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PREDICTION OF REINFORCED CONCRETE COLUMNS LIMIT STATES USING MACHINE LEARNING ALGORITHM

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Abstract

The assessment methods for estimating the behavior of the complex mechanics of reinforced concrete structural elements were primarily based on experimental investigation, followed by collective evaluation of experimental databases from the available experimental literature. There is still a lot of uncertainty today about the strength and deformability criteria that have been derived from tests due to the differences in the experimental test setups of the individual research studies that fed into the databases. Following these investigations, the regulatory methods of seismic assessment were developed. The topic covered in this research is the effect of test setup on the derived criteria, and the second-order effects that the test setups have introduced into the behavior of structural elements. The research focuses on elements that exhibit pronounced strength degradation with plastic deformation and brittle failure characteristics. The shear strength reduction that has been attributed to the magnitude of the imposed ductility is investigated, and it is determined how much of this degradation is recognizable, i.e., how much is a consequence of the experimental setup nonlinearity. While the available methods of assessing shear strength differ because they are all empirical, they all acknowledge the contribution of individual resistance mechanisms, such as concrete, transverse reinforcement, and axial load. The experimental setup nonlinearity has an impact on the last of these three contributions. In this work, the experimental results are correlated with a revised formulation of column shear strength after the values have been corrected, with a special focus on elements with inadequate structural detailing configuration. Finally, through the use of machine learning algorithms the development of an improved formula for predicting the shear capacity of reinfroced concrete columns is performed.

Keywords: Seismic Assessment, Reinforced Concrete Columns, Shear Strength, Machine Learning

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1 INTRODUCTION

Following the development of Performance–Based Assessment (PBA) frameworks, between 1995 and 2010, practical evaluation of the seismic behavior of reinforced concrete (RC) became a priority on account of the large number of existing RC buildings in urban centers. Earthquakes that occurred in the last 30 years affected urban regions such as Loma-Prieta (1989), Northridge (1994, California), Athens (1999, Parnitha), Izmit (1999, Turkey), ChiChi (1999), L'Aquila (2009, Italy), Haiti (2010), Turkey (2023), etc., all highlighted the catastrophic potential and risk to human life imparted by old construction. Damage was more intense in RC buildings with soft storeys.

For the first time in this period, the explicit interest in the literature is focused on the drift capacity of columns at collapse. A large number of studies have been published thus far, attempting to quantify the deformation capacity of columns, with reference to the seismic risk presented by existing construction. In particular, crucial parameters that affect the seismic behavior of this type of element at advanced stages of deformation are of significant importance especially when elements with inadequate steel reinforcing configuration that represent old-type practices are evaluated.

An important factor responsible for the dispersion of results is the perceived insensitivity of the analytical models to some critical parameters that control the onset of failure. In columns controlled by flexural yielding before failure (flexure-shear elements), the load-carrying capacity against horizontal load is generally controlled by flexure. On the other hand, the deformation capacity is generally much lower than that specified by the analytical models, which superimpose a limiting envelope on the resistance curve. This approach aims to effectively control the interplay between shear and flexure after yielding, based on the ratio $V_n(\mu)/V_{flex}$, by limiting drift capacity which is suggested in KANEPE 2014. Flexural strength is hardly the only controlling variable; for example, strength loss in lap splices, exacerbated by cyclic deformation reversals may alter the hierarchy expressed by the preceding ratio. For these reasons, the estimation of the shear capacity of RC columns is still an open problem that requires further investigation and the development of more accurate design formulae.

For the needs of the present work, a dataset was extracted from the PEER database of columns [1], which contained a large volume of tests collected from published experimental literature. In incorporating any specimen in the selected dataset, the type of failure of the RC column specimen was investigated and used as the main criterion. Using the extracted data, the proposed model for shear strength calculation was compared with the reported values, and a specific methodology was followed to determine whether or not the experimental results had been previously corrected for second-order effects (i.e., in the original test reports), as well as when assembled in the PEER database in [1]. To improve the investigation, an optimization methodology was used to augment and improve the existing models that are used to evaluate the shear strength of RC columns. The proposed model that is developed through the use of machine learning algorithms is compared to the model suggested by [2] and that proposed in [3].

2 IMPORTANT FACTOR OF RC COLUMNS BEHAVIOR

A qualifying criterion for the type of failure and the behavior of RC columns is the yielding of the longitudinal reinforcement before the occurrence of shear failure. If longitudinal bar yielding precedes stirrup yielding, the failure is described as of flexure-shear type, whereas if the sequence is reverse, the failure is referred to as brittle-shear. For the brittle-shear type of failure the drift capacity is particularly small and in any case, is less than the nominal yielding drift of the element θ_y.

The RC column shear strength, V_n for the needs of seismic assessment are obtained from [4] and [2], respectively, using mean values for material strengths:

$$V_n^A = V_c + V_w = \eta^A \lambda \left(\frac{0.5\sqrt{f_c}}{\frac{M}{Vd}} \sqrt{1 + \frac{P}{0.5\sqrt{f_c}A_g}} \right) 0.8A_g + \eta^A \frac{A_{s,tr} f_{y,tr} d}{s} \quad (1)$$

$$V_n^E = V_c + V_w + V_N = \eta^E(\mu) \cdot 0.16\sqrt{f_c}(0.8A_c)[max\{0.5, 100\rho_{tot}\}] \cdot (1 - 0.16 \cdot min\left\{5, \frac{L_s}{h}\right\})] + \eta^E(\mu)\frac{A_{st}f_{tt}(d-d')}{s} + min\{N, 0.55A_c f_c'\} \cdot tan\,\alpha \quad (2)$$

Indices A and E given in the form of superscripts refer to the two reference standards [4] and [2], respectively, which are using different approaches for the discussed factor. Angle α in the EN1998-3, 2005 approach refers to the angle of inclination of the diagonal compression with reference to the longitudinal axis of the element as shown in Fig. 1. The angle is defined by the line that connects the centroids of the compression zones in the opposite ends of the member.

