Shear Strength Prediction of Unusual Interior Reinforced Concrete Beam-Column Joint Using Multi-Layer Neural Network: A Data Collection by Digital 3D Finite Element Simulation

Christ John L. Marcos
School of Graduate Studies
Mapua University
Manila, Philippines
engr.cjlmarcos@gmail.com

Dante L. Silva
School of Civil, Environmental, and Geological Engineering
Mapua University
Manila, Philippines
dantesilva2000@yahoo.com

***Abstract*—One of the controversial topics in the literature on structural engineering is retrofitting existing substandard interior reinforced concrete beam-column joints. However, these retrofitting methods gave an unusual shape to the joints, causing the unpredictability of their strength. A machine learning application was developed to predict the shear strength of unusual joint, farther finite element analysis was utilized to generate 3D samples as a training dataset. The paper presented detailed methodologies and discussions of the two disciplines. Powerful digital technologies and computer systems shown dominance by presenting the performance and regression analysis through different trained neural network models. Sensitivity analysis was conducted utilizing connection weights algorithm to determine the relative importance factor.**

***Keywords*—shear strength, unusual interior beam-column joint, reinforced concrete, neural network, finite element**

I. Introduction

Because of its numerous advantages, reinforced concrete (RC) has been the most extensively used structural material nowadays. Using this material with a moment-resisting frame (MRF) has been famous for economic and architectural reasons. MRF requires rigid beam-column joints (BCJs) to disperse earthquake energy and prevent brittle failure that could cause catastrophic building collapse. However, some RC MRF constructions were poor or lacked transverse reinforcement in the BCJ. Many researchers recommend various ways to improve these weak joints. One of the literature's most recent and robust ways is to extend the inner joint area by forming an unsymmetrical chamfer with fiber mortar material [1], to resist the governing joint shear failure [2]. Envision what will be happened to poor RC buildings with no transverse reinforcement in the joint and has high shear stresses, a dangerous event will have occurred, killing the inhabitant, so retrofitting and constructing a larger BCJ is required to avoid unwillingness. Nevertheless, strengthening the RC BCJs could create a new issue by changing the joints' regular shape to irregular. The product's unusual shape precludes the application of theoretical, analytical, and empirical models in the literature, which cannot forecast shear strength. Because models are seen and evolved from conventional ones, predicting the unconventional structural component shape was difficult. Even though the joint was strengthened, it is still essential to assess the strength considering other structural components affected, global structure analysis, and user cost.

Machine learning (ML) is currently widely used to handle complicated forecasting. Employing the ML or its advanced application artificial neural network (ANN) could give an excellent prediction output [3–6]. However, using this algorithm required a set of data wherein uncommon joint types have only a few.

Physical data collection has been both costly and unsafe during the COVID-19 pandemic. A Finite element (FE) analysis is a computer workbench that can simulate (SIM) unusual components digitally to produce samples that would generate a dataset.

This paper aims to utilize FE simulations to generate a training dataset for the ANN prediction of unconventional joint shear strength (V_{jh}). This study will be extended by assessing the impact of independent variables on the dependent variable using sensitivity analysis.

II. Methodology

This section covers detailed processes and procedures combining FE simulations to produce samples, ML modeling to create a prediction model, and sensitivity analysis to evaluate the prediction's output. A total of 6 phases and 13 stages are presented in Fig. 1.

