IOWA STATE UNIVERSITY
College of Engineering

Data- and Machine Learning-Driven Approaches to Analyses of Complex Reinforced Concrete Structures

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ACI Convention
26, March 2024

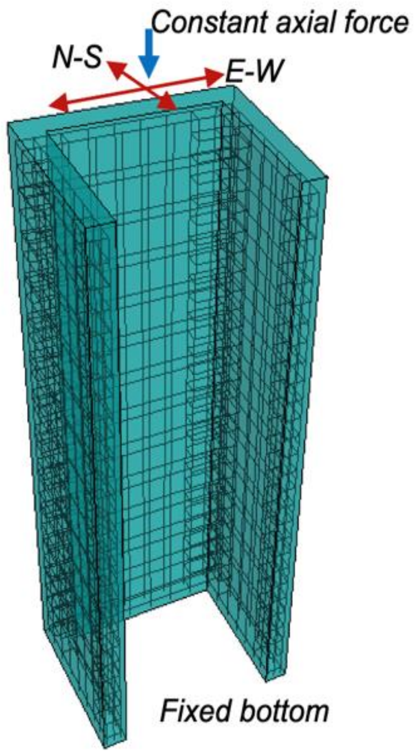
THE WORLD'S GATHERING PLACE FOR ADVANCING CONCRETE

aci CONCRETE CONVENTION

Diverse Data-Driven Approaches to RC Structures

Machine Learning (Black box)
- Multi-target regression model
- Artificial neural network (Deep neural network)

Limitation of Black Box
- The limited description of the internal complexity of heterogeneous materials and diverse boundary conditions (BC's).
- The lack of interpretability when directly applying black-box ML methods.



Glass-Box Machine Learning
- generalized additive model (GAM)
- New feature generation
- Material rule-learning

Physics-Ingrained Features and Information Convolutions

+

Hidden Rule-Learning by Bayesian Evolution Algorithm

Cited from [Bentley Systems]

Length scale

0.001 m → ***1 m*** → ***~10 m*** → ***City scale***

- **From millimeters to meters**
- **From black-box learning to glass-box learning**

Basic Learning Setting: Overall Sketch

***p*-dimensional input vector**

$\mathbf{X} \in \mathbb{R}^p$

- Material properties
- Boundary conditions
- Loading conditions
- Static/Dynamic
- Etc.

Learner

Black-box learner

Glass-box learner

- Material Rules And Expressions
- Interpretable relationships between **X** and **Y**

***s*-dimensional output vector**

$\mathbf{Y} \in \mathbb{R}^s$

- If $s = 1$, single-target learning
- If $s > 1$, multiple-target learning

Basic Learning Setting: Overall Sketch

***p*-dimensional input vector**

$\mathbf{X} \in \mathbb{R}^p$

Learner

***s*-dimensional output vector**

$\mathbf{Y} \in \mathbb{R}^s$

Global Behaviors
[~ m]

- Global strengths
- Global performance measure of structure as a whole

Local/Microscopic Behaviors
[~ mm]

- Individual material constituents
- Millimeter length scale Possible to micro or nano scale

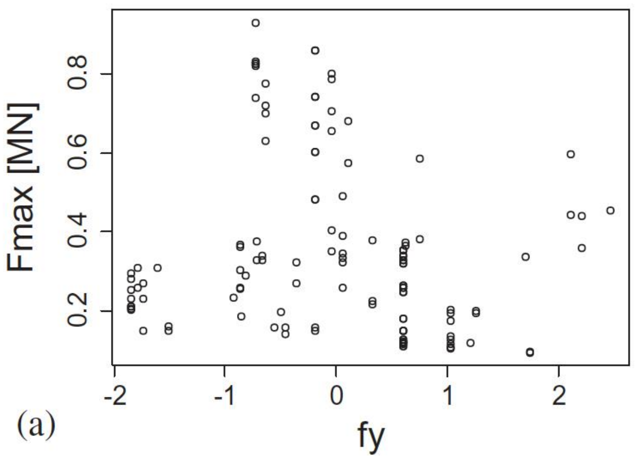
Advanced Statistical Learning

Statistical Learning

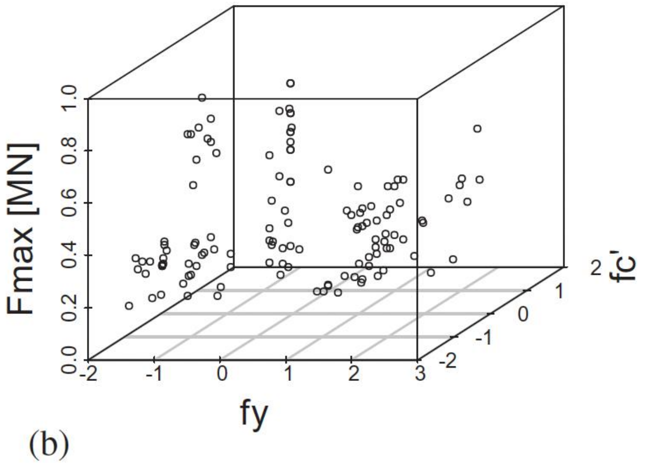
- **Parametric model**
  e.g., Linear regression, Multiple regression
- **Non-parametric model**
  e.g., generalized additive model (GAM)

Statistical Learning Challenges of RC Structures' Data

- **Complexity**
- **Nonlinearity**
- **Variability**
- **High-Dimensional Space**



(2D) scatter plot



(3D) scatter plot

Generalized Additive Model (GAM)

- Early works by Hastie and Tibshirani (1986, 1990).
- GAM is a non-parametric extension of the generalized linear model (GLM)
- Involves a sum of smooth functions:

$$g(E(Y_i)) = f_1(x_{1i}) + f_2(x_{2i}) + f_3(x_{3i}) + \cdots$$

where,

- g is a smooth link function
- f_j is the smooth function of the covariate(s) x_{ji}.
- Y_i is a response variable, and x_i is ith vector of data points comprising multiple variables.

Flexible Basis for f(x)

For instance, consider a single variable case,

$$f(x) = \sum_{j=1}^{q} b_j(x)\beta_j \,.$$

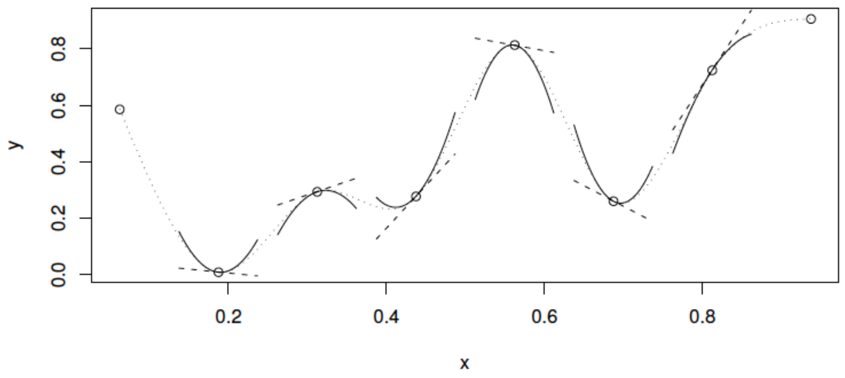
where b_j is the j_{th} basis function; β_j are parameters to be estimated from data.

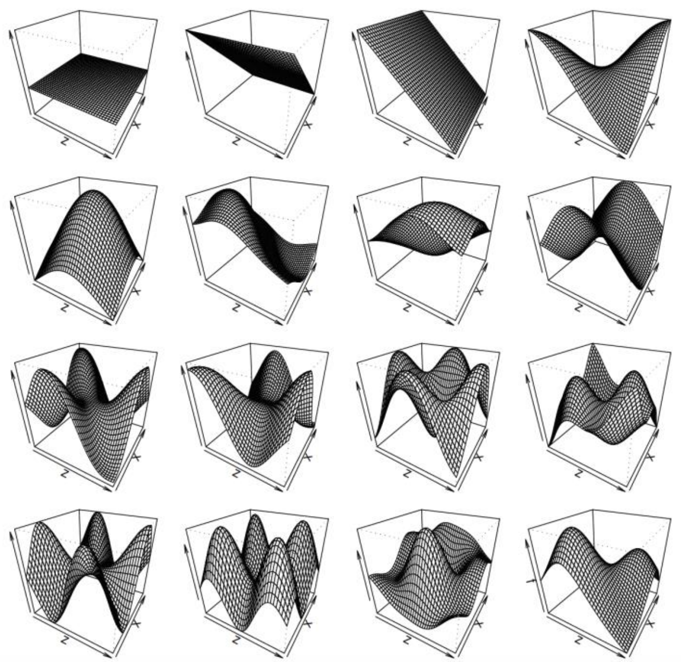
Advanced Statistical Learning

Types of Regression Splines

(1) Cubic Regression Splines (CRS)

(2) Thin Plate Regression Splines (TPRS)



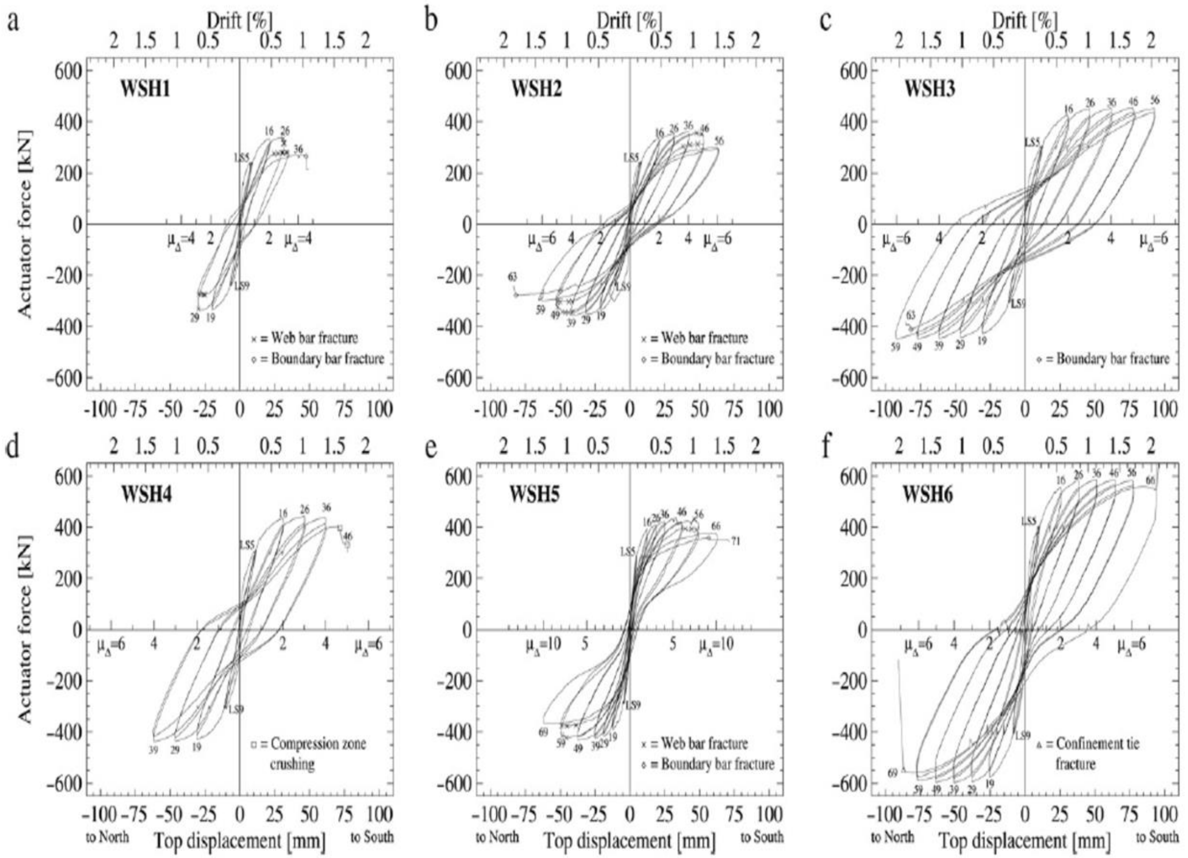


- Thin Plate Regression Splines (TPRS) used for different covariate numbers and knots free.
- Cubic Plate Regression Splines (CPRS) that the knot must select their location, limited to one variable.

