Predicting the Shear Strength of RC Beams without Stirrups using Bayesian Neural Network

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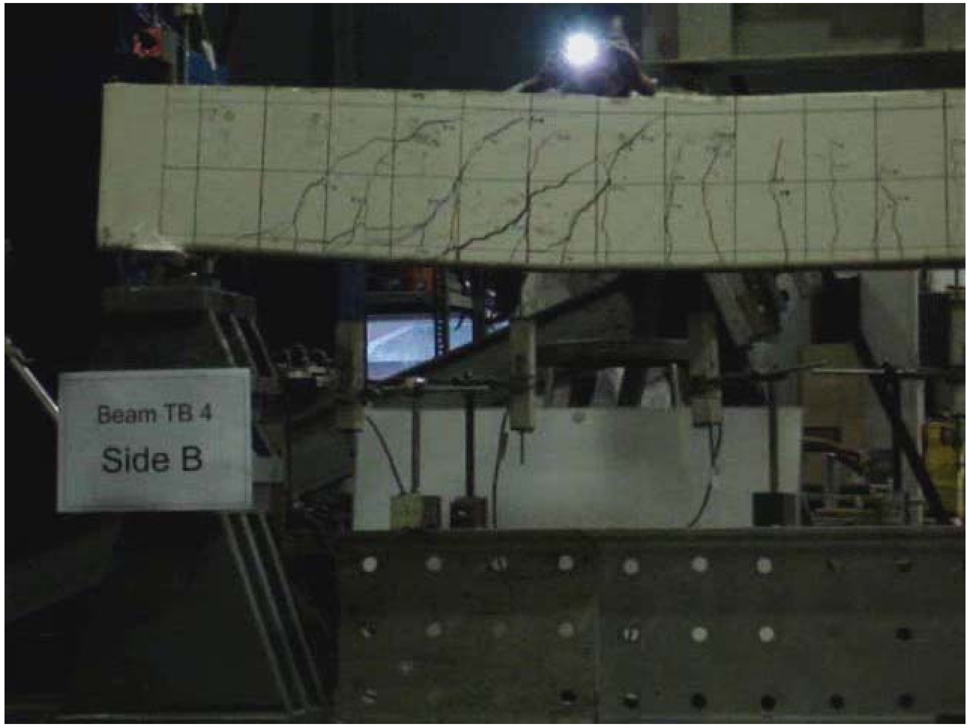
Outline

- Background
- Aims and Objectives
- Bayesian Artificial Neural Network
- Application to Shear Strength Prediction
- Conclusions
- Future Work

Shear in RC members

Unlike flexural failure, shear failure of RC members is:

- Sudden and Brittle
- No consensus on best approach to predict shear strength of RC members



Why is shear Strength Prediction difficult?

- Too many influencing parameters (i.e. over 20)
- Deficiencies in experimental test data (i.e. d<500mm)
- Complex and not fully understood

- 1962 ACI-ASCE committee concluded that a " fully rational design approach does not seem possible at this time"
- Despite, several shear theories, no consensus on best approach
- Nevertheless, further simplifications are required to implement, rational theories in design codes

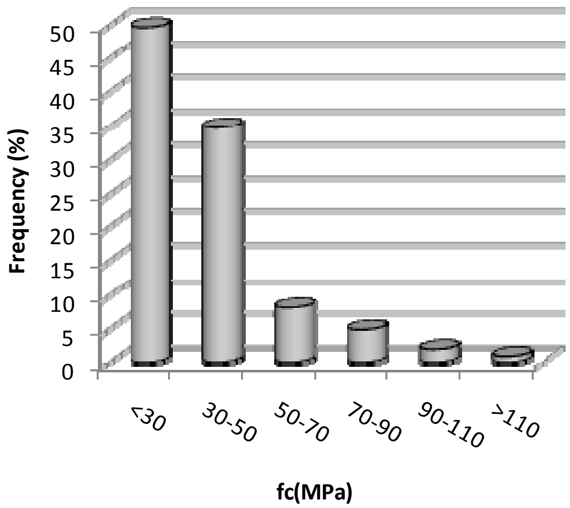
Regression analysis

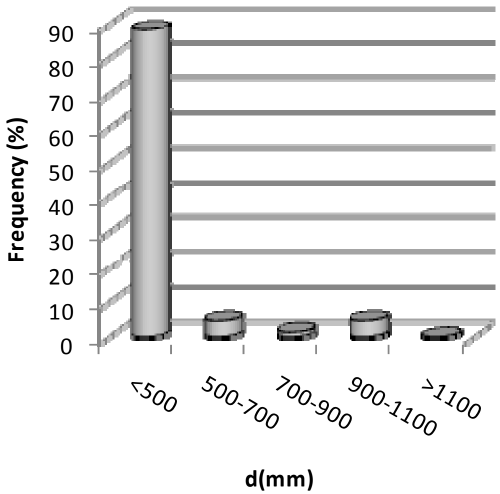
- Code writers recommend empirical approach based on regression analysis.

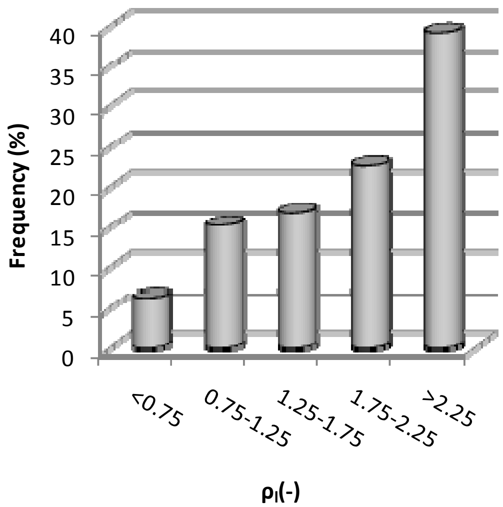
Code	Provision	Comments
EN1992:2004	$V_{Rd,c} = 0.18k(100\rho_l f_c)^{1/3} b_w d \geq 0.035k^{3/2} f_c^{1/2} b_w d$	$f_c < 100\ MPa;\quad k = 1 + \sqrt{\frac{200}{d}} \leq 2.0$ $\rho_l = \frac{A_l}{b_w d} \leq 0.02$
BS8110:1997	$V_c = \left[0.79\rho_l^{1/3}\left(\frac{400}{d}\right)^{1/4}\left(\frac{f_{cu}}{25}\right)^{1/3}\right] b_w d$	$f_{cu} \leq 40\ MPa;\quad \frac{400}{d} \geq 1.0$
ACI 318-08 Eq. 11-3	$V_c = \left(\frac{\sqrt{f_c}}{6}\right) b_w d$	$f_c \leq 70\ MPa$

Regression analysis

- **Limitations**
  - Assume relationship between parameters
  - Deficiency in database not taken into account
    - Variability due to testing conditions
    - Bias of test data to members of particular size and properties



