Framework to Define Performance Requirements for Structural Component Models

and

Application to Reinforced Concrete Wall Shear Strength

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Dec. 2022

Personal Background

2008 - 2012	B.S., Structural Engineering University of Chile, Chile
2013 - 2015	P.E., Structural Engineering University of Chile, Chile
2014 - 2015	M.S., Structural Engineering University of Chile, Chile
2014	Structural Engineer Ruben Boroschek & Associates Santiago, Chile
2015 - 2018	Structural Engineer Moffatt & Nichol Santiago, Chile

Outline

Part 1: Introduction

Part 2: Framework to Define Performance Requirements for Structural Component Models

Part 3: Methodology to Obtain an Equation with Code-Oriented Format

Part 4: Further analyses of the Proposed Equation

Part 5: Conclusions

Part 1

Introduction

Motivation

- Equation in ACI is based on limited data and has a large error
- Availability of the UCLA-RC Walls Database

Literature Review

- Physics + Relevant parameters + Statistics
- Relevant parameters + Machine Learning (ML)

Drawbacks of “Classic” Approach

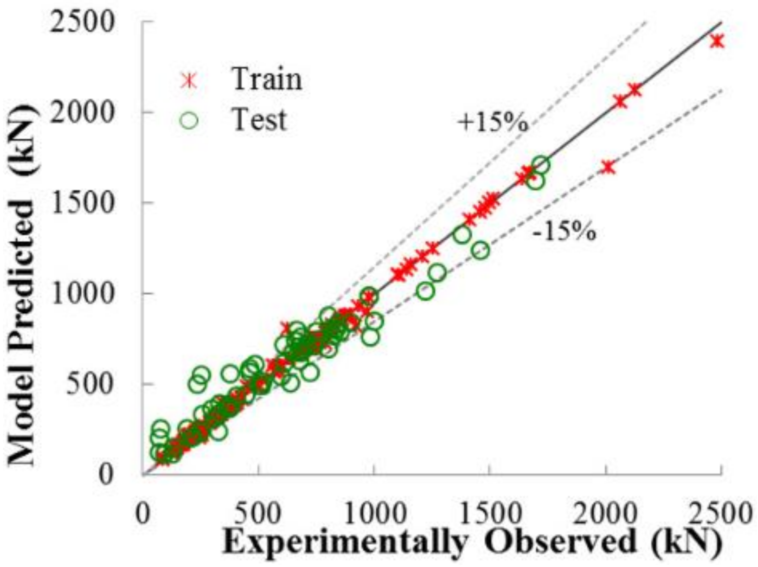
- Different number of tests in the databases
- Different parameters
- Different range of parameters
- Different criteria/assumptions to create the database
- Calibration process → Statistical inferences

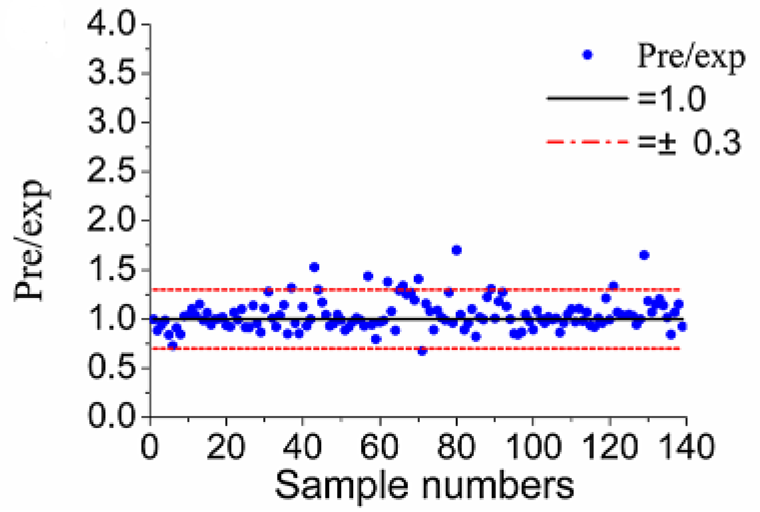
Unseen data?

Drawbacks of ML Models

- Criteria/assumptions to create the database
- Well-known error indicator should be included
- Comparisons should include other ML models
- Make the database representative of reduce-scale tests and full-scale tests
- Appropriate error indicator in the training process
- Training set vs testing set performance properly assessed

Drawbacks of ML Models





- Not appropriate error indicator in the training process

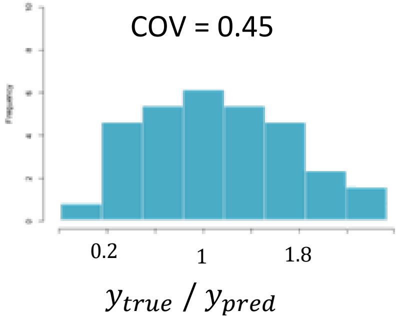
- Training test vs. testing set performance not properly assessed

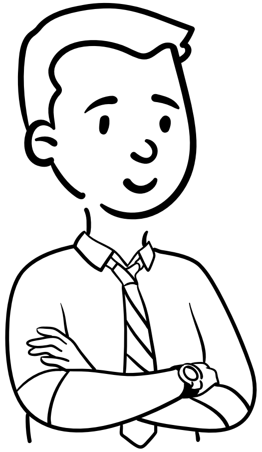
Another Problem…

$$y = \frac{a}{\sqrt{x_3}} x_2 + c\, x_1$$

Mean = 1.08

COV = 0.45

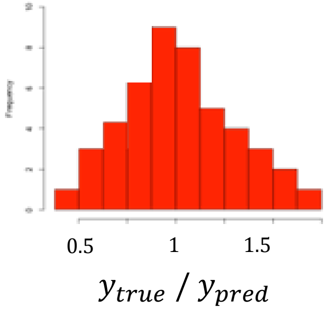




$$y = a\, log\left(\frac{x_2}{b x_3}\right) + c\sqrt{x_1}$$

Mean = 1.04

COV = 0.35



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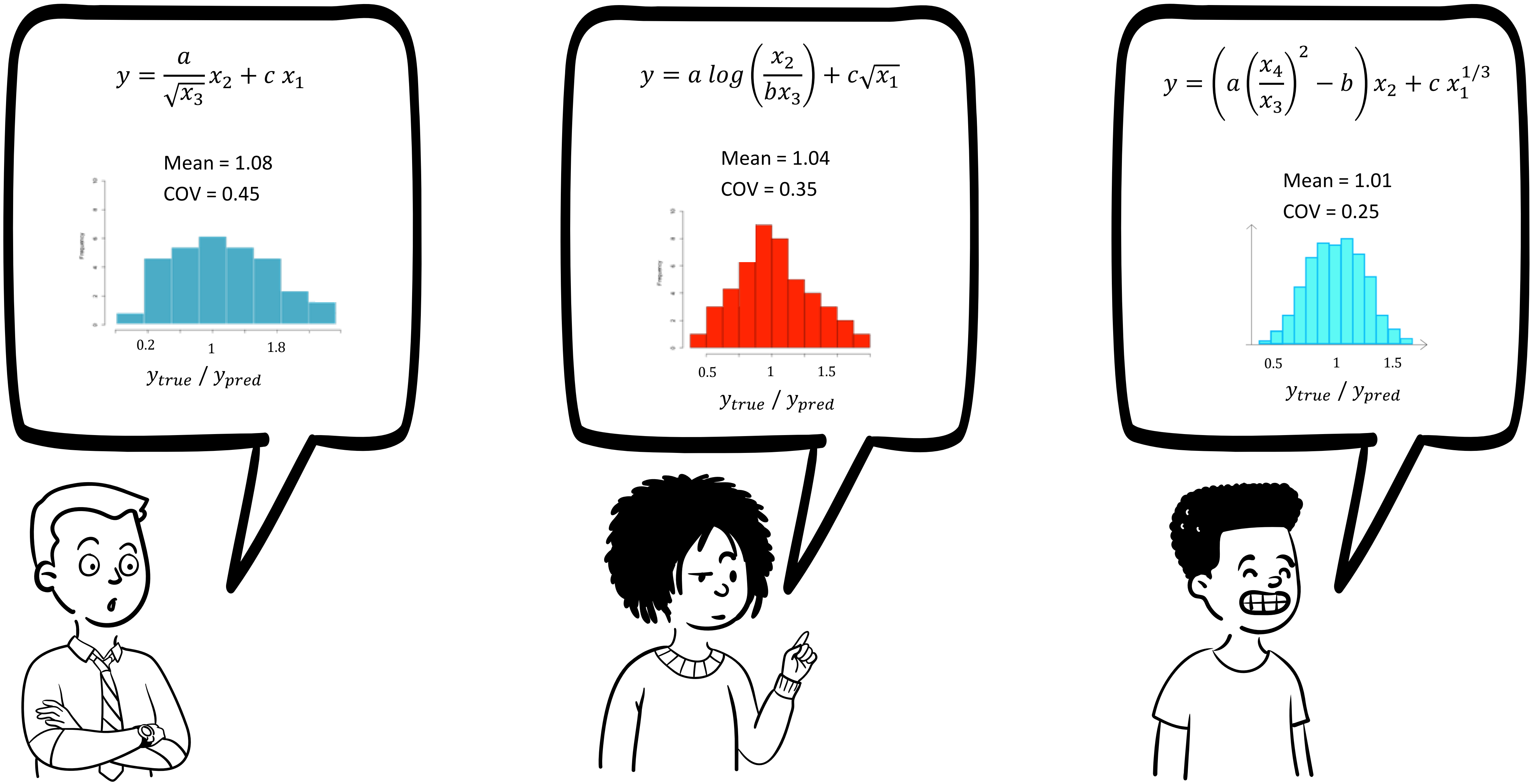

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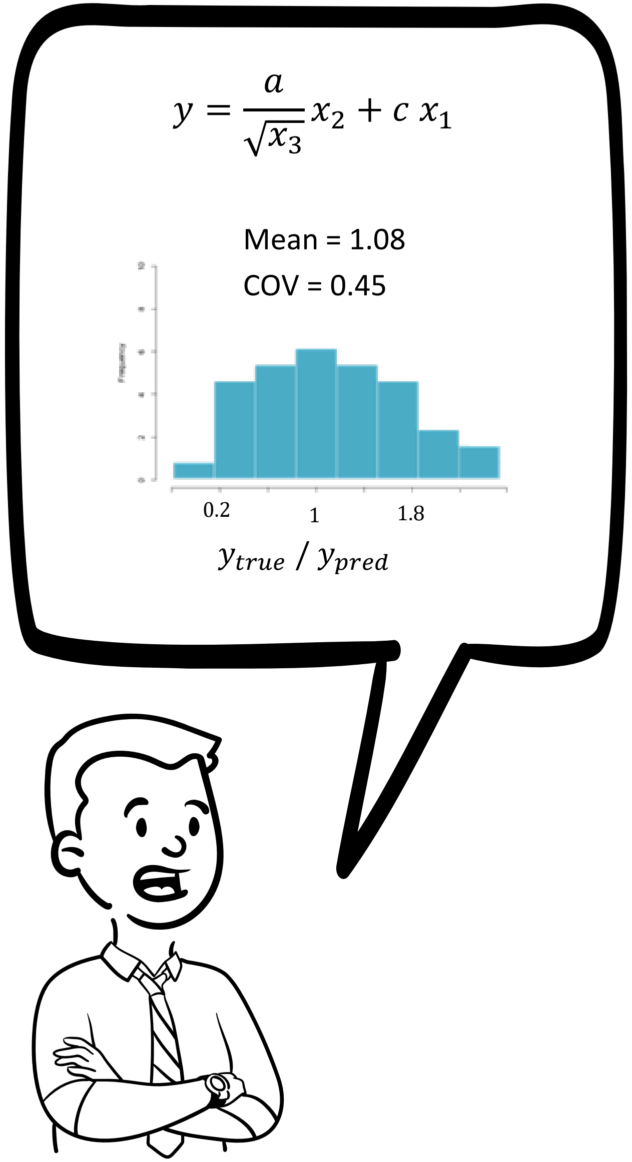
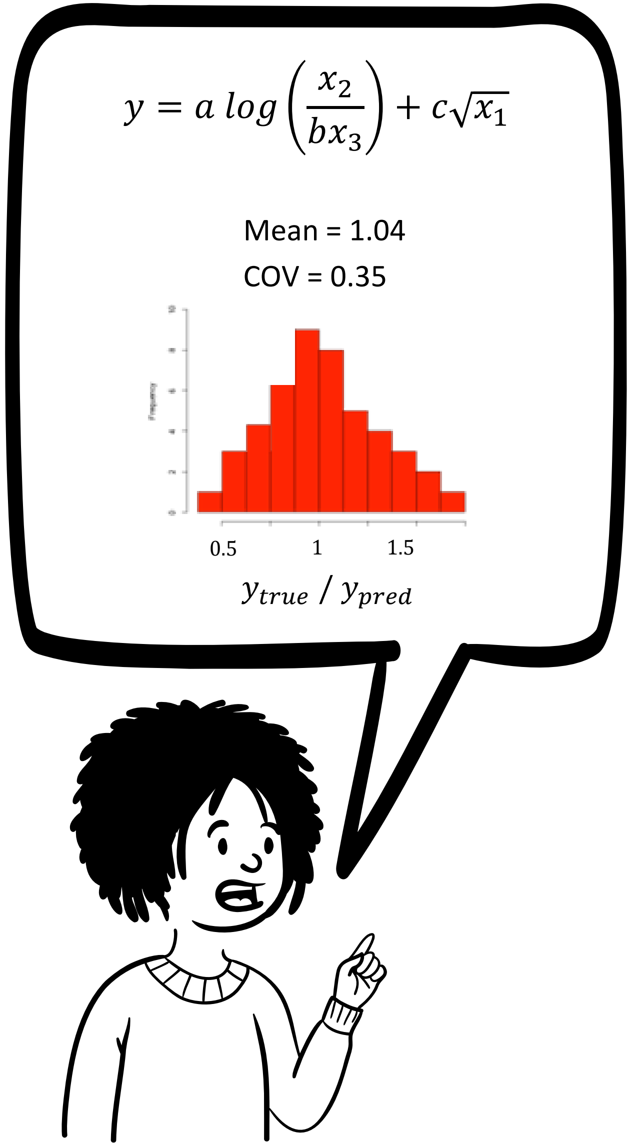
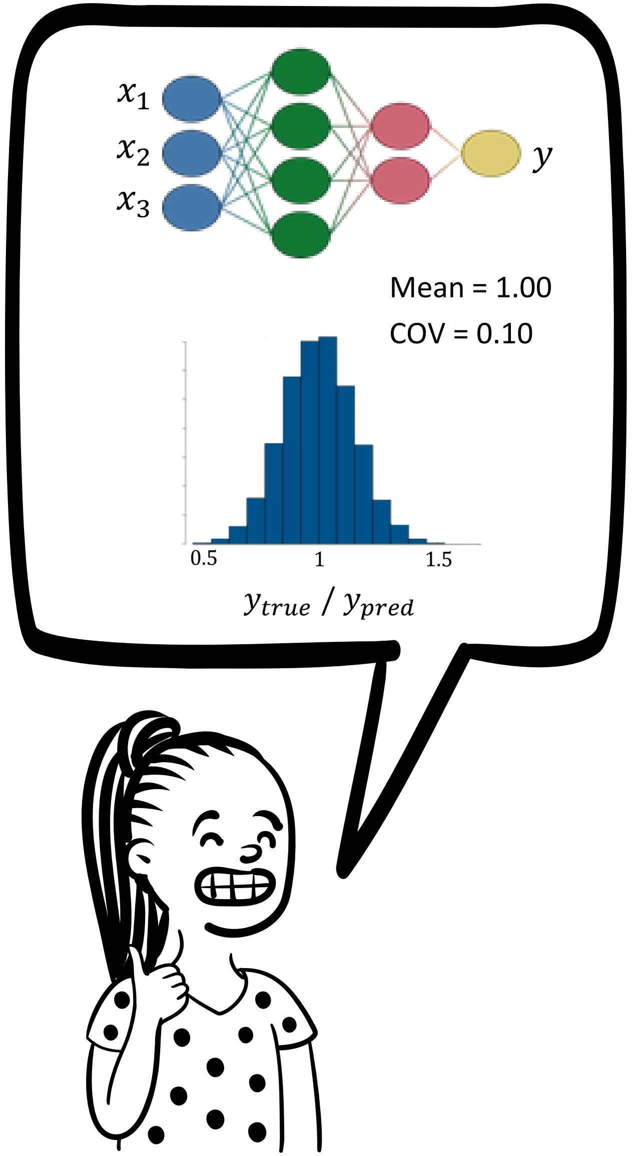
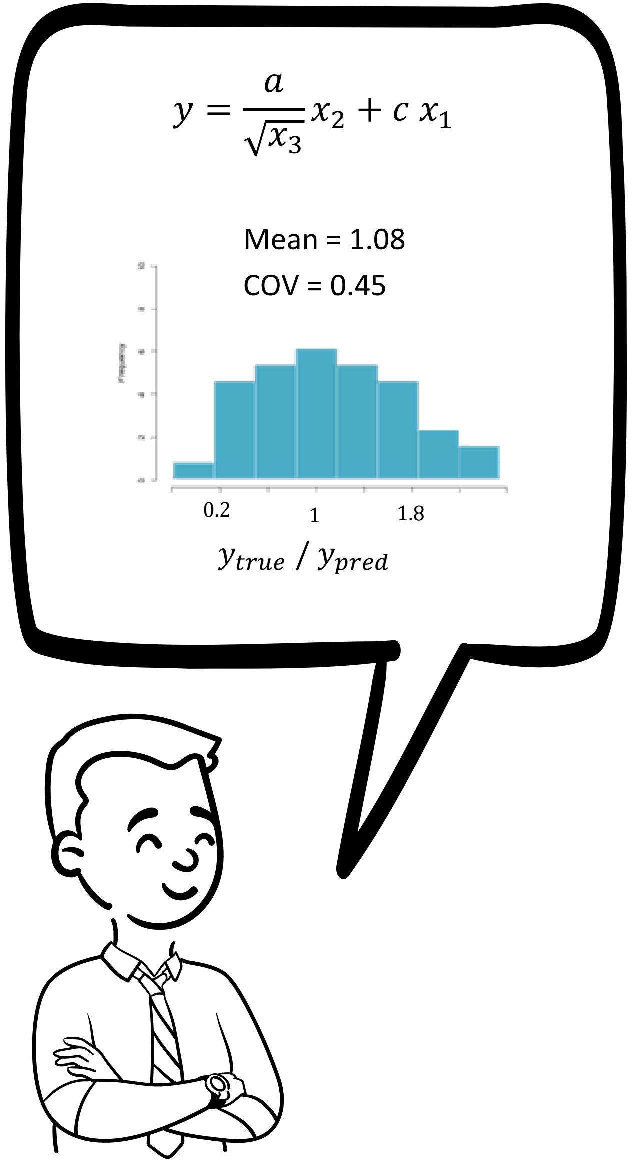




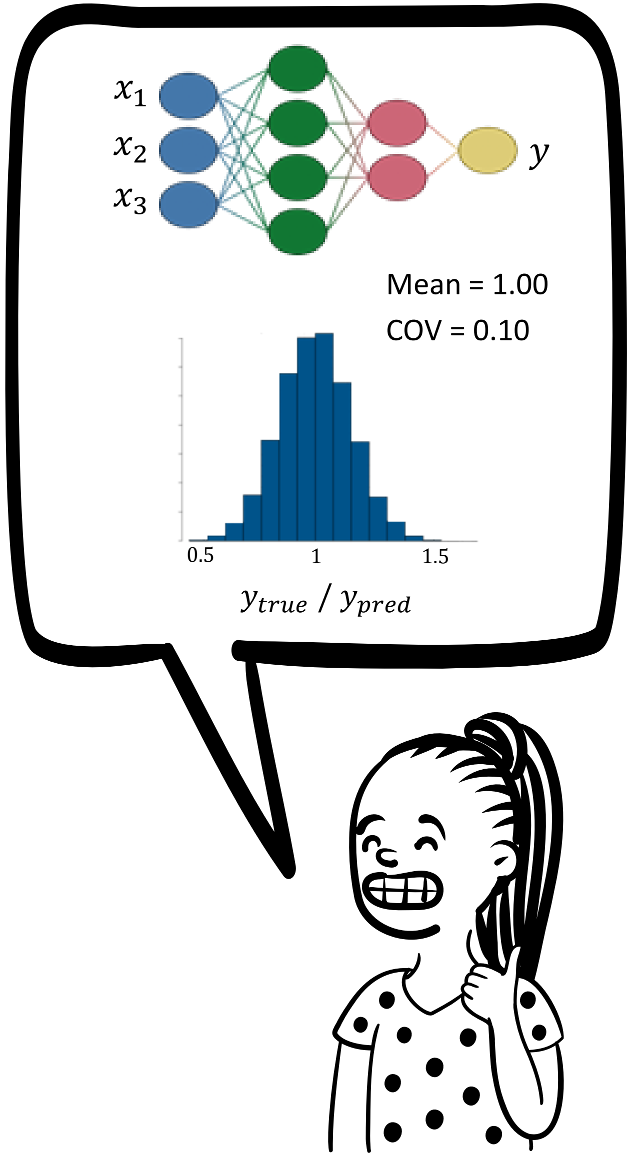


Another Problem: Model Performance vs Complexity Level?



