Leveraging machine learning to better understand structural behavior under extreme loads

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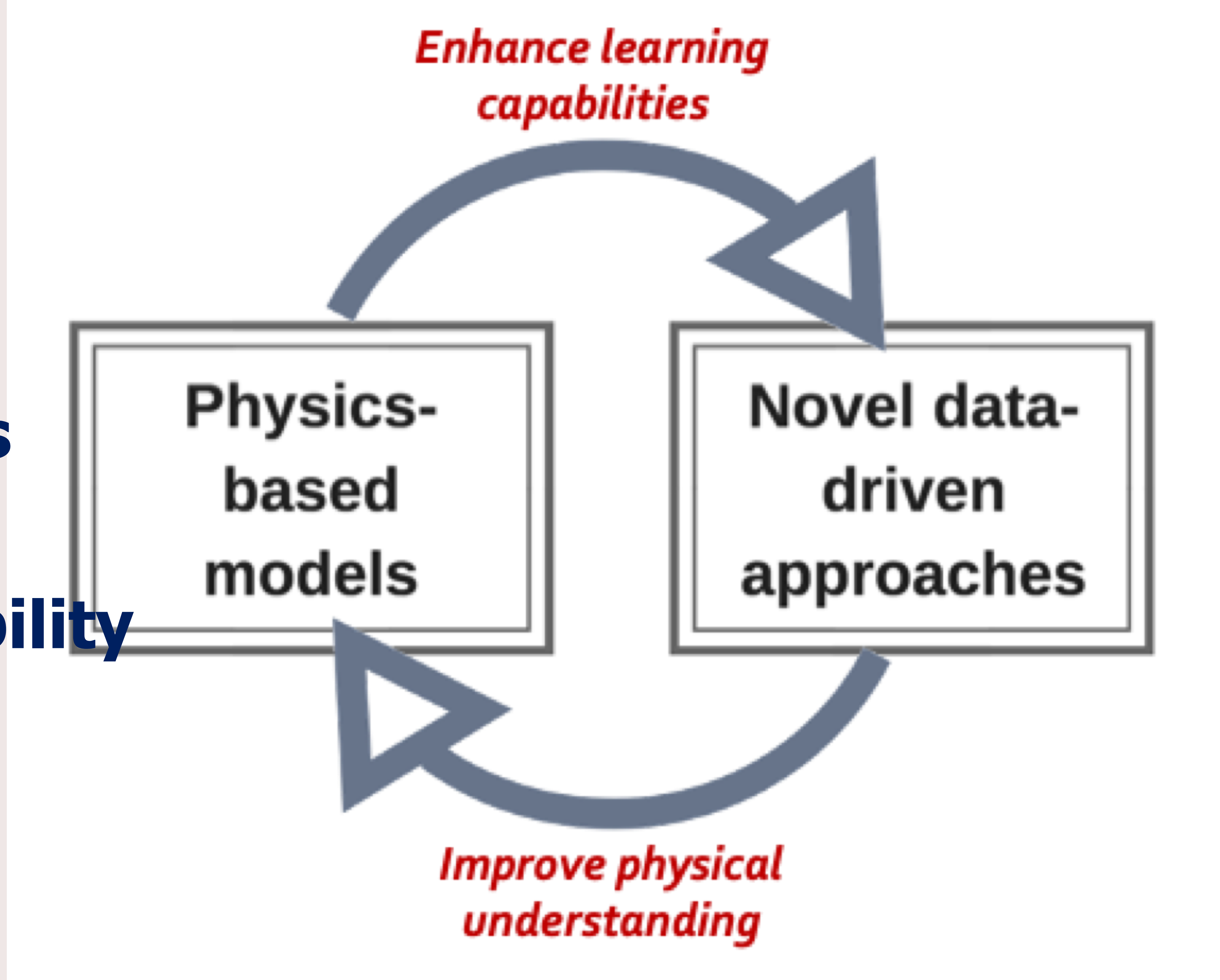
The goal is to use machine learning to understand *more* not to understand less.

Developed symbiotically, hybrid data-driven (AI)-physics-based approaches allow us to get the best of both worlds.

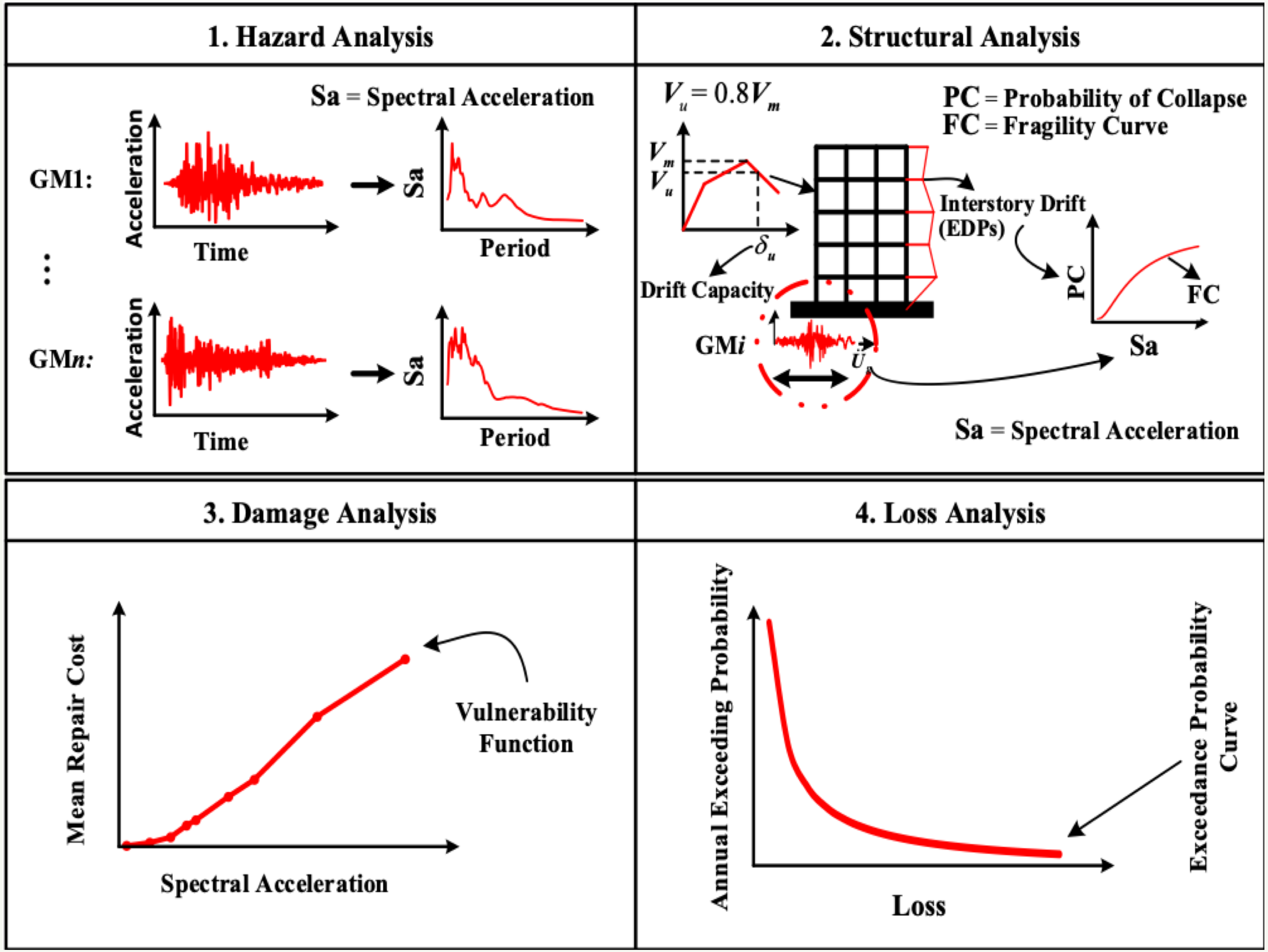
Governed by physical laws
Specificity
Explainability/Interpretability



High accuracy
Computational efficiency
Tendency towards real-time
Generalization capabilities

Example:

Seismic performance of RC structures


1. Hazard Analysis
Sa = Spectral Acceleration
GM1:
Acceleration
Time
Sa
Period
GMn:
Acceleration
Time
Sa
Period
2. Structural Analysis
$V_u = 0.8V_m$
PC = Probability of Collapse
FC = Fragility Curve
V_m
V_u
δ_u
Drift Capacity
Interstory Drift
(EDPs)
PC
FC
Sa
GMi
$\ddot{U}_g$
Sa = Spectral Acceleration
3. Damage Analysis
Mean Repair Cost
Spectral Acceleration
Vulnerability
Function
4. Loss Analysis
Annual Exceeding Probability
Loss
Exceedance Probability
Curve

Objectives

- Develop large databases to validate framework and individual approaches
- ML-based seismic performance prediction at the component-level
- Hybrid ML-physics-based seismic performance prediction at the system-level
- Provide solutions to data-related problems: missing data, outliers, small data