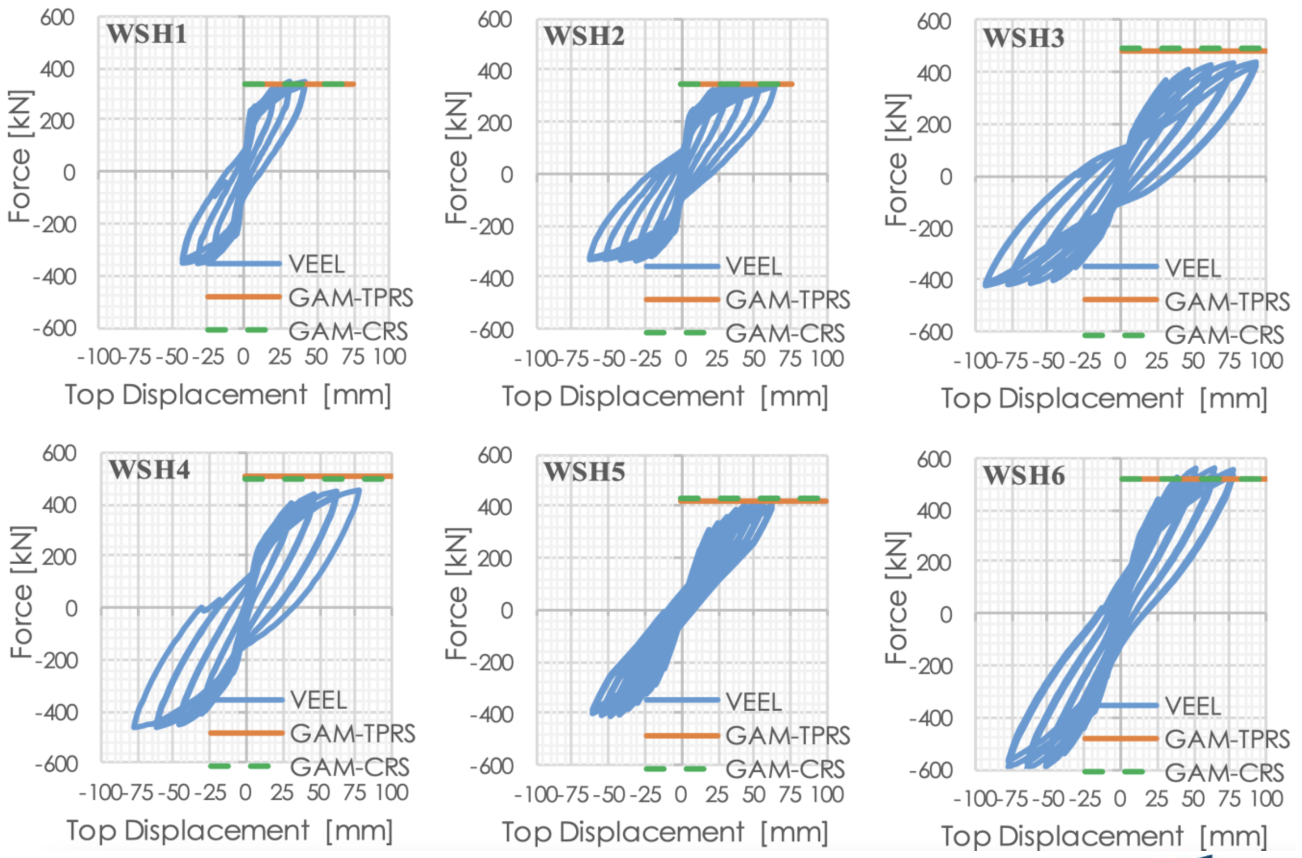
(Wood, (2006).“*Generalized Additive Model An Introduction with R*,”. CRC press, Boca Raton, FL.”)

Advanced Statistical Learning

GAM Prediction of the global behavior of RC shear walls



Experiment (cited Orakcal and Wallace 2006)



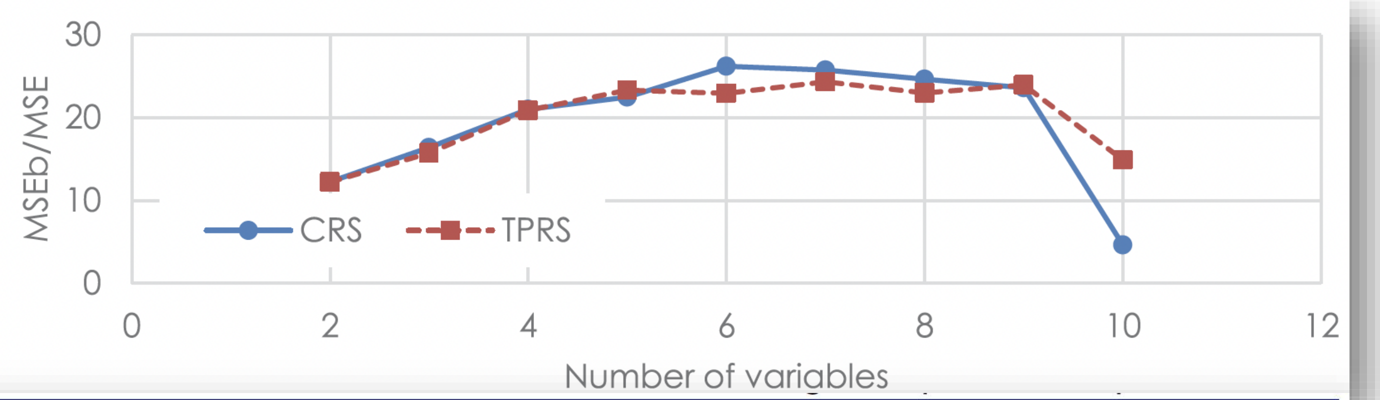
GAM-TPRS and GAM-CRS using up to 10 variables.
VEEL: high-precision parallel multiscale FEA

Advanced Statistical Learning

Strengths of Statistical Learning

- **Optimal/Efficient Prediction**
  Model Construction
  > How many variables ?
  > Which combinations ?

- **High Interpretability**
  > Relative importance of variables ?



Number of variables	Number of combination	Best combination of variables			CVE_b/ CVE	Pearson	R^2
2	45	height(6.24e-11)	h_b(1.85e-05)		12.24	0.958	0.918
3	120	height(<2e-16)	h_b(3.71e-11)	dia(0.00272)	16.39	0.969	0.939
4	210	height(<2e-16) dia(1.57e-08)	afr(3.11e-13)	h_b(5.51e-10)	21.00	0.976	0.952
5	252	height(<2e-16) h_b(5.59e-06)	afr(1.73e-13) fc(0.292)	dia(5.51e-08)	22.46	0.978	0.955
6	210	afr(<2e-16) height(9.51e-08)	thickness(<2e-16) fy(7.01e-08)	h_b(1.27e-11) dia(3.26e-06)	**26.21**	**0.981**	**0.962**
⋮	⋮						

❖ **Program available: *mgcv package in R; parallel version Rmpi***
❖ **For detailed code, program, data, and theory; Song, Cho, Wong, (2020). "An Advanced Statistical Approach to Data-Driven Earthquake Engineering". *J. Earthq. Eng.***

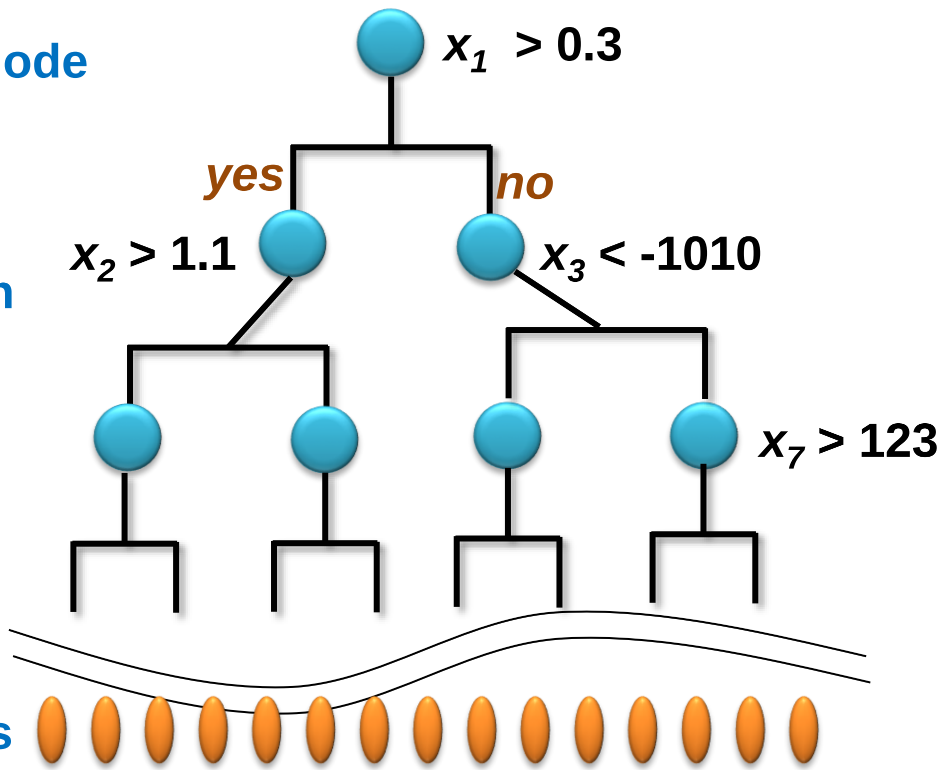
Multi-Objective Predictive Clustering Trees: Basic Setup

Single Tree

Root Node

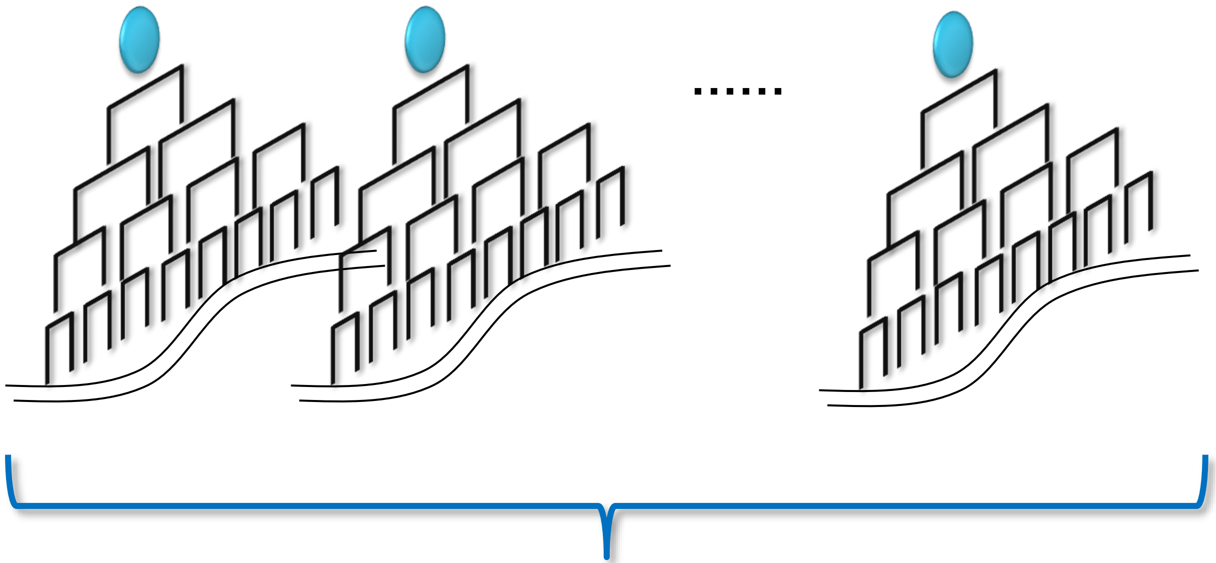
Branch

Leaves



Expression $\mathbf{Y} = \sum weight_i \times x_i$[condition of x_i]

Ensemble of Many Trees



Final Prediction $\mathbf{Y_{final}}$ = average of $\mathbf{Y}$'s from trees

Strength:

- Enable accurate multi-objective predictions
- Obtain expressions of the prediction model
- Efficient uncertainty quantification
- Easy to construct and interpret

Multiple Target Regression Model

- For multiple-target global behaviors

(a) Extraction of 46 outermost points from force-displacement responses.

