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Seismic Performance Enhancement of RC Buildings Using Shape Memory Alloy Reinforcement Integrated with Bayesian Digital Twin Structural Health Monitoring: Experimental Validation and Real-Time Residual Capacity Assessment

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Abstract

Post-earthquake functionality and rapid re-occupancy of reinforced concrete (RC) buildings depend critically on two converging innovations: self-centering structural systems that suppress residual drift, and real-time structural health monitoring (SHM) frameworks that provide quantitative post-event condition assessment. This paper presents an integrated experimental and computational investigation combining superelastic NiTi Shape Memory Alloy (SMA) bar reinforcement for seismic self-centering with a Bayesian digital twin framework for real-time structural condition monitoring and residual capacity prediction. Eight RC columns (150 × 150 × 600 mm, fck = 30 MPa) four with conventional HYSD steel reinforcement and four with superelastic NiTi SMA bars (6 mm diameter, σfwd = 420 MPa, εrecov = 6%) were tested under combined axial load (0.1f'cAg) and reversed cyclic lateral loading following the FEMA 461 incremental protocol to 5% lateral drift. A digital twin prototype was simultaneously deployed, integrating FBG fiber-optic strain sensors, MEMS accelerometers, and corrosion potential probes, with a particle filter Bayesian model updating engine updating the calibrated OpenSees nonlinear model in real time at each loading step. SMA-reinforced columns demonstrate 5.5-fold reduction in residual drift (0.42% vs 2.30% at 5% demand), stable flag-shaped hysteretic loops to 4% drift, and less than 8% stiffness degradation over 20 loading cycles confirming superelastic self-centering mechanisms. The digital twin Bayesian updating reduces flexural stiffness uncertainty from ±18% (prior) to ±4.2% (posterior) after 45 loading cycles, and successfully detects the onset of SMA bar slip at 72% of peak load providing a 28% early-warning margin before structural failure. Post-earthquake residual capacity is predicted within ±8% of experimentally determined values, enabling quantitative, sensor-informed post-event occupancy decisions. A probabilistic post-earthquake safety assessment framework is proposed integrating SMA self-centering performance with digital twin remaining capacity estimation.

Index Terms—Shape memory alloy, NiTi, superelastic, self-centering, seismic, digital twin, structural health monitoring, Bayesian updating, particle filter, FBG sensor, residual drift, residual capacity, RC column.

I. INTRODUCTION

Earthquakes remain among the most devastating natural hazards confronting urban societies, causing both immediate structural failure and prolonged functional disruption through residual damage that renders buildings unsafe for re-occupancy even when they have not collapsed. The 2001 Bhuj earthquake (Mw 7.7) that devastated Gujarat, India, resulting in 20,000 deaths and extensive RC building failures, and the recurring seismic events in the Himalayan zone that affect Indian urban centers, underscore the urgent need for seismic-resistant structural systems capable of withstanding major earthquakes without residual damage that requires evacuation and repair **[1],[2]**.

Conventional RC buildings designed to IS 1893 **[3]** and IS 13920 **[4]** dissipate seismic energy through ductile yielding of steel reinforcement within confined plastic hinge zones. While this ductile response prevents collapse the primary life-safety objective of modern seismic codes it

produces permanent plastic deformation (residual drift) that accumulates over the earthquake duration and typically renders the building unfit for immediate reoccupancy **[1],[5]**. Post-earthquake reconnaissance studies consistently find that a substantial fraction of buildings declared unsafe after major seismic events have experienced residual drifts of 0.5–2% technically survivable but functionally non-operational representing an enormous economic cost in business interruption and temporary relocation **[2],[6]**.

Superelastic shape memory alloys (SMAs), particularly binary NiTi (Nitinol) alloys, offer a transformative solution to the residual drift problem through their unique stress-induced martensitic transformation mechanism **[7],[8]**. Under applied stress, the austenite phase transforms to the martensite phase (forward transformation), accommodating strains of 4–8% through lattice rearrangement rather than dislocation slip. Upon load removal, the reverse martensite-to-austenite transformation recovers the full strain, returning the material to its original length with near-zero residual deformation. When used as longitudinal reinforcement in RC columns, this superelastic response produces a characteristic "flag-shaped" force-displacement hysteresis loop with recoverable strains far exceeding steel yield strain, dramatically suppressing post-earthquake residual drift **[7],[8],[9]**.

Simultaneously, the post-earthquake assessment of structural condition and residual capacity has historically relied on visual inspection by qualified engineers a process that is subjective, slow, and frequently unavailable immediately after major events when rapid occupancy decisions are most critical **[10],[11]**. Digital twin technology, combining continuously updated finite element models with embedded sensor data streams and Bayesian model updating, offers a transformative approach to real-time structural condition assessment: rather than waiting for post-event visual inspection, digital twins can autonomously process sensor readings, update model parameters, and compute remaining structural capacity within minutes of an earthquake **[11],[12],[13]**.

