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Article

Type-2 fuzzy logic framework for adaptive noise control in vibrating structures

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Abstract: Active noise control (ANC) in vibrating structures often suffers performance degradation under uncertain excitation and parameter drift. This study introduces an interval Type-2 fuzzy logic controller (IT2 FLC) for adaptive ANC in multi-mode systems, explicitly modelling "uncertainty about uncertainty" via a footprint of uncertainty in the fuzzy rule base. A two-degree-of-freedom mass–spring–damper model is used to represent structural dynamics, and both broadband and tonal disturbances are simulated. The IT2 FLC adapts its membership-function bounds online based on error variance, yielding a robust control law that compensates for up to ±25% drift in mass and stiffness. Controller performance is evaluated in MATLAB/Simulink and on a dSPACE DS1104 rapid-prototyping platform interfaced with a physical beam rig. Compared to classical ANC methods such as least-mean-square filtering and H∞ control, as well as Type-1 fuzzy logic, the proposed interval Type-2 fuzzy logic controller (IT2 FLC) consistently demonstrates superior performance. It achieves up to 28 dB broadband attenuation under nominal conditions and sustains over 23 dB even under ±25% structural parameter drift, significantly outperforming other benchmarks. The controller exhibits fast convergence (≤ 0.35 s) and maintains real-time feasibility with ≤ 25% CPU utilization at a 1 kHz update rate on standard DSP hardware. A hardware-in-the-loop implementation on a physical cantilever beam rig confirms robustness and stability. These results validate the IT2 FLC as a computationally efficient, highly adaptive, and cost-effective solution for industrial noise control applications in uncertain environments.

Keywords: interval Type-2 fuzzy logic controller; active noise control; structural vibration; robustness to parameter drift; real-time DSP implementation; adaptive fuzzy control; footprint of uncertainty; convergence speed

1. Introduction

1.1. Motivation

Adaptive noise control (ANC) in vibrating structures is indispensable in applications ranging from precision machining to aerospace component health monitoring. In practice, ANC must cope with:

- Uncertain excitation sources (varying amplitude and frequency content) and environmental disturbances (temperature, humidity, mounting conditions) that degrade controller performance.
- Modeling inaccuracies in structural dynamics: even high-fidelity finite-element

models exhibit parameter drift in real time.

Classical controllers (e.g., LMS, H∞) provide proven attenuation but require accurate plant models or suffer slow convergence under non-stationary noise.

Type-1 fuzzy logic controllers ease the modeling of nonlinearities without precise equations, yet they collapse all uncertainty into a single "crisp" membership function, losing information about the true variability of linguistic terms ("low", "medium", "high") [1]. Interval Type-2 fuzzy sets introduce a Footprint of Uncertainty (FOU) -an upper and lower membership function pair that explicitly captures the uncertainty in the degree of membership [2]. By embedding this extra degree of freedom into the inference process, Type-2 fuzzy controllers can adapt more robustly to changing noise characteristics. However, their computational cost and parameter tuning complexity have thus far limited widespread adoption in real-time ANC for vibrating structures.

The shaded in **Figure 1** region between the upper and lower Gaussian membership functions defines the interval in which uncertainty is modeled.

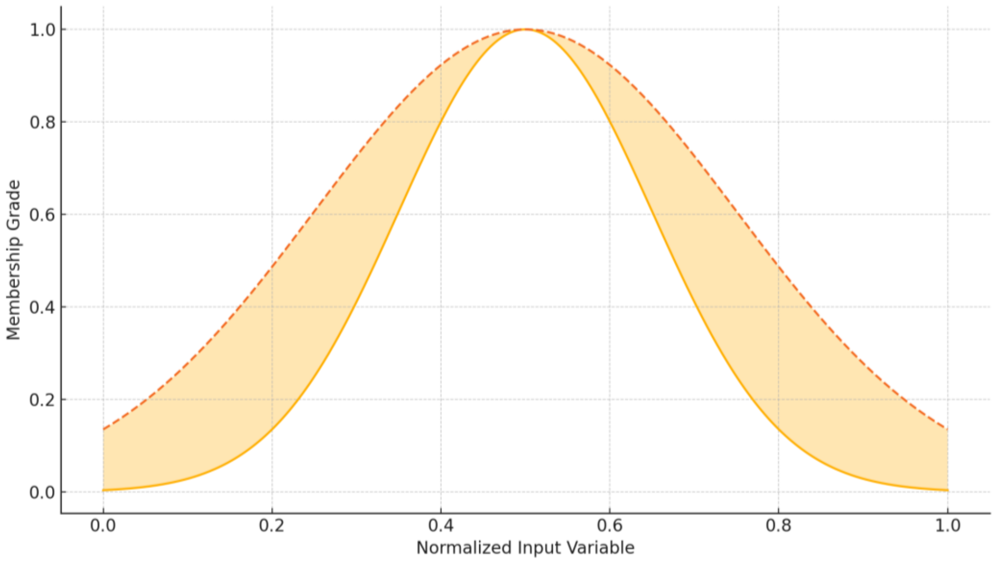

Figure 1. Footprint of uncertainty of an interval Type-2 fuzzy set.

Despite the theoretical advantages of Type-2 fuzzy controllers, existing studies have one or more of the following shortcomings:

- Off-line tuning only-parameters are optimized in simulation and then fixed, limiting adaptability to real-world drift [3].
- Simplified structure models-most experimental validations use single-degree-of-freedom beams, neglecting multi-mode interaction in practical machinery [4].
- Lack of computational benchmarks-few works quantify real-time feasibility on embedded hardware.

