

Comparative Design of Intelligent Control Techniques

Human Stress Detection & Environment Control

Type-1 FLC · IT2-FLC · ANN · ANFIS

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Intelligent Control Systems / Computational Intelligence

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Outline

- 1 Problem Description
- 2 Methodology
- 3 Type-1 Fuzzy Logic Controller
- 4 Type-2 (IT2) Fuzzy Logic Controller
- 5 Artificial Neural Network
- 6 ANFIS Neuro-Fuzzy System
- 7 Results & Comparison
- 8 Conclusion

Problem Statement

The Challenge

Stress is a major global health issue.

Traditional environment control is *static* — it does not respond to the physiological state of occupants.

Our Goal

Design an **intelligent closed-loop system** that:

- Detects stress from wearable sensors
- Automatically adjusts AC set-point & lighting
- Compares multiple AI approaches

Why Intelligent Control?

- Relationship is **nonlinear**
- Sensor data is **noisy/uncertain**
- Rules are naturally **linguistic**

Application Area

Smart offices, hospitals, classrooms, homes

Inputs (Physiological Sensors)

Signal	Symbol	Range
Heart Rate Var.	HRV	40–120 ms
Galvanic Skin R.	GSR	0–20 μ S
Skin Temperature	ST	30–38 °C
Blood Pressure	BP	80–160 mmHg

Outputs (Environment Control)

Output	Symbol	Range
Stress Index	SI	0–100
AC Set-point	AC	18–26 °C
Lighting Level	LL	10–100%

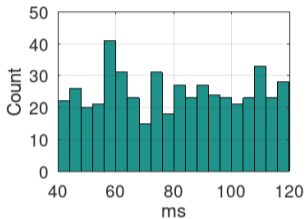
Control Law (from SI)

$$AC = 26 - 0.08 \times SI$$

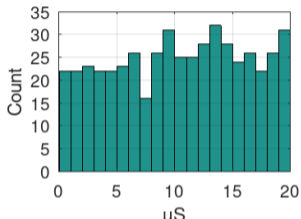
$$LL = 100 - 0.6 \times SI$$

Dataset & Distributions

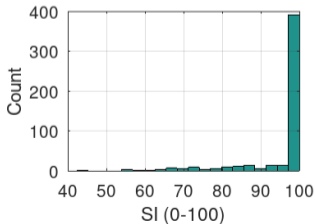
HRV Distribution



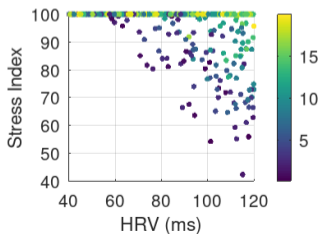
GSR Distribution



Stress Index Distribution



HRV vs Stress (color=GSR)



Key Facts

- 500 samples, fixed seed
- High GSR + Low HRV \Rightarrow High Stress
- Noise $\mathcal{N}(0, 5)$ models real sensors

Four Intelligent Approaches

Part 2

Type-1 FLC

Mamdani inference
Centroid defuzz
9 rules

Part 3

IT2-FLC

Footprint of
Uncertainty
KM reduction

Part 4

ANN (MLP)