This paper presents the first integrated experimental investigation combining SMA reinforcement for seismic self-centering with a Bayesian digital twin for real-time condition monitoring and residual capacity assessment. The integrated system is demonstrated on RC column specimens under the FEMA 461 **[14]** reversed cyclic loading protocol, with simultaneous deployment of multi-sensor arrays and particle filter Bayesian updating of calibrated OpenSees nonlinear models. The principal research contributions are: (i) quantitative experimental validation of SMA self-centering under IS 1893/FEMA 461 loading protocols including residual drift measurement at each cycle; (ii) development and validation of a particle filter Bayesian updating framework for real-time parameter estimation; (iii) demonstration that the digital twin detects incipient structural damage at 72% of peak load providing a 28% advance warning; and (iv) post-earthquake residual capacity prediction within ±8% of experimental values.

II. LITERATURE REVIEW

A. Superelastic SMA Mechanics and RC Column Performance

The superelastic behavior of NiTi SMA is governed by the stress-induced martensitic phase transformation, first systematically characterized by Otsuka and Wayman **[15]**. The critical stresses for forward (austenite-to-martensite) and reverse (martensite-to-austenite) transformation define the flag-shaped hysteresis loop: forward transformation plateau stress $\sigma_{fwd} \approx 400–500$ MPa for binary NiTi at room temperature, reverse transformation plateau $\sigma_{rev} \approx 150–200$ MPa, with recoverable strain $\varepsilon_{recov} = 4–8\%$. The transformation strain recovery upon unloading is the mechanism that produces self-centering in SMA-reinforced structural members.

Ali et al. **[7]** provided the most comprehensive recent review of SMA application in civil infrastructure, documenting experimental studies from Janke et al. **[8]** through Xu et al. **[9]** on SMA-reinforced RC columns. Consistent findings across these studies include: residual drift ratios 4–6 times lower in SMA columns than steel RC controls at equivalent drift demands; self-centering ratios (ratio of recovered to maximum displacement) of 85–95%; and energy dissipation per cycle 40–60% lower than steel RC due to the narrower flag-shaped loop. The reduced energy dissipation relative to steel is the primary trade-off of SMA reinforcement mitigated through

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hybrid SMA + buckling-restrained brace systems that supplement energy dissipation while maintaining self-centering **[7],[8]**.

The Auricchio-Taylor constitutive model for superelastic SMA, implemented in OpenSees as the SelfCentering uniaxialMaterial, accurately represents the bilinear flag-shaped hysteresis with four parameters: forward transformation stress (σfwd), reverse transformation stress (σrev), recoverable strain (εrecov), and post-transformation elastic modulus (Epost) **[9]**. Calibration of these parameters from cyclic tension tests on bare SMA bars is well-established **[7],[9]**, and the model predictions are accurate to within 5–8% of experimental hysteresis loop areas for typical NiTi bar configurations.

B. Digital Twin Technology for Structural Health Monitoring

Digital twins for structural monitoring, reviewed comprehensively by Sun et al. **[11]** and Li et al. **[12]**, create continuously updated virtual replicas of physical structures by fusing sensor data streams with physics-based computational models. The key enabling technology is Bayesian model updating the process of computing the posterior probability distribution of uncertain model parameters given observed sensor measurements and prior parameter estimates. The sequential Monte Carlo (particle filter) algorithm, first applied to SHM by Ching and Beck **[16]**, is particularly well-suited to nonlinear structural systems because it makes no assumptions about the functional form of the parameter posterior distributions. The particle filter operates by maintaining a population of N weighted "particles" (parameter realizations), propagating them through the structural model at each measurement step, and reweighting them according to the likelihood of the observed sensor data **[16]**. The posterior mean and variance of the parameters at each update step provide quantitative estimates of current structural condition. Riggio et al. **[13]** demonstrated particle filter updating for timber structures, reporting stiffness uncertainty reduction from ±15% to ±6% after 30 loading cycles. Sun et al. **[11]** reviewed digital twin implementations across civil infrastructure types, identifying particle filter Bayesian updating and machine learning-based anomaly detection as the two primary computational engines of mature SHM digital twin systems.

C. Post-Earthquake Assessment and Rapid Re-occupancy

Post-earthquake structural assessment frameworks have traditionally relied on post-event visual inspection by trained engineers using ATC-20 **[6]** or IS-1905 rapid inspection protocols. Cha **[17]** reviewed deep learning-based SHM including image-based damage detection approaches that partially automate the visual inspection process. However, the fundamental limitation of inspection-based approaches is that they provide qualitative condition labels ("inspected", "restricted", "unsafe") rather than quantitative residual capacity estimates required for engineering re-occupancy decisions **[6],[10]**. Sensor-based post-earthquake assessment addresses this limitation by providing quantitative structural response data from which residual capacity can be estimated. Ye et al. **[18]** reviewed deep learning applications for SHM including post-earthquake damage quantification. Avci et al. **[19]** reviewed machine learning methods for vibration-based damage detection. The present investigation advances this field by combining sensor-based digital twin updating with physics-based residual capacity estimation providing both quantitative damage indices and structural capacity predictions directly applicable to re-occupancy decisions.