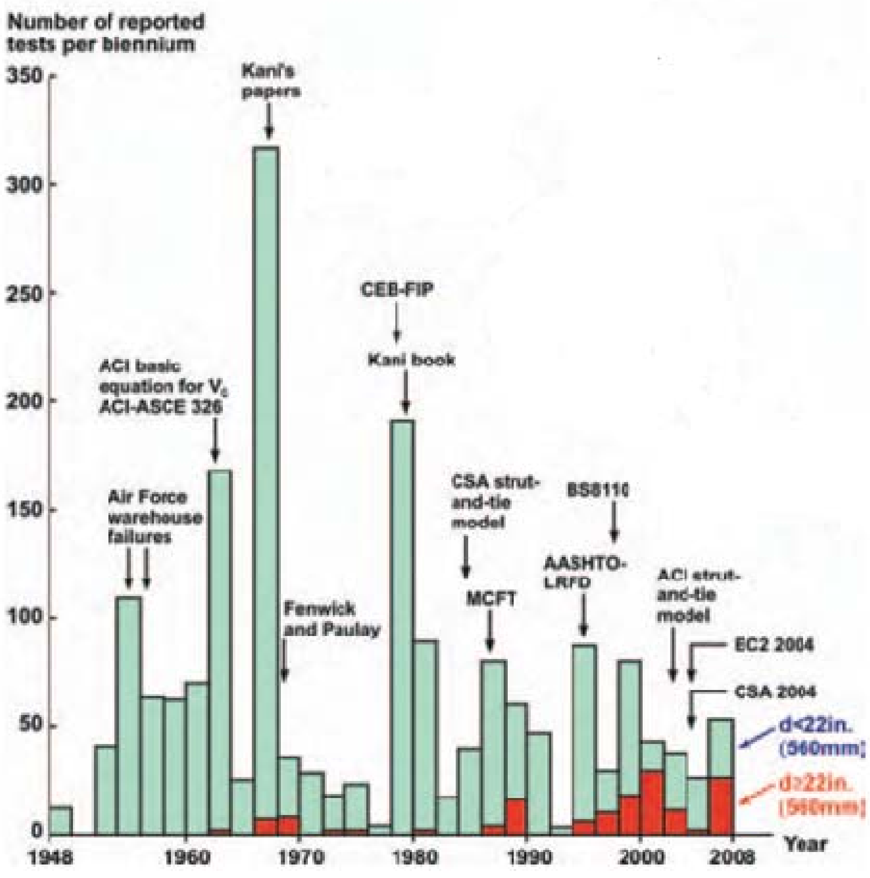




Regression analysis

- **Limitations (Contd.)**

- 1864 shear test



- Typical RC beam > 500mm

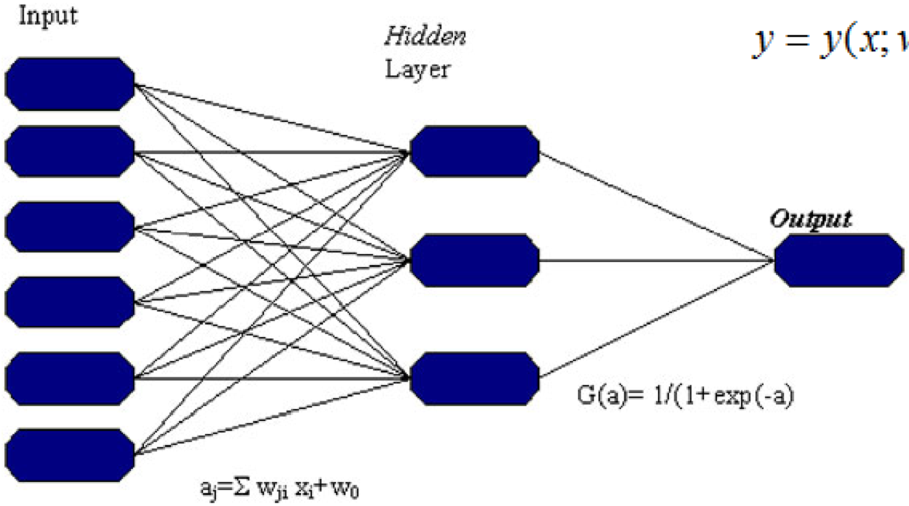
Artificial Neural Network(ANN)

- Artificial neural network offers better promise.

- **Strength**
- No need for relationships between variables
- Can account for noise /uncertainties in test database
- Several Researchers have showed that showed that shear strength predictions from ANN predictions are superior to existing empirical provisions

Artificial Neural Network(ANN)

- Structure



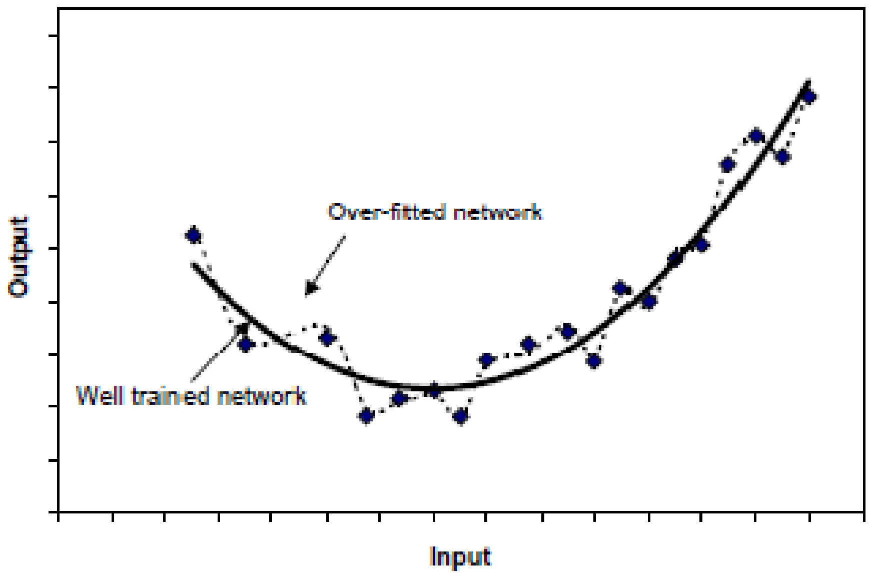
- ANN output

$$y = y(x;w) = g\left\{b_0 + \sum_{j=0}^{h}\left[w_{0j} f\left(b_{jh} + \sum_{i=0}^{N} w_{ji}\cdot x_i\right)\right]\right\}$$

- Objective Function

$$E_D(w) = \frac{1}{2}\sum_{i=1}^{N}\{y(x_i;w) - t_i\}^2 = \frac{1}{2}\sum_{i=1}^{N} e_i^2$$

- Over-fitting



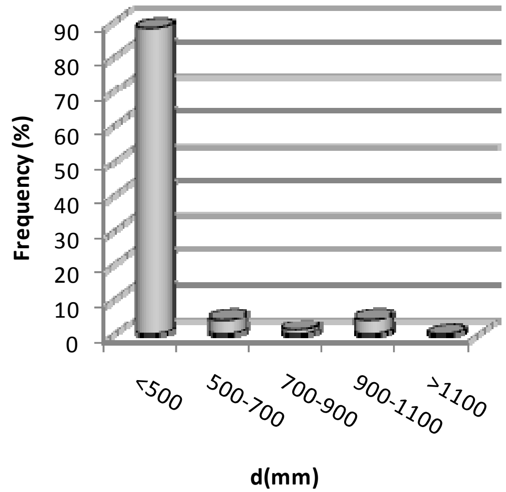
- **Limitations**

- Determination of optimal network architecture(i.e. Over-fitting or under-fitting)

