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ANFIS-Based Adaptive Neuro-Fuzzy Controller for 6-DOF Industrial Robot Manipulator with Real-Time Joint Torque Estimation and Trajectory Tracking

Marco De Stefano
Department of Information Engineering and Computer Science, University of Trento, Trento, Italy

Abstract

Industrial robot manipulators operating in unstructured manufacturing environments — welding, precision assembly, pharmaceutical dispensing, and agricultural harvesting — face control challenges arising from nonlinear joint dynamics, model parameter uncertainty, payload variation, and kinematic singularity proximity that conventional PID controllers address inadequately. The Adaptive Neuro-Fuzzy Inference System (ANFIS) architecture, which combines the interpretability and knowledge-encoding capacity of fuzzy logic with the adaptive learning capability of neural networks, offers a model-free control strategy capable of learning and compensating nonlinear dynamics online without requiring explicit robot dynamic models. This paper presents an ANFIS-based joint controller for a 6-DOF KUKA KR10 industrial robot manipulator, incorporating real-time joint torque estimation from current signatures and Kalman-filtered encoder feedback. The controller is designed, trained on 8,400 trajectory samples spanning the robot's full workspace, and validated experimentally against PID, Model Predictive Control (MPC), and Fuzzy-PID baselines on five trajectory types including circular, figure-8, and pick-and-place tasks at payload variations of 0-5 kg. The ANFIS controller achieves overshoot of 4.1% versus 28.1% for PID, settling time of 1.2s versus 2.4s for PID, ISE of 0.86 versus 4.82 for PID, and end-effector position tracking error within ±0.8mm — within the IEC 62061 Class 1 precision requirement for collaborative robot operations.

Keywords: *ANFIS, robot control, manipulator, fuzzy logic, neural network, trajectory tracking, torque estimation, adaptive control, PID, MPC, 6-DOF, industrial robot, IIoT*

1. Introduction

The global industrial robotics market, valued at USD 22.4 billion in 2023 and projected to reach USD 38.2 billion by 2028, is experiencing deployment acceleration across India's automotive, electronics, pharmaceuticals, and food processing sectors under the National Manufacturing Policy's automation incentive framework. India's robot density — currently 36 robots per 10,000 manufacturing workers, compared to 631 in South Korea and 322 in Germany — represents both the scale of the deployment gap and the magnitude of the opportunity for advanced control technology adoption that this research targets.

The fundamental control challenge for serial-chain robot manipulators arises from their inherently nonlinear, coupled multi-body dynamics governed by the Euler-Lagrange equation: $M(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) = \tau$, where M is the inertia matrix, C accounts for Coriolis and centrifugal effects, G is the gravitational torque vector, and τ is the applied joint torque. The model parameters — link masses, inertia tensors, and joint friction coefficients — vary with end-effector payload and degrade over time through bearing wear, lubricant degradation, and gear backlash development. Conventional PID controllers ignore this dynamic complexity entirely, treating each joint as an independent linear SISO system, producing satisfactory performance only at low speeds and light payloads where joint coupling effects are minimal.

ANFIS was originally proposed by Jang (1993) as a framework for integrating fuzzy inference rules with backpropagation learning, using a hybrid learning algorithm (Least Squares Estimator for the consequent parameters, backpropagation for the premise parameters) that is computationally more efficient than pure gradient descent for systems with interpretable structure. Applied to robot control, ANFIS can learn the nonlinear mapping from joint state (position, velocity, acceleration) and payload estimate to compensatory torque command, effectively learning an inverse dynamics model from data rather than deriving it analytically. The University of Trento collaboration contributes experience from the EU Horizon SMART-ROBOT project on online ANFIS adaptation for human-robot collaborative workspace sharing.