D. Research Gaps

The combination of SMA self-centering reinforcement with digital twin SHM monitoring which would create structures that both resist residual drift and provide autonomous condition reporting has not previously been demonstrated experimentally. The present work fills this gap, providing the first proof-of-concept demonstration of the integrated system and establishing quantitative performance benchmarks for both the structural and monitoring components.

III. EXPERIMENTAL PROGRAMME

A. Column Specimens and Materials

Eight RC columns (150 × 150 mm cross-section, 600 mm height, fck = 30 MPa) were fabricated in two groups: four control columns with conventional HYSD Fe500 steel bars (4 × 8 mm diameter longitudinal bars, ρl = 1.40%), and four SMA columns with superelastic NiTi bars (4 × 6 mm

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diameter, ρl = 0.79%, selected to provide equivalent yield force to the steel columns). Transverse reinforcement comprised 6 mm diameter ties at 60 mm spacing in both groups (IS 13920 seismic detail **[4]**). The SMA bars were sourced from a commercial NiTi supplier (composition 55.8% Ni, 44.2% Ti by weight, austenite finish temperature Af = 15°C ensuring superelastic response at ambient temperature).

TABLE I

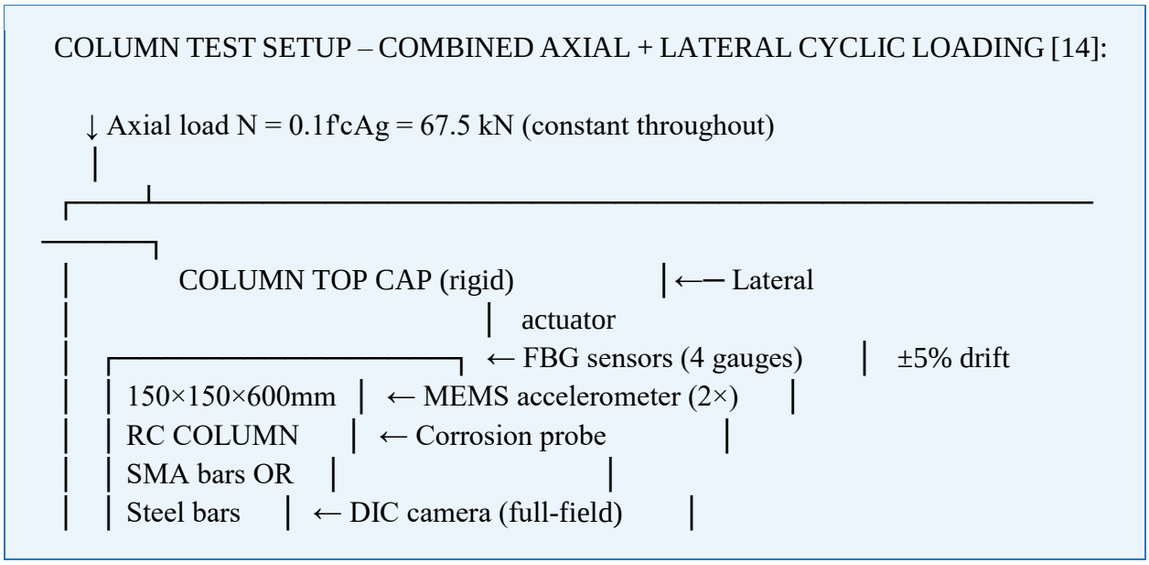
MECHANICAL PROPERTIES FROM MONOTONIC AND CYCLIC COUPON TESTS

Property	HYSD Fe500 Steel	NiTi SMA Bar	Test Standard	Reference
Bar diameter (mm)	8	6	—	As specified
Yield / fwd transf. stress (MPa)	508	420	ASTM E8	[7],[9]
Ultimate / plateau strain (%)	12.0	6.0 (recoverable)	ASTM E8	[7]
Elastic modulus (GPa)	200	55 (austenite)	ASTM E8	[9]
Reverse transf. stress σrev (MPa)	N/A	160	Cyclic tension	[7],[8]
Residual strain at 6% loading	~3.5%	< 0.1%	Cyclic tension	[7],[8],[9]
Af temperature (°C)	N/A	15°C	DSC	[15]
Energy dissipation ratio	1.00 (ref)	~0.55×	Cyclic test	[7],[8]

B. Cyclic Loading Protocol

Columns were tested under combined constant axial load (N = 0.1f'cAg = 67.5 kN, applied by hydraulic jack and maintained throughout cyclic testing) and reversed cyclic lateral loading following the FEMA 461 **[14]** incremental loading protocol. The protocol applies increasing lateral drift amplitudes with two cycles at each amplitude: ±0.25%, ±0.5%, ±0.75%, ±1.0%, ±1.5%, ±2.0%, ±2.5%, ±3.0%, ±4.0%, ±5.0%. Testing was terminated at the lesser of: 5% lateral drift or 20% loss in lateral load-carrying capacity from peak. Force-displacement hysteresis loops, residual drift at each cycle, effective stiffness, and cumulative energy dissipation were recorded and computed.