Artificial Neural Network(ANN)

- Conventional solution to over fitting is to adopt the Early stopping technique
- Early stopping Technique
  - Division of data to two independent set(i.e. training and test set)
  - Train ANN until error increases in test set

- **Limitations**
- Division of test data can be impractical
  - Large and lightly reinforced beams
  - Evaluation is biased if the test set is not a representative subset
- determination of network parameters still subjective



Bayesian Neural Network

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•Mackay (1992) and Neal (1992) proposed the use of Bayesian inference in back propagated networks to overcome over-fitting

•In the Bayesian framework, a probability distribution is assumed over weight values

•Objective function: $S(w) = \beta E_D + \alpha E_w$

$$E_D(w) = \frac{1}{2}\sum_{i=1}^{N}\{y(x_i;w) - t_i\}^2 = \frac{1}{2}\sum_{i=1}^{N} e_i^2 \qquad E_W(w) = (1/2)\sum_{i=1}^{m} w_i^2$$

•Bayes' rule: $Posterior = \frac{Likelihood \times Prior}{Evidence}$

•Weight

$$p(w|D,\alpha,\beta,A) = \frac{p(D|w,\beta,A)\,p(w|\alpha,A)}{p(D|\alpha,\beta,A)}$$

•Hyper parameters

$$p(\alpha,\beta|D,A) = \frac{p(D|\alpha,\beta,A)\,p(\alpha,\beta|A)}{p(D|A)}$$

Bayesian Neural Network

Advantages

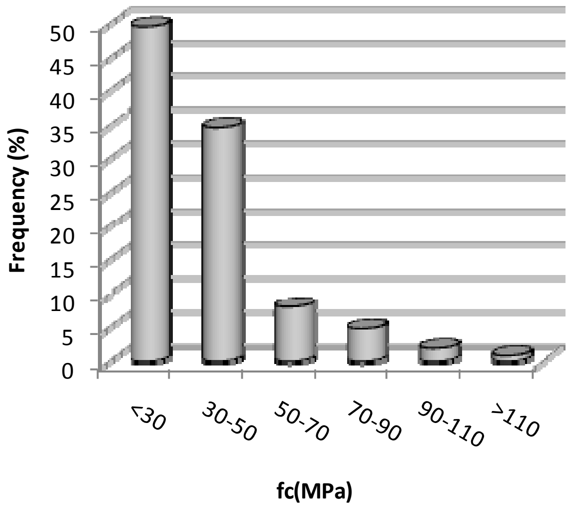
- Optimum network architecture automatically determined
- Since over-fitting is eliminated, gives good generalisation
- Relative importance of input variables can be determined(I.e. ARD)
- Allows choices to be made about where in input spaces new data should be collected
- Error bars or confidence intervals can be assigned to predictions generated by a network.

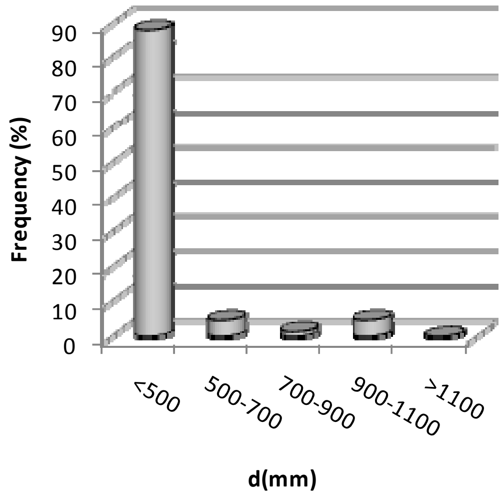
Methodology

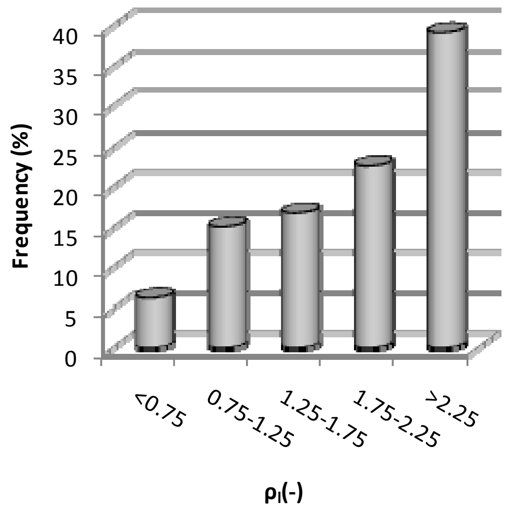
Range of input variables

b_w(mm)	d(mm)	f_c(MPa)	ρ_l(%)	a/d(-)	d/b_w(-)	Fy(MPa)	V_u(kN)
150-2010	152-2000	12.2-110.9	0.14-5.01	2.2-8.52	0.35-7.22	283-1779	19.9-1272

Experimental test data







Methodology

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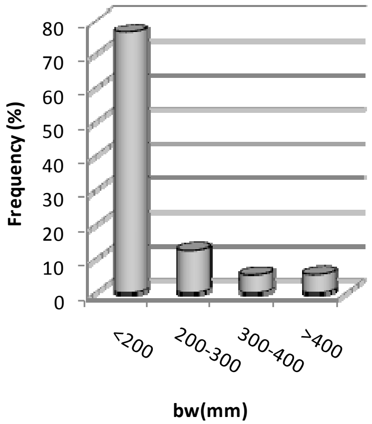
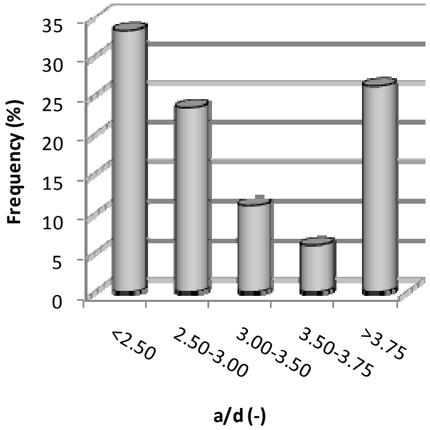
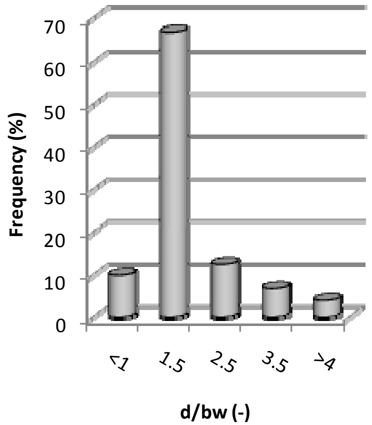
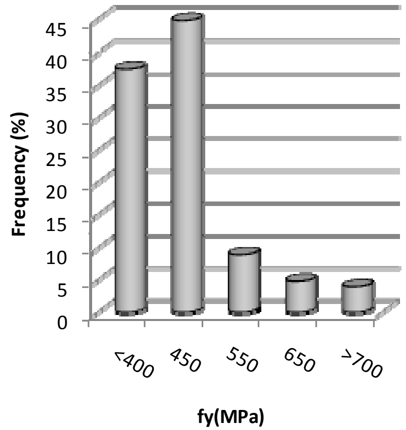