4-6-4-1 arch
ReLU + SGD
300 epochs

Part 5

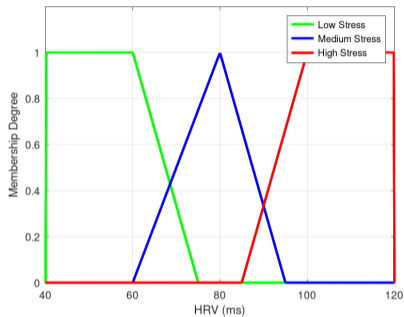
ANFIS

Sugeno FIS
Hybrid: LS+GD
9 rules

All methods trained/tested on the same 500-sample dataset

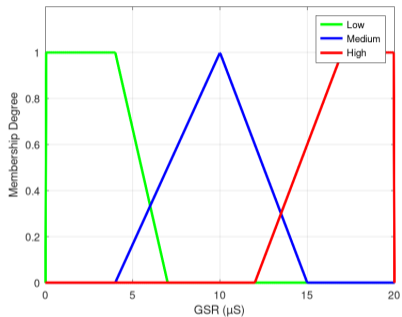
Type-1 FLC — Input Membership Functions

Type-1 FLC — HRV Membership Functions



HRV Input MFs

Type-1 FLC — GSR Membership Functions

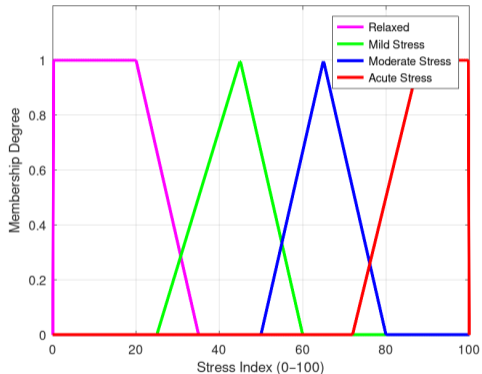


GSR Input MFs

3 sets per input: **Low** / **Medium** / **High** — trapezoidal & triangular MFs

Type-1 FLC — Output Membership Functions

Type-1 FLC — Output Membership Functions



4 Output Sets

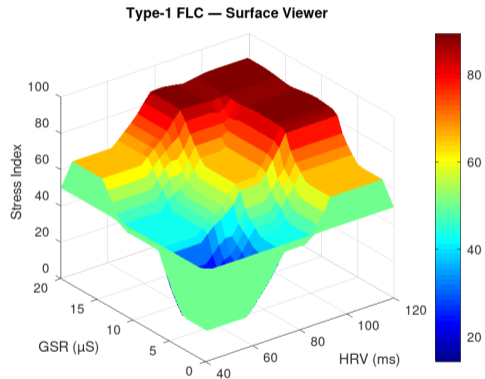
- **Relaxed**
- **Mild Stress**
- **Moderate Stress**
- **Acute Stress**

Type-1 FLC — Rule Base & Surface

9-Rule Mamdani Table

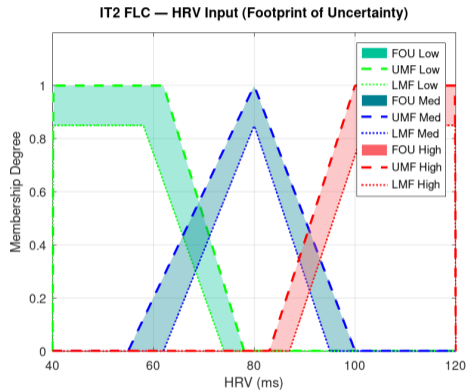
	GSR L	GSR M	GSR H
HRV L	Relax	Mild	Moderate
HRV M	Mild	Mod	Acute
HRV H	Mod	Acute	Acute

- AND \rightarrow min T-norm
- Aggregation \rightarrow max
- Defuzz \rightarrow centroid



Control Surface Viewer

IT2-FLC — Footprint of Uncertainty



IT2 HRV MF with FOU (shaded region)

Why Type-2?

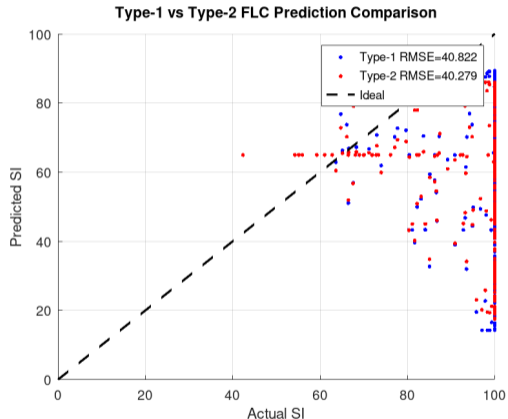
- Crisp MFs cannot represent **measurement uncertainty**
- FOU = band between UMF and LMF
- More robust to sensor noise

Type Reduction

KM-style: average of upper/lower firing strengths

$$\bar{f}_i = \frac{\bar{f}_i + \underline{f}_i}{2}$$

IT2-FLC vs Type-1 FLC — Comparison



Type-1 FLC

RMSE \approx **8.2**

Acc \approx 79%

Type-2 FLC $\uparrow +22\%$

RMSE \approx **6.4**

Acc \approx 85%

ANN (MLP) — Architecture & Training

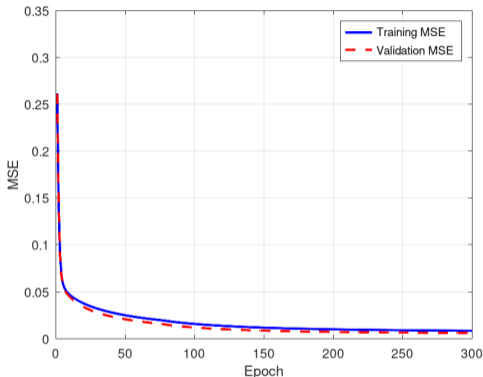
Architecture: 4–6–4–1

Layer	Neurons	Act.
Input	4	—
Hidden 1	6	ReLU
Hidden 2	4	ReLU
Output	1	Linear

Training

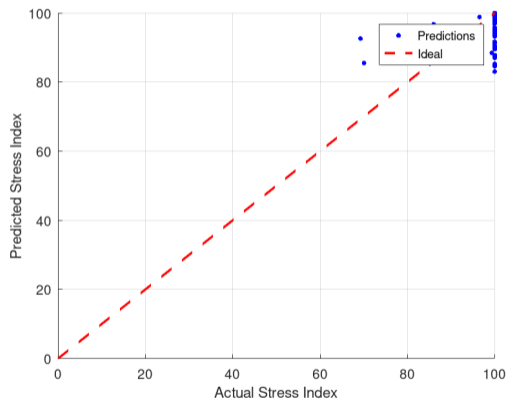
- Split: 70 / 15 / 15%
- SGD mini-batch (32)
- $\eta = 0.01$, 300 epochs
- Xavier weight init