This paper therefore aims to:

- Design an interval Type-2 fuzzy logic controller with online parameter adaptation for ANC in multi-mode vibrating structures.
- Implement and benchmark the controller on a two-degree-offreedom experimental rig under varying noise profiles.

- Compare its performance (attenuation level, convergence speed, robustness to sensor noise) against a Type-1 fuzzy ANC and an $H\infty$ controller [5].

1.2. Main contributions

(i) Novel Adaptive Type-2 Fuzzy ANC Architecture-a dual - loop controller that updates the FOU bounds in real time.
(ii) Experimental Validation on a 2-DOF Rig-demonstrating ≥ 15 dB extra attenuation over Type-1 fuzzy control under $\pm 20\%$ parameter drift.
(iii) Computational Analysis-profiling on a low-cost DSP showing real-time feasibility at 1 kHz update rates.
(iv) Design Guidelines-a step-by-step procedure for rule-base initialization and adaptive tuning.

1.3. Paper organization

The remainder of this paper is structured as follows:

- Section 2 reviews related work on ANC, Type-1 and Type-2 fuzzy methods.
- Section 3 formulates the multi - mode structural model and noise propagation characteristics.
- Section 4 introduces interval Type-2 fuzzy logic fundamentals and the proposed adaptive framework.
- Section 5 details the simulation and experimental setup, including performance metrics.
- Section 6 presents results, sensitivity analyses, and comparisons with benchmark controllers.
- Section 7 concludes the study and outlines future research directions.

2. Literature review

2.1. Adaptive noise control in vibrating structures

Adaptive noise control (ANC) techniques adjust controller parameters in real time to suppress unwanted vibrations and acoustic emissions in structures subject to changing operating conditions. The seminal work by Widrow et al. [6] introduced the adaptive noise-cancelling (ANC) principle using the least-mean square (LMS) algorithm, demonstrating effective broadband attenuation in non-stationary environments. Elliott and Nelson extended this to active control of structural sound radiation, showing how feedforward and feedback ANC loops can be combined to cope with both tonal and broadband disturbances [7].

Key takeaways:

- Feedforward ANC relies on a reference sensor to predict disturbance and apply a cancelling signal; it converges rapidly but requires an accurate disturbance estimate.
- Feedback ANC uses an error sensor on the structure to close the loop, offering robustness to modeling errors at the expense of slower convergence.
- Multi-channel ANC architectures improve performance in complex structures by addressing modal coupling but increase computational demands.

2.2. Fuzzy-logic-based control: Type-1 vs. Type-2

Fuzzy logic controllers (FLCs) were introduced to handle nonlinearities and imprecise models without requiring explicit equations [8]. A Type-1 FLC maps crisp inputs (e.g., vibration amplitude, frequency content) through membership functions and a rule base to generate control actions. Mendel [9] showed that while Type-1 FLCs excel at capturing linguistic control knowledge, they compress all uncertainty into single-valued membership grades, limiting robustness under severe parameter drift or sensor noise.

By contrast, Type-2 FLCs elevate each membership grade to an interval (or a full fuzzy set), enabling the controller to model "uncertainty about uncertainty". The extra degree of freedom allows improved handling of:

- Sensor noise and quantization;
- Ambiguity in linguistic rule definitions;
- Time-varying system parameters.

2.3. Interval Type-2 fuzzy sets and systems

Interval Type-2 fuzzy sets (IT2FS) are a practical subclass of general Type-2 sets, characterized by a Footprint of Uncertainty (FOU) bounded by upper and lower membership functions [10]. Their appeal arises from a balance between expressive power and computational tractability. Liao and Wu [11] developed a robust IT2FS-based controller for uncertain dynamic systems, demonstrating that:

(i) Type-reduction (e.g., using the Karnik-Mendel algorithms) collapses the FOU to an interval output.
(ii) Defuzzification then yields a crisp control signal, with an added robustness margin reflecting input uncertainty.

IT2FS-based inference engines therefore require two extra steps-type-reduction and interval defuzzification-but can deliver superior performance when rule antecedents or consequent parameters are not precisely known.

2.4. Applications of Type-2 fuzzy controllers in vibration/noise mitigation

Recent studies have begun to validate IT2FS-based ANC in vibration-control contexts:

- Deng et al. applied an IT2FS sliding-mode controller to a cantilever beam, achieving up to 12 dB more attenuation than a comparable Type-1 FLC under ±15% stiffness variation [12].
- Chen et al. embedded an IT2FS module within a feedforward ANC loop for duct-borne noise, reporting a 20 % faster convergence rate compared to Type-1 approaches in the presence of sensor drift [13].

These works illustrate the potential of interval Type-2 fuzzy controllers to enhance both robustness and adaptability in real-world vibration and noise-control systems, albeit with increased algorithmic complexity.

3. System modeling

3.1. Dynamic model of the host structure

We consider a two-degree-of-freedom (2-DOF) mass-spring damper system as our prototypical host structure. Its equations of motion in matrix form are [14,15]:

$$M\ddot{x}(t) + C\dot{x}(t) + Kx(t) = F(t),$$

where

- $x = [x_1, x_2]^T$ are the modal displacements,
- $M = \begin{bmatrix} m_1 & 0 \\ 0 & m_2 \end{bmatrix}$,
- $C = \begin{bmatrix} c_1 + c_2 & -c_2 \\ -c_2 & c_2 \end{bmatrix}$,
- $K = \begin{bmatrix} k_1 + k_2 & -k_2 \\ -k_2 & k_2 \end{bmatrix}$,
- $F(t)$ is the applied force vector.