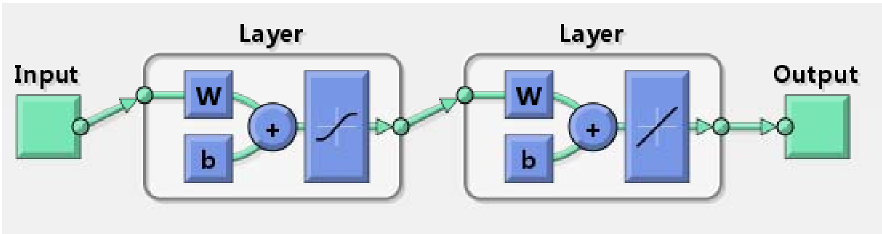
- Pre-processing

Input and output normalised to [1 -1]

$$\left(x_i\right)_n = \frac{2(x_i - (x)_{\min})}{(x)_{\max} - (x)_{\min}} - 1$$

$$x_i = \frac{\left[\left(x_i\right)_n + 1\right]\left[(x)_{\max} - (x)_{\min}\right]}{2} + (x)_{\min}$$

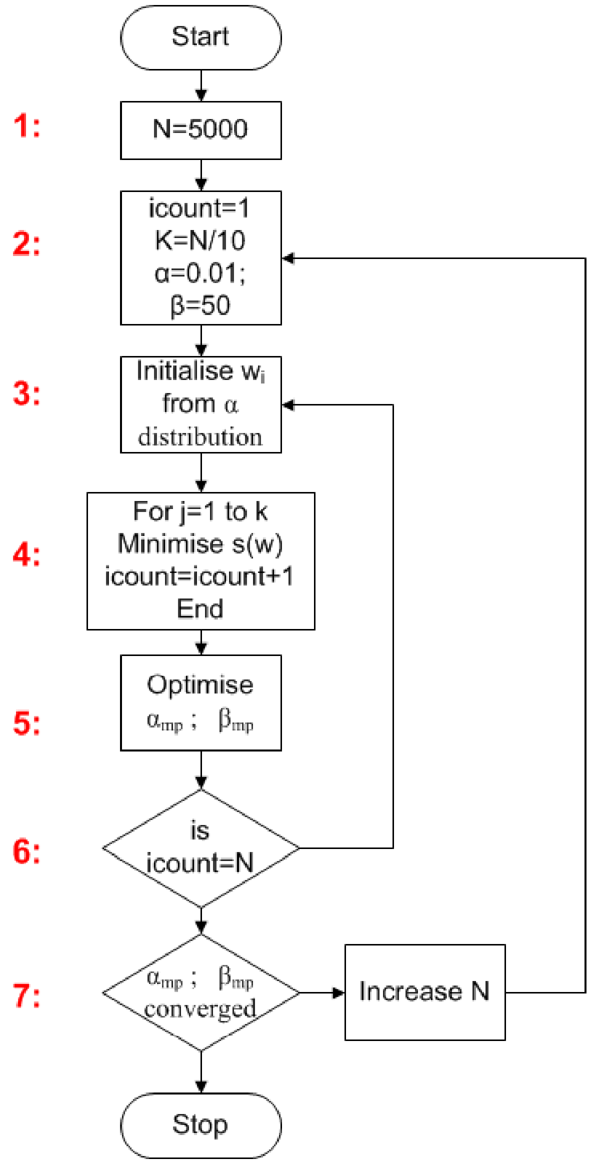
- Topology



Training Procedure

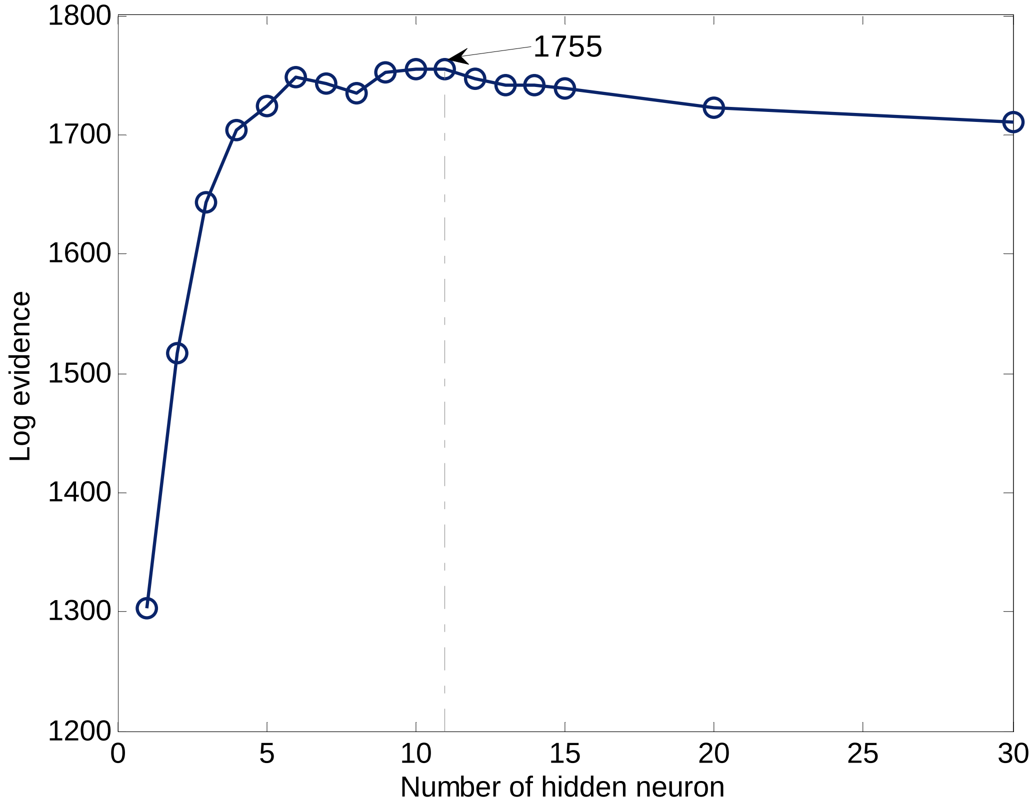
Implemented using a MATLAB toolbox called NETLAB (Nabney, 2002)

1. Set total training cycle
2. Initialise hyper parameters
3. Initialise weight using Gaussian distribution
4. Minimise s(w)
5. Optimise hyper parameters(i.e. compute evidence)
6. Check if training cycle exceeded
7. Is hyper-parameters converged