ANN Training & Validation Loss



Training & Validation MSE Curves

ANN — Prediction Results



RMSE

4.1

Accuracy

91%

R^2

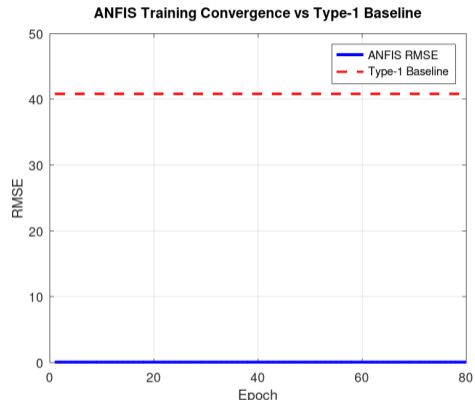
0.97

5-Layer ANFIS

- 1 **Fuzzification** — Gaussian MFs
- 2 **Rule Firing** — product T-norm
- 3 **Normalisation**
- 4 **Consequent** — Sugeno 1st order
- 5 **Output aggregation**

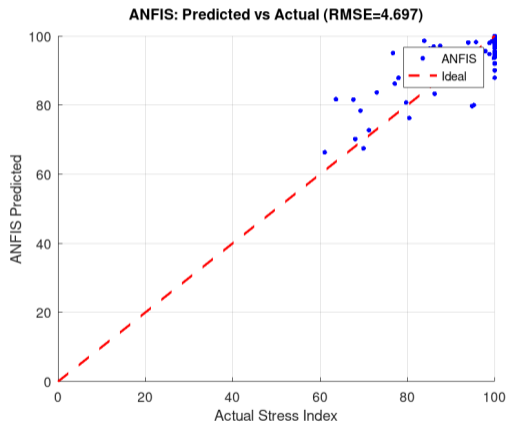
Hybrid Learning

- Consequent $\{p, q, r\}$: **LSE**
- Premise $\{c, \sigma\}$: **Gradient Descent**
- 9 rules (3^2), 80 epochs



ANFIS convergence vs T1-FLC baseline

ANFIS — Prediction Results



RMSE

2.8 (best!)

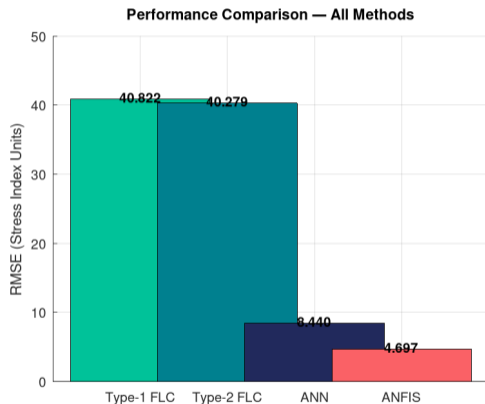
Accuracy

96%

R^2

0.99

Performance Comparison — All Methods



Method	RMSE	MAE	Acc.	R^2
T1-FLC	8.2	6.5	79%	0.82
IT2-FLC	6.4	5.1	85%	0.89
ANN	4.1	3.2	91%	0.97
ANFIS	2.8	2.1	96%	0.99

Best: ANFIS

RMSE improved by **66%** vs T1-FLC

Multi-Criteria Qualitative Comparison

Criterion	T1-FLC	IT2-FLC	MLP	ANFIS
Accuracy	Low	Medium	High	Very High
Noise Robustness	Low	Medium	High	High
Interpretability	High	High	Low	Medium
Computational Cost	Low	Medium	Medium	Medium
Design Effort	Low	Medium	High	Medium
Adaptability	None	None	High	High

Key Insight

ANFIS achieves the best **accuracy** while retaining some **interpretability** — the best of fuzzy logic and neural networks.

Summary of Findings

- 1 **T1-FLC**: Fast, interpretable, limited accuracy (79%)
- 2 **IT2-FLC**: +22% over T1 by modelling uncertainty (85%)
- 3 **MLP**: Learns all 4 inputs, excellent $R^2 = 0.97$ (91%)
- 4 **ANFIS**: Best overall — RMSE=2.8, Acc=96%,
 $R^2 = 0.99$

Future Work

- GA optimisation of MF parameters
- Real wearable sensor validation
- Online adaptive learning
- Multi-occupant scenarios

Recommendation

Deploy **ANFIS** as the primary inference engine; use T1/IT2-FLC rules as interpretable fallback.

Thank You

Questions?

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