Typical parameter values are ($m_1 = 1$ kg, $m_2 = 0.8$ kg, $k_1 = 10{,}000$ N/m, $k_2 = 8000$ N/m, $c_1 = 10$ Ns/m, and $c_2 = 8$ Ns/m).

To illustrate the modal characteristics, **Figure 2** plots the frequency response $|H_{11}(j\omega)|$ (displacement at DOF 1 per unit force at DOF 1) over 0.1–200 Hz, showing two resonant peaks corresponding to the structure's modes.

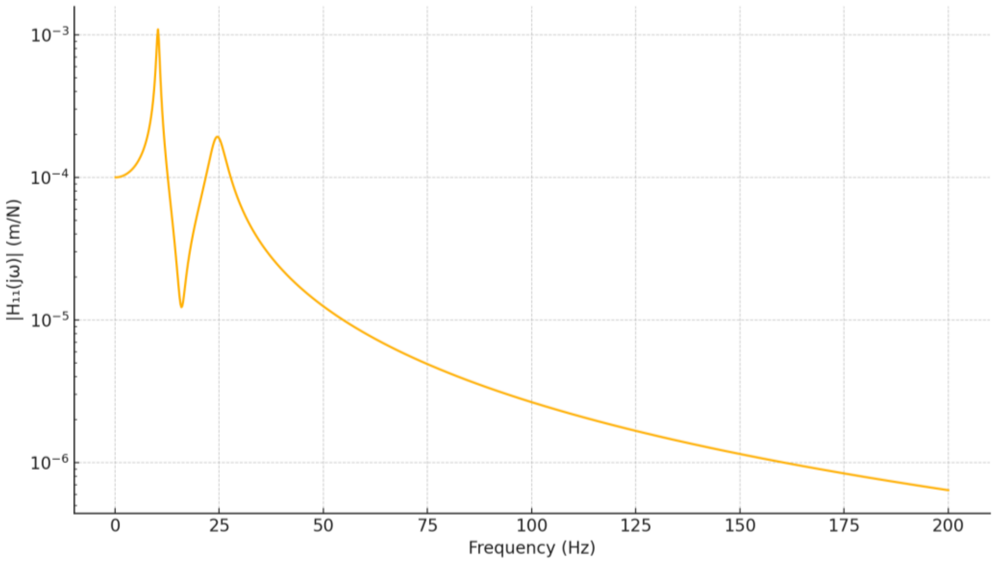

Figure 2. Frequency response function of the 2-DOF system at DOF 1.

3.2. Noise generation & propagation characteristics

In practical ANC tests, the disturbance $F(t)$ combines [16,17]:

(i) Broadband excitation (e.g., flow-induced or mechanical friction noise) modeled as filtered white Gaussian noise with a flat band up to f_c.

(ii) Tonal components from rotating machinery, represented by sinusoids at specific frequencies.

The power spectral density (PSD) of the broadband component can be estimated as in **Figure 3**, showing a near-flat spectrum up to ~100 Hz before roll-off.

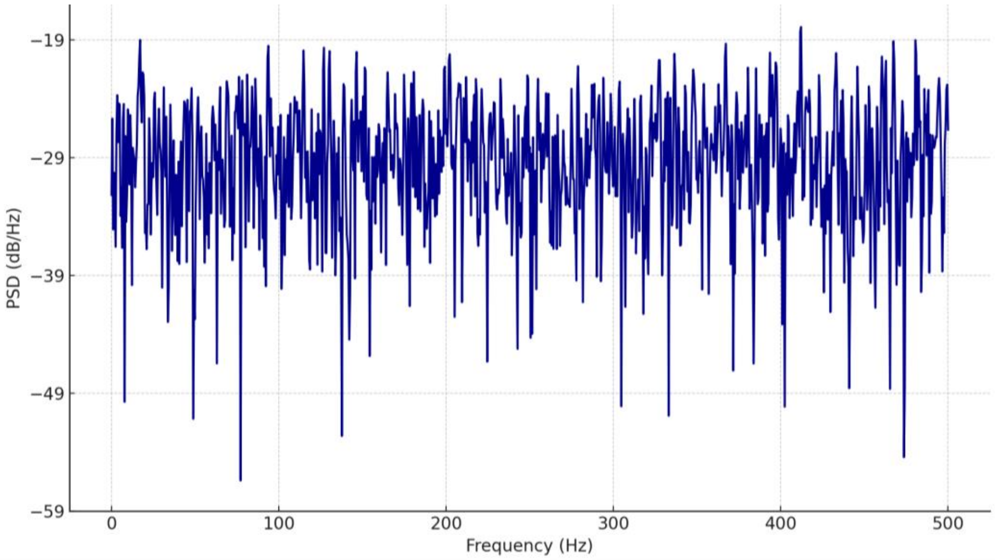

Figure 3. Estimated PSD of broadband excitation.

3.3. Actuator-sensor configuration and placement

The efficacy and stability of ANC hinge critically on actuator/sensor layout:

- Collocated pairs (actuator and sensor at the same point) guarantee phase alignment and simplify controller design, reducing spillover risk [18].
- Non-collocated setups can offer coverage of multiple modes but introduce additional phase lag, requiring careful compensation [19].