Network Selection

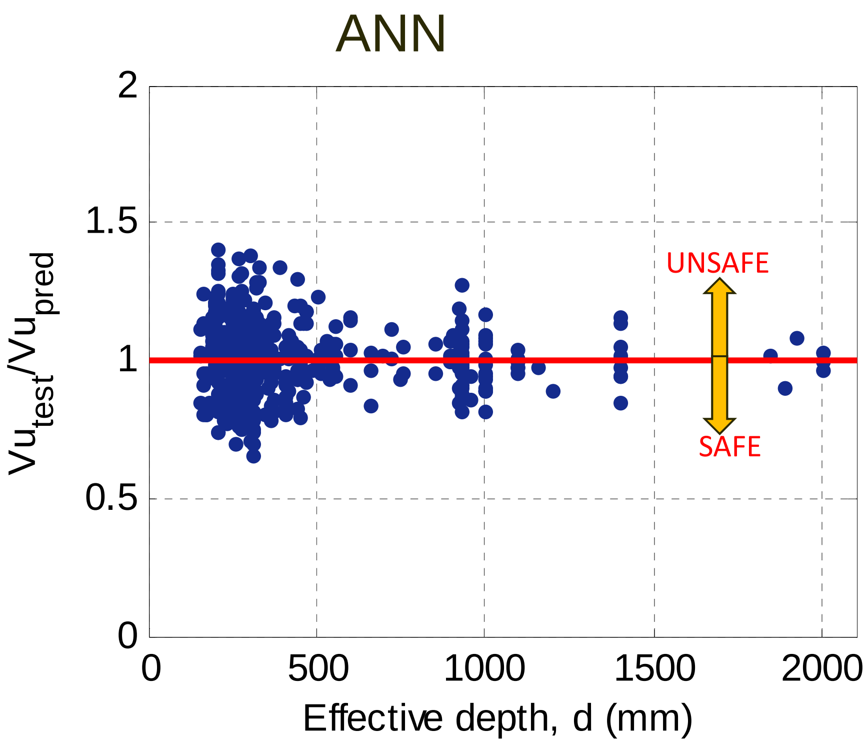
- Determination of Artificial Neural Network Architecture