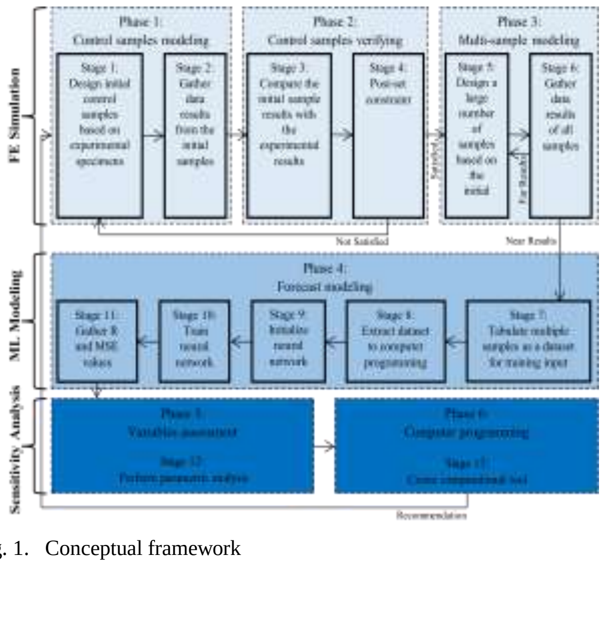


Fig. 1. Conceptual framework

The researchers are sincerely grateful to the Department of Science and Technology – Science Education Institute and to the Engineering Research and Development for Technology for their grants and funding. Also, to Mapua University for their support in making this research happen

A. Finite Element Simulation

Stage 1 is about the computer simulation of IJ-NC and IJ-C150FM specimens from the literature [1]. Considering the prime numerical model for the joint through the ABAQUS/Standard software [2]. Fig. 2 shows the physical and simulated control models, and Table I presents the inelastic behavior parameters considered for simulation. Stage 2 involves garnering the simulation data results as the initial designs for this study.

Stage 3 verifies the force-displacement analysis results of experimental IJ-NC and IJ-C150FM with simulated SIM-IJ-NC and SIM-IJ-C150FM.

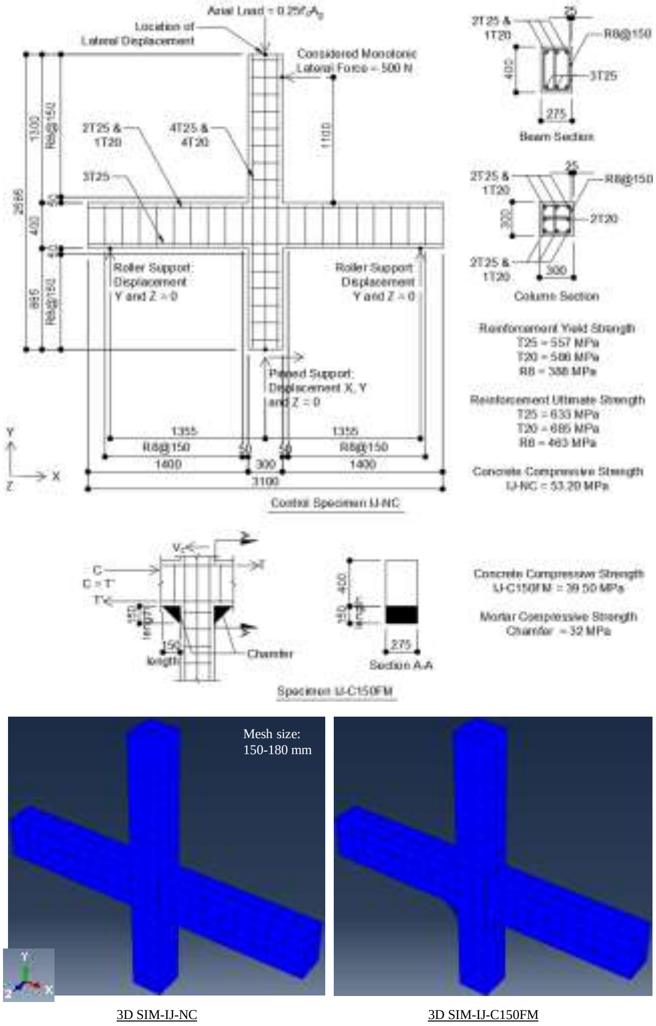


Fig. 2. Dimensions, conditions, analysis approaches and 3D FE models

TABLE I. CONCRETE DAMAGE PLASTICITY

Parameters	SIM-IJ-NC	SIM-IJ-C150FM
Dilation Angle (calibrated)	10	37.50
Eccentricity (default)	0.10	0.10
Stresses Ratio (default)	1.16	1.16
Coefficient (default)	0.667	0.667
Viscosity Parameter (calibrated)	0.00675	0.006875

Stage 4 post-setting constraint which the experimental and simulated maximum lateral force (V_c) results must be at least 10 % different for acceptance, determining V_{jh} (1).

$$V_{jh} = T + T' - V_c - V_{sh} \tag{1}$$

wherein T and T' are longitudinal reinforcements based on strain, and V_{sh} was neglected since the substandard joint has no transverse reinforcement.