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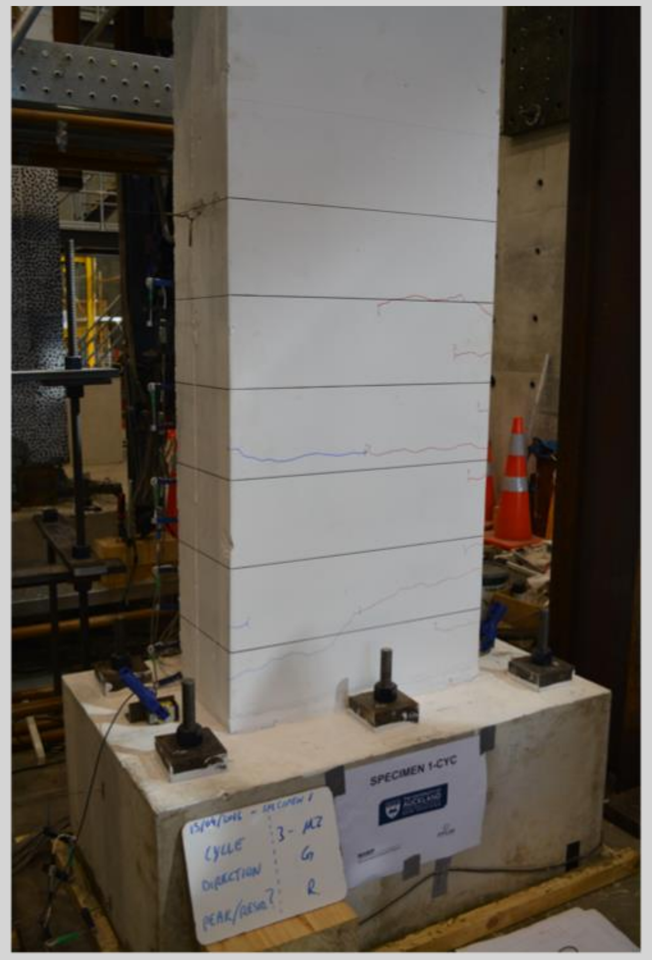
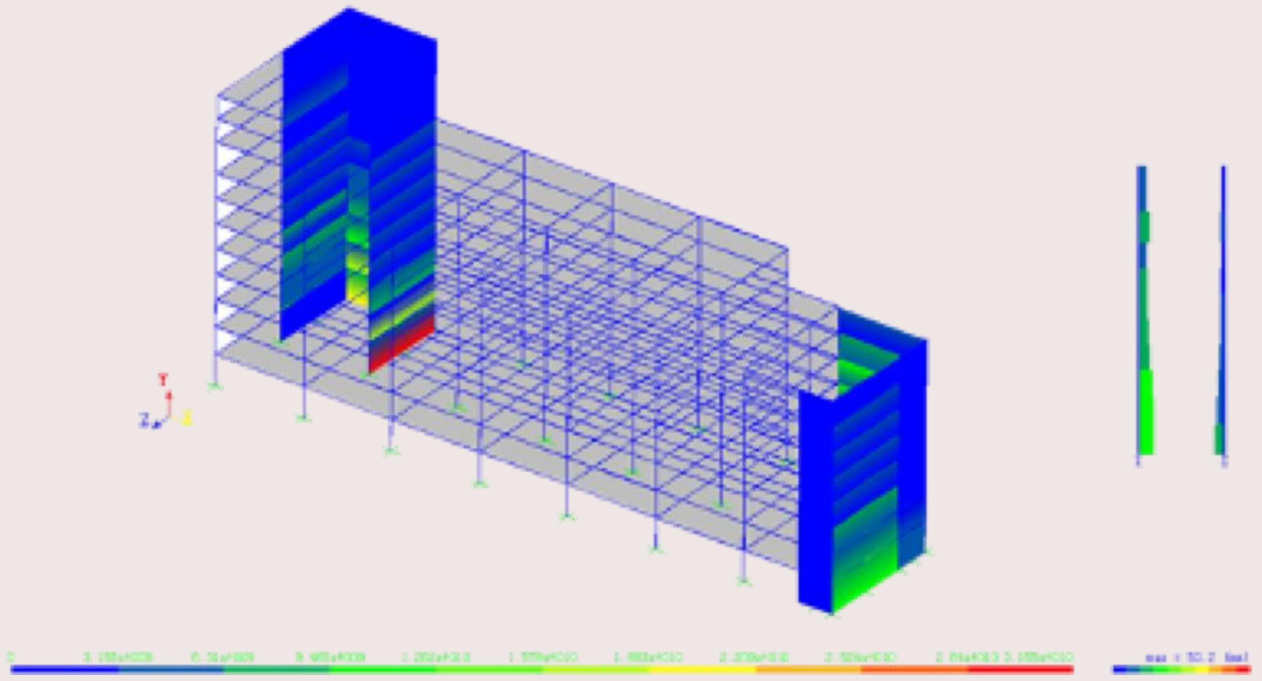
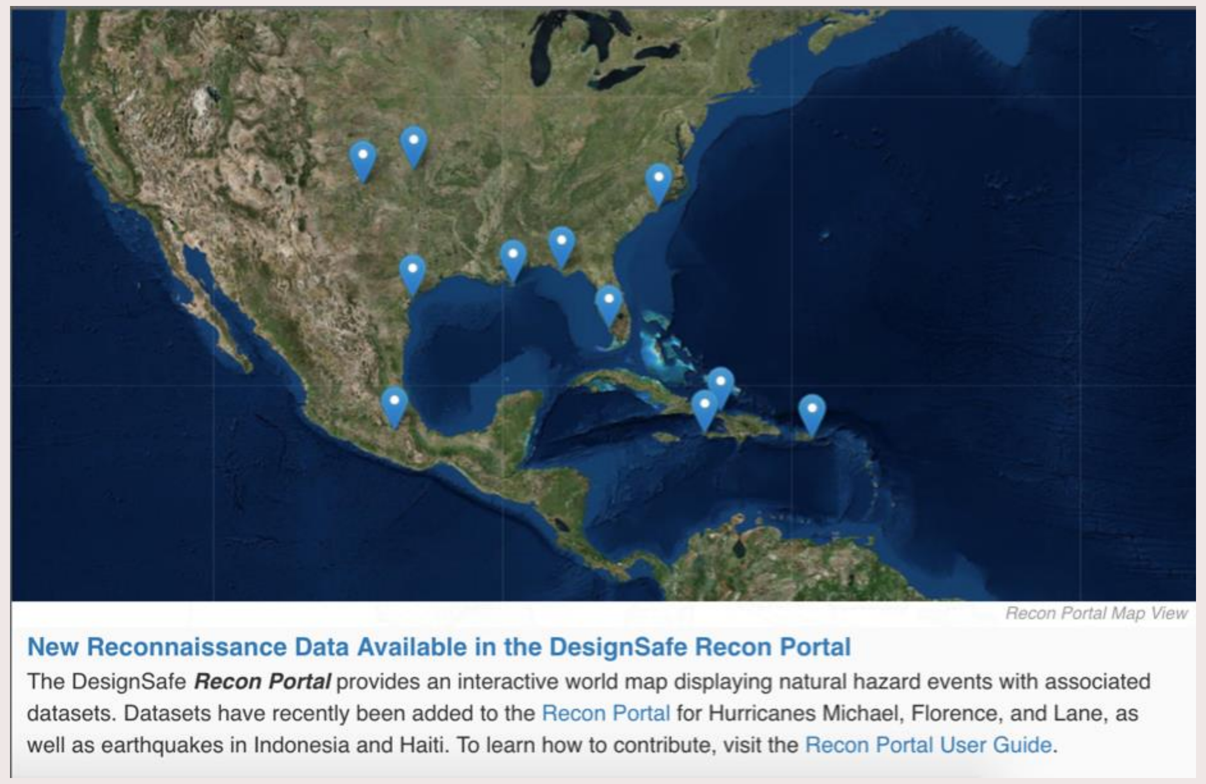
The data…



Marder and Elwood, Seismic testing of ductile RC beams (doi:10.17603/DS2SQ2K)





Building the database

422 reinforced concrete columns under pseudo-static cyclic loading

- 262 rectangular columns
- 160 circular columns
- Spanning all failure modes (306 ductile | 116 non ductile)

Property	Min	Max	Mean	Std
Shear span to effective depth ratio	1.08	8.40	3.84	1.57
Stirrup spacing to effective depth	0.11	1.14	0.32	0.21
Concrete compressive strength	16	118	50.40	28.72
Longitudinal reinf. yield stress	318	635	437.6	65.9
Transverse reinf. yield stress f_{yt}	249	1424	486.9	217.6
Longitudinal reinf. ratio	0.01	0.06	0.02	0.01
Transverse reinf. ratio	0.0006	0.03	0.008	0.005
Axial load ratio ($P/A_g f_c$)	0	0.9	0.26	0.19

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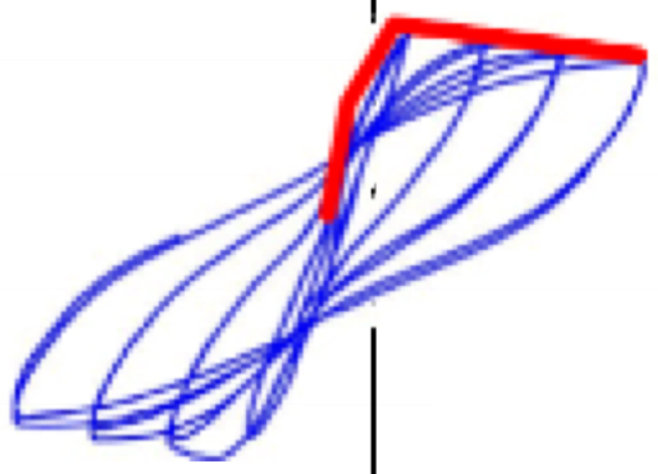
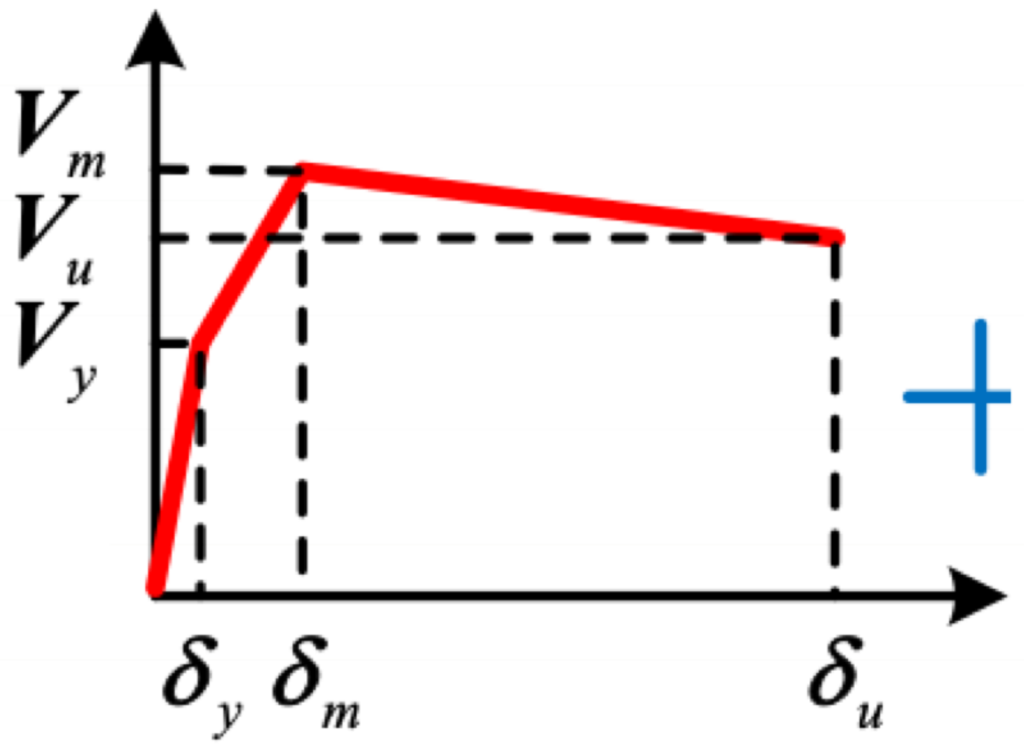
Component-level prediction