A noteworthy difference in approach is underlying the two empirical models, despite that the expressions have been calibrated against the same database of tests. For one, the ASCE approach accounts for the influence of the axial load within the concrete contribution term, whereas in the EN approach, the contribution of the axial load is considered as a standalone independent component – the value of $N \tan \alpha$ represents the horizontal component of the inclined strut that is visualized as transferring the axial load to the support of the column [3, 5]. Another difference is that in the ASCE approach, the axial load component degrades with increasing displacement ductility together with all other terms, its contribution is moderated by the ½ exponent.

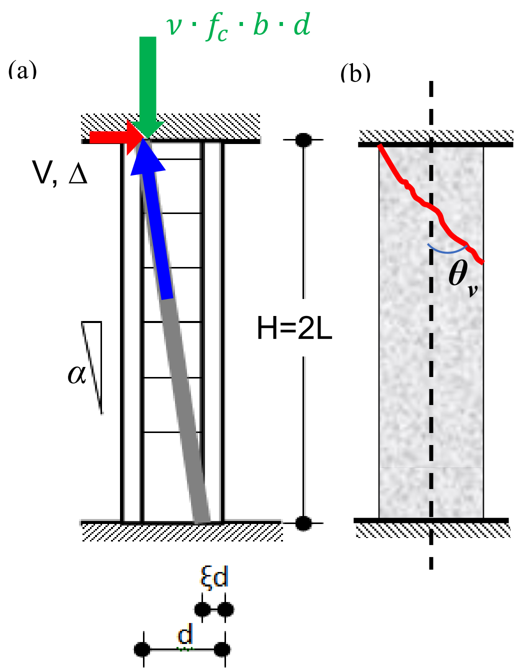

Figure 1: EN model for the contribution of the diagonal strut to shear strength (a) Definition of the strut angle, and (b) definition of the critical crack angle, θ_v.

It is easy to understand that computing the shear capacity of RC columns or even describing the mechanical response of this problem is highly complicated. For this reason, the objective of this work was to find experimental data and use a polynomial regression algorithm [6, 7] to extract an improved formula that will be able to provide accurate predictions. For this reason, a dataset was assembled as is discussed in the next section.

3 SELECTION OF DATASET ENTRIES

The dataset used in the present study comprised 74 specimens containing steel reinforcement configurations that classify as old type. Before using the data, a correction was considered on account of the apparent loss of strength caused by second-order effects which were kept separate from the actual degradation. Through this process, the post-peak reduction of the envelope became milder (see Fig. 2b which schematically illustrates the resulting differentiated envelope resistance curve as modified from the original experimental result).

The influence of the correction is negligible for low levels of relative drift (<1%) but it becomes significant at higher levels. The conceptional failure point at 20% loss of shear strength was defined to quantify the ductility that led to this degradation (i.e., in 80% residual strength, see Fig. 2c). This displacement divided by the yielding displacement gives the ductility level at shear failure, $\mu_{\Delta,Sh-fail}$. For this value of ductility, the estimated degradation of the code models was calculated and compared with the 20% loss that was used as an anchor point reference (nominal shear failure).

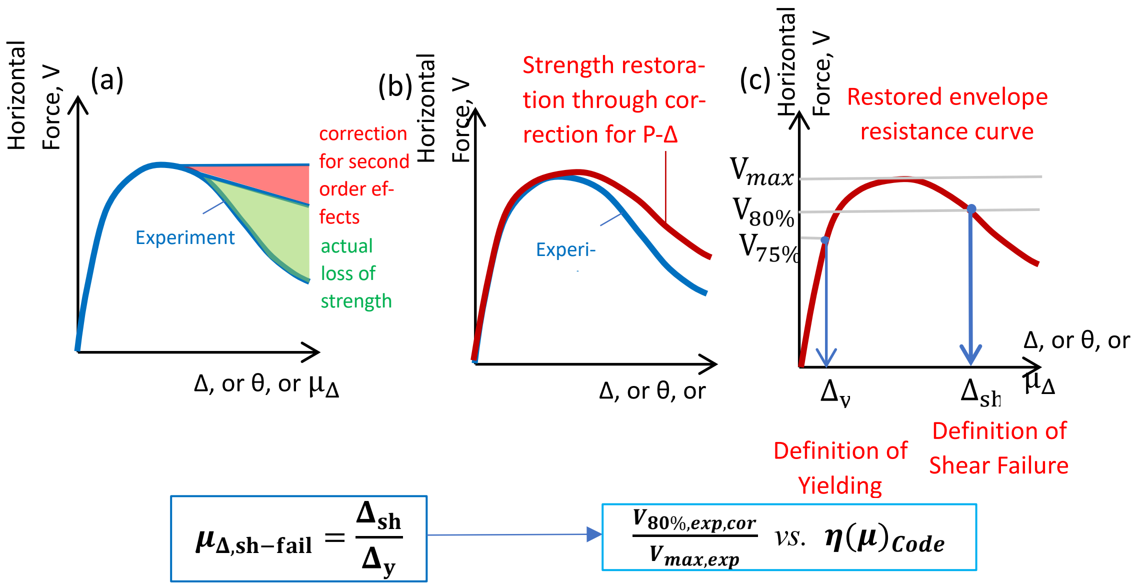

Figure 2: Schematic representation of the influence of second-order effects in the envelope resistance curve.

A comprehensive selection and correction of the available experimental results were carried out, which aimed to remove any experimental bias and the statically quantifiable effects such as P-Δ from the strength degradation relationships. In the selected dataset, RC columns with rectangular cross sections, tested under static cyclic loading to single or double curvature were included. The criterion for the specimens' selection was the reporting of a pure shear or a flexure-shear failure, which meant that longitudinal reinforcement yielding preceded the observed shear failure. Several of the specimens were extracted from available databases from [1] and [8]. RC column specimens in the dataset are drawn from the experimental studies of, [8-26]. The collection of data is given in Appendix A, which were used for the training of the proposed predictive formula.