Model Complexity – Acceptable Error

Trade Off



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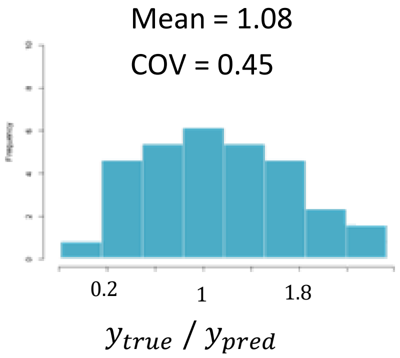

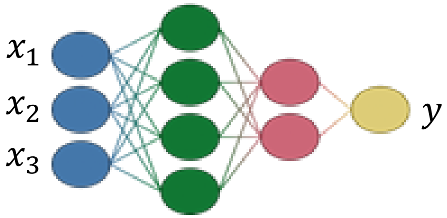

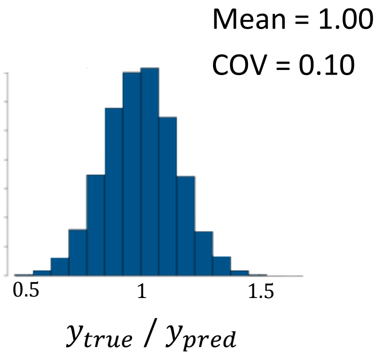

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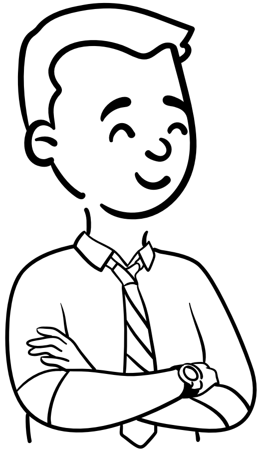

Requirements	Model Complexity Level	
	Complex ML Models	Simplified Models
Number of parameters	-	~ 3 - 6
V_{true}/V_{pred} mean ratio	0.99 – 1.01	0.98 – 1.02
COV	$\leq$ 0.12	0.16 – 0.19
Train. vs Test. Error Margin	$\pm$20% of the converging error	$\pm$10% of the converging error

Part 2

Framework to Define Performance Requirements for Structural Component Models

Framework to Set Target Errors for Different Model Complexity Levels

(1) Collection and preparation of data

(2) Feature selection

- Mechanics + Literature Review
- Normalized/scaled features + Mechanics → Engineered Features

(3) Choice of ML algorithm

- Complex ML model (e.g., ANN, RF regression)
- ENMs

(4) Selection hyper-parameters

- Sensitivity analysis with iterative k-Fold CV
- Define underfitting levels to be used for the ENMs training

(5) Model training

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Identification of input parameters (from literature and FBD)

UCLA RC-Walls Database

→ Reported Shear Failures (Flexure-Shear, Diagonal Tensions, or Diagonal Compression) → 412 tests

→
- 6 tests with artificial cracks for corrosion studies
- 9 tests with reported lateral load readings not matching the values in the figures
- 20 tests with asymmetric cross-section shapes
- 37 tests with $f_c' \leq 3\ ksi$
- 7 tests with $f_y \geq 100\ ksi$ & $f_c' \leq 5$

→ **Database of 333 wall tests reported to have failed in shear**

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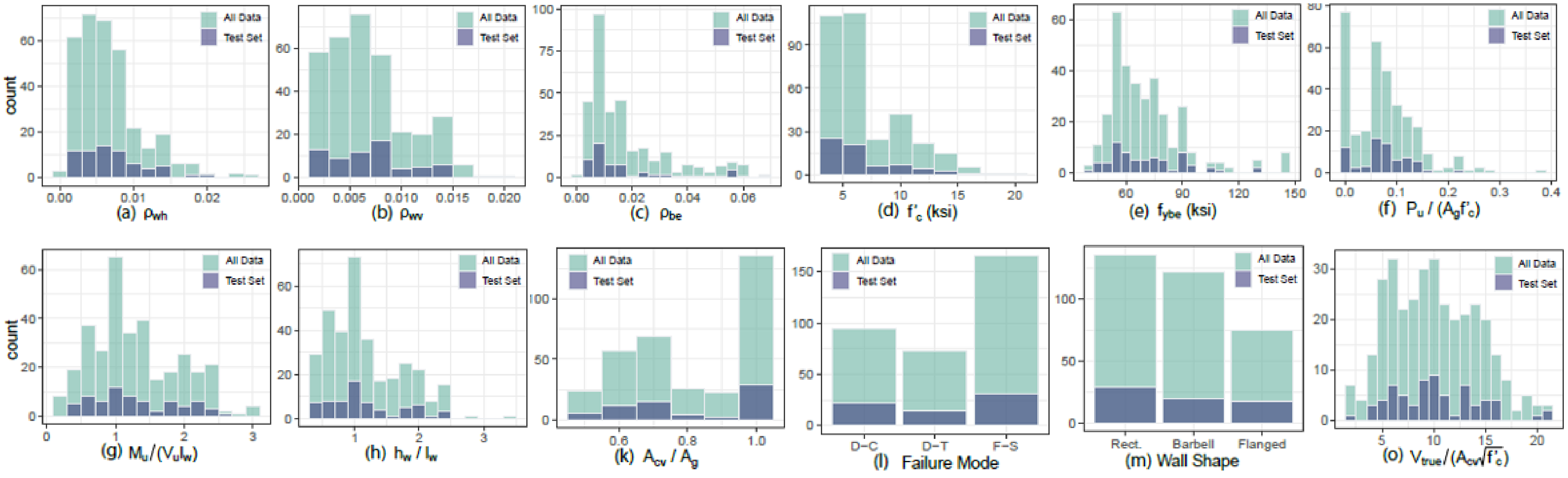


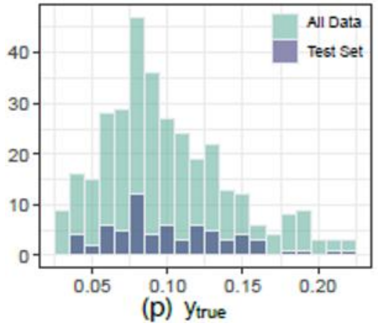
Input (starting) features:

$$x_1 = \rho_{wh}\frac{f_{ywh}}{f_c'} \quad x_2 = \rho_{wv}\frac{f_{ywv}}{f_c'} \quad x_3 = \rho_{wbe}\frac{f_{ybe}}{f_c'} \quad x_4 = 1 + \frac{P_u}{A_g f_c'} \quad x_5 = \frac{c}{l_w}$$

$$x_6 = \frac{M_u}{V_u l_w} \quad x_7 = \frac{t_w}{l_w} \quad x_8 = \frac{t_w}{h_w} \quad x_9 = \frac{h_w}{l_w} \quad x_{10} = \frac{A_{be}}{A_g}$$

Output variable:

$$y_{true} = \frac{V_{true}}{A_g f_c'}$$



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Predicted variable: $y_{true} = \frac{V_{true}}{A_g f_c'}$

Feature engineering

Starting features $x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}$

"Typical functions" identity, $(\cdot)^{-1}$, $(\cdot)^{2}$, $(\cdot)^{-2}$, $(\cdot)^{1/2}$, $(\cdot)^{-1/2}$, $(\cdot)^{3}$, $(\cdot)^{-3}$, $(\cdot)^{1/3}$, $(\cdot)^{-1/3}$, $\exp(\cdot)$, $\exp(-\cdot)$, $\log(\cdot)$, and $-\log(1+\cdot)$

Basic relations

$$V_u \overset{\propto}{\sim} A_g f_c' \quad (1)$$

$$V_u \overset{\propto}{\sim} \rho_{wh} f_{ywh} h_w t_w \quad (2)$$

$$V_u h_{eff} \overset{\propto}{\sim} \rho_{wv} f_{ywv} (l_w - c)^2 t_w \quad (3)$$

$$V_u h_{eff} \overset{\propto}{\sim} \rho_{be} f_{ybe} A_{be} l_w \quad (4)$$

$$V_u h_{eff} \overset{\propto}{\sim} \left(f_c' + \frac{P}{A_g}\right) t_w c^2 \quad (5)$$

$$V_u h_{eff} \overset{\propto}{\sim} \left(f_c' - \frac{P}{A_g}\right) t_w (l_w - c)^2 \quad (6)$$

Engineered features $\boldsymbol{X}$, $\widetilde{\boldsymbol{X}}$, $\boldsymbol{X_{poly}}$, $\widetilde{\boldsymbol{X}}_{\boldsymbol{poly}}$

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Basic relations

$$\frac{V_u}{A_g f_c'} \mathrel{\underset{\sim}{\propto}} 1 \quad (1)$$

$$\frac{V_u}{A_g f_c'} \mathrel{\underset{\sim}{\propto}} \frac{\mathrm{\rho_{wh} f_{ywh}}}{f_c'} \frac{\mathrm{h_w}}{l_\mathrm{w}} \quad (2)$$

$$\frac{V_u}{A_g f_c'} \mathrel{\underset{\sim}{\propto}} \frac{\mathrm{\rho_{wv} f_{ywv}}}{f_c'} \frac{l_\mathrm{w}}{\mathrm{h_{eff}}} \quad (3)$$

$$\frac{V_u}{A_g f_c'} \mathrel{\underset{\sim}{\propto}} \frac{\rho_{be} \mathrm{f}_{ybe}}{f_c'} \frac{c}{l_\mathrm{w}} \frac{l_\mathrm{w}}{\mathrm{h_{eff}}} \quad (4)$$

$$\frac{V_u}{A_g f_c'} \mathrel{\underset{\sim}{\propto}} \left(1 + \frac{\mathrm{P}}{\mathrm{A_g f_c'}}\right) \frac{c}{l_\mathrm{w}} \frac{l_\mathrm{w}}{\mathrm{h_{eff}}} \quad (5)$$

$$\frac{V_u}{A_g f_c'} \mathrel{\underset{\sim}{\propto}} \left(1 - \frac{\mathrm{P}}{\mathrm{A_g f_c'}}\right) \frac{l_\mathrm{w}}{\mathrm{h_{eff}}}^2 \quad (6)$$

Engineered features $\boldsymbol{X}$, $\widetilde{\boldsymbol{X}}$, $\boldsymbol{X}_{poly}$, $\widetilde{\boldsymbol{X}}_{poly}$

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- Artificial Neural Network (ANN)
- Random Forest (RF) Regression
- 10 Elastic Net Models (ENMs)

Model	Reference
1	$y \sim \mathbf{X}$
2	$y \sim \widetilde{\mathbf{X}}$
3	$\sqrt[3]{y} \sim \widetilde{\mathbf{X}}$
4	$\log(y) \sim \widetilde{\mathbf{X}}$
5	$y \sim \mathbf{X}_{\mathbf{poly}}$
6	$\sqrt[3]{y} \sim \mathbf{X}_{\mathbf{poly}}$
7	$\log(y) \sim \mathbf{X}_{\mathbf{poly}}$
8	$y \sim \widetilde{\mathbf{X}}_{\mathbf{poly}}$
9	$\sqrt[3]{y} \sim \widetilde{\mathbf{X}}_{\mathbf{poly}}$
10	$\log(y) \sim \widetilde{\mathbf{X}}_{\mathbf{poly}}$

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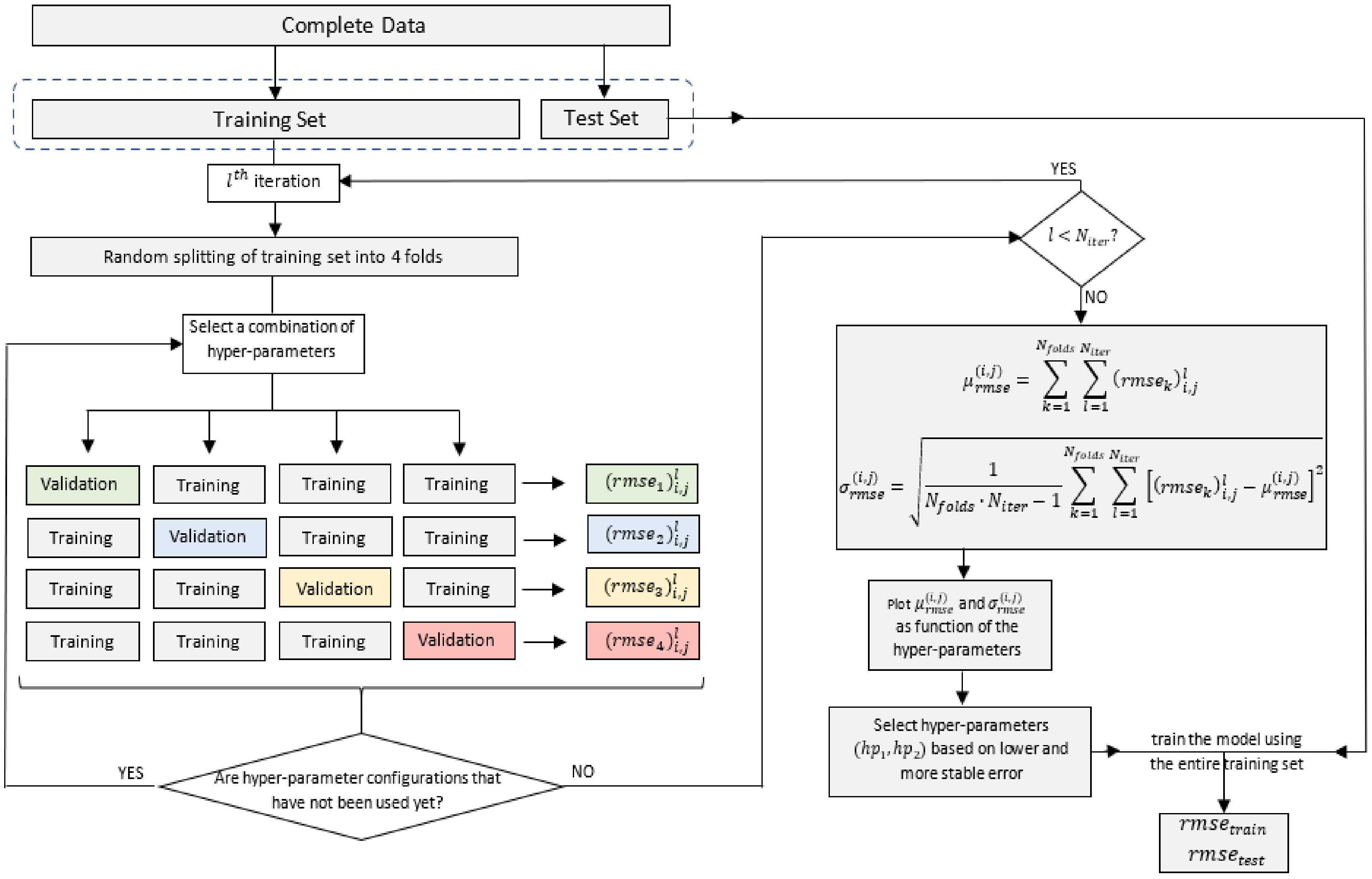
- Algorithm to assess the sensitivity analysis on the hyper parameters



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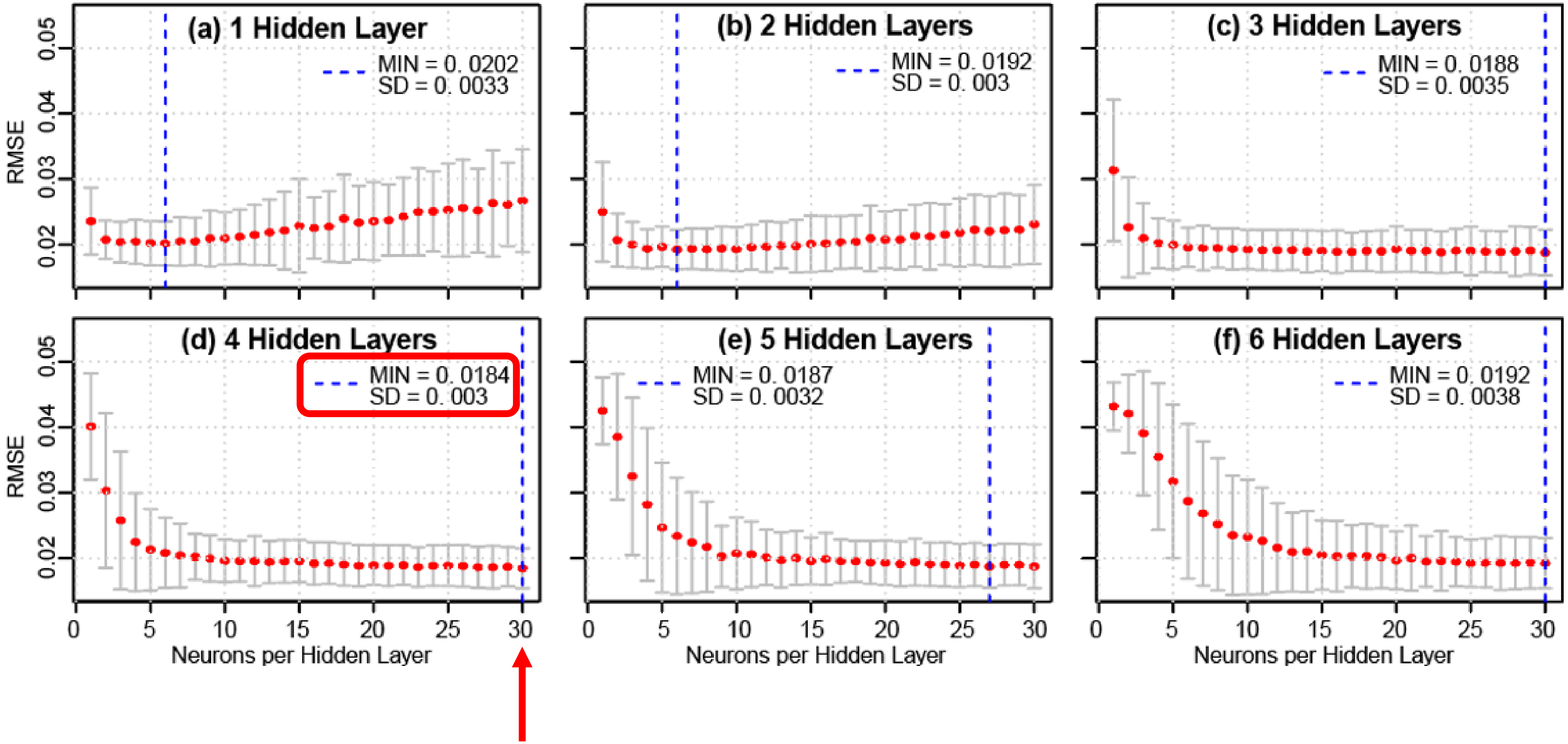
- Artificial Neural Network

Sensitivity Analysis → 180 ANN were trained



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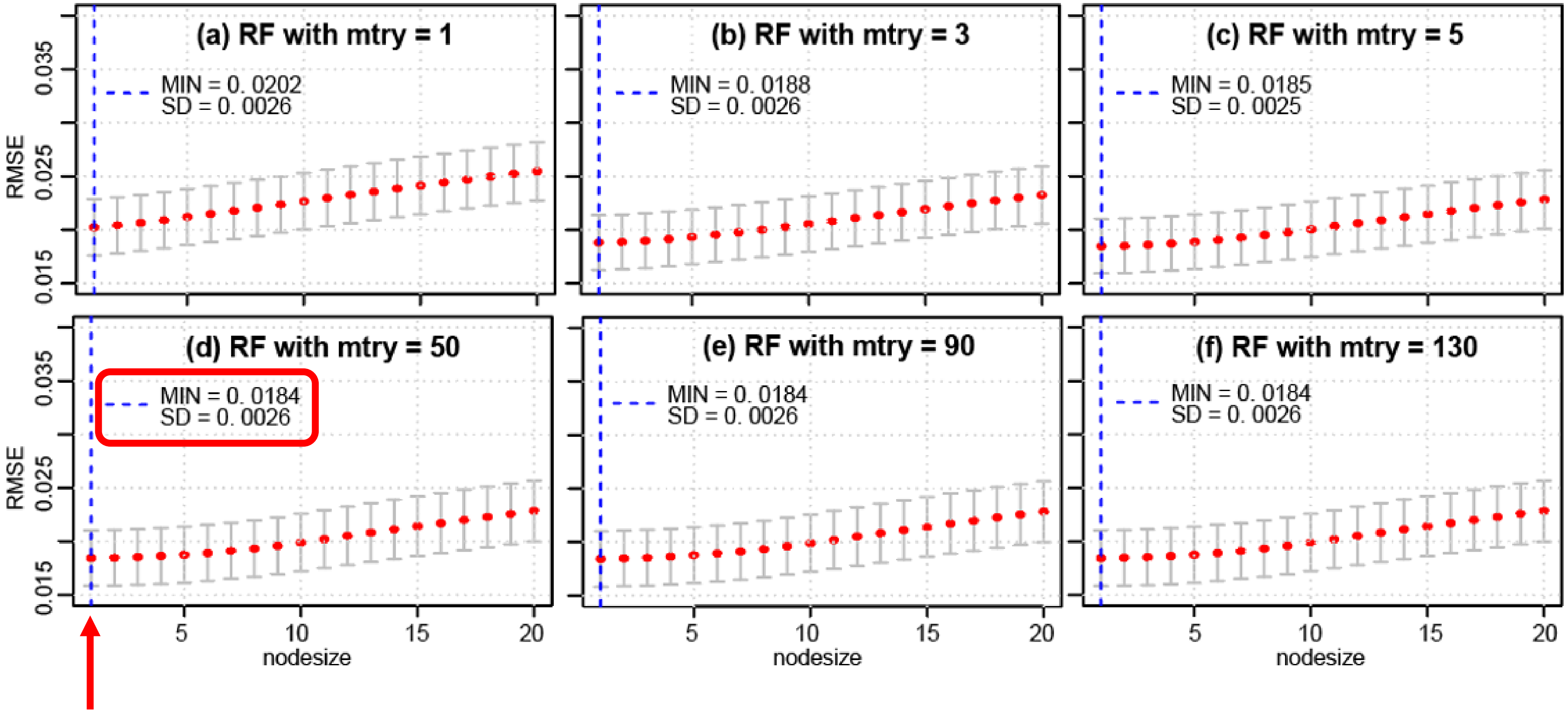
- RF Regression

Sensitivity Analysis → 120 RF Regressions were trained



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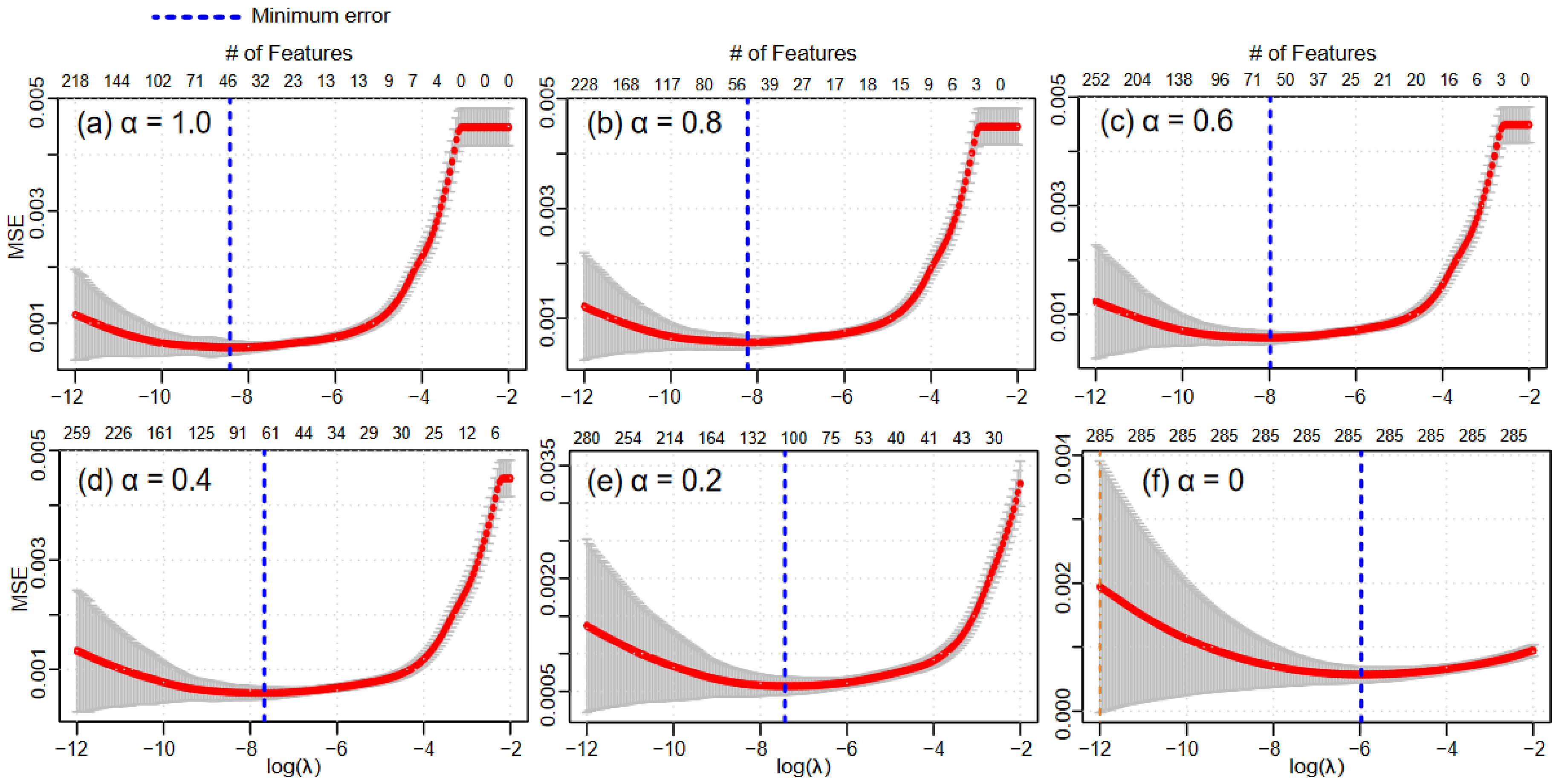
- ENM

Sensitivity Analysis → 10 models



Sensitivity analysis results for ENM6: $\sqrt[3]{y_j} \sim N(\mu_j, \sigma), \mu_j = \mathrm{x}'_{\mathrm{poly}_j}\beta$.