Least square Method

(b) Parameterize capacity curve C as 3rd-degree polynomial function $C(d; \mathbf{y}), \mathbf{y} \in \mathbb{R}^8$

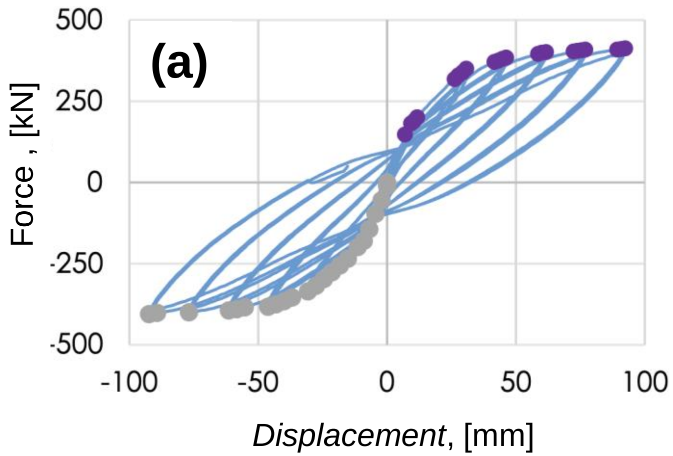
4 variables for positive and negative range, respectively

(c) Construct training data $\{\mathbf{x_i}, \mathbf{y_i}\}$ Input features $\mathbf{x_i} \in \mathbb{R}^{32}$ $i = 1, \ldots, n$

(d) Train and predict $\mathbf{y}$ by Multiple Target Regression Model

CLUS

With predicted $\mathbf{y}$, one can draw capacity curve C

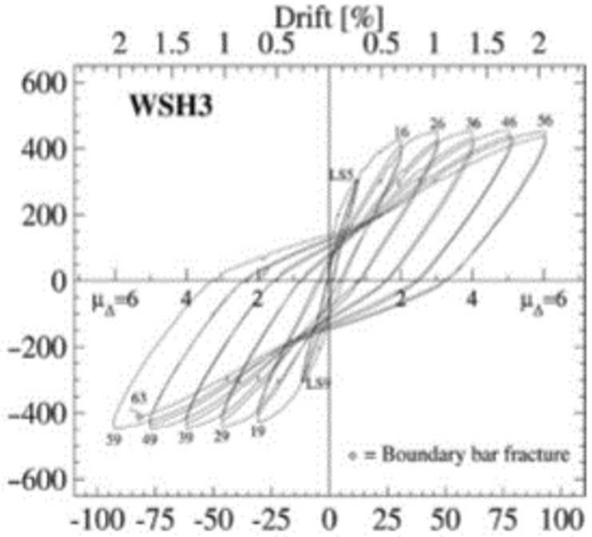


Multiple Target Regression Model

- **Uncertainty quantification of prediction by bootstrapping**

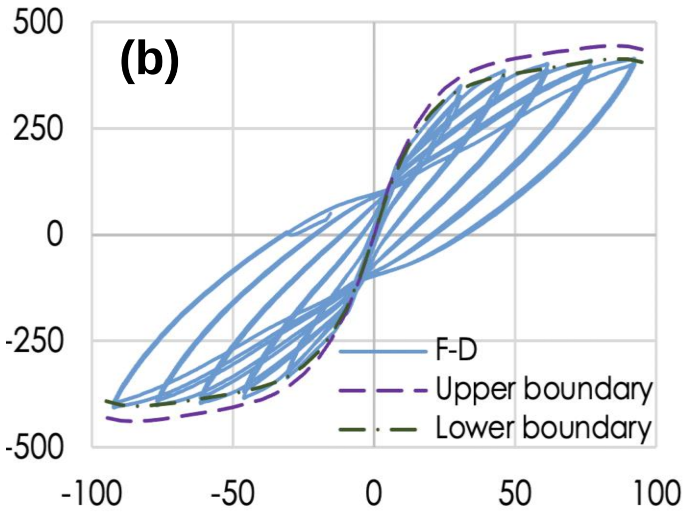
95% confidence interval

(a)



Real experiment [Beyer et al. 2008]

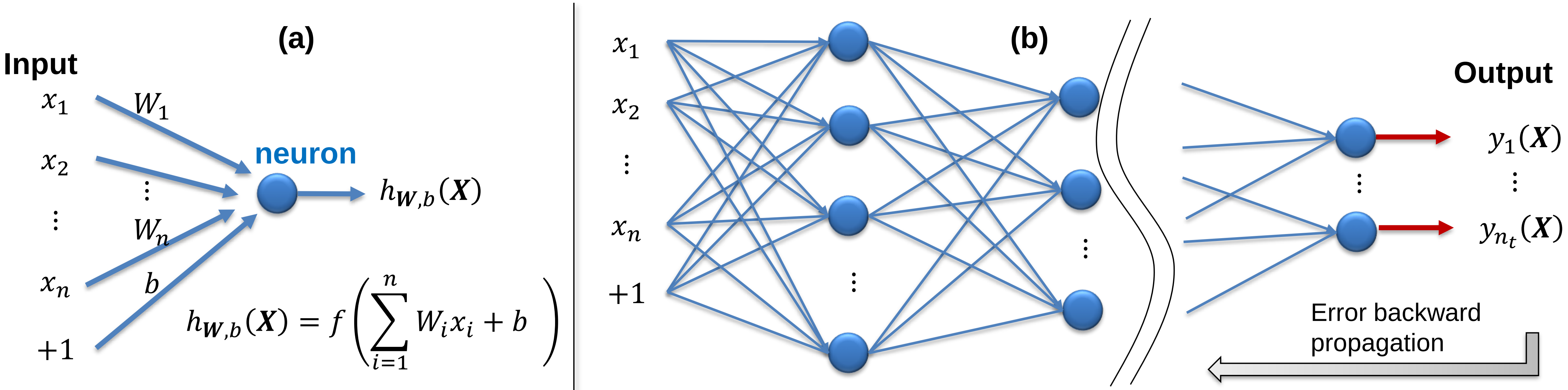
(b)



- ❖ **Program available:** ***CLUS***
- ❖ **For detailed code, program, data, and theory; Yang, and Cho. (2021). "Multiple Target Machine Learning Prediction of Capacity Curves of Reinforced Concrete Shear Walls". *SCCE.***

Deep Neural Networks

- **For single- or multiple-target global behaviors**



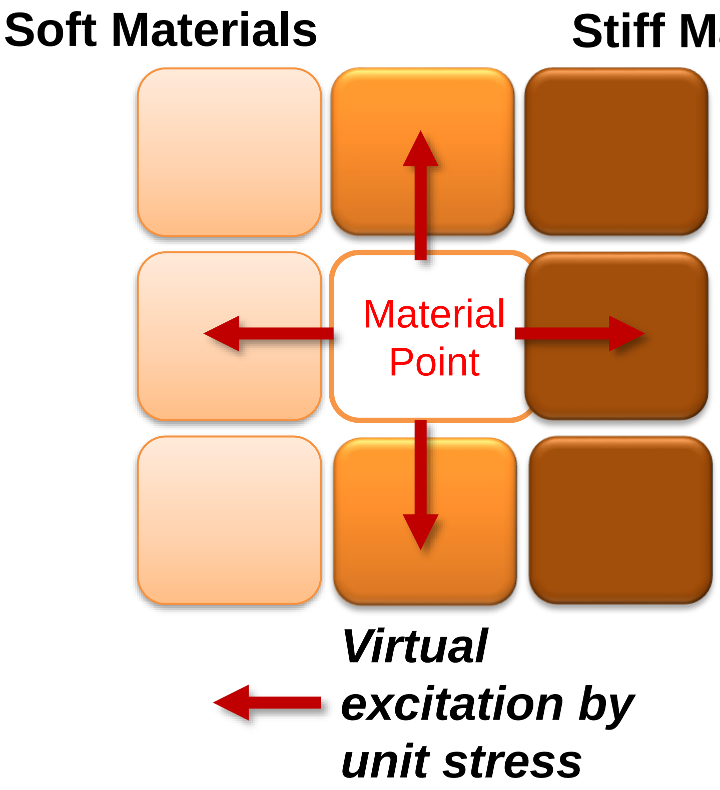
Strength:

- Enable accurate multi-objective predictions
- Easy to construct and train
- Abundant open-source libraries

❖ **Program available:** ***TensorFlow; H2O package in R***

New Feature Generation by Information Convolution

- The new feature (called information index (II)) enables ML to learn and improve material model.
- The II can help internal material points "**feel**" **adjacent heterogeneity and varying BC's.**



Virtual stress-based II is defined as

$$II = \exp\left[1 - \frac{1}{3}\sum_{j=1}^{3}\left|\frac{\varepsilon_{v,pr}^{(m)}(j)}{\varepsilon_{v,pr}^{(m)}(j) - \varepsilon_{VI,pr}^{(m)}(j)}\right|\right]$$

The spatial convolution is conducted with Gaussian weight

$$\omega(r) = \left(L\sqrt{2\pi}\right)^{-N} \exp\left(-\frac{r^2}{2L^2}\right)$$

Giving rise to convolved information index

$$\overline{II}(\mathbf{x}) = \int \omega(\mathbf{x}, \boldsymbol{\xi})\, II(\boldsymbol{\xi}) d\boldsymbol{\xi}$$