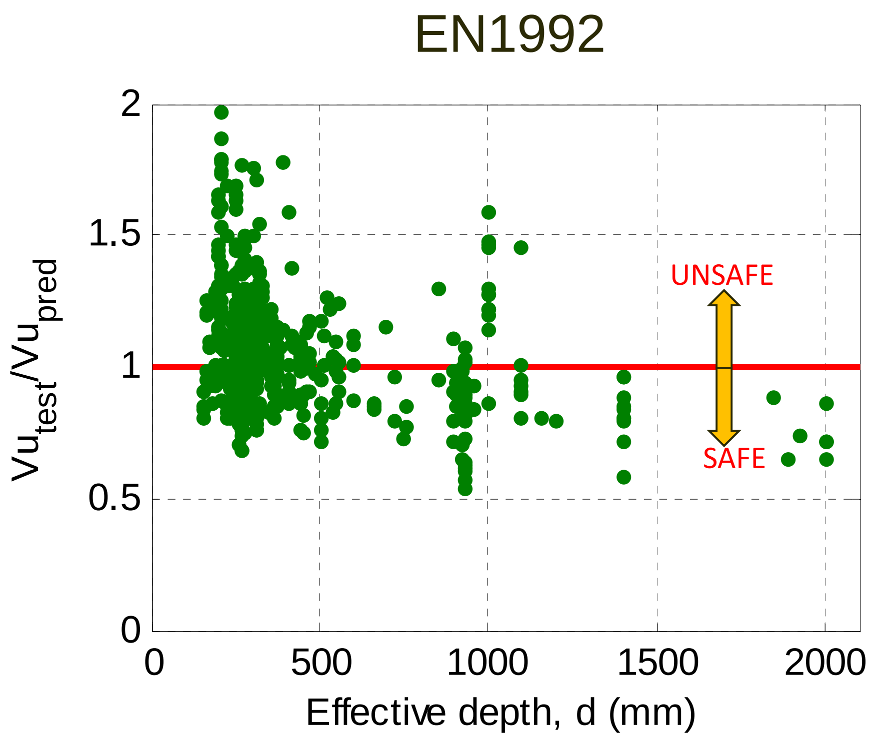


Log evidence of different NN models

Network Performance

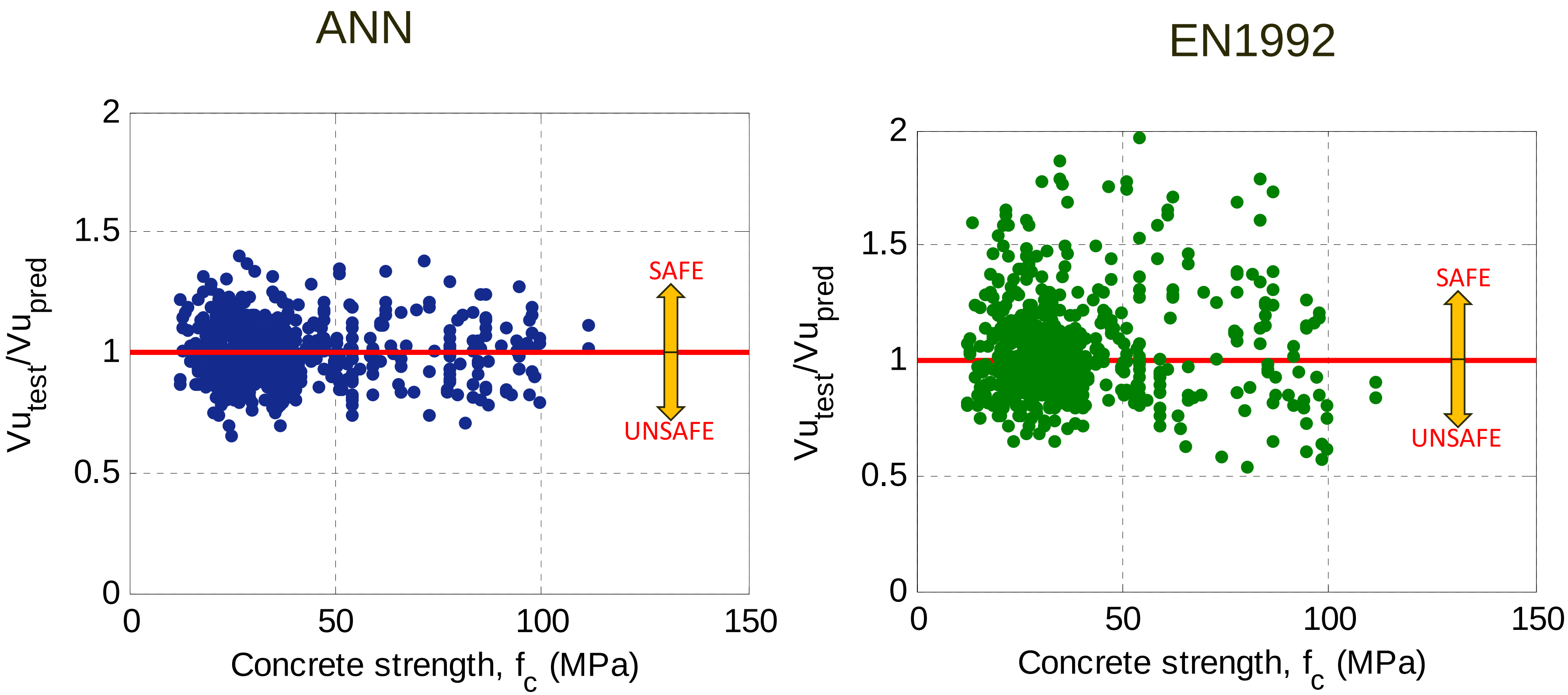
- Artificial Neural Network Performance





Strength ratios of ANN approach

Network Performance



Strength ratios of ANN approach

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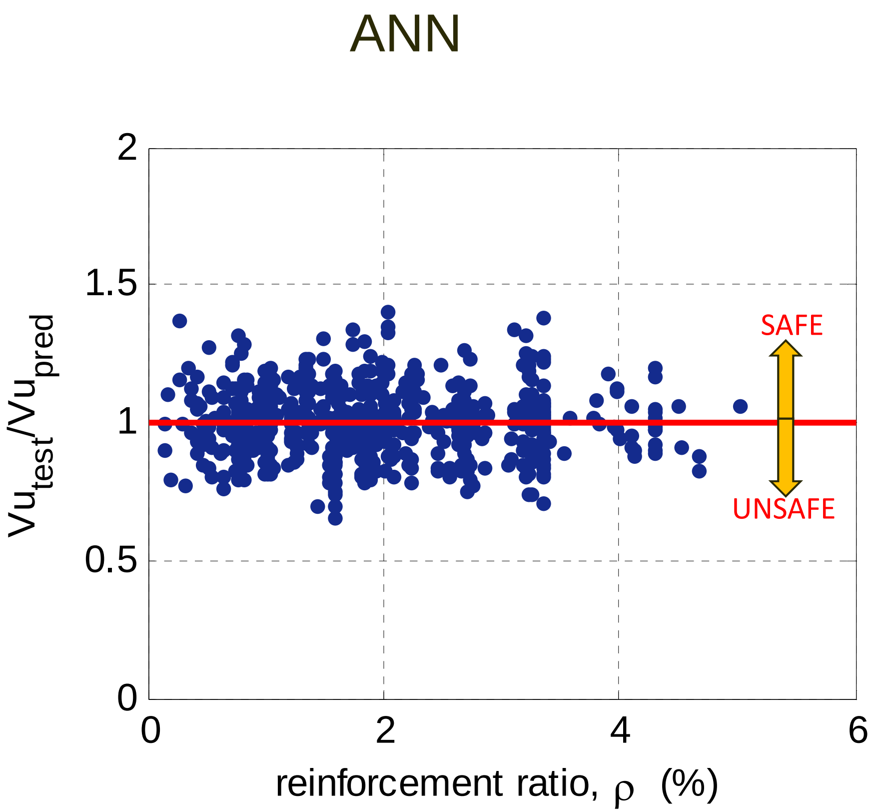