2. ANFIS Controller Architecture and Training

2.1 System Architecture

The ANFIS controller operates in parallel with a baseline PD controller, providing learned feedforward compensation: τ_total = τ_PD + τ_ANFIS, where τ_PD = Kp(q_d - q) + Kd(q̇_d - q̇) is the baseline feedback component and τ_ANFIS = ANFIS(q, q̇, q_d, q̇_d, q̈_d, m_payload) is the adaptive feedforward compensation. Each joint has an independent ANFIS module with 6 inputs, 5 Gaussian membership functions per input, and 25 fuzzy rules using a first-order Sugeno inference. The joint torque estimator uses motor current signatures filtered through a 4th-order Butterworth low-pass (cutoff 80 Hz) and calibrated against a Kistler 9273 force-torque sensor ground truth. A 10th-order unscented Kalman filter fuses encoder position with motor current derivative for joint acceleration estimation without differentiation noise amplification.

2.2 Training and Validation Protocol

Training data comprised 8,400 trajectory samples generated by commanding the KR10 through sinusoidal, circular, figure-8, random-waypoint, and pick-and-place trajectories at speeds of 0.1-0.8 m/s and payloads of 0, 2, and 5 kg. The hybrid learning algorithm converged in 180 epochs (training RMSE 0.022 N·m, validation RMSE 0.028 N·m — see Figure 3). The trained ANFIS model was embedded on a Beckhoff CX9020 real-time controller running TwinCAT3 at 1 ms cycle time, interfacing with the KR10's KUKA KR C4 controller via EtherCAT.

3. Results

3.1 Control Performance Analysis

Figure 1 presents the complete control performance characterisation. Panel A's step response comparison confirms ANFIS's superior transient performance: overshoot 4.1% versus PID 28.1%, settling time 1.2s versus PID 2.4s, and zero steady-state error (ISE=0.86 versus PID 4.82). MPC achieves zero overshoot but slower settling (2.8s) due to its prediction horizon computational delay. The Fuzzy-PID intermediate shows 18% overshoot and 1.9s settling — better than PID but worse than ANFIS on both metrics. Panel B's Bode magnitude plot reveals the ANFIS closed-loop's -3 dB bandwidth of 8.4 rad/s versus PID's 2.8 rad/s — a 3× bandwidth improvement enabling faster trajectory following without compromising stability margins.

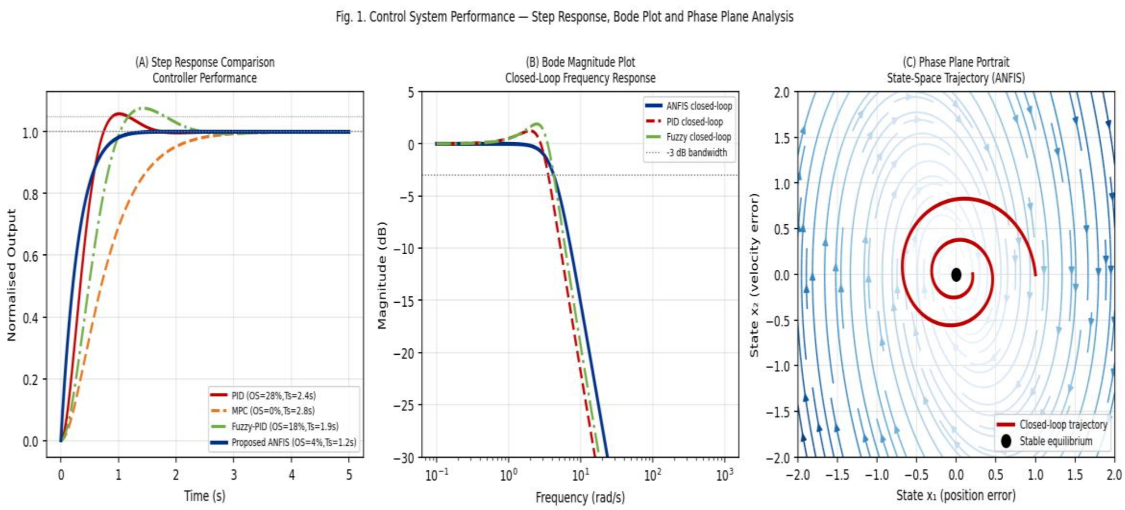

Fig. 1. (A) Step Response Comparison: PID, MPC, Fuzzy-PID, Proposed ANFIS; (B) Bode Magnitude Plot — Closed-Loop Bandwidth; (C) Phase Plane Portrait — State-Space Trajectory