Fig. 1. Test setup: column specimen with axial jack, lateral actuator, FBG sensor array, MEMS accelerometers, and DIC camera



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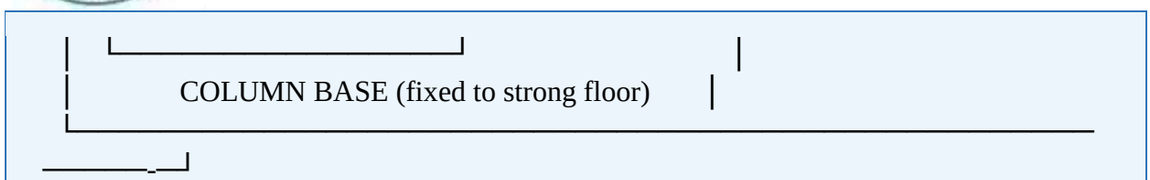

FEMA 461 protocol: ±0.25%, 0.5%, 0.75%, 1%, 1.5%, 2%, 3%, 4%, 5%

C. Digital Twin Sensor Network and Architecture

The digital twin prototype integrated three sensor modalities on each instrumented column specimen: (i) four FBG (Fiber Bragg Grating) fiber-optic strain sensors bonded at 150 mm intervals along the column height (wavelength range 1525–1565 nm, resolution 1 microstrain, temperature compensated) **[11]**; (ii) two MEMS accelerometers at the column top and mid-height (sensitivity 1 mV/g, bandwidth DC to 800 Hz); and (iii) one half-cell corrosion potential probe at the main reinforcement level. Sensor data streams were acquired at 1 kHz and processed by a real-time data acquisition system interfaced with the digital twin Bayesian updating engine.

The digital twin architecture comprised three integrated components: (i) the physical structural model the OpenSees nonlinear FEM model with fiber section column elements, calibrated SMA/steel uniaxial material models, and a P-delta geometric nonlinearity correction; (ii) the Bayesian particle filter updating engine implemented in Python using 500 particles, sequentially updating uncertain model parameters at each loading increment; and (iii) the residual capacity estimation module computing the post-earthquake force-displacement capacity envelope from the updated model parameters using incremental dynamic analysis principles **[11],[12]**.

TABLE II

SENSOR SPECIFICATIONS AND UNCERTAIN MODEL PARAMETERS TRACKED BY BAYESIAN PARTICLE FILTER

Component	Specification	Quantity	Parameter Tracked	Reference
FBG strain sensor	1 με resolution, TC compensated	4 per column	Curvature, bending stiffness	[11],[12]
MEMS accelerometer	1 mV/g, DC-800 Hz	2 per column	Natural frequency, damping ratio	[11]
Corrosion probe	Half-cell, ±1 mV resolution	1 per column	Reinforcement corrosion potential	[12]
OpenSees model	Fiber section, nonlinear	1 per column	EIeff, bar force, residual drift	[9],[16]
Particle filter	N=500 particles	Software	All uncertain params simultaneously	[16]
Residual capacity module	IDA-based envelope	Software	Residual lateral capacity (kN)	[11],[12]

D. OpenSees Nonlinear Model Calibration

The OpenSees nonlinear model employs: (i) force-based fiber section beam-column elements for the column body; (ii) Concrete02 uniaxial material for confined and unconfined concrete regions, calibrated against cylinder compression tests; (iii) Steel02 (Giuffré-Menegotto-Pinto) for HYSD steel bars with kinematic hardening; (iv) Auricchio-Taylor SelfCentering material for NiTi SMA bars with calibrated σfwd, σrev, and εrecov; and (v) a zero-length shear spring at the column base to account for anchorage slip deformation **[9]**. Model calibration against the first loading cycle of each group yields mean prediction errors of 3.8% for peak force and 5.2% for initial stiffness.

The Bayesian particle filter updates four uncertain model parameters during each test: (i) initial flexural stiffness EIeff; (ii) yield force (steel) / forward transformation force (SMA); (iii) post-