4 INVESTIGATION OF PROPOSED AND EXISTENT FORMULAE

Figure 3 shows a comparison of the experimental values from the dataset in Appendix A against the proposed model related to the shear strength evaluation of Equation 3 [3] and the respective suggested model from [2] (see Equation 2). The purpose of the study was to verify the consistency of the examined models in terms of actual experimental RC column shear or flexure-shear failures to propose an improved model using a numerical methodology as detailed in the following section.

$$V_n = 0.4\xi bd\sqrt{f_c{}'} + \lambda \cdot \nu \cdot (bdf_c)\tan\alpha + A_{st}f_{yt}\frac{d(1-\xi)}{s} \cdot \cot\theta_v \quad (3)$$

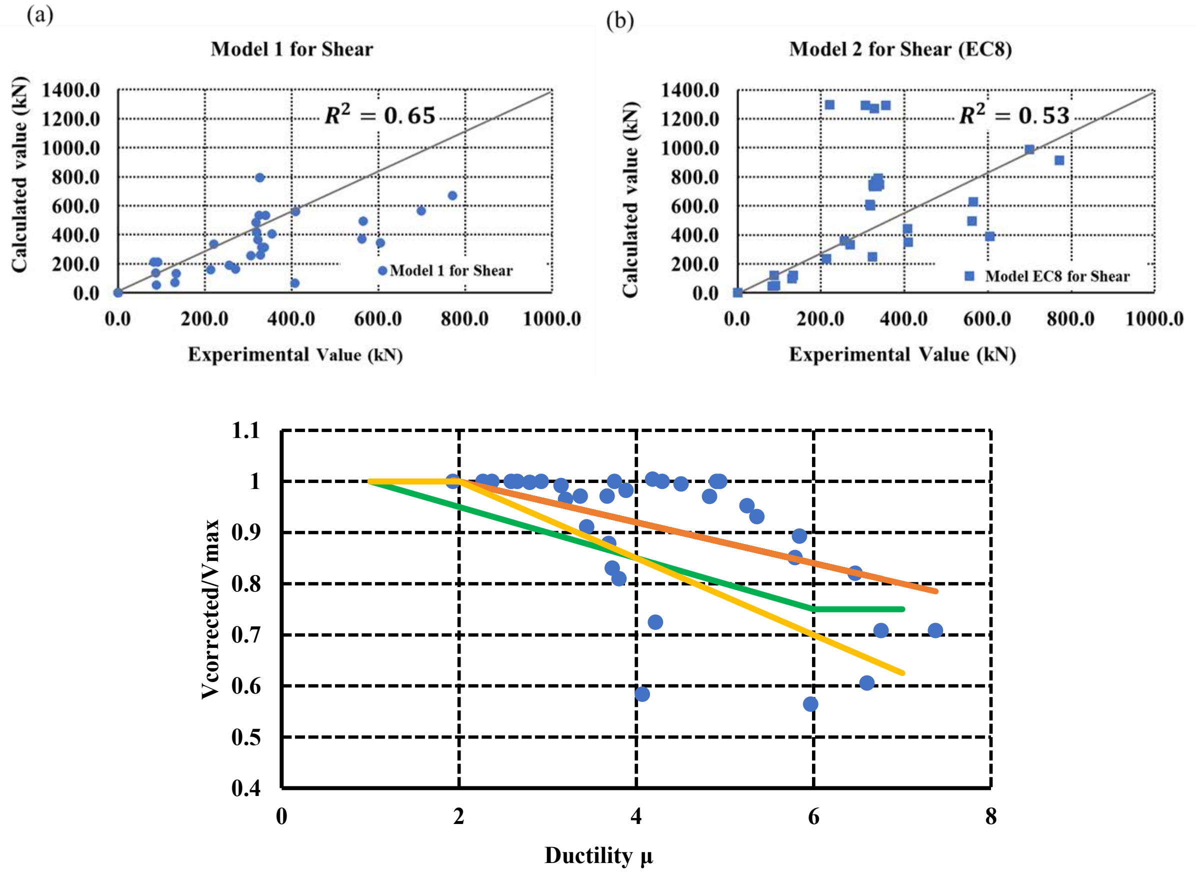

Figure 3: Correlation of data base elements experimental corrected maximum shear strength vs. proposed models (a) Proposed model by [3]; (b) Proposed model by [2]; Degradation models of flexure-shear failures after correction of the data. (Green line: Eurocode; Yellow: ASCE/SEI -41).

In Fig. 3, the 45° line represents the equal value case, whereas points found above it are cases where the analytical estimate overestimates the experiment and points below are conservative estimates. Consistent overestimation suggests the need for the introduction of a safety factor, while distant dispersion from the equal value line suggests poor predictive capacity. It is easy to observe that the model proposed by [3] has a higher correlation value of $R^2 = 0.65$ than the current [2] model, which has a correlation coefficient of $R^2 = 0.53$. This result underscores the need for improvement of the maximum shear strength estimate and to achieve this objective, machine learning has been used.

5 OPTIMIZATION OF SHEAR STRENGTH ESTIMATION USING A MACHINE LEARNING ALGORITHM

The machine learning (ML) algorithm's basic concepts are based on the polynomial regression method with hyperparameter tuning [6, 7, 22] and are focused on the formation of nonlinear terms made up of various combinations of independent variables up to the third degree. The method may choose nonlinear features that correlate to the lowest prediction error automatically [22] deriving the best predictive model that avoids overfitting.