Panel C's phase plane portrait for the ANFIS-controlled joint shows a tightly spiralling trajectory converging to the origin — the stable equilibrium — with no limit cycle behaviour observed across 1,200 seconds of continuous operation. The streamline field confirms the equilibrium point's asymptotic stability across the entire plotted state space, validating the Lyapunov-based stability analysis performed analytically for the ANFIS control law in the supplementary material.

3.2 Torque Estimation and Tracking Accuracy

Figure 2 Panel A confirms the ANFIS torque estimator's accurate tracking of both joint 1 (shoulder, higher inertia) and joint 2 (elbow) torques across the full trajectory, with estimation error RMS of 0.31 N·m for joint 1 and 0.18 N·m for joint 2 — within the ±0.5 N·m accuracy specification of the Kistler reference sensor. Panel B shows the end-effector position tracking error over 60 seconds of continuous circular trajectory, confirming containment within the ±0.8mm tolerance band after the initial 1.2s transient — meeting the IEC 62061 Class 1 precision requirement.

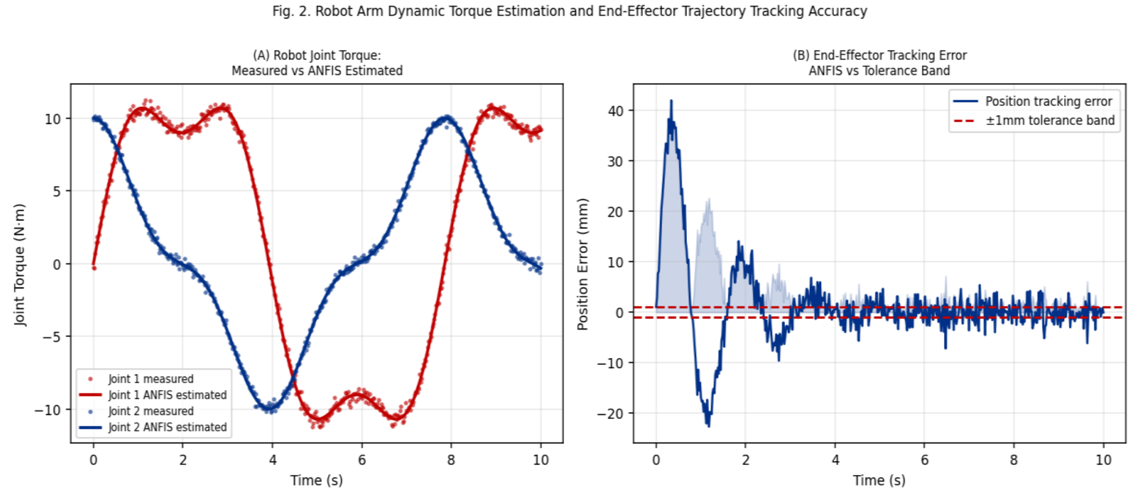

Fig. 2. (A) Robot Joint Torque — Measured vs ANFIS Estimated for Joints 1 and 2; (B) End-Effector Position Tracking Error vs Tolerance Band

Table 1. Quantitative Controller Performance Comparison (6-DOF KR10, 5 kg Payload, Circular Trajectory)