Independent (**Input**) Variables	Dependent (**Output**) Variables
X_1: Column failure mode	Y_1: Yield shear force
X_2: Column gross sectional area	Y_2: Maximum shear force
X_3: Concrete compressive strength	Y_3: Drift ratio at yield shear
X_4: Longitudinal reinforcement yield stress	Y_4: Drift ratio at maximum shear
X_5: Longitudinal reinforcement area	Y_5: Ultimate shear
X_6: Column effective depth	Y_6: Drift ratio at ultimate shear
X_7: Transverse reinforcement yield stress	$\boldsymbol{Y}$: Hysteretic parameters
X_8: Transverse reinforcement area	
X_9: Stirrup spacing to effective depth ratio	
X_{10}: Shear span to effective depth ratio	
X_{11}: Applied axial load	
X_{12}: Longitudinal reinforcement ratio	
X_{13}: Transverse reinforcement ratio	
X_{14}: Axial load ratio	
X_{15}: Maximum normalized shear stress	





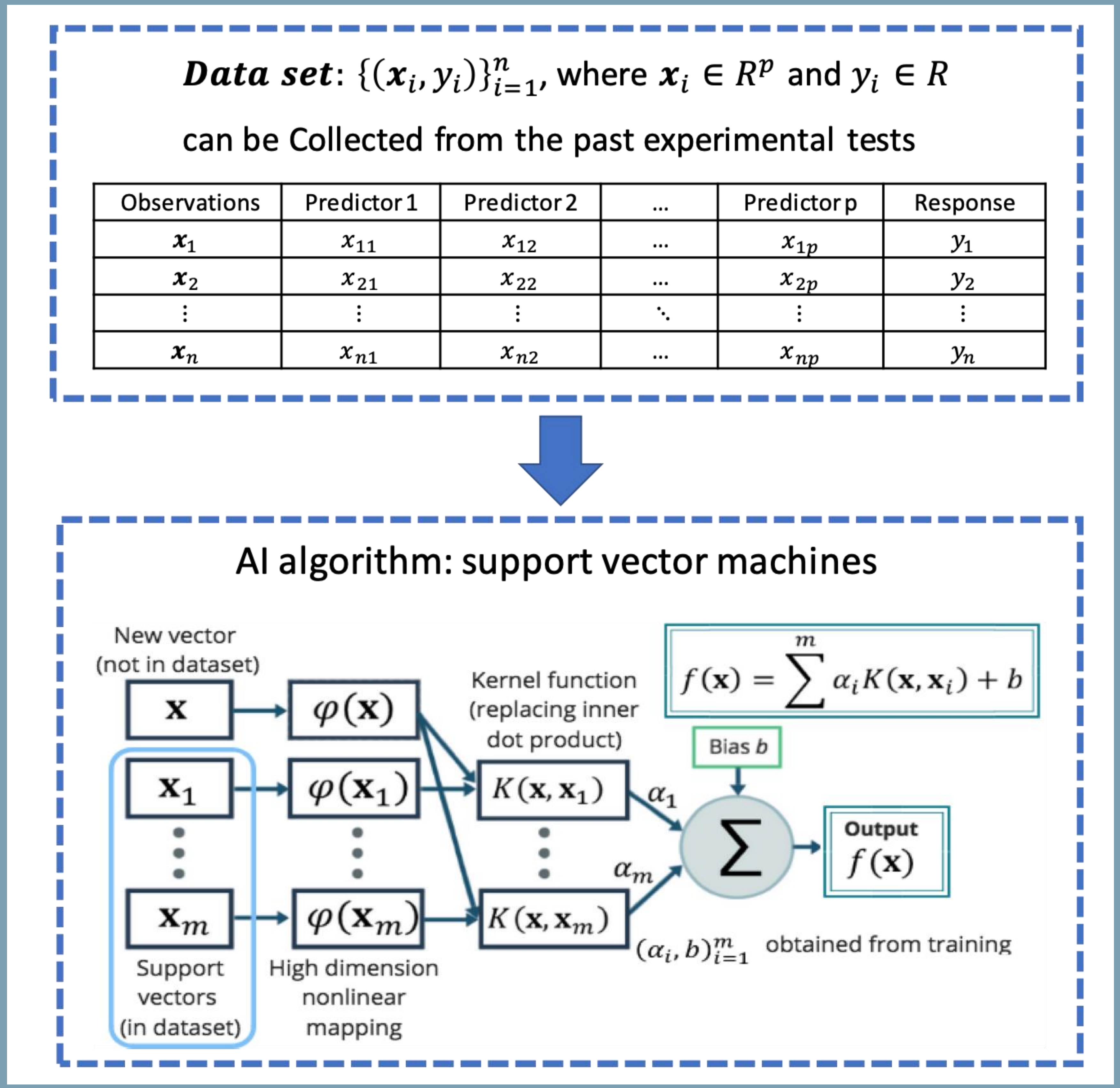
Component-level prediction

Independent (**Input**) Variables

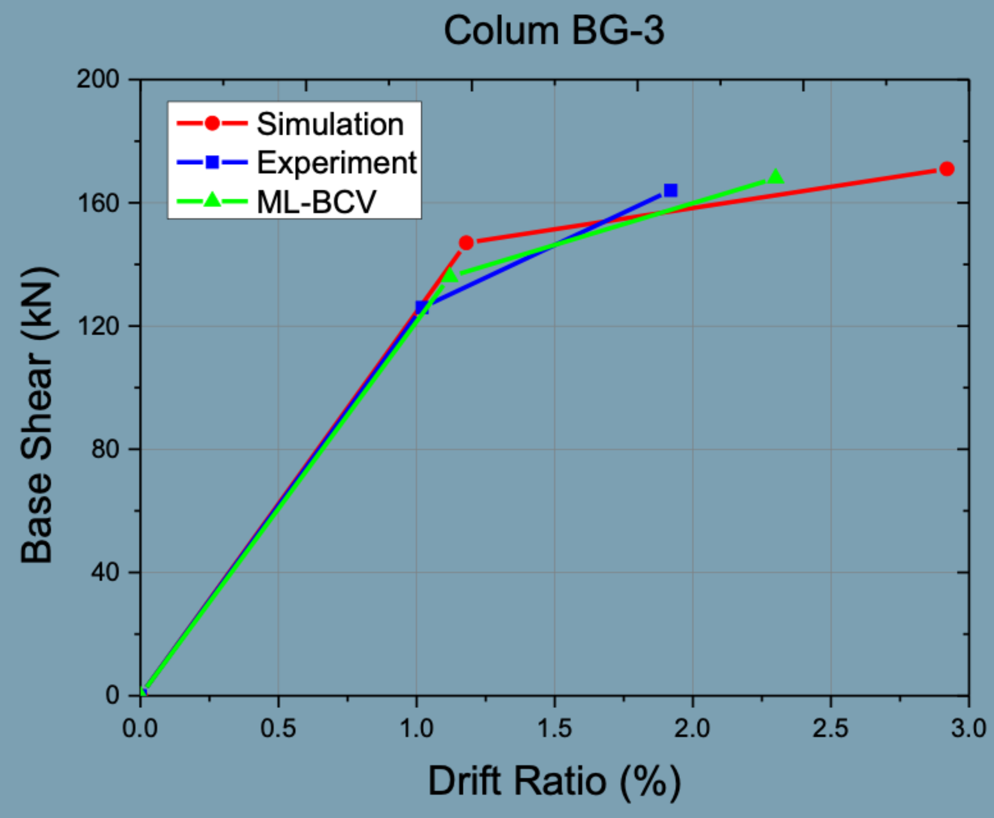
X_1: Column gross sectional area
X_2: Concrete compressive strength
X_3: Longitudinal reinforcement yield
X_4: Longitudinal reinforcement area
X_5: Column effective depth