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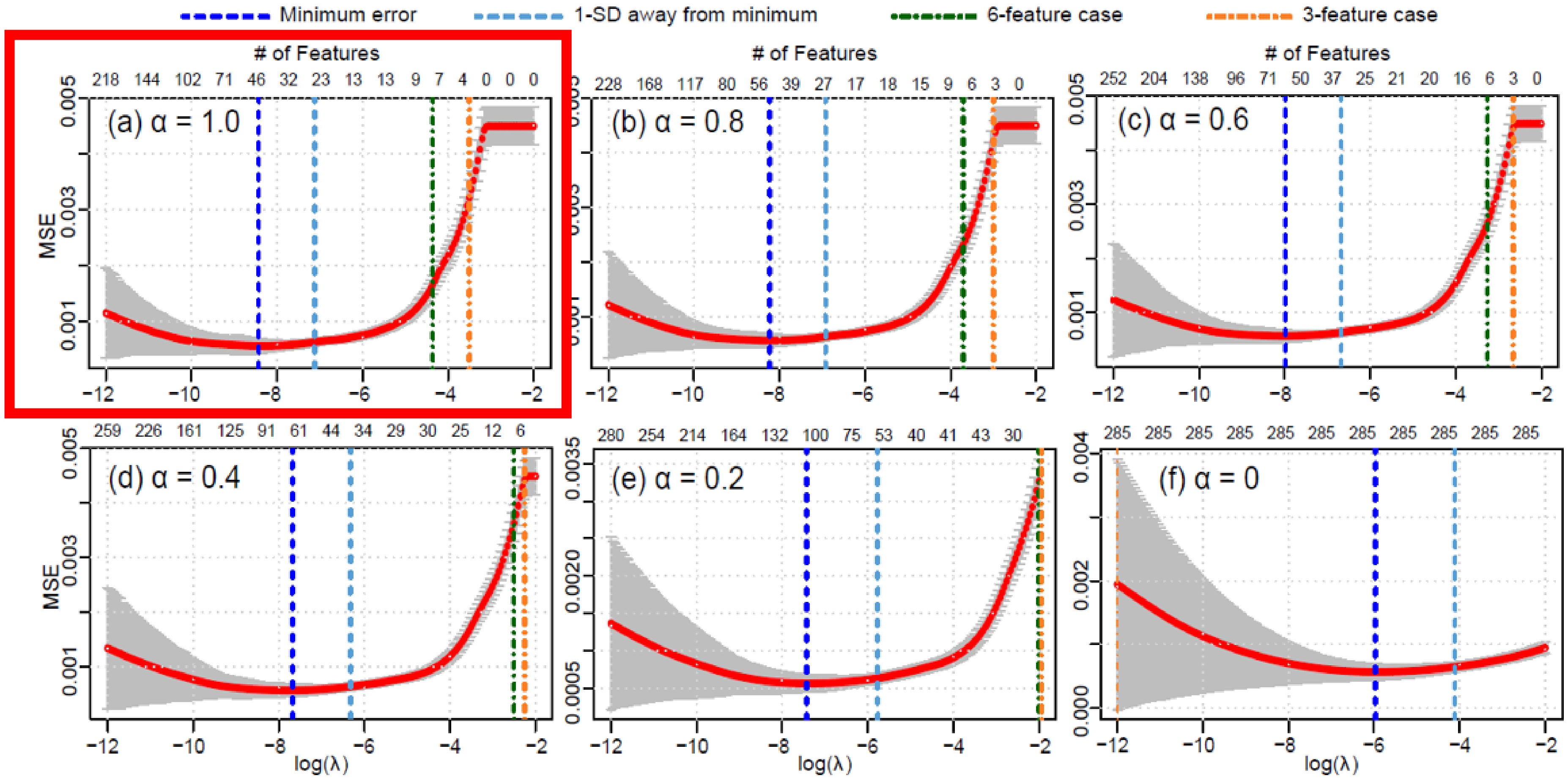
- # ENM

Sensitivity Analysis → (10 models) x (4 complexity levels) = 40 ENMs are selected



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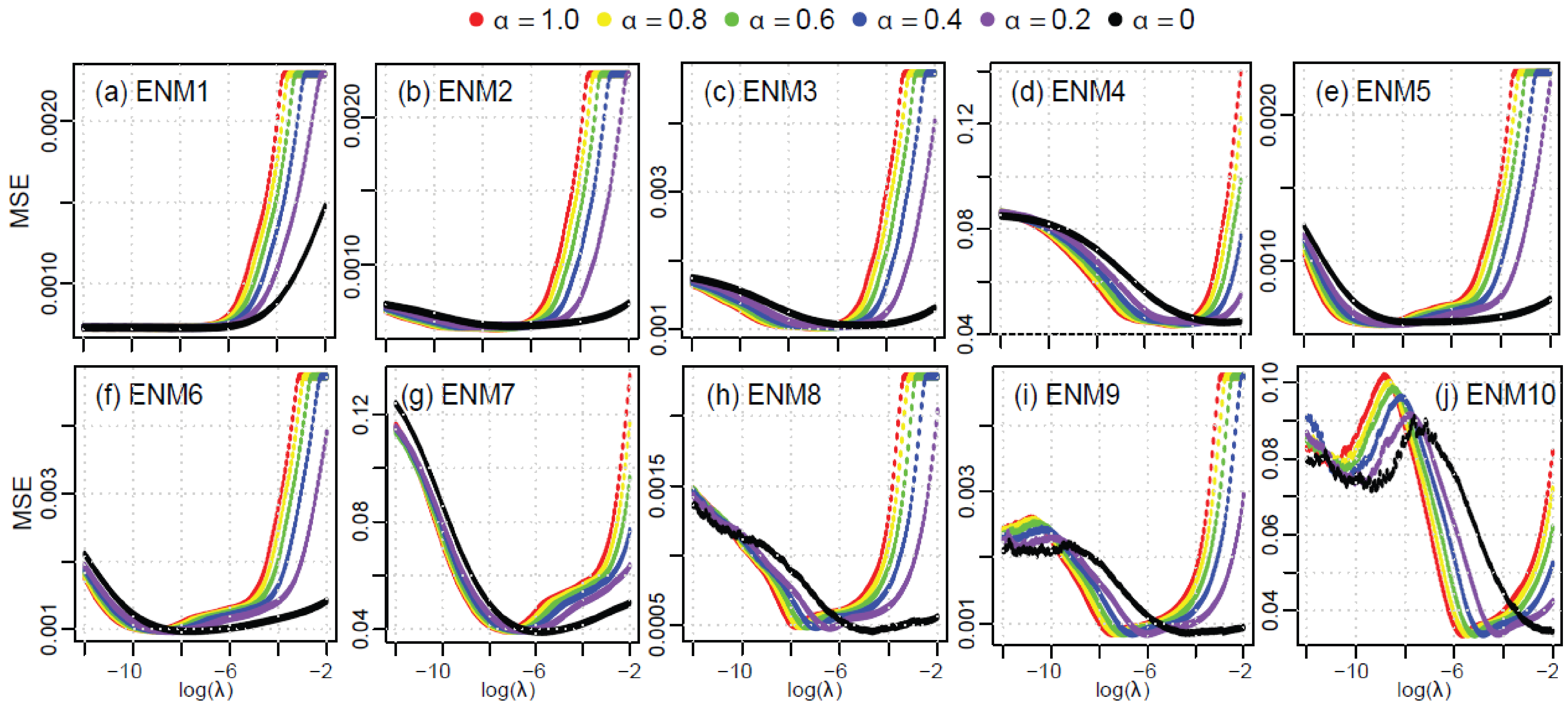

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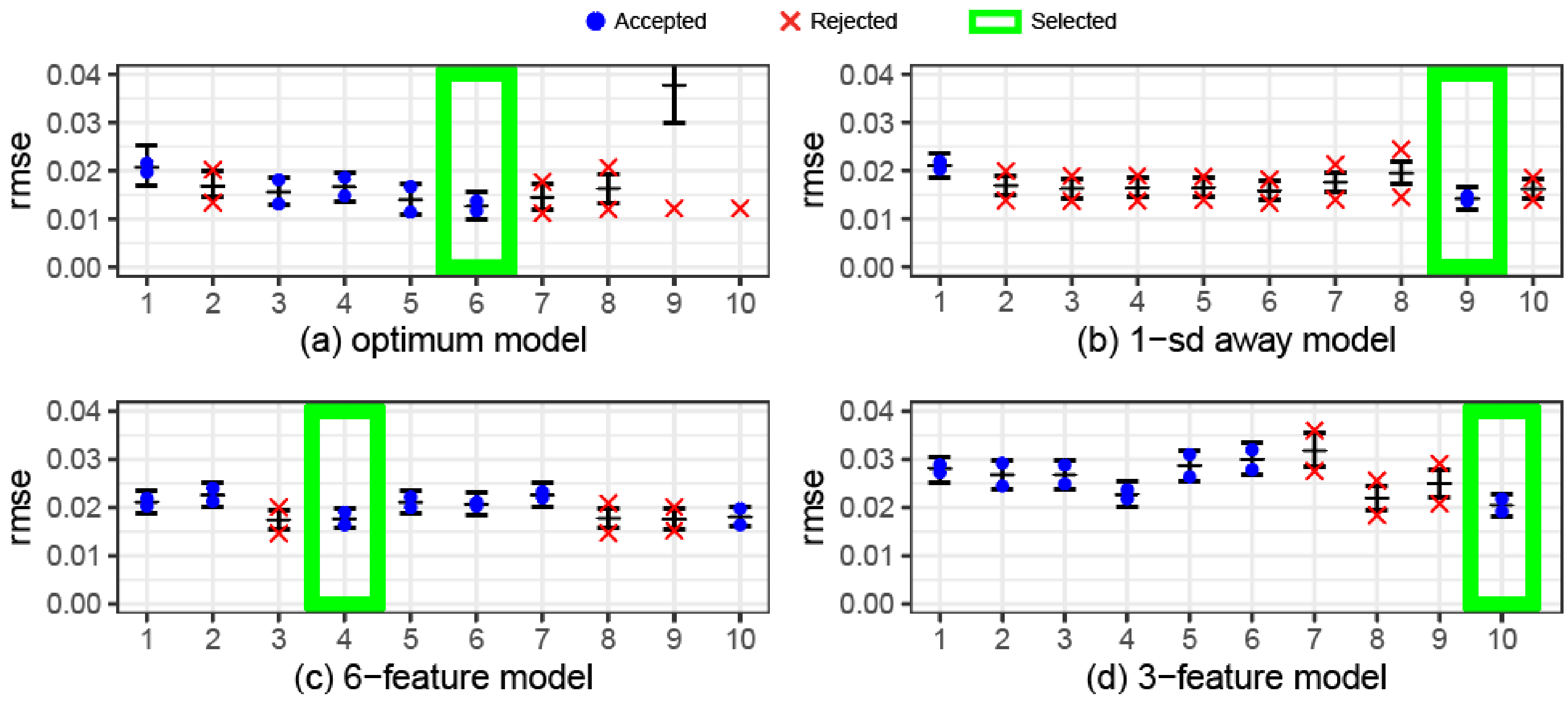
- Selected LASSO Models

Acceptance Criterion
- Optimum Model Version: Converging Error ± 20%
- Underfitted Model Version: Converging Error ± 10%



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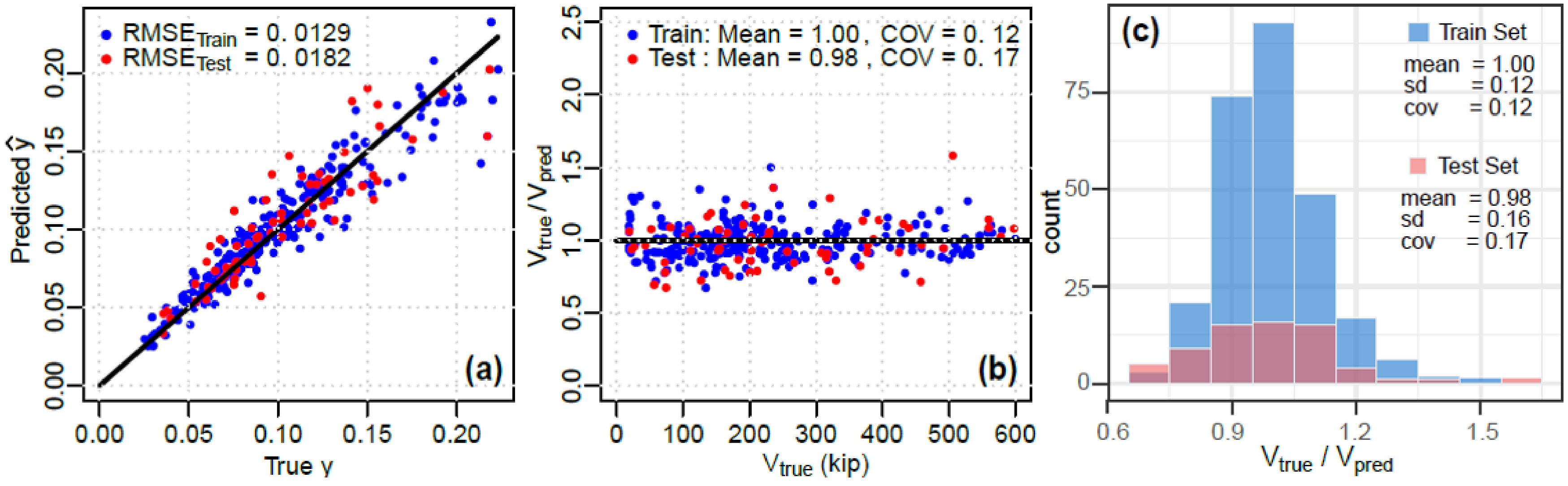
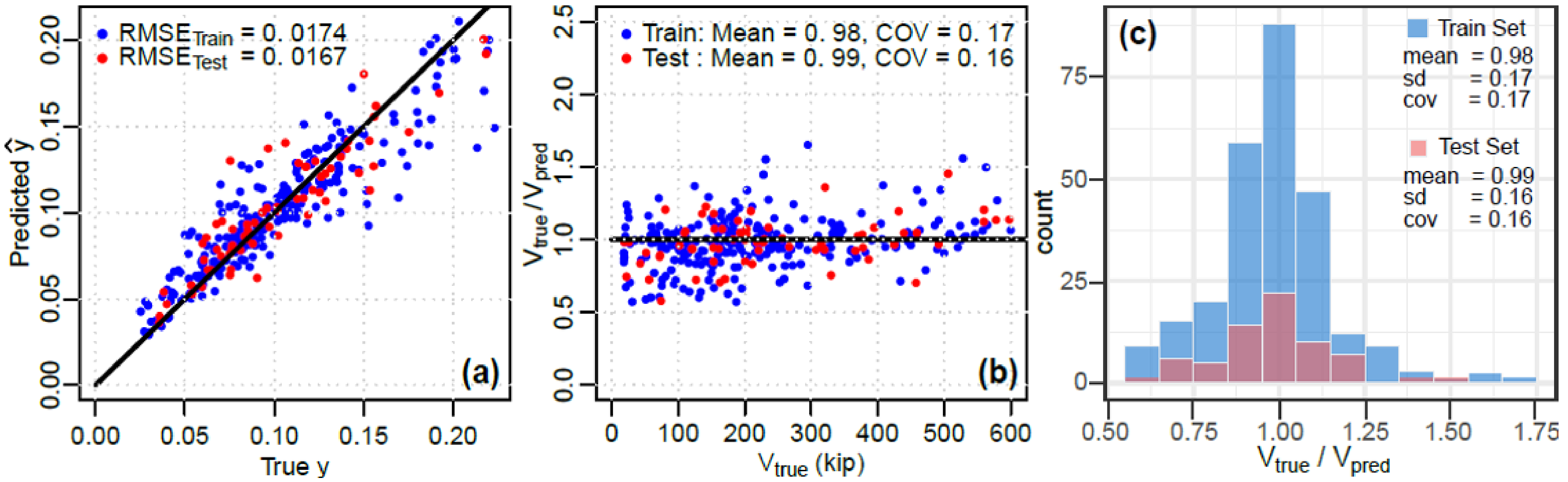
- Selected ANN



- Selected RF Regression



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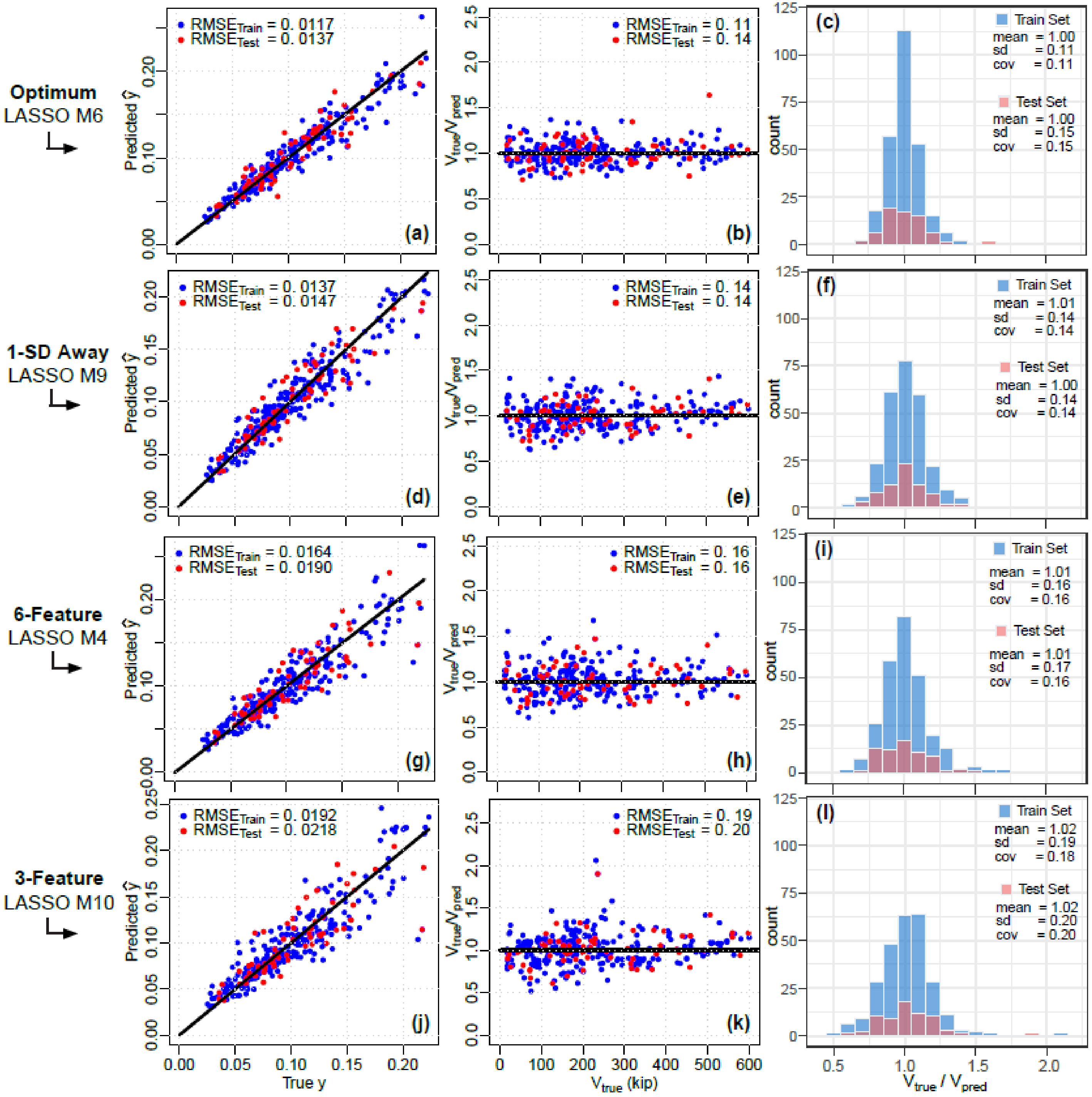

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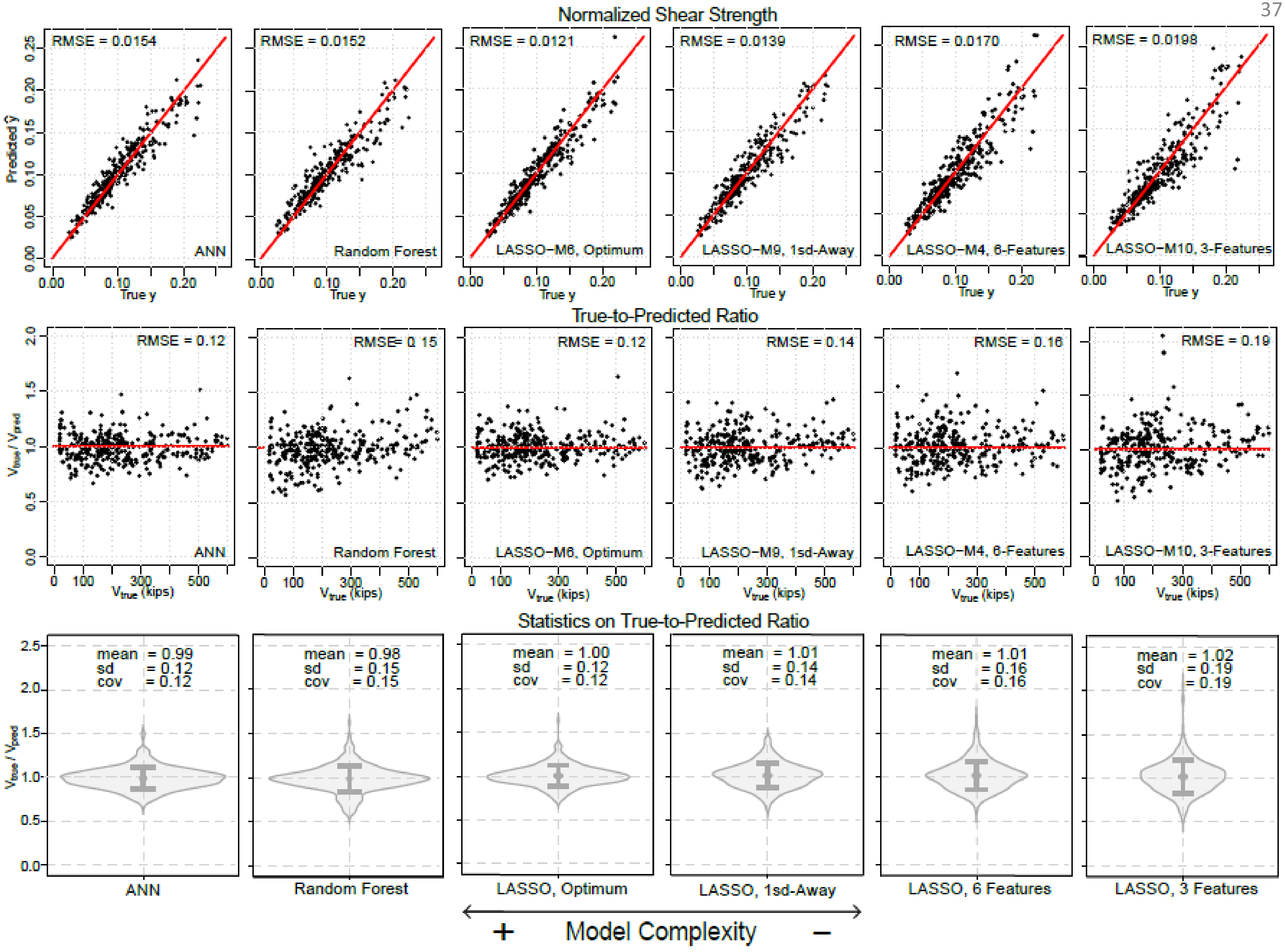

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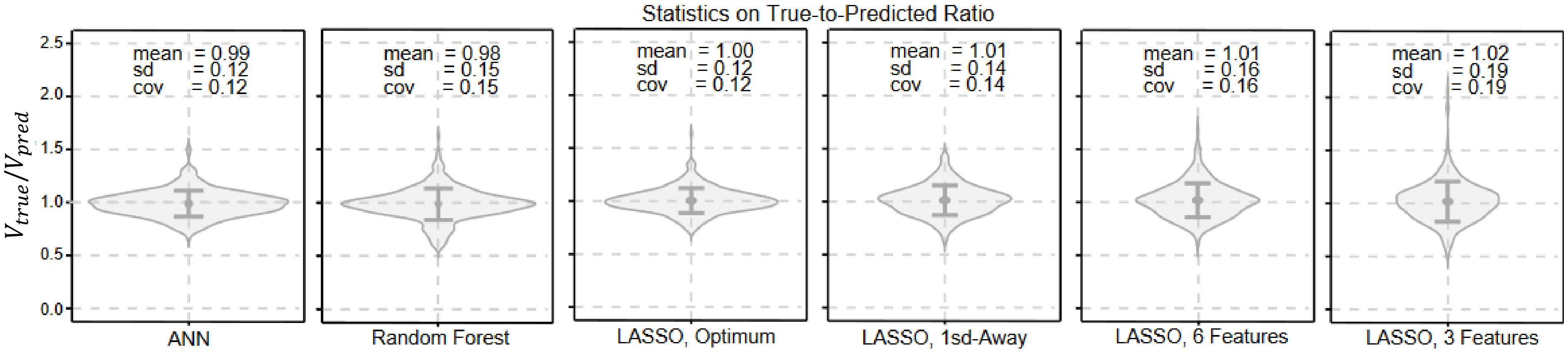
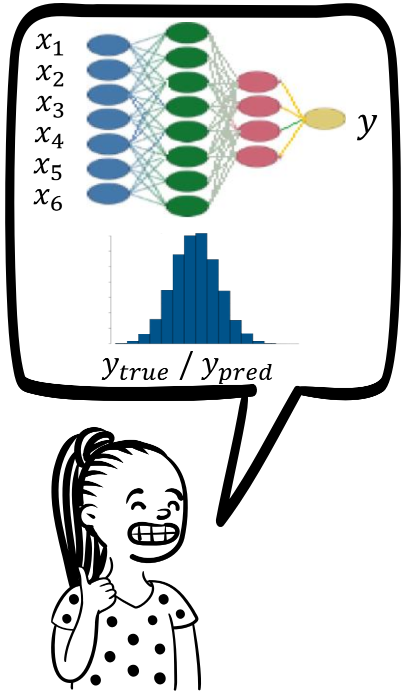
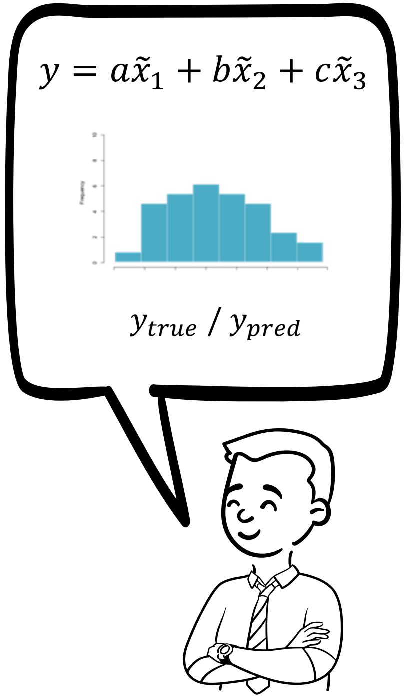
Target Errors for Different Model Complexity Levels





