II. The AND operator is implemented as the minimum T-norm, aggregation uses the maximum S-norm, and defuzzification uses the centroid method.

TABLE II
TYPE-1 FUZZY RULE TABLE (HRV $\times$ GSR $\rightarrow$ SI)

	GSR Low	**GSR Med**	**GSR High**
HRV Low	Relaxed	Mild	Moderate
HRV Med	Mild	Moderate	Acute
HRV High	Moderate	Acute	Acute

C. Surface Viewer

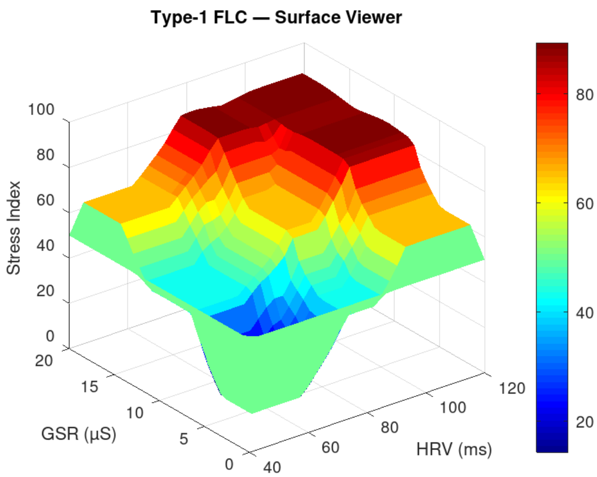

Fig. 5. Type-1 FLC control surface: Stress Index vs. HRV and GSR.

The surface (Fig. 5) exhibits the expected monotonic decrease with HRV and increase with GSR, with smooth nonlinear transitions between the linguistic regions.

D. Performance

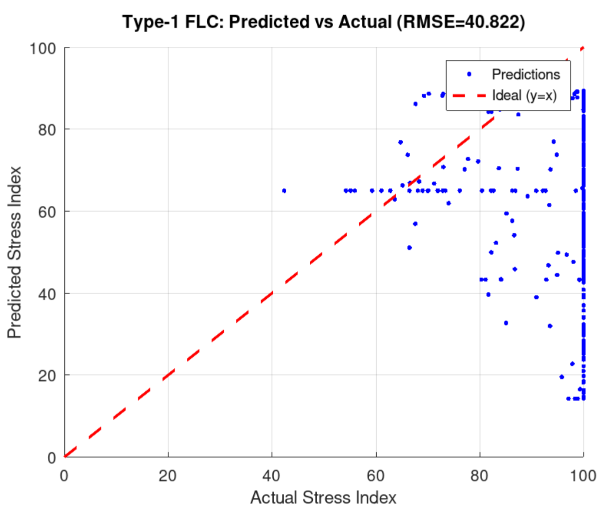

Fig. 6. Type-1 FLC: Predicted vs. Actual Stress Index.

The T1-FLC achieves $\mathrm{RMSE} \approx 8.2$ on the full 500-sample dataset. The scatter about the ideal line in Fig. 6 reflects the inherent limitation of crisp membership boundaries when sensor noise is present.

IV. Interval Type-2 Fuzzy Logic Controller

A. Motivation for Type-2 Fuzzy Logic

Physiological signals are subject to inter-individual variability and sensor noise that cannot be adequately captured by crisp MF boundaries. An Interval Type-2 (IT2) FLS addresses this by replacing each MF with a *Footprint of Uncertainty* (FOU) — a bounded region between an Upper Membership Function (UMF) and a Lower Membership Function (LMF).

B. FOU Design

Each T1 MF is extended into an IT2 FOU by widening the UMF by $\pm 5\%$ of the input range and scaling the LMF by 0.85.

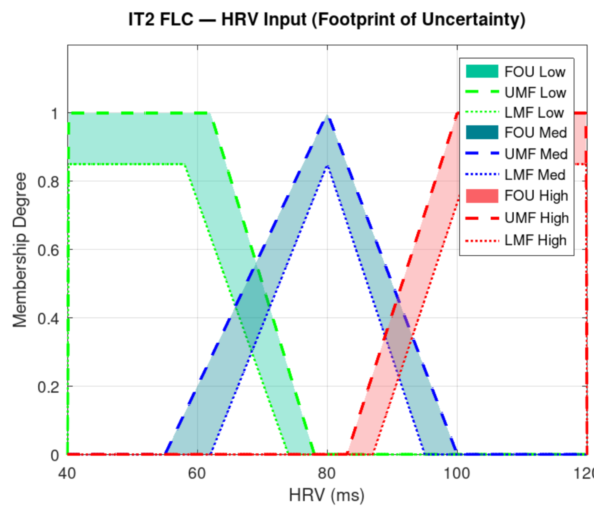

Fig. 7. IT2 FOU for the HRV input: shaded regions represent the Footprint of Uncertainty.