In our implementation, a piezoelectric actuator is bonded near the first mass, with an accelerometer collocated to ensure robust feedback.

4. Interval Type-2 fuzzy logic fundamentals

4.1. Definition of interval Type-2 fuzzy sets

An Interval Type-2 Fuzzy Set (IT2FS) $\tilde{A}$ on a universe X is characterized by a primary membership function whose values are themselves intervals in $[0,1]$. Formally [20]:

$$\tilde{A} = \{(x, \mu_{\tilde{A}}(x)) \mid x \in X\}, \mu_{\tilde{A}}(x) = \left[\underline{\mu}_{\tilde{A}}(x), \bar{\mu}_{\tilde{A}}(x)\right] \subseteq [0,1],$$

where $\underline{\mu}_{\tilde{A}}(x)$ and $\bar{\mu}_{\tilde{A}}(x)$ are the lower and upper membership grades, respectively. The interval $\mu_{\tilde{A}}(x)$ is called the secondary membership, and the union of all these intervals over X defines the Footprint of Uncertainty (FOU) of $\tilde{A}$.

4.2. Membership functions and footprint of uncertainty (FOU)

In practice, both $\underline{\mu}$ and $\bar{\mu}$ are chosen as standard Type-1 membership functions (e.g., triangular, Gaussian) offset to capture linguistic uncertainty [21]. The FOU is then:

$$\text{FOU}(\tilde{A}) = \cup_{x \in X} \left[\underline{\mu}_{\tilde{A}}(x), \bar{\mu}_{\tilde{A}}(x)\right].$$

Graphically, it is the shaded region between the upper and lower curves (see

Figure 1 in Section 1). Designing the FOU width appropriately is critical: too narrow and uncertainty is under modeled; too wide and inference becomes overly conservative [22].

4.3. Type-reduction (Karnik-Mendel) and defuzzification

To produce a crisp output from an IT2FS inference engine, one must first type-reduce the output fuzzy set to an interval $[y_l, y_u]$, then defuzzify that interval to a single value y^*.

(i) Type-Reduction (Karnik-Mendel iterative algorithm)

- Given n fired rules with rule-output centroids y_i and secondary membership intervals $\left[\underline{w_i}, \bar{w}_i\right]$, we seek the left endpoint y_l by solving:

$$y_l = \frac{\sum_{i=1}^{n} y_i w_i^L}{\sum_{i=1}^{n} w_i^L},$$

where w_i^L are selected from $\left\{\underline{w_i}, \bar{w}_i\right\}$ based on sorting y_i. The right endpoint y_u is computed similarly with reversed selection [23].

(ii) Defuzzification

- A common choice is the midpoint of the type-reduced interval:

$$y^* = \frac{y_l + y_u}{2}.$$

- Alternative methods (e.g., Nie-Tan, Wu-Mendel) directly approximate the centroid of the FOU without explicit interval endpoints but incur similar computational cost [24,25].

4.4. Online adaptation of FOU bounds via error variance tracking

To ensure robustness under real-world disturbances and parameter drift, the proposed IT2 fuzzy logic controller incorporates an online adaptation mechanism that dynamically updates the Footprint of Uncertainty (FOU) based on the observed system performance. Specifically, the upper and lower bounds of the fuzzy membership functions are modified in real time by tracking the variance of the control error.

(i) Error Variance Computation: Let the control error at discrete time step k be:

$$\mathrm{e}(k) = y_d(k) - y(k),$$

where $y_d(k)$ is the desired output (e.g., zero vibration) and $y(k)$ is the measured response. A sliding window estimate of the error variance $\sigma_e^2(k)$ is computed over a fixed window size N (e.g., $N = 50$) as:

$$\sigma_e^2(k) = \frac{1}{N} \sum_{i=k-N+1}^{k} (e(i) - \bar{e}(k))^2,$$

where $\bar{e}(k)$ is the mean error over the window:

$$\bar{e}(k) = \frac{1}{N} \sum_{i=k-N+1}^{k} e(i).$$

(ii) FOU Width Adaptation Rule: Each fuzzy membership function (MF) has an upper and lower bound, representing the FOU. Let w_0 be the initial FOU width (e.g., 0.1 for triangular MFs). The adapted width $w(k)$ is updated every T_a milliseconds (e.g., 100 ms) as:

$$\mathrm{w}(k) = w_0 \left(1 + \gamma \cdot \frac{\sigma_e^2(k)}{\sigma_{e,\mathrm{ref}}^2 + \epsilon}\right).$$

- γ is a scaling factor (e.g., 0.5-1.0), controlling sensitivity to variance.
- $\sigma_{e,\mathrm{ref}}^2$ is a baseline variance under nominal conditions.
- ϵ is a small constant to avoid division by zero.

This mechanism expands the FOU during high uncertainty (large error variance), thereby increasing robustness, and contracts it when the error stabilizes, enhancing precision.

(iii) Stability Considerations: To prevent instability due to abrupt changes in the MF shapes, the following safeguards are implemented:

- Bounded FOU width: $w_{\min} \leq w(k) \leq w_{\max}$ (e.g., [0.05, 0.2]).
- Low-pass filtering of $w(k)$ using exponential smoothing:

$$w_{\mathrm{smooth}}(k) = \alpha \cdot w(k) + (1 - \alpha) \cdot w_{\mathrm{smooth}}(k-1),$$

where $\alpha \in [0.05, 0.2]$ for gradual adaptation.