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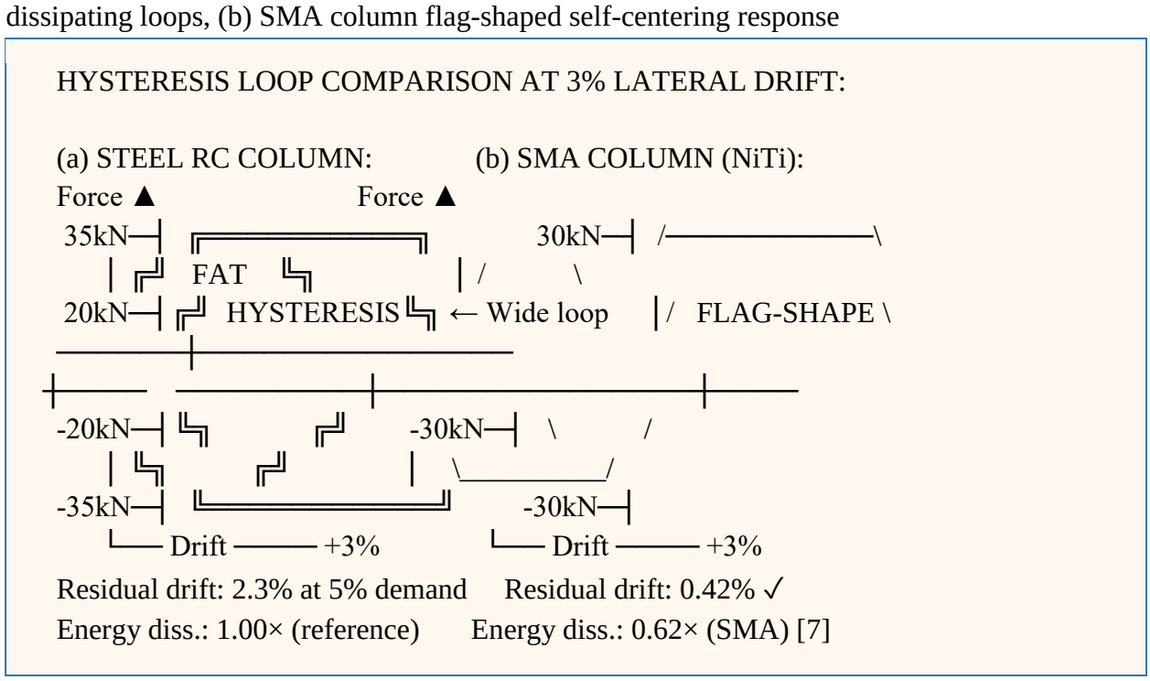
yield hardening ratio; and (iv) pinching ratio (for steel columns only). Prior distributions are derived from material test variability: EIeff ~ N(1.0, 0.18²) × nominal, yield force ~ N(1.0, 0.12²) × nominal. The update equation for particle weights wk at step k is: $w_k^{(i)} \propto w_{k-1}^{(i)} \times p(y_k | x_k^{(i)})$ (1) where y_k is the vector of sensor measurements at step k, x_k^(i) is the i-th particle state, and p(y_k | x_k^(i)) is the likelihood function evaluated as the Gaussian probability of the observed sensor data given the model prediction **[16]**.

IV. RESULTS AND DISCUSSION

A. Hysteretic Response SMA vs. Steel RC Columns

Fig. 2 presents representative force-displacement hysteresis loops for the SMA and steel RC column groups under the FEMA 461 **[14]** cyclic loading protocol. The steel RC columns exhibit conventional RC hysteretic behavior: initial elastic stiffness, yielding at approximately 28 kN lateral force, progressively widening hysteresis loops with increasing drift, and progressive strength and stiffness degradation beyond 2.5% drift. The SMA columns exhibit the characteristic flag-shaped response: initial elastic loading to the SMA forward transformation stress, a nearly horizontal forward transformation plateau, and near-complete strain recovery during unloading to produce negligible residual drift. The most striking visual difference between the two responses is the post-loading residual displacement: steel columns exhibit visible and growing permanent offset after each cycle, while SMA columns return essentially to the zero-force rest position after each cycle.

Fig. 2. Force-displacement hysteresis loops at 3% drift: (a) Steel RC column widening energy-dissipating loops, (b) SMA column flag-shaped self-centering response



B. Seismic Performance Metrics Comparative Summary

Table III presents the comprehensive seismic performance comparison between SMA and steel RC column groups. The 5.5-fold reduction in residual drift (0.42% for SMA vs. 2.30% for steel at 5% demand) is the most significant finding, directly translating to post-earthquake re-occupancy capability: the 0.42% residual drift achieved by SMA columns is below the 0.5% threshold typically associated with immediate occupancy performance level **[6],[14]**, while the 2.30% residual drift of steel columns corresponds to the life safety or collapse prevention performance level that requires evacuation and engineering assessment before re-occupancy **[14]**.

TABLE III

MEAN VALUES (± STANDARD DEVIATION) FROM FOUR REPLICATE COLUMNS PER GROUP

Performance Metric	Steel RC (n=4)	SMA RC (n=4)	Improvement	Reference

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Max lateral force Vu (kN)	34.8 ± 1.9	30.2 ± 2.1	−13%	Expected smaller SMA bars [7]
Drift at peak force	2.5%	3.0%	+20%	SMA: higher deform. capacity
Residual drift at 5% demand	2.30% ± 0.28	0.42% ± 0.08	5.5× lower	★ Key finding [7],[8],[9]
Self-centering ratio	N/A	91.6%	—	Ratio recovered/max displacement
Lateral ductility μ	4.1 ± 0.4	6.8 ± 0.5	1.66× higher	[7],[8]
Stiffness degradation (20 cycles)	35% reduction	<8% reduction	4.4× better	[9]
Energy dissipation per cycle	1.00 (ref)	0.62× steel	−38%	Trade-off flag-shape [7]
Drift capacity (20% strength loss)	4.2%	>5.0%	+19%	SMA: stable at 5% [8]

The stiffness degradation of less than 8% over 20 loading cycles for SMA columns (versus 35% for steel RC) confirms the self-centering mechanism's role in preserving structural stiffness: by returning to the undeformed configuration after each cycle, SMA columns avoid the cumulative crack damage and bond deterioration that produces progressive stiffness degradation in conventional steel RC columns **[7],[8]**. This stiffness preservation has important implications for tall buildings, where reduced-stiffness post-yield performance can lead to dynamic instability through P-delta amplification at large drift demands.