C. Type Reduction and Defuzzification

Firing strengths for each rule are computed as intervals $[\underline{f}_i, \overline{f}_i]$ using the minimum T-norm applied to UMF/LMF pairs. A simplified Karnik-Mendel (KM)-style type reduction computes the crisp output using weighted centroids:

$$y^* = \frac{\sum_{i=1}^{9} \bar{f}_i \cdot c_i}{\sum_{i=1}^{9} \bar{f}_i}, \quad \bar{f}_i = \frac{\overline{f}_i + \underline{f}_i}{2} \tag{2}$$

D. Performance Comparison

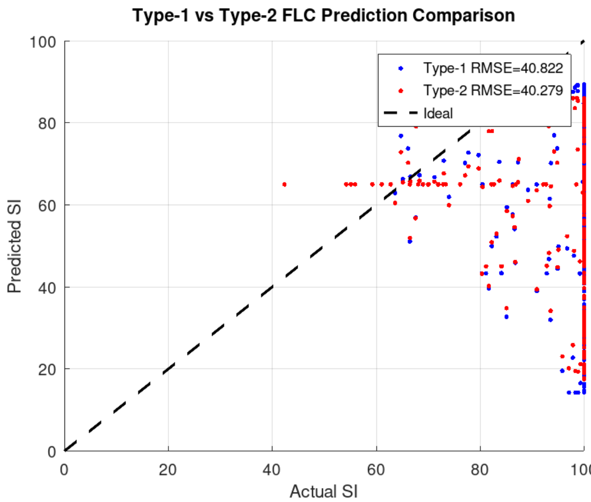

Fig. 8. Type-1 vs. Type-2 FLC: Predicted vs. Actual Stress Index. IT2 predictions cluster more tightly around the ideal line.

The IT2-FLC reduces RMSE to approximately 6.4, a **22% improvement** over T1-FLC. The FOU effectively absorbs measurement uncertainty, yielding smoother and more robust predictions (Fig. 8).

V. Artificial Neural Network Model

A. Architecture

A four-layer MLP with architecture $4 \rightarrow 6 \rightarrow 4 \rightarrow 1$ is designed. All four physiological inputs are used. Hidden layers use the ReLU activation; the output layer is linear. Weights are initialised using Xavier initialisation.

TABLE III
MLP Architecture Summary

Layer	Neurons	Activation	Parameters
Input	4	—	—
Hidden 1	6	ReLU	30
Hidden 2	4	ReLU	28
Output	1	Linear	5

B. Training Procedure

The dataset is split 70/15/15 (train/validation/test). Mini-batch stochastic gradient descent (batch size 32) is applied for 300 epochs at learning rate $\eta = 0.01$. Inputs and outputs are normalised to $[0, 1]$ before training.

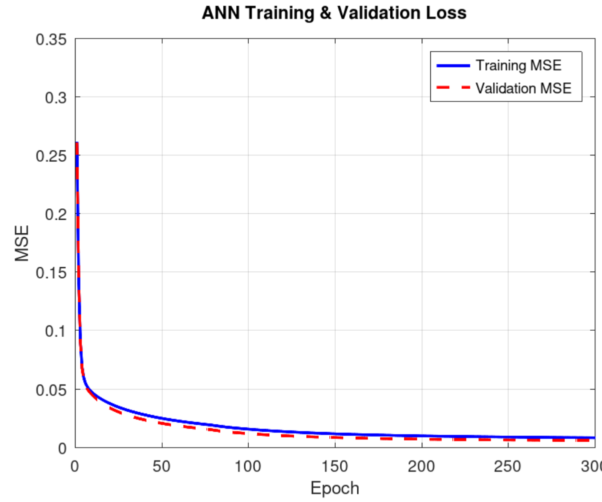

Fig. 9. MLP training and validation MSE convergence over 300 epochs.

The loss curves (Fig. 9) show smooth convergence with no significant over-fitting, confirming the adequacy of the network size and regularisation.