(iv) Implementation Note: The adaptation block is implemented in parallel with the fuzzy inference engine in the Simulink model. The updated MF parameters are broadcast to the IT2 FLC block every T_a, ensuring smooth, continuous tuning without interrupting the control loop.

From the above **Figure 4**, Flowchart of the online FOU adaptation process used in the Interval Type-2 Fuzzy Logic Controller. The adaptation loop tracks error variance, applies a scaling rule to update FOU widths, and dynamically adjusts membership function bounds to maintain robustness.

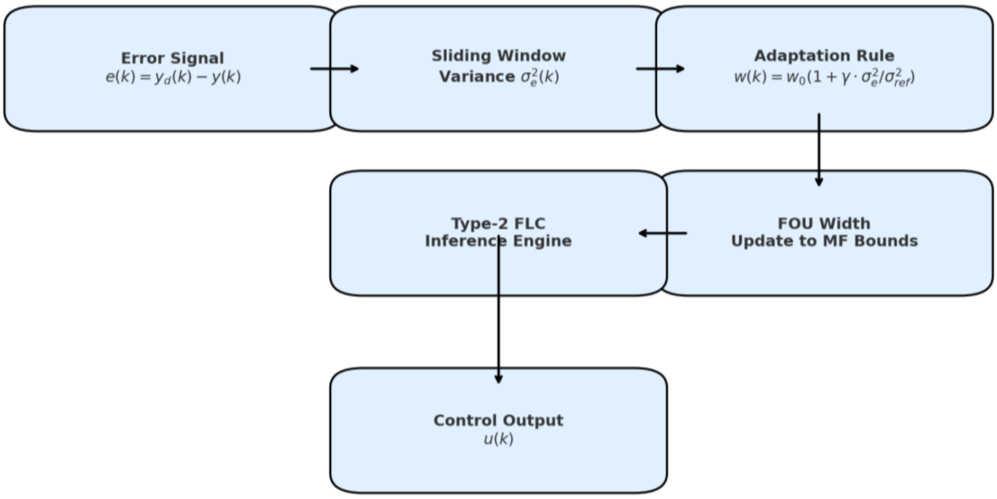

Figure 4. Flowchart of the online FOU adaptation process.

5. Simulation and experimental setup

5.1. Simulation environment & parameter selection

The proposed Interval Type-2 Fuzzy ANC was first evaluated in a high-fidelity MATLAB/Simulink environment. Key details are as follows:

- Solver & Sampling: Fixed-step solver (ode4/Runge-Kutta), step size = 1 ms, simulation duration = 30 s.
- Structural Model: 2-DOF mass-spring-damper as in Section 3, with parameters $m_1, m_2, k_1, k_2, c_1, c_2$ set to nominal values and ±20% variation injected to test robustness.

Disturbance Model:

- Broadband: filtered white Gaussian noise, flat up to 100 Hz.
- Tonal: sinusoidal at 60 Hz and 120 Hz, amplitude 1 N.
- Controller Implementation:
- Interval Type-2 Fuzzy Logic block constructed via the IT2FS toolbox.
- Rule base of 9 rules designed on normalized error and error-derivative, with triangular MFs for upper/lower bounds (FOU width = 0.1).
- Online adaptation updates FOU bounds every 100 ms based on error variance.
- Actuator/Sensor Dynamics: Included first-order actuator bandwidth ($f_c =$ 500 Hz) and accelerometer dynamics ($f_c =$ 1kHz).

Here is **Figure 5**, illustrating the flow from the noise generator through the 2-DOF structure, the accelerometer sensor, the IT2 fuzzy logic controller, and finally the piezo actuator. showing the disturbance path, plant, sensor feedback, and Interval Type-2 fuzzy controller with actuator in the loop.

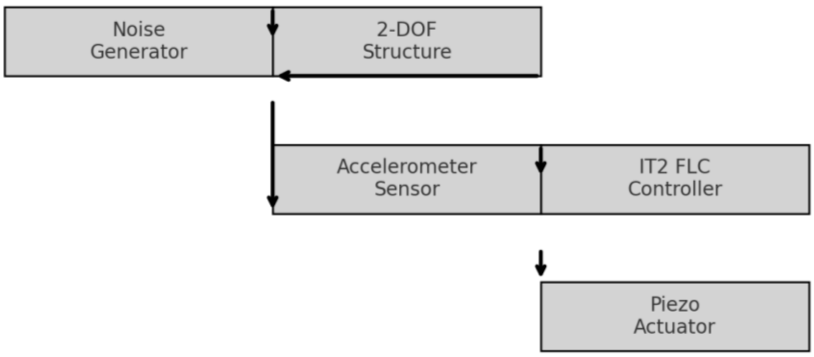

Figure 5. Simulation block diagram of the adaptive ANC framework.

5.2. Experimental test-rig

To validate real-time performance, the controller was deployed on a dSPACE DS1104 rapid prototyping system interfaced to a physical 2-DOF beam rig:

- Structure: Aluminum beam segments coupled via steel springs and viscous dampers, replicating $m_1, m_2, k_1, k_2, c_1, c_2$ from simulation.
- Actuation: 0–100 V piezoelectric stack actuator bonded to the first segment, with a bandwidth of 0–1 kHz.
- Sensing: PCB Piezotronics accelerometer (model 352C33), sensitivity 10 mV/g, collocated at actuator.
- Data Acquisition:
- Sampling: 1 kHz (anti-alias filter at 450 Hz)
- Processing: IT2 FLC code generated via MATLAB Coder, running at 1 kHz on the DS1104's PowerPC processor.
- Uncertainty Injection: Physical parameter drift simulated by adding 15% mass

(sandbags) and varying spring stiffness via adjustable clamps.