+ Model Complexity -



(1) Collection and preparation of data

(2) Feature selection
- Mechanics + Literature Review
- Normalized/scaled features + Mechanics → Engineered Features

(3) Choice of ML algorithm
- Complex ML model (e.g., ANN, RF regression)
- ENMs

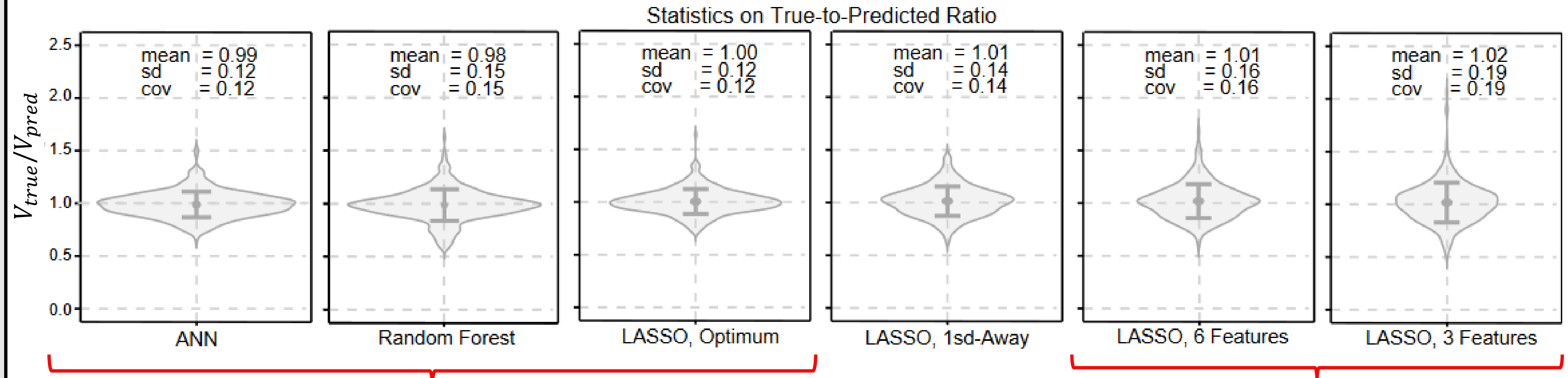
(4) Selection hyper-parameters
- Sensitivity analysis with iterative k-Fold CV
- Define underfitting levels to be used for the ENMs training

(5) Model training

(6) Model performance evaluation

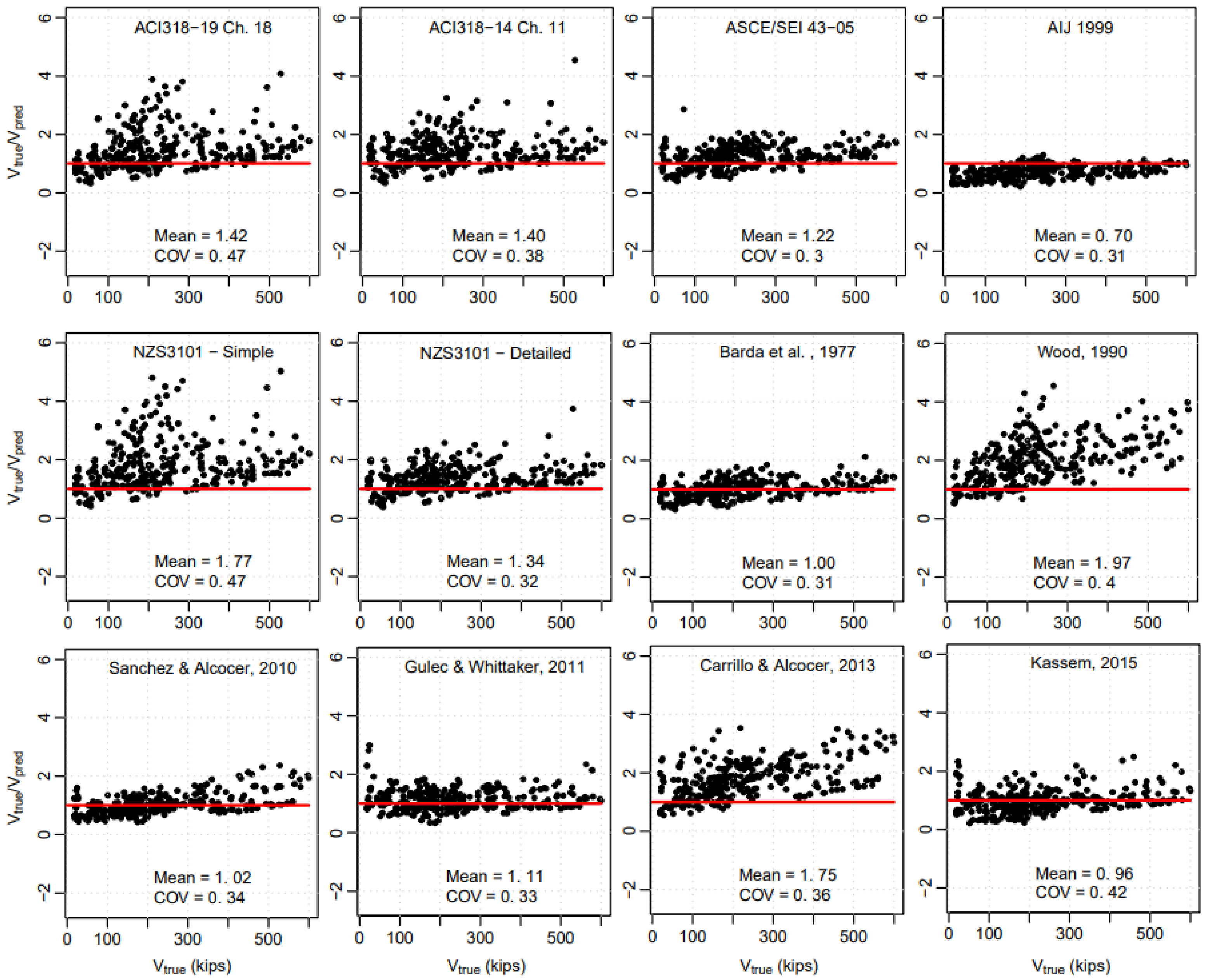
(7) Set target errors for different model complexity levels

Target Errors for Different Model Complexity Levels



Requirements	Model Complexity Level	
	Complex ML Models	**Simplified Models**
Number of parameters	-	~ 3 - 6
V_{true}/V_{pred} mean ratio	0.99 – 1.01	0.98 – 1.02
COV	$\leq$ 0.12	0.16 – 0.19
Train. vs Test. Error Margin	$\pm 20\%$ of the converging error	$\pm 10\%$ of the converging error

Assessed Models → None Meets the Requirements



Part 3

Methodology to Get an Equation with a Code-Oriented Format

Methodology to Get an Equation with a Code-Oriented Format

(1) Identification of relevant parameters

(2) Differentiate parameters between:

- Materiality-related parameters (V_i)
- Other parameters $(\gamma_{j,i})$

(3) Re-arrange parameters ("$V_c + V_s$" format):

$$V_n = \beta_0 V_c + \sum_{i}^{N_i} \beta_i \left(\prod_{j}^{N_j} \gamma_{j,i} \right) V_i$$

(4) Re-write equation in its normalized version

(5) Train model

(6) Drop less significant variable until reaching target error

(7) Verify performance

(1) Identification of relevant parameters

(2) Differentiate parameters between:
- Materiality-related parameters (V_i)
- Other parameters $(\gamma_{j,i})$

(3) Re-arrange parameters into this equation format:

$$V_n = \beta_0 V_c + \sum_i^{N_i} \beta_i \left(\prod_j^{N_j} \gamma_{j,i} \right) V_i$$

(4) Re-write the equation in its normalized version

(5) Use iterative k-fold analysis to find regression coefficients and p-values

(6) Drop less significant parameter and go back to step (5) until reaching the target error

(7) Verify performance of the proposed equation

$$y = \beta_0 + \beta_1 \left(\frac{M_u}{V_u l_w}\right)^{a_c} \left(\frac{h_w}{l_w}\right)^{b_c} \left(1 + \frac{P_u}{A_g f_c'}\right)^{c_c}$$

$$+ \beta_2 \left(\frac{M_u}{V_u l_w}\right)^{a_{be}} \left(\frac{h_w}{l_w}\right)^{b_{be}} \left(1 + \frac{P_u}{A_g f_c'}\right)^{c_{be}} \frac{\rho_{be} f_{ybe}}{f_c'} \frac{A_{be}}{A_g}$$

$$+ \beta_3 \left(\frac{M_u}{V_u l_w}\right)^{a_{wh}} \left(\frac{h_w}{l_w}\right)^{b_{wh}} \left(1 + \frac{P_u}{A_g f_c'}\right)^{c_{wh}} \frac{\rho_{wh} f_{ywh}}{f_c'} \frac{A_{cv}}{A_g}$$

$$+ \beta_4 \left(\frac{M_u}{V_u l_w}\right)^{a_{wv}} \left(\frac{h_w}{l_w}\right)^{b_{wv}} \left(1 + \frac{P_u}{A_g f_c'}\right)^{c_{wv}} \frac{\rho_{wv} f_{ywv}}{f_c'} \frac{A_{cv}}{A_g}$$

$$V_n = \alpha_c A_g' f_c' + \alpha_s (\rho_{sb} f_y + \rho_{wh} f_{ywh}) A_{cv}$$

(1) Identification of relevant parameters

(2) Differentiate parameters between:

- Materiality-related parameters (V_i)
- Other parameters ($\gamma_{j,i}$)

(3) Re-arrange parameters into this equation format:

$$V_n = \beta_0 V_c + \sum_i^{N_i} \beta_i \left(\prod_j^{N_j} \gamma_{j,i} \right) V_i$$

(4) Re-write the equation in its normalized version

(5) Use iterative k-fold to find regression coefficients and p-values

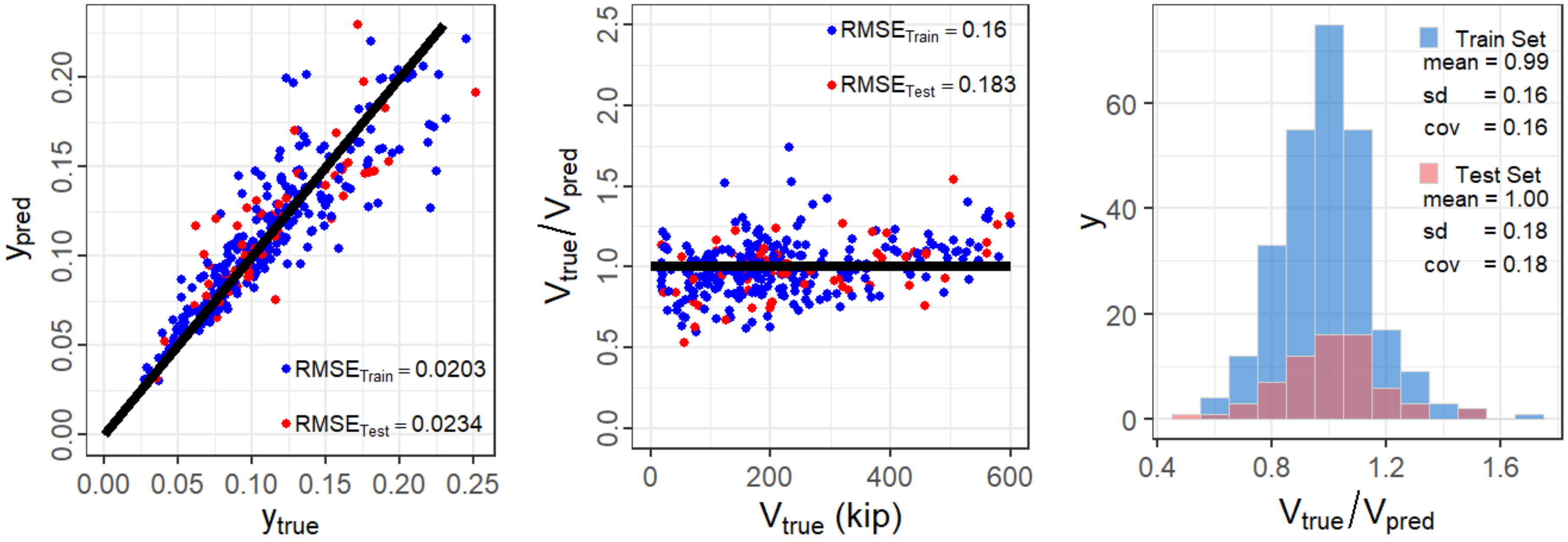
(6) Drop less significant parameter and go back to step (5) until reaching the target error

(7) Verify performance of the proposed equation

- Performance verification – Symmetrical Walls

$$V_n = \alpha_c A_g' f_c' + \alpha_s \left(\rho_{sb} f_y + \rho_{wh} f_{ywh} \right) A_{cv}$$

$$\alpha_c = \frac{1}{100} \left(9 \frac{\left(1 + \frac{P_u}{A_g' f_c'} \right)^3}{\left(\frac{M_u}{V_u l_w} \right)^{1/3}} - 6 \right) \qquad \alpha_s = \frac{2}{5 \left(\frac{M_u}{V_u l_w} \right)^{1/3}}$$



(1) Identification of relevant parameters

(2) Differentiate parameters between:
- Materiality-related parameters (V_i)
- Other parameters ($\gamma_{j,i}$)

(3) Re-arrange parameters into this equation format:

$$V_n = \beta_0 V_c + \sum_{i}^{N_i} \beta_i \left(\prod_{j}^{N_j} \gamma_{j,i} \right) V_i$$

(4) Re-write the equation in its normalized version

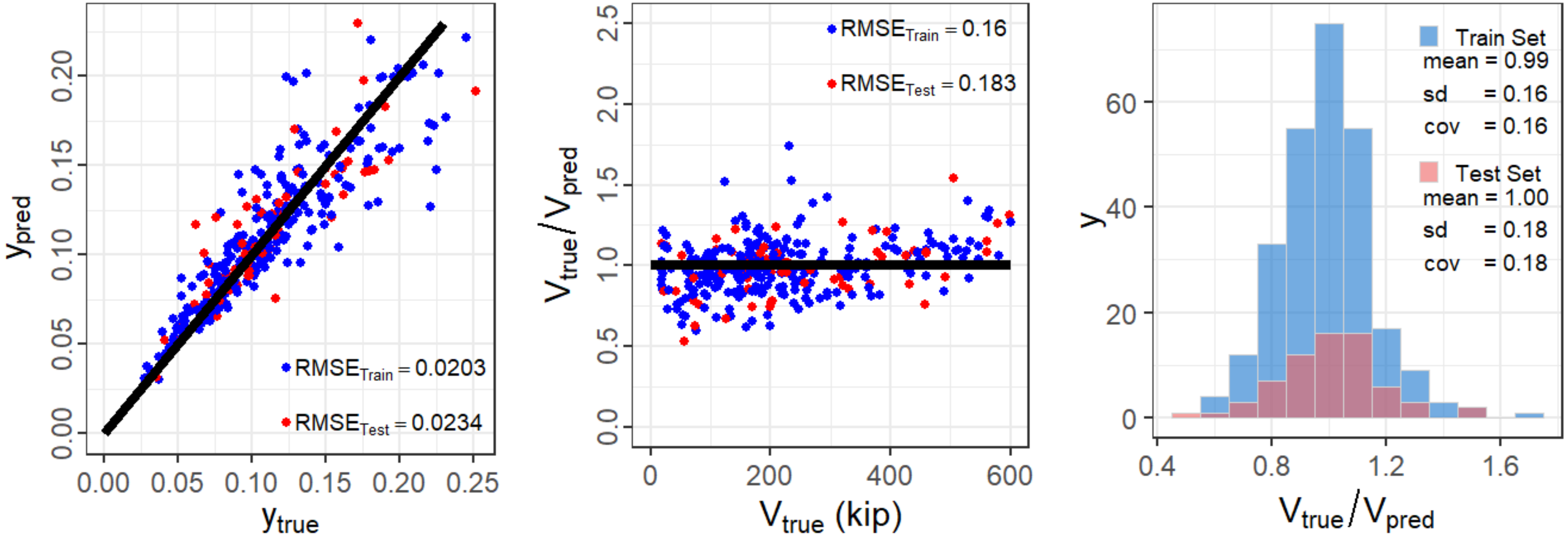
(5) Use iterative k-fold to find regression coefficients and p-values

(6) Drop less significant parameter and go back to step (5) until reaching the target error

(7) Verify performance of the proposed equation

• Performance verification – Symmetrical Walls

Requirements	Simple Models	
Number of parameters	~ 3 - 6	✓
V_{true}/V_{pred} mean ratio	0.98 – 1.02	✓
COV	0.16 – 0.19	✓
Train. vs Test. Error Margin	$\pm 10\%$ of the converging error	✓



(1) Identification of relevant parameters

(2) Differentiate parameters between:
- Materiality-related parameters (V_i)
- Other parameters ($\gamma_{j,i}$)

(3) Re-arrange parameters into this equation format:

$$V_n = \beta_0 V_c + \sum_{i}^{N_i} \beta_i \left(\prod_{j}^{N_j} \gamma_{j,i} \right) V_i$$

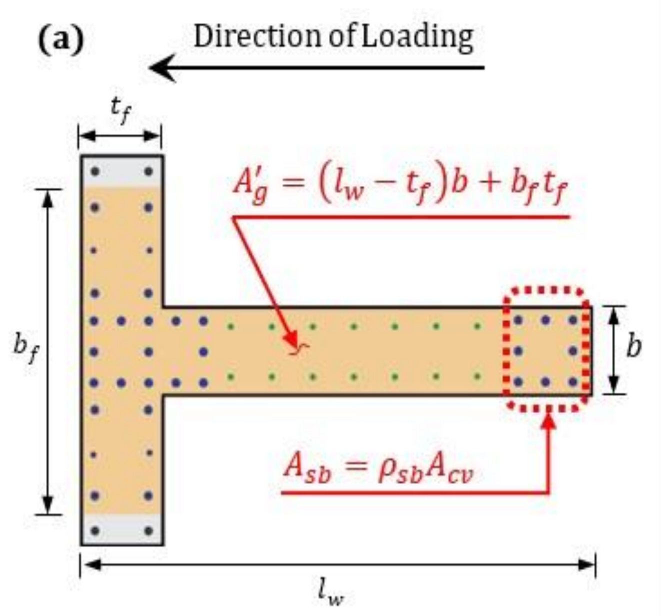
(4) Re-write the equation in its normalized version

(5) Use iterative k-fold to find regression coefficients and p-values

(6) Drop less significant parameter and go back to step (5) until reaching the target error

(7) Verify performance of the proposed equation

• Performance verification – Asymmetrical Walls



(a) Flange in Compression	(b) Flange in Tension
A'_g = Cross-sectional A_{cv} area plus the area of the compressed overhanging effective flange = $b_f t_f + (l_w - t_f)b \le 1.5A_{cv}$	A'_g = Cross-sectional A_{cv} area plus the area of the compressed overhanging effective flange = $l_w b$
A_{sb}= Area of longitudinal reinforcement at the wall boundary in tension including area within effective flange width = all the area of longitudinal reinforcement at the right side in this case	A_{sb}= Area of longitudinal reinforcement at the wall boundary in tension including area within effective flange width = Area of longitudinal reinforcement at the left side in this case, excluding one layer of bars at each side of the flange

(1) Identification of relevant parameters

(2) Differentiate parameters between:
- Materiality-related parameters (V_i)
- Other parameters $(\gamma_{j,i})$

(3) Re-arrange parameters into this equation format:

$$V_n = \beta_0 V_c + \sum_i^{N_i} \beta_i \left(\prod_j^{N_j} \gamma_{j,i} \right) V_i$$

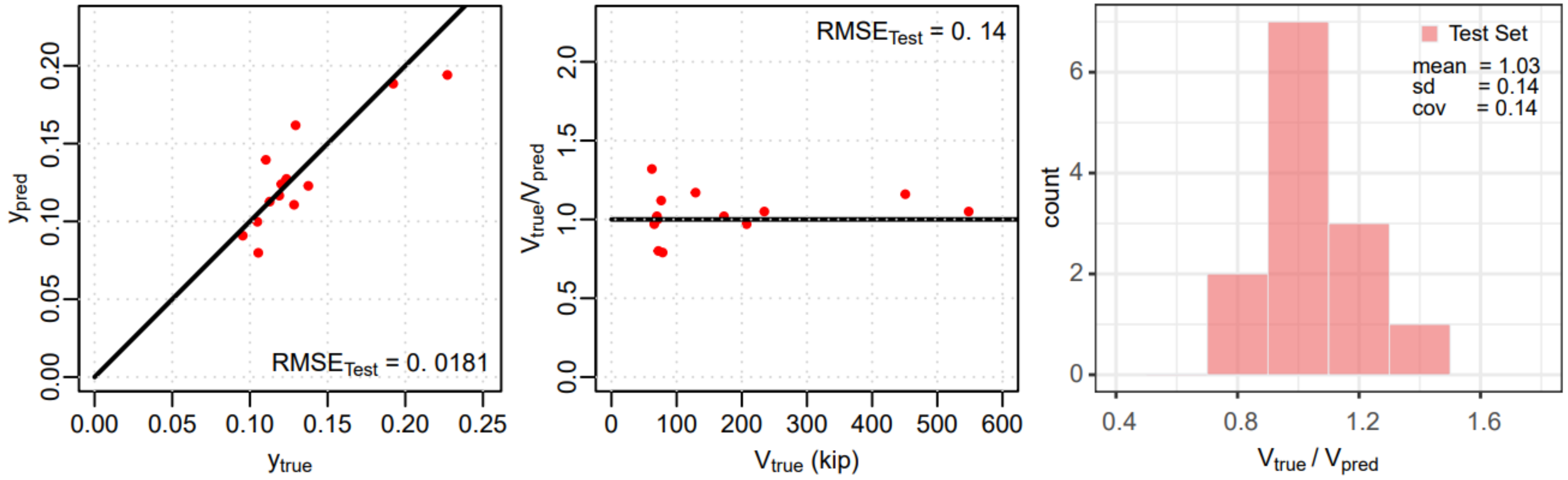
(4) Re-write the equation in its normalized version

(5) Use iterative k-fold to find regression coefficients and p-values

(6) Drop less significant parameter and go back to step (5) until reaching the target error

(7) Verify performance of the proposed equation

- Performance verification – Asymmetrical Walls



Still need to address more points:

(1) Does the equation make sense?

(Contribution from each term, parameter ranges, etc.)

(2) How to use the equation on asymmetrical cross-section-shaped walls? (already addressed)

(3) Modification of wall shear strength upper limit?

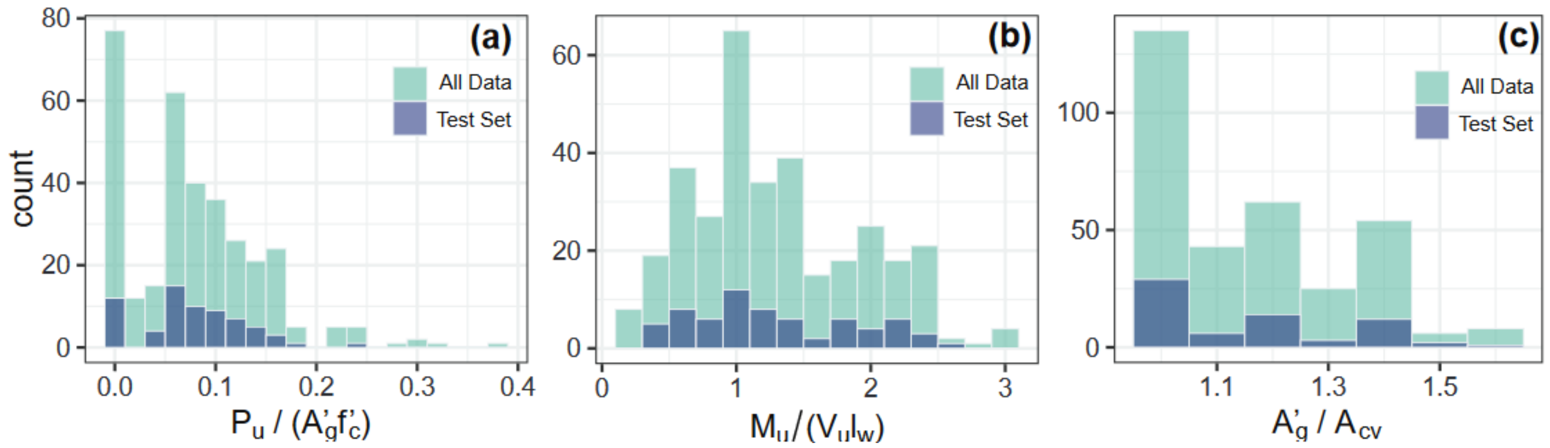
(4) Is the model complexity level acceptable?