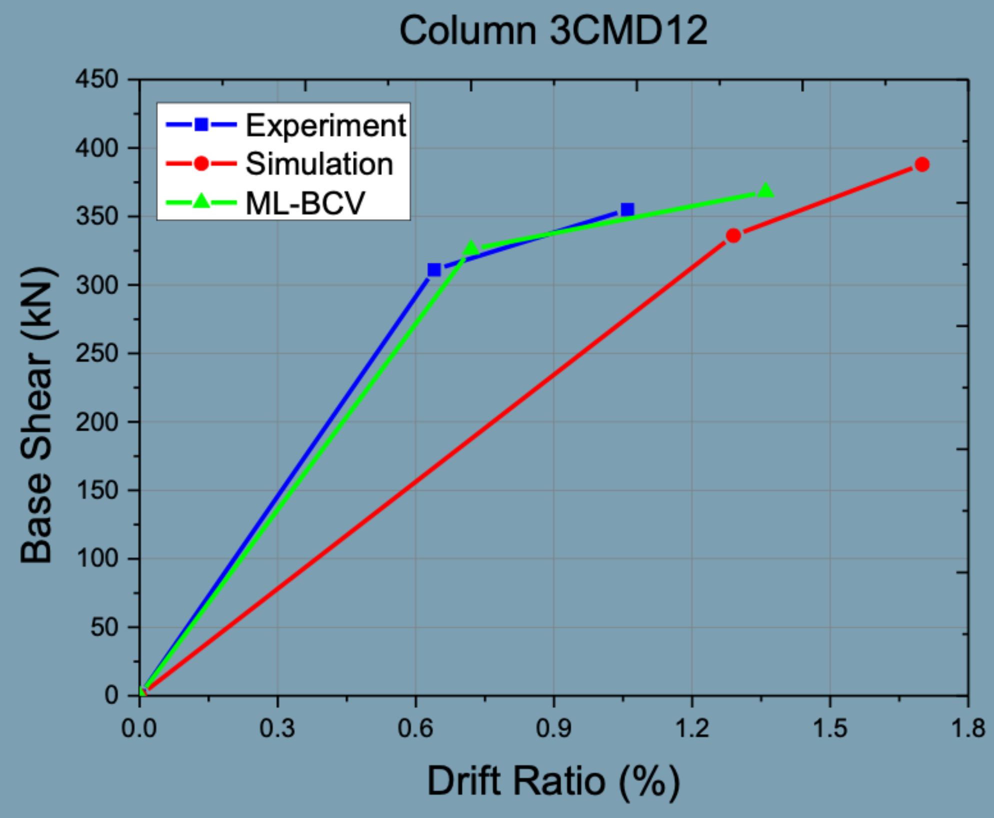
Dependent (**Output**) Variables

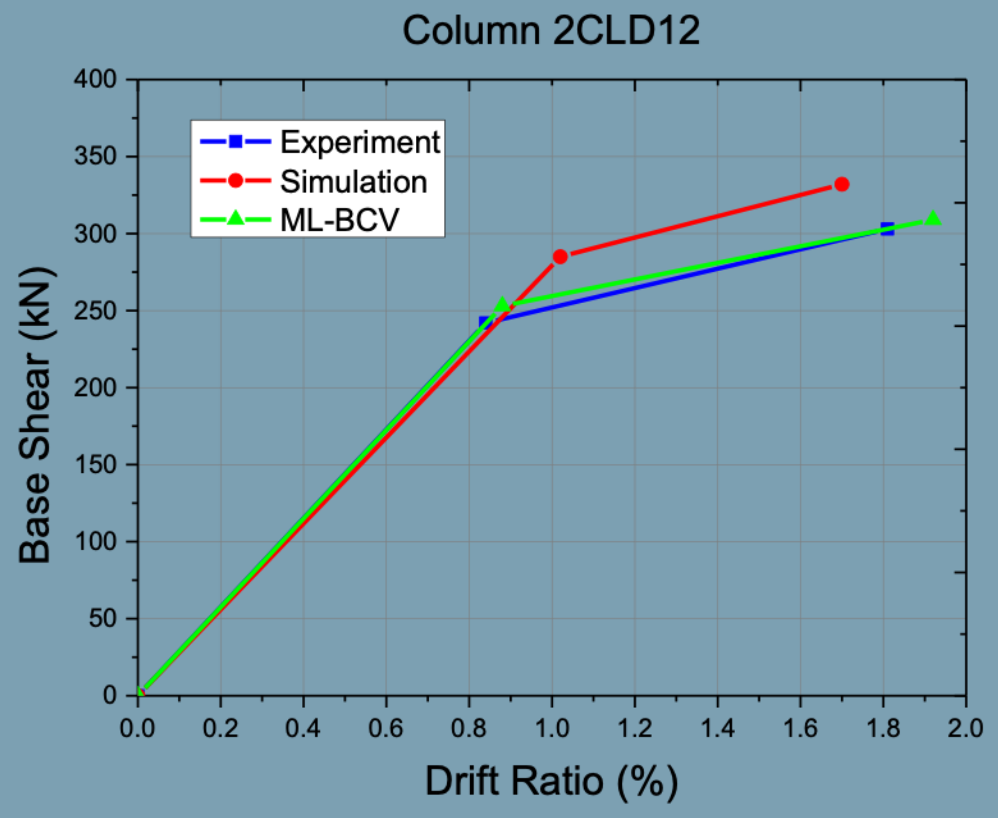
Y_1: Yield shear force
Y_2: Max shear force
Y_3: Drift ratio @ yield
Y_4: Drift ratio @ max



Comparison to traditional modeling approaches



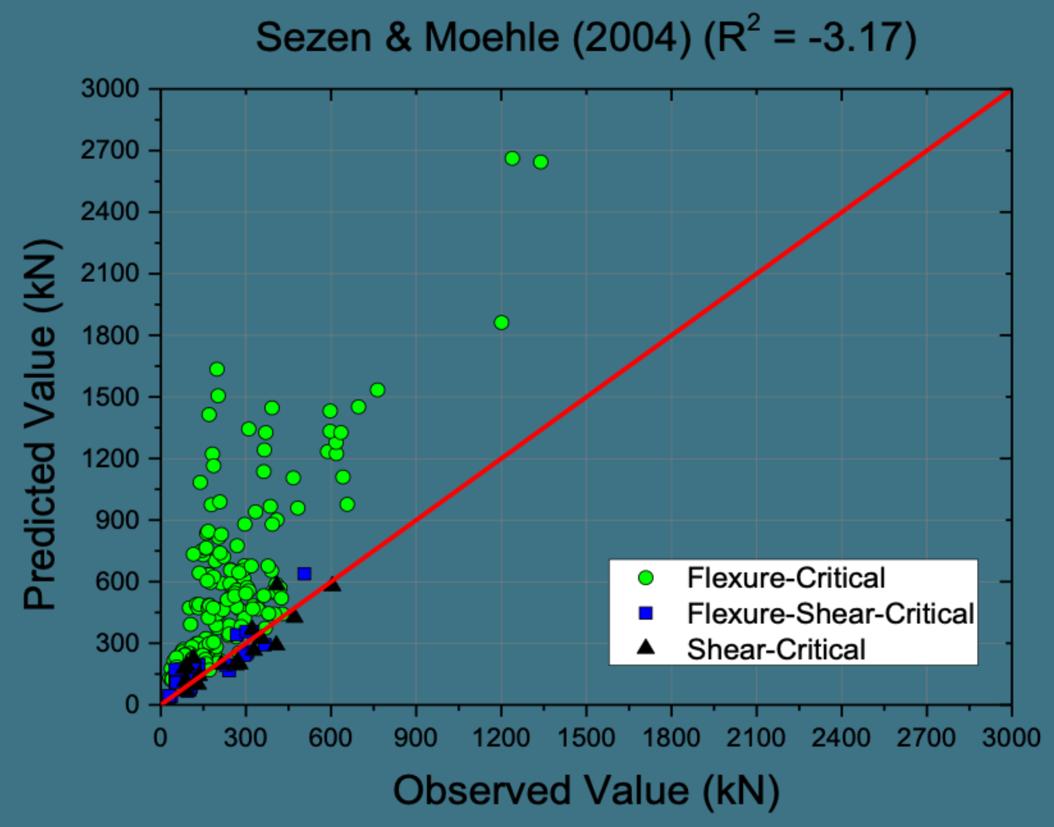


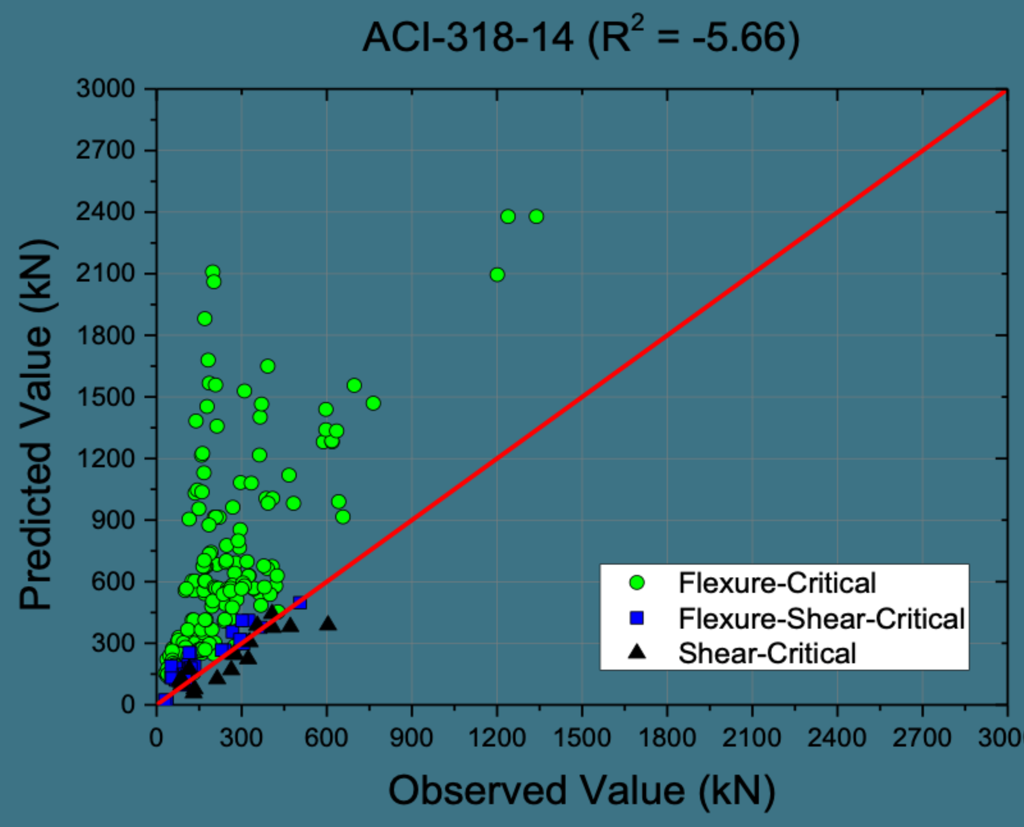


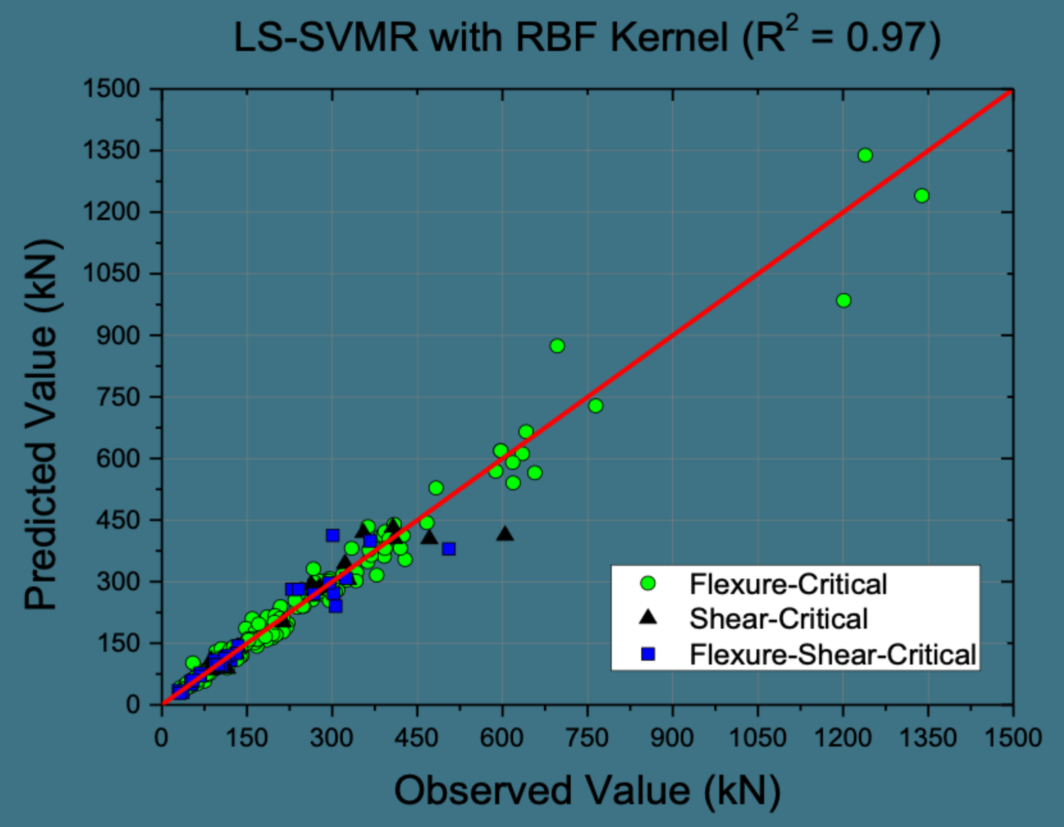
Flexure-critical[1-4]