New Feature (Convolved Information Index) for Diverse BC's

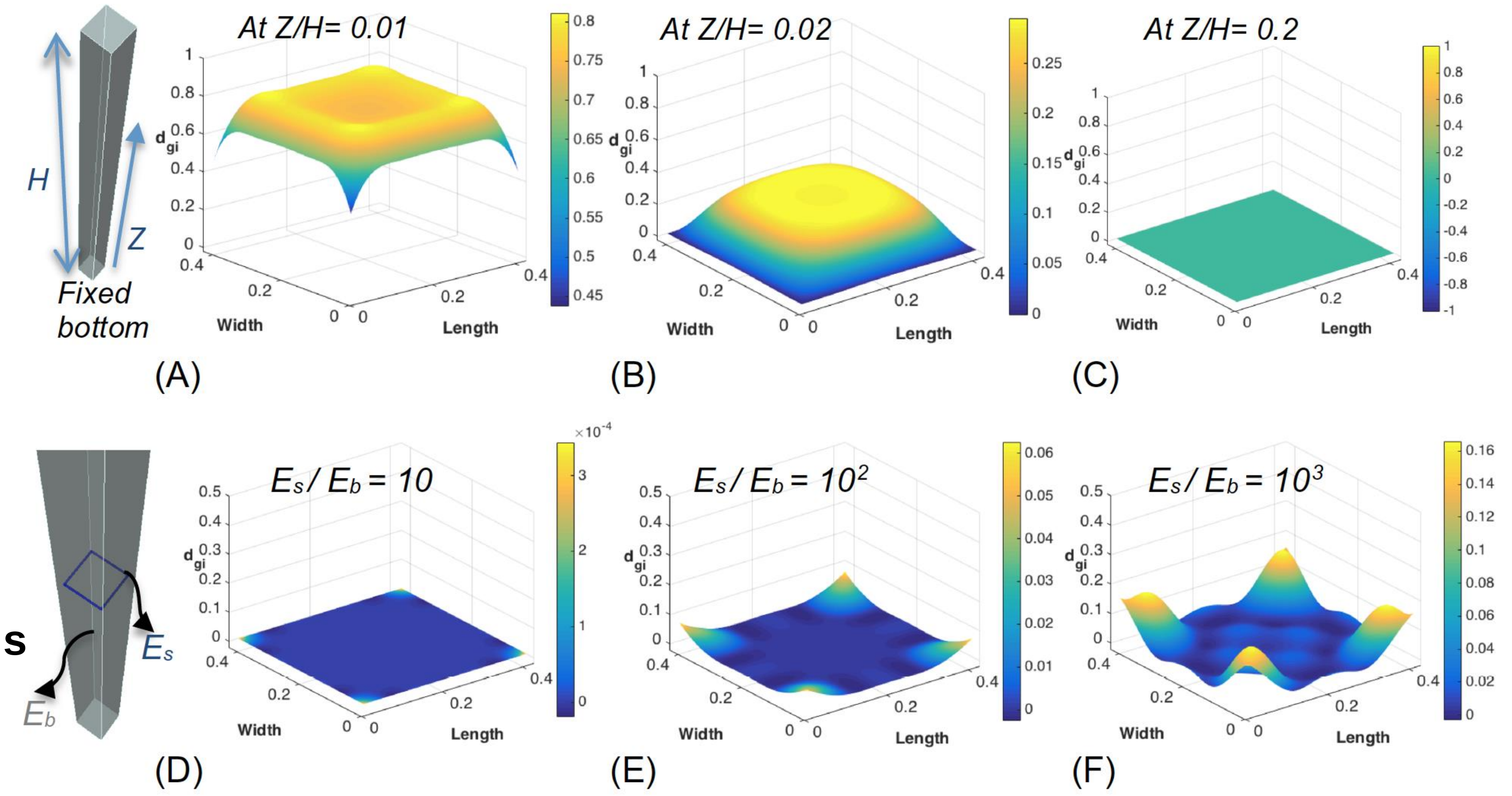
Physical Meaning of Information Index

~ 0 :

- **Free to deform**
- **Close to free BC's**
- **Far from stiff materials**

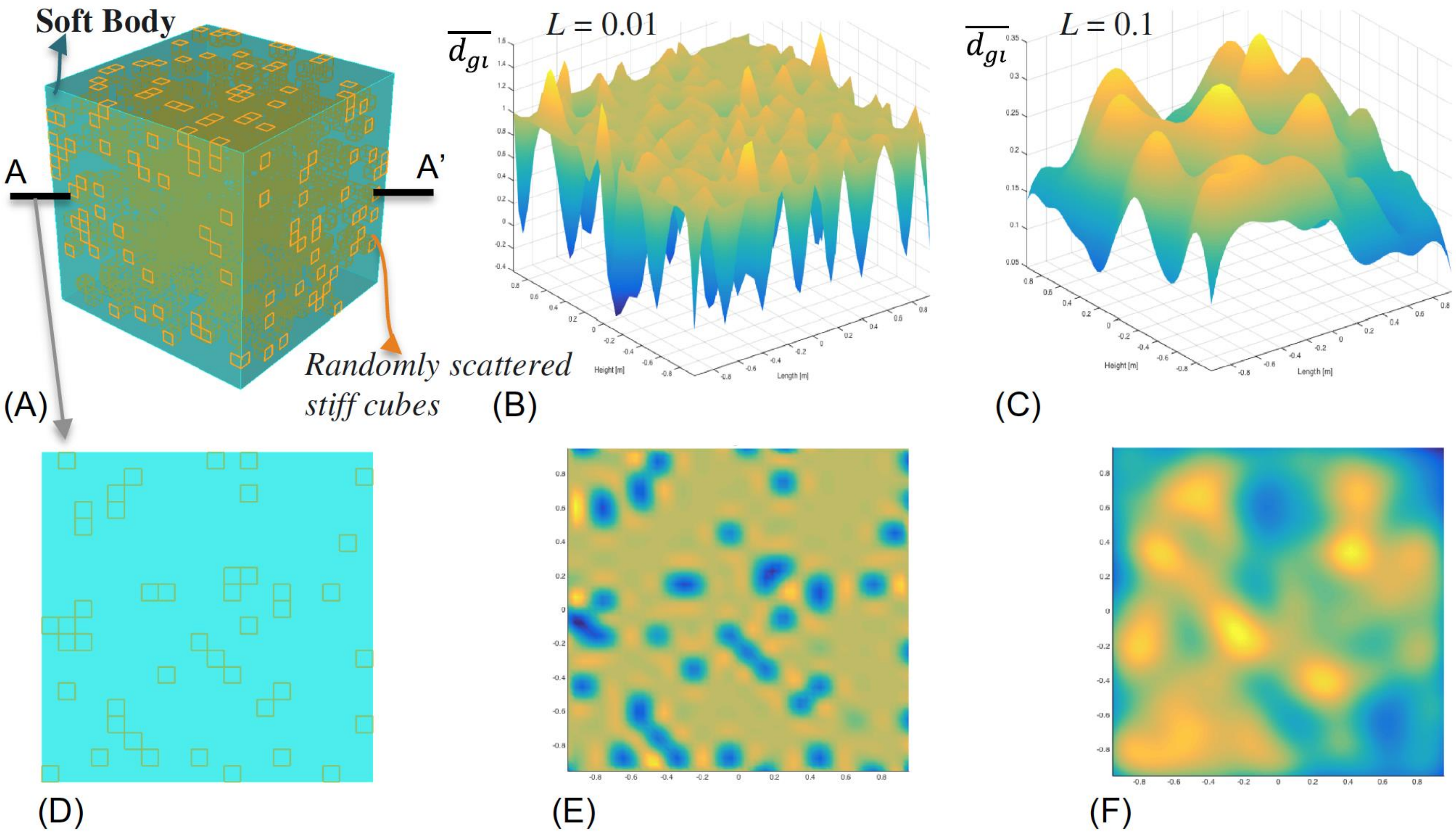
~ 1 :

- **Cannot deform**
- **Close to fixed BC's**
- **Adjacent to stiff materials**



New Feature (Convolved Information Index) for Random Heterogeneity

- A unitless soft cube (dimensions of 2 × 2 × 2) containing small stiff cubes (0.1 × 0.1 × 0.1), used to test the model's ability to perceive heterogeneity within a material.



[For detailed code, program, data, and theory; Cho (2019). "A framework for self-evolving computational material models inspired by deep learning". *Int. J. Numer. Methods Eng.*]

Glass-Box Learning Applied to Material Models

New Feature of Convolved Information Index (II)

$$\overline{\boldsymbol{II}}(\mathbf{X})$$

Given: Unknown
decisive coef. c
of a material model M

Link Function $\mathcal{L}$

$$\mathcal{L}_{\boldsymbol{M}}(\overline{\boldsymbol{II}}(\mathbf{X});\mathbf{a}) \rightarrow \boldsymbol{c}$$

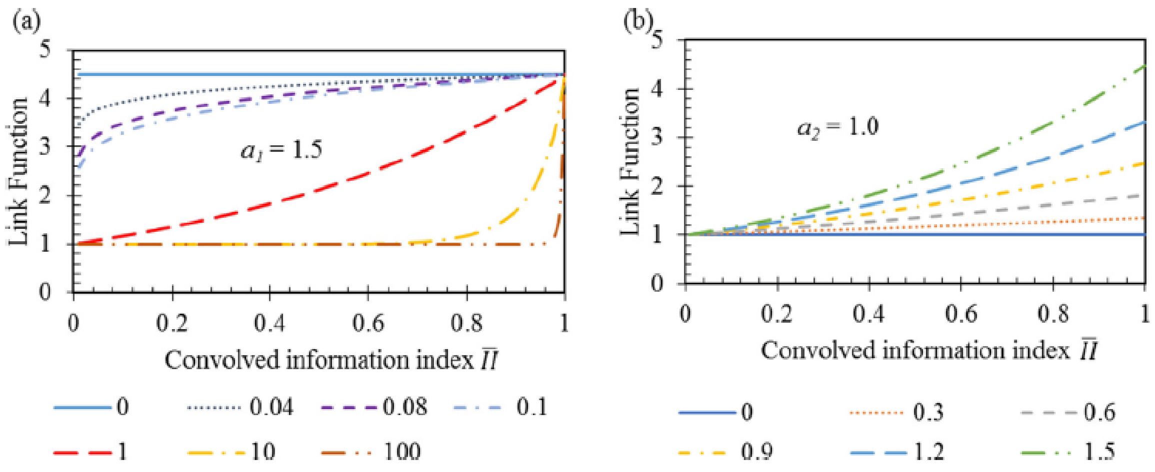
- Defined at a material point $\mathbf{X}$
- Can quantify BC's
- Can quantify heterogeneity
- Invariant to external stress

- Expressions of material coefficient $\boldsymbol{c}$
- Interpretable relationships of $\boldsymbol{c}$ and $\overline{\boldsymbol{II}}(\mathbf{X})$
- Now $\boldsymbol{c}$ can be different at every material point depending upon BC's and heterogeneity
- Bayesian evolutionary algorithms to update the model parameters.