(5) How to use the equation in the design?

(6) Consequences of the equation in the design

Part 4
Further Analyses of the Proposed Equation

Parameter Ranges Limitations



$$\textbf{(1)} \quad 0 \le \frac{P_u}{A'_g f'_c} \le 0.20$$

$$\frac{M_u}{V_u l_w} \le 2.5$$

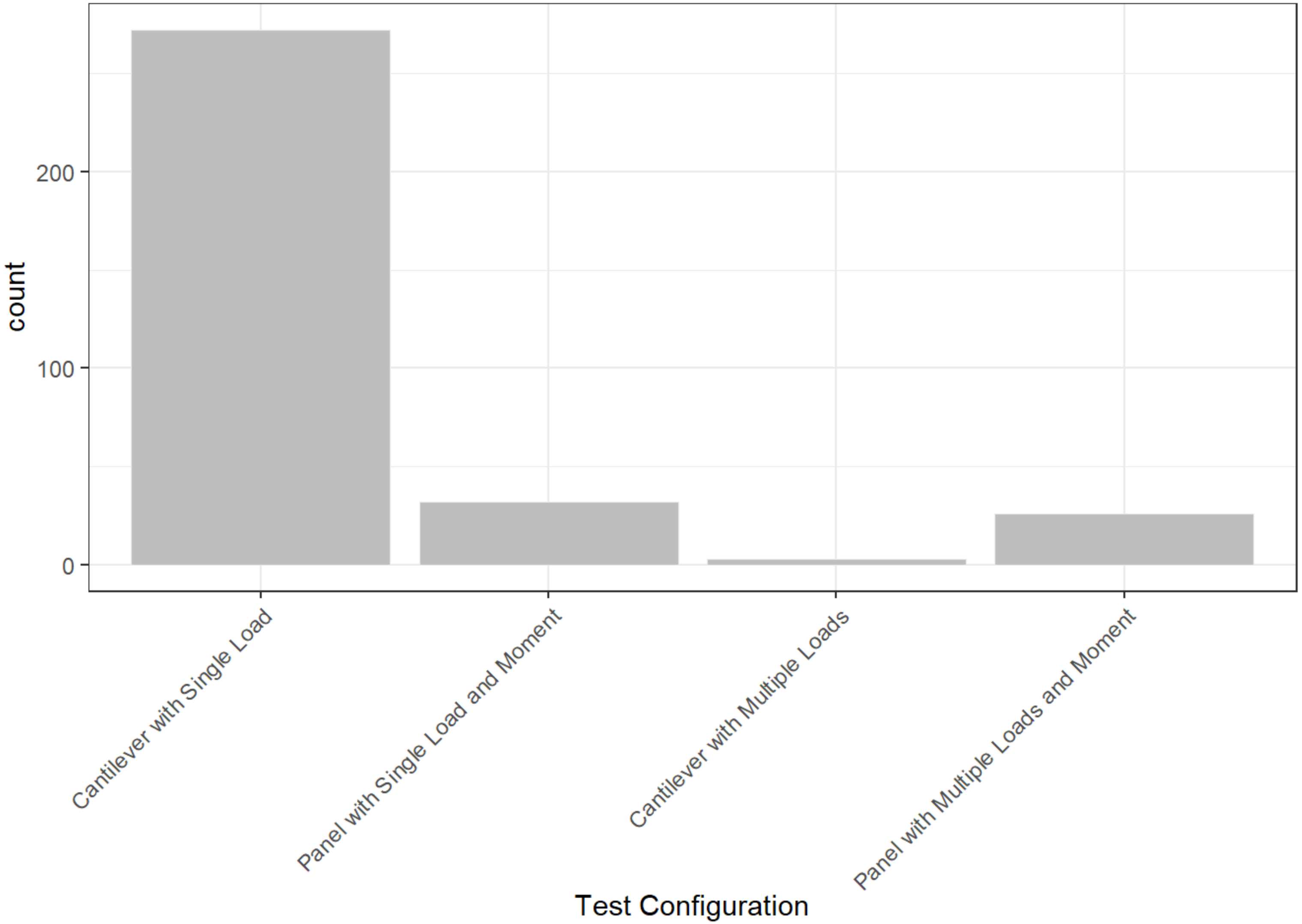
$$\textbf{(2)} \quad \frac{A'_g}{A_{cv}} \le 1.5$$

$$\alpha_s = \frac{2}{5\left(\frac{M_u}{V_u l_w}\right)^{1/3}} \ge 0.30 \qquad \textbf{(3)}$$

$$\frac{M_u}{V_u l_w} = 2.5 \;\; \& \;\; \frac{P_u}{A'_g f'_c} = 0.02 \longrightarrow$$

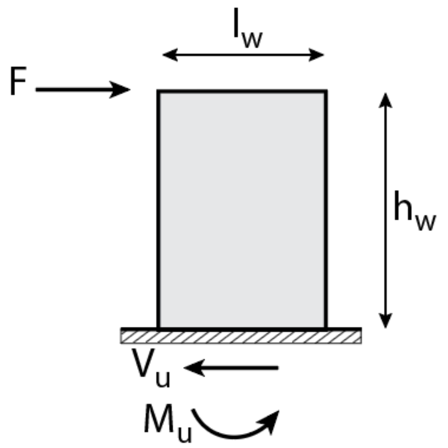
$$\alpha_c = \frac{1}{100}\left(9\frac{\left(1+\frac{P_u}{A'_g f'_c}\right)^3}{\left(\frac{M_u}{V_u l_w}\right)^{1/3}} - 6\right) \ge 0.010 \qquad \textbf{(4)}$$

Use of $M_u/(V_u l_w)$ instead of h_w/l_w



Use of $M_u/(V_u l_w)$ instead of h_w/l_w

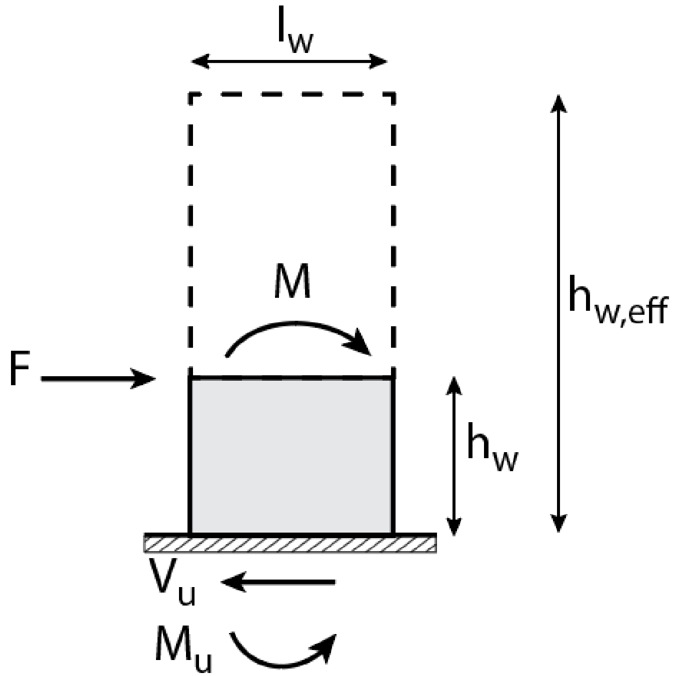
- Cantilever walls with single load applied near the top



$$\frac{M_u}{V_u l_w} = \frac{F\, h_u}{V_u l_w} = \frac{V_u h_u}{V_u l_w} = \frac{h_w}{l_w}$$

- Partial height wall with applied lateral load and moment at the top

It is necessary to define a $h_{w,\text{eff}}$ to prior computing the aspect ratio $h_{w,\text{eff}}/l_w$



$$h_{w,\text{eff}} = \frac{M_u}{V_u} \longrightarrow \frac{h_{w,\text{eff}}}{l_w} = \frac{M_u}{V_u l_w}$$

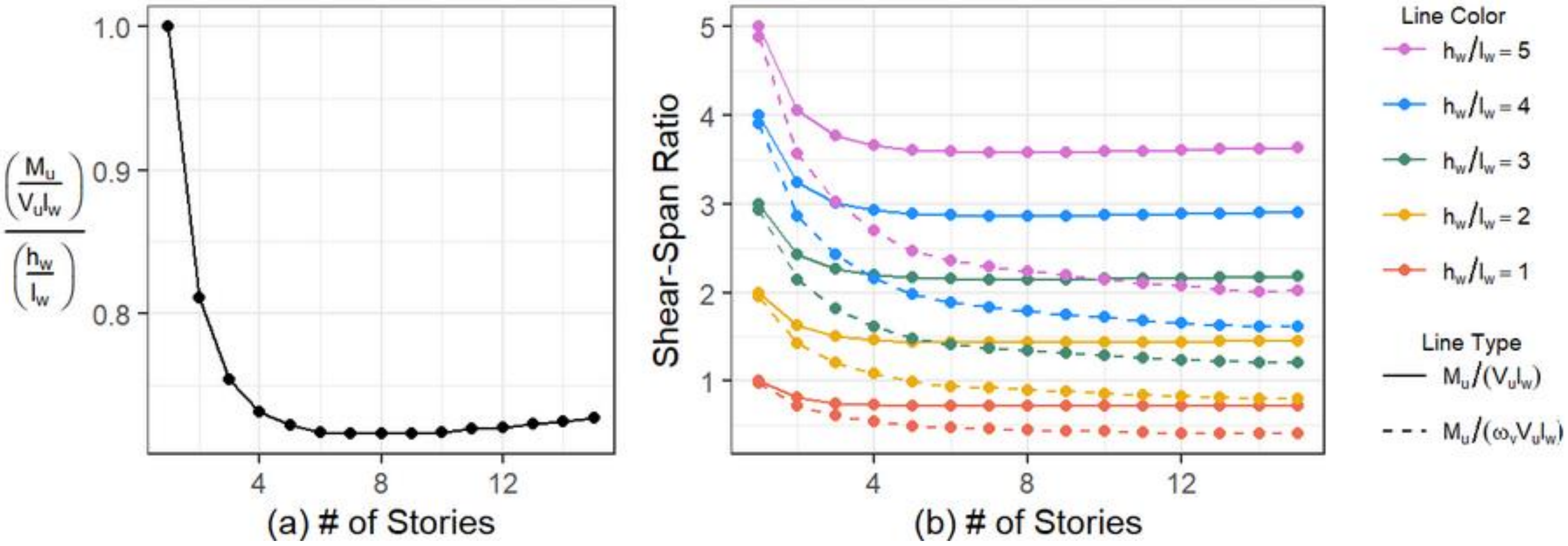
Shear-Span Ratio in the Design Process

Overstrength amplification / Dynamic amplification

Shear Demand → $V_e = \omega_v \Omega_v V_u$

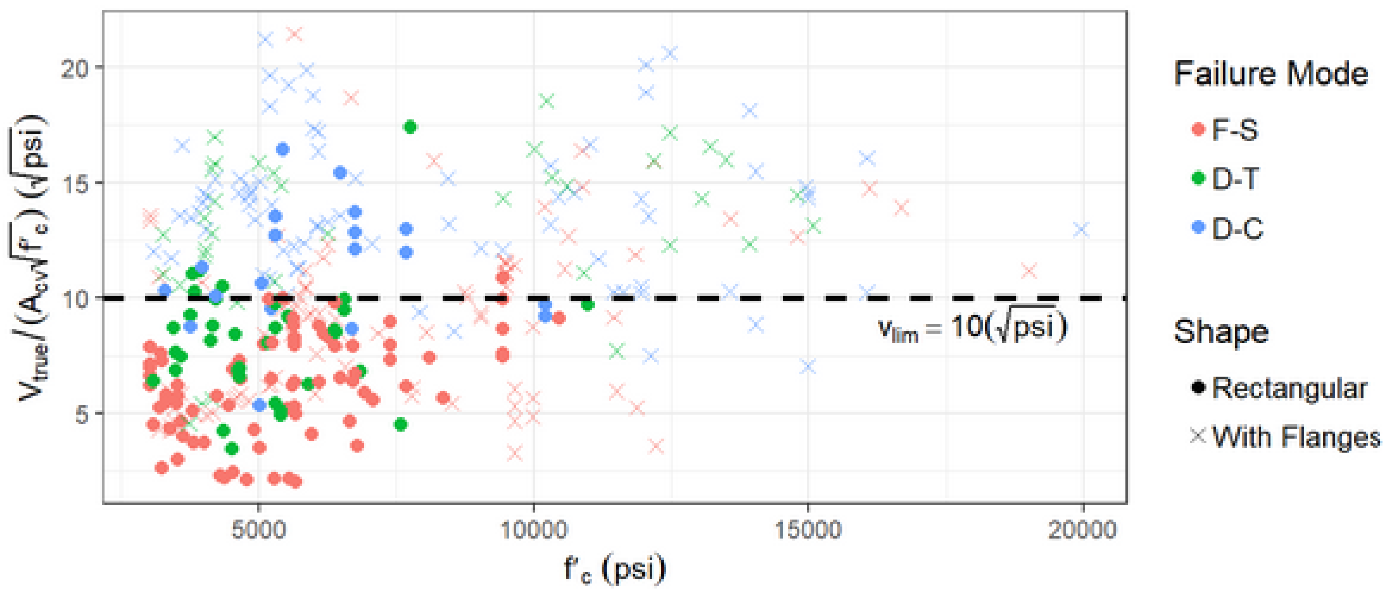
Moment Demand → $M_{pr} = \Omega_v M_u$

Shear-Span Ratio →
$$\frac{M_{pr}}{V_e l_w} = \frac{\Omega_v M_u}{\omega_v \Omega_v V_u l_w} = \frac{M_u}{\omega_v V_u l_w}$$



Shear Stress Upper Limit

Current limit in ACI 318-19 → $v_n = \frac{V_n}{A_{cv}} \leq 10\sqrt{f_c'}$



Shear Stress Upper Limit

Logistic Regression

$p(z) > 0.5$ → Diag.-Comp
$p(z) \leq 0.5$ → No Diag.-Comp

$$p(z) \leq 0.5 \rightarrow \frac{1}{1+e^{-z}} \leq 0.5$$

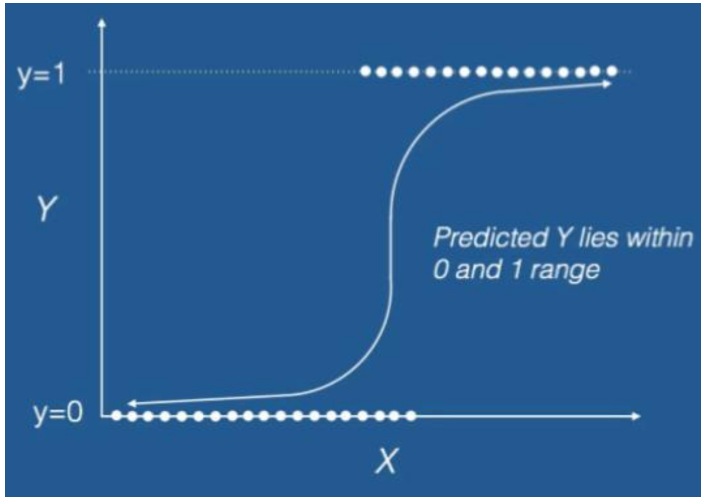
$$z \leq 0$$

$$\beta_0 + \sum_i \beta_i \tilde{x}_i \leq 0$$

$$\tilde{x}_i = \log(x_i)$$

$$\beta_0 + \sum_i \beta_i \log(x_i) \leq 0$$

$$e^{\beta_0} \prod_i x_i^{\beta_i} \leq 1$$



$$\underbrace{x_1}_{\frac{V_{true}}{A_{cv}\sqrt{f_c'}}} \leq \underbrace{e^{-\frac{\beta_0}{\beta_1}} \prod_{i\neq 1} x_i^{-\frac{\beta_i}{\beta_1}}}_{V_{lim}}$$

(1) Parameter ranges limitations

(2) Comments on $M_u/(V_u l_w)$

(3) Shear stress upper limit

(4) Steel contribution

(5) Concrete contribution

(6) Further interpretations

(7) Reliability Analysis

Shear Stress Upper Limit

$$v_n = \frac{V_n}{A_{cv}} \le \alpha_{\text{shape}}\, 10\sqrt{f_c'}$$

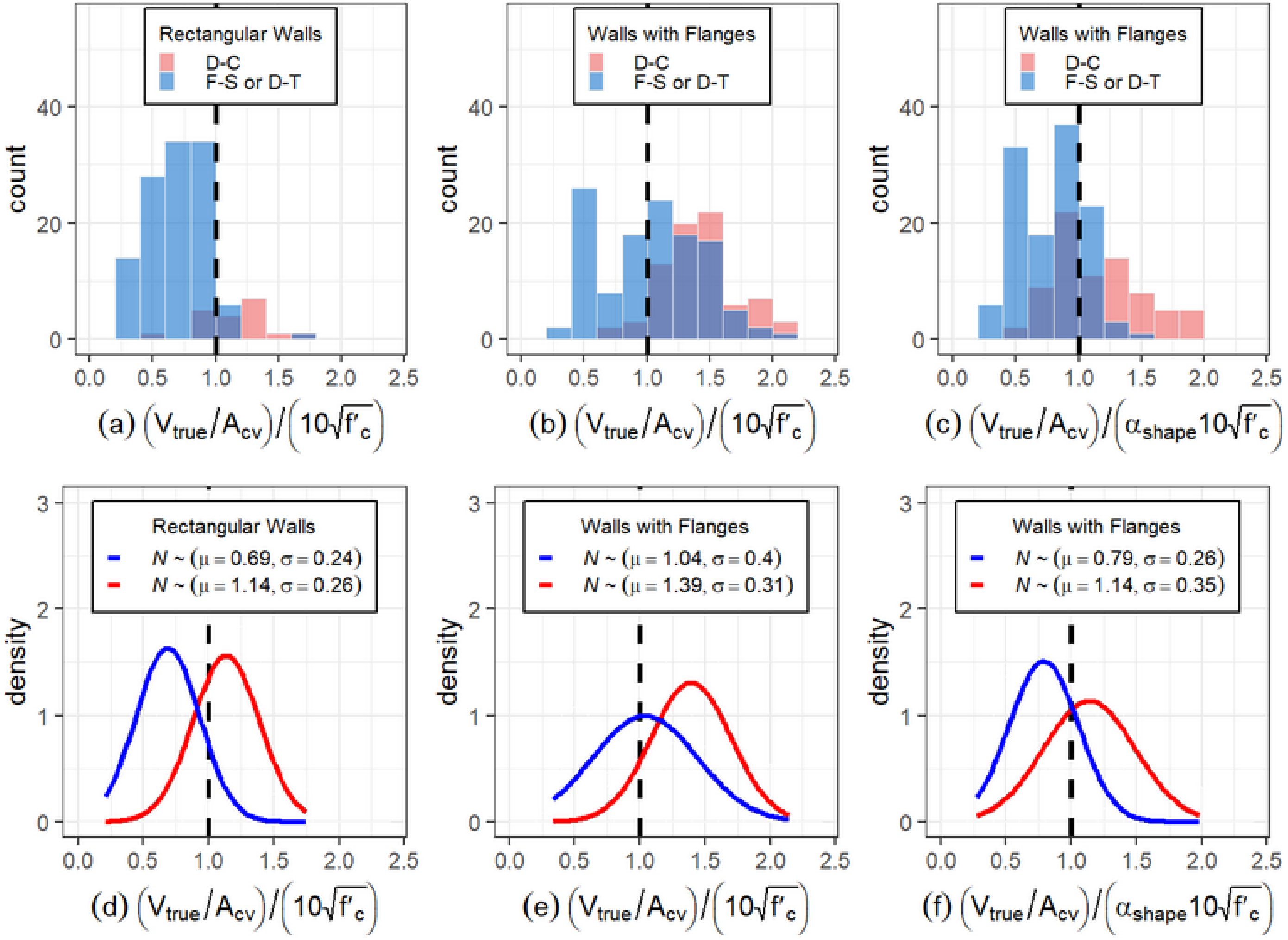
$$\alpha_{\text{shape}} = 0.7\left(1 + \frac{b_f t_f}{A_{cv}}\right)^2$$

$$1.0 \le \alpha_{\text{shape}} \le 1.5$$

Failure Mode	Below Limit	Above Limit
D-C	6	13
F-S or D-T	110	7

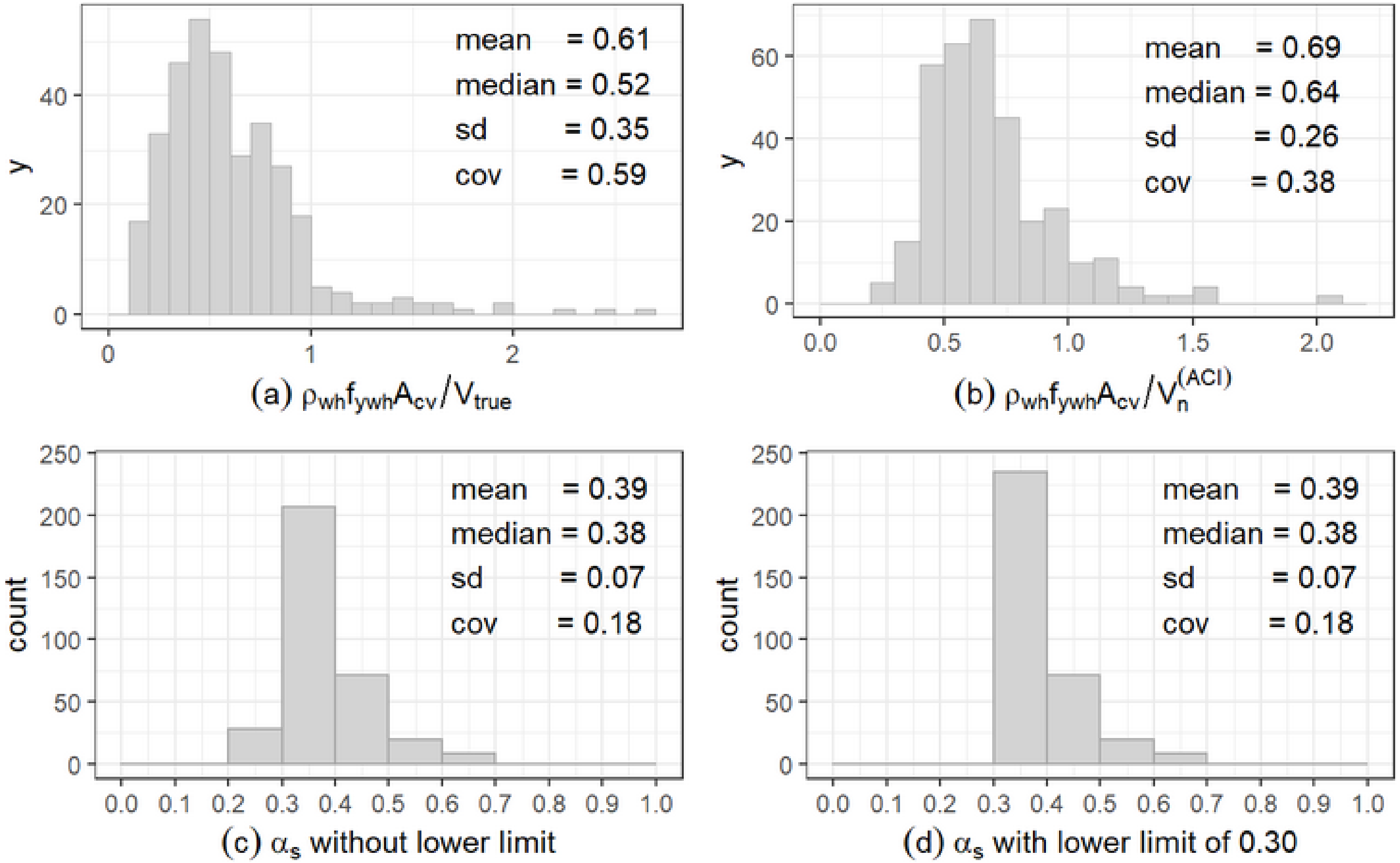
Failure Mode	Below Limit	Above Limit
D-C	5	71
F-S or D-T	54	67