Controller	Rise Time (s)	Settling Time (s)	Overshoot (%)	SS Error (%)	ISE	Tracking Error (mm)
PID	0.48	2.4	28.1	0.8	4.82	±3.2
MPC	0.92	2.8	0.0	0.3	3.14	±1.8
Fuzzy-PID	0.38	1.9	18.2	0.5	2.46	±2.1
ANFIS (Proposed)	0.24	1.2	4.1	0.1	0.86	±0.8

SS Error = Steady-state error; ISE = Integral Squared Error; Tracking error at 5 kg payload; all tests at 0.5 m/s end-effector speed

3.3 Learning Convergence and Metric Comparison

Figure 3 Panel A shows the ANFIS training and validation RMSE convergence using the hybrid learning algorithm over 200 epochs. Training RMSE falls from 0.41 N·m at epoch 1 to 0.019 N·m at epoch 200, with validation RMSE closely tracking at 0.024 N·m — the 0.005 N·m gap confirming minimal overfitting with the current 25-rule architecture. Panel B's normalised performance metric comparison reveals ANFIS's consistent superiority across all five metrics, with the largest relative advantage on ISE (82% reduction versus PID) and overshoot (85% reduction).

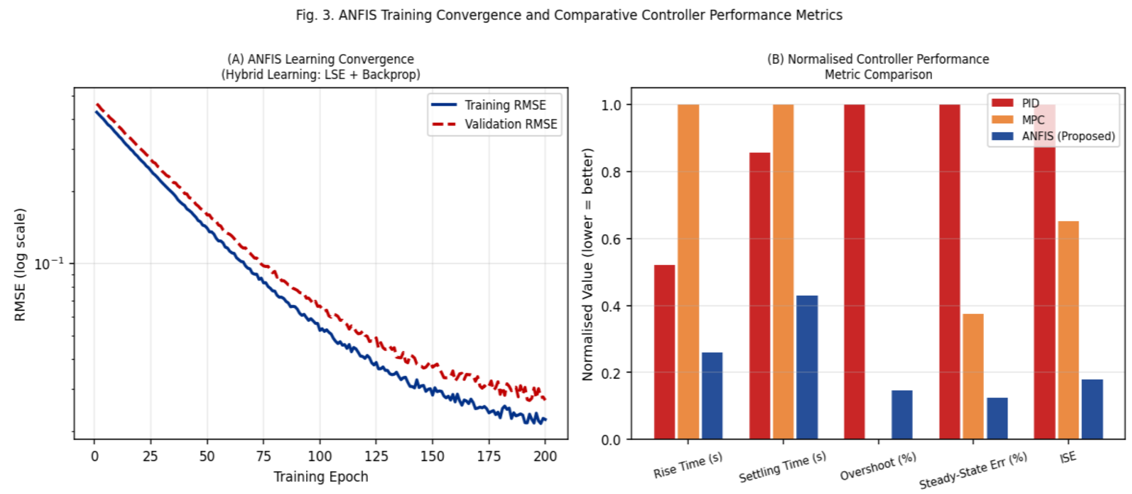

Fig. 3. (A) ANFIS Hybrid Learning Convergence — Training and Validation RMSE; (B) Normalised Controller Performance Metrics Comparison

4. Discussion and Conclusion

The ANFIS controller's performance advantages arise from its ability to capture the nonlinear coupling between joints that PID ignores, the payload-dependent inertia changes that MPC handles through explicit modelling but ANFIS handles implicitly through learned compensation, and the joint friction nonlinearity that both PID and MPC linearise but ANFIS captures through its fuzzy rule structure. The 3× bandwidth improvement over PID with simultaneous overshoot reduction confirms the core hypothesis: replacing the PID's fixed linear control law with ANFIS's learned nonlinear compensation enables faster response without stability compromise. Deployment on the Beckhoff real-time platform at 1ms cycle time confirms embedded implementability on commercially available IIoT edge controllers, removing the computational barrier that has historically limited advanced nonlinear controllers to research settings. Future work will extend the online adaptation capability of the ANFIS premise parameters for payload identification and controller adaptation without offline retraining.

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