Learning Hidden Rules by Flexible Link Function (LF)

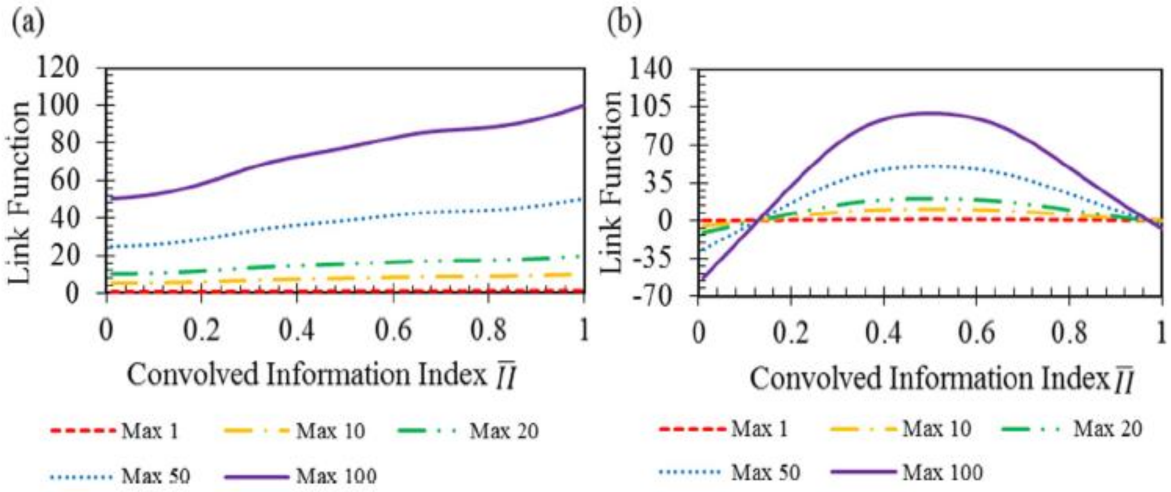
(1) Two-Parameter Exponential LF

$$\mathcal{L}_M(\overline{II};\mathbf{a}) \equiv \exp[a_1(\overline{II})^{a_2}]$$



(2) CRS-based LF

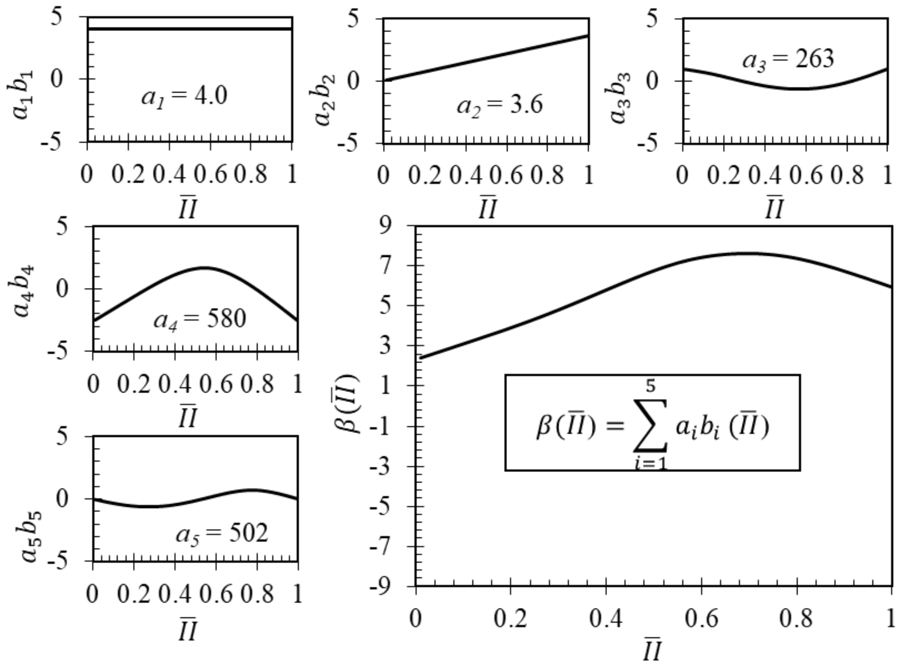
$$\mathcal{L}_M(\overline{II};\mathbf{a}) = a_1\, b_1\,(\overline{II}) + a_2\, b_2\,(\overline{II}) + \textstyle\sum_i a_{i+2}\, b_{i+2}\,(\overline{II})$$



Glass Box Interpretation of Identified Rules

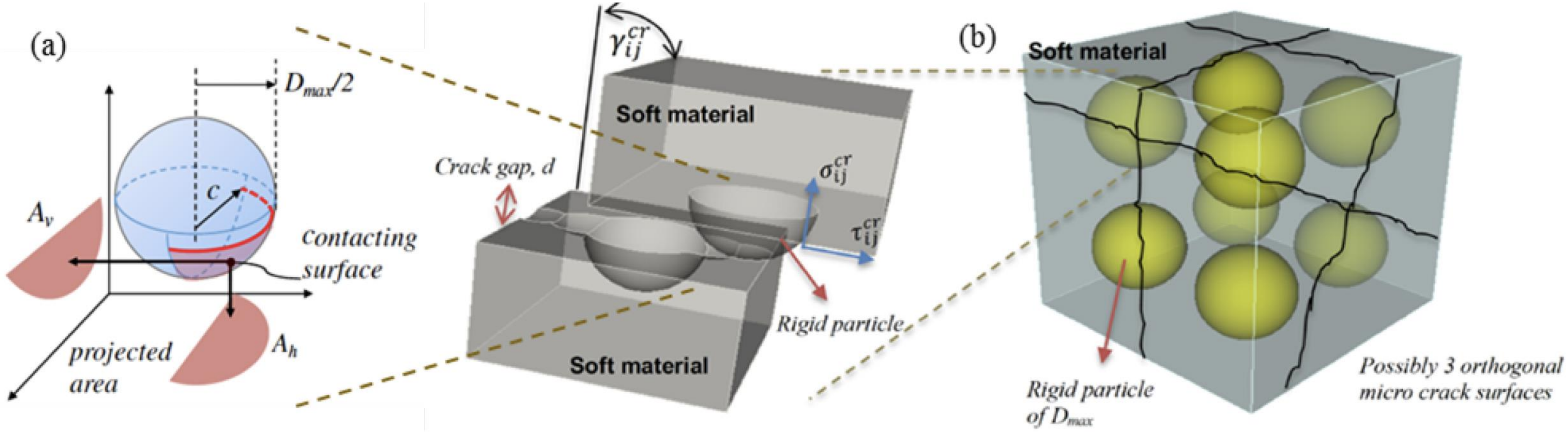
- Learn the hidden rules by providing mathematical expressions about the target material coefficients and the convolved information index through LF.
- For instance, the identified rule about β as the smooth function, and the convolved information index in a CRS form is given by

$$\beta\left(\mathbf{x}_{(i)}\right) = a_1 + a_2 \times \overline{II}\left(\mathbf{x}_{(i)}\right) + \sum_{j=1}^{3} a_{j+2} \times b_{j+2}\overline{II}\left(\mathbf{x}_{(i)}\right)$$



Glass-Box Approach to Learn Decisive Parameters of Concrete

3D nonlinear shear model **_3D crack model_**

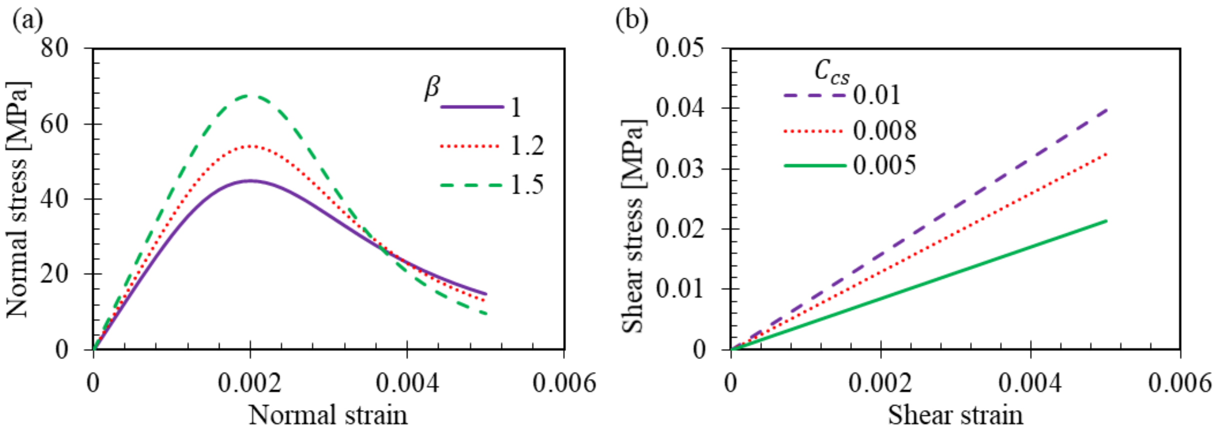


$$\Psi_n(\varepsilon_i^{cr}) = \begin{cases} \varepsilon_i^{cr} < 0 & \sigma_i^{cr} = -(\beta\,\sigma_c)\zeta\left(\dfrac{n}{n-1+\zeta^{n\cdot k}}\right) \\ \varepsilon_i^{cr} > 0 & \sigma_i^{cr} = \begin{cases} (f_t/\varepsilon_t)\varepsilon_i^{cr} & 0 < \varepsilon_i^{cr} \le \varepsilon_t \\ f_t\left[1-\left\{\dfrac{\varepsilon_i^{cr}-\varepsilon_i}{\varepsilon_u-\varepsilon_t}\right\}^c\right] & \varepsilon_t < \varepsilon_i^{cr} \le \varepsilon_u \\ 0 & \varepsilon_u < \varepsilon_i^{cr} \end{cases} \end{cases}$$

$$G(\tilde{\varepsilon}) = C_{cs}\frac{G_0}{(1+\mu)}\frac{2}{\pi}\left\{\tan^{-1}\sqrt{\tilde{\varepsilon}^{-2}-1} - \tilde{\varepsilon}\sqrt{1-\tilde{\varepsilon}^2} + \frac{\pi}{2}\mu(1-\tilde{\varepsilon}^2)\right\}$$

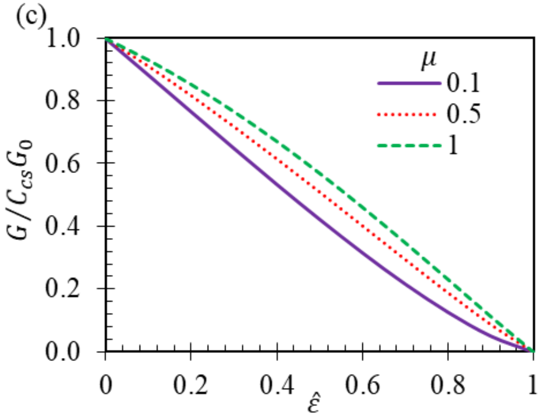
Glass-Box Approach to Learn Decisive Parameters of Concrete

β is the ambient condition-dependent **strength enhancement** factor



C_{cs} is the ambient condition-dependent empirical coefficient for **nonlinear shear of cracked concrete**

μ is the coefficient of **friction between cracked surfaces**



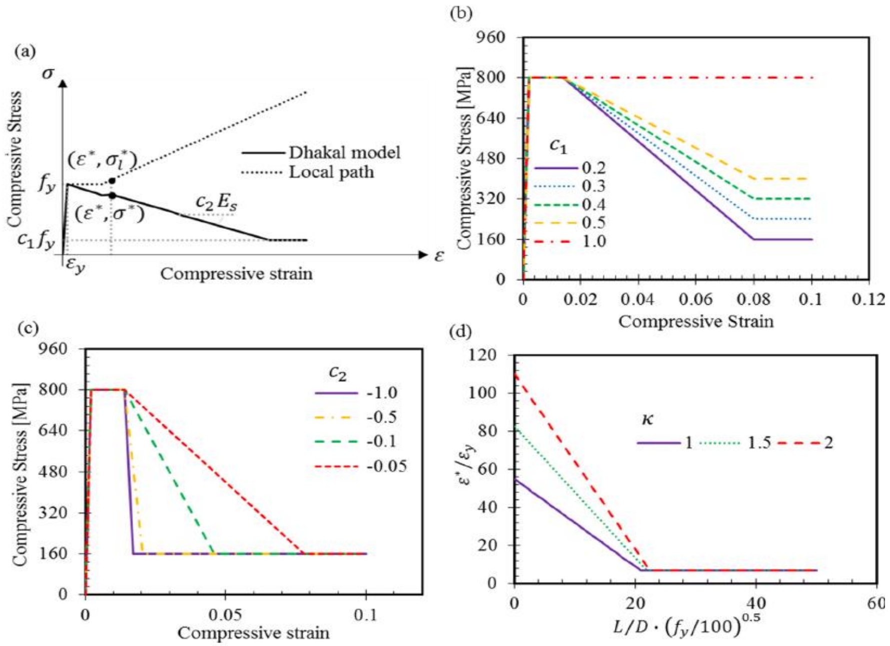
$\beta, C_{cs},$ and μ are the unknown decisive material coefficients, which have critical roles in the material mechanisms