Shear-critical[1-7]

Flexure-shear-critical[1-7]



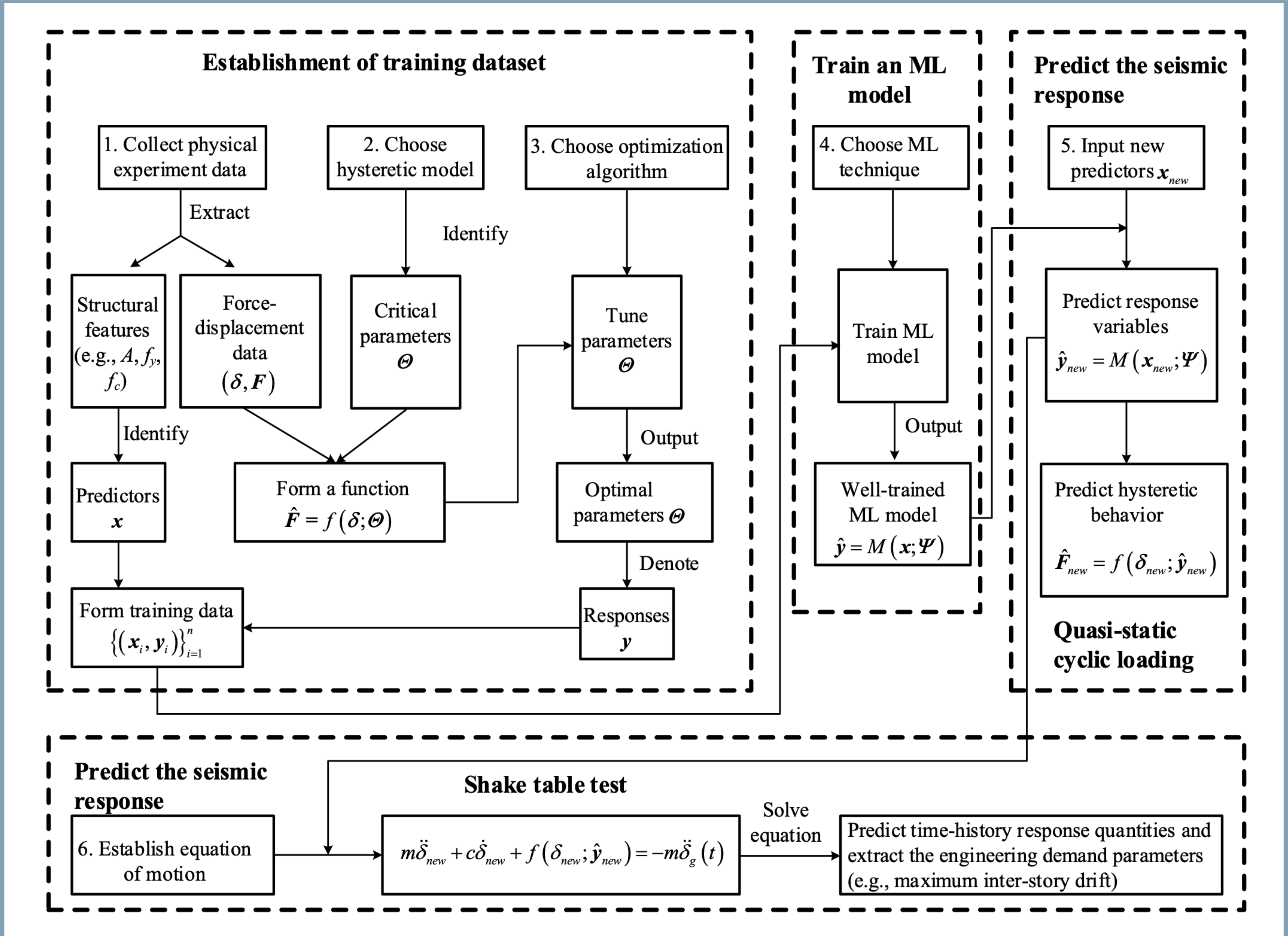




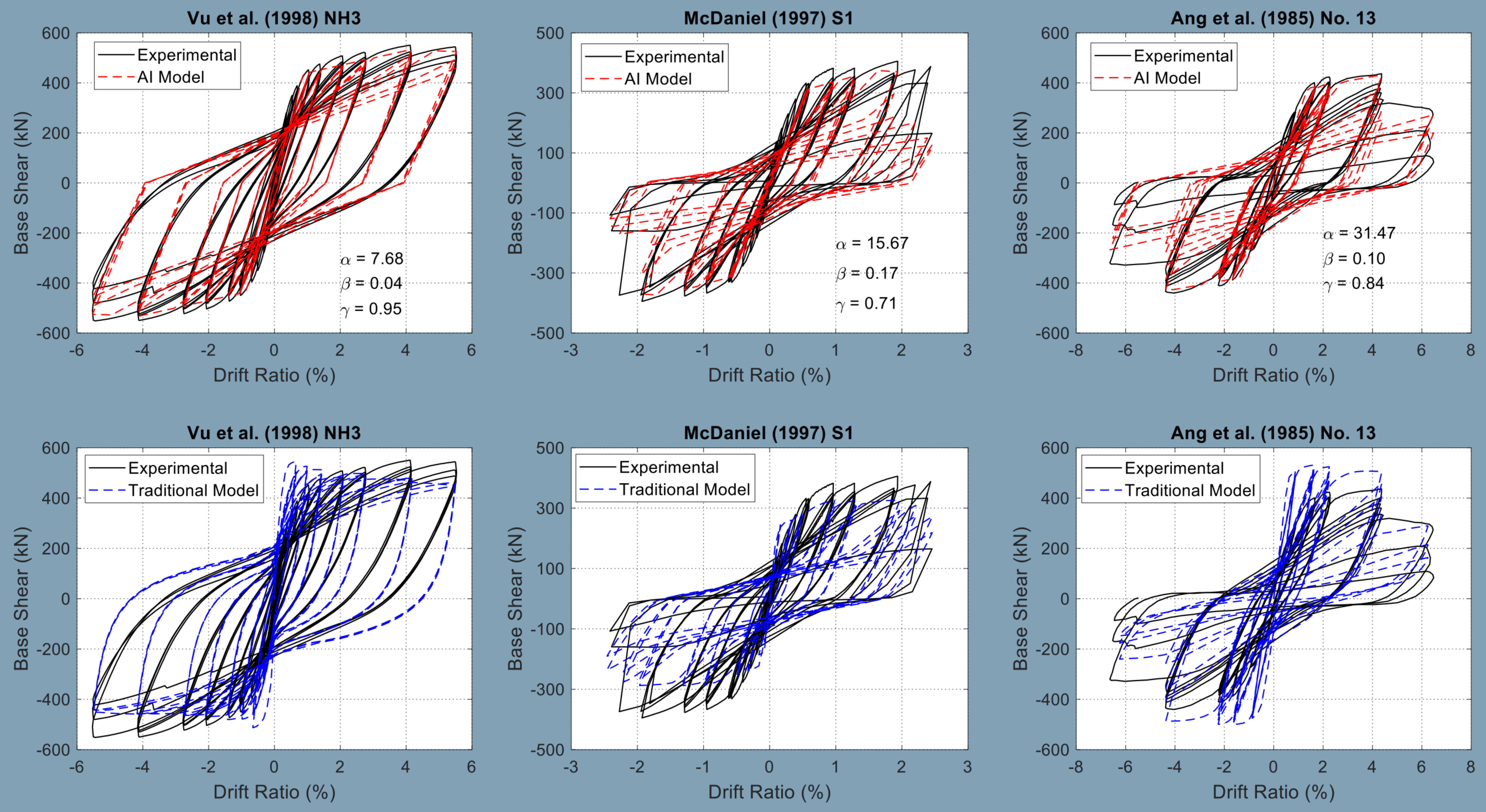
Comparison to traditional formula-based approaches

Component-level prediction

Developed two different data-driven solvers using the experimentally available data to define critical parameters for a structure under quasi-static cyclic loading and ground motions.