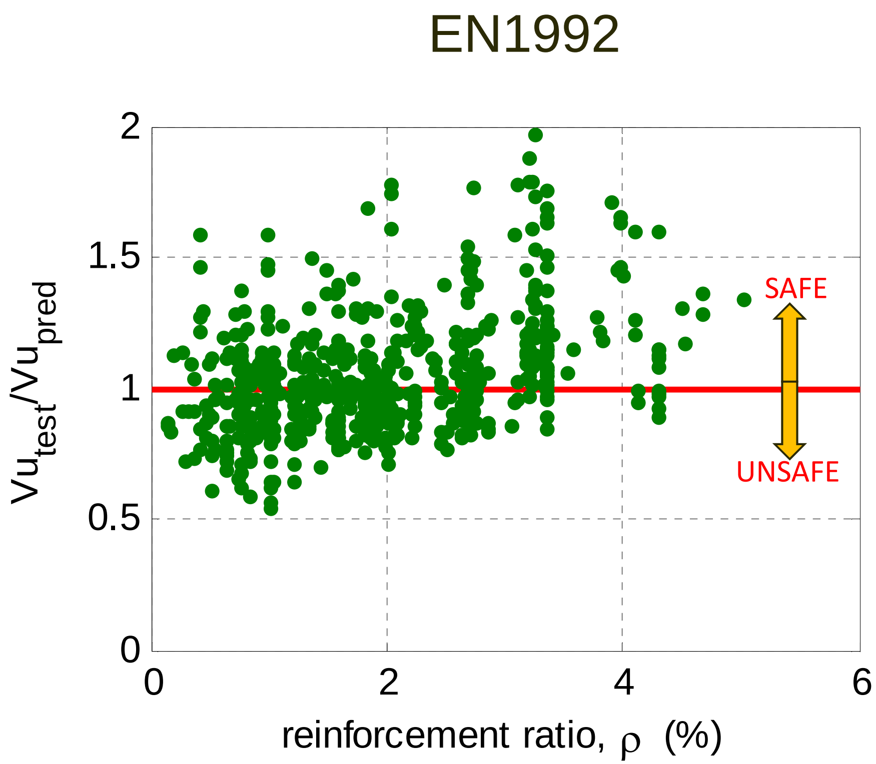

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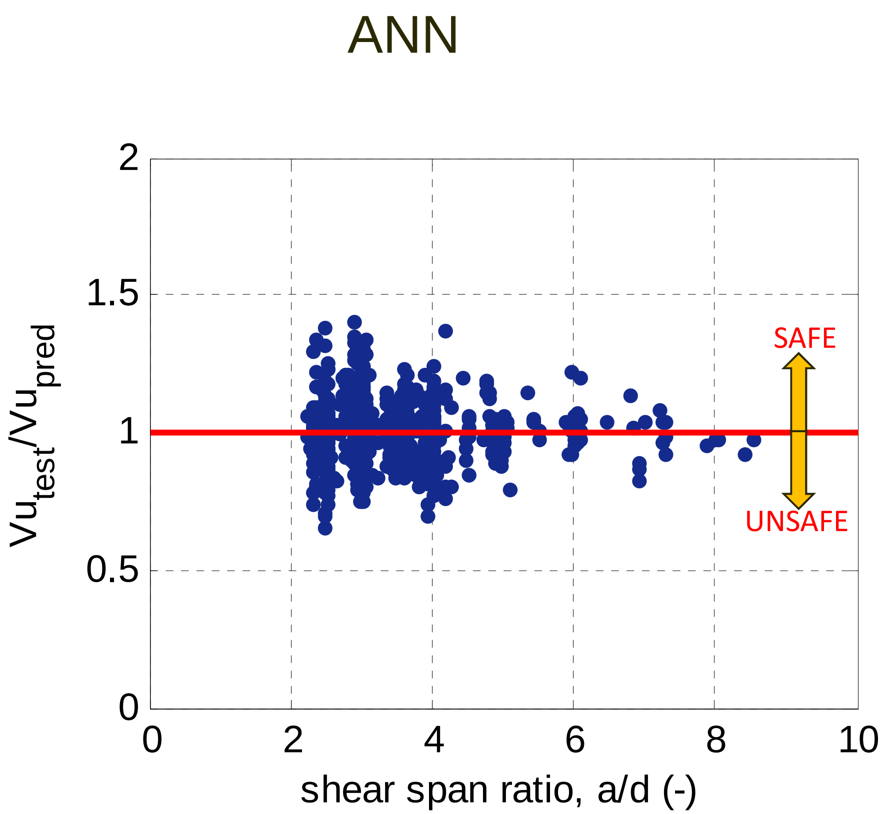
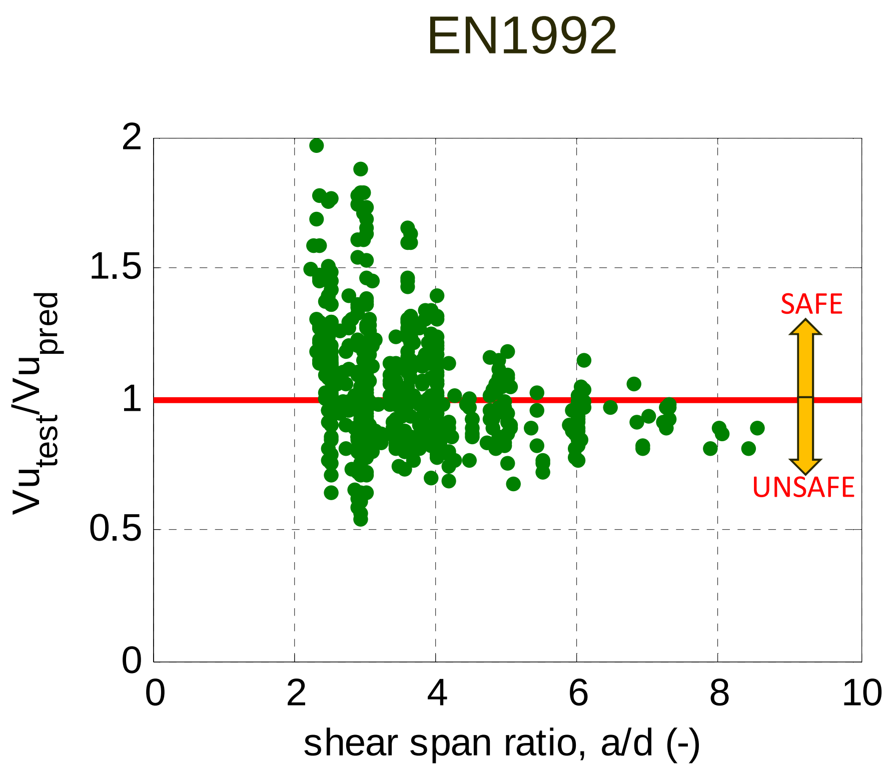
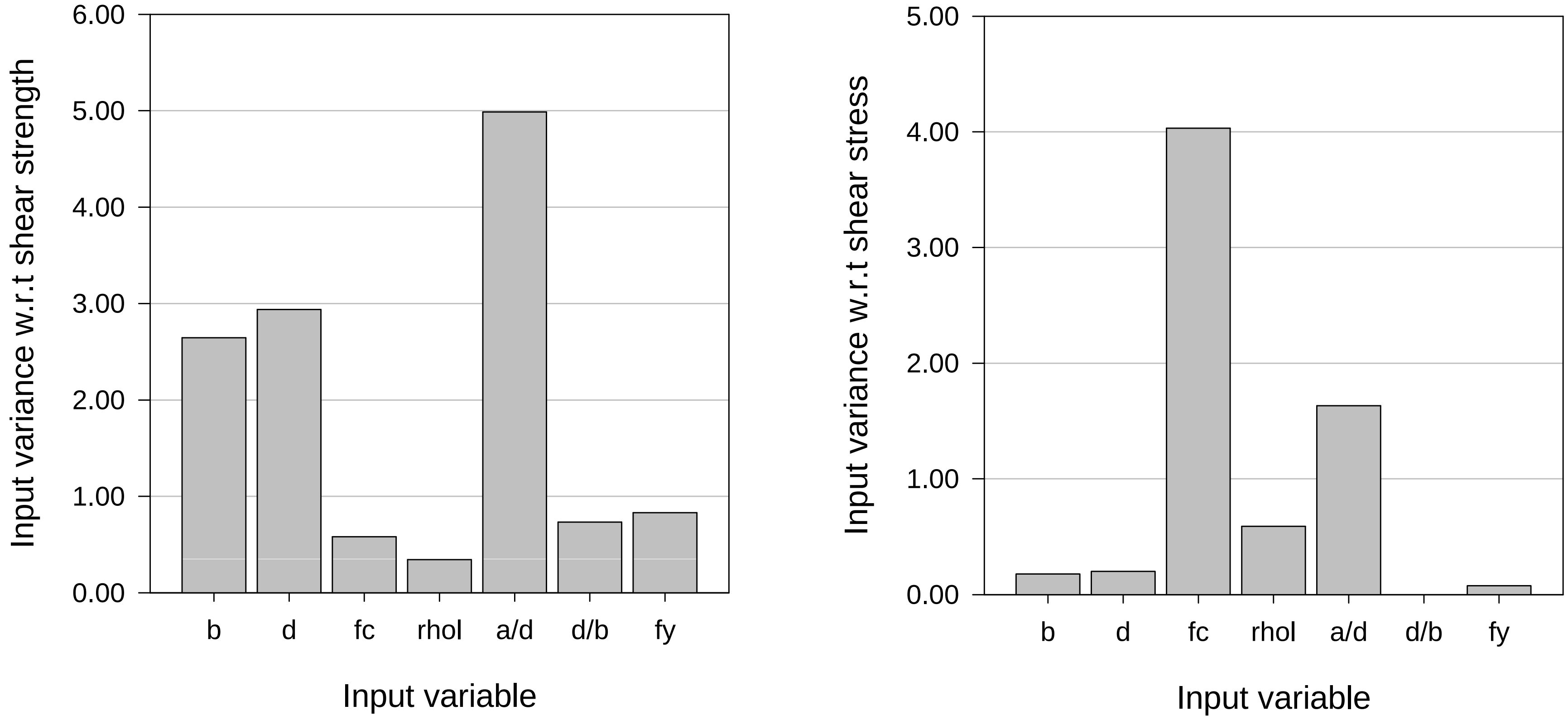