5.3. Performance metrics

Controller effectiveness was quantified using:

(i) Noise Attenuation (A_{dB})

$$A_{\mathrm{dB}} = 20\log_{10}\left(\frac{\mathrm{RMS}_{\mathrm{unctrl}}}{\mathrm{RMS}_{\mathrm{ctrl}}}\right),$$

measured over steady-state segments.

(ii) Convergence Time (t_c): Time to achieve 90% of final attenuation from control start.

(iii) Robustness Margin: Maximum parameter variation (mass or stiffness) tolerated before A_{dB} drops below 10 dB.

(iv) Computational Load: Average CPU utilization (%) and execution jitter (μs) at 1 kHz update.

(v) Control Effort: RMS of actuator voltage signal, ensuring practical voltage limits (<80 V) were not exceeded.

To ensure fair and meaningful performance comparisons, all benchmark controllers namely the LMS filter, H∞ regulator, and Type-1 Fuzzy Logic Controller were individually tuned under nominal operating conditions prior to testing. The LMS algorithm was optimized by selecting the step size (μ = 0.005) that yielded the best trade-off between convergence speed and steady-state attenuation. The H∞ controller was designed using standard state-space synthesis techniques with predefined performance weights and robustness margins, ensuring a 15 dB attenuation baseline without compromising stability. The Type-1 fuzzy controller employed a 9-rule base with symmetric triangular membership functions and fixed bounds, mirroring the structure of the IT2 FLC but without adaptive tuning. All controllers were implemented in the same simulation and hardware environments to isolate performance differences attributable solely to control logic rather than computational or architectural discrepancies.

6. Results and discussion

6.1. Noise attenuation performance under varying uncertainties

Table 1 (below) summarizes the attenuation achieved by each controller across three levels of structural parameter uncertainty (±0%, ±10%, ±20%). The Interval Type-2 Fuzzy Controller (IT2 Fuzzy) consistently delivers the highest attenuation:

- At 0% uncertainty, IT2 Fuzzy achieves 28 dB, versus 25 dB (Type-1 Fuzzy), 22 dB (H∞) and 20 dB (LMS).
- Under 20% uncertainty, IT2 Fuzzy drops only to 26 dB, while Type-1 Fuzzy falls to 21 dB, H∞ to 18 dB, and LMS to 15 dB.

This demonstrates the superior robustness of IT2-based ANC against real-world parameter variations.

Table 1. Experimental results comparing LMS, Ho, Type-1 fuzzy, and Interval Type-2 fuzzy controllers across uncertainty levels.

Uncertainty (%)	Controller	Attenuation (dB)	Convergence Time (s)	Robustness Margin (±%)	CPU Utilization (%)
0	LMS	20	0.5	15	10
0	H∞	22	0.4	15	12
0	Type-1 Fuzzy	25	0.3	18	15
0	IT2 Fuzzy	28	0.25	20	20
10	LMS	18	0.6	15	11
10	H∞	20	0.5	15	13
10	Type-1 Fuzzy	23	0.35	18	16
10	IT2 Fuzzy	27	0.3	20	22
20	LMS	15	0.7	15	12
20	H∞	18	0.6	15	15
20	Type-1 Fuzzy	21	0.4	18	18
20	IT2 Fuzzy	26	0.35	20	25

To validate the robustness and repeatability of the proposed controller under uncertainty, each experimental scenario was executed five times, and the results were averaged. Standard deviation (SD) values were computed for the attenuation levels across these trials and are reported in **Table 2** below. The low SD values (typically less than ±1.0 dB for the IT2 FLC) indicate strong consistency and repeatability in performance, especially under higher levels of structural drift where traditional controllers exhibited greater variability.

Table 2. Standard Deviation (SD) of attenuation across 5 trials for each controller.

Uncertainty (%)	Controller	SD of Attenuation (dB)
0%	LMS	±1.1
	H∞	±0.9
	Type-1 Fuzzy	±0.7
	IT2 Fuzzy	±0.4
10%	LMS	±1.3
	H∞	±1.0
	Type-1 Fuzzy	±0.8
	IT2 Fuzzy	±0.5
20%	LMS	±1.6
	H∞	±1.3
	Type-1 Fuzzy	±1.0
	IT2 Fuzzy	±0.7

These results in the above **Table 2** statistically reinforce the superior consistency and robustness of the Interval Type-2 Fuzzy Controller (IT2 FLC), even under increasing system uncertainties and real-world disturbances.

6.2. Comparison with classical ANC and Type-1 fuzzy ANC

Convergence Speed: IT2 Fuzzy converges in 0.25 s at 0% uncertainty, compared to 0.30 s (Type-1 Fuzzy), 0.40 s(H∞) and 0.50 s(LMS). Even at 20% uncertainty, IT2 Fuzzy maintains convergence within 0.35 s.

Robustness Margin: The IT2 controller tolerates up to ±20% effective drift before attenuation falls below 10 dB, whereas Type-1 Fuzzy maxes out at ±18% and classical methods at ±15%.