The algorithm was set to train on 90% of the data by discovering relative relationships, where the remaining 10% of the data were then used to evaluate the performance of the developed shear strength equations after training. This procedure was repeated 100 times, by choosing randomly permutated subsets of the training set, in a cross-validation setting. The ML algorithm has been developed in Julia programming language [27, 28] and now is also available in Python. Through this research work, it was also confirmed that the proposed ML algorithm is efficient in supplying the necessary tools for constructing the prediction formula based on the numerical inquiry performed for achieving the purposes of this research work. Eq. 4 shows the resulting predictive formula that is proposed herein after the training with the ML algorithm took place. Fig. 4 shows the results of the numerically derived model for the case of the 3-feature formula.

$$V_{3-feat.} = a \cdot d \cdot f_{yw} \cdot \theta_v + b \cdot f_{yl} \cdot A_{tr} \cdot v + c \cdot s^2 \cdot v \quad \text{all units in mm, MPa, and degrees} \quad (4)$$

$$\theta_v = 45^o \; f, or \; v \leq 0.10 \;\; \theta_v = 45^o - \; 15^o . \frac{v}{0.25} \geq 30^o \; for \; v \geq 0.25$$

$$a = 4x10^{-4}, b = 4.1x10^{-3}, c = 2.87 \times 10^{-2}$$

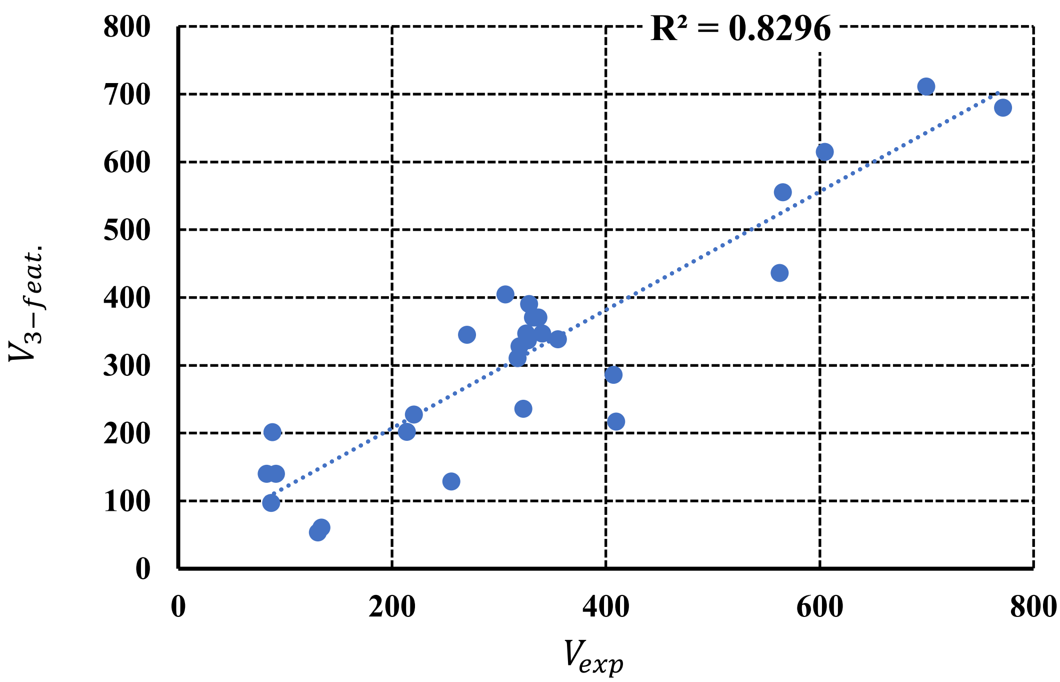

Figure 4: Validation data for the proposed model. Correlation of the 3-feature formula.

6 CONCLUSIONS

The present study investigated the strength and deformation parameters defining the mechanical behavior of RC columns under lateral sway such as what is occurring during seismic loading, focusing on the details of the failure mechanisms of columns. A carefully chosen collection of specimens from the experimental database that highlights the behavior of columns experiencing shear failure after flexural yielding was assembled in order to study the parametric sensitivity of the examined data, while at the same time, an evaluation of existing relationships for the limit state failure in strength term was carried out (shear mechanism failure and bearing capacity at failure). It was seen that a fraction of the apparent strength degradation of columns is actually a manifestation of second-order effects, where the remaining fraction of shear strength reduction, which is an effect of internal damage of the shear resisting mechanism, although significant, is relatively milder than originally accounted for in terms of ductility.

A dataset of 74 samples of RC columns was assembled to train a predictive model through an ML algorithm that uses polynomial regression and hyperparameter tuning. Following the training and testing, the numerically obtained predictive formula was evaluated and compared to the currently available models found in the international literature. The proposed formula's predictions demonstrated an improved accuracy with a correlation factor $R^2 = 0.83$, which is significantly more accurate than the EC8 equation ($R^2 = 0.53$) and the respective model in [3] that resulted in a correlation factor of $R^2 = 0.65$. Future work foresees the enhancement of the dataset found in Appendix A, where more ML algorithms will be used in the development of more objective and accurate predictive models.

REFERENCES

[1] Berry, M. Parrish, M.; Eberhard, M. PEER Structural Performance Database User's Manual (Version 1.0). 44, 2004.

[2] European Committee for Standardization. EN 1998-3:2005, Design of Structures for Earthquake Resistance – Part 3: Assessment and Retrofitting of Buildings, 2005.

[3] Pardalopoulos, S. J.; Thermou, G. E.; Pantazopoulou S. J. Preliminary Seismic Assessment Method for Identifying R. C. Structural Failures. In Computational Methods in Earthquake Engineering; Springer Dordrecht Heidelberg New York London, Vol. 2, 2013.

[4] ASCE/SEI 41. Seismic Rehabilitation of Existing Buildings, American Society of Civil Engineers, 2007.

[5] Chasioti, S.; Megalooikonomou, K.; Pantazopoulou, S. J. Shear Strength Assessment of Reinforced Concrete Columns. In Proceedings of the 4th International Conference on Computational Methods in Structural Dynamics and Earthquake Engineering (COMPDYN 2013); Institute of Structural Analysis and Antiseismic Research School of Civil Engineering National Technical University of Athens (NTUA) Greece: Kos Island, Greece; pp 927–940, 2013. https://doi.org/10.7712/120113.4567.C1506.

[6] Markou, G.; Bakas, N. P. Prediction of the Shear Capacity of Reinforced Concrete Slender Beams without Stirrups by Applying Artificial Intelligence Algorithms in a Big Database of Beams Generated by 3D Nonlinear Finite Element Analysis, 2021.

[7] Taljaard, V.-L.; Gravett, D. Z.; Mourlas, C.; Markou, G.; Bakas, N.; Papadrakakis, M. Development of a New Fundamental Period Formula by Considering Soil0 Structure

Interaction with the Use of Machine Learning Algorithms; Athens, Greece; pp 3801–3809, 2021. https://doi.org/10.7712/120121.8748.18534.