Strength ratios of ANN approach

Input parameter Relevance

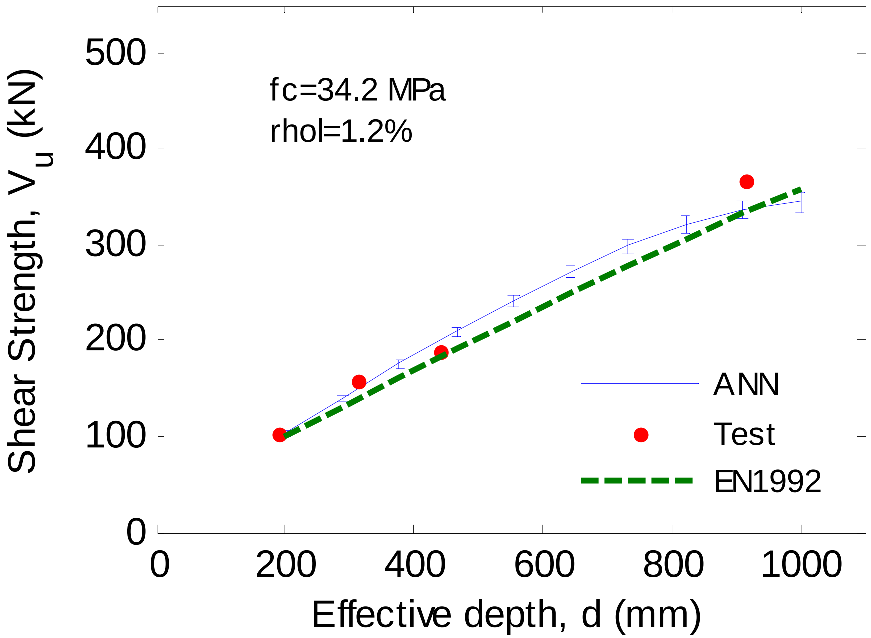
- Relevance of Input Parameters

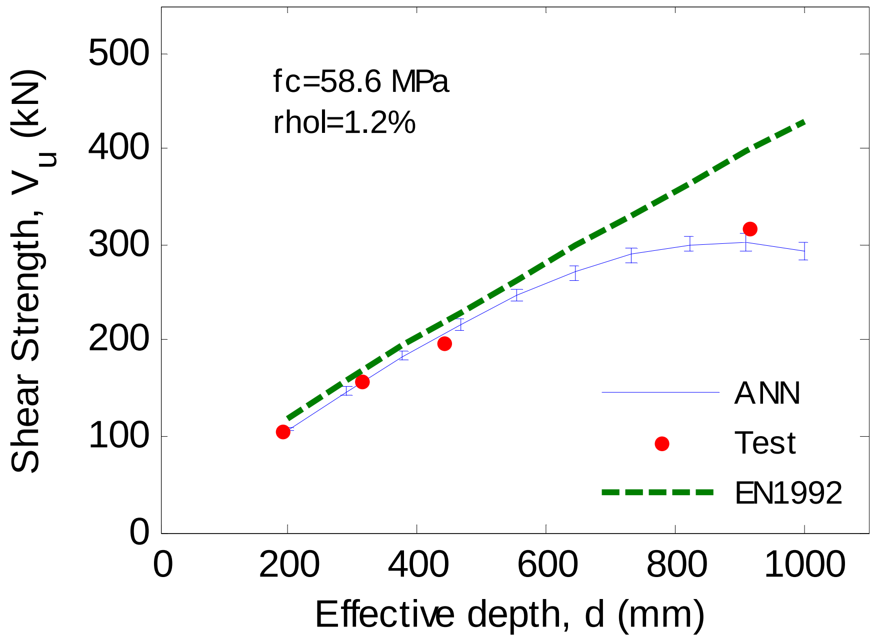


ARD technique: relevance of the input variables to (a) shear strength and (b) shear stress

Test Simulation

Simulation of experimental test and code comparison





ANN predictions of RC beams tested by Ghannoum(1998)

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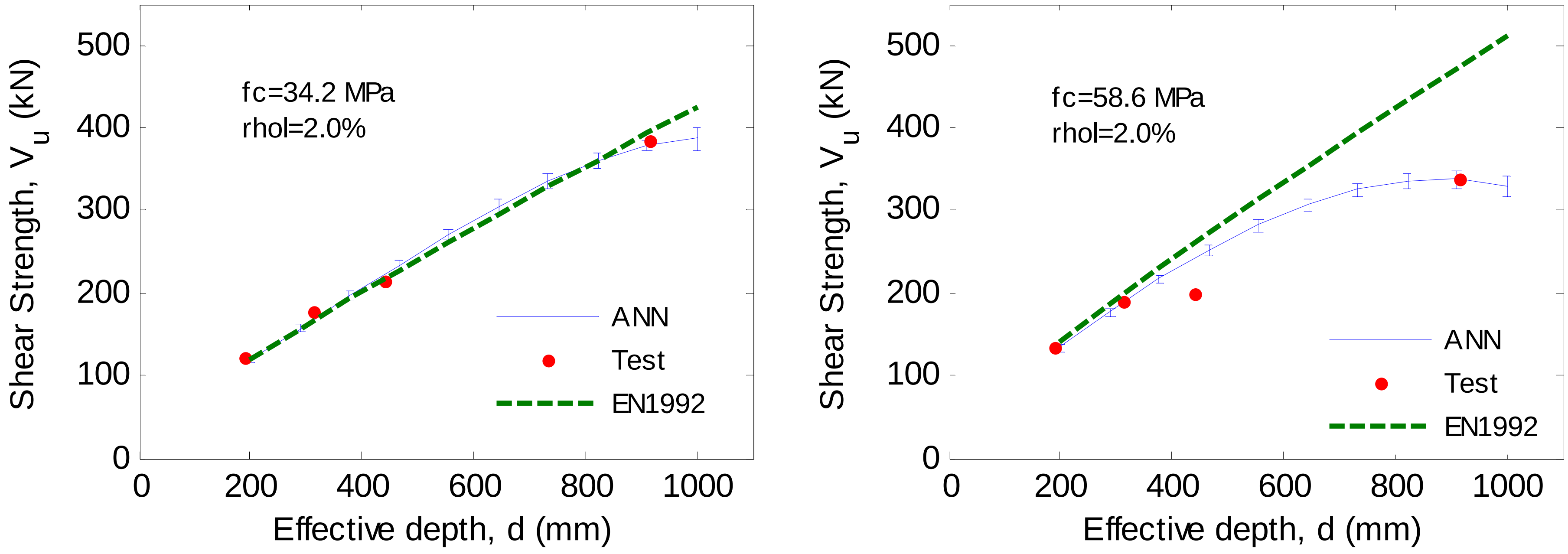

ANN predictions of RC beams tested by Ghannoum(1998)

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Conclusion

The following conclusions can be drawn from this study:

- A Bayesian neural network was developed to predict the shear strength of beams without stirrups.
- The neural network eliminates subjectivity and over-fitting
- The predictions of the network provides a uniform level of safety across the range of input parameters
- With the Bayesian neural network , the influence of different shear parameters have been investigated
- Although the Bayesian Neural network is a more robust approach, there is still a need to understand the shear behavior and generate test data for the deficient members in database(i.e. large and lightly reinforced members)

Future work

•Laboratory constraint and Prohibitive cost can make further experimentation difficult.
•More fundamental approach may be to adopt analytical models such as FEA .

Thank you

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