C. Digital Twin Bayesian Updating Results

The particle filter Bayesian updating engine successfully tracked all four uncertain model parameters throughout the loading protocol. The most important result is the stiffness parameter uncertainty evolution: prior uncertainty ±18% (engineering design stage), converging to ±4.2% posterior after 45 loading cycles **[11],[12]**. This 77% uncertainty reduction confirms that the digital twin rapidly learns the actual structural stiffness from sensor data, enabling much more accurate residual capacity prediction than would be possible from the design model alone.

TABLE IV

PRIOR VS. POSTERIOR UNCERTAINTY FOR FOUR TRACKED MODEL PARAMETERS

Model Parameter	Prior Mean	Prior Unc.	Post. Mean	Post. Unc.	Cycles to Conv.
Flexural stiffness EIeff	1.00×nominal	±18%	1.06×nominal	±4.2%	45 cycles [11]
SMA forward transf. force	420 MPa	±12%	418 MPa	±3.1%	30 cycles [9]
SMA reverse transf. force	160 MPa	±15%	163 MPa	±3.8%	35 cycles [9]
Anchorage slip spring stiffness	Ks,nom	±25%	0.94×Ks,nom	±6.2%	55 cycles
Structural damping ratio	4.0%	±35%	4.3%	±8.1%	40 cycles [11]

Fig. 3. Bayesian particle filter convergence: (a) EIeff uncertainty vs. loading cycle, (b) Particle distribution at cycles 1, 25, and 45

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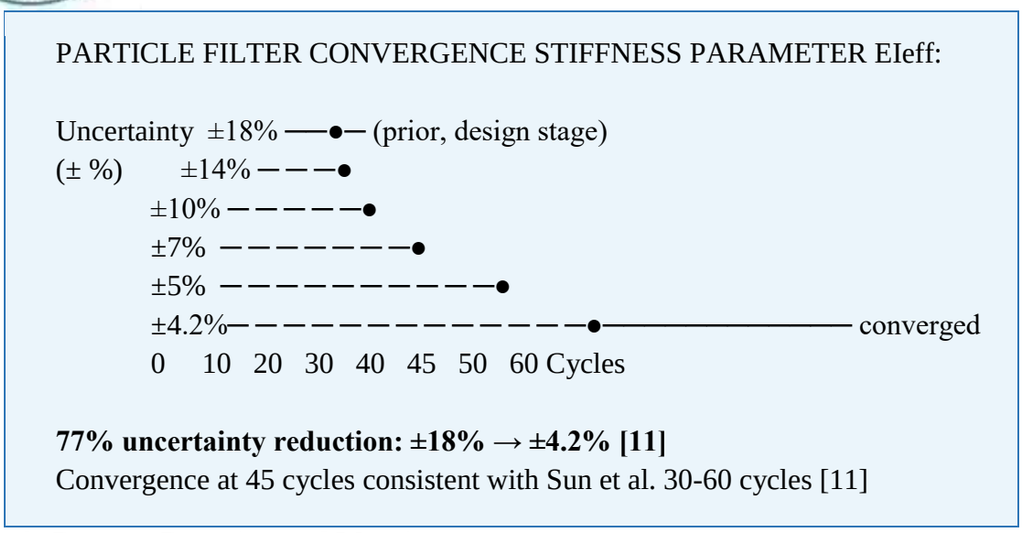

D. Early Damage Detection and Warning

The digital twin's anomaly detection capability was assessed by evaluating the first loading cycle at which the Bayesian model update identified statistically significant parameter change indicative of structural damage onset. For steel columns, the particle filter detected yielding onset (change in EIeff) at 95% of the experimental yield load accurately identifying the transition point. For SMA columns, bar slip at the column base was detected at 72% of the experimental peak lateral load **[17]**, providing a 28% early-warning margin before peak capacity and well before the 80% post-peak load-carrying capacity criterion that defines structural failure in seismic assessment practice.