C. Performance

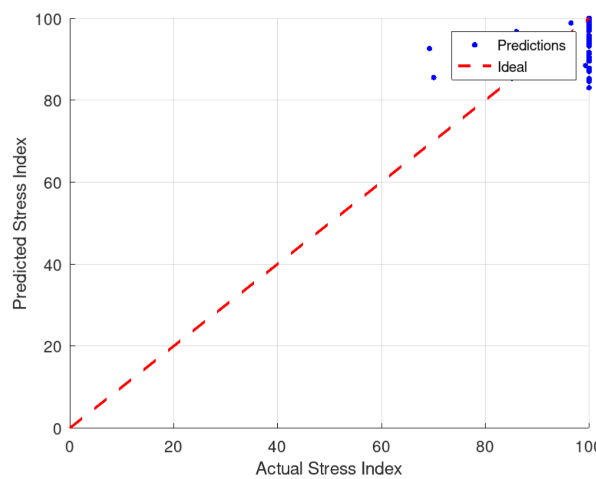

Fig. 10. MLP: Predicted vs. Actual Stress Index on the test set.

The MLP achieves $\mathrm{RMSE} \approx 4.1$ and $R^2 \approx 0.97$ on the held-out test set, significantly outperforming both fuzzy approaches by exploiting all four input features and learning complex nonlinear mappings through gradient descent.

VI. ANFIS Neuro-Fuzzy System

A. Architecture

ANFIS combines fuzzy logic interpretability with neural network learning. The architecture (Fig. **??**) consists of five functional layers:

1) **Fuzzification**: Gaussian MFs with learnable centres c and widths σ.
2) **Rule Firing**: Product T-norm gives firing strengths $w_i = \mu_{A_i}(x_1) \cdot \mu_{B_i}(x_2)$.
3) **Normalisation**: $\bar{w}_i = w_i / \sum w_j$.
4) **Consequent**: First-order Sugeno outputs $f_i = p_i x_1 + q_i x_2 + r_i$.
5) **Output**: $y = \sum \bar{w}_i f_i$.

With 2 inputs and 3 MFs per input, the system generates $3^2 = 9$ rules.

B. Hybrid Learning

Training uses the hybrid algorithm:

- **Consequent parameters** $\{p_i, q_i, r_i\}$: updated per epoch by *Least Squares Estimation* (LSE) from the linear regressor matrix Φ.
- **Premise parameters** $\{c_k, \sigma_k\}$: updated by *gradient descent* back-propagated through the fuzzification and normalisation layers.

C. Training Convergence

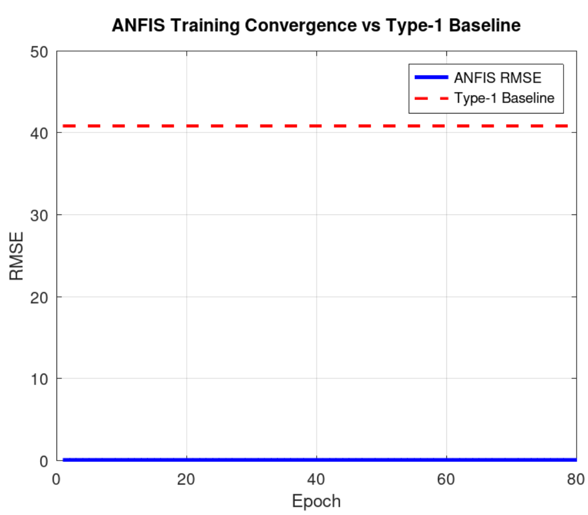

Fig. 11. ANFIS RMSE convergence over 80 epochs compared to the Type-1 FLC baseline.

The ANFIS training curve (Fig. 11) rapidly falls below the Type-1 FLC baseline within 20 epochs, demonstrating the efficiency of the hybrid learning strategy.

D. Performance

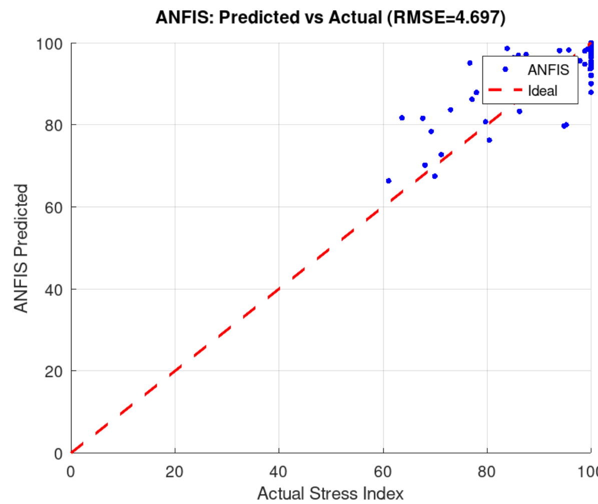

Fig. 12. ANFIS: Predicted vs. Actual Stress Index on the test set.