Comparison to traditional modeling approaches

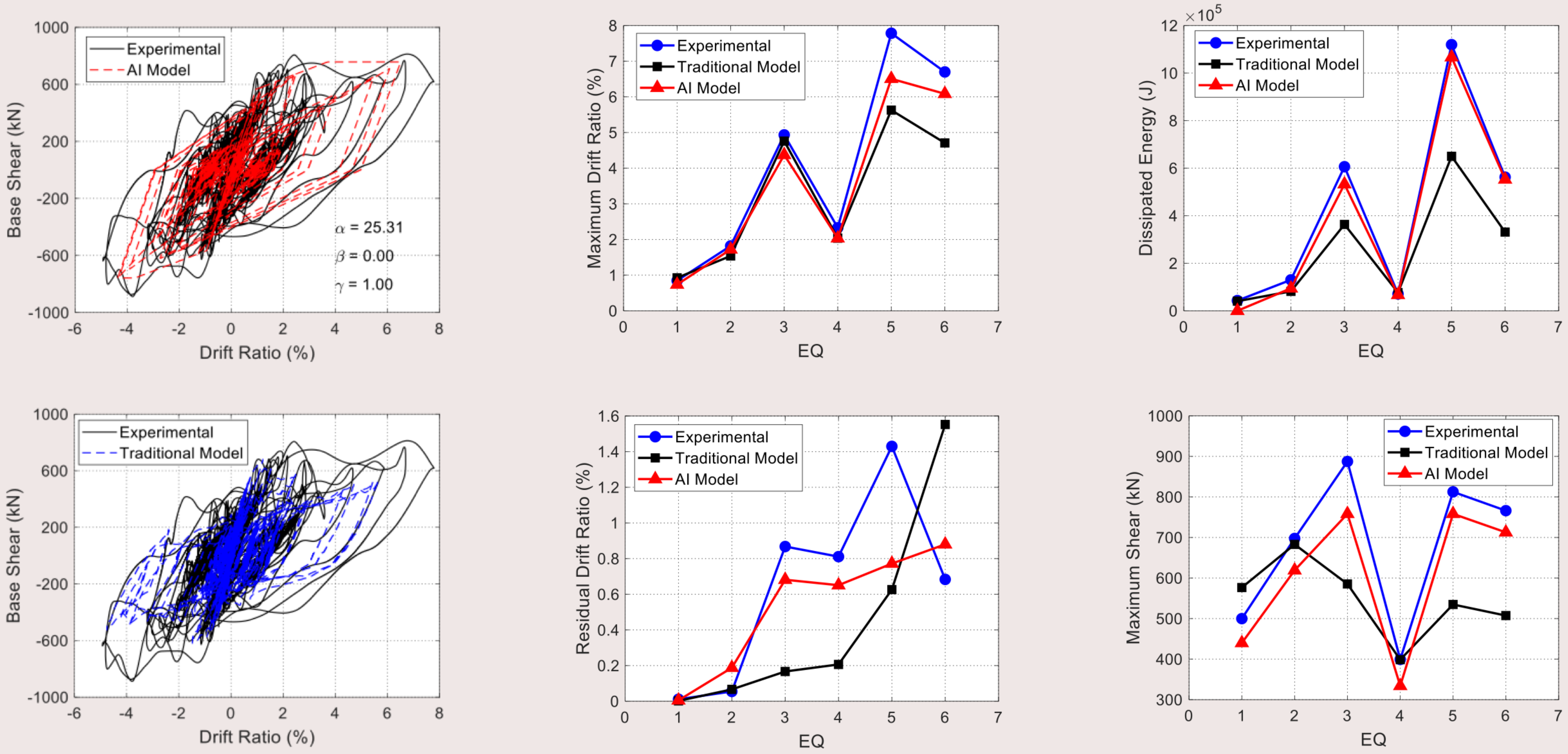


Comparison to traditional modeling approaches

Quantification Indicators	AI Model			Traditional Model		
	R^2	RMSE	MAE	R^2	RMSE	MAE
V_y (kN)	0.995	9.34	5.99	0.678	77.40	63.68
δ_y (%)	0.946	0.06	0.04	-1.595	0.40	0.35
V_m (kN)	0.991	16.13	12.84	0.907	50.51	33.00
δ_m (%)	0.944	0.25	0.21	-2.139	1.90	1.36
V_u (kN)	0.965	29.38	20.74	0.819	66.71	52.94
δ_u (%)	0.871	0.66	0.40	0.542	1.25	0.73
Dissipated Energy	0.987	9.49	7.13	0.723	44.12	30.62
Comp Time (s)	4			1016		

Near-real-time prediction of the capacity of reinforced concrete columns based only on design and hazard characteristics.

Component-level seismic response history



Quantification Indicators	AI Model			Traditional Model		
	R^2	RMSE	MAE	R^2	RMSE	MAE
Maximum Drift Ratio (%)	0.9391	0.64	0.49	0.7793	1.21	0.83
Residual Drift Ratio (%)	0.6198	0.30	0.22	-0.5633	0.61	0.50
Maximum Shear (kN)	0.7964	78.04	73.49	-0.3449	200.61	155.11
Dissipated Energy (kJ)	0.9872	43.64	36.46	0.6241	236.40	166.64
Computational Time (s)	137			10991		

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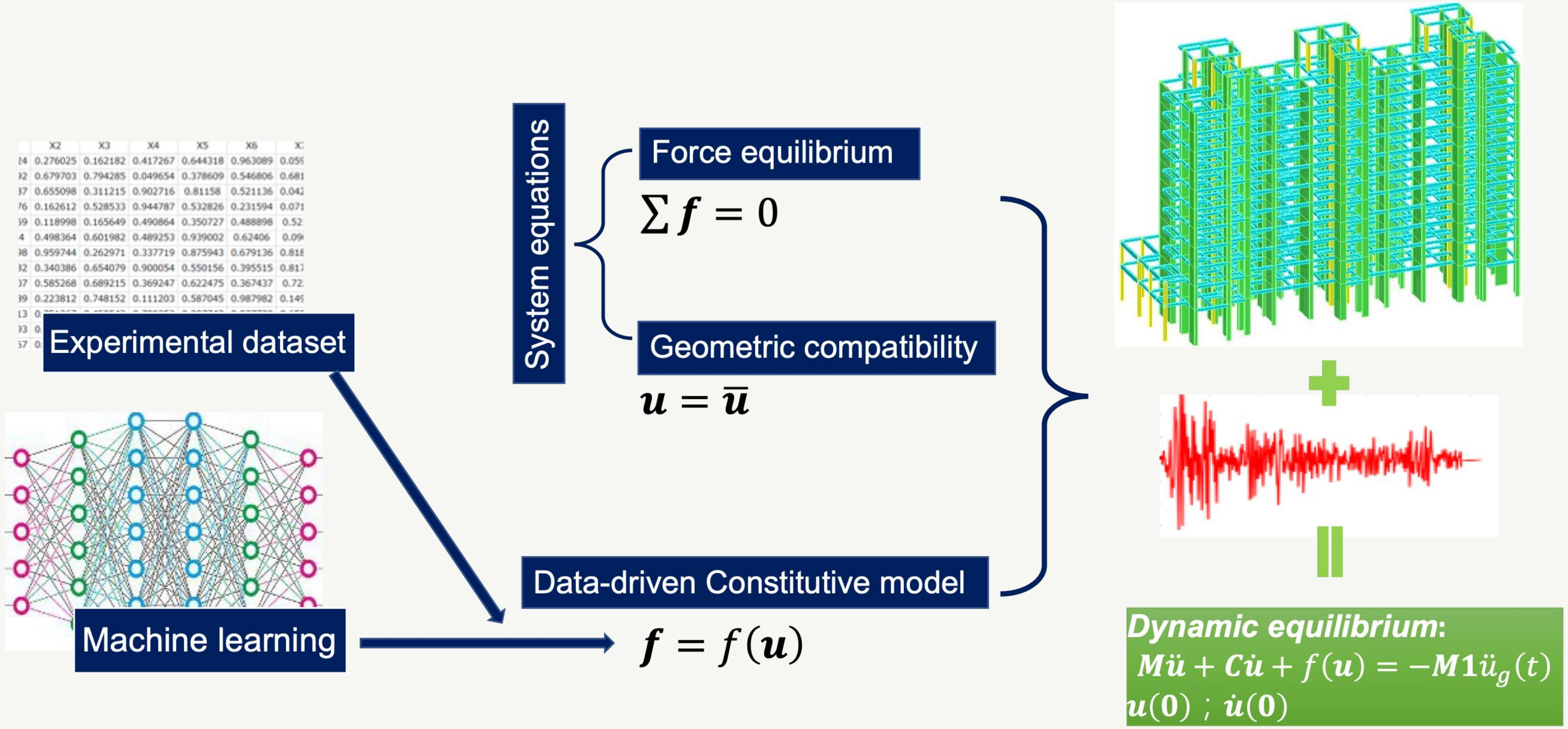
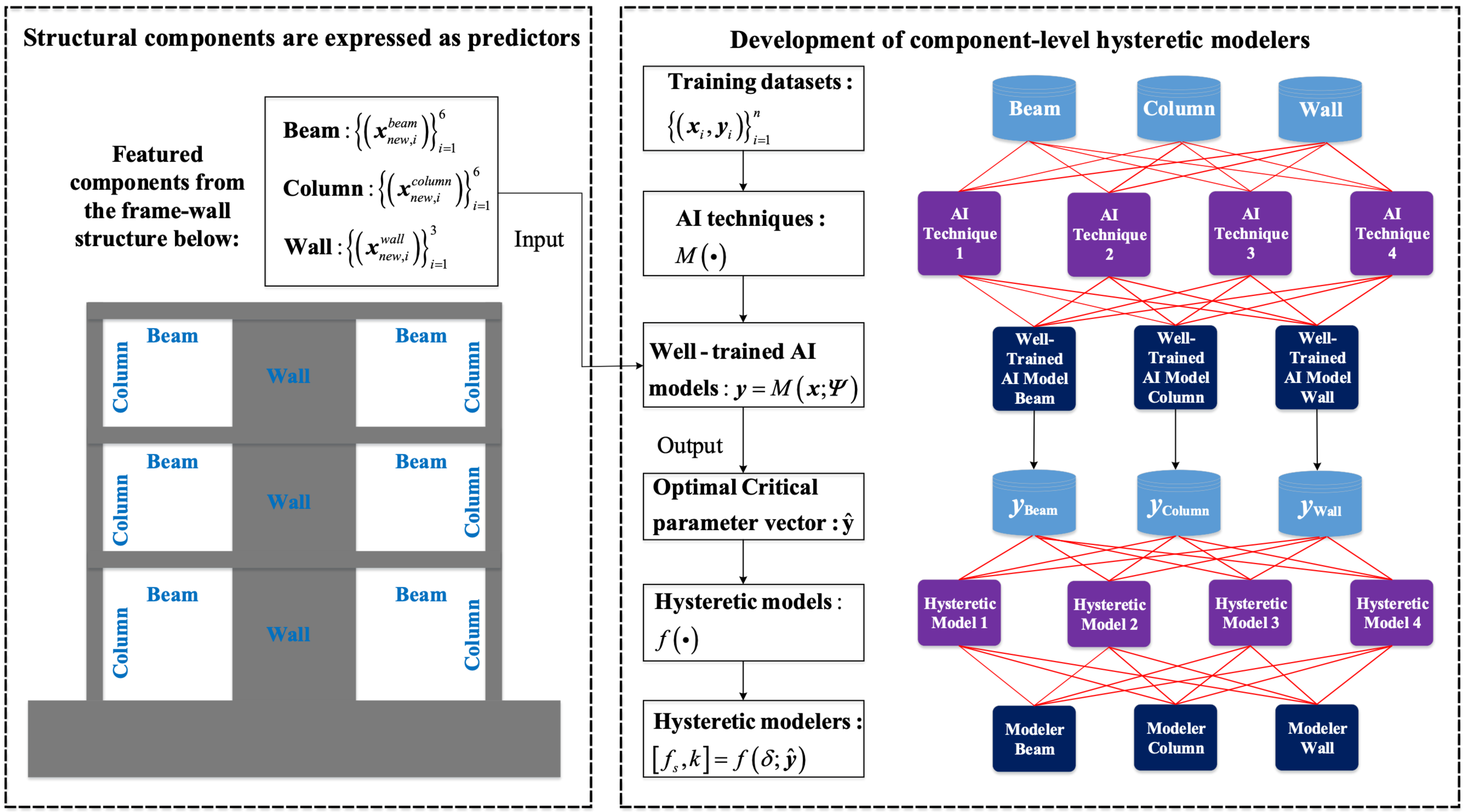
A hybrid approach



Uses experimental data in conjunction with machine learning to predict the seismic performance of an RC system.