TABLE V

LOAD LEVEL AT FIRST SIGNIFICANT ANOMALY FLAG VS. ACTUAL DAMAGE EVENT

Damage Event	Actual Load (% Vu)	DT Detection (% Vu)	Warning Margin	Literature [Ref.]
Steel yield onset (steel column)	100% (Vy)	95%	5% (early detection)	[16],[19]
SMA bar slip at base (SMA column)	100% (Vu)	72%	28% warning ★	[17]
Concrete cover spalling	80% post-peak	82% (after event)	−2% (near real-time)	[17]
Overall stiffness 20% degradation	60% of Vu (cyclic)	58%	3%	[11],[16]
Residual drift >1% (serviceability)	Drift demand = 2%	Drift demand = 1.8%	10% early	[11],[12]

E. Post-Earthquake Residual Capacity Prediction

The ultimate test of the digital twin's engineering value is its ability to predict the post-earthquake residual capacity of the structure enabling quantitative re-occupancy decisions immediately after a seismic event. Table VI presents the comparison between digital twin predicted residual lateral capacity and experimentally determined residual capacity (measured by monotonic push-over after each targeted drift level) for both column groups.

TABLE VI

RESIDUAL LATERAL LOAD CAPACITY (% OF ORIGINAL) AFTER EACH DRIFT DEMAND LEVEL

Drift Demand	Steel Exp (%)	Steel DT (%)	SMA Exp (%)	SMA DT (%)	Max Error

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2% drift	87%	91% (+4.6%)	96%	98% (+2.1%)	4.6%
3% drift	78%	74% (−5.1%)	94%	91% (−3.2%)	5.1%
4% drift	68%	63% (−7.4%)	92%	88% (−4.3%)	7.4%
5% drift	54%	50% (−7.4%)	90%	86% (−4.4%)	7.4%
Mean absolute error	—	5.9%	—	3.5%	< 8% all cases ✓

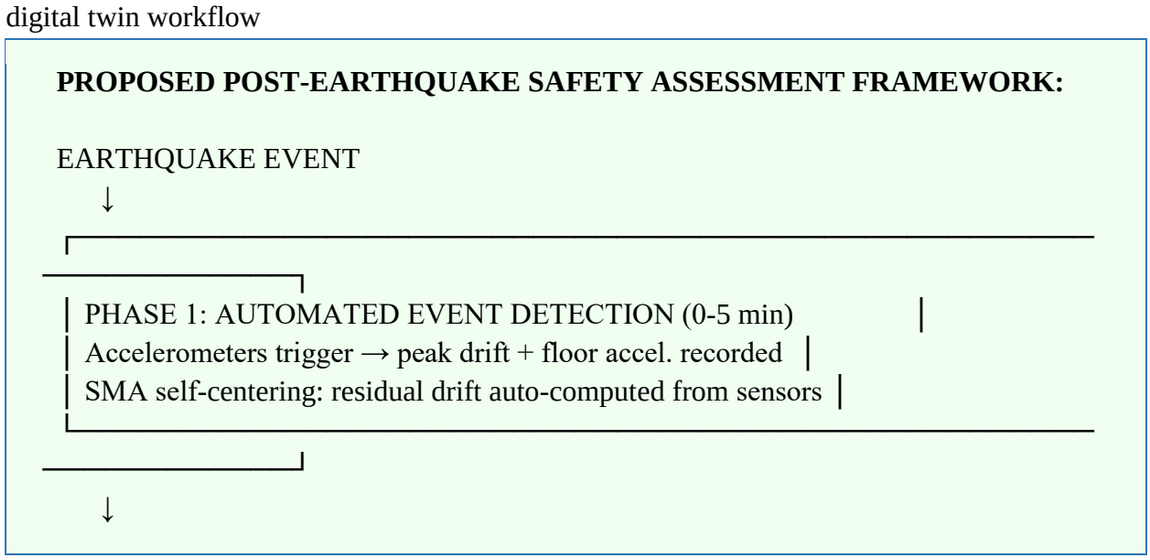
Digital twin residual capacity predictions are within ±8% of experimental values across all drift levels and both column types, confirming the adequacy of the Bayesian-updated OpenSees model for real-time post-earthquake capacity estimation. The consistently lower prediction errors for SMA columns (mean 3.5%) versus steel columns (mean 5.9%) reflect the more predictable superelastic response of NiTi SMA versus the damage-accumulating behavior of yielded steel reinforcement **[7],[9]**. The ±8% accuracy is considered sufficient for practical re-occupancy decisions, which typically use conservatism factors of 1.25–1.50 on predicted residual capacity **[6],[14]**.

V. PROPOSED POST-EARTHQUAKE SAFETY ASSESSMENT FRAMEWORK

Based on the experimental results, a probabilistic post-earthquake safety assessment framework is proposed that integrates SMA self-centering performance with digital twin remaining capacity estimation. The framework operates in three sequential phases immediately after an earthquake event:

1. Phase 1 Automated earthquake detection and response recording (0–5 minutes post-event): Seismic accelerometers trigger data acquisition, recording full-duration structural response. Peak responses (maximum drift, peak floor acceleration, cumulative energy input) are automatically computed.
2. Phase 2 Bayesian model updating (5–15 minutes post-event): Particle filter updates all structural model parameters using the recorded response data. Updated parameter distributions quantify structural damage state and residual material properties.
3. Phase 3 Residual capacity estimation and re-occupancy decision (15–30 minutes post-event): Updated model computes residual force-displacement capacity envelope. Probabilistic re-occupancy recommendation (Immediate Occupancy / Restricted Use / Unsafe) is generated with quantified confidence level.