Failure Mode	Below Limit	Above Limit
D-C	33	43
F-S or D-T	94	27



Steel Contribution

ACI 318-19 → $V_s = \rho_{wh} f_{ywh} A_{cv}$ ⟷ $V_s = 1.0 \times \rho_{wh} f_{ywh} A_{cv}$



Prop. Eq. → $V_s = \alpha_s \rho_{wh} f_{ywh} A_{cv}$

$$\alpha_s = \frac{2}{5\left(\frac{M_u}{V_u l_w}\right)^{1/3}} \geq 0.30$$

Steel Contribution

Database with 333 test $\longrightarrow$ 55,278 different pairs of tests

66 pairs of companion tests

- Difference in $\rho_{wh} f_{ywh} A_{cv} \geq 3\%$
  (Average difference in $\rho_{wh} f_{ywh} A_{cv} = 72\%$)
- Difference in other parameters $\leq 10\%$

Estimated variation in shear strength

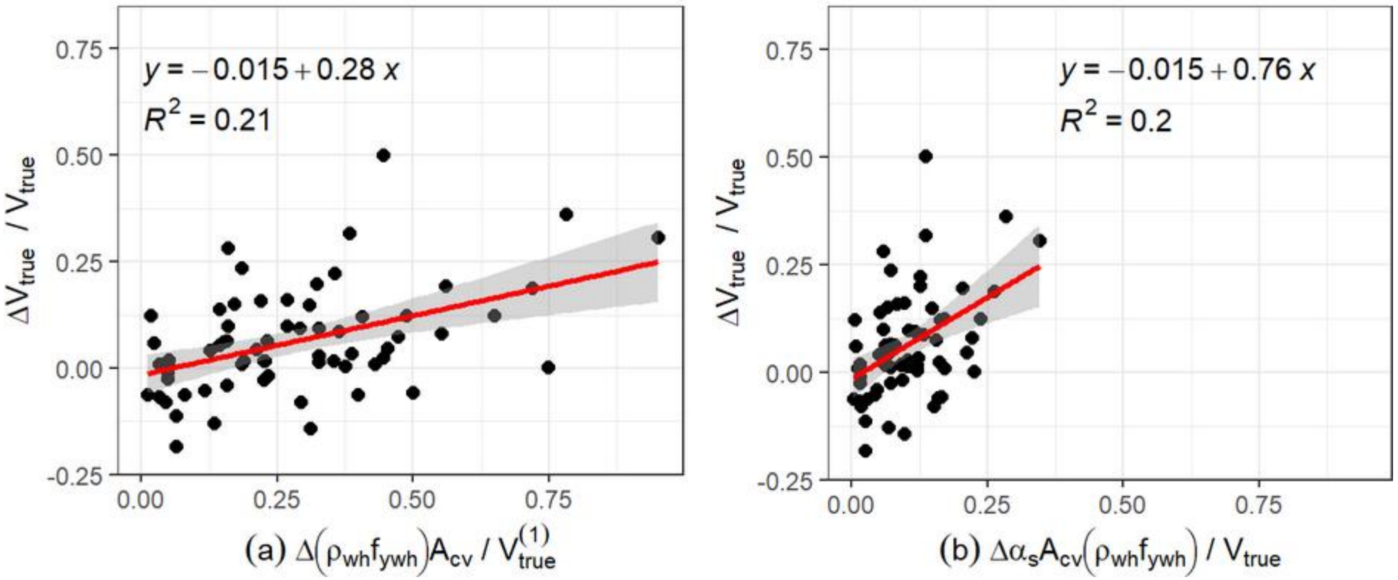
ACI 318-19 $\longrightarrow$

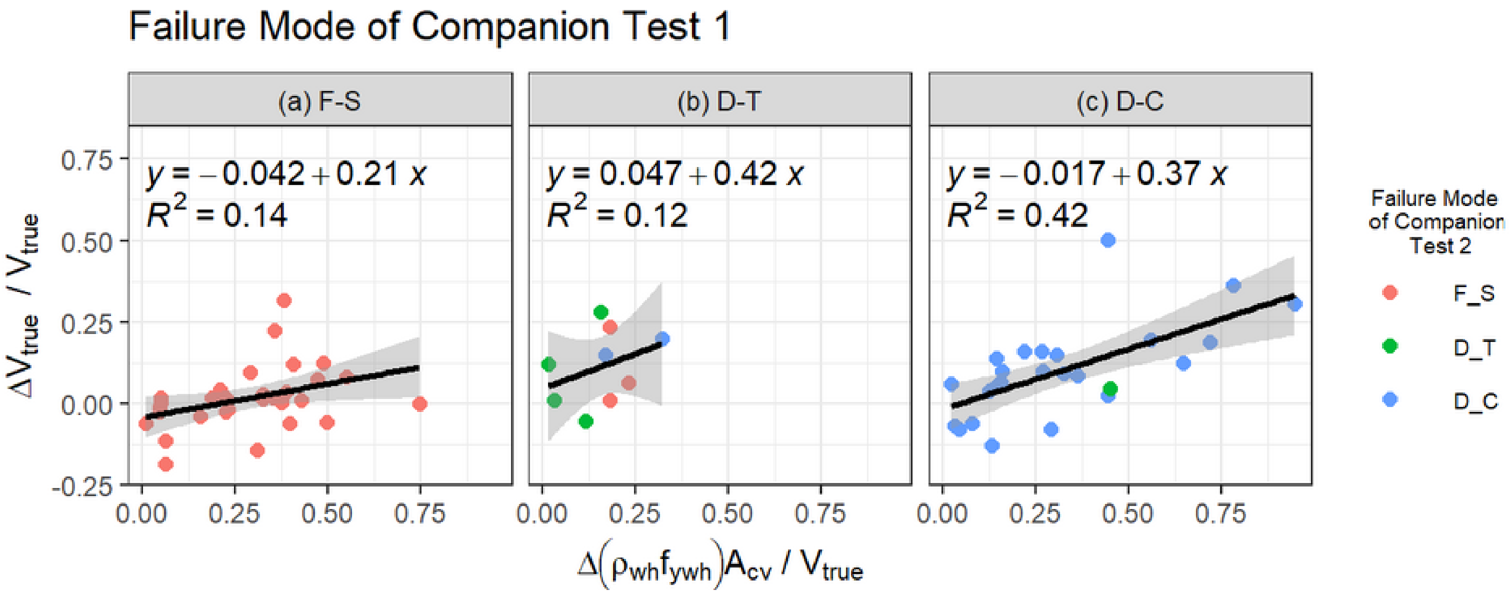
$$\Delta V_n^{(\mathrm{ACI})} = \Delta\left(\cancel{\alpha_c \sqrt{f_c'}} A_{cv} + \rho_{wh} f_{ywh} A_{cv}\right) = \Delta \rho_{wh} f_{ywh} A_{cv}$$

Prop. Eq. $\longrightarrow$

$$\Delta V_n^{(\mathrm{Prop.Eq})} = \Delta\left(\cancel{\alpha_c A_g' f_c'} + \alpha_s\left(\cancel{\rho_{sb} f_{ysb}} + \rho_{wh} f_{ywh}\right) A_{cv}\right) = \Delta \alpha_s \rho_{wh} f_{ywh} A_{cv}$$

Steel Contribution





Concrete Contribution

Database with 333 test → 55,278 different pairs of tests

675 pairs of companion tests

- Difference in $\rho_{wh} f_{ywh} A_{cv}$ ≤3%

  (Difference in $\rho_{wh} f_{ywh} A_{cv} = 0$ for 238 pairs)

- Difference in other parameters: No restriction

Estimated variation in shear strength

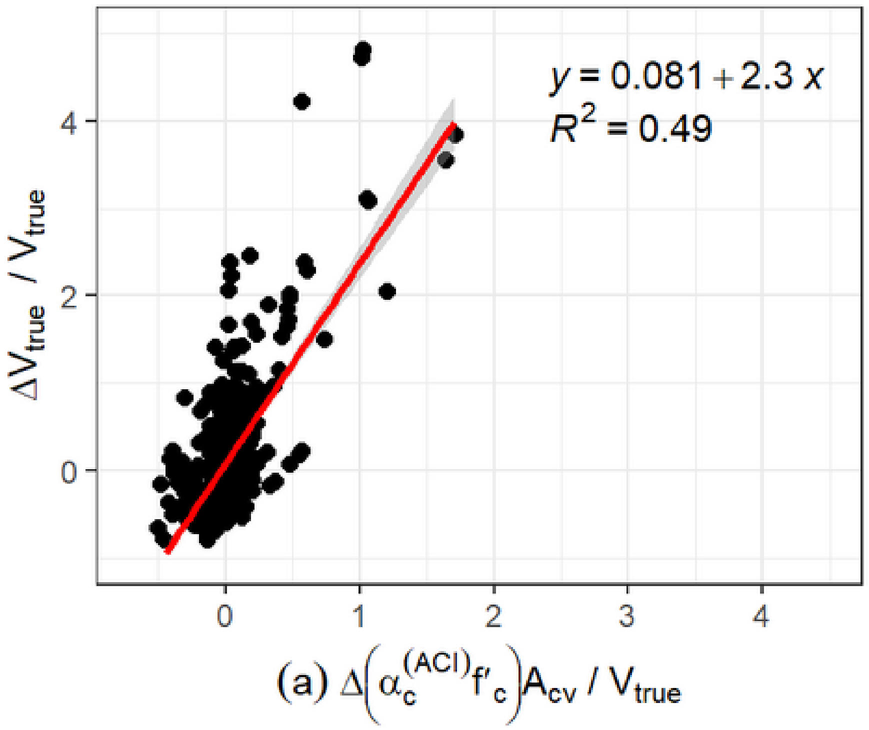
ACI 318-19 →

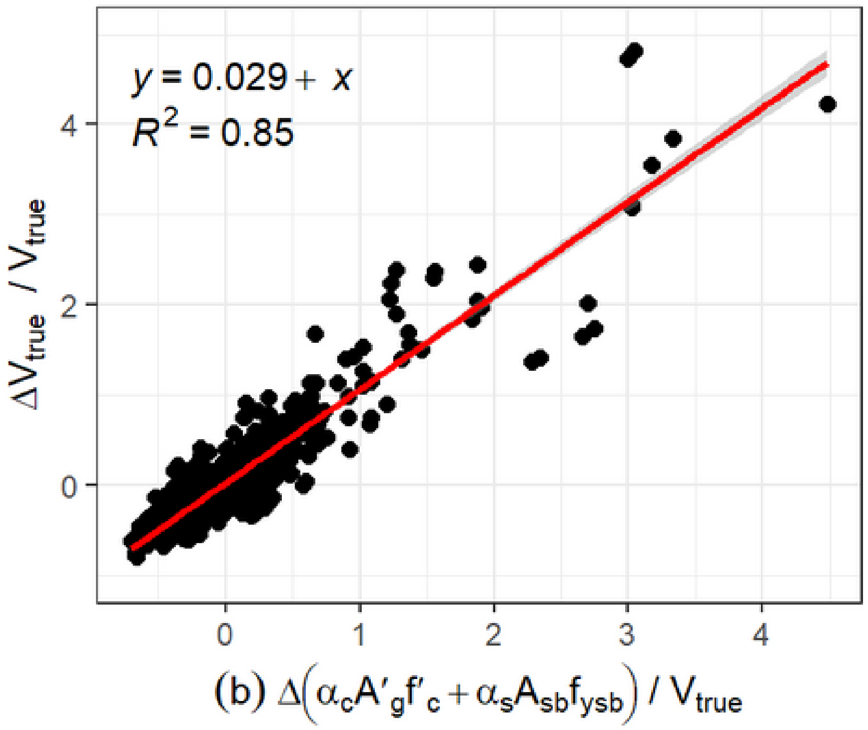
$$\Delta V_n^{(\mathrm{ACI})} = \Delta\left(\alpha_c \sqrt{f_c'} A_{cv} + \cancel{\rho_{wh} f_{ywh}} A_{cv}\right)$$
$$= \Delta \alpha_c \sqrt{f_c'} A_{cv}$$

Prop. Eq. →

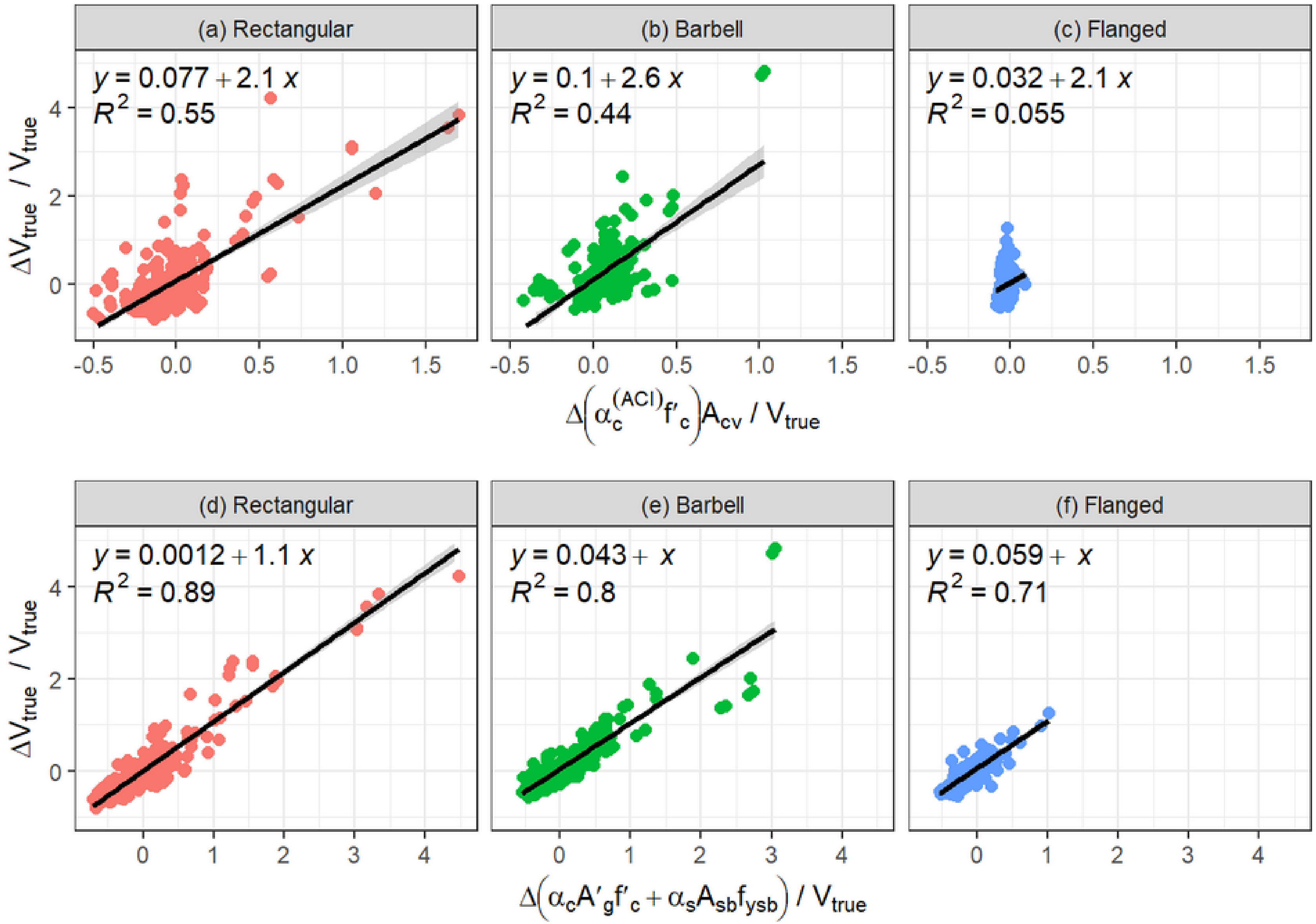
$$\Delta V_n^{(\mathrm{Prop.Eq})} = \Delta\left(\alpha_c A_g' f_c' + \alpha_s\left(\rho_{sb} f_{ysb} + \cancel{\rho_{wh} f_{ywh}}\right) A_{cv}\right)$$
$$= \Delta\left(\alpha_c A_g' f_c' + \alpha_s \rho_{sb} f_{ysb} A_{cv}\right)$$

Concrete Contribution





Concrete Contribution



Concrete Contribution

ACI 318-19

$$V_c = \alpha_c \lambda A_{cv}\sqrt{f_c'}$$

$$\alpha_c = \begin{cases} 3 & \dfrac{h_w}{l_w} \le 1.5 \\ 2 & \dfrac{h_w}{l_w} \ge 2.0 \\ 3 - 2\cdot\left(\dfrac{h_w}{l_w} - 1.5\right) & Otherwise \end{cases}$$

Concrete Contribution

ACI 318-19

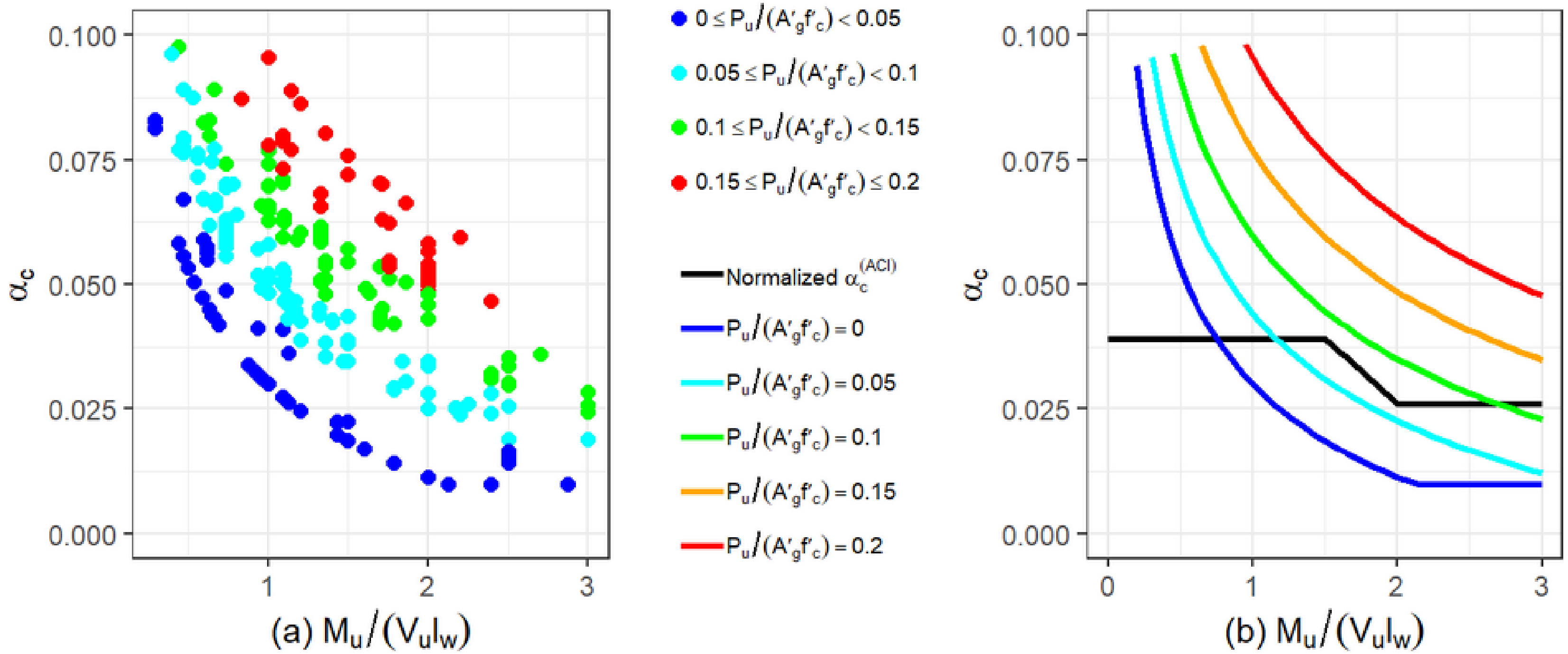
$$V_c = \left(\alpha_c \cdot \frac{1}{\sqrt{f_c'}}\right) \cdot \lambda A_{cv}\sqrt{f_c'} \cdot \sqrt{f_c'}$$

$$\alpha_c = \begin{cases} 3 & \frac{h_w}{l_w} \leq 1.5 \\ 2 & \frac{h_w}{l_w} \geq 2.0 \\ 3 - 2\cdot\left(\frac{h_w}{l_w} - 1.5\right) & Otherwise \end{cases}$$

$$\alpha_{c,norm} = \frac{1}{\sqrt{f_c'}}\alpha_c$$

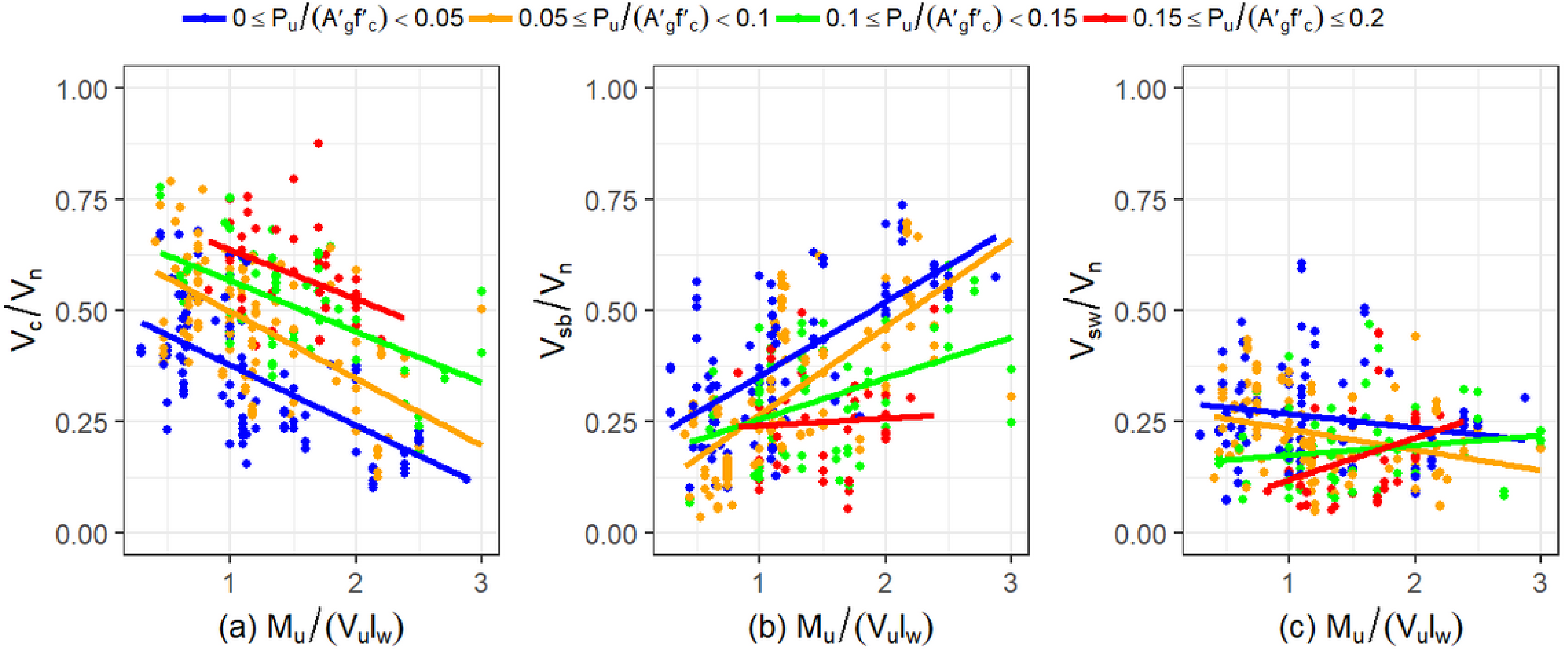
From the database:

$$mean\left(\frac{1}{\sqrt{f_c'}}\right) = \frac{0.013}{\sqrt{psi}}$$



Further Interpretation and Comparisons

$$V_n = \alpha_c A'_g f'_c + \alpha_s(\rho_{sb} f_y + \rho_{wh} f_{ywh}) A_{cv}$$