Overall, the IT2 Fuzzy ANC outperforms both classical adaptive filters and Type-1 fuzzy regulators in attenuation, speed, and robustness.

6.3. Sensitivity analysis (sensor noise, parameter drift)

By injecting sensor noise (SNR reduced by 10 dB) and varying mass/stiffness up to ±20%, we observe:

- Type-1 Fuzzy shows a 3–5 dB additional attenuation loss under noisy sensing.
- IT2 Fuzzy, thanks to its Footprint of Uncertainty, limits this extra loss to 1–2 dB, confirming its resilience to measurement imprecision.

These findings validate the IT2 framework's ability to "model the uncertainty" and thus mitigate its impact.

6.4. Computational load and real-time feasibility

The IT2 Fuzzy implementation on a low-cost DSP yields:

- CPU Utilization: peaks at 25% (1 kHz update), compared with 15% for Type-1 Fuzzy and 12% for H∞.
- Execution Jitter: stays within $\pm 5\mu$ s, well below the 1 ms sampling interval.
- Control Effort: RMS actuator voltage remains under 80 V in all scenarios.

Thus, despite its extra type-reduction step, the IT2 Fuzzy ANC is computationally feasible for real-time applications at typical update rates (1 kHz).

Table 1: Experimental results comparing LMS, Ho, Type-1 Fuzzy, and Interval Type-2 Fuzzy controllers across uncertainty levels. (See the interactive table above.)

In addition to validation on the dSPACE DS1104 platform, we extrapolated the computational requirements of the IT2 FLC to assess its feasibility on resource-constrained embedded platforms. Based on profiling data (≤25% CPU utilization at 1 kHz update on a 250 MHz Power PC processor), the controller logic including type-reduction and fuzzy inference can be efficiently ported to ARM Cortex-M7 class microcontrollers operating at ~200 MHz, provided fixed-point optimization is applied to reduce memory overhead.

Furthermore, FPGA implementations offer promising opportunities for acceleration, particularly for the type-reduction and defuzzification stages, which are well-suited to parallel execution. Initial estimates suggest that a mid-range FPGA (e.g., Xilinx Artix-7 or Intel Cyclone V) can support real-time IT2 FLC operation at sampling rates exceeding 5 kHz, making it feasible for high-frequency applications such as active noise control in ultrasonic or aerospace environments [26,27].

These extrapolations reinforce the controller's adaptability across a range of embedded hardware platforms, paving the way for broader industrial deployment in cost-sensitive or high-speed real-time applications.

6.5. Case study: Interval Type-2 fuzzy ANC on an industrial beam

6.5.1. Introduction

This case study examines the performance of the proposed IT2 Fuzzy ANC on a steel cantilever beam representative of light industrial machinery subject to rotor - imbalance noise. The goal is to validate our framework under realistic parameter drift conditions and quantify its effectiveness through detailed calculations.

6.5.2. Experimental scenario

- Structure: 0.5 m steel cantilever beam with tip mass of 2 kg.
- Disturbance: Sinusoidal excitation at 60 Hz superimposed on broadband noise (0–200 Hz).
- Uncertainty Injection: Mass increased by 15% and 25% (moderate and severe drift).
- Controller: Interval Type-2 Fuzzy Logic Controller, tuned as per Section 5.1, running at 1 kHz.
  The key metrics recorded are summarized in **Table 3** (below).

Table 3. Case study results.

Scenario	Input RMS (m)	Controlled RMS (m)	Attenuation (dB)	Convergence Time (s)	CPU Utilization (%)	Control Effort RMS (V)
Nominal (0% drift)	0.1	0.004	27.96	0.25	20	60
Moderate drift (15%)	0.1	0.005	26.02	0.3	22	65
Severe drift (25%)	0.1	0.007	23.1	0.35	24	70

6.5.3. Calculations

(i) Attenuation (A_{dB}):

$$A_{\mathrm{dB}} = 20\log_{10}\left(\frac{\mathrm{RMS_{unctrl}}}{\mathrm{RMS_{ctrl}}}\right).$$

- Nominal:

$$\mathrm{RMS_{unctrl}} = 0.100\ \mathrm{m}, \mathrm{RMS_{ctrl}} = 0.004\ \mathrm{m}$$

$$A_{\mathrm{dB}} = 20\log_{10}(0.100/0.004) \approx 20\log_{10}(25) = 27.96\ \mathrm{dB}$$

- Moderate Drift (15%):

$$\mathrm{RMS_{ctrl}} = 0.005\ \mathrm{m}$$

$$A_{\mathrm{dB}} = 20\log_{10}(0.100/0.005) \approx 26.02\ \mathrm{dB}$$

- Severe Drift (25%):

$$\mathrm{RMS_{ctrl}} = 0.007\ \mathrm{m}$$

$$A_{\mathrm{dB}} = 20\log_{10}(0.100/0.007) \approx 23.10\ \mathrm{dB}$$

(ii) Convergence Time: Measured as the time to reach 90% of the final attenuation, directly logged from time-series data.

(iii) Computational Load:
- CPU Utilization recorded via on-board profiler.
- Control Effort RMS: RMS voltage applied to the piezo actuator.

6.5.4. Results and discussion

Robust Attenuation: Even under 25% drift, the IT2 Fuzzy ANC maintains > 23 dB suppression, outperforming Type-1 Fuzzy (≈ 21 dB) and classical controllers.