System-level prediction



System-level prediction

AI Model to define parameters at each story

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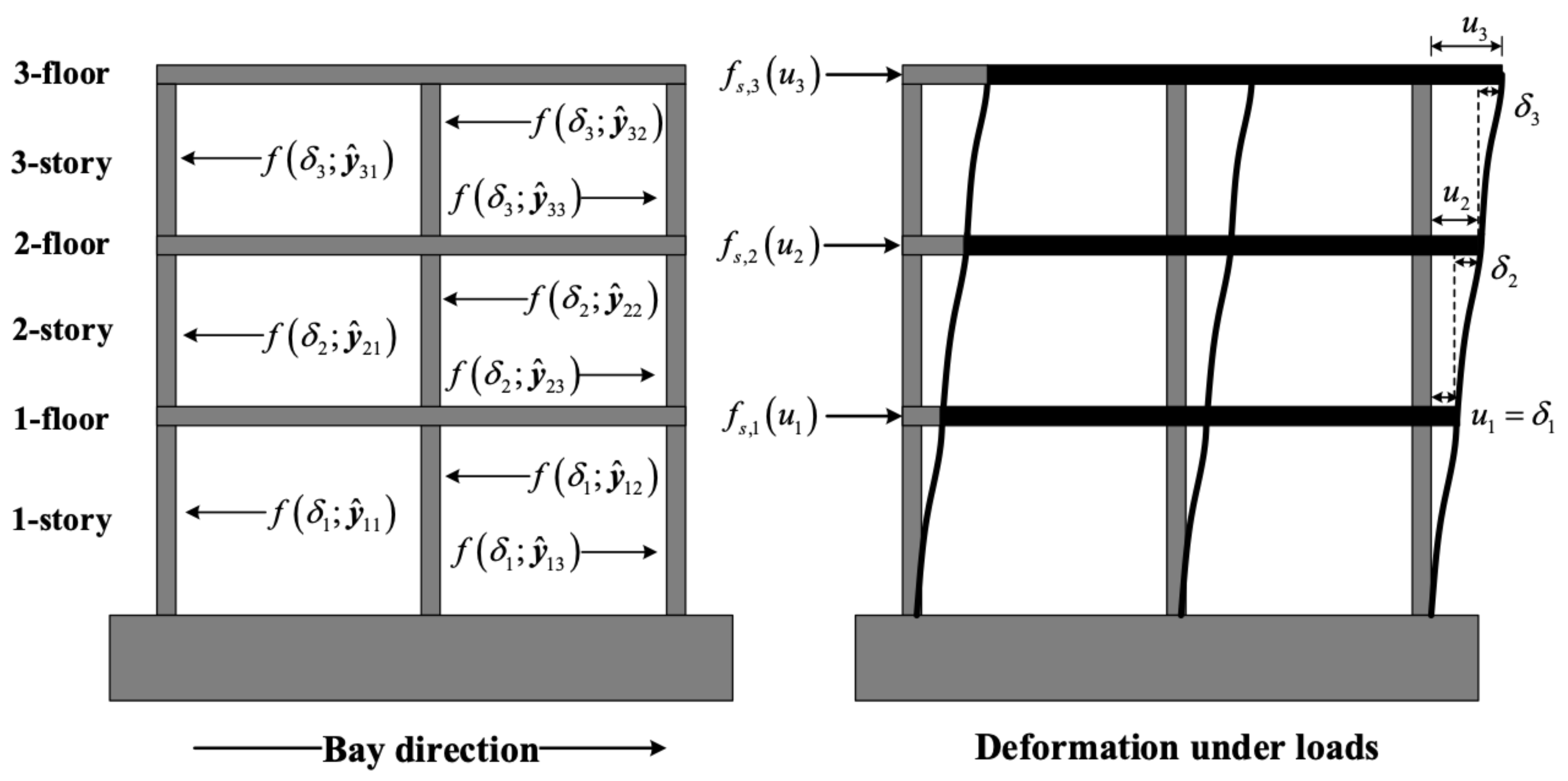

Test specimen: planar large scale (1:2), 3-bay, 3-story RC frame subjected to quasi-static cyclic loading

Xie et al. (2015)

System-level prediction

AI Model to define parameters at each story

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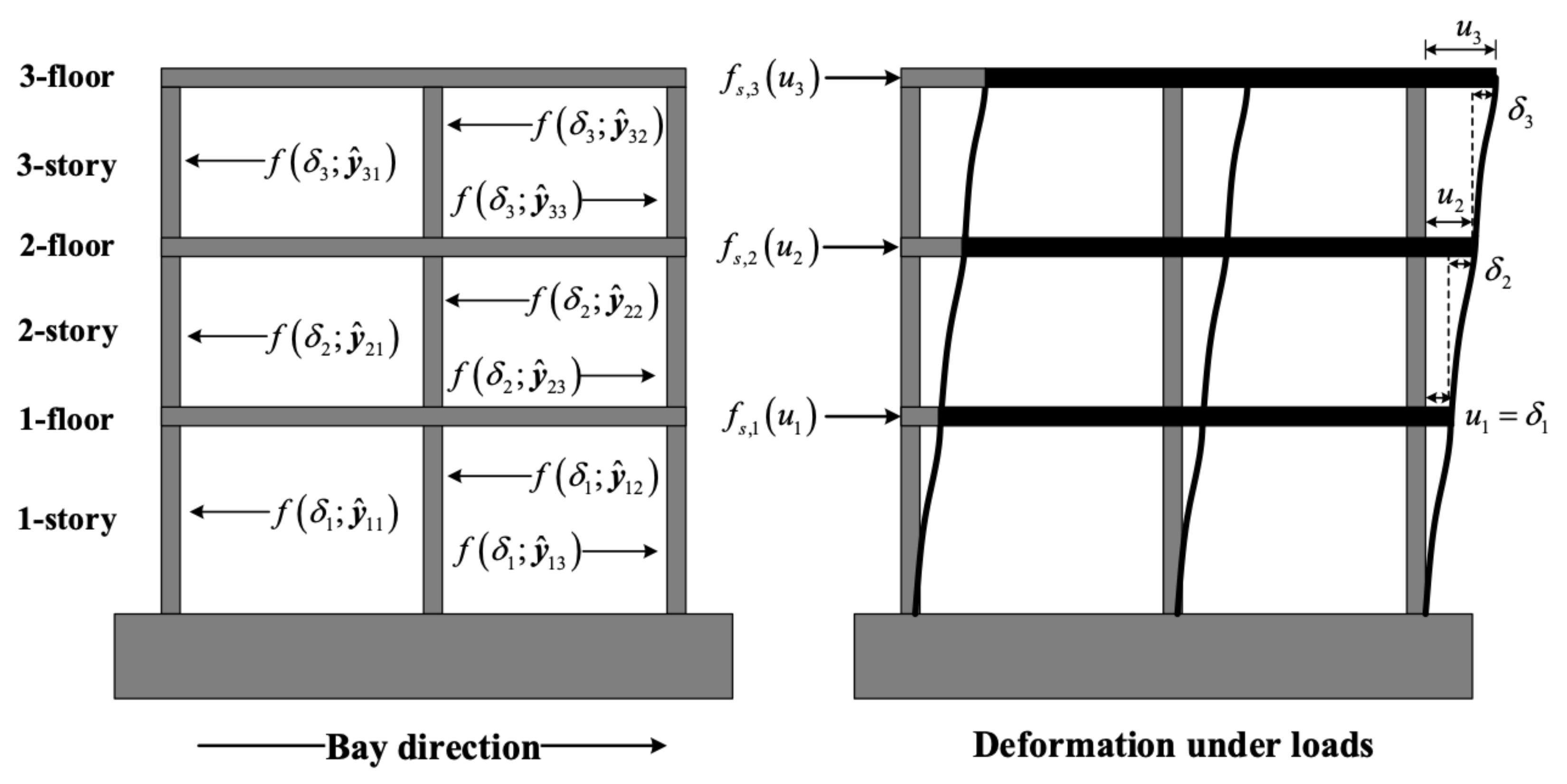