(1) Parameter ranges limitations

(2) Comments on $M_u/(V_u l_w)$

(3) Shear stress upper limit

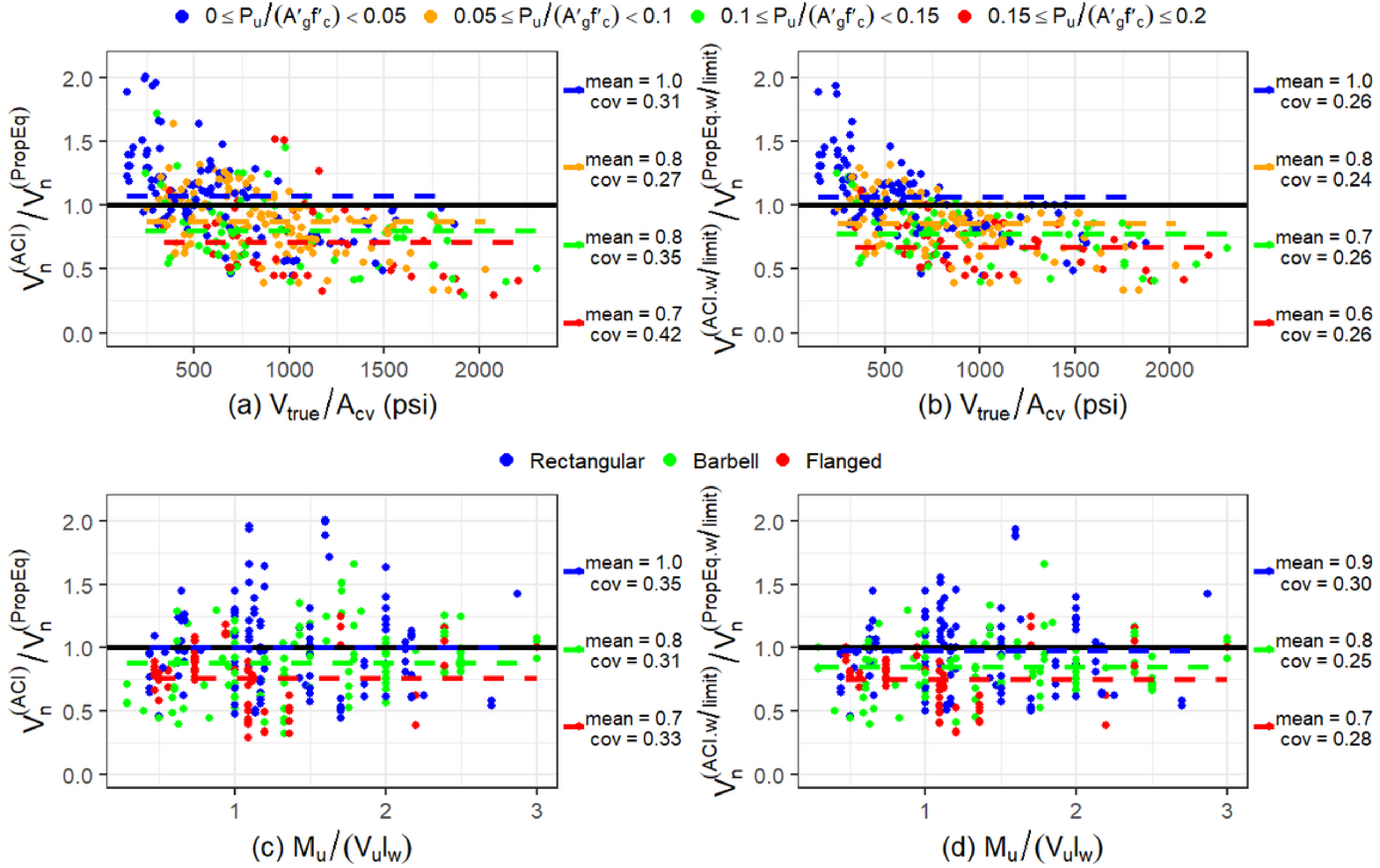
(4) Steel contribution

(5) Concrete contribution

(6) Further interpretations

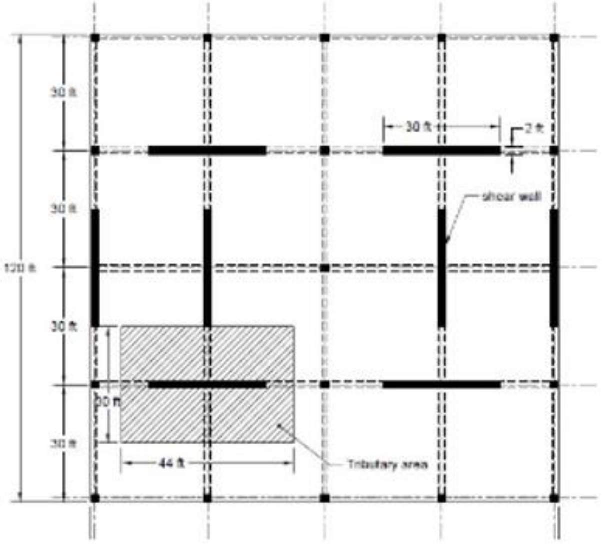
(7) Reliability Analysis

Further Interpretation and Comparisons

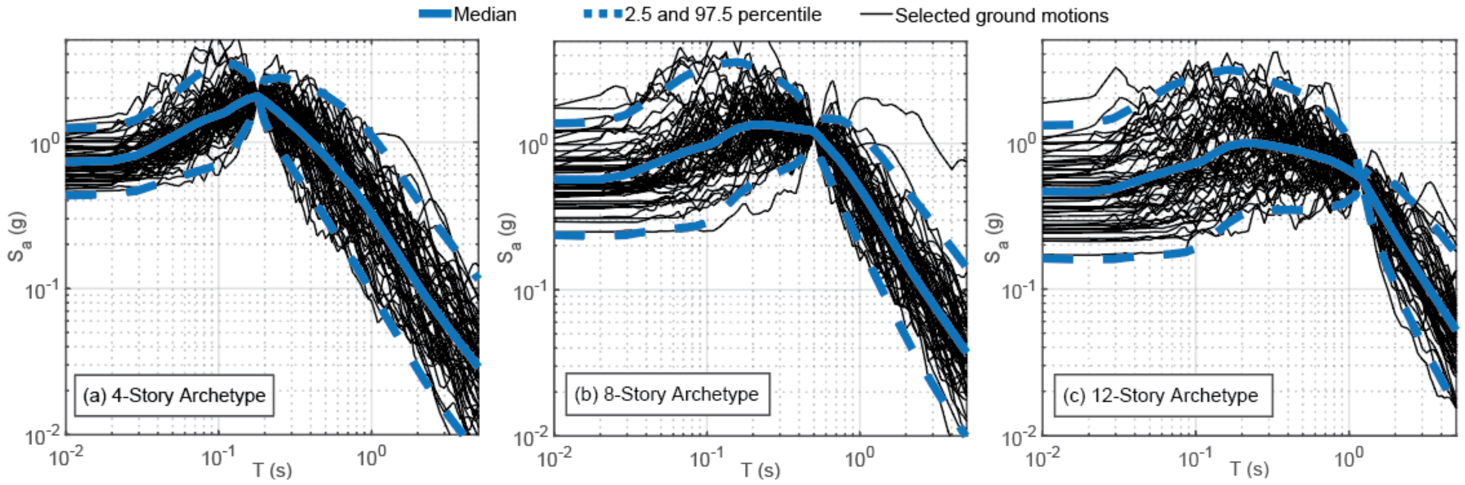


Reliability Analysis of ACI 318-19 Compliant Archetypes

- Monte Carlo Simulation
- 3 archetypes
  - 4-story archetype
  - 8-story archetype
  - 12-story archetype
- 3 load combinations
  - $(0.9 - 0.2S_{DS})D$
  - $D + 0.25L$
  - $(1.2 + 0.2S_{DS})D + 0.5L$

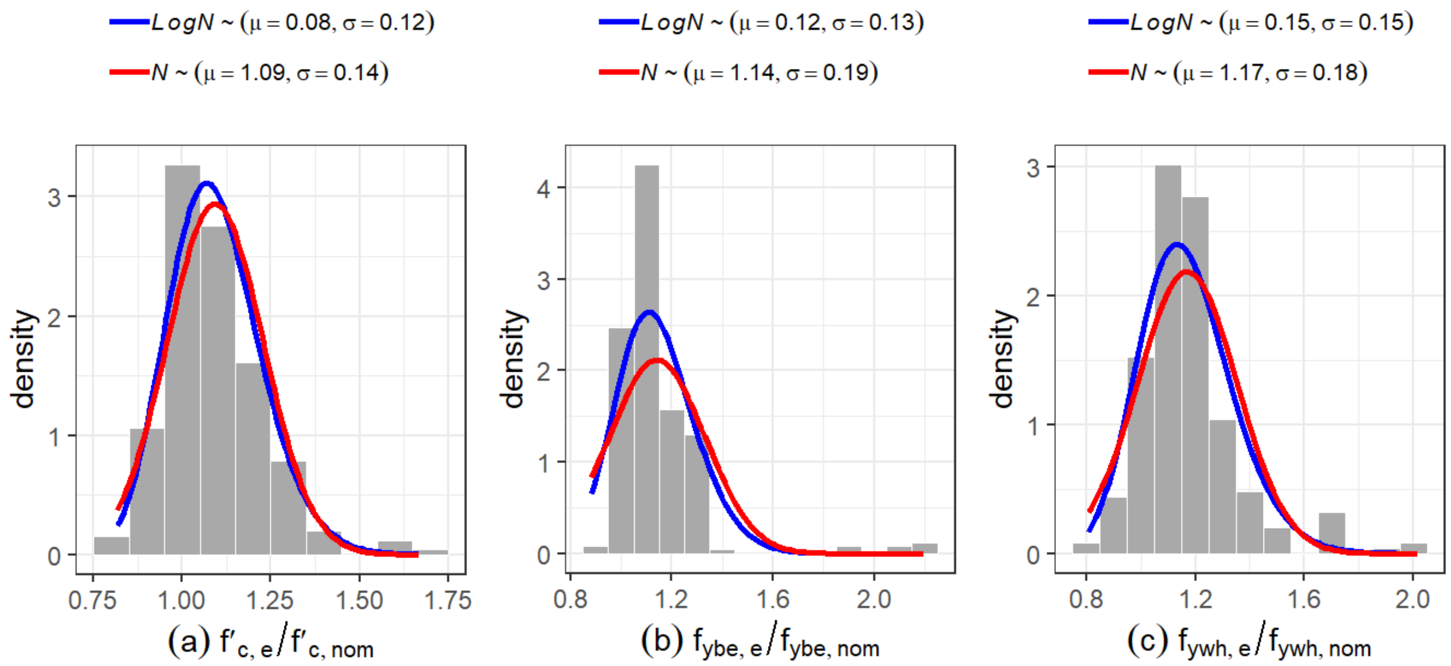


Archetype	Fundamental Period, T_1 (s)	Spectral Acceleration, S_a	# of GMs (MCE_R level)
4-Story Archetype	0.18	2.05g	42
8-Story Archetype	0.52	1.18g	43
12-Story Archetype	1.20	0.57g	46



Reliability Analysis

- Probability distributions for actual-to-nominal material properties



Variable	Distribution Type	Parameter 1	Parameter 2
$f'_{c,e}/f'_{c,nom}$	Log-Normal	$\mu_{log} = 0.08$	$\sigma_{log} = 0.12$
$f_{ysb,e}/f_{ysb,nom}$	Log-Normal	$\mu_{log} = 0.12$	$\sigma_{log} = 0.13$
$f_{ywh,e}/f_{ywh,nom}$	Log-Normal	$\mu_{log} = 0.15$	$\sigma_{log} = 0.15$

- (1) Parameter ranges limitations
- (2) Comments on $M_u/(V_u l_w)$
- (3) Shear stress upper limit
- (4) Steel contribution
- (5) Concrete contribution
- (6) Further interpretations
- **(7) Reliability Analysis**

Reliability Analysis: 4-Story Archetype (ACI Compliant)

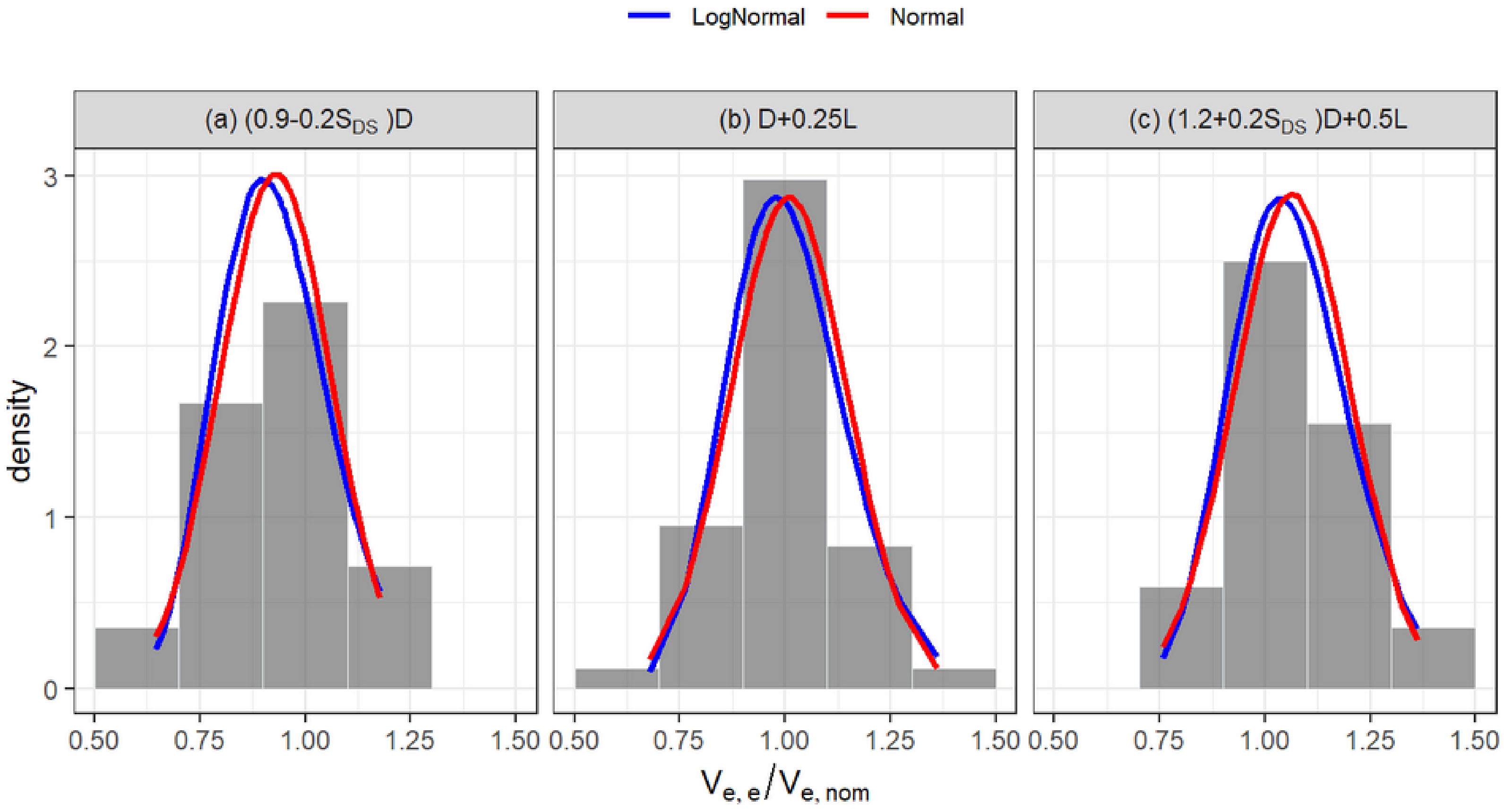
- Probability distributions for actual-to-nominal demands

Load Combination	Variable	Distribution Type	Parameter 1	Parameter 2
$(0.9\text{-}0.2S_{DS})D$	$V_{e,e}/V_{e,\text{nom}}$	Log-Normal	$\mu_{log} = -0.08$	$\sigma_{log} = 0.15$
	$V_{e,e}/V_{u,\text{nom}}$	Log-Normal	$\mu_{log} = 0.42$	$\sigma_{log} = 0.15$
	$P_{u,e}/P_{u,\text{nom}}$	Normal	$\mu_i = 0.73 + 0.58\left(\frac{V_{e,e}}{V_{e,\text{nom}}}\right)_i$	$\sigma = 0.12$
	$M_{u,e}/M_{u,\text{nom}}$	Normal	$\mu_i = 0.57 + 0.81\left(\frac{V_{e,e}}{V_{e,\text{nom}}}\right)_i$	$\sigma = 0.07$
D+0.25L	$V_{e,e}/V_{e,\text{nom}}$	Log-Normal	$\mu_{log} = 0.00$	$\sigma_{log} = 0.14$
	$V_{e,e}/V_{u,\text{nom}}$	Log-Normal	$\mu_{log} = 0.50$	$\sigma_{log} = 0.14$
	$P_{u,e}/P_{u,\text{nom}}$	Normal	$\mu_i = 1.02 + 0.14\left(\frac{V_{e,e}}{V_{e,\text{nom}}}\right)_i$	$\sigma = 0.07$
	$M_{u,e}/M_{u,\text{nom}}$	Normal	$\mu_i = 0.56 + 0.85\left(\frac{V_{e,e}}{V_{e,\text{nom}}}\right)_i$	$\sigma = 0.07$
$(1.2+0.2S_{DS})D+0.5L$	$V_{e,e}/V_{e,\text{nom}}$	Log-Normal	$\mu_{log} = 0.05$	$\sigma_{log} = 0.13$
	$V_{e,e}/V_{u,\text{nom}}$	Log-Normal	$\mu_{log} = 0.56$	$\sigma_{log} = 0.13$
	$P_{u,e}/P_{u,\text{nom}}$	Normal	$\mu_i = 0.86 + 0.24\left(\frac{V_{e,e}}{V_{e,\text{nom}}}\right)_i$	$\sigma = 0.04$
	$M_{u,e}/M_{u,\text{nom}}$	Normal	$\mu_i = 0.45 + 0.97\left(\frac{V_{e,e}}{V_{e,\text{nom}}}\right)_i$	$\sigma = 0.07$

- (1) Parameter ranges limitations
- (2) Comments on $M_u/(V_u l_w)$
- (3) Shear stress upper limit
- (4) Steel contribution
- (5) Concrete contribution
- (6) Further interpretations
- **(7) Reliability Analysis**