[8] Kim, C.-G.; Park, H.-G.; Eom, T.-S. Cyclic Load Test and Shear Strength Degradation Model for Columns with Limited Ductility Tie Details. J. Struct. Eng., 145 (2), 04018249, 2019. https://doi.org/10.1061/(ASCE)ST.1943-541X.0002254.

[9] Abraham Christopher Lynn, J. P. M. Seismic Evaluation of Existing Reinforced Concrete Building Columns. Thesis, University of California at Berkley, California, 2001.

[10] Henkhaus, K.; Pujol, S.; Ramirez, J. Axial Failure of Reinforced Concrete Columns Damaged by Shear Reversals. J. Struct. Eng., 139 (7), 1172–1180, 2013. https://doi.org/10.1061/(ASCE)ST.1943-541X.0000673.

[11] Zhou, X.; Satoh, T.; Jiang, W.; Ono, A.; Shimizu, Y. Behavior of Reinforced Concrete Short Column Under High Axial Load, 1987.

[12] Nagasaka, T. Effectiveness of Steel Fibre as Web Reinforcement in Reinforced Concrete Columns, 1982.

[13] Arakawa, T.; Arai, Y.; Mizoguchi, M.; Yoshida, M. Shear Resisting Behavior of Short Reinforced Concrete Columns Under Biaxial Bending-Shear, 1989.

[14] Umehara, H.; Jirsa, J. O.; ASCE, M. Short Rectangular RC Columns Under Bidirectional Loadings. Journal of Structural Engineering 110(3), 605–618, 1984.

[15] Riyad S. Aboutaha, M. D. E.; James O. Jirsa, M. E. K. Rehabilitation of Shear Critical Concrete Columns by Use of Rectangular Steel Jackets. SJ, 96 (1), 1999. https://doi.org/10.14359/597.

[16] Sokoli, D.; Ghannoum, W. M. High-Strength Reinforcement in Columns under High Shear Stresses. ACI Structural Journal, 113 (3), 2016. https://doi.org/10.14359/51688203.

[17] Matchulat, L.; Adolfo, M. Mitigation of Collapse Risk in Vulnerable Concrete Buildings. University of Kansas, No. Master of Science, 122, 2008.

[18] Halil Sezen, J. P. M.; Khalid M. Mosalam. Seismic Behavior and Modeling of Reinforced Concrete Building Columns, University of California, 2002.

[19] Pujol, S. Drift Capacity of Reinforced Concrete Columns Subjected to Displacement Reversals, Purdue University, 2002.

[20] Ohue, M.; Morimoto, H.; Fujii, S.; Morita, S. The Behavior of R. C. Short Columns Failing in Splitting Bond-Shear Under Dynamic Lateral Loading. Transactions of the Japan Concrete Institute 1985.

[21] Amitsu, Shigeyuki; Shirai, Nobuaki; Adachi, Hiromi; and Ono, Arata (1991). "Deformation of Reinforced Concrete Column with High or Fluctuating Axial Force," Transactions of the Japan Concrete Institute, Vol. 13, pp. 355-362, 1991.

[22] Martirossyan, A.; Xiao, Y. Flexural-Shear Behavior of High-Strength Concrete Short Columns. Earthquake Spectra, 17 (4), 679–695, 2001. https://doi.org/10.1193/1.1423656.

[23] Zhou, X.; Higashi; Yoichi, J.; Weishan, S.; Yasushi. Behavior of Reinforced Concrete Column Under High Axial Load, 1985.

[24] Imai; Hiroshi; Yamamoto; Yoshie. A Study on Causes of Earthquake Damage of Izumi High School Due to Miyagi-Ken-Oki Earthquake in 1978, 1986.

[25] Ono, A.; Shirai, N.; Adachi, H., and Sakamaki, Y. "Elasto-Plastic Behavior of Reinforced Concrete Column with Fluctuating Axial Force," Transactions of the Japan Concrete Institute, Vol. 11, pp. 239-246, 1989.

[26] Van der Westhuize, A.; Markou, G.; Bakas, N. Development of a New Fundamental Period Formula for Steel Structures Considering the Soil-Structure Interaction with the Use of Machine Learning Algorithms: In Proceedings of the 14th International Conference on Agents and Artificial Intelligence; Science and Technology Publications: pp 952–957, 2022. https://doi.org/10.5220/0010978400003116 .

[27] Bezanson, J.; Edelman, A.; Karpinski. S., S., V. B. Julia: A Fresh Approach to Numerical Computing. 59 (1), 65–98, 2017. https://doi.org/10.1137/141000671.

[28] Murphy, K. P. Machine Learning: A Probabilistic Perspective; Adaptive computation and machine learning series; MIT Press: Cambridge, MA, 2012.