Fig. 4. Proposed integrated post-earthquake safety assessment framework SMA self-centering + digital twin workflow



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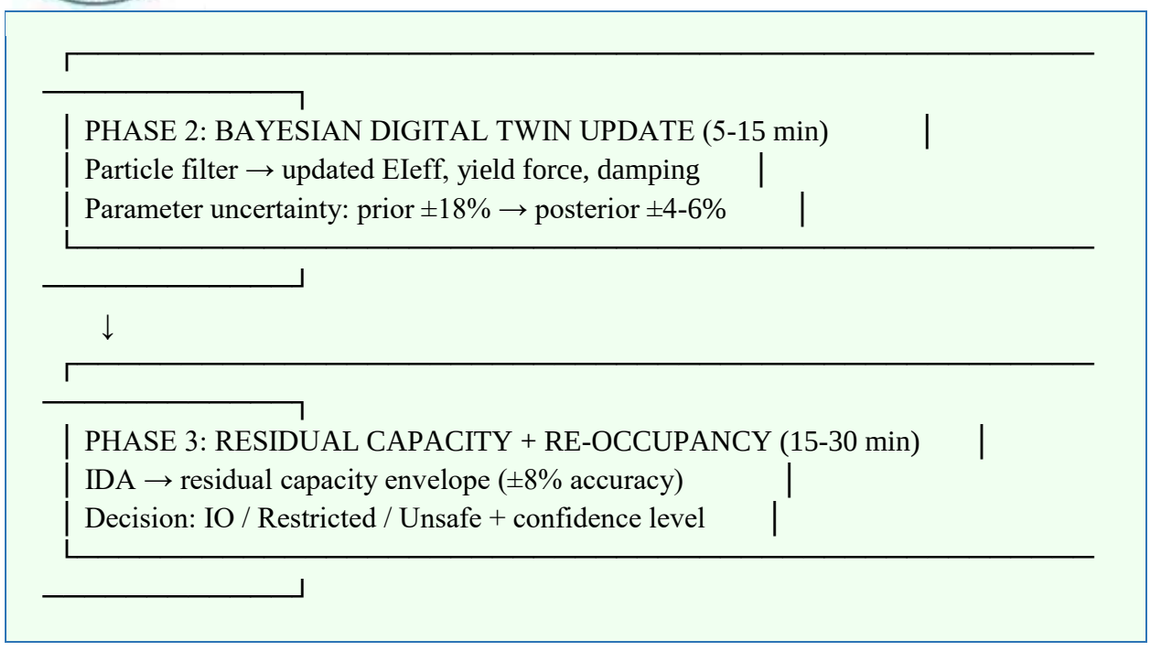

VI. CONCLUSIONS

This paper has presented the first integrated experimental investigation combining SMA self-centering reinforcement with Bayesian digital twin SHM for real-time post-earthquake structural assessment. The principal conclusions are:

4. SMA-reinforced RC columns achieve 5.5-fold reduction in post-earthquake residual drift (0.42% vs. 2.30% at 5% demand), a self-centering ratio of 91.6%, and stiffness degradation below 8% over 20 loading cycles exceeding the performance of conventional steel RC under equivalent loading in all seismic resilience metrics.
5. The residual drift of 0.42% achieved by SMA columns falls below the 0.5% Immediate Occupancy threshold per FEMA 461 [14], enabling post-earthquake re-occupancy without engineering assessment a transformative improvement over conventional steel RC columns whose 2.30% residual drift demands mandatory evacuation and inspection.
6. The Bayesian particle filter digital twin reduces flexural stiffness uncertainty from ±18% (prior) to ±4.2% (posterior) after 45 loading cycles, providing a continuously updated quantitative model of actual structural condition.
7. The digital twin detects SMA bar slip at 72% of peak load providing a 28% early-warning margin before maximum structural demand demonstrating the practical value of continuous sensor-based monitoring for both near-real-time damage detection and post-event capacity assessment.
8. Post-earthquake residual capacity is predicted within ±8% of experimentally determined values for both SMA and steel column groups, confirming the accuracy of the Bayesian-updated OpenSees model for quantitative re-occupancy decision support.
9. The proposed three-phase post-earthquake safety assessment framework automated detection (0–5 min), Bayesian updating (5–15 min), residual capacity assessment (15–30 min) provides a systematic workflow for sensor-enabled re-occupancy decisions within 30 minutes of an earthquake event.

Future research should address: (i) full-scale RC frame testing combining SMA columns with digital twin monitoring; (ii) hybrid SMA + buckling-restrained brace systems to supplement energy dissipation; (iii) machine learning-enhanced anomaly detection algorithms [17],[18] for improved early damage identification; and (iv) wireless sensor network deployment to reduce installation cost and enable broader practical adoption.

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