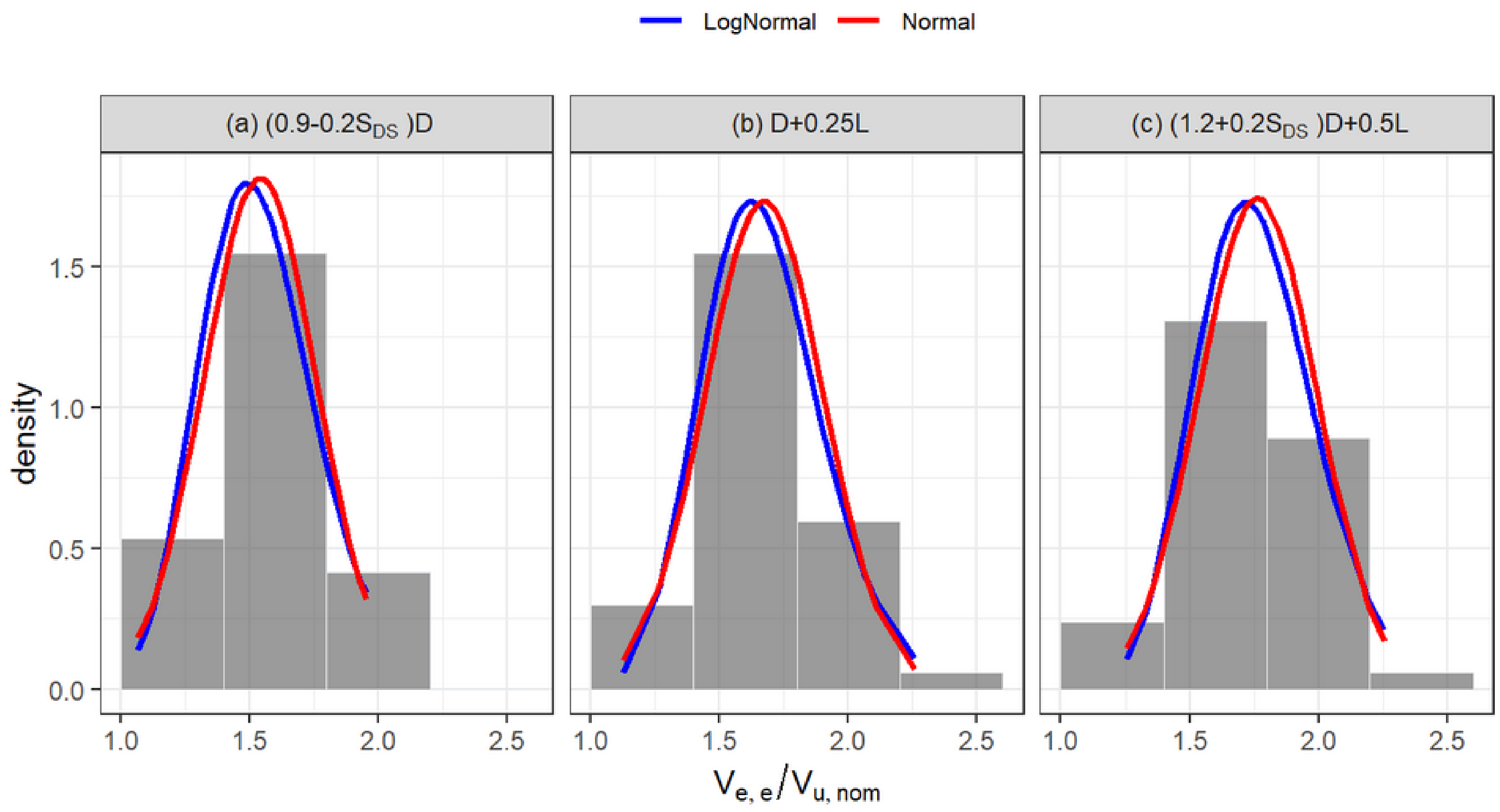
Reliability Analysis: 4-Story Archetype

- Probability distributions for actual-to-nominal demands



Reliability Analysis: 4-Story Archetype

- Probability distributions for actual-to-nominal demands

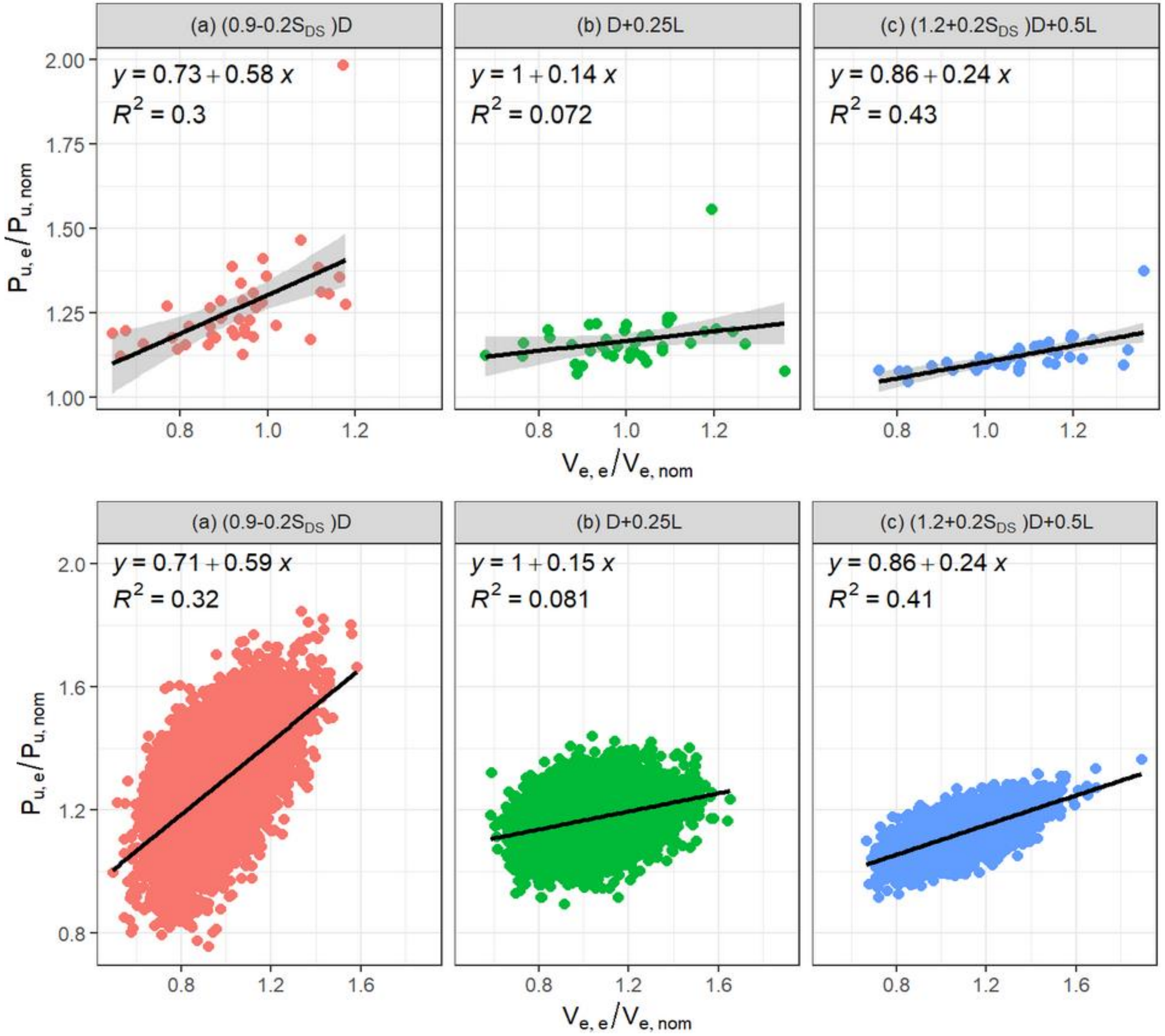


Reliability Analysis: 4-Story Archetype

- Probability distributions for actual-to-nominal demands

Dynamic Analyses →

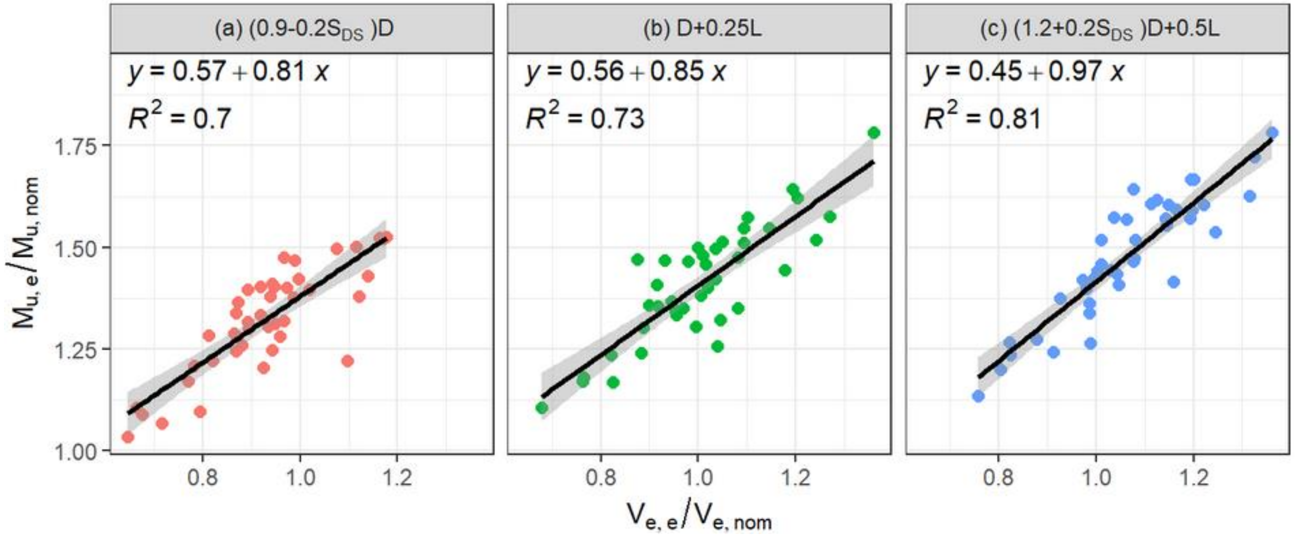
Simulated Data →



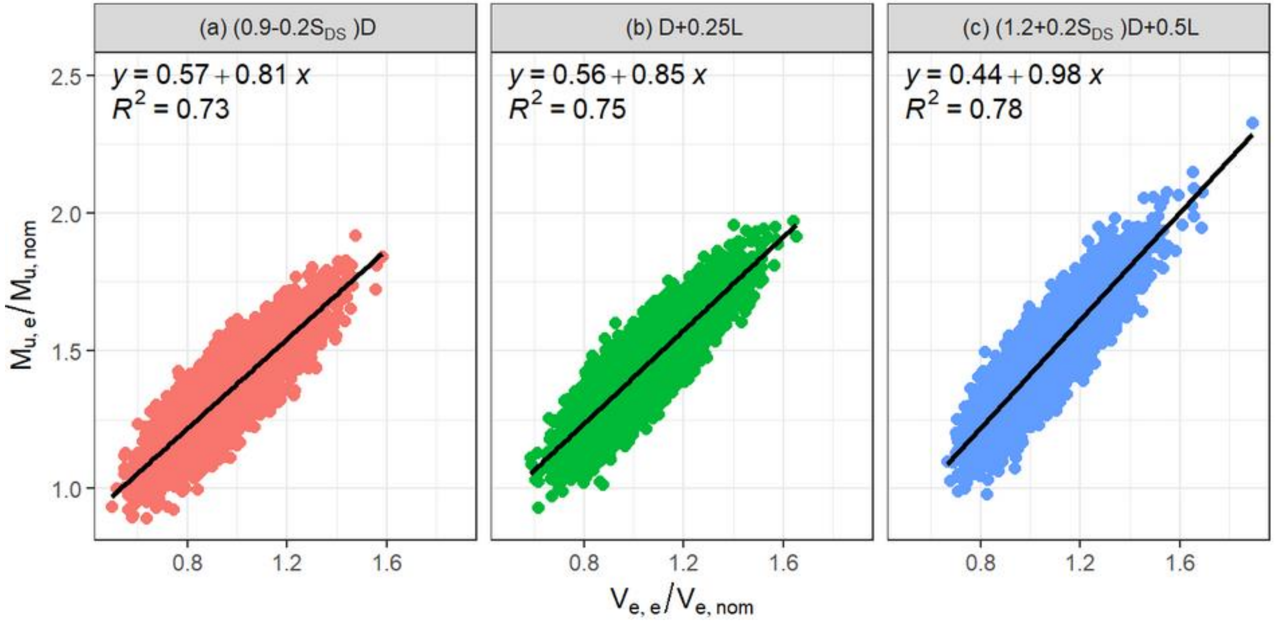
Reliability Analysis: 4-Story Archetype

- Probability distributions for actual-to-nominal demands

Dynamic Analyses →



Simulated Data →



(1) Parameter ranges limitations

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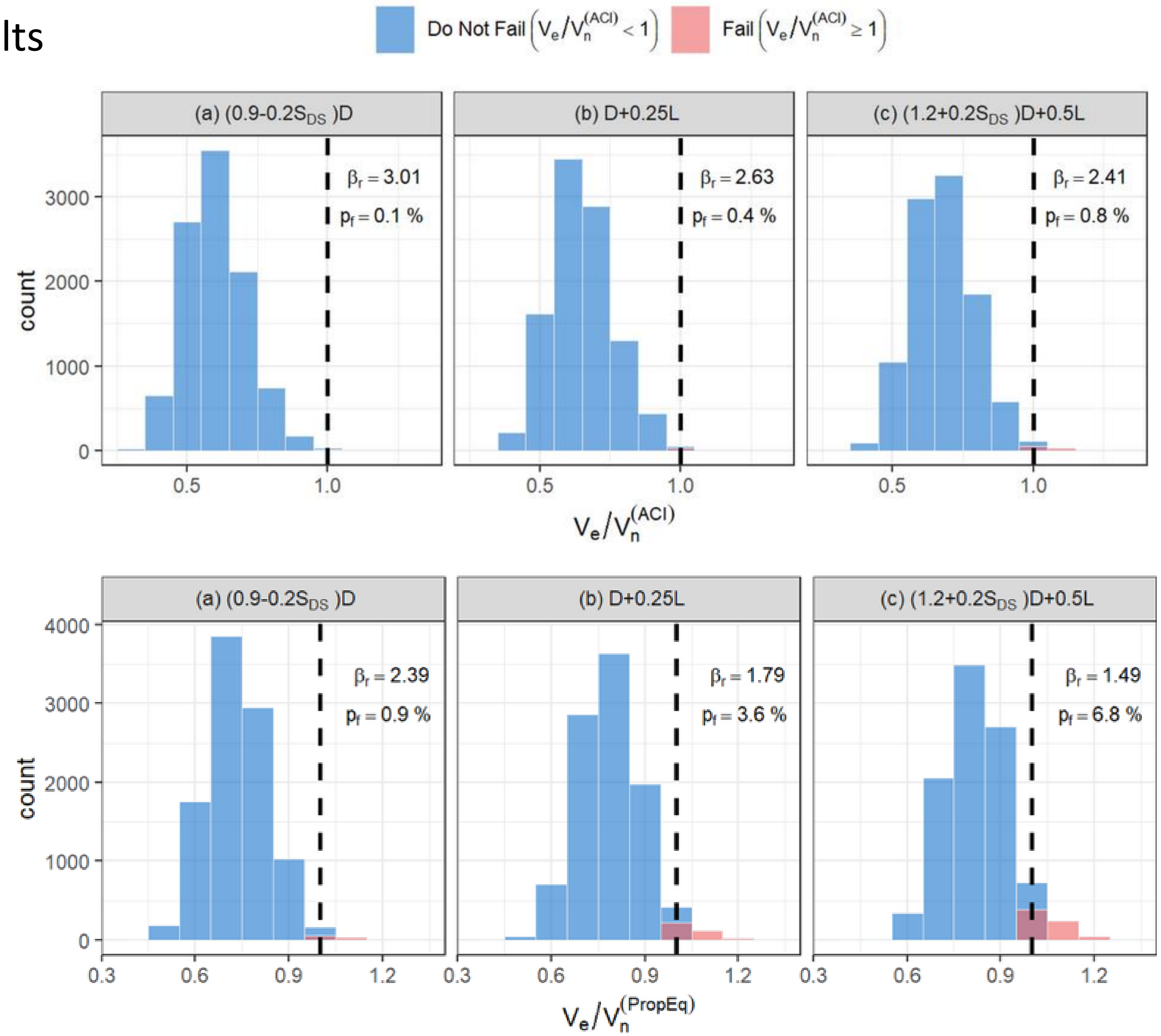
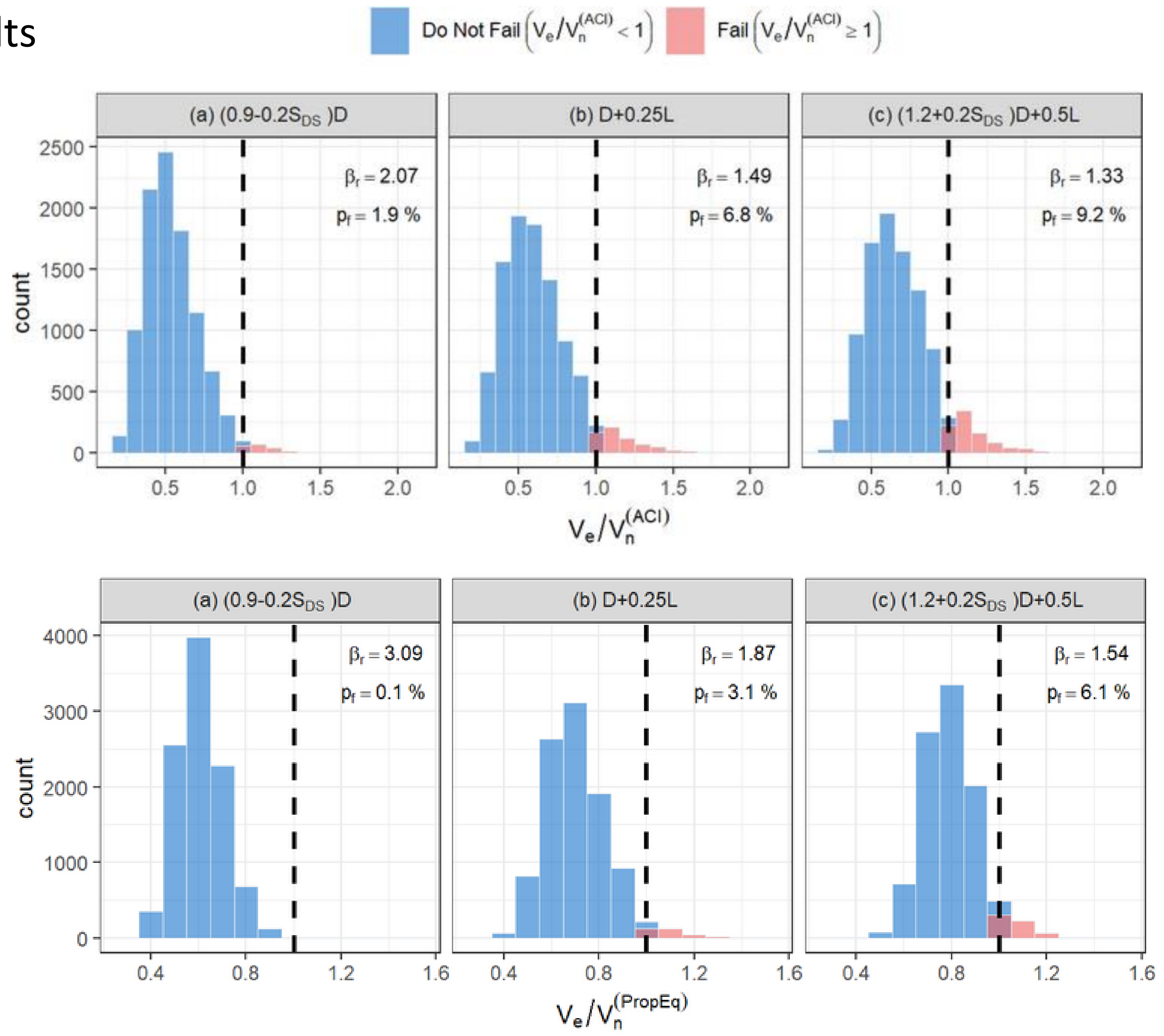
Reliability Analysis: 4-Story Archetype

- Results



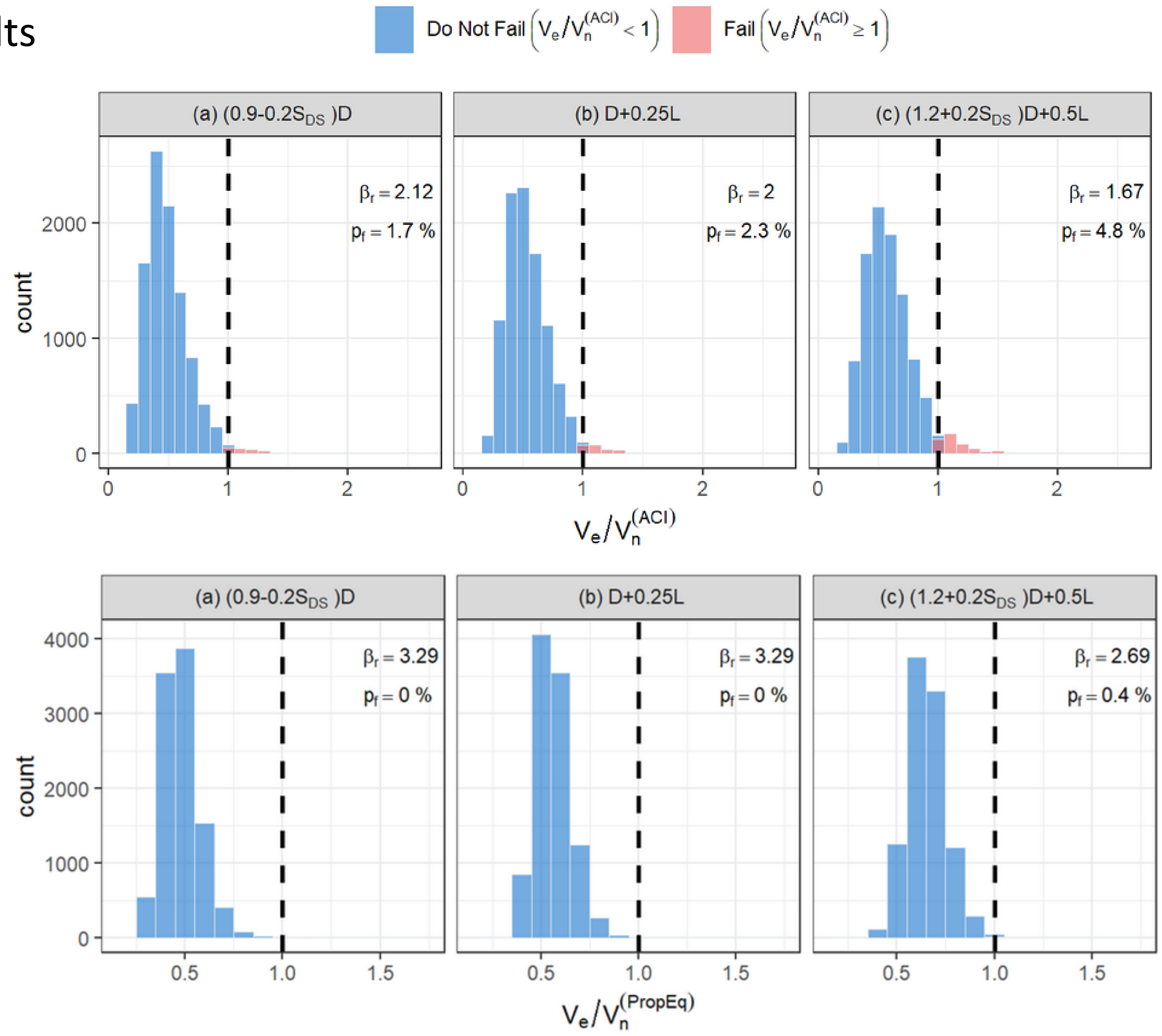
Reliability Analysis: 8-Story Archetype

- Results



Reliability Analysis: 12-Story Archetype

- Results



Reliability Analysis: Aggregate Results

$\phi V_n \geq V_e \rightarrow \phi V_n = 1.05 \times V_e \rightarrow \phi_{eq}^{(\text{PropEq})} = \frac{1.05\, V_e}{V_n^{(\text{PropEq})}}$

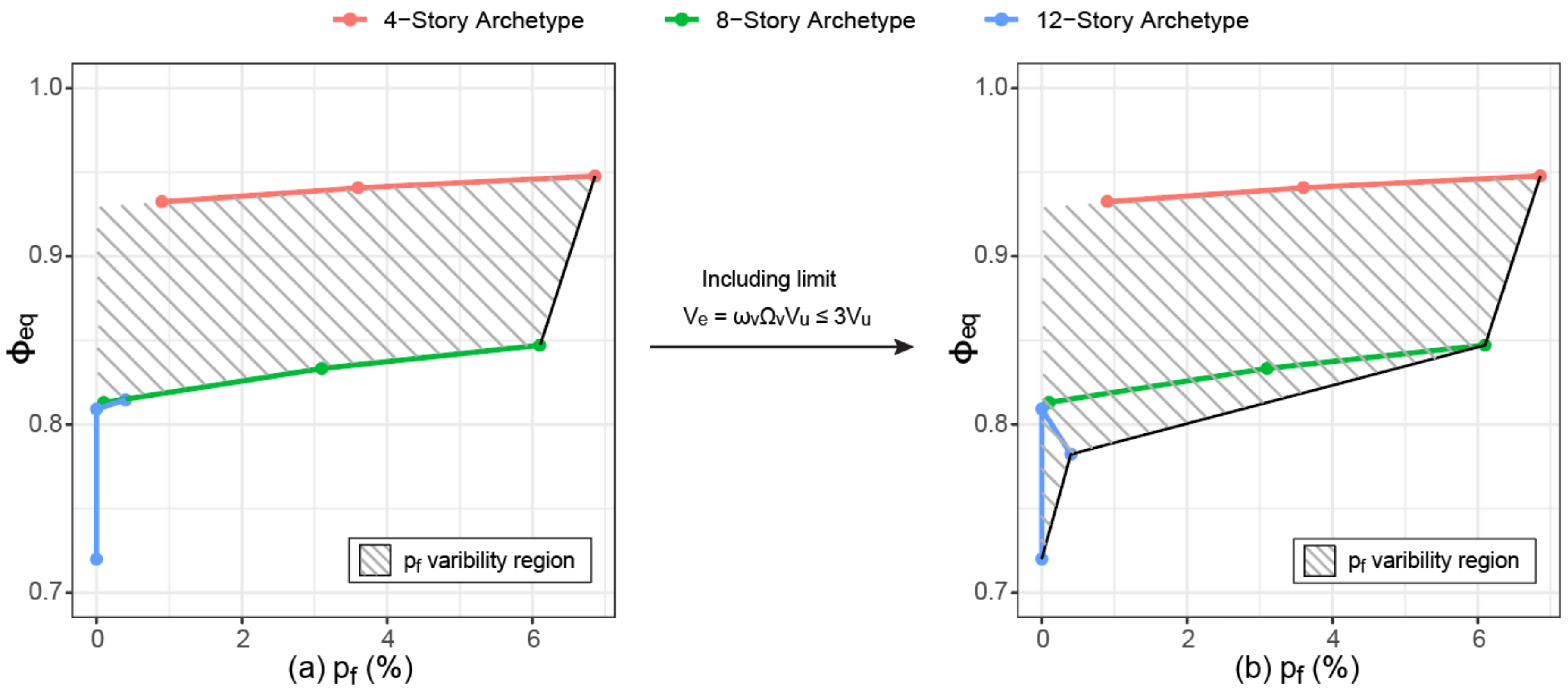
Archetype	Load ** Combination	P_u (kip)	M_{pr} (kip-ft)	V_e (kip)	ALR (%)	SSR	$V_n^{(PropEq)}$ (kip)	$\frac{V_e}{V_n^{(PropEq)}}$	p_f (%)	$\phi_{eq}^{(PropEq)}$
4-Story Archetype	LC_min	684	110,572	2,692	1.6	1.37	3,031	0.89	0.9	0.93
	LC_avg	1,157	115,891	2,826	2.7	1.37	3,154	0.90	3.6	0.94
	LC_max	1,741	122,361	2,984	4.0	1.37	3,306	0.90	6.8	0.95
8-Story Archetype	LC_min	1,584	107,716	2,487	2.9	1.44	3,212	0.77	0.1	0.81
	LC_avg	2,674	120,058	2,772	5.0	1.44	3,493	0.79	3.1	0.83
	LC_max	4,018	134,678	3,110	7.4	1.44	3,855	0.81	6.1	0.85
12-Story Archetype	LC_min	2,426	117,283	2,716	4.5	1.44	3,961	0.69	0.0	0.72
	LC_avg	4,098	135,520	3,138	7.6	1.44	4,072	0.77	0.0	0.81
	LC_max	6,159	156,260	3,618	11.4	1.44	4,663	0.78	0.4	0.82

*This value changes respect to the other SSR of this same archetype because of the upper limit imposed for the amplification factor in the ACI 318-19, i.e., $\omega_v \Omega_v \leq 3.0$.

**LC_min = (0.9-S_{DS})D ; LC_avg = D+0.25L ; LC_max = (1.2+0.2S_{DS})D+0.5L

Reliability Analysis: Aggregate Results

- ϕ factor vs. probability of failure when using the Proposed Equation.



* p_f varies for each archetype depending on the Load Combination.

Part 5
Conclusions

From Introduction

- Existing models generally have **significant variance and bias**
- Typically, **ML models** have **not** been **adequately trained** when assessing wall shear strength
- No approaches to judge the **relative merits** of models with **different complexity levels**

About Proposed and Implemented Framework

- Can be implemented to obtain relationships between model **performance requirements** for different model **complexity levels** (mechanics, limited data)

- Iterative sensitivity analysis enables **clear ML hyper-parameter trends**

- When applied to the RC wall shear strength estimation problem:

  - Optimum **LASSO** model **equivalent** to Complex ML models (**ANN**, **RF** Regression)

  - **No** existing assessed simple **model** or ML model **meets** their respective **performance requirements**

About Proposed RC Wall Shear Strength Equation

- Meets the **target model performance**
- It is applicable to walls with **asymmetrical cross sections**; rectangular, barbell, and flanged (C-, H-, T-, and L-shaped) .
- Practically the **same performance** for walls with different cross-section shapes, axial load ratios, shear-span ratios, or aspect ratio
- Shear strength **contribution of each of its terms** is more accurate than contributions from the ACI 318-19 equation terms.

Significantly underestimates V_c and overestimates V_s

About Proposed RC Wall Shear Strength Equation

- Coefficients in the equation are unitless
- Proposed shear strength **upper limit** is **simple** and designed to perform **similarly** to the limit in ACI 318-19 for rectangular walls but for **all walls**.
- Proposed shear strength upper limit allows $\boldsymbol{v_n = V_n/A_{cv}}$ **up to** $\boldsymbol{15\sqrt{f'_c}}$ for walls with flanges
- Strength reduction factor $\boldsymbol{\phi}$ on archetypes vary between **0.75 and 0.95**, keeping $\boldsymbol{p_f < 10\%}$ **for** $\mathbf{MCE_R}$ **level**

Next Steps

- Analyze the impact of the proposed equation on the design (e.g., wall thickness, material take-off)

- Simplified equation accepting an increase in the error?