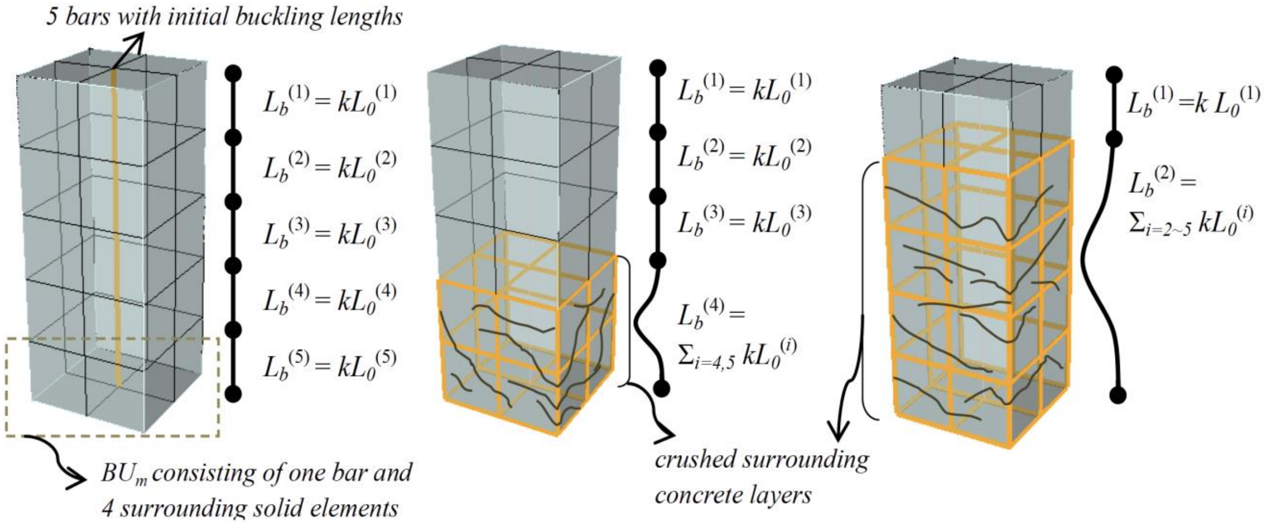
Glass-Box Approach to Learn Decisive Parameters of Progressive Bar Buckling

- c_1 : coefficient that determines **ultimate residual strength** after buckling.
- c_2 : coefficient that determines **post-buckling softening** after buckling.
- κ : coefficient that determines the **onset strain of buckling**

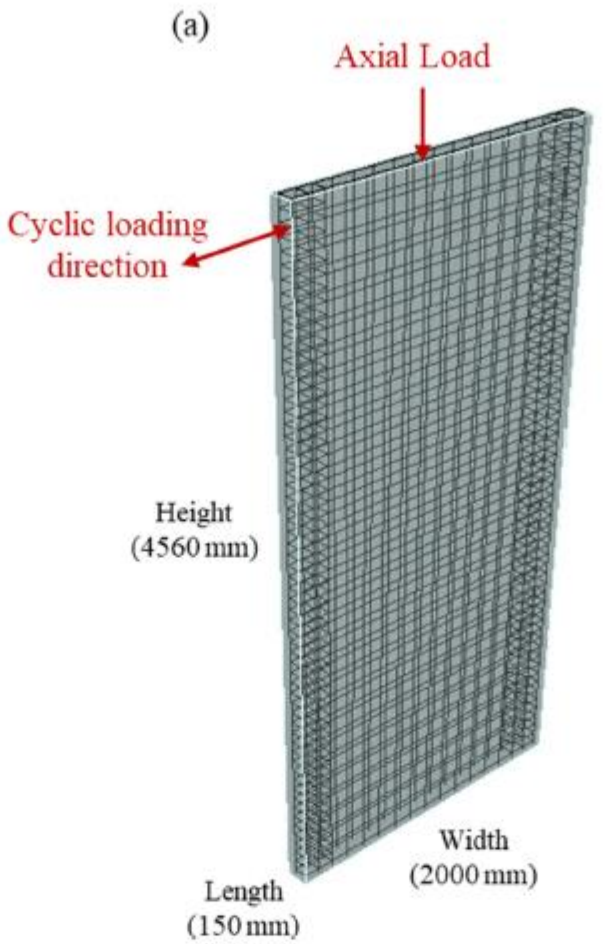
Cited from [Dhakal, and Maekawa. 2002]

$$\frac{\varepsilon^*}{\varepsilon_y} = \kappa\left(55 - 2.3\sqrt{\frac{f_y}{100}\frac{L_b}{D_s}}\right); \qquad \text{otherwise } \varepsilon^* \geq 7\varepsilon_y$$

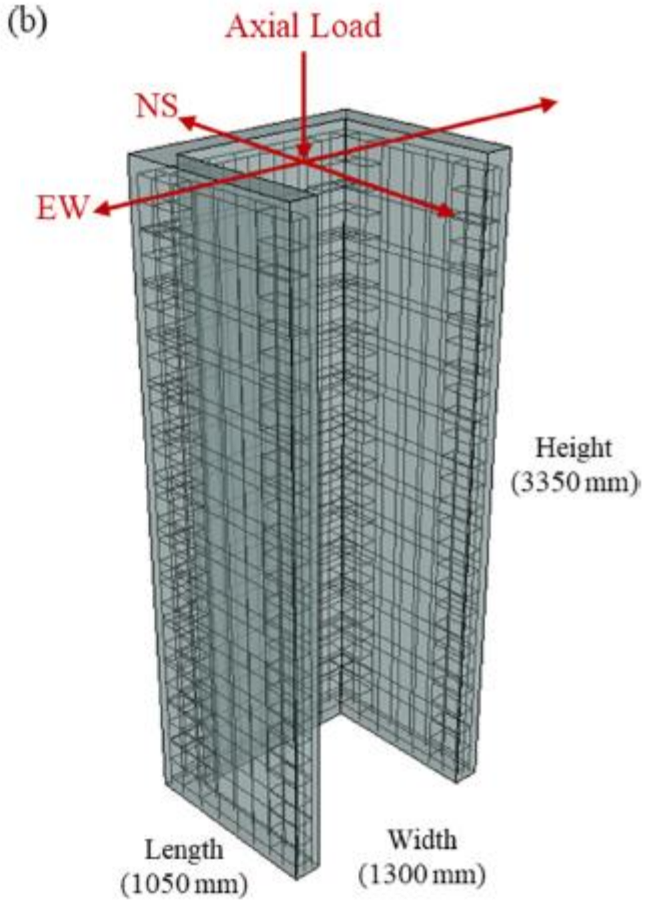




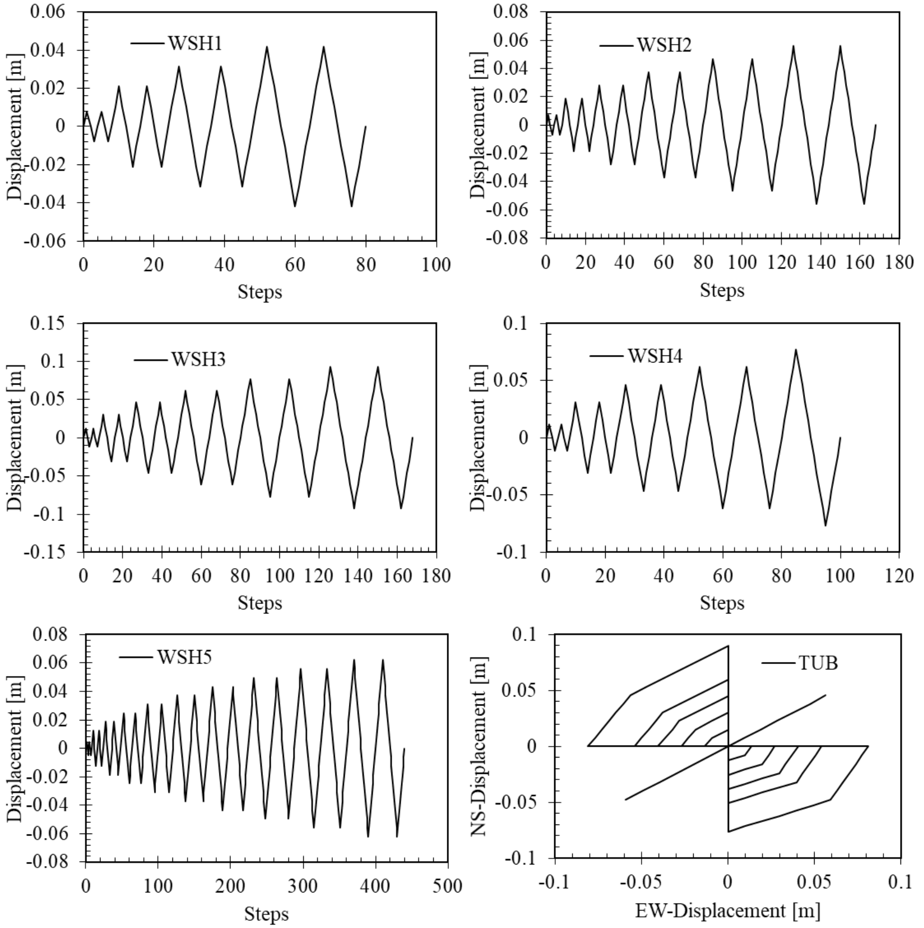
Diverse Large-scale Specimens for Feasibility Tests