APPENDIX A

Table A: Data set with specimen details

Reference	Test	Member	Loading	L_s	h_{col}	b	h	a/d	d	cover(mm)	ρ_{tot}	f_{yl}	d_{bl}	f'_c	d_{bw}	A_{tr}	s	f_{yw}	ρ_w	v	P(KN)	Failure Mode
				(mm)	(mm)	(mm)	(mm)		(mm)		(%)	Mpa	(mm)	(Mpa)	(mm)		(mm)	(Mpa)	(%)	max	max	
Lynn et al(1996)	3SLH18	Column	Cycling	1473.0	2946.0	457.0	457.0	3.2	381.0	38.1	3.0	331.0	31.8	26.9	9.5	141.8	457.0	400.0	0.1	0.1	503.0	S
Lynn et al(1996)	3CMD12	Column	Cycling	1473.0	2946.0	457.0	457.0	3.2	381.0	38.1	3.0	331.0	31.8	27.6	9.5	241.0	305.0	400.0	0.2	0.3	1512.0	S
Lynn et al(1996)	3CMH18	Column	Cycling	1473.0	2946.0	457.0	457.0	3.2	381.0	38.1	3.0	331.0	31.8	27.6	9.5	141.8	457.0	400.0	0.1	0.3	1512.0	S
Henkhaus et al. 2013	B1	Column	Cycling	736.5	1473.0	457.0	457.0	1.6	401.4	35.0	1.5	455.0	22.2	20.0	9.5	141.8	457.0	490.0	0.1	0.4	1545.5	S
Henkhaus et al. 2013	B2	Column	Cycling	736.5	1473.0	457.0	457.0	1.6	404.6	35.0	1.5	455.0	22.2	19.3	6.4	63.3	203.0	455.0	0.1	0.4	1531.7	S
Henkhaus et al. 2013	B3	Column	Cycling	736.5	1473.0	457.0	457.0	1.6	401.4	35.0	1.5	455.0	22.2	22.1	9.5	141.8	457.0	490.0	0.1	0.2	969.3	S
Henkhaus et al. 2013	B4	Column	Cycling	736.5	1473.0	457.0	457.0	1.6	399.7	35.0	2.5	441.0	25.6	24.1	9.5	241.0	457.0	490.0	0.1	0.4	2164.3	S
Henkhaus et al. 2013	B5	Column	Cycling	736.5	1473.0	457.0	457.0	1.7	399.7	35.0	2.5	441.0	25.6	23.4	9.5	241.0	457.0	490.0	0.1	0.5	2248.1	S
Henkhaus et al. 2013	B6	Column	Cycling	1473.0	2946.0	457.0	457.0	3.2	399.7	35.0	2.5	490.0	25.6	27.6	9.5	241.0	305.0	469.0	0.2	0.1	634.1	S
Henkhaus et al. 2013	B7	Column	Cycling	1473.0	2946.0	457.0	457.0	3.2	399.7	35.0	2.5	490.0	25.6	28.3	9.5	241.0	305.0	469.0	0.2	0.1	650.1	S
Henkhaus et al. 2013	B8	Column	Cycling	1473.0	2946.0	457.0	457.0	3.2	399.7	35.0	2.5	490.0	25.6	29.0	9.5	241.0	305.0	469.0	0.1	0.1	666.2	S
Zhou et al. 1987	104-08	Column	Cycling	160.0	320.0	160.0	160.0	1.0	137.8	12.5	2.2	341.0	9.5	19.8	5.0	39.3	40.0	559.0	0.7	0.8	406.0	S
Zhou et al. 1987	114-08	Column	Cycling	160.0	320.0	160.0	160.0	1.0	137.8	12.5	2.2	341.0	9.5	19.8	5.0	39.3	40.0	559.0	0.7	0.8	406.0	S
Kim et al 2018	SBd2	Column	Cycling	1200.0	1200.0	400.0	400.0	3.0	334.8	40.0	2.5	571.0	25.0	32.0	12.7	253.4	165.0	500.0	0.4	0.2	870.4	S
Kim et al 2018	SBd4	Column	Cycling	1200.0	1200.0	400.0	400.0	3.0	334.8	40.0	2.5	571.0	25.0	32.0	12.7	253.4	82.0	500.0	0.8	0.2	870.4	S
Kim et al 2018	SCd2	Column	Cycling	1200.0	1200.0	400.0	400.0	3.0	334.8	40.0	2.5	571.0	25.0	32.0	12.7	253.4	165.0	500.0	0.4	0.2	870.4	S
Kim et al 2018	SDd2	Column	Cycling	1200.0	1200.0	400.0	400.0	3.0	334.8	40.0	2.5	571.0	25.0	32.0	12.7	253.4	165.0	500.0	0.4	0.1	512.0	S
Kim et al 2018	SDd4	Column	Cycling	1200.0	1200.0	400.0	400.0	3.0	334.8	40.0	2.5	571.0	25.0	32.0	12.7	253.4	82.0	500.0	0.8	0.2	870.4	S