Stage 5 additionally designed 19 samples with minimal and practical adjustments based on the initial unusual SIM-IJ-C150FM. Stage 6 involves gathering the data of 19 and SIM-IJ-C150FM samples for a total of 20 samples as a dataset.

B. Machine Learning Modeling

Stage 7 requires the tabulation of significant independent and dependent variables of 20 samples. The significant independent variables for V_{jh} of conventional interior RC BCJ are compressive strength (f'_c), beam longitudinal reinforcement ratio (p_b), joint width (b_j), joint aspect ratio (h_b/h_c), and joint transverse reinforcement (A_{sj}) [7]. However, A_{sj} was neglected for a substandard joint, so chamfer length (l_c) shall be substituted. Stage 8 entails extracting data into a computer application using MATLAB software. Stage 9 initializes neural network models (NNMs) with 15%, 15%, and 70% of validation, testing, and training data, respectively [4-5]. This paper has 3 cases consisting of different hidden layer numbers but the same counts of hidden neurons per layer as shown in Fig. 3. Table II presents the adopted NNM properties [3] except of the transfer function, because this study also considered 1 hidden layer model contrast to the authors' statement by utilizing deep neural network (DNN) to be more superior than gene expression programming [7].

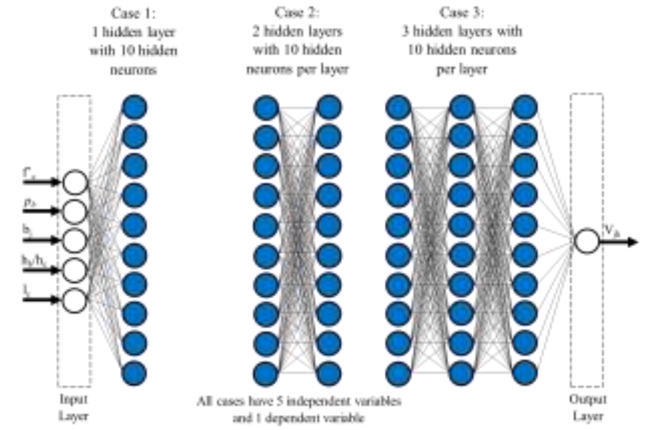


Fig. 3. Multi-layer neural network architectures

TABLE II. NEURAL NETWORK PROPERTIES

Function	Network Type
Network	Feed-Forward Back Propagation
Training	Levenberg-Marquardt Algorithm
Learning	Gradient Descent with Momentum
Performance	Mean Squared Error
Transfer	Tansig

Stage 10 observes the training. Stage 11 automatically calculates regression (R) and mean squared error (MSE) to evaluate the forecast. The study was set with the constraint that R must be more outstanding than 95 % and MSE less than 1 % for case 3 with 3 hidden layers or DNN. Then the R and MSE of cases 1 and 2 should be compared to case 3 and manifest if case 3 was necessary for this type of problem, joint shear strength prediction.

C. Sensitivity Analysis

Stage 12 is concerned with the correlation of variables. The most extreme R was extended to be studied parametrically: (1) to determine the behavior of predictions using graphical analysis of independent variables versus output to target ratio, and (2) the sensitivity analysis or the relative importance factor of independent to dependent variables using the connection weights algorithm (2).

$$\mathrm{Input_X} = \sum_{Y=1}^{M} \mathrm{Hidden_{XY}} \quad (2)$$

wherein $\mathrm{Input_X}$ is the input importance value, $\sum_{Y=1}^{M}$ is the sum of the connection weight products, and $\mathrm{Hidden_{XY}}$ is the product of connection weights from input to output.

Stage 13 involves creating or saving the best trained NNM for future use, which must also be applied to the other inputs not associated with the training dataset but within the limits.

III. Results and Discussions

A. Input Verification

To ensure that the input data is reliable, a verification must be considered. Comparative analysis through a behavior graph of the forces versus displacements is presented in Fig. 4 between the initial simulated designs and experimental specimens from the literature. Table III shows the satisfaction of simulation using the percentage difference of V_c.