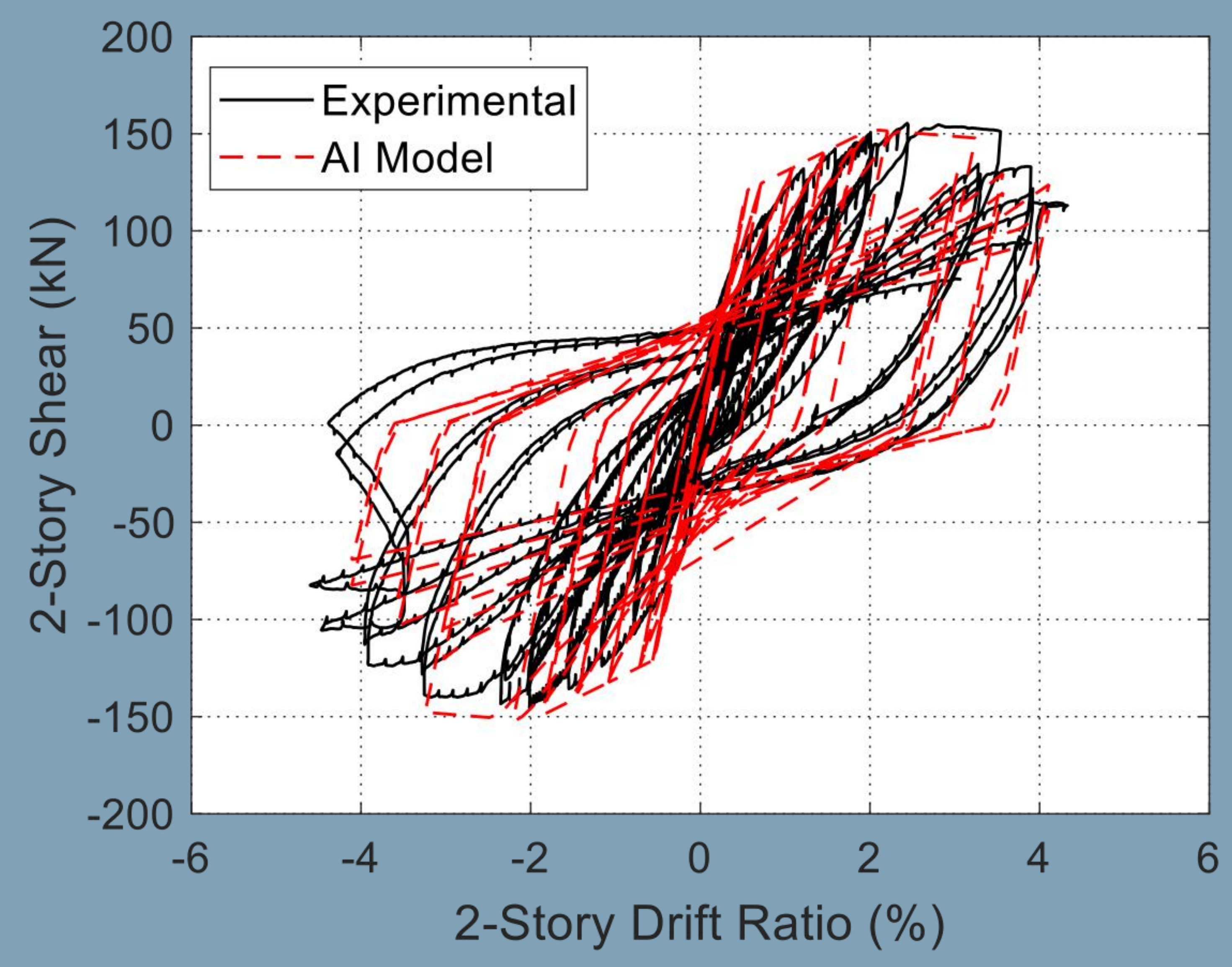

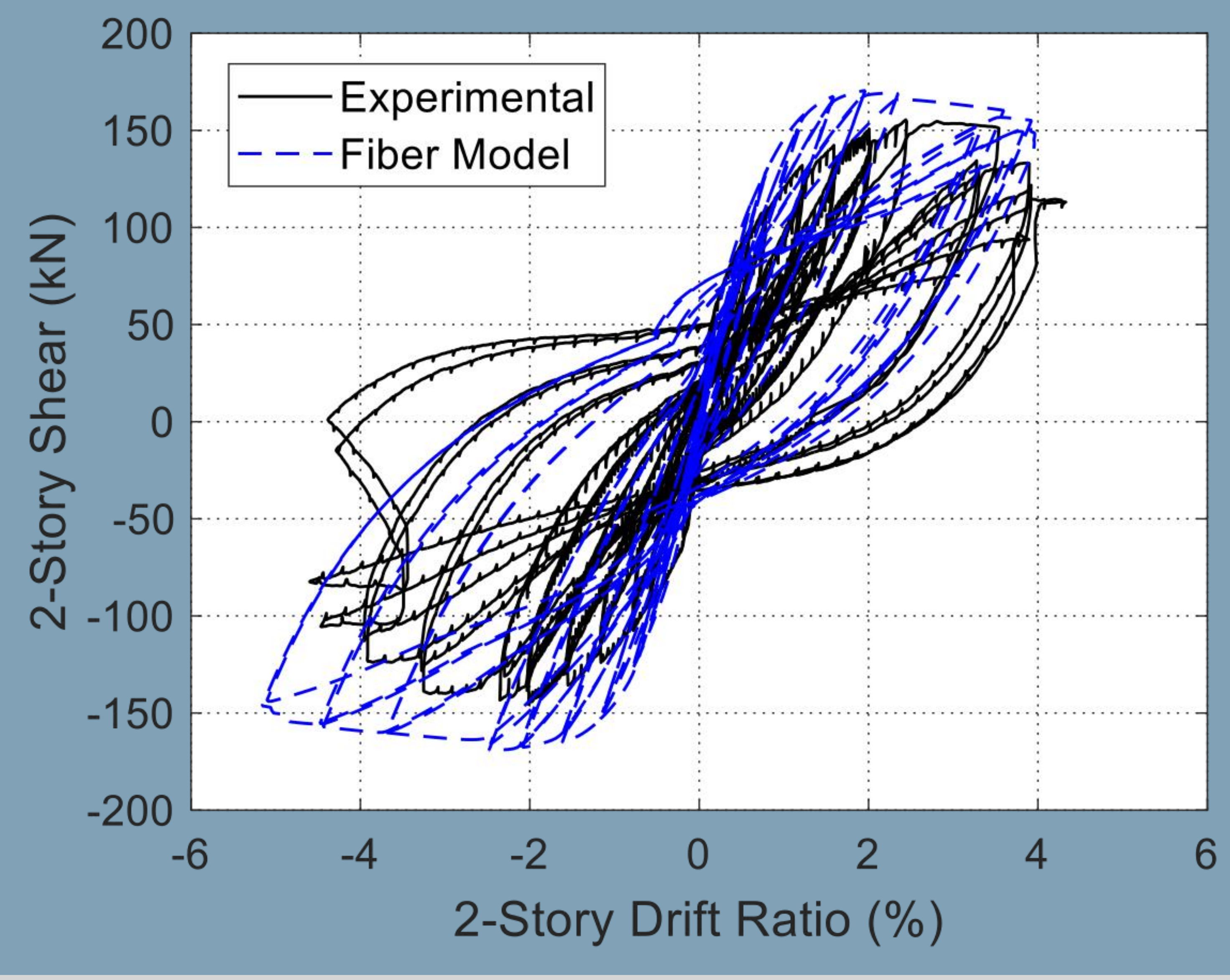

10s vs. 30’

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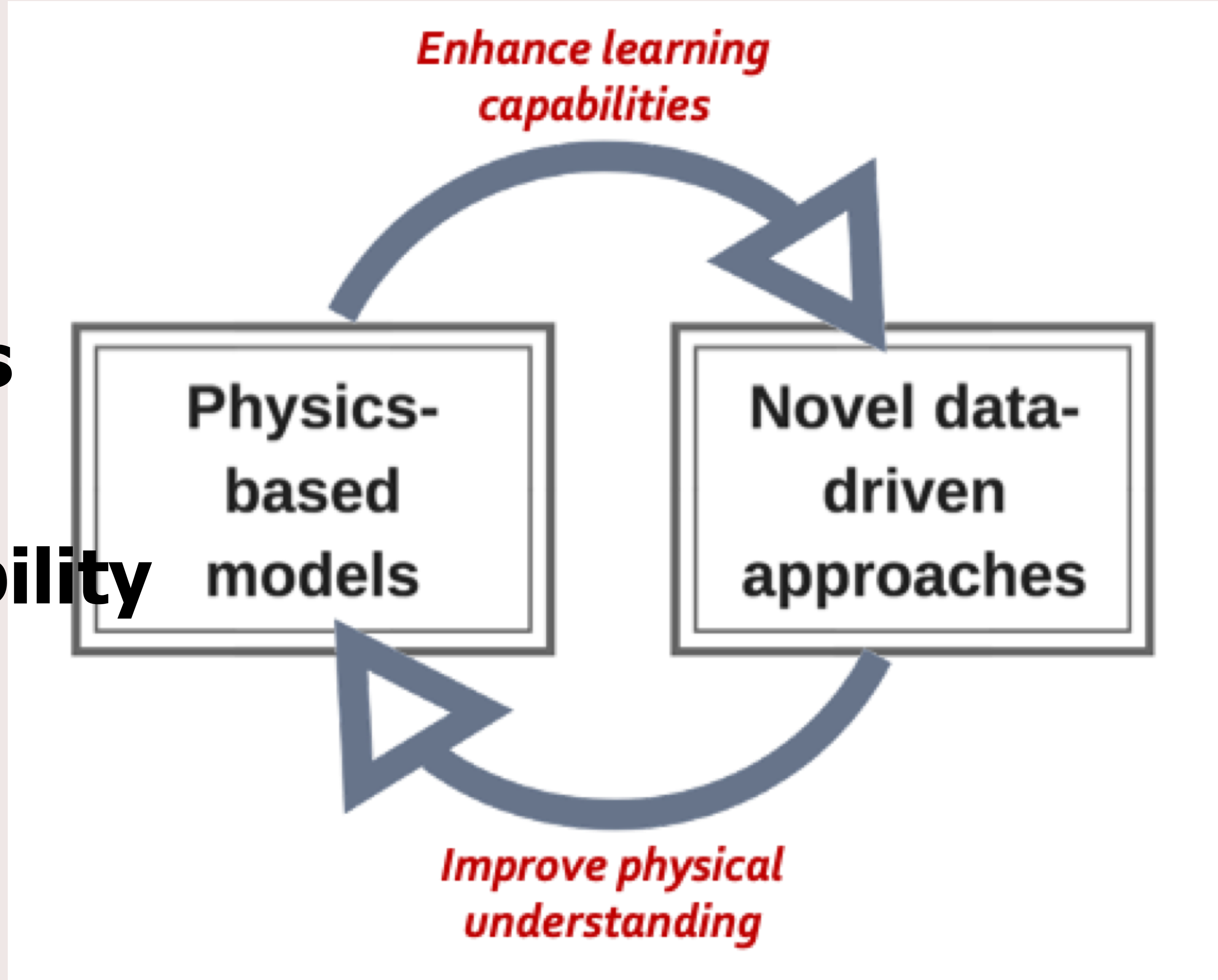
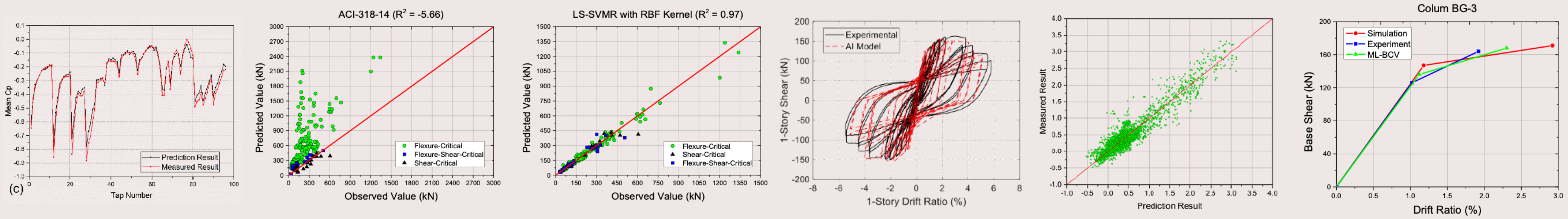


High accuracy
Computational efficiency
Tendency towards real-time
Generalization capabilities



But, can we also make advances far beyond what we can imagine with existing approaches?

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