Kim et al 2018	RFd2	Column	Cycling	1200.0	1200.0	250.0	640.0	4.8	187.4	40.0	2.4	566.0	22.2	32.0	9.5	212.6	105.0	530.0	0.8	0.2	870.4	S
Nagasaka 1982	HPRC10-63	Column	Cycling	300.0	600.0	200.0	200.0	1.5	176.2	12.0	1.3	371.0	12.7	21.6	5.5	47.5	35.0	344.0	0.7	0.2	146.9	S
Arakawa et al 1989	OA2	Column	Cycling	225.0	450.0	180.0	180.0	1.3	132.8	10.0	3.1	340.0	12.7	31.8	4.0	25.1	64.3	249.0	0.2	0.2	189.6	S
Arakawa et al 1989	OA5	Column	Cycling	225.0	450.0	180.0	180.0	1.3	132.8	10.0	3.1	340.0	12.7	33.0	4.0	25.1	64.3	249.0	0.2	0.4	475.8	S
Umehara and Jirsa 1982	CUS	Column	Cycling	455.0	910.0	410.0	230.0	1.1	369.5	25.0	3.0	441.0	19.0	34.9	6.0	56.5	89.0	414.0	0.3	0.2	533.2	S
Umehara and Jirsa 1982	CUW	Column	Cycling	455.0	910.0	230.0	410.0	2.0	189.5	25.0	3.0	441.0	19.0	34.9	6.0	56.5	56.0	414.0	0.3	0.2	533.2	S
Umehara and Jirsa 1982	2CUS	Column	Cycling	455.0	910.0	410.0	230.0	1.1	369.5	25.0	3.0	441.0	19.0	42.0	6.0	56.5	89.0	414.0	0.3	0.3	1069.4	S
Bet et.al. 1985	1_1	Column	Cucling	457.0	914.0	305.0	305.0	1.5	264.5	25.0	2.4	462.0	19.0	29.9	6.0	96.1	210.0	414.0	0.2	0.1	289.3	S
Aboutaha et al 1999	SC3	Column	Cycling	1219.2	1219.2	457.2	914.4	2.7	397.2	38.0	1.9	434.0	25.0	21.9	9.5	354.4	406.4	400.0	0.1	0.0	0.0	S
Aboutaha et al 1999	SC9	Column	Cycling	1219.2	1219.2	914.4	457.2	1.3	854.4	38.0	1.9	434.0	25.0	16.0	9.5	141.8	406.4	400.0	0.1	0.0	0.0	S
Sokoli and Ghannoum(2016)	CS-60	Column	Cycling	1066.8	2133.6	457.2	457.2	2.3	419.1	38.1	4.7	464.0	32.0	26.4	16.0	804.2	140.0	472.0	1.5	0.3	290.0	FS
Sokoli and Ghannoum(2016)	CS-100	Column	Cycling	1066.8	2133.6	457.2	457.2	2.3	419.1	38.1	2.9	700.0	25.0	32.0	10.0	314.2	114.0	820.0	0.7	0.3	1806.0	FS
Lynn et al(1996)	2CLH18	Column	Cycling	1473.0	2946.0	457.0	457.0	3.2	381.0	38.1	2.0	331.0	25.4	33.1	9.5	141.8	457.0	400.0	0.1	0.1	503.0	FS
Lynn et al(1996)	3CLH18	Column	Cycling	1473.0	2946.0	457.0	457.0	3.2	381.0	38.1	3.0	331.0	31.8	25.6	9.5	141.8	457.0	400.0	0.1	0.1	503.0	FS
Lynn et al(1996)	2SLH18	Column	Cycling	1473.0	2946.0	457.0	457.0	3.2	381.0	38.1	2.0	331.0	25.4	33.1	9.5	141.8	457.0	400.0	0.1	0.1	503.0	FS
Lynn et al(1996)(lap splice)	2CMH18	Column	Cycling	1473.0	2946.0	457.0	457.0	3.2	381.0	38.1	3.0	331.0	25.4	25.7	9.5	141.8	457.0	400.0	0.1	0.3	1512.0	FS
Lynn et al(1996)(lap splice)	3SMD12	Column	Cycling	1473.0	2946.0	457.0	457.0	3.2	381.0	38.1	3.0	331.0	31.8	25.6	9.5	241.0	305.0	400.0	0.2	0.3	1512.0	S
Matchulat et al. 2005	Sp.1	Column	Cycling	1473.0	2946.0	457.0	457.0	3.2	388.8	39.7	2.5	441.3	28.6	20.7	9.5	141.8	460.0	372.3	0.3	0.5	2159.5	FS
Matchulat et al. 2005	Sp.2	Column	Cycling	1473.0	2946.0	457.0	457.0	3.2	388.8	39.7	2.5	441.3	28.6	23.4	9.5	141.8	460.0	372.3	0.3	0.3	1663.0	FS