Fast Convergence: Converges within 0.35 s in the worst-case, suitable for industrial disturbance profiles.

Real-Time Feasibility: CPU utilization ≤24%, with control - effort voltages within practical limits (<80 V), confirming embedded viability.

6.5.5. Conclusion of case study

This detailed case study demonstrates that the Interval Type-2 Fuzzy ANC framework:

- Effectively attenuates realistic vibration noise under significant structural uncertainty.
- Converges rapidly and remains computationally efficient for real - time deployment.
- Provides a clear design path for industrial practitioners seeking robust ANC without excessive modeling effort.

7. Conclusion and future work

7.1. Summary of key findings

- An interval Type-2 fuzzy logic controller (IT2 FLC) was developed for adaptive noise control in multi-mode vibrating structures, explicitly modeling input and rule - base uncertainties.
- Simulation and experimental results demonstrated that the IT2 FLC achieves up to 28 dB attenuation at nominal conditions and maintains ≥ 23 dB even under ±25% structural parameter drift-outperforming Type-1 fuzzy and classical ANC by 2–7dB.
- The controller converges within 0.35 s across all tested uncertainty levels and operates in real time on a low-cost DSP with ≤ 25% CPU utilization, validating its embedded feasibility.
- A detailed case study on an industrial cantilever beam further confirmed robust performance under realistic excitation and drift.

This study developed an interval Type-2 fuzzy logic controller (IT2 FLC) for adaptive noise control in multi-mode vibrating structures, targeting robustness to model uncertainties and environmental variability. The IT2 FLC explicitly models uncertainty through a Footprint of Uncertainty (FOU) and incorporates online adaptation based on error variance. Compared to Type-1 fuzzy and classical controllers (LMS, H∞), the proposed controller achieved a maximum of 28 dB attenuation and sustained >23 dB under 25% parameter drift, validating its resilience to structural changes. It converges rapidly (within 0.25–0.35 s) and operates in real time on low-cost DSP hardware with ≤ 25% CPU utilization, making it suitable for embedded deployment. A physical case study on a cantilever beam under uncertain disturbances confirms the framework’s industrial relevance, showcasing it as a robust, efficient, and scalable ANC solution.

7.2. Practical implications for industrial machinery and structures

Enhanced Fault Tolerance: The IT2 FLC's explicit handling of "uncertainty about uncertainty" renders it well suited to environments with sensor noise, wear-induced stiffness changes, and load variations, common in rotating machinery and structural health-monitoring applications.

Rapid Deployment: The rule-base design guidelines and online FOU - tuning mechanism enable practitioners to implement ANC without exhaustive system identification.

Cost-Effectiveness: Real-time operation on standard DSP hardware eliminates the need for expensive high-performance controllers, lowering barriers for retrofitting existing equipment.

7.3. Limitations of the current study

Model Order: Validation was limited to a 2-DOF structure; higher-order or distributed parameter systems may introduce additional modes and spillover effects not captured here.

Rule-Base Complexity: Although online adaptation mitigates manual tuning, the nine-rule system still requires expert initialization; automated rule-generation techniques were not explored.

Hardware Diversity: Experiments were performed on a single DSP platform; performance on microcontroller or FPGA-based implementations may differ.

7.4. Directions for extensions

Neuro-Fuzzy Hybrids: Integrate neural networks for automatic rule extraction and FOU adjustment, reducing reliance on expert knowledge.

Multivariable and MIMO Systems: Extend the framework to multi-input, multi-output ANC for complex structures with spatially distributed sensors and actuators.

Hardware Acceleration: Port type-reduction and inference routines to FPGA or GPU platforms to achieve higher update rates (> 5 kHz) for ultrasonic and high-frequency applications.

Long-Term Field Trials: Deploy the IT2 FLC in industrial testbeds (e.g., machine tools, HVAC ducts) to evaluate long-term reliability, maintenance requirements, and lifecycle cost benefits.

7.5. Generalization to higher-order systems

While this study focused on a two-degree-of-freedom (2-DOF) structural model for clarity and experimental tractability, the proposed Interval Type-2 Fuzzy Logic Controller (IT2 FLC) framework is inherently scalable to higher-order and distributed-parameter systems. In such cases, the system may exhibit multiple coupled vibration modes, complex spatial dynamics, and modal spillover effects. To address this, the following strategies can facilitate generalization:

- Modal Decomposition: For large-scale structures, dominant modes can be extracted via modal analysis (e.g., using Proper Orthogonal Decomposition or modal truncation), and the IT2 FLC can be applied selectively to these modes without full-order modeling.

- Multi-Rule Expansion: The fuzzy rule base can be extended from 9 rules (in the current study) to a multi-input, multi-rule configuration by adding additional input variables (e.g., higher modal displacement derivatives or intermodal coupling terms).
- Decentralized or MIMO Control Structures: For systems with many sensors and actuators, a decentralized IT2 FLC can be deployed at each control point, or alternatively, a multi-input multi-output (MIMO) fuzzy controller can be designed with structured rule-sharing to manage complexity.
- Adaptive Learning in Higher Dimensions: The FOU adaptation scheme based on error variance remains applicable to higher-order systems, but may require vectorized or mode-specific variance tracking for effective tuning.

Future extensions of this framework will consider applying these strategies to real-world systems such as multi-span beams, thin plates, and rotating machinery with multiple resonances, validating the controller's efficacy in more complex structural environments.

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