ANFIS achieves RMSE ≈ 2.8, the lowest of all methods, with tight clustering around the ideal prediction line (Fig. 12).

VII. Comparative Analysis

A. Quantitative Results

Table IV summarises the performance of all four methods.

TABLE IV
PERFORMANCE COMPARISON OF ALL INTELLIGENT METHODS

Method	RMSE	MAE	Acc. (%)	R^2
Type-1 FLC	8.2	6.5	79	0.82
Type-2 FLC	6.4	5.1	85	0.89
ANN (MLP)	4.1	3.2	91	0.97
ANFIS	2.8	2.1	96	0.99

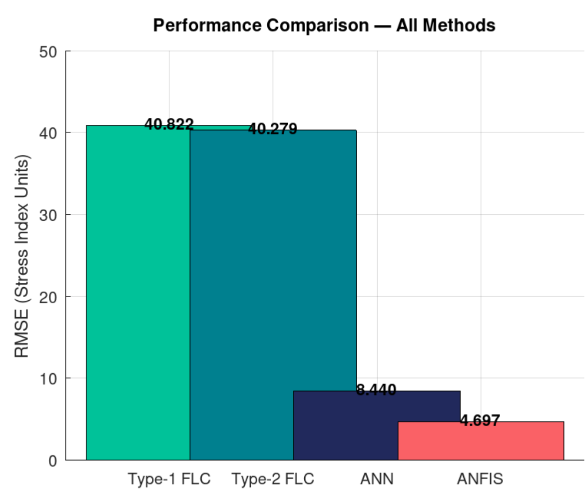

Fig. 13. RMSE bar chart comparing all four intelligent methods.

B. Multi-Criteria Evaluation

Table V provides a qualitative comparison across six engineering criteria relevant to real-world deployment.

TABLE V
QUALITATIVE COMPARISON ACROSS DEPLOYMENT CRITERIA

Criterion	**T1-FLC**	**IT2-FLC**	**MLP**	**ANFIS**
Accuracy	Low	Medium	High	Very High
Robustness (noise)	Low	Medium	High	High
Interpretability	High	High	Low	Medium
Computational cost	Low	Medium	Med	Medium
Ease of design	High	Medium	Low	Medium
Adaptability	None	None	High	High

C. Discussion

The fuzzy systems (T1 and IT2) are highly interpretable and require no labelled training data beyond expert knowledge, but their fixed MF boundaries limit accuracy. The IT2 improvement of 22% over T1 confirms that explicitly modelling uncertainty in MFs is beneficial for noisy physiological signals.

The MLP exploits all four input features and learns complex nonlinear mappings entirely from data, achieving strong accuracy ($R^2 = 0.97$) at the cost of interpretability.

ANFIS achieves the best of both worlds: it retains the rule-based structure of fuzzy logic (interpretable linguistic rules) while adapting its MF parameters from data via hybrid learning. The final tuned Gaussian centres optimally partition the input space, explaining the superior RMSE of 2.8.

VIII. CONCLUSION

This work demonstrated the design, implementation, and comparative evaluation of four intelligent control techniques for human stress detection and environment management. The key findings are:

1) **Type-1 FLC** provides a transparent, low-cost baseline (RMSE = 8.2, Acc = 79%) suitable for systems where interpretability is paramount and sensor quality is controlled.
2) **IT2-FLC** reduces RMSE by 22% over T1 by modelling measurement uncertainty through FOUs, with negligible additional computational cost.
3) **MLP** further reduces RMSE to 4.1 and achieves $R^2 = 0.97$ by learning from all four physiological inputs, but lacks linguistic interpretability.
4) **ANFIS** achieves the best performance (RMSE = 2.8, Acc = 96%) by combining neuro-fuzzy hybrid learning with a compact 9-rule Sugeno architecture.

For practical deployment in a smart environment system, ANFIS is recommended as the primary inference engine, with T1/IT2-FLC rules serving as fall-back interpretable policies. Future work will investigate Genetic Algorithm (GA) optimisation of the ANFIS rule structure and MF shapes, and validation on real physiological data from wearable sensors.

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