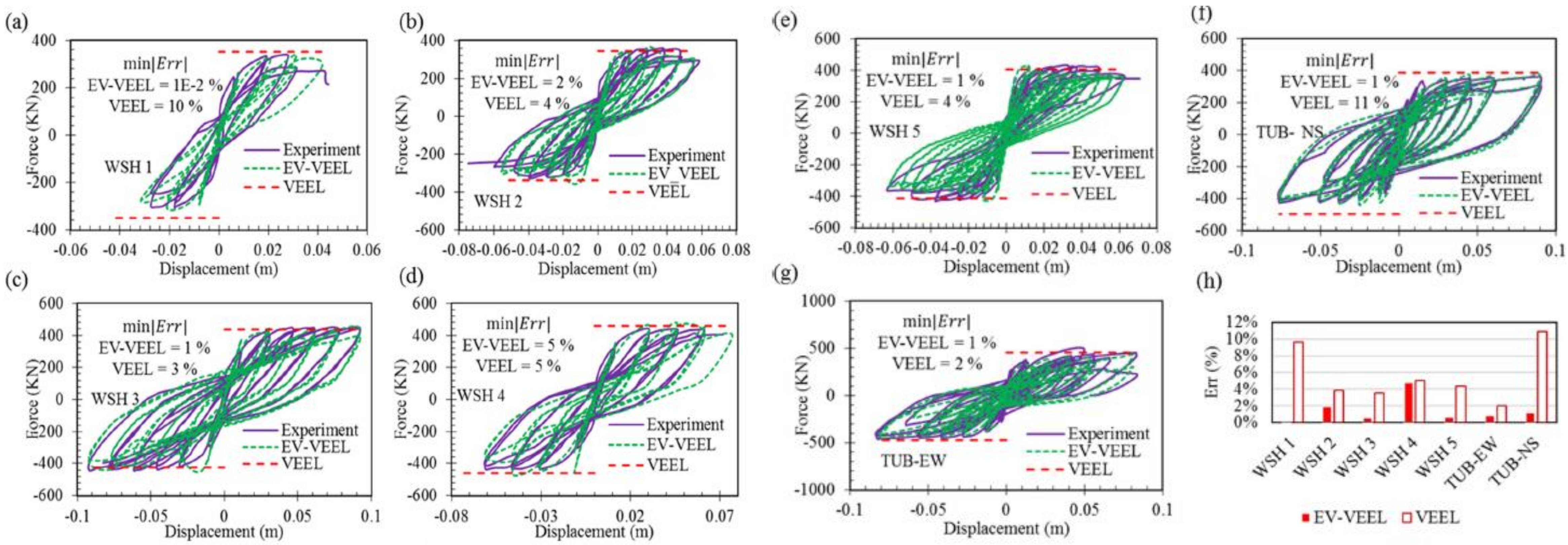
Rectangular wall



U-shaped wall



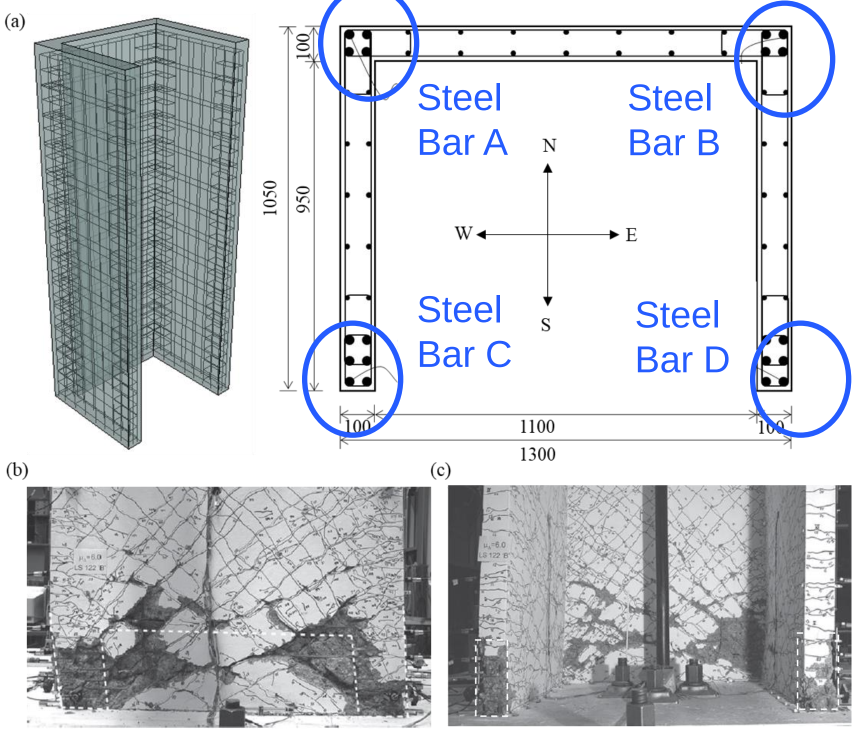
Glass-Box Approach Versus Manually Calibrated High-Precision FEAs



- **VEEL**(Virtual Earthquake Engineering Laboratory): a High-Precision Parallel Multiscale FEA Platform.
- **EV-VEEL**(Evolving VEEL): Integration of Glass-Box Learner and VEEL, EV-VEEL outperforms manually calibrated material models of VEEL

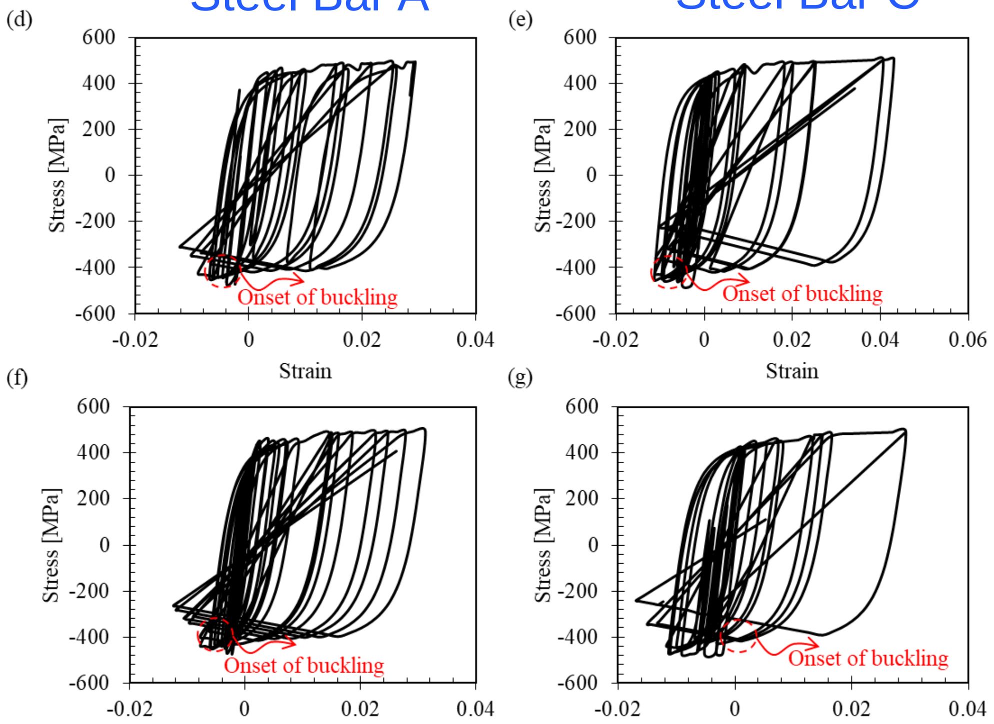
Glass-Box Approach Capturing Microscopic Damage

Bars at the Outermost Corners



Real experimental data (b) and (c) are cited from [Beyer et al. 2008]

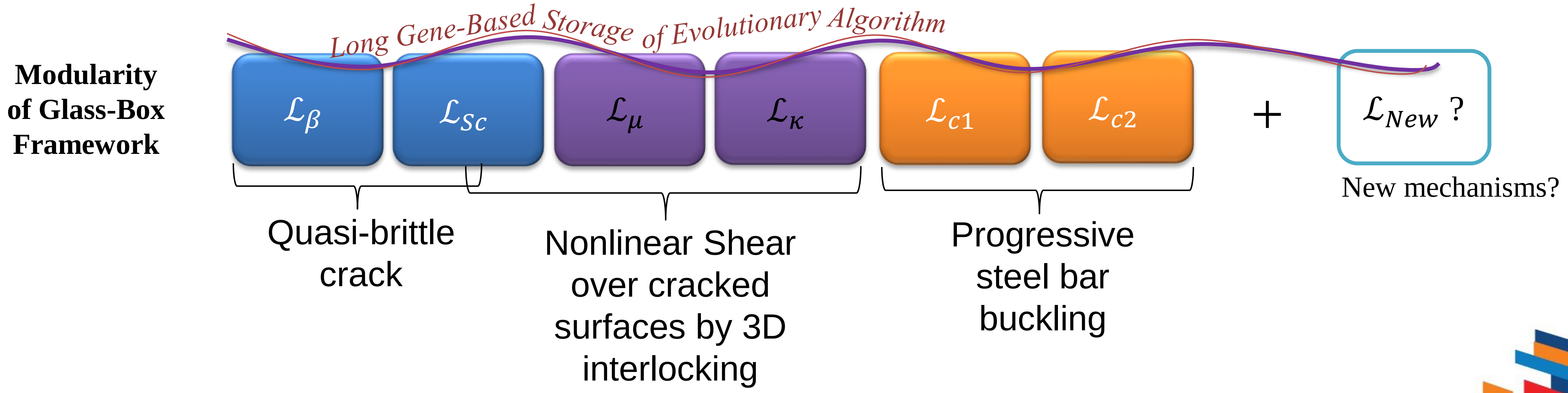
Detailed Stress-Strain Hysteresis



[For detailed code, program, data, and theory; From Bazroun, Yang, Cho (2022). "Flexible and interpretable generalization of self-evolving computational materials framework." *Computers and Structures*].

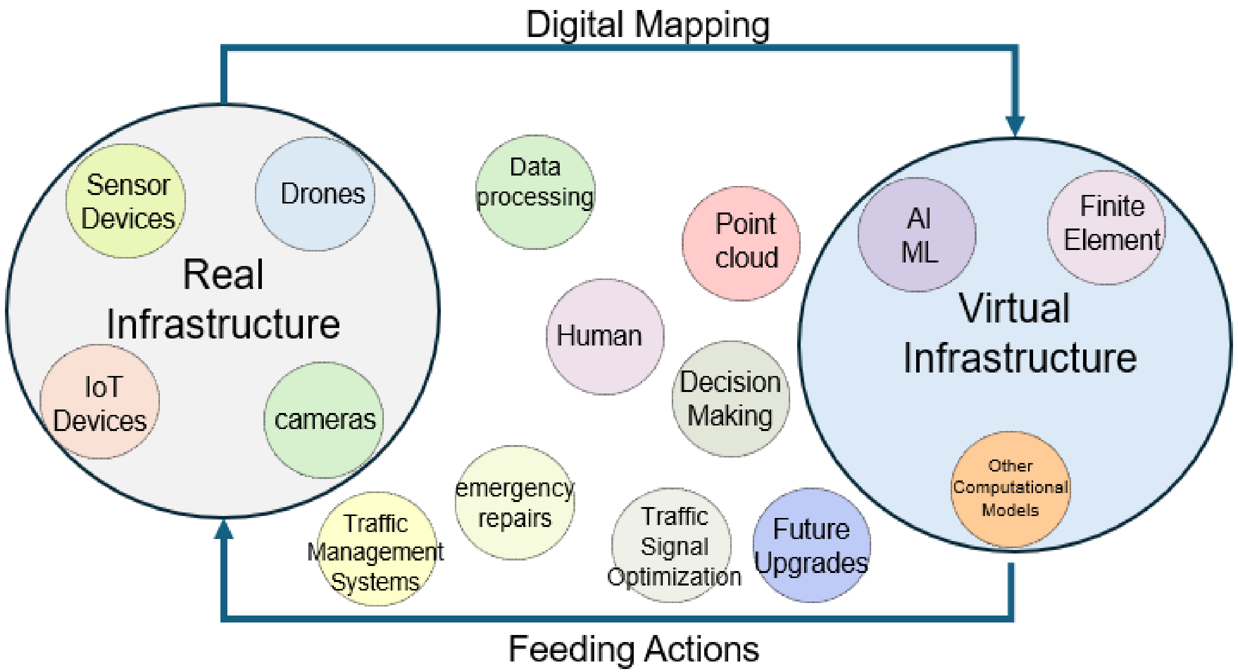
Expandability of Glass-Box Machine Learning

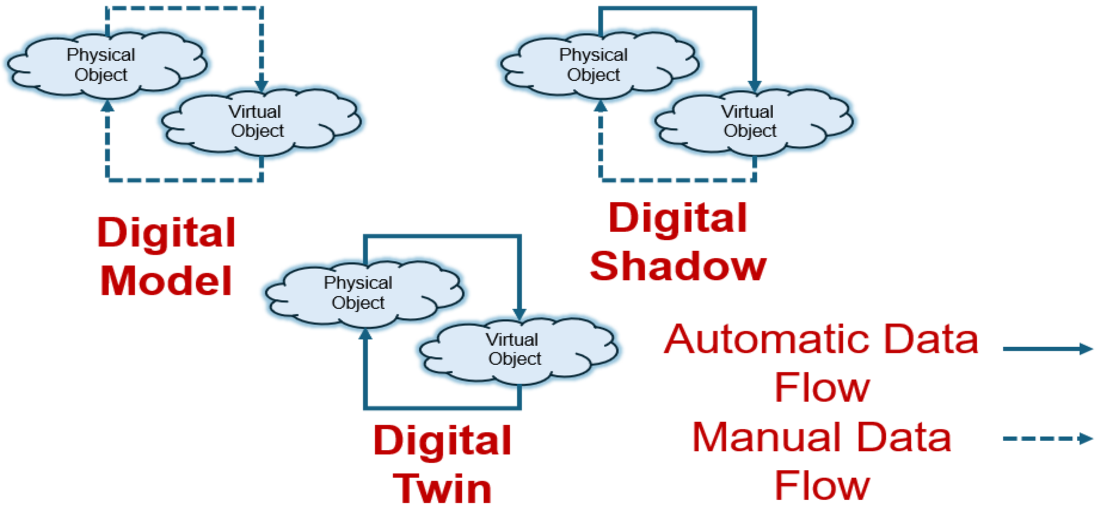
- **Expandable to as many mechanisms as needed**
- **Keeping higher interpretability**
- **Easy to replace, edit, and evolve**



DIGITAL TWIN DEFINITIONS AND TERMS

The digital twin concept is the virtual representation of a physical product, process, or system, including lifecycle management information with bi-directional data interaction mirroring the physical entity (Grieves 2014).