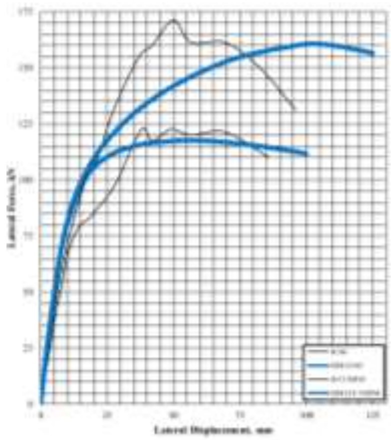


Fig. 4. Force-Displacement envelope of control joints

TABLE III. PERCENTAGE DIFFERENCE

Description	Maximum Lateral Force, kN	Difference, %
IJ-NC	121.51	3.25
SIM-IJ-NC	117.56	
IJ-C150FM	171.75	6. 46
SIM- IJ-C150FM	160.65	

Fig. 5 shows the behavior of SIM-IJ-C150FM and other 19 unusual samples. Table IV summarizes the minimum and maximum values of 20 samples, as well as calculated mean and standard deviation.

B. Output Assessment

The results were obtained in different cases: (1) first case R = 0.99648 & MSE = 0.49769, (2) second case R = 0.9997 & MSE = 0.45737, and (3) third case R = 0.99574 & MSE = 0.13178. Fig. 6 depicts the best result of R from case 2 and MSE from case 3. It is undeniable that all cases of NNMs with any number of hidden layers were superior and suitable for use.

Two parametric studies were limited only for the highest value of R. First parametric results were gathered by comparing the effect of significant input parameters to the ratio of output to target results, as seen in Fig. 7 with a reflecting trendline along with scattered data. Second parametric results were gathered to check the critical independent variables as shown in Fig. 8 depicting that p_b has an enormous impact.

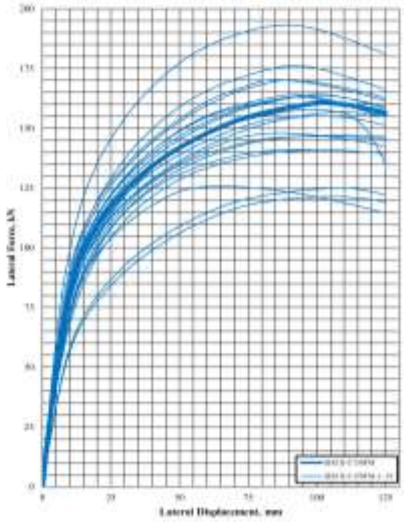


Fig. 5. Force-Displacement envelope of 20 unusual joints

TABLE IV. STATISTICS OF INDEPENDENT VARIABLES

Description	f'c, MPa	p_b	b_j, mm	h_b/h_c	l_c, mm
Minimum	35	0.0061	275	1.1429	125
Mean	39.25	0.0143	302	1.3104	151.25
Maximum	42	0.0190	350	1.5000	200
Standard Deviation	1.46	0.0030	15.42	0.0885	17.16

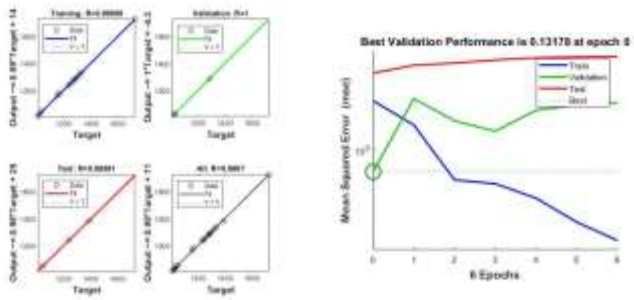
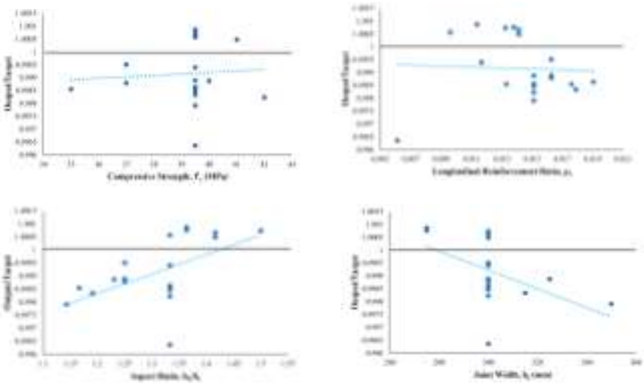