Reference	Test	Member	Loading	L_s	h_{col}	b	h	a/d	d	cover(mm)	ρ_{tot}	f_{yl}	d_{bl}	f'_c	d_{bw}	A_{tr}	s	f_{yw}	ρw	v	P(KN)	Failure Mode
Sezen and Moehle 2002	Specimen 1	Column	Cycling	1451.6	2903.2	457.0	457.0	3.2	368.1	65.1	2.5	434.4	28.7	21.1	9.5	241.0	304.8	476.0	0.2	0.2	665.4	FS
Sezen and Moehle 2002	Specimen 2	Column	Cycling	1451.6	2903.2	457.0	457.0	3.2	368.1	65.1	2.5	434.4	28.7	21.1	9.5	241.0	304.8	476.0	0.2	0.6	2666.1	FS
Sezen and Moehle 2002	Specimen 4	Column	Cycling	1451.6	2903.2	457.0	457.0	3.2	368.1	65.1	2.5	434.4	28.7	21.8	9.5	241.0	304.8	47.0	0.2	0.1	664.7	FS
Wight and Sozen 1973	40.033a(East)	Column	Cycling	876.0	876.0	152.0	305.0	2.9	254.2	32.0	2.5	496.0	19.0	34.7	6.3	62.3	127.0	345.0	0.3	0.1	188.2	FS
Wight and Sozen 1973	40.033a(west)	Column	Cycling	876.0	876.0	152.0	305.0	2.9	254.2	32.0	2.5	496.0	19.0	34.7	6.3	62.3	127.0	345.0	0.3	0.1	188.2	FS
Wight and Sozen 1973	40.048.(East)	Column	Cycling	876.0	876.0	152.0	305.0	2.9	254.2	32.0	2.5	496.0	19.0	26.1	6.3	62.3	89.0	345.0	0.5	0.1	177.9	FS
Wight and Sozen 1973	40.048(West)	Column	Cycling	876.0	876.0	152.0	305.0	2.9	254.2	32.0	2.5	496.0	19.0	26.1	6.3	62.3	89.0	345.0	0.5	0.1	177.9	FS
Wight and Sozen 1973	40.033(East)	Column	Cycling	876.0	876.0	152.0	305.0	2.9	254.2	32.0	2.5	496.0	19.0	33.6	6.3	62.3	127.0	345.0	0.3	0.1	177.6	FS
Wight and Sozen 1973	40.033(West)	Column	Cycling	876.0	876.0	152.0	305.0	2.9	254.2	32.0	2.5	496.0	19.0	33.6	6.3	62.3	127.0	345.0	0.3	0.1	177.6	FS
Wight and Sozen 1973	25.033(East)	Column	Cycling	876.0	876.0	152.0	305.0	2.9	254.2	32.0	2.5	496.0	19.0	33.6	6.3	62.3	127.0	345.0	0.3	0.1	110.6	S
Wight and Sozen 1973	25.033(West)	Column	Cycling	876.0	876.0	152.0	305.0	2.9	254.2	32.0	2.5	496.0	19.0	33.6	6.3	62.3	127.0	345.0	0.3	0.1	110.6	FS
Wight and Sozen 1973	40.067(East)	Column	Cycling	876.0	876.0	152.0	305.0	2.9	254.2	32.0	2.5	496.0	19.0	33.4	6.3	62.3	64.0	345.0	0.7	0.1	178.1	FS
Wight and Sozen 1973	40.067(West)	Column	Cycling	876.0	876.0	152.0	305.0	2.9	254.2	32.0	2.5	496.0	19.0	33.4	6.3	62.3	64.0	345.0	0.7	0.1	178.1	FS
Wight and Sozen 1973	40.147(East)	Column	Cycling	875.0	875.0	152.0	305.0	2.9	254.0	32.0	2.5	496.0	19.0	33.5	9.5	141.8	64.0	317.0	1.5	0.1	178.6	FS
Wight and Sozen 1973	40.147(West)	Column	Cycling	875.0	875.0	152.0	305.0	2.9	254.0	32.0	2.5	496.0	19.0	33.5	9.5	141.8	64.0	317.0	1.5	0.1	178.6	FS
Wight and Sozen 1973	40.092(East)	Column	Cycling	875.0	875.0	152.0	305.0	2.9	254.0	32.0	2.5	496.0	19.0	33.5	9.5	141.8	102.0	317.0	0.9	0.1	178.6	FS
Wight and Sozen 1973	40.092(West)	Column	Cycling	875.0	875.0	152.0	305.0	2.9	254.0	32.0	2.5	496.0	19.0	33.5	9.5	141.8	102.0	317.0	0.9	0.1	178.6	FS
Ohue et al. 1985	2D16RS	Column	Cycling	400.0	800.0	200.0	200.0	2.0	174.5	11.0	2.0	369.0	16.0	32.0	5.5	47.5	50.0	316.0	0.6	0.1	183.0	FS
Ohue et al. 1985	4D13RS	Column	Cycling	400.0	800.0	200.0	200.0	2.0	176.0	12.0	2.7	370.0	13.0	29.9	5.5	47.5	50.0	316.0	0.6	0.2	183.0	FS
Zhou et al. 1987	124-08	Column	Cycling	160.0	320.0	160.0	160.0	1.0	137.8	12.5	2.2	341.0	9.5	19.8	5.0	66.8	40.0	559.0	1.8	0.8	406.0	FS
Zhou et al. 1987	204-08	Column	Cycling	320.0	640.0	160.0	160.0	2.0	137.8	12.5	2.2	341.0	9.5	21.1	5.0	39.3	40.0	559.0	0.7	0.8	432.7	FS
Zhou et al. 1987	223-09	Column	Cycling	320.0	640.0	160.0	160.0	2.0	137.8	12.5	2.2	341.0	9.5	21.1	5.0	66.8	40.0	559.0	1.8	0.9	486.1	FS
Zhou et al. 1987	302-07	Column	Cycling	480.0	960.0	160.0	160.0	3.0	137.8	12.5	2.2	341.0	9.5	28.8	5.0	39.3	40.0	559.0	0.7	0.7	516.8	FS
Zhou et al. 1987	312-07	Column	Cycling	480.0	960.0	160.0	160.0	3.0	137.8	12.5	2.2	341.0	9.5	28.8	5.0	39.3	40.0	559.0	0.6	0.7	516.8	FS
Zhou et al. 1987	322-07	Column	Cycling	480.0	960.0	160.0	160.0	3.0	137.8	12.5	2.2	341.0	9.5	28.8	5.0	66.8	40.0	559.0	1.0	0.7	516.8	FS
Amitsu et al. 1991	CB060C	Column	Cycling	323.0	646.0	278.0	278.0	1.2	230.0	28.0	4.1	441.0	28.0	46.3	6.0	90.5	52.0	414.0	0.9	0.7	2633.6	FS
Xiao and Martirossyan 1998	HC4-8L16-T6-0.1P	Column	Cycling	508.0	1016.0	254.0	254.0	2.0	226.7	13.0	2.5	510.0	15.9	86.0	6.4	96.5	51.0	449.0	1.6	0.1	532.6	FS
Xiao and Martirossyan 1998	HC4-8L16-T6-0.2P	Column	Cycling	508.0	1016.0	254.0	254.0	2.0	226.7	13.0	2.5	510.0	15.9	86.0	6.4	96.5	51.0	510.0	1.6	0.2	1065.3	FS
Kim et al 2018	SAd2	Column	Cycling	1200.0	1200.0	400.0	400.0	3.0	334.6	40.0	2.5	571.0	25.4	32.0	12.7	253.4	165.0	500.0	0.4	0.2	870.4	FS
Kim et al 2018	RGd2	Column	Cycling	1200.0	1200.0	250.0	640.0	4.8	187.4	40.0	2.4	566.0	22.2	32.0	9.5	212.6	105.0	530.0	0.8	0.2	870.4	FS
Nagasaka 1982	HPRC19-32	Column	Cycling	300.0	300.0	200.0	200.0	1.5	176.2	12.0	1.3	371.0	12.7	21.0	5.5	47.5	20.0	344.0	1.2	0.4	294.0	FS
Zhou et al 1985	No.806	Column	Cycling	80.0	80.0	80.0	80.0	1.0	63.0	10.0	1.8	336.0	6.0	32.3	4.0	25.1	80.0	341.0	0.4	0.6	124.0	FS
Zhou et al 1985	No. 1007	Column	Cycling	80.0	80.0	80.0	80.0	1.0	63.0	10.0	1.8	336.0	6.0	34.0	4.0	25.1	80.0	341.0	0.4	0.7	152.3	FS
Zhou et al 1985	No.1309	Column	Cycling	80.0	80.0	80.0	80.0	1.0	63.0	10.0	1.8	336.0	6.0	32.8	4.0	25.1	80.0	341.0	0.4	0.9	188.9	FS
Imai and Yamamoto 1986	No 1	Column	Cycling	825.0	825.0	500.0	400.0	1.7	443.0	37.0	2.7	318.0	22.0	27.1	9.0	127.2	100.0	336.0	0.3	0.1	390.2	FS
Ono et al. 1989	CA025C	Column	Cycling	300.0	300.0	200.0	200.0	1.5	170.3	19.0	2.1	361.0	9.5	25.8	6.0	113.1	70.0	426.0	0.8	0.3	265.2	FS
Ono et al. 1989	CA060C	Column	Cycling	300.0	300.0	200.0	200.0	1.5	170.3	19.0	2.1	361.0	9.5	25.8	6.0	113.1	70.0	426.0	0.8	0.6	635.7	FS