Digital Model:
Manual transformation of the data without referring to the real-time state.

Digital Shadow:
Automated and unidirectional interaction from the physical to the digital but not vice versa.

Digital Twin:
Bi-directional interaction of data reflecting real-time states.

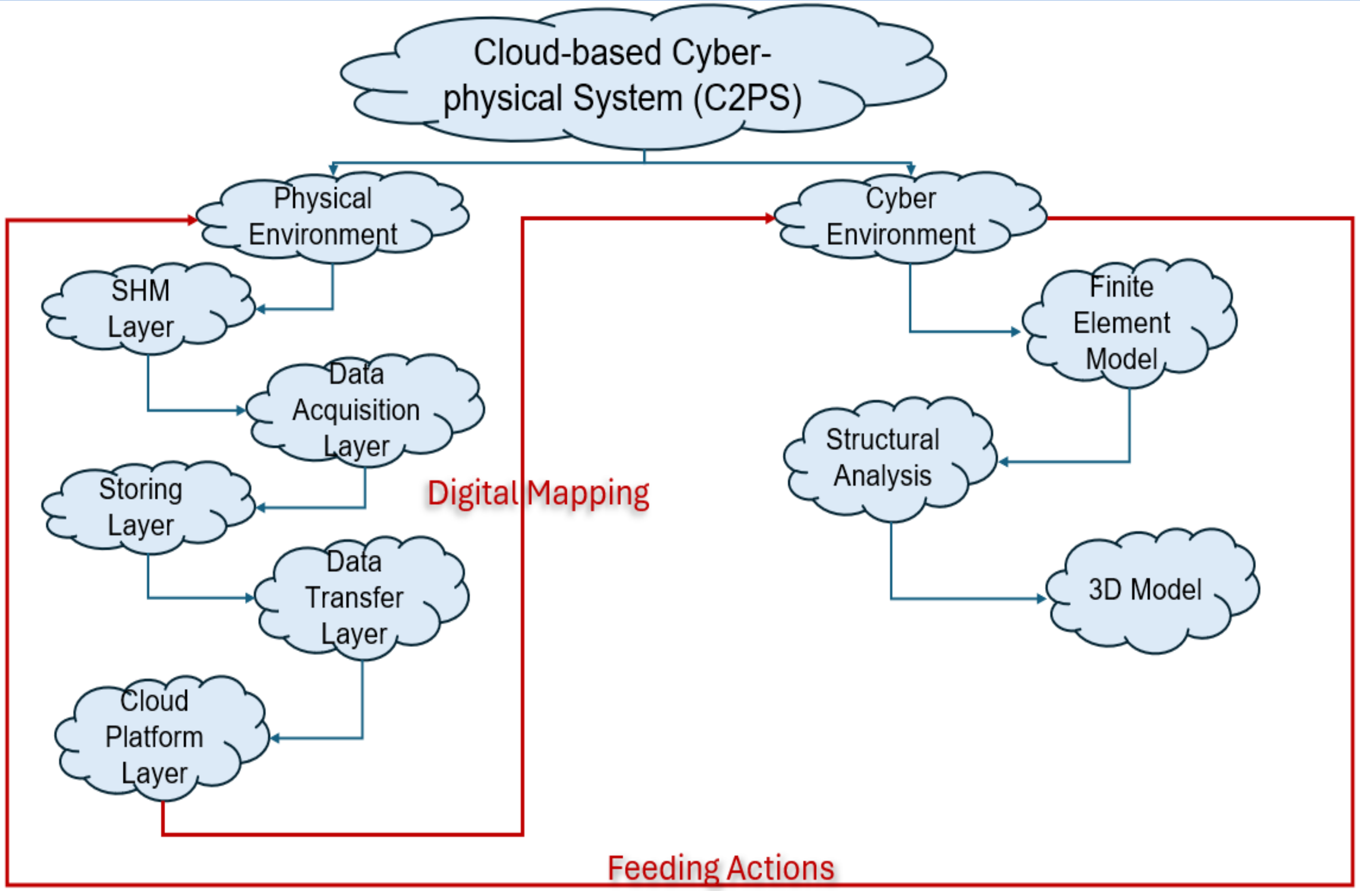
LEVEL AND ARRANGEMENTS OF DIGITAL TWIN

Simulation Level	Description	Data Processing Techniques
Individual Component	Any singular element within an extensive system or process is characterized by its unique properties and functions.	•Image, Sensor data, and 3D laser scanner for detection. •Data processing and digitalization for real time monitoring.
System	The integrated combination of diverse individual components, with each having unique functional properties.	•Advanced numerical modeling and real-time data capturing method. •Emergency response and crisis management.
Urban/City	The complex combination of multifarious systems, each a connection of related componentsts and process functioning to creat the level.	•Advanced mapping techniques and movement analysis. •Disaster response and monitoring of the resource.
National or Global	Computational methods to represent, analyse and predict the behaviour of complex system spanning entire countries or the globe.	•Integration of multiple data sources. •Mathematical modeling and prediction with advanced AI and ML.

DIGITAL TWIN DATA COLLECTION METHODS:

- Data-Driven Method
- Cloud Computing
- Internet of Thing (IoT)
- Cameras And Drones
- Sensors
- Laser Scanner
- GPS

Case Study



- Broo et al. (2022) studied the SHM of a railway bridge.
- A fiber optic sensor system was installed during bridge construction for monitoring.
- Data was transmitted to a cloud server for structural load analysis.
- Results were displayed on3D dashboard.

Cited from [Broo et al. 2022]

[**For detailed code, program, data, and theory;** **From Broo, Bravo-Haro, and Schooling. (2022). "Design and implementation of a smart infrastructure digital twin."** ***Automation in Construction.***]

Conclusions

- Data- and machine learning-driven approaches are rapidly growing in the research communities of complex RC structures.

- Global behaviors of complex RC structures can be accurately learned and predicted by advanced statistical learning and ML methods.

- Millimeter-scale material behaviors can be learned and evolved by glass-box learners while accounting for varying BC’s and heterogeneous materials prediction.

- Researchers should decide on a suitable method based on its accuracy, interpretability, expandability, and evolvability for their own research goals.

- In the recent development of digital twins for urban planning, infrastructure systems, or individual components, the concept of DT presents as a transformative framework enabling real-time updating, monitoring, and making accurate decisions.

Thank you.

For programs, data sets, and discussion, feel free to contact *icho@iastate.edu*

Acknowledgement: Generous support from
National Science Foundation, USA

NSF CMMI-2129796

- **Relevant Publications**
  - **Cho (2022). *Nature, Scientific Reports***
  - **Bazroun, Yang, Cho (2022). *Computer and Structures.***
  - **Yand and Cho (2021). *J. of Soft Computing Civil Engineering.***
  - **Cho et al. (2020). *Communications Physics.***
  - **Song, Cho, Wong (2020). *J. of Earthquake Engineering.***
  - **Cho (2019). *Int. J. Numerical Methods Engineering.***

Supplementary Materials

LEVEL AND ARRANGEMENTS OF DIGITAL TWIN

Simulation Level	Description	Data Processing Techniques	Digital Category (DM,DS,DT)	Reference
Individual Component	DT for road user classification, including road modeling, SFM, and user movement digitalization with R-CNN, and creating 3D bounding boxes with cameras and vanishing points simulating different scenarios to improve prediction efficiency.	Includes creating a 3D point cloud model with (SFM) and 2D image trained with R-CNN deep learning model, followed by 3D bounding boxes for road users using camera and vanishing points to integrate the model for road infrastructure and user movement.	DS	Lu and Dai (2023)
	The bogie in high-speed train fault monitoring with the DT model integrates the physical and virtual twins, considering the geometry, dynamics, and vibration of the bogie system. Processing the signal data for faults diagnosis and monitoring.	Processing the data with signal methods to estimate the faults by algorithms for sensor data measuring the bogie faults. The bogie condition is classified with CNNs based on vibration signals. The fault model and DT are used to decide maintenance and repairing.	DS	Wu et al. (2023)
System	Use different data collection methods to digitalize and analyse the railway state using the ARIANE version of RAILTOPOMODEL software. The captured images and data view the state of the system.	Data processing carried out with IT programmes to improve the system output, quality of data. The decision-making phase is based on accurate reflecting of the system state using realistic images from drones.	DS	•ISSA et al., (2023)
	Digital model for Railway Bridge located in the UK with FO sensors embedded during the construction phase in both flange and deck. The collected data saved on minicomputer then transfer to point cloud server with 4G network.	The collected data is stored on a minicomputer on the bridge and then transferred by a 4G network to a point cloud Docker platform for processing. The web interface allows for visualization, analysis, and access by API Hub.	DS	•Broo et al. (2022)
Urban/City	•Create DT for the Kaunas University campus and part of the Lithuania city to estimate the energy performance and CO2 emissions of the buildings and infrastructure with data collected by drones. The information was collected with drones processing	•The data processing includes analyzing point cloud data, images of buildings, and energy performance with Bentley OpenCities Planner for simulating energy performance over real-time planning. For UAV-based reality modeling use, Bentley's ContextCapture	DS	•Robertson (2024)
	•Creating DT of Singapore 3D mapping in two phases: aerial in 2014 and street mobile mapping in 2015. The main goal of this model is to map the entire country with data-capturing devices to build an efficient and reliable map for planning and risk	•The data processing phase includes analyzing and managing a large set of data collected from aerial and street mapping, including point cloud maps, imagery, and other geospatial data using software solutions like Bentley Orbit. The updating of DT mapping with	DS	•Wegena (2022)
National or Global	Prediction of future climate changes, extreme events taking actions for energy designing process, new observation system, and extreme weather emergencies actions.	Data processing is carried out by FE model, ML, and statistical analysis with high computing tools dealing with massive data and visualisation methods.	DS	National Academies of Sciences, Engineering, and Medicine. (2023).
	DT dynamic interactive earth system focusing on the water cycle scenarios for capturing and detecting impacts. The model is integrated, observed, and analyzed within the created framework.	Data processing using mathematical models, modeling the flood, and use of AI and ML algorithms for flood prediction.	DS	Huang et al. (2022)