Fig. 6. Best R and MSE values



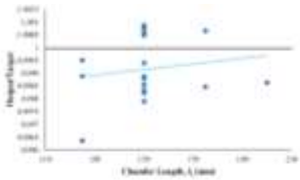


Fig. 7. Correlation of independent variables versus output to target ratio

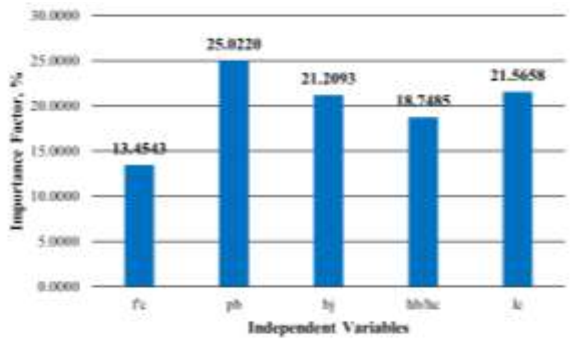


Fig. 8. Relative importance factor of independent variables

IV. Conclusion

This study demonstrates digital technology capabilities through FE simulation, ML modeling, and sensitivity analysis. The primary findings are as follows:

1. Samples are vital for research. FE modeling effectively produced unusual samples as shown on the force-displacement results with less than 10 % difference of V_c.

2. Formulation or prediction is very important for reusing frameworks. ML or subset ANN prediction has a strong ability to solve uncommon or unorthodox problems, as shown on the R and MSE values of greater than 95 % and less than 1%, respectively.

3. Output evaluation is crucial in order to judge the processes and procedures of prediction. Independent variable l_c was used despite insufficient evidence to utilize it. But based on the output of sensitivity analysis, l_c has 21.5658 % and was ranked as the 2nd out of 5 independent variables showing acceptance for utilization.

V. Recommendation

This study is limited to unconventional joints, which encourages other researchers to use the presented research method to develop and predict the other unusual components and elements that have insufficient data and are unpredictable.

Acknowledgment

The researchers are sincerely grateful to the Department of Science and Technology – Science Education Institute and to the Engineering Research and Development for Technology for their grants and funding. Also, to Mapua University for their support in making this research happen.

References

[1] E.S. Lam, Z. Xue, S. Fang, and S. Masqood, "Interior beam column joints with nominal joint shear reinforcement versus unsymmetrical chamfers", Engineering Structures 220, 2020.

[2] M.A. Najafgholipour, S.M. Dehghan, A. Dooshabi, and A. Niroomandi, "Finite element analysis of reinforced concrete beam-column connections with governing joint shear failure mode", Latin American Journal of Solids and Structures 14(7), 2017, pp. 1200-1225.

[3] S.H. Park, D. Yoon, S. Kim, and Z.W. Geem, "Deep neural network applied to joint shear strength for exterior RC beam-column joints affected by cyclic loadings", Structures 33, 2021, pp. 1819-1832.

[4] D. Silva, et al., "Prediction of tensile strength and erosional effectiveness of natural geotextiles using artificial neural network", 2021 13th International Conference on Computer and Automation Engineering ICCAE, 2021, pp. 121-127.

[5] D. Silva, et al., "Sensitivity analysis and strength prediction of fly ash – based geopolymer concrete with polyethylene terephtalate using artificial neural network", 2020 IEEE 12th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management HNICEM, 2020.

[6] D. Silva, K.L. de Jesus, B. Villaverde, and E. Adina "Hybrid artificial neural network and genetic algorithm model for multi-objective strength optimization of concrete with surkhi and buntal fiber", ACM International Conference Proceeding Series, 2020, pp. 47-51.

[7] Y.Z. Murad, R. Hunifat, and W. Al-Bodour, "Interior reinforced concrete beam-to-column joints subjected to cyclic loading: Shear strength prediction using gene expression programming", Case Studies in Construction